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DEADWOOD ASSESSMENT USING LIDAR TECHNOLOGY IN DISTURBANCE ECOLOGY

PhD Program Coordinator: Prof. Davide Matteo Pettenella

Supervisor: Prof. Emanuele Lingua

PhD candidate: Niccolò Marchi

A mamma e papà,

per dimostrarmi ogni giorno il significato della parola "amore".

A mio fratello e a tutti gli amici,

che passo dopo passo addobbano di curiosità e bellezza ogni mia giornata.

Ai miei nipoti,

per ricordarmi che giocare non è una cosa da bambini.

CONTENTS

Abstract

Deadwood is a key component of the forest ecosystems, due to its importance as a life substrate for several organisms, such as plants, animals, fungi and lichens. This huge versatility is being recognised only in the last decades also by legislation after the increasing findings by the scientific community what biodiversity is and on what it is based. Nevertheless, at an operational level, deadwood conservation measures are not so well implemented yet because it is still widely considered as an issue for many of the forest stakeholders). While from a production point of view it can be seen as an income loss, it is generally evaluated as a risk for all the ones who frequent forests for work or leisure. While this applies mostly to finer scales, at larger scales the presence of big amounts of deadwood surely derives from an economical damage for the land manager and appears as a sign negligence to the local population. Such is the case of natural disturbances, e.g. wildfires, windstorms, ice and snow damages, events that strongly affect communities both in ecological and economical terms. Due to an estimated increase of extreme events in the future in relation to global warming, it is important to timely assess wide scale processes in order to understand the underlying dynamics and properly manage the available forest resources. Extreme events can indeed alter the ecosystem functionality threatening the provision of forest services such as conservation of drinking water, protection from natural hazards and preservation of biodiversity. Deadwood is strictly connected to fine and large scale disturbances, enhancing (e.g. severity of wildfires) or mitigating them (e.g. favouring the natural regeneration after a destructive event), but the dynamics at landscape level are not always well known. Related data, indeed, was always collected through ground surveys, methods that required huge efforts in terms of time and energies. In this perspective, remote sensing technologies can help to catch useful information within less time across wide areas or with higher detail. Optical sensors, such as aerial photographs, became more easily accessible in the last decades but the information that can be obtained, even with the application of photogrammetry techniques, lacks of reliability for what concerns structural parameters of forests. The recent advent and development of active sensors provided the possibility of extracting information on all the three dimensions of the forest structure, allowing the study of structure characteristics and the identification of what lies beneath canopies. It is the case of Light Detection and Ranging (LiDAR), a laser-based technology that is widely proving its effectiveness in providing valuable data in the forestry field.

LiDAR technology was chosen as main tool within the present research project dedicated to the application and development of methodologies for the identification and quantification of several deadwood components. The research approach followed a thorough literature review to describe the state-of-the-art on the topic and define the knowledge gaps and future perspectives. This work lead to the definition of three specific study cases that would have deepened: 1) the assessment of ice-storm damages on alpine

production stands, 2) the characterisation of deadwood and the description of its role in the regeneration establishment within a post-fire restoration site and 3) the quantification and description of the three-dimensional spatial distribution of surface fuels in conifer-dominated stands. The results obtained in the three case studies show the feasibility of capturing important structural information about different elements of deadwood, useful to describe local and global processes for the study of ecological dynamics related deadwood in the context of natural disturbances.

Riassunto

La necromassa legnosa è un elemento chiave degli ecosistemi forestali, per via della sua importanza come substrato utile alla vita di numerosi organismi, come piante, animali, funghi e licheni. Solo negli ultimi decenni questa grande versatilità sta trovando riconoscimento anche a livello normativo, supportata da una sempre più ampia letteratura scientifica relativa alla definizione di biodiversità e gli elementi che la compongono. Ciò nonostante, su un piano operativo, le misure per la conservazione della necromassa legnosa non sono adeguatamente implementate in quanto viene ancora considerata come un problema da molti di coloro che frequentano gli ambienti forestali. Mentre infatti può essere vista come un mancato reddito dal punto di vista economico, la presenza di necromassa può risultare come un pericolo per chi svolge attività in foresta (utilizzazioni forestali, turismo). Se questo si può applicare a ragionamenti di piccola scala, abbondanti quantità di necromassa su vasta scala sono sicuramente legate ad un danno economico per i gestori forestali e vengono viste come segno di abbandono dalla popolazione. È il caso dei disturbi naturali, come incendi, trombe d'aria, danni da neve e ghiaccio, eventi che interessano le comunità antropiche sia in termini ecologici che economici. Considerando un incremento stimato degli eventi meteorologici estremi dovuto alle dinamiche di riscaldamento globale, è importante effettuare accertamenti tempestivi su vasta scala per capire le dinamiche che intercorrono e gestire prontamente le risorse forestali a disposizione. Gli eventi estremi infatti possono alterare la funzionalità degli ecosistemi minacciando l'approvvigionamento di servizi ecosistemici quali la fornitura di acqua potabile, la protezione dal dissesto idrogeologico e la conservazione della biodiversità. La necromassa legnosa è strettamente connessa a disturbi su piccola e grande scala, nei confronti dei quali può amplificarne gli effetti (come nel caso di incendi) o mitigarli (favorendo la rinnovazione naturale in siti percorsi da disturbi di alta severità), anche se le dinamiche su grande scala non sono ancora ben chiare. I dati infatti sono sempre stati raccolti tramite rilievi di campo, metodi molto dispendiosi in termini di tempo e denaro. In questa prospettiva, le tecnologie di telerilevamento possono aiutare a raccogliere informazioni in minor tempo su estensioni maggiori e con maggior dettaglio. I sensori ottici, come la fotografia aerea, è diventata di largo uso negli ultimi decenni ma le informazioni che se ne possono estrarre, anche con l'ausilio di tecniche di fotogrammetria, manca di affidabilità per quanto riguarda i parametri strutturali forestali. Il recente avvento e sviluppo di sensori attivi ha offerto la possibilità di ottenere dati su tutte e tre le dimensioni della struttura forestale, permettendo di studiarne le caratteristiche e identificare quanto nascosto dalla copertura delle chiome. È il caso del LiDAR, una tecnologia basata sull'utilizzo di laser che sta dando prova delle sue potenzialità nel settore forestale.

La tecnologia LiDAR è stata scelta come strumento principale del presente progetto di ricerca, dedicato allo sviluppo e applicazione di metodologie per

l'identificazione e la quantificazione di diversi componenti di necromassa legnosa. L'approccio del lavoro ha previsto una rigorosa ricerca bibliografica per definire lo stato dell'arte sull'argomento e identificare carenze e possibilità di approfondimento. Questo lavoro ha portato alla definizione di tre casi studio che avrebbero trattato: 1) la stima dei danni da ghiaccio su popolamenti produttivi alpini, 2) la caratterizzazione della necromassa legnosa e la descrizione del suo ruolo nei processi di affermazione della rinnovazione naturale in una situazione post-incendio e 3) la quantificazione e la descrizione della distribuzione spaziale nelle tre dimensioni dei combustibili forestali all'interno di popolamenti di conifere. I risultati ottenuti nei tre casi studio dimostrano la capacità del LiDAR di catturare importanti informazioni strutturali relative a diversi elementi di necromassa legnosa, utili a descrivere processi su piccola e larga scala per lo studio delle dinamiche che interessano la necromassa forestale nel contesto dei disturbi naturali.

1 Introduction

1.1 Importance of deadwood

Deadwood is becoming an increasingly important element for what concerns forestry. Its relevance as a key component of forest ecosystems is finally being recognised under different perspectives. Several studies related to different scientific areas (botany, entomology, wildlife management) and dealing with the evaluation of biodiversity in forest ecosystems converged towards the conclusion that deadwood is a source of opportunities for numerous taxa (Blaser et al., 2013; Grove, 2002; Lachat et al., 2007; Larrieu et al., 2014; Lassauce et al., 2011; Mason and Zapponi, 2016; Rondeux and Sanchez, 2010; Stokland et al., 2012; Venier et al., 2015). In the last decades, a major need for biodiversity protection led to an evolution of national and international laws in order to include conservation measures for deadwood (e.g. European Commission, 1992; Forest Europe and Ministerial Conference on the Protection of Forests in Europe, 2002).

Nevertheless, approaching to the topic is not simple due to the huge variety of considerations that should be taken into account. Deadwood indeed can be divided into different classes according to several characteristics origin (species), typology (snag, log, dead branch, etc.), size and decay status. Two classification systems widely used (and adopted also for the present work) are the schemes proposed by Harmon and Sexton (1996) and Hunter (1990). These provide respectively a classification of the different components that constitute deadwood and some key dimensional parameters (Figure 1) while the latter helps in the definition of the decay stages for the coarser elements (i.e. snags and logs; Figure 2)

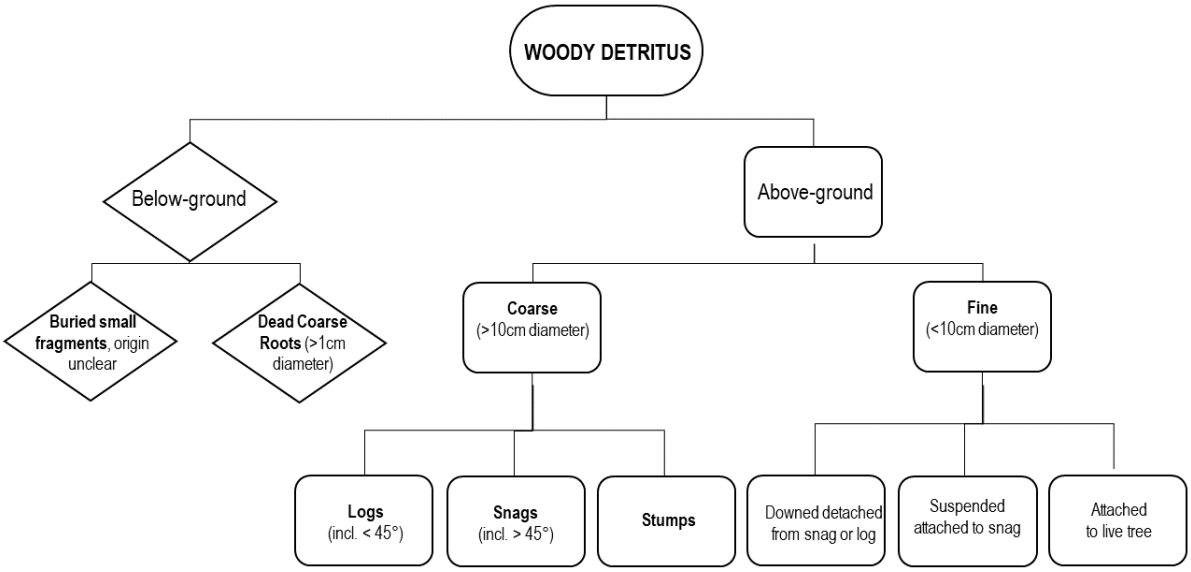

Figure 1: identification key for deadwood elements (from Harmon and Sexton, 1996, modified).

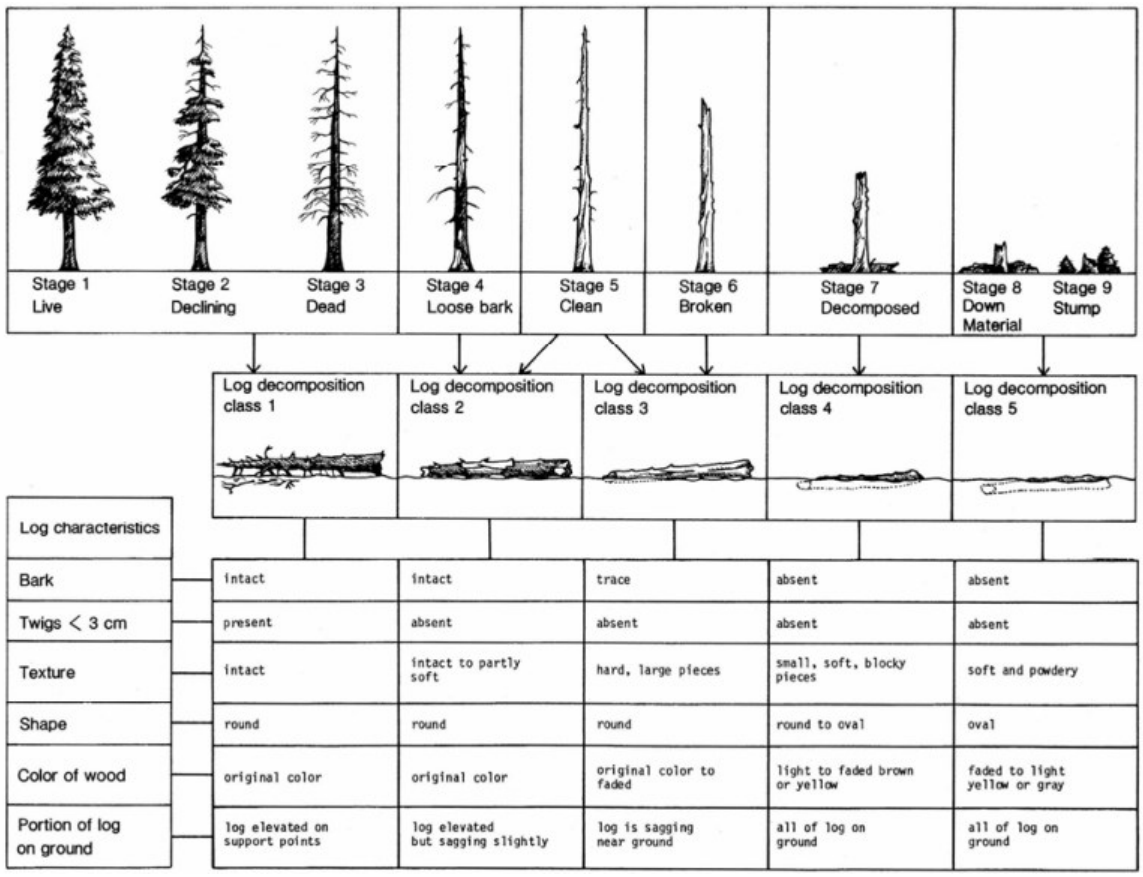

Figure 2: Decay status scheme for snags and downed logs (Hunter, 1990).

Forestry is progressively including all these information in operational planning and management, even if is not always an easy task to achieve. Deadwood has always had a negative reputation among forest managers, that considered it as a threat for forest workers and a possible source of pathogens (Merganičová et al., 2012). In addition, it can be perceived as a loss of income when the amount on a stand is set too high. For instance, for some European forest typologies, Müller and Bütler (2010) proposed deadwood amount ranges between 20–30 m^3/ha for boreal coniferous forests, 30–40 m^3/ha for mixed-mountain forests and 30–50 m^3/ha for lowland forests. Such values should be pursued at a landscape scale through a network of stands with a variable amount. This approach finds also an alternative in the "senescence islands", areas specifically planned for the purposes of deadwood retention. The abandonment of forest management would not help to achieve the proposed quantities in a short time (Bouget et al., 2014) and that's why in the recent years this has been thought as an active process to be favoured by specific actions (Cavalli and Mason, 2003; Mason et al., 2003).

In the overall understanding of the deadwood cycle, natural disturbances (e.g. wildfires, windstorms, snowstorms, pest outbreaks, etc.) play a dominant role at medium or large scales. In the period 1950-2000, natural disturbances caused a damage of 35 million m^3 of trees in the sole European forests (Schelhaas et al., 2003). Most of this material was then recovered through salvage logging but the strong impact that these events had at a landscape level and on the forest planning is pretty neat. Only in some cases the deadwood was not removed and consequences of such choice are still under evaluation (Leverkus et al., 2018). These alterations are supposed to be more pronounced in coniferous forests and the boreal biome even if, at the current stage, understanding of the effects on a large scale is still scarce (Seidl et al., 2017). In this perspective, the need for wide scale assessments to study such dynamics should rely on new technologies, capable of providing cheaper and more complete information (i.e. also from hardly accessible areas).

Figure 3: Senescent dead wood microhabitats (image from De Cinti et al (2016), nomenclature from Stokland et al. (2012) and Read (2000)): 1. Aerial roots feeding in the hole woody detritus, 2. Bark covered by mosses, 3. Small basal cavity, 4. Wet basal cavity, 5. Bird lime, 6. Bracket fungi, 7. Brocken main trunk with deep cavity, 8. Coarse decaying fallen limbs on the ground, 9. Crevices in the bark, 10. Dead branches in the canopy, 11. Dead roots, 12. Dead sun exposed trunk, 13. Decaying branches, 14. Phytotelm, 15. Detached bark with dry wooded detritus, 16. Dry bark pocket with fine woody detritus, 17. Dry medium dead limbs, 18. Epiphytic plants, 19. Holes in branches, 20. Lichens living on senescent trees (i.e. *Lobaria pulmonaria*), 21. Lightning strike, 22. Natural water pools, 23. Open wound surrounded with callus issue, 24. Proliferation of twigs caused by bacteria, 25. Root damage from browsing, 26. Root fungal colonization, 27. Saproxylic fungal colonization, 28. Suspended dead broken limb, 29. Water filled rot hole, 30. Wet pocket with fine woody detritus, 31. Woodpecker foraging holes, 32. Woodpecker nesting hole, 33. Wound with sap run flux. Drawing from Franco Mason.

1.2 Remote sensing applications in forestry

In the recent years a very strong change is concerning the sector connected to the environmental mapping and management.

Ground surveys have always been time and energy consuming, a characteristic that pushed the innovation of such process as long as the modern society needed data on wider and wider scales for the management of natural resources. In this perspective, in the 1850s photo interpretation moved the first step in this direction, permitting to explore and understand processes that before were restricted to the eyesight and personal interpretation. During the first half of the 20th century, photogrammetry transformed these observations into quantitative data for cartographical and topographical products. Nevertheless, only during 1970s, with the support of the innovative GPS systems, this technique acquired a definitive importance in the creation of Digital Terrain Models. As presented in Konecny (1985) this technological dynamic seems built up of 50-years cycles where, after the invention of a new instrumentation, it becomes of common use for the first 25 years and in the following 25 it shares the market with the new one of the next cycle. In the last decades we are observing a pretty important shift, not only in the sensors but also in the technique, a passage between passive to high power active sensors, from indirect to direct acquisition or encoding of 3D coordinates (Baltsavias, 1999). It is the case of RADAR and LiDAR technologies, based respectively on RAdio or Light Detection And Ranging.

The LiDAR technology was initially used for topographical purposes but its wide versatility made it become well known also to engineers for applications like the analysis of structural integrity of buildings or to meteorologists for the analysis of the atmosphere composition (*see* Measures, 1992). Strongly competing with photogrammetry for what concerns topographical and hydrological applications, the LiDAR technology showed its potential in the generation of Digital Terrain Models due to the laser ability of penetrating forest canopies. As a general example, experimentations from the University of Stuttgart found out that penetration rates to the ground could range from 20-40% in European coniferous stands to 70% in deciduous leaf-off ones (Ackermann, 1999). Thanks to the ability of describing a whole vegetation profile, LiDAR saw a rapidly increasing interest from the forestry community.

Only in the last decades the research is focusing on several applications (Lefsky et al., 2002), but, since the first studies, the suitability of LiDAR data for forestry activities on wide-scale such as stand characterization and management (Akay et al., 2009; Andersen et al., 2002; Maltamo et al., 2004; Moskal et al., 2009; Næsset and Økland, 2002; Reutebuch et al., 2005; Sherrill et al., 2008; Zimble et al., 2003), forest wildfire management (Andersen et al., 2005; Mutlu et al., 2008; Riaño et al., 2004, 2003) and forest road planning (Akay et al., 2003; Aruga et al., 2005) was clear.

In a short time span, this technology received many technical improvements and developments, reducing gradually the initial disadvantages mostly related to the high data collection costs. High-density datasets started to be available at an accessible price and consequently new algorithms were developed to reach a higher detail possible, shifting the point of view from a plot-based to a single-tree perspective. In the case of Italy, the use of LiDAR data was recognised as a good solution for continuing the historical series of dendrometrical data of the management plans, even in those small local administrations that cannot afford the costs of ground surveys (Abramo et al., 2007). Nevertheless, across Europe, still such technology did not fully entered the application in the operational planning in many Countries (Barrett et al., 2016).

1.3 LiDAR: a quick overview

A laser scanner is an active sensor which emits a laser (Light Amplification by Stimulated Emission of Radiation) beam in the infra-red range to measures the distance between the sensor and the illuminated spot, retrieving three-dimensional information by transmitting short-duration pulses and recording the reflected echoes, every one of which is identified by the three spatial coordinates (x, y, z; Gobakken and Næsset, 2008). The characteristics of the beam's waveform can be analysed according to two techniques: discrete return or full-waveform. The first approach filters the energy peaks directly during the data collection while the second maintains the waveform information for each pulse. The discrete return approach is the most used one (Evans et al., 2009) because of its light weight and due to the established set of techniques that allow for the analysis of the derived data. Full-waveform data indeed are more difficult to elaborate and have higher computational requirements, reason why they are usually filtered (or "decomposed") in order to keep only the peaks, like for the discrete return approach.

The dataset containing the generated points create the so called "point cloud" which is often evaluated on the base of the density of points per square metre, a parameter that, in the case of ground-based sensors, can reduce measurement errors to only few millimetres (Bienert et al., 2006).

In the most recent years a wide number of review papers tried to summarise the evolution and availability of platforms and sensors (Toth and Józków, 2016). Focussing on the forestry sector, laser scanning systems can be divided as follows:

1. Aerial scanning:
    a. Spaceborne: satellite platforms; they often take the name from the project/satellite in charge (e.g. ICESat; *see* Lefsky et al. (2005), Simard et al. (2008)).

   b. Airborne: long-range flying vehicles (i.e. airplanes, helicopters; *see* (White et al., 2016))
   c. UAVborne: unmanned short-range flying vehicles (*see* (Zhang et al., 2016)).
2. Ground-based scanning:
   a. Terrestrial: sensor mounted on a tripod (*see* (Liang et al., 2016; White et al., 2016); Figure 5).
   b. Mobile: sensor mounted on vehicles (e.g. cars, trucks, trains, etc.)
   c. Hand-held: sensor carried around by an operator (*see* (Bauwens et al., 2016; Ryding et al., 2015)).

Most of the platforms provide for the possibility of dynamic surveys, while the terrestrial is the only static one. For what concerns dynamic surveys (vehicles, aircrafts or satellites) the scanning system is integrated by other sensors, such as a position and orientation system (POS), realised by an integrated differential GPS (DGPS) and an inertial measurement unit (IMU), and the control unit. In this case, the parameters related to the mentioned sensors are associated to each point, in order to define flight-lines, scanning angle and other information useful for further elaborations. Even if since 2002 a first step has been done towards a standardization of the exchange file format thanks to LAS format proposed by the American Society of Photogrammetry and Remote Sensing (ASPRS, 2013), still many efforts should be made for what concerns a wide application of it, the acquisition parameters and data processing (Evans et al., 2009).

Focussing on the systems that have been used in this thesis work, in Figure 4 are presented some basics about airborne LiDAR data characteristics, following the framework given in Gatziolis and Andersen (2008):

- Scanning frequency: the number of pulses or beams emitted by the instrument in one second and, thus, defined in Hertz (Hz). With the increasing in frequency is possible to achieve higher densities of discrete returns even increasing the speed and elevation of the aircraft, accelerating the survey and reducing the relative costs;
- Scanning pattern: the spatial arrangement of the pulse returns on the target surface; can vary from seesaw to linear or elliptical, depending on the mechanism used to direct pulses across the flight line (oscillating or rotating mirror);
- Beam divergence: the beam tends not to keep the cylindrical shape of the true laser and creates a narrow cone. This divergence is measured in millirad (mrad, usually between 0.1 and 1.0) and, spreading the energy on a bigger area, brings to a lower signal-to-noise ratio
- Scanning swath: the width of the scanned path, given by the combination of the scanning angle and the aboveground flight height,

- Footprint diameter: is the diameter of the beam on the ground from a specific height; the energy is not uniform over its extent and decreases radially from the centre following a two-dimensional Gaussian distribution;
- Number of returns per beam: is the maximum number of individual returns that can be extracted from a single beam;
- Pulse density: measures the spatial resolution and depends on the ratio 1/(footprint spacing)^2, where the denominator is the distance between the centres of two beams' footprints on the same scanning line;
- Return density: often confused with the pulse density, is the mean number of returns per square metre.

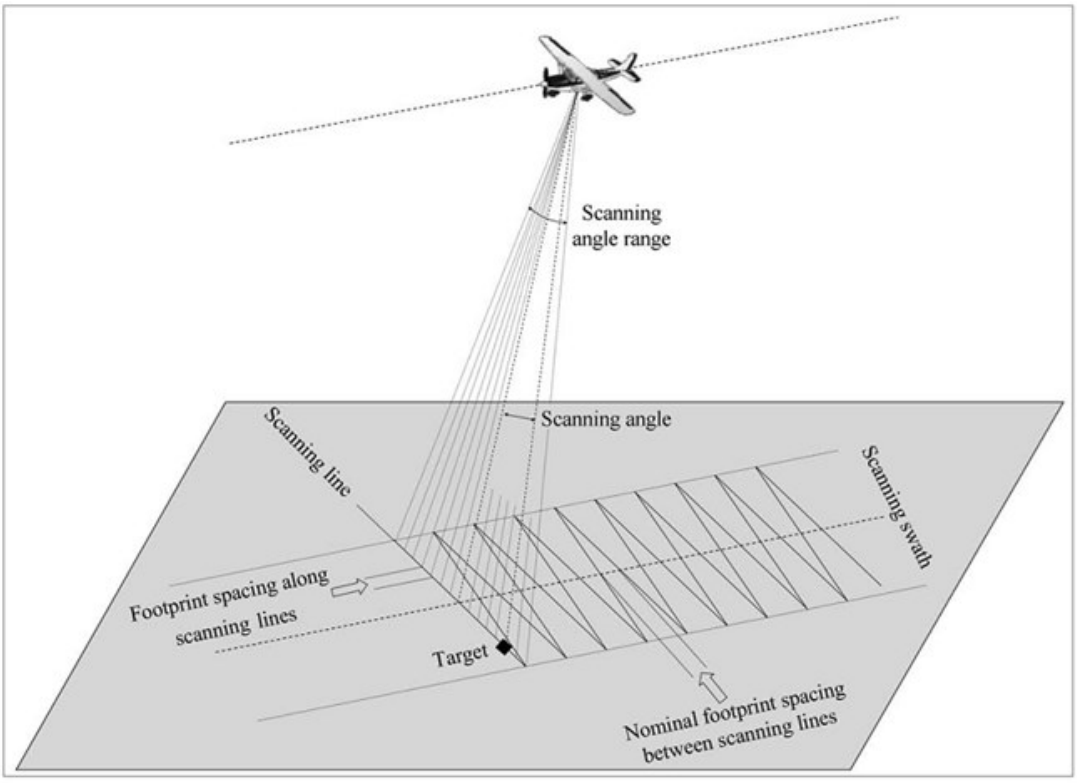

Figure 4: General scheme of an ALS survey and basic terminology (from Gatziolis and Andersen, 2008).

Figure 5: TLS system Riegl V400-I (photo: N. Marchi).

1.4 Objectives

In order to provide useful information for forest planning and to reduce economic expenditure connected to ground surveys, this research has its bases on three guiding questions:

- Can large-scale assessment for deadwood be reliably carried out through discrete LiDAR data?
- Can high detail surveys with TLS be useful for understaing the relationship between dead biomass distribution and environmental factors?
- Can high Density ALS-data contribute to better assess how do natural disturbances affect dead biomass presence and distribution?

The research project aimed at the development of a procedure for deadwood identification, quantification and quality assessment through remote sensed data under different site conditions (conifer/broadleaf stands) and for several deadwood components. Therefore, the technical parameters for planning effective laser scanning surveys (minimum point density, platform, etc.) were identified.

In detail, the main objectives can be summarised as follows:

1. Methodologies: develop and test the best approaches to identify and quantify different deadwood components;
2. Spatial distribution 1: evaluation of stand- and tree-level response to ice-storm damage as source for deadwood;
3. Spatial distribution 2: identify indicators that can describe the presence and abundance of lying deadwood among environmental parameters (e.g. aspect, slope, Heat Load Index) and morphological indexes (e.g. terrain roughness).
4. Spatial distribution 3: Characterise the 3D spatial distribution of forest fuels in fire-prone conifer stands.

Recent extreme events within the whole Alpine range (e.g. ice storms, wildfires) and the Sierra Nevada range (i.e. wildfires) have altered the local management and planning, due to their big impact on forest stands. Remote sensed data are capable to provide effective data in short time for fast problem solving and decision-making dealing with the necessary actions to take and the update of management plans.

1.5 Hypotheses

Large scale ecological modelling can provide useful information for forest planning in order to reduce economic expenditure connected to specific ground surveys and enhance forest management.

Following this perspective, the project has its bases on three guiding hypotheses:

- Large scale assessment for deadwood can be reliably detected through discrete LiDAR surveys.
- High-detail surveys can describe the relation between dead biomass distribution and environmental factors.
- Disturbances affect dead biomass presence and distribution and these characteristics can be captured using ALS data.

1.6 Structure of the manuscript

In order to meet the previously described objectives, the present manuscript was structured according to chapters concerning single case studies chosen to address specific aspects of the research topic. Each chapter is based on a published manuscript or unpublished drafts of scientific papers to be submitted on international journals A general introduction (Chapter 1) introduce the reader to the basic notions necessary for a better understanding of the presented works. A literature review is reported in Chapter 2 in order to provide an in deep overview of the application of LiDAR technologies for the identification and quantification of several deadwood components. The present work underlined the presence of knowledge gaps and hence the possibilities connected to the use or development of new approaches to describe some ecological processes through remote sensed data. Once highlighted the research topics of interest, some study cases were selected for the development and application of a specific methodology.

A first case study is presented in Chapter 3, where the use of a high-density airborne LiDAR dataset was used to assess the crown damages derived from a heavy ice-storm in Slovenia as a source of deadwood. The study provides some insights on the possible useful information that can be extracted to characterise such events and its applicability at different point densities.

Chapter 4 introduces the use of Terrestrial Laser Scanning data for the identification and quantification of forest fuels within the stands of the Sierra Nevada mountain range (U.S.A.). The work presents the development of a standardized procedure to

automatically describe the typology and abundance of the material that might potentially burn on the forest ground layer.

The case study reported in Chapter 5 takes in consideration the sensitivity of several roughness indexes for the description of the abundance and the characterisation of deadwood derived from four different post-fire treatments applied to a burnt site in the Aosta valley (Italy).

Finally, a discussion of the results obtained in the abovementioned Chapters and some general conclusions are reported in Chapter 6.

2 Airborne and Terrestrial Laser Scanning data for the assessment of standing and lying deadwood: current situation and new perspectives.[1]

2.1 Abstract

LiDAR technology is finding uses in the forest sector, not only for surveys in producing forests but also as a tool for a deeper understanding of the importance of the three dimensional component of forest environments. Developments of platforms and sensors in the last decades highlighted the capacity of this technology to catch relevant details even at finer scales. This drives its usage towards more ecological topics and applications for forest management. In recent years nature protection policies have been focussing on deadwood as a key element for the health of forest ecosystems and wide-scale assessments are necessary for the planning process on a landscape scale. Initial studies showed promising results in the identification of bigger deadwood components (e.g. snags, logs, stumps), also with data not specifically collected for the purpose. Nevertheless, many efforts should still be made to transfer the available methodologies to an operational level. Newly available platforms (e.g. Mobile Laser Scanner) and sensors (e.g. Multispectral Laser Scanner) might provide new opportunities for this field of study in the near future.

2.2 Keywords:

LiDAR; deadwood; Airborne Laser Scanning; Terrestrial Laser Scanning

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[1] The present work is based on the following published paper:

Marchi, N., Pirotti, F., Lingua E. 2018. Airborne and Terrestrial Laser Scanning Data for the Assessment of Standing and Lying Deadwood : Current Situation and New Perspectives. Remote Sens. 10. doi:10.3390/rs10091356

2.3 Introduction

Deadwood in forest stands was often considered a management problem in the past and its presence is still an issue, especially in producing forests, since it can be a possible source of pest outbreak, enhance fire risk, and be a threat to workers/public safety (Merganičová et al., 2012). On the other hand, deadwood is one of the most important indicators of habitat quality, hosting and providing nourishment to many of the most threatened forest species among insects (Grove, 2002), bryophytes and lichens (Dittrich et al., 2014), small mammals and birds (Hagar and Survey, 2007). Furthermore, deadwood is important in microsite enhancement for forest regeneration, particularly after high-severity disturbances (Marzano et al., 2013) and for this reason deadwood cover may be used as an indicator of microclimatic and micro-topographic habitat availability and heterogeneity (Leverkus et al., 2018). Deadwood also plays a fundamental role in the carbon balance of forest ecosystems. Due to its increasing importance, National Forest Inventories (NFI) worldwide are now progressively including deadwood as a target component and its quantification is becoming of great interest (Böhl and Brändli, 2007; Crecente-Campo et al., 2016; Garbarino et al., 2015; Ligot et al., 2012; Pignatti et al., 2009; Ritter and Saborowski, 2014; Teissier du Cros and Lopez, 2009). Countries with a longer tradition of productive forestry are already assessing the impacts of biomass exploitation and strict production management (Green and Peterken, 1997; Moussaoui et al., 2016; Russell et al., 2012; Verkerk et al., 2011), and their effect on deadwood presence.

Quantity is no longer considered the only valuable parameter for deadwood assessment, both for carbon sequestration (Domke et al., 2011; Russell et al., 2015) and biodiversity conservation purposes. For the latter, many authors highlight the importance of size and decay stage of the deadwood component (Gossner et al., 2016; Lachat et al., 2007; Lachat and Bütler, 2009; Venier et al., 2015), even proposing specific taxa-based forest management (Lutz et al., 2012; Mason and Zapponi, 2016).

This perspective is leading researchers to define new methodologies (e.g. Ritter and Saborowski, 2012; Travaglini et al., 2000) for its identification and assessment of the amount and quality in different landscapes and throughout forest development stages (Brin et al., 2008; Larrieu et al., 2014; Pedlar et al., 2002). In this direction, techniques from the field of remote sensing provide a valuable set of approaches for the study across wide scales. Among these, LiDAR is becoming an established technology for large scale monitoring within the environmental sector (Pirotti et al., 2012), passing from direct applications in meteorology, topography and forest planning. Within the latter, assessment of the aboveground biomass is no longer such a priority issue. There are many reported results from direct experiences of local administrations, academia and funded projects (e.g. NEWFOR for EU; Lingua et al., 2012).

Ecological studies are increasingly using this technology, due to its capacity of collecting 3D metrics of vegetation structure. As Davies and Asner (2014) described in their review, most forest wildlife depends on all three dimensions of the environment. Using LiDAR-derived data on wildland structure, it is possible to better link species' ecology to prediction mapping of occurrence or habitat suitability (Zellweger et al., 2013).

Although on the one hand it is true that mapping large areas has become quite easy and less expensive, on the other not all remotely sensed data are able to respond in the same way to small-scale events. As the general approach is progressively shifting from global to local scale, the UAV (Unmanned Aerial Vehicle) technology has seen a rapid evolution within recent years and its easily affordable price has driven research to a further change in viewpoint. Rapid and complete remotely sensed monitoring can be conducted with UAVs, allowing for small-scale updates/adjustments of the original database. Indeed, their versatility allows point-clouds to be obtained both from UAV borne LiDAR sensors and from a Structure From Motion procedure applied on photogrammetry surveys.

While LiDAR technology has become a reliable tool for forest structural parameter definition (Corona et al., 2011; Pirotti et al., 2014), the integration of different sources of remote sensing data (e.g. aerial imagery and LiDAR) is still an open frontier for forest ecologists (Dalponte et al., 2008).

This paper aims at giving an overview on the current situation and future perspectives of this specific but heterogeneous topic. The first section introduces the definition and classification of deadwood in forest ecology and the importance of remote sensing LiDAR technology for its assessment. In the second, the specific applications of the two main remote sensing approaches (i.e. airborne and terrestrial) are discussed and compared. The third section reports on data-integration between the two approaches and data-fusion with other data sources. The fourth section describes multi-temporal applications for change detection and quantification. Examples of operational applications are provided to broaden the discussion within the perspective of environmental management. In the conclusions, critical points and future prospects are highlighted for the identification of knowledge gaps and research opportunities.

Coarse woody debris (CWD), its properties and dynamics were thoroughly described for the first time by Harmon et al. (1986). This wide category covers a variety of types and size of materials, including snags (or standing deadwood), logs, chunks of wood (as a result of disintegration of the two previous types), large branches, stumps and coarse roots. The same authors reported how size varied differently depending on the country and type of study, ranging from 2.5 to 7.5 cm as concerns minimum diameter. Ten years later, Harmon and Sexton (1996) defined the first specific guidelines for the U.S. forest inventories, setting 10 cm and 1 metre as diameter and length thresholds to distinguish CWD from finer

material called fine woody debris (FWD). An exception was proposed for forest fuels assessment, providing a minimum threshold of 7.5 cm (1996).

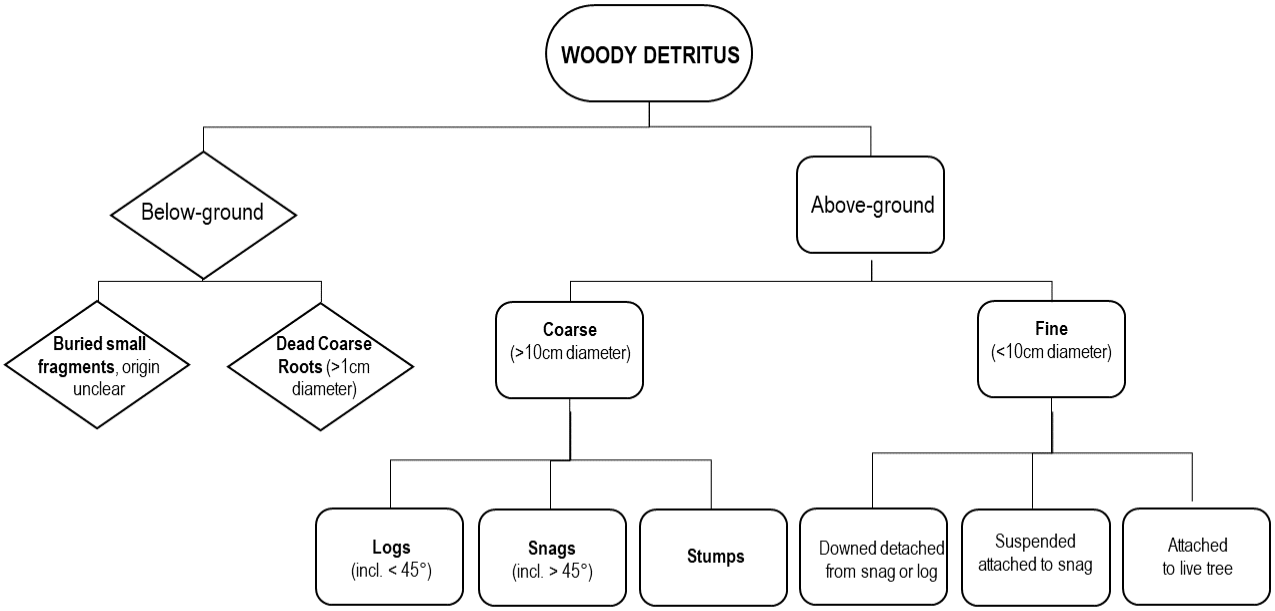

Figure 6: identification key for deadwood elements (from Harmon and Sexton, 1996, modified).

The use of common thresholds by the scientific community has increased since their first proposal (see Harmon et al., 1986; Harmon and Sexton, 1996), but differences can still be found, in terms of both terminology and adopted thresholds. This lack of harmonization leads to a flaw in the comparison among different studies (Yan et al., 2006) or data sources. As an example, within the National Forest Inventories (NFI) of some European countries the distinction between CWD and FWD is made according to a threshold of 10 cm in the Scandinavian countries (Sweden, Norway and Finland) and Italy, 7 cm in Switzerland and France, and 20 cm in Austria and Germany (Pignatti et al., 2009).

No ecological study has provided a clear threshold for distinguishing between fine and coarse woody debris (Maltamo et al., 2014), even though the choice of a specific definition can have a strong effect on deadwood quantification. Indeed, testing the exclusion of different deadwood elements from the total amount derived from the available NFI data, it is possible to see how adding just stumps can cause a 44% increase in volume (Söderberg et al., 2014).

Due to the diverse types of dead material that can be found within the forest environment, the literature search was conducted starting from specific keywords (e.g. "LiDAR" AND "deadwood", "LiDAR" AND "coarse woody debris", etc.) on the main research platforms (e.g. Science Direct, Web of Science). Additional material was collected searching through the bibliography available in each paper and including relevant grey literature. The selected papers were then screened to assess the real presence of the research topic, often present as a side¬ line of main methodologies developed for other purposes.

2.4 Airborne Laser Scanning

2.4.1 State of the art: data types and analysis

Within the last decade, due to technology developments and the increase in expertise, the LiDAR sector has been facing a progressive shift from different points of view:

1. Data quality: improved accuracy in terms of data localization and measures
2. Data density: from low- to high-density (e.g. single photon counting LiDAR)
3. Data types: from discrete return to full waveform
4. Analysis approach: from area-based to single tree

Analysis of the data may differ depending on the aggregation level at which the point-cloud information is studied. The target information can be represented at a single-tree level (Hyyppä and Inkinen, 1999) or according to a regular grid, where each cell summarises the characteristics of the individuals included. The latter method is known as "area based approach" (ABA). The aggregation level is entangled with the point-cloud quality due to the fact that low-density data can hardly be processed to obtain detailed information at a single-tree level. For this reason, the ABA was mostly used in early studies, when the available point densities were pretty low (i.e. < 2 pts/m^2). It leads to very good results, even if mostly for mapping purposes such as biomass estimation (e.g. Andersen et al., 2005; Maltamo et al., 2004; Næsset, 1997; Popescu, 2002; Zimble et al., 2003), information for forest fire management (Riaño et al., 2004, 2003) and habitat modelling (Martinuzzi et al., 2009). Even if high-density datasets are becoming more available, finer elaborations (i.e. single tree) are still performed mainly for research purposes.

2.4.2 Area-based approach

Assessment of deadwood amount through the area-based approach was mainly indirectly derived from living biomass parameters of forest stands. Ranius et al. (2004) modelled the amount of deadwood from the growth of living trees, tree mortality rate and

CWD decomposition rate. They achieved accurate results only at landscape level for Norway spruce stands without disturbances.

Common point cloud statistics extracted from low density datasets have been used to estimate different components of deadwood such as standing and downed dead trees (Pesonen et al., 2008; Sherrill et al., 2008) or the potential logging residues following forest management operations (Hauglin et al., 2012). The models, applied mostly to boreal/temperate conifer stands, resulted in accuracies ranging between 50 and 80%. Within a natural old-growth forest, canopy gaps have been classified according to the presence/absence of CWD using metrics extracted from the data between ground and 5 metres height (Vehmas et al., 2009).

The predictive power of ABA models mainly increases with stand maturity, but the accuracy of the models for predicting CWD volume using characteristics of living trees as predictors has been rather poor (Maltamo et al., 2014).

In a case study in the coastal forest of the U.S. Pacific North West (Bater et al., 2009) LiDAR derived variables from a low density dataset (<1 pts/m^2) were compared to field data dividing deadwood in wildlife tree (WT) classes depending on its decay status. The coefficient of variation (log transformed) was found to be the best predictor variable within the modelling of the WT classes and, therefore, for the presence of deadwood. This result is consistent with those obtained by other authors (e.g. Andersen et al., 2005; Næsset, 2002; Næsset and Økland, 2002) for the description of canopy structural attributes.

The Random Forest (RF) algorithm was adopted using LiDAR-derived metrics to predict total, live, dead and percentage of dead basal area (BA; Bright et al., 2013). The investigation proved the significance of height and density metrics for predicting total BA, intensity and density metrics for predicting living BA, and intensity metrics (mean, CV and kurtosis) for predicting dead and percentage dead BA. Furthermore, in one plot the intensity normalization improved RF models predicting Dead and %Dead BA, demonstrating the importance of the use of intensity for distinguishing dead from live canopies.

Finally, Sumnall et al. (2015) compared the use of Discrete Return (DR) and Full Waveform (FWF) data for modelling 23 different forest structure and composition parameters, including deadwood volume and decay stages for both standing and downed trees. Among the best performing models standing deadwood volume obtained a prediction accuracy equal to a NRMSE of 16%. However, it was pointed out that the selection of LiDAR survey season (leaf-on/leaf-off) had greater importance than data type (i.e. DR or FWF) when determining the predictive power of the best performing models.

2.5 Single tree approach

2.5.1 Standing deadwood

The identification of single standing dead trees (snags) using LiDAR data has only recently been addressed, due to the increase in high quality and high-density data availability as well as segmentation methods required to work directly with the point cloud. Segmentation is the process aimed to delineate an object and its characteristics which, in forestry, means tree crowns, tree position and dendrometric parameters (i.e. DBH, height), from remotely sensed data. The analysis approaches evolved from image segmentation techniques developed for aerial imagery and lately applied to 3D data (i.e. LiDAR).

It is possible to say that the paper by Reitberger et al. (2008) was a forerunner in the field. In their study, indeed, some of the main approaches for canopy segmentation were tested with both DR and FWF LiDAR data. Not considering the difference in computation effort between the two data types, it is important to note that the "normalised cut segmentation" algorithm (Shi and Malik, 2000) was introduced into the analysis process. The technique has been successfully used through voxels applied on 3D point clouds, in order to differentiate points belonging to each single tree. If compared to watershed segmentation that relies on a 52% detection rate, its application increases the detection rate to 60%, both considering the support given by the stem detection method (Reitberger et al., 2007). An important aspect is the increase in detection of individuals in the lower and mid canopy layers, often rather difficult to identify due to clustering with the upper ones (e.g. Wing et al., 2014). Most studies were conducted on conifer stands where size and shape of tree crowns are quite well defined. As described in Vauhkonen et al. (2012), these assumptions allow site/species specific methods to be applied that cannot be easily used in different stand conditions. In order to overcome this issue, Hamraz et al. (2016) defined a procedure for the identification of the single tree that does not require assumptions on size and shape of tree crowns and thus opens new perspectives towards generally applicable methods.

The first complete procedure for the detection of standing dead trees at a single-tree level was presented by Yao et al. (2012). They made use of a high-density dataset (25 pts/m^2) derived from FWF and waveform information to classify living and dead trees in a mountain mixed stand, selecting a group of metrics based on previous experiences in the same site (e.g. (Heurich and Thoma, 2008; Polewski et al., 2015a; Yao et al., 2012b). The calculated metrics were related to the outer tree geometry, crown shape and penetration rate by laser, pulse width and reflectance intensity. A Support Vector Machine algorithm was run to classify dead and living trees, reaching an overall accuracy of 73% with leaf-on conditions.

Kim et al. (2009) developed regression equations to predict living and standing dead tree biomass from DR LiDAR data. By using the intensity values it was possible to distinguish between living and dead biomass. The LiDAR data were stratified at a threshold intensity value and the regression analyses were conducted using stratified values (high for live biomass and low for deadwood) and the full value range (divided by type). No transformations were applied to the datasets. For dead biomass, the best estimator was the peak of the low intensity frequency distribution, whose model alone had an R^2 of 0.52. Lastly, the derived regression equations were tested to map live and dead biomass across a portion of the North Rim of Grand Canyon National Park (U.S.), in stands with a relatively high percentage of dead trees.

Mücke et al. (2012) used the correct tree locations, defined with a topographic field survey as centre points, in order to proceed with the extraction of a subset of the point cloud using a clipping cylinder with a 2.5 m radius. Echo distribution and echo amplitudes were found to be the strongest indicators for discrimination between standing living and dead trees, and the increase in echoes was directly linked with a better discriminatory power. As possible enhancements for area wide identification of standing dead trees, they suggested a penetration index map on a grid basis which comprises the number of echoes in certain height intervals compared to all echoes. Furthermore, a map incorporating the ratio of amplitudes from the top 30% of all echoes could help in distinguishing living from dead trees.

In order to overcome the difficulty in separating LiDAR returns reflected from living or dead trees as stated in Pesonen et al. (2008), Wing et al. (2014) applied a filtering algorithm based on the intensity values and neighbourhood statistics of first return and single points. This method was tested in a managed Ponderosa pine (*Pinus ponderosa* Douglas ex C. Lawson) forest, with single- and multi-layered stands, and a predominantly forested area subjected to wildfire. Intensity values were corrected and statistically selected, in order to exclude those related to live vegetation and then evaluated depending on their approximation to a geometrical shape (i.e. cylinder). Despite the relatively low point density for this type of analysis (6.9 pts/m^2), the results show a promising potential of the method for real forestry applications.

In order to identify snags, Casas et al. (2016) used intensity normalised data applying a two step procedure. The point cloud with values above 2 metres were rasterised to a smoothed CMH, subsequently segmented into regions representing individual trees. For each subset of points belonging to the crowns, 25 metrics were calculated, related to height, intensity, crown shape and porosity. Lastly, tree classification and DBH estimation was performed using Gaussian processes and the metrics derived from ALS (Airborne Laser Scanning) data. The overall classification achieved high scores (snag/living: 91.8%; conifer/hardwood: 85%) but one of the most important results is that the Gaussian process-

based method provided a significant improvement over the traditional use of site-specific conifer allometric equations.

Polewski et al. (2015b) proposed a two-step strategy for detecting individual dead trees. In the first step, similarly to Yao et al. (2012b) they segmented the 3D point cloud into individual trees with the segmentation procedure from Reitberger et al. (2009) using the Normalized Cut clustering algorithm (Shi and Malik, 2000). Each identified segment was then linked to the corresponding patch in the georeferenced aerial image. Features were then extracted from the patch utilizing the per-channel intensity means of pixels inside the polygon as well as their cross-channel covariance matrix. The procedure led to an overall accuracy of 89% using fewer than 10% of the data pool as training examples.

In recent studies, a whole set of technical expedients may help in improving both single tree and area based approaches. Among these, the filtering of points located at the lowest height level (i.e. below 2 m) has become a standard step (e.g. Abalharth et al., 2015; Hamraz et al., 2016; Keränen et al., 2015; Mücke et al., 2012), in order to minimise the noise caused by small elements present in the forest understory (suppressed trees, shrub vegetation, etc.).

Another hint comes by approaching to the topic from an ecological perspective. Zellweger et al. (2013), pointed out how the geographical localisation of the target stand may help in identifying areas prone to dead or dying trees. High values of the Topographic Position Index describe ridges or hilltops, sites that are usually subject to harsher water and soil conditions and thus where deadwood amount may be higher.

For inventory purposes, Keränen et al. (2015) demonstrated that the inclusion of standing dead trees in field measurements had no significant effect on the accuracy of the area-based model used within the study area. Even if the result may be promising, it has to be pointed out that the presence of CWD in the site was pretty low. Further studies are hence needed to define the effect of higher quantities of snags.

2.5.2 Downed logs

The detection of downed trees seems to be one of the most difficult tasks, since many factors affect their correct identification. The most important are canopy cover (for laser beam penetration), shrub cover and rocks (creating noise or partially covering the target).

One of the first methodological approaches to detect lying logs was the rasterization of different point statistics used as layers in object-based image analysis (Blanchard et al., 2011). Proximity of stems to the ground vegetation and clusters of downed trees were

recognised as error factors due to the further complexity they provide. In addition, the process relies on multiple user-defined parameters, making it pretty site-specific and therefore less flexible. Nevertheless, the procedure was able to successfully delineate downed logs (73%) but was inefficient in terms of automation due to the time required for manual and visual setting and refinements.

The line-template matching method has been used extensively to identify downed logs in uncovered areas, such as those hit by a windstorm. Lindberg et al. (2013) applied it directly to a laser point cloud to utilize the data information without a rasterization step. Later, Nyström et al. (2014) worked on the same area to test a new approach reaching an 82% detection rate on the few pine trees available, probably due to the low number of branches and larger mean diameter (37 cm) in comparison to the other species present (22 cm).

Concerning forested areas, Mücke et al. (2012) decomposed a FWF point cloud filtered with a 2 metres height threshold in order to create a raster product. The derived image contained elongated features but also spot-like ones, representing downed logs and standing trees respectively. The latter had been removed through a mask built from values between 2 and 7 metres, allowing a clean map of downed wood to be obtained. The procedure has been refined with further studies (Mücke et al., 2013a, 2013b), giving a strong importance to the echo width. This allowed a classification scheme to be built up based on shape and surface roughness in and around the area of the identified feature, in order to filter out the well detectable logs from all possible noise (i.e. low vegetation). However, the promising results obtained were partly explained by the size threshold adopted (DBH >30cm), hence considering only relatively big logs.

In their study, Polewski et al. (2015a) confirmed the complexity of the task working directly on the point cloud, but foresaw that methods which try to learn the appearance from reference data based on shape descriptors could help solve some of the problems. Developing the early approach presented in Polewski et al. (2014), they focused on the clustering step, taking in consideration the Normalized Cut algorithm to merge the identified segments in order to reconstruct the shape of the stem. The initial similarity function applied to a training dataset and chosen to identify segments was then refined to optimise the computational efforts required by the point search method. Further developments in stem segmentation followed the introduction of a specialized constrained conditional random field that allowed an increase of between 7 and 9% in detection correctness and completeness (Polewski et al., 2016).

Airborne Laser Scanning data have been used for the identification and characterisation of logjams along a river in western U.S. Abalharth et al. (2015) evaluated the ability of recognising logjams by comparing use of the full point cloud and a filtered one, keeping only points below a height threshold of 3 metres. The obtained Object Height Model and traditional normalised Digital Surface Model were then assessed manually, allowing to

recognise logjams with results similar to fieldwork. Even if the method was objectively time inefficient and partly subjective, it is still worthwhile in comparison to fieldwork.

In a similar situation, lying deadwood was assessed in a riparian area using a UAV-borne LiDAR sensor, obtaining very promising results thanks to the extremely high point density (i.e. 1500 pts/m^2) almost comparable to a Terrestrial Laser Scanner (Mandlburger et al., 2015).

2.6 Terrestrial Laser Scanning

Recent studies focus on the efforts at closer scales on the elements that are usually hard to identify by ALS below the tree crowns (e.g. logs) or even with the human eye. Some forerunner studies using Terrestrial Laser Scanning (TLS) evaluated the fuelbed characteristics (heights, volume, biomass and leaf area) (Loudermilk et al., 2009) and the variation of fire behaviour in relation to fuel variation (Loudermilk et al., 2012) within longleaf pine (*Pinus palustris*) stands in the U.S. The approach showed a potential for this technology in the description of fine scale processes related to fire ecology. Thanks to the high-density datasets coming from TLS sensors, new analysis' methodologies are being developed. Advanced techniques using a voting scheme and fitting simple 3D models were used by Polewski et al. (Polewski et al., 2017) to fit a cylinder shape over a point cloud, thus obtaining a 10% improvement in the detection completeness rate of fallen trees.

Finer components such as lowest dead attached branches were identified as part of a stem quality assessment procedure with a RMSE equal to 42.9% (Kankare et al., 2014).

TLS data have also been successfully applied for the detection and quantification of the structural loss on standing dead trees. The approach proposed by Putman et al. (2018) makes use of the TreeVolX algorithm, a voxel-based methodology developed by Putman and Popescu (2018) which segments the voxelised point-cloud by layer in order to identify stem or branch sections. When identified, these sections are then filled with further voxels recreating a solid voxel model. The volume loss estimation is made by difference of voxels per height bin. The approach, tested on 29 specimens from both coniferous and broadleaved species, took into consideration two different time span scans for each of them.

2.7 Integrating methods and data-sources

Nowadays, multi-sensors and collaborative sensing (the use of more than one technology/support at a time) are driving research towards merging information from different sources (Toth and Józków, 2016). FWF systems are capable of acquiring high quality data thanks to the echo width and amplitude, important parameters in the case of deadwood identification (Mücke et al., 2013b; Sumnall et al., 2015). Nevertheless, it is still quite onerous to manage such data across the wide scales on which the forestry sector operates. In this perspective, new methods are testing the feasibility of integrating datasets with information coming from different sources, such as aerial imagery (from airplanes or UAVs) and LiDAR (ALS and TLS). This approach seems quite promising, due to the fact that it is possible to select the best information from what a specific source can offer. For example, imagery can help with crown detection and stand classification (species, health status), while LiDAR can provide estimation of structural parameters (e.g. height, DBH, etc.). A recent case study reached an overall accuracy of 81% in the identification of dieback-affected eucalyptus trees within a floodplain forest in Australia (Shendryk et al., 2016) through the use of LiDAR data and imaging spectroscopy. The combination/fusion of ALS with TLS data has already shown positive application for single tree inventory in Finland (Kankare et al., 2015) but the delineation and quantification of downed logs should be implemented (Blanchard et al., 2011).

Polewski et al. (2015b) used a single tree segmentation approach through the identification of crowns on imagery and then clipped the point cloud based on the detected objects, while Aicardi et al. (2016) integrated a point cloud derived from UAV photogrammetry and TLS data to characterise a forest stand in northern Italy. Finally, applications related to the use of SAR have been reviewed in Li and Guo (2015), where different technologies (imagery, LiDAR and SAR) are taken into consideration for the evaluation of non-photosynthetic vegetation (i.e. dead material).

The use of three different approaches for data integration was tested to monitor the hazard from standing dead trees along the forest roads of the Bialowieza Forest in Poland (Stereńczak et al., 2017). The forest (conifers, broadleaves and mixed stands in almost a similar proportion) was flown over with a CIR camera and scanned with a full-waveform sensor under leaf-on conditions, with an average point density of 6 pts/m^2. The colorized point cloud was then used for deriving some high resolution raster products: plain imagery, imagery with associated height information derived from the forest database and imagery with associated height information derived from ALS data. In comparison to the techniques using passive sensors, the use of ALS data information allowed a single tree segmentation to be performed and hence a risk assessment on a per tree basis, identifying the individual characteristics and prioritizing those which threatened more roads at the same time.

Nevertheless, not all experiences are positive. Compared to aerial imagery fused with ALS data, ALS data alone have been found to be a preferable auxiliary source of information for sampling efficiency (Pesonen, 2011).

2.8 Multi-temporal approach

LiDAR acquisitions are being evaluated not only as a single good quality product, but also as an optimal information source for a multi-temporal approach. Some of the abovementioned experiences take into consideration the comparison of CMHs from different years or operate directly on the point cloud to locate the availability of CWD. Among the former, Vastaranta et al. 2012b) identified canopy gaps though the difference between CMHs in order to monitor snow-damaged trees.

Similarly, Tanhuanpää et al. (2015) detected and classified some (conifer/deciduous) downed logs with high accuracy through the difference of two high-density datasets: 97.8% and 89% respectively. Individual tree crowns were delineated using the watershed algorithm and then compared with the most recent canopy raster: if the tree locations fell in a new canopy gap, then the tree was considered as fallen. Furthermore, quantification (volume) and description (DBH) were assessed with RMSE of 0.5 m^3 and 8.7 cm respectively. The novel approach does not require calibration or training data, thus allowing a flexible use.

Dealing with cloud-to-cloud analyses requires a high number of data per investigation unit (e.g. pts/m^2) in order to be able to compare two datasets. Korpela et al. (2010) found that the fusion of two datasets originated by different instruments could be improved by the normalisation of the intensity values. Hamraz et al. (2016) instead homogenised the point spacing to merge two datasets with different point density and seasonality. This allowed them to use the novel segmentation approach proposed for broadleaved species described in Section 9.

A multi-temporal approach can also favour the segmentation process, as shown by Pietrzyk (2015). Using a cloud to cloud comparison, the author experimented the use of 3 datasets to assess the change detection within a forest stand for the identification of harvested and fallen trees. The process was able to identify broadleaves and could rely on an overall accuracy of 94%, probably mostly due to the very high average point densities used (between 64 and 118 pts/m^2).

As concerns very high-density data, recent experiences in the Alpine region show an application of the LiDAR technology for the recognition of snow/ice damaged trees. Using two datasets from 2013 and 2014, Kobal et al. (2014) quantified the damage (broken branches, dying crowns, etc.) that followed the extensive ice-break event that in February

2014 impacted almost 50% of Slovenia's forests. A similar approach, even if not directly related to real deadwood, was applied by Wallace et al. (2014) using a UAV borne LiDAR sensor (point densities between 145 and 220 pulses/m^2) for the quantification of pruning residues in a Eucalyptus production stand in Australia. Results ranged between 96 and 125% of the pruning rate, but the success of the procedure confirmed the suitability of LiDAR data for fine scale estimations.

2.9 Examples from land and environmental management

The application of LiDAR technology for the assessment of habitat quality has recently been gaining in interest (Coops et al., 2016; Vihervaara et al., 2017; Zlinszky et al., 2015), stimulating the development of a new multidisciplinary field of study connecting different research areas, from Information Technology to biology and resource management.

2.9.1 Habitat modelling

LiDAR has proved its ability to characterise the vertical and horizontal forest structure under different conditions, allowing for the classification of stands into natural or managed (Sverdrup-Thygeson et al., 2016). This particular ability has then been repeatedly tested in the field of animal ecology, as reviewed by Davies and Asner [33]. As the authors pointed out, the experiences are biased by efforts spent on specific taxa (i.e. birds) and by geographical distribution. In the latter case, indeed, the studies are mostly concentrated in North America and Europe, similar to those related to deadwood identification and quantification (see Table 1).

Among the others, two studies highlighted the importance of including stand structural information coming from LiDAR data in order to model deadwood type and abundance. Martinuzzi et al. (2009) analysed three categories of snags (DBH >15, >25 and >30 cm) recognised as a key factor for the presence of woodpeckers. Through the use of 34 LiDAR-derived metrics (19 related to canopy and 15 to topography) and selection by random forest algorithm, they were able to model local snag availability with an overall accuracy ranging between 86 and 88%. In the study by Ackers et al. (Ackers et al., 2015) the use of different remote sensing sources (orthophoto, Landsat, LiDAR) were compared for habitat assessment of the spotted owl (*Strix occidentalis caurina*), a species that requires large amounts of deadwood as fundamental component. The estimations using LiDAR data were better than those from other sources but the main disadvantage is related to the minor scale at which this technology is usually available.

2.9.2 *Post disturbance and forest fire management*

The use of LiDAR data for forest fire management purposes has concentrated on fuel characterisation and quantification, as reviewed in Gajardo et al. (2014), mostly through an area-based approach.

The use of LiDAR shows that, in comparison to studies made with Landsat data, with LiDAR it is possible to identify real canopy (and stand) dynamics. Indeed, even if a stand tends to grow when analysed on a global scale, it is possible to recognise the small variations that occur on a local one. The possibility of merging the information from the two different sources allowed Wulder et al. (2009) to evaluate post fire forest conditions and burn-induced structural changes. They found that metrics calculated from Landsat on post-fire forest conditions were related to structural parameters derived from LiDAR, mostly for dense forests (cover >60%). A similar study (Bolton et al., 2015) assessed the long-lasting impact of high-severity fire on forest structure in the 10 years since fire, where snags characterise the vertical structure till their progressive fall while being covered by the growth of the regeneration. These rather diversified environments constitute an important wildlife habitat in a post-fire condition. Vogeler et al. (2016) compared the use of variables from LiDAR and Landsat data and mixed models for the evaluation of snags and shrubs availability. Landsat performed a little better when used alone but the fusion of datasets provided moderate errors and acceptable accuracy. It should be pointed out that the good predictive performance obtained may be related to the large DBH thresholds adopted for snags (DBH >40 cm).

2.10 Critical points and future perspectives

Although in the last decade numerous studies have been addressed to automatic deadwood parameters extraction using LiDAR data, several issues still require to be tackled exhaustively.

From a general point of view, there is a tendency to propose new algorithms, even if not always fully successful, but not enough information is available on how the existing ones work within different forest types. The need to investigate this aspect is underlined by different authors (Hamraz et al., 2016; Kim et al., 2009; Latifi et al., 2015b; Russell et al., 2015; Wing et al., 2014) but only a few analyse benchmarks (Eysn et al., 2015; Pirotti et al., 2017; Vauhkonen et al., 2012). Furthermore, these are limited to the extraction of inventory parameters on living trees whereas, as concerns deadwood, only the sampling methods related to CWD are compared (Pesonen et al., 2009).

From an operational point of view, there is a good availability of ABA models that can guarantee reliable estimations. Area-based approaches lack classification of the tree

species but better manage the intermediate and lower stories that are usually poorly detected by single-tree approaches. ABAs are strictly linked to local variables, so NFI are still the main source of data for such a wide-scale assessment.

The single tree segmentation process, on the other hand, relies only on LiDAR data and temporarily stable empirical information (e.g. allometric equations), showing the potential for the exclusion of ground surveys on the short term. Nevertheless, while Pirotti et al. (2017)proposed a minimum point density for the segmentation of living trees (5 pts/m^2), a threshold for dead ones is harder to define. Wing et al. (2014) considered 4 pts/m^2 (first return and single) as the minimum density value to apply their segmentation procedure. Casas et al. (2016) defined 19 pts/m^2 as minimum for a proper classification and DBH estimation. Reitberger et al. (2008) pointed out how the increase in point density (from 10 to 25 pts/m^2) becomes useful only for stem identification in the case of standing deadwood. Instead, in the case of log identification, Polewski et al. (2015a) proposed a minimum of 20 pts/m^2 for the application of their algorithm. At present, sensor quality and the cost of a wide-scale LiDAR survey provide datasets with an average point density of 10 pts/m^2 at an accessible price. For this reason, the selected studies listed in Table 2 have been divided into high- or low-point density, accordingly to this threshold.

The situation depicted in Table 2 shows that most studies make use of high-density datasets and we did not find studies that compared the viability of the proposed method with different point densities. This is just the case of three studies focussed on the segmentation process(Khosravipour et al., 2014; Pirotti et al., 2017; Reitberger et al., 2008).

The majority of studies dealing with CWD modelling obtained good results but, according to Maltamo et al. (2014), this is due to their setting in natural areas where mortality conditions are more homogenous; these authors indeed point out how it is much harder to statistically model CWD in managed forests where management operations altered its presence across the landscape. Nevertheless, for DDW, area-based techniques and associated measurements of DDW cover should be pursued, as single tree log detection techniques are still problematic.

The volume of standing dead trees is very difficult to model due to the high variability of stem dimensions; this depends on the breakage height and decay status, and for these reasons common allometric equations are not always effective. While the inclusion of small quantities seems not to have any significant effect on an area-based plot estimation (Keränen et al., 2015), the exclusion may determine an increase of 0.2 concerning the coefficient of determination of the basal area estimation both for coniferous and deciduous forests, whereas the height measurements decrease in accuracy by 0.22 for mixed stands (Heurich and Thoma, 2008). As concerns the single-tree approach, instead, Latifi et al. (2015a) noted an increase in accuracy for the plot estimation when deadwood was

excluded, while Casas et al. (2016) managed this great variability through the use of Gaussian processes.

Regardless of the data source or estimation method used, the best results have been reached when considering medium to large size deadwood elements. Recent studies provided good accuracy (>50%) in identifying lying deadwood using thresholds of DBH >25 cm (Blanchard et al., 2011), or DBH >30 cm (Mücke et al., 2013a; Nyström et al., 2014) but some of them showed similar results in middle-aged forests with stems bigger than 10 cm (Keränen et al., 2015; Polewski et al., 2016, 2015a, 2014).

The quality of DTMs greatly influence lying deadwood characterization(Lindberg et al., 2013; Mücke et al., 2013a, 2012; Nyström et al., 2014). Indeed, in the case of DR LiDAR data, it is extremely difficult to separate ground, logs and low vegetation, differently from FWF (Mücke et al., 2013a). Linear topographic features (e.g. ditches, channels, etc.), may then interfere with recognition of elongated shapes such as fallen trees(Lindberg et al., 2013; Mücke et al., 2013a). Another source of noise in the identification of lying logs can be the scanning pattern used. A commonly used one is the zig-zag pattern that may create strips of data and no-data due to the irregular point spacing. Such a situation requires a homogenisation process that is difficult and time consuming (Blanchard et al., 2011).

Papers collected in Table 1 show quite a wide range of canopy conditions under which testing has been done. Not all LiDAR acquisitions have been for the specific purpose of deadwood recognition. Adjacency results as a common issue for the correct detection of all CWD categories. Snags are often clustered with living individuals close by and identified as a whole (Wing et al., 2014), while logs are frequently overlying and their separation is very difficult (Blanchard et al., 2011; Lindberg et al., 2013; Nyström et al., 2014).

It is not straightforward to draw specific guidelines but it seems pretty clear that leaf on conditions perform better for snag identification when the snag appears as a different object in a homogeneous environment, even if relevant differences have not been noticed (Mücke et al., 2012). On the contrary, leaf off conditions favour the laser beam penetration and hence the recognition of downed material, but it only helps in the case of a low percentage of evergreen species in the plots. Canopy cover around 66%, indeed, may lead to a difficult detection due to the sparse points that are able to reach the ground (Polewski et al., 2015a).

All the mentioned drawbacks lead us to think that high technical skills and specific software are still needed, as pointed out by Bütler and Schlaepfer (2004). In addition, a recent questionnaire based review by Barrett et al. [124] demonstrates that none of the 45 interviewed countries make use of remotely sensed data coming from radar or LiDAR sources for their NFI.

Future perspectives are mainly focussed on the integration among different technologies or techniques.

From a technological point of view, DR LiDAR sensors have almost reached their potential in point density, but the research is moving towards multi-sensors and the exploitation of information-rich data (i.e. full waveform). Wing et al. (2014) highlighted the importance of the intensity attribute for further developments of discrete data. The relevance of intensity has already been demonstrated in previous works (e.g. Reitberger et al., 2008) and several correction and calibration methods are available (see Kashani et al., 2015; Vain et al., 2010).

Better exploitation of radiometric information such as amplitude or echo width from FWF has been supported in Lindberg et al. (2013) and successfully used in recent studies (Mücke et al., 2013a, 2013b, 2012; Polewski et al., 2015c). Furthermore, new sensors such as the photon counting ALS may offer novel positive perspectives allowing wide areas to be mapped with high point density (65 pts/m^2; Nyström et al., 2014). As remarked in Pfeifer et al. (Pfeifer et al., 2015), single photon counting sensors also have the possibility of detecting very weak signals and promising results are already available from early experiments in forestry (Awadallah et al., 2014).

We found only two studies that compared the use of DR or FWF LiDAR data (Mücke et al., 2013b; Reitberger et al., 2008), pointing out how better results' quality is mostly related to the possibilities given by the use of echo width and amplitude. Furthermore, decomposing the FWF makes it possible to work with a higher number of discrete points (a factor of 2-3 in comparison to first/last pulse; Reitberger et al., 2008) and richer in information, depending on the canopy density (Pirotti, 2011).

Finally, new algorithms specific for LiDAR data or coming from other fields of the remote sensing sector may provide improved results. A line matching template method using normalized cross correlation kernel was successfully applied at varying angles over a raster orthophoto by Pirotti et al. (2016) to estimate the volume of damaged trees. Further tests might aim at evaluating its reliability if applied to a rasterised ALS point cloud.

Concerning innovative single tree segmentation approaches, instead, Hamraz et al. (2016) achieved an accuracy of 77% using a not site specific algorithm within broadleaved stands, usually considered as a "worst case scenario" situation. Among the segmented trees, the model identified 39% of the dead ones, leaving open the prospect that with further refinements it might be applied with good results on conifers and other standing deadwood. As reported in Latifi et al. (2015b), current methods can still be refined but, as they already provide a time reduction of 90% when recording the data, it must be assessed if the added value is significant.

New LiDAR sensors and platforms have recently been attracting more attention on the market, mostly related to the close range. As an example, (handheld) Mobile Laser Scanning has already proved to be a fast and efficient tool for collecting data for forest inventory purposes (Bauwens et al., 2016; Ryding et al., 2015). There is the hope that new data acquisitions, implementations of new methodologies and enhancement of the already available algorithms will provide improved and sound datasets, helping us to increase our ecological processes knowledge and develop more efficient survey schemes.

Table 1: Main studies related to deadwood (standing or lying) identification through ALS data.

Author		Aim	Seasonality	Site type	Scanning type	High density (pts/m²)	Low density (pts/m²)	DBH threshold (cm)	Accuracy (%)
Blanchard et al., 2011	U.S.A.	Downed logs	n.d.	Mostly open area	DR	10.5 (20)	No	25	73
Lindberg et al., 2013	Sweden	Downed logs	Leaf-off	Conifer forest	DR	69	No	n.d.	Corr.: 32 Compl.: 41
Nyström et al., 2014	Sweden	Downed logs	Leaf-off	Conifer forest	DR	65	No	6.9	Corr.: 64 Compl.: 38
Mücke et al., 2012 [75]	Germany	Standing dead trees, downed logs	Leaf-on/ Leaf-off	Beech stand	FWF	21.8 (leaf-on) 16.9 (leaf-off)	No	30	
Mücke et al., 2013a [84]	Germany/ Hungary	Downed logs	Leaf-off	Old-growth broadleaved forest	FWF	29.4 (all) 10.9 (single/last)	No	30	Corr.: 75.6 Compl.: 89.9
Polewski et al., 2014	Germany	Downed logs	Leaf-off	Mountain mixed forest	FWF	30	No	n.d.	
Polewski et al., 2015	Germany	Downed logs	Leaf-off	Mountain mixed forest	DR (from FWF)	30	No	10	Corr.: 55-90 Compl.: 56-82

Polewski et al., 2016	Germany	Downed logs	Leaf-off	Mountain mixed forest	DR (from FWF)	30	No	10	Corr.: 47-97 Compl.: 34-71
Abalharth et al., 2015	U.S.A.	River logjams	n.d.	Dense forest	n.d.	9-27	No	n.d.	Omiss.: 5 Comm.: 10
Tanhuanpää et al., 2015	Finland	Downed logs/ classification	Leaf-off	Urban conifer stand	n.d.	20 pulses	No	n.d.	97.8 (logs) 89 (classif.)
Bright et al., 2013	U.S.A.	Dead trees' basal area	Leaf-on/ Leaf-off	Different conifer forests	DR	No	0.5-8.7	n.d.	24.9-43.8
Bater et al., 2009	U.S.A.	Standing dead trees class distribution	Leaf-on	Conifer forests	DR	No	<1	10	
Casas et al., 2016	U.S.A.	Standing dead trees	n.d.	Mixed landscape	DR	19	No	10	84.8
Polewski et al., 2015b	Germany	Standing dead trees	Leaf-on	Mountain mixed forest	FWF + NIR imagery	30-40	No	n.d.	89
					DR (from FWF)		No		Corr.: 77.8 Compl.: 63.1
Yao et al., 2012a	Germany	Classification live/dead trees	Leaf-on/ Leaf-off	Mountain mixed forests	DR (from FWF)	25	No	7	73

Wing et al., 2014	U.S.A.	Standing dead trees	Leaf-on	Mostly conifer stands	DR	No	6.9	Live: 9 Dead: 12	40-60 (DBH < 37cm) 55-80 (DBH >37cm)
						No	6.7	Live: 9 Dead: 12	>65 (DBH >37cm)
Kobal et al., 2014	Slovenia	Snow/ice damages	Leaf-off	Mountain mixed forests	DR	~200 points	No	-	
Wallace et al., 2014	Australia	Crown pruning	Leaf-on	Eucalyptus plantation	UAV DR	145-220	No	-	
Sherrill et al., 2008	U.S.A.	CWD	Leaf-off	Subalpine conifer stands	DR	No	1.57-2.36	All	
			Leaf-on		DR	No	2.36	All	
Keränen et al., 2015	Finland	Forest inventory	Leaf-on	Boreal mixed forest	DR	No	<1	3	n.d.
Maltamo et al., 2014	Finland	CWD	Leaf-on	Boreal mixed forest	DR	No	2.8	5	
Pesonen et al., 2008	Finland	Standing/ downed	Leaf-on	Spruce-dominated stands, aspen stands	DR	No	0.5	5	Standing: 78.8 Downed: 51.6
Kim et al., 2009	U.S.A.	Standing dead tree	Leaf-on	Mainly conifer forest	DR	No	>6	10	

Martinuzzi et al., 2009	U.S.A.	Standing deadwood for habitat modelling	Leaf-on	Temperate conifer forests	DR	No	1.95m post spacing	2.7	86-88
Ackers et al., 2015	U.S.A.	Standing deadwood for habitat modelling	Leaf-on	Conifer-dominated forests	DR	9 pulses with 4 returns	No	n.d.	

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3 Using high-resolution LiDAR data to evaluate natural hazard - A case study of ice-break forest damage assessment.[2]

3.1 Abstract

Natural disturbances act as a driver in forest communities at different scales shaping both structure and species composition. In the anthropogenic landscape of the Alps, several small communities depend on forest management for the sustainability of their economy and such events appear as an economical damage more than an ecological process. In a climate change perspective, disturbances are meant to increase both in number and in severity, highlighting the necessity for forest managers of quick decision-making for adequate resource planning. Among the recent extreme events in the Alps, the ice-storm that took place during the late winter 2014 was noticeable for its extension, affecting three Countries, one of which got damaged for more than 50% of its forest property. In the last decades, the use LiDAR technology proved the capability of providing reliable information on forest structure at a landscape scale. By the means of high-density Airborne Laser Scanning data, a procedure was developed for the assessment and quantification of ice-storm damages on stands of three typical Alpine species: Norway spruce (*Picea abies* Karst.), silver fir (*Abies alba* Mill.) and European beech (*Fagus sylvatica* L.). The use of the Leaf Area Density index showed the possibility of identifying the damage across the vertical profile of the stand and describing how each species was affected. On a wider perspective, with the use of LiDAR it was possible to catch the difference between pre- and post- event in terms of basal area and volume.

3.2 Introduction

Forests in the Alps play crucial roles ranging from timber production to important services such as conservation of drinking water, protection from natural hazards and preservation of biodiversity just to name a few (FAO, 2011) . There is an increasing concern that provision of these services may be adversely affected by global change, as this impacts

[2] The present work is based on the following paper in preparation:

Kobal M., Marchi N., Pirotti F., Lingua E., Firm D., Nagel T. A., 2018. Using high-resolution LiDAR data to evaluate natural hazard - A case study of ice-break forest damage assessment.

over very large areas, and its effect is not clearly defined (Bonan, 2008). One of the main concerns is that climate change may increases frequency and severity of regimes (Mirza, 2003; Quayle et al., 2002) which may have a greater effect on forest structure and function than changes in temperature.

These alterations are supposed to be more pronounced in coniferous forests and the boreal biome even if, at the current stage, the understanding of the effects on a large scale is still scarce (Seidl et al., 2017).

Among the wide variety of disturbances, icestorms are a major driver in vegetation shaping across the Appalachians (Warrillow, 1999) and a well-know issue in the whole North-East America (Tremblay et al., 2005) but are not reported as a problem within the European forests (Gardiner et al., 2010). Nevertheless, the importance of the impact is scale-dependant, even more in a territory characterised by several different administrative institutions, as Europe and its States is. An example can be found in the recent event that affected the area among Italy, Austria and Slovenia damaging in the latter one the 60% of the national forests.

On small communities, an extreme event can have a strong impact on local economy, especially when based on logging and related activities. For such reason, it is very important to assess the impact of extreme events on forests. Wood quality and quantity in particular are an important aspect to be determined if it has changed between pre- and post- event.

In the Alps, forest dynamics are influenced by anthropogenic disturbances, directly through forest management for timber harvesting or for obtaining other forest functions, and by natural disturbances, which can be windthrows, ice and snow break, and insect outbreaks. These natural disturbances often impact on a substantial portion of timber which may be potentially harvested under regular silvicultural plans. This results in rather severe logistical problems due to the urgency of post disturbance harvest operations, with evident added expenses.

Currently, management decisions following natural disturbances are largely based on data which is rapidly collected in the field. There are several problems or challenges associated with field-based approaches. First, it is costly and time consuming to properly sample large forest areas damaged by disturbance. Second, widespread, but less severe disturbances, are often completely ignored or missed in field sampling, yet they may have an important influence of forest structure and function because their return intervals are shorter than stand replacing events. Many natural disturbances, in fact, create heterogeneous damage patterns across large forested landscapes, ranging from small gaps, intermediate sized patches of partial canopy damage, to large areas of total canopy removal. This variability is difficult to capture with field-based methods of inventory.

There is a variety of remote sensing approaches that would provide ideal solutions to address these challenges. Remotely sensed data would improve the decision making process by reducing the response time of managers, cover large landscapes with less cost, and improve objectivity of the quantification of damage patterns and post disturbance forest structure (needed to assess potential recovery patterns). Taken together, remotely sensed data would facilitate and optimize post disturbance management strategies, such as whether to use salvage logging and actively or passively restore disturbed areas.

A number of studies have shown the comparative advantages of LiDAR for detecting changes in forest structure (Vepakomma et al., 2008), since instruments directly measure the vertical and horizontal structure. Previous studies (Vastaranta et al., 2012b) approached the assessment of snow-damaged stands through the difference between bi-temporal high-density scans (7-9 pts/m^2). The analyses have been carried out on younger stands (avg DBH ~20 cm) where the snow impacted not only with partial removal of the living canopy but also with stem breakages, creating larger gaps. The ΔCHM has then been converted to a binary image in order to identify the groups of connected pixels and filter local noise. A pretty similar approach has been used by Tanhuanpää et al. (Tanhuanpää et al., 2015) to determine the fallen trees within some urban mixed stands in the city of Helsinki and the subsequent modellisation of coarse woody debris, in order to evaluate its removal according to the national laws. Finally, the approach was positively tested also for the assessment of canopy damages for urban tree management, where the ALS data allowed highly reliable estimations for tree height/stem and canopy damage (Rahman and Rashed, 2015).

3.3 Materials and methods

3.3.1 Study area

The study areas are located in Slovenia within mountainous monospecific forest stands of Norway spruce (*Picea abies* Karst.), European beech (*Fagus sylvatica* L.) and silver fir (*Abies alba* Mill.). A set of 24 plots (~1000 m^2 each) have been selected stratified according to the dominance of one of the aforementioned tree species across mature stands. LiDAR data were acquired under leaf-off conditions with a Riegl LM5600 sensor before and after a highly destructive ice-break event during winter 2013, respectively in October 2013, April and October 2014. The average point density of the data sets is ~200 points per square meter. The same analysis procedure was tested at three different point densities (i.e. 5, 10 and 200 pts/m^2) in order to verify the suitability of low-, high- and very high- density datasets for such an assessment. Differently from what suggested by Wilke, the thinning of the point cloud was done on the single points and not on the pulses. This choice was done due to the specific data collection process which saw a helicopter hovering over the

area and providing a really high point density but with pretty low pulse number (i.e. ~0.31).

Finally, the field data included inventory information such as tree location, species and diameter at breast height. Additional information is related to the calculated height, volume, basal area and if the tree was cut during the sanitation felling carried out during 2014.

3.3.2 *Data pre-processing*

The data have been processed in the R statistical environment (http://www.r-project.org/) using the algorithms implemented in the package "lidR" (Roussel and Auty, 2017) for the elaboration of the raster products, the segmentation and the analyses of the point-cloud. All the analyses were carried out on point-clouds classified by the vendor and height-normalised on a second stage.

The segmentation of the single trees was done making use of the algorithm proposed by Dalponte and Coomes (Dalponte and Coomes, 2016) and carried out on a raw CHM with pixels of 0.5 m per side, where no gap-filling and/or smoothing operations were applied. The method has been preferred to other available ones due to its fast and computationally low-requiring characteristics that offer the chance of a use over wider areas. The choice of a raw CHM for the segmentation process was preferred to other approaches, such as smoothing or the one developed from Khosravipour et al. (Khosravipour et al., 2014) in order to reduce as much as possible the noise related to the artefacts (e.g. smoothed values, non-coherent crowns) introduced by such processes.

3.3.3 *LiDAR metrics*

Each point-cloud has been filtered by return and scan angle to provide the necessary conditions to perform the elaboration of several metrics related to height and intensity (min, mean, max, std.dev.). Among these, the Leaf Area Density as described by Bouvier et al. (Bouvier et al., 2015) specifically the use of first and single returns only. This index was calculated on height bins of one metre and, to be considered accurate, has been elaborated using points within a scan angle range of ±23° in accordance with the recent findings from Liu et al. (Liu et al., 2018). Values exceeding this threshold indeed are considered "large off-nadir" points and for this reason related to lateral canopy penetration and not the vertical one, as required by the metrics. As a matter of discussion, this filtering process made the original point density drop with an average decrease of 33%.

Per each plot, Diameters at Breast Height (DBH) and the total dry Above-Ground Biomass (AGB) have been estimated using the generalised equations provided in Jucker et al. (Jucker et al., 2017). With these data, it was possible to calculate the total basal area and the tapering coefficient H/DBH. Finally, the wood density values for the selected species were chosen from the Global Wood Density Database ((Chave et al., 2009; Zanne et al., 2009)) in order to be used for the conversion between the biomass and volume values.

3.3.4 *Statistical analyses*

In order to evaluate if the difference between field and LiDAR data was statistically significant, some tests were run on the coupled measurements. The normality of distribution was tested with the Shapiro-Wilk test at the 95% and, in case the condition was not met, a Mann-Whitney test was run instead. On the other hand, in case the variances were found unequal by the Levene's test, a Welch test was used instead.

In the case of the LAD index, The statistical significance of the difference between the same bin from different period was tested with a paired T-Test in the case in which the data were normally distributed while a Wilcoxon signed-rank test was run in the opposite case.

3.4 Results

The field data includes the information coming from the survey carried out on October 2013 and October 2014, where the removed trees were assessed. The mean stand parameters (height, DBH, basal area and volume) are summarised in Table 2 for both the periods and the relative change.

Table 2: Inventory data from pre- and post-event by dominant species.

	ABIES				**FAGUS**				**PICEA**			
	2013		***2014***		***2013***		***2014***		***2013***		***2014***	
n	24.8	±8.4	18.3	±7.9	26.1	±6.6	22.3	±5.9	37.5	±18.0	20.9	±11.4
DBH (cm)	37.5	±2.1	38.5	±2.4	34.9	±4.2	35.3	±4.5	34.2	±4.3	36.5	±3.9
H (m)	24.5	±1.0	25.0	±1.6	25.8	±2.4	26.0	±2.5	25.4	±1.7	26.7	±1.4
V (m^3)	43.9	±14.9	35.3	±18.8	42.3	±7.6	36.5	±6.1	47.6	±15.6	31.8	±13.5
G (m^2)	3.3	±0.9	2.6	±1.3	2.9	±0.5	2.5	±0.4	3.6	±1.2	2.3	±1.0

Focussing on tree density distribution (Figure 7), it is possible to see a strong underestimation derived from LiDAR segmentation in the pre-event period. Due to the

intuitively relevant effects that such situation could have on the estimation of all the other parameters, it was decided to evaluate the comparability between field and LiDAR data in terms of relative damage instead of direct measurements.

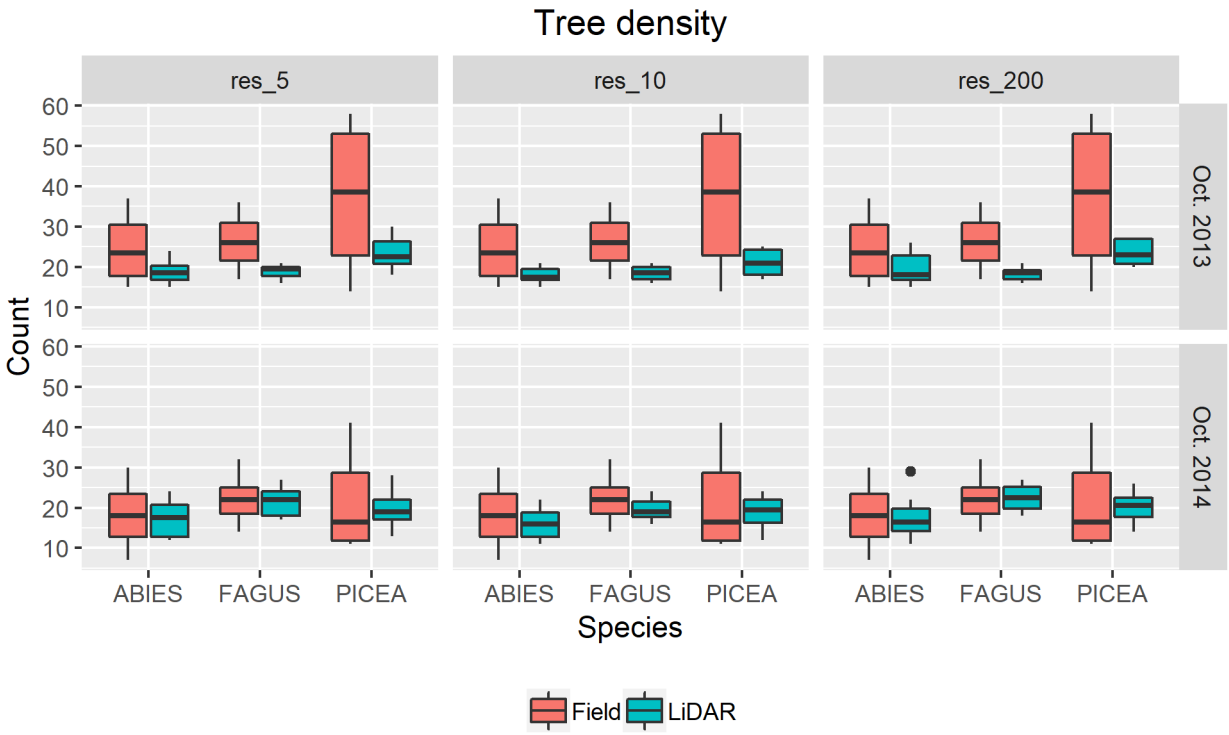

Figure 7: Comparison of tree density values between field and LiDAR data, before and after the event.

3.4.1 *Damage estimation*

The estimation of the damage was carried out for three main parameters: tree density, basal area and volume. Additional evaluations were carried out on the Leaf Area Density index along the stand vertical profile.

3.4.1.1 *Tree density*

The reference tree density shows a relevant decrease for what concerns the PICEA stands, while the other species seem to suffer a less intense damage. LiDAR underestimates in all the three cases, especially within PICEA stands, reducing progressively the error range across the datasets along with the increase in point density.

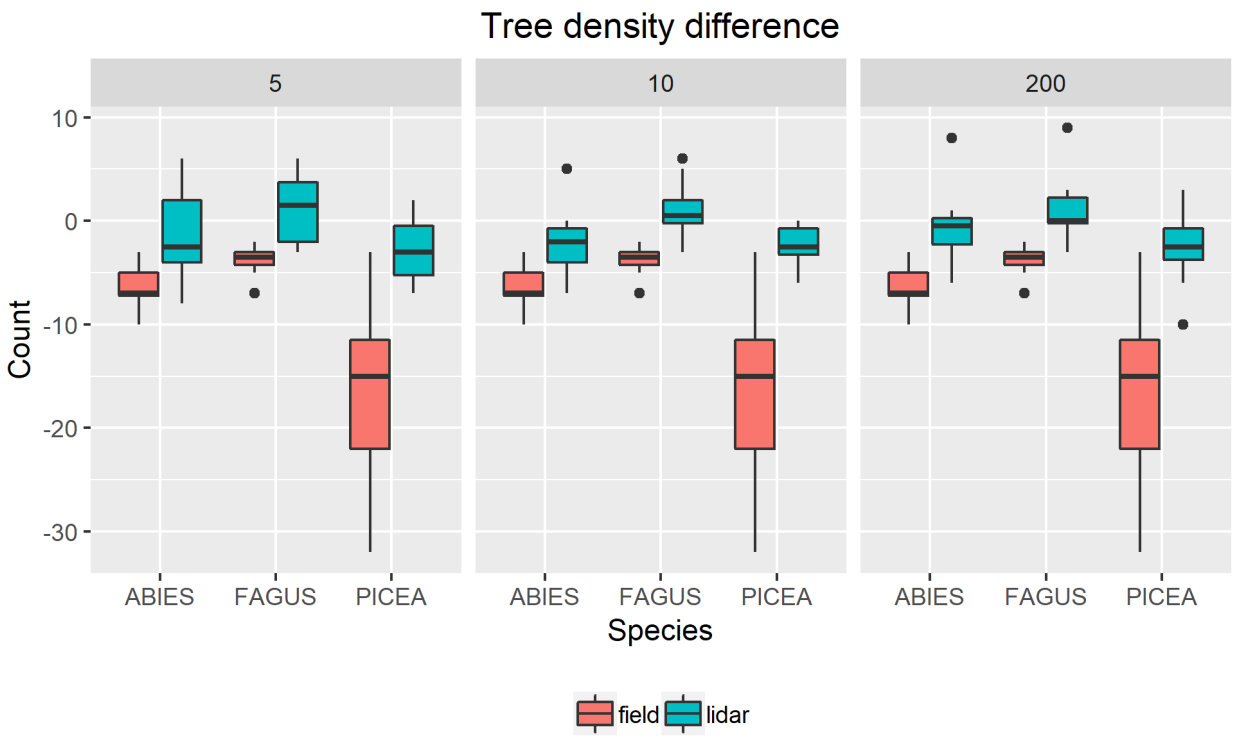

Figure 8: Comparison of tree density difference values.

The results of the tests show that all the differences are statistically significant. Values are reported in Table 3 according to species and dataset.

Table 3: Significance tests for the tree density.

		ABIES			FAGUS			PICEA		
	Test	*t*	*df*	*p*	*t*	*df*	*p*	*t*	*df*	*p*
res_5	*Student*	-4.239	14	<0.001	-4.664	14	<0.001	-3.723	14	0.002
	Welch				-4.664		0.001			
res_10	*Student*	-3.138	14	0.007	-4.19	14	<0.001	-4.284	14	<0.001
	Welch							-4.284	7.707	0.003
res_200	*Student*	-3.402	14	0.004	-6.250	14	<0.001	-4.028	14	0.001
	Welch				-6.250		<0.001	-4.028	7.651	0.004

3.4.1.2 Basal area

LiDAR data overestimates the decrease in basal area for FAGUS stands in the case of low-density datasets, while, on the contrary, it underestimates the difference in the dataset with the highest point density.

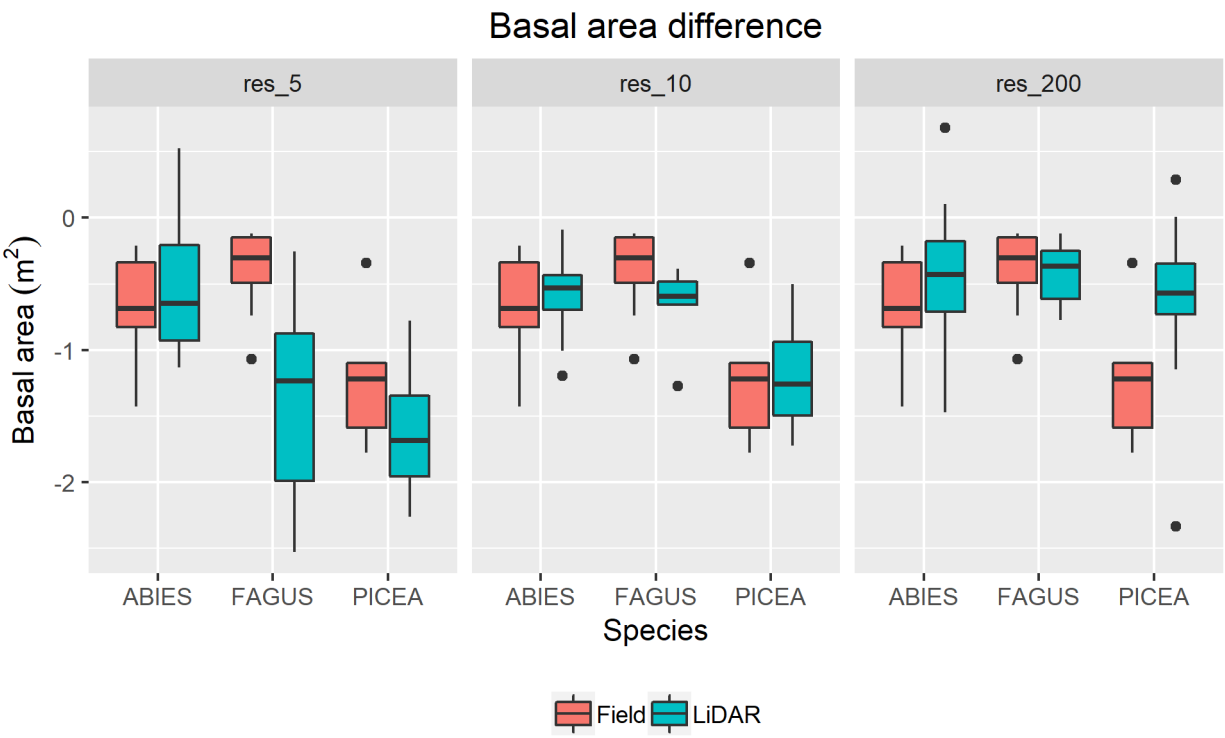

Figure 9: Comparison of basal area difference values

The results of the tests show that only the difference for FAGUS stands using the low point density datasets is statistically significant. Values are reported in Table 4 according to species and dataset.

Table 4: Significance tests for basal area difference.

		ABIES			FAGUS			PICEA		
	Test	*t*	*df*	*p*	*t*	*df*	*p*	*t*	*df*	*p*
res_5	*Student*	-0.619	14	0.546	3.263	14	0.006	1.604	14	0.131
	Welch				3.263	9.519	0.009			
res_10	*Student*	-0.495	14	0.628	1.512	14	0.153	-0.224	14	0.826
res_200	*Student*	-1.019	14	0.325	0.14	14	0.891	-1.783	14	0.096

3.4.1.3 Volume

For what concerns the volume difference, LiDAR estimations got closer to the field measurements with the increase in point density. In the low and medium density datasets, indeed, the decrease in volume is always overestimated.

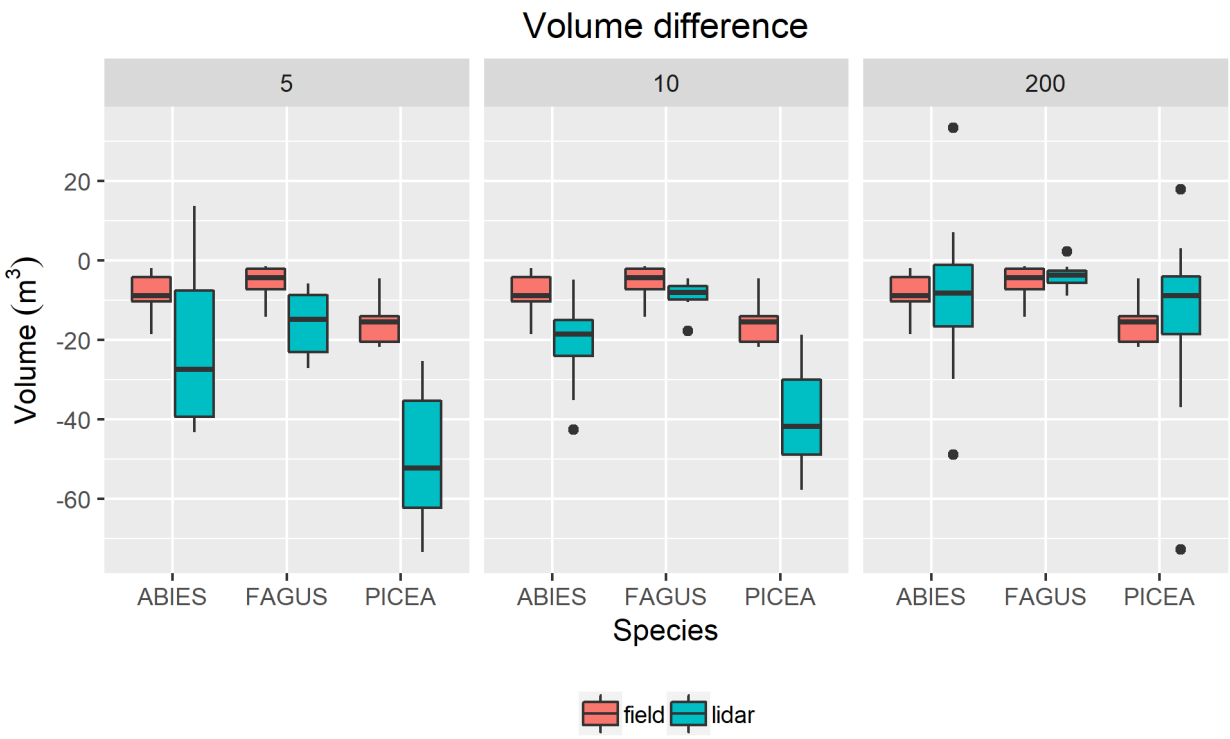

Figure 10: Comparison of volume difference values.

The results of the tests show that the differences in FAGUS and PICEA stands with the low-density datasets and ABIES and PICEA stands with the medium-density datasets are statistically significant. Values are reported in Table 5 according to species and dataset.

Table 5: Significance tests for volume.

		ABIES			**FAGUS**			**PICEA**		
	Test	*t*	*df*	*p*	*t*	*df*	*p*	*t*	*df*	*p*
res_5	*Student*	1.369	14	0.193	2.687	14	0.018	6.039	14	< .001
	Welch	1.369	8.147	0.208				6.039	8.624	< .001
	Mann-Whitney				53		0.028			
res_10	*Student*	2.385	14	0.032	1.325	14	0.206	4.56	14	< .001
	Welch							4.56	9.201	0.001
	Mann-Whitney				48		0.105			
res_200	*Student*	0.666	14	0.516	-0.827	14	0.422	0.53	14	0.604
	Mann-Whitney				28		0.721			

3.4.1.4 *Leaf Area Density*

The variability of the LAD parameter was evaluated at a single height-bin level (1 metre) for the highest density dataset. A visual inspection indeed showed a similar response among datasets and hence we decided to focus on just the most reliable (Figure 11).

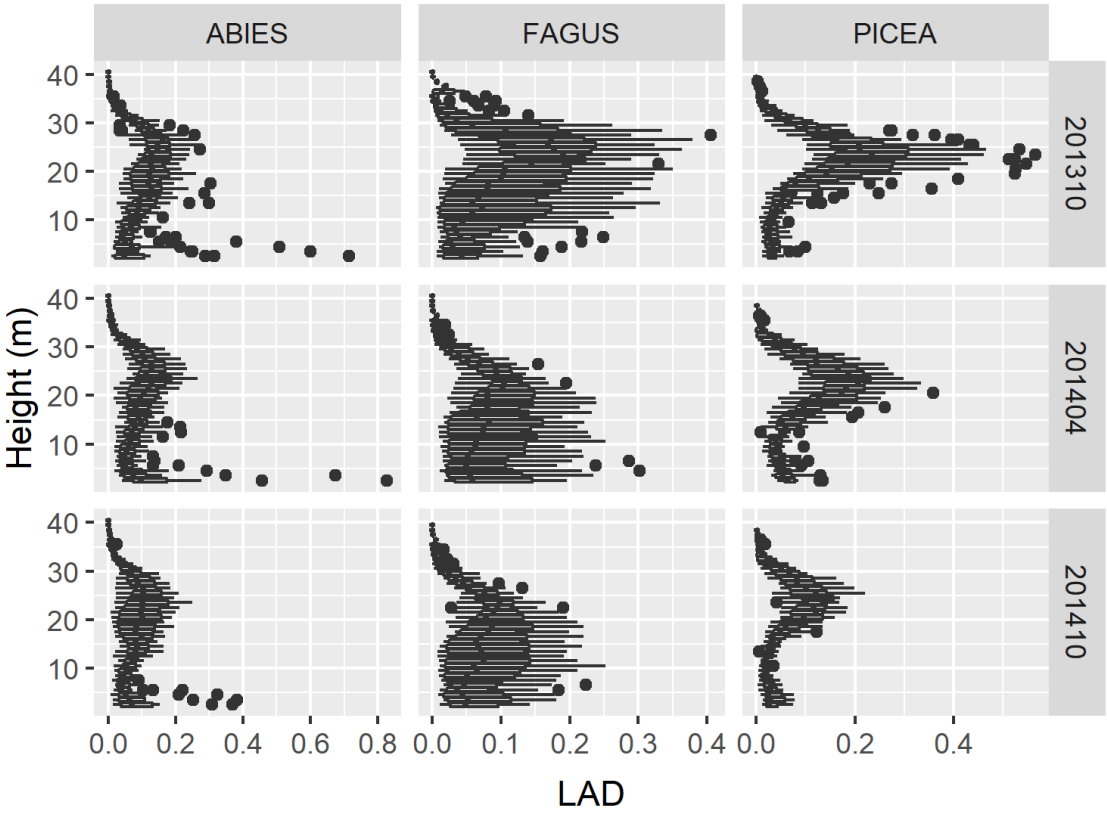

Figure 11: Leaf Area Density profiles through the three study periods (height bins: 1m; point density: 200 pts/m^2).

In the plots reported in Figure 12 the statistical significance has been represented across the whole vertical profile with three values: "yes" and "no" as result of the mentioned tests and "NA" when the tests were non applicable due to scarcity of data (n<3) or impossibility of pairing the observations (different number of measurements).

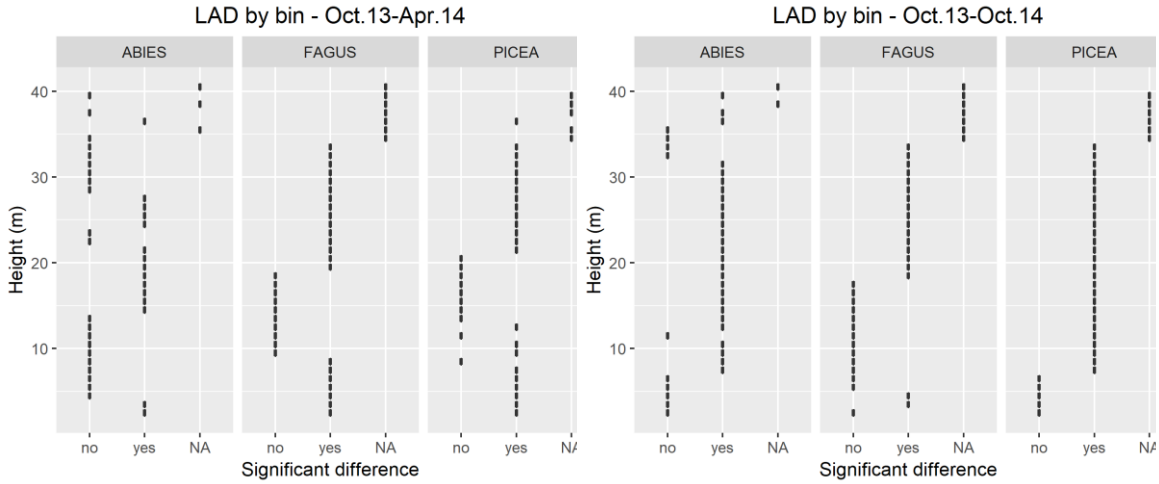

Figure 12: Statistical significance of the change in Leaf area Density by height-bin. On the left is shown the difference between the October 2013 and April 2014, on the right between October 2013 and October 2014.

3.5 Discussion

The direct comparison between measurements of the main stand parameters (i.e. tree density, tree height, DBH, basal area, volume) at plot level could not be achieved due to incomplete field information. Inventory data came from rapid field surveys that were not meant to be used as a precise reference. Nevertheless, this allowed to compare the methodologies for quick damage assessment. A general overview of the results show an overall better performance of the very high-density dataset.

3.5.1 Tree density

The estimated tree density is affected by many sources of errors, among which the segmentation process should be considered as the first step. Top-down algorithms (e.g. watershed-based, Li et al., 2012) are known to perform better within conifer stands thanks to the conical architecture that characterises the species belonging to this group.

When compared to the method proposed by Li et al. (2012), the watershed-based algorithms suffer from a strictly 2D approach related to the use of a rasterised canopy model to segment the point-cloud below, losing the ability of identifying the co-dominant trees or those partially included in the understory. The identification of the tree is done only from the top layer and this can be seen even more when the method is applied to damaged stands. Across time, damaged trees may indeed lose the seed point (i.e. treetop) and this may lead to a different segmentation output, resulting in a different number of individuals per each scan (Figure 13).

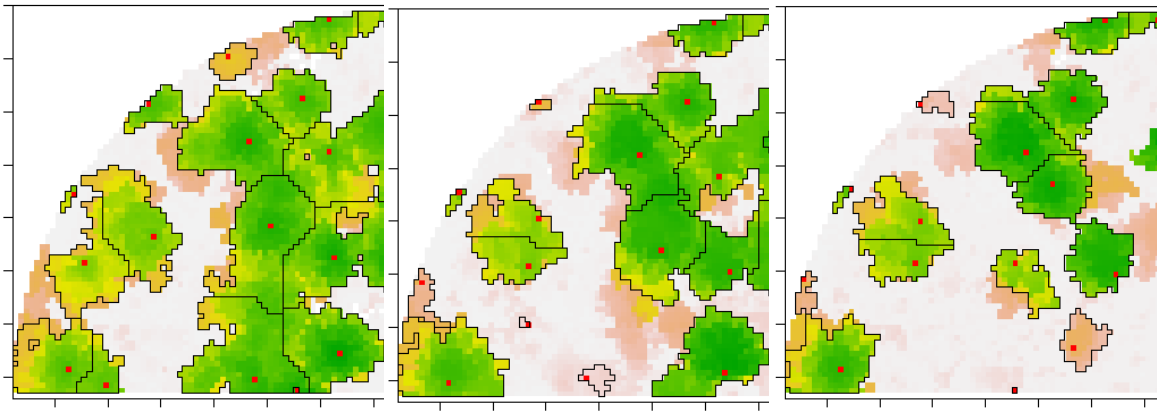

Figure 13: PICEA_050_4, res 200 (Oct. 2013, Apr. 2014 and Oct. 2014; coloured by height; the red dots are the identified treetops).

In the case of tree density (Figure 7), this effect can be noted across all the point densities and between periods. The segmented number of trees indeed, gets closer to the surveyed ones in the scan from October 2014. This might be related to a decluttering effect of the crown damages that enhanced the separation of canopies allowing for a better segmentation of the single individuals. Nevertheless, with the used approach, LiDAR shows to be unable to catch the signal in terms of damaged trees if they belong to dominated stories.

3.5.2 *Basal area and volume*

Estimations of the basal area did not significantly differ from the field ones (Figure 9). Even if the number of trees can change between scans (as described above), this change is mostly related to the smaller trees. In the same way, this applies to volume estimations. In addition, volume errors may be also derive from the fact that it has been estimated using yield tables and not measured in the field.

Nevertheless, at a plot scale field and LiDAR derived values can be reliably compared.

3.5.3 *Leaf Area Density*

The analysis of the LAD profiles (Figure 11) well represents the sensitivity of such index in describing the damages at a stand scale using bins of one metre in height.

From Figure 12 it is possible to see how the ABIES stands were the less affected by tree-topping while the major damages were on the understory and the lower canopy, as it is possible to see from an increase of the average DBH in the field data after the event

(Table 2). FAGUS stands were mostly affected along the whole crown profile but with no evident changes at the stem level, probably related to the debranching action that the icestorm provided. The significant changes in the lower level that can be seen in Figure 12 may be related to the accumulation on the ground of the damaged material (i.e. branches, treetops).

Finally, for what concerns the PICEA stands the damages concentrated at the stem level affecting trees mostly with stem break and uprooting (Figure 14), similarly to what described for unmanaged pine stands (Päätalo et al., 1999). While stem breaking occurs mainly in adult stands (Nykänen et al., 1997) and uprooting may be due to the shallow root system, no specific reference can be done in relation to the tree tapering that results on average lower than the observed one for damaged spruces (Pellikka and Järvenpää, 2003). Furthermore, in the difference between October 2013 and 2014, it is possible to notice the effect of the intense sanitation cuts that were carried out as main tending operation in order to avoid bark beetle outbreaks (Veselič et al., 2014).

All the treetops were not always comparable due to a scarcity of data per bin or data that could not be paired. These cases are represented ad NA values in the plot and should be commented with care. It is not possible indeed to evaluate the significance of the difference.

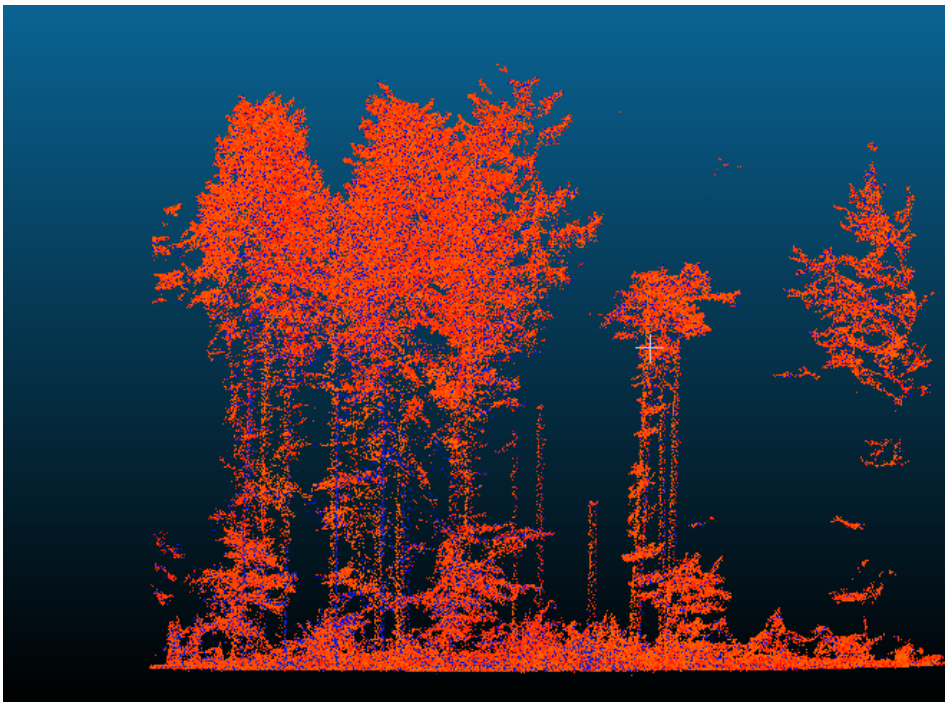

Figure 14: A PICEA plot heavily damaged by the ice storm.

3.6 Conclusions

As reported in Irland (Irland, 2000), one method applied for the assessment of ice damages includes a trained observer noting crown conditions from an aerial survey. The proposed methodology aims at providing a quantitative and objective output for large-scale events. For this reason, the study took in consideration a single segmentation algorithm in order to test a procedure that could rely on a widely available product (i.e. CHM) and that requires low-computational requirements. The purpose of comparing among point densities imposed the necessity of a constant pixel resolution for the raster products. This did not allow to extract relevant information from the data set with 5 pts/m^2 due to the abundance of empty cells in the CHM that impeded a proper segmentation. Nevertheless, this does not affect the feasibility of the procedure with coarser resolutions (i.e. 1 m) more appropriated for the point density.

Better segmentation performance in terms of identified trees may derive from other available algorithms that are applied directly at the point-cloud level (i.e. (Li et al., 2012)) and, within those datasets with a point density that can provide information related to the stem, also from bottom-up approaches (i.e. (Hamraz et al., 2016; Lu et al., 2014; Vega et al., 2014)). These methods could increase the number of identified trees, especially the ones in the understory, as shown for some specific studies (Ayrey et al., 2017; Kandare et al., 2014). Further improvements may be provided by novel approaches to the analysis of the point cloud in order to support the segmentation process through a stratification of the canopy layer (Hamraz et al., 2017).

The use of general allometric equations (Chave et al., 2009; Jucker et al., 2017; Zanne et al., 2009), allowed to set a reference point for what concerns an area-based approach to the topic. Their use indeed can be easily implemented in automatic procedures for the extraction of structural parameters from remote sensed data, in particular from LiDAR. Previous experiences that estimated the DBH for single trees and clusters modelling tree height and crown projection as predictors obtained an R^2 of 0.71 within different stands of *Eucalyptus* spp. in Australia (Verma et al., 2014). Nevertheless, additional work is needed to understand the effects of their use on wide scale forest planning but the use of our procedure in hardly accessible areas or when the costs of fieldwork must be minimized could be evaluated (Vastaranta et al., 2012a).

Even if not in terms of direct measurement, LiDAR confirms in this case to be a useful tool for change detection purposes, allowing the assessment of the magnitude of variation caused by an ice-storm event. Furthermore, it offers the capability of characterising the damage through the profile, allowing for immediate understanding of structure's modification. This has revealed as well species-specific information on ice damages to canopies. The data, analysed through the use of the Leaf Area Density index, provided an insight on the different response attitude of each single species at a stand level.

A possible benefit deriving from a multi-temporal approach through the years may be the monitoring of the damaged stands making use of other structural indexes such as the Vertical Complexity Index (Van Ewijk et al., 2007) and studying the canopy gaps for the characterisation of the stand dynamics. Beech stands are considered to be more resilient to such disturbances in the short period, favouring mainly the advanced regeneration and shade-tolerant species (Beaudet et al., 2007). On the other side, the formation of wide gaps may promote early successional species within the conifer stands, as stressed by Tremblay et al. (2005).

4 Characterisation of the three-dimensional distribution of forest fuels using TLS data

Niccolò Marchi[1], Peter J. Weisberg[2], Jonathan A. Greenberg[2], Emanuele Lingua[1].

[1] *University of Padova, Department TESAF, viale dell'Università, 16, I-35020 Legnaro (PD), Italy*
[2] *University of Nevada, Reno, Department of Natural Resources and Environmental Science, 1664 N. Virginia St., Mail Stop 186, Reno, Nevada 89557, USA*

4.1 Abstract

Global warming is increasing weather extremes, enhancing the favourable conditions for wide-scale disturbances. In a warmer world, wildfires are supposed to increase in frequency and severity, threatening areas not previously affected. Such events play a major role in shaping some vegetation communities and knowing the fuels' availability can help in preventing habitat loss or managing wildfires in a beneficial way. New technologies (e.g. LiDAR) are proving their feasibility for wide scale assessment but ground data is still relying on field surveys that require time and efforts.

The present work aimed at the development of a procedure for the identification, quantification and description of the spatial distribution of surface forest fuels within the Sierra Nevada mountain range (South-West U.S.A.) using Terrestrial Laser Scanning data. The analysis of the point-cloud included the application of common statistics and indexes to raw and voxelised spatial data. Preliminary results show that the vertical spatial continuity can be described through a voxel approach with good approximation.

4.2 Introduction

Surface fuels, meant as needles, leaves, grass, forbs, dead and low branches and boles, stumps, shrubs, and short trees (Scott and Reinhardt, 2001), constitute an important element within a forest stand. This layer is tightly connected to the main stand dynamics, being on one hand the product of the mortality of the different tree parts and on the other hand the growth substrate for the establishment of the future regeneration. When focussing on the dead component, the horizontal and vertical distribution of the material

may enhance or suppress different processes taking place at the ground level but influencing the whole stand, such as providing nourishment and shelter for the regeneration (Marzano et al., 2013) or acting as a ladder in case of surface fires.

Wildfires are an important driver within the forest landscapes, being able to radically change the stand structure dynamics or simply reset them. In a warming world fire regimes are predicted to change increasing in fire frequency and severity (Lindner et al., 2014; Schelhaas et al., 2003) or size (Miller et al., 2012; Westerling et al., 2006). These changes will affect especially coniferous forests and the boreal biome, however, at the current stage, the understanding of the effects on a large scale is still scarce (Seidl et al., 2017). It is therefore fundamental an accurate mapping of the fire potential on a wide scale but, till now, the assessment required long and expensive procedures for field data collection. New technologies, such as laser scanning technologies (airborne and terrestrial) are progressively finding their way in the characterisation and classification of forest fuels often combined to other remote sensing data sources (e.g. satellite or aerial imagery), due to the three dimensional information that can be derived. The use of Airborne Laser Scanning (ALS) data has started to be widely adopted (Andersen et al., 2005; Casas et al., 2016; Gajardo et al., 2014; Garcìa et al., 2011; Price and Gordon, 2016; Riaño et al., 2004, 2003; van Aardt et al., 2011), even if it suffers the limitation that mainly tree fuels (i.e. crown bulk and its parameters) can be accurately quantified. Terrestrial laser scanning (TLS), on the other side, previously defined as expensive and intensive to implement (Hopkinson et al., 2004), is only recently gaining the attention of fire scientists due to the high precision data that it can provide. Indeed, while the application for forest inventory purposes (Liang et al., 2016) or for rangeland shrubs characterisation (Chen, 2017; Li et al., 2015; Olsoy et al., 2016, 2014) has already been proven to be effective, surface forest fuels characterisation using TLS is still in its early stages (Chen et al., 2016; García et al., 2011; Loudermilk et al., 2009; Wallace et al., 2016). TLS can provide detailed data by ensuring a fast collection during field campaigns. Its capability of catching the reality with a really high accuracy can provide for automated procedures that can be applied on larger samples than the traditional single line transects (i.e. "Brown's transect", (Brown, 1974)).

While many methods and protocols have been defined for the field estimation of the amount of forest fuels (e.g. (Brown, 1974; Hines et al., 2010; Lutes and Keane, 2006; Pesonen et al., 2009; Riccardi et al., 2007)), their spatial distribution did not receive the same attention. Recent studies focussed at fine scale fuels' continuity using remote sensing data. These experiences have been carried out mostly within savannah and open woodlands environments, showing the possibility of describing fuel loads and fire behaviour at a sub-metre scale (Caccamo et al., 2012; Loudermilk et al., 2012, 2009; Wallace et al., 2016).

The present study aimed at the identification and quantification of dead woody material and its 3-dimensional spatial distribution characterisation within the northern Sierra Nevada mountain range.

4.3 Materials and methods

4.3.1 Study area

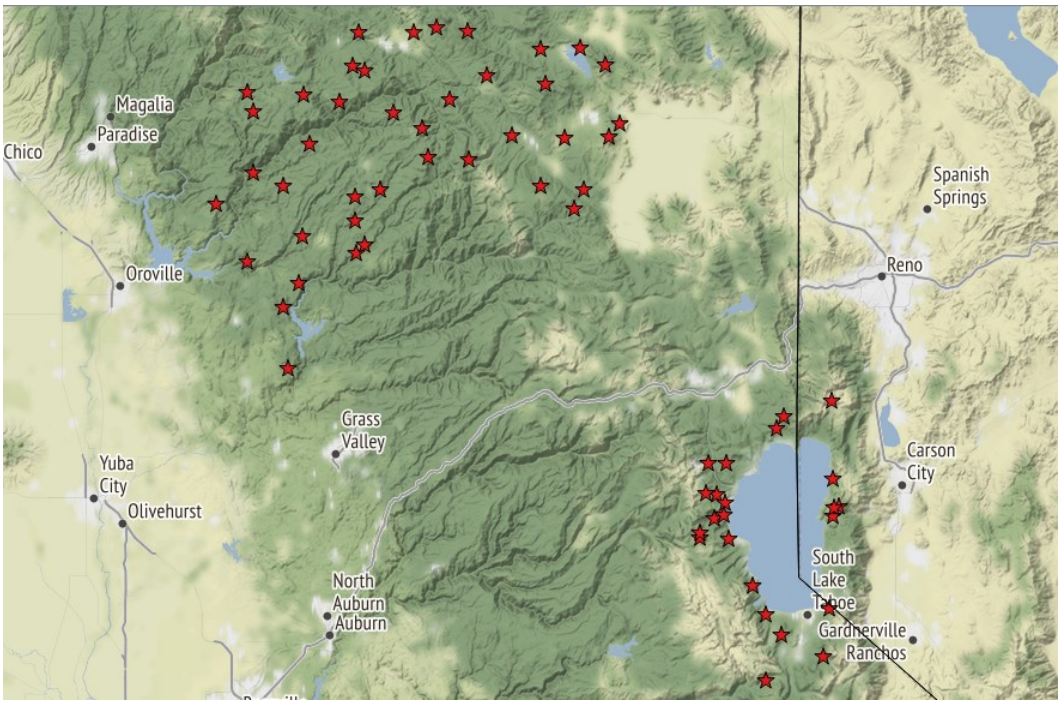

Figure 15: Overview of the study areas.

The study was carried out across the Sierra Nevada mountain range (California, USA), within the area of the Plumas National Forest and the Lake Tahoe basin management unit (Figure 15). The altitudinal gradient along which the plots are distributed ranges between 970 and 2500 m.a.s.l.. The main forests types refer to the lower- and upper-montane and subalpine conifer-dominated stands. The most representative tree species are sugar pine (*Pinus lambertiana* Dougl.), ponderosa pine (*Pinus ponderosa* Douglas ex C. Lawson), Jeffrey pine (*Pinus jeffreyi* Murray), lodgepole pine (*Pinus contorta* Douglas ex Loudon), western white pine (*Pinus monticola* Douglas ex D.Don), incense cedar (*Calocedrus decurrens* (Torr.)Florin), red fir (*Abies magnifica* Murray), Douglas-fir (*Pseudotsuga menziesii* (Mirb.)Franco) and white fir (*Abies concolor* (Gordon) Lindley ex Hildebrand).

Within these plots, two types of "ladder fuels" can be distinguished: shrubs and the woody debris (FWD and CWD) coming from both trees and shrubs. The main shrub

species are greenleaf manzanita (*Arctostaphylos patula*), snowberry (*Symphoricarpos* spp.), serviceberry (*Amelanchier alnifolia*), whitethorn (*Ceanotus cordulatus*), *Ribes* spp., etc. .

4.3.2 *Field protocol*

The field survey was conducted in 63 plots selected through a double stratified sampling process in order to cover a specific area and altitude range. The complex study scheme follows the one depicted in Figure 16 and it is constituted by a main square plot 30x30 m in size and three outer areas within which three fuel-plots (FP) have been identified. These were set up to describe the three-dimensional distribution and quantify the volume of forest fuels over an area of one square metre. As a matter of comparison, fuel loadings were then assessed at site level using the line transect approach proposed by Brown (Brown, 1974), traditionally used by the U.S. forest authorities.

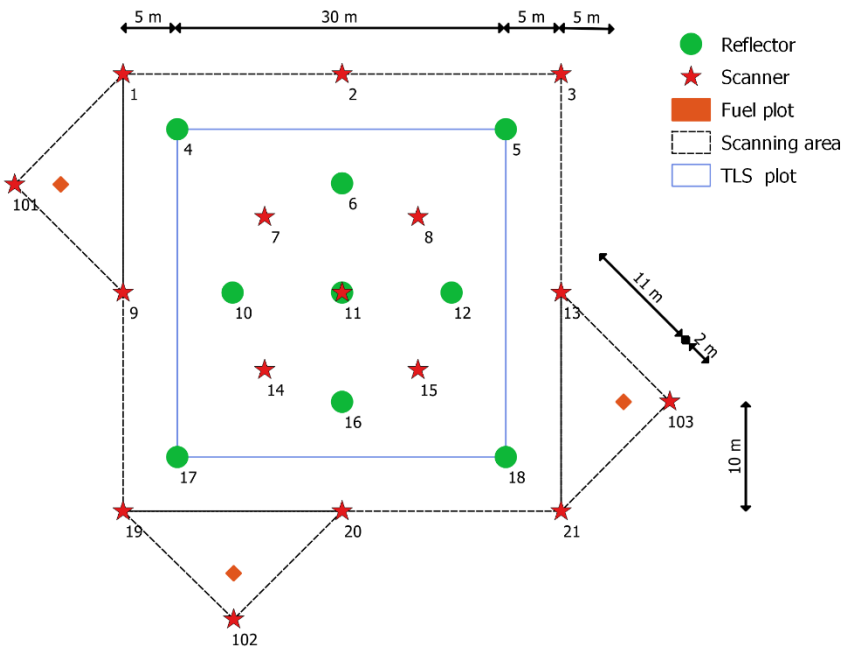

Figure 16: General setting of a plot.

4.3.2.1 *Fuel-plots*

As represented in Figure 16, FPs were set up at an external location of the 30x30 m plot to avoid the overlap and hence disturbance of the fuel layer by the operators. Within each FP, the ground layer data required several measurements such as:

1. Fuel-bed height, describes the vertical distribution of the fuels within the sub-plot. The average was evaluated by taking measurements at the three nearest downed woody debris intersections to the FP.
2. The vertical distribution of fuels was assessed using a so called "Layer Cake" structure (Figure 17) by dividing a 2-metre tall volume of space over the FP into four layers five decimetres tall:
   - Upper elevated fuel layer (1.5 – 2m),
   - Lower elevated fuel layer (1 – 1.5m),
   - Near surface fuel layer (0.5 – 1m),
   - Surface fuel layer (0 – 0.5m).

   Per each layer, the aerial cover has been estimated according to twelve cover classes (1-12)[3].

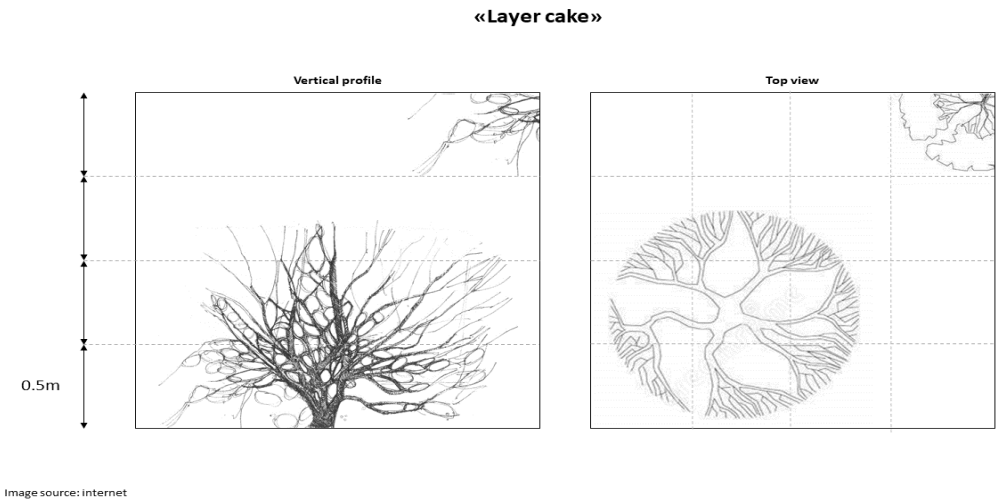

Figure 17: "Layer cake" scheme (side and top view).

4. All the fine branches (FWD – Fine Woody Debris) within the fuel plot were collected, packed in a bag and weighed using a handheld scale.
5. All the CWD (Coarse Woody Debris; diameter >8 cm and length >1 m) has been assessed within a 3-metres radius area and classified according to the species and the decay status (Figure 2). Furthermore, diameter and length were measured. For all the tilted trees, the "45 degrees" rule was applied in order to distinguish snags (>45°) from logs (<45°).

[3] **1**: <1%, **2**: 1-5%, **3**: 6-15%, **4**: 16-25%, **5**: 26-35%, **6**: 36-45%, **7**: 46-55%, **8**: 56-65%, **9**: 66-75%, **10**: 76-85%, **11**: 86-95%, **12**: >95%

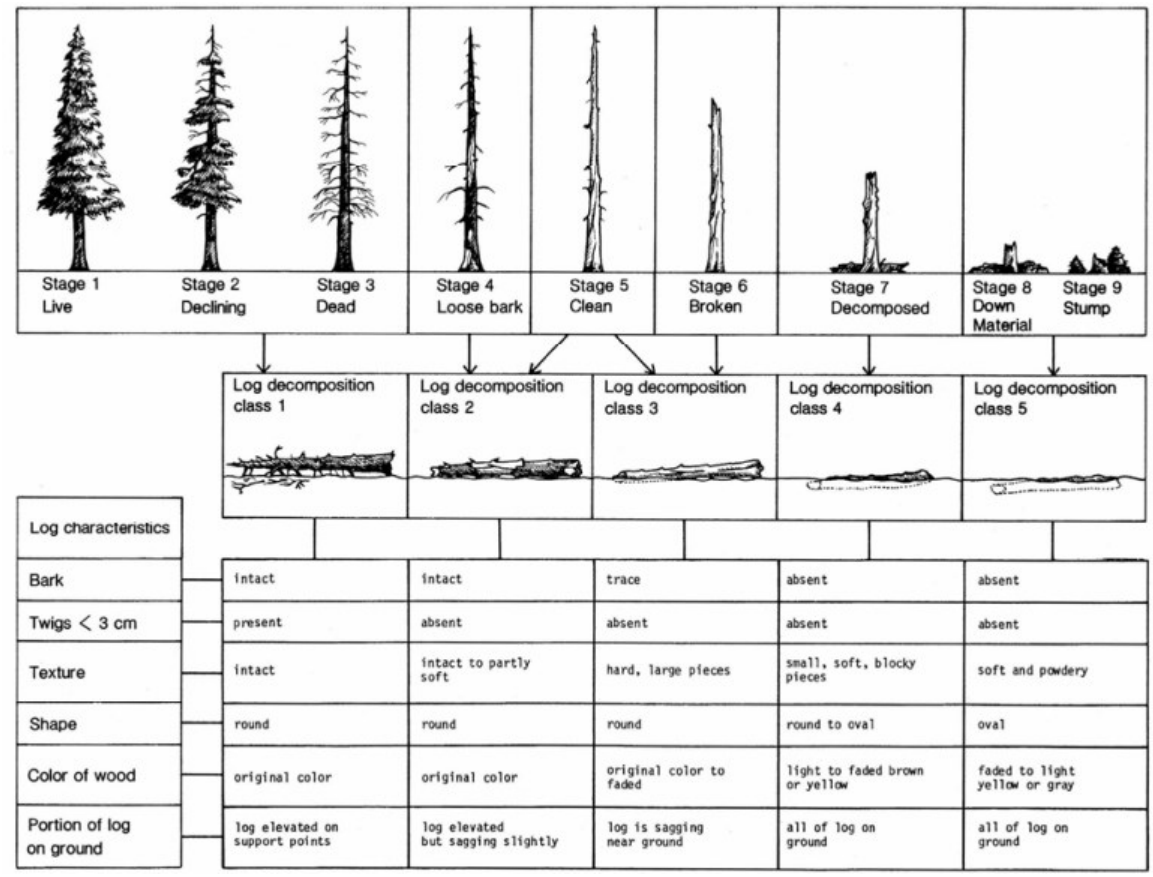

Figure 18: Decay status scheme for snags and downed logs (Hunter, 1990).

Finally, additional information related to the plots were extracted from GIS datasets available online (accessed in 2018):

- Topographical variables: altitude, aspect and slope were derived from the Shuttle Radar Topography Mission (SRTM) dataset (Farr et al., 2007). Slope was then divided into classes according to the FAO classification[4];
- Environmental and management variables: available on the online portal of the USDA Forest Service[5]:
    - Vegetation: following the CALVEG classification[6]; the study plots fell in the following classes: Conifer (greater than 10 percent conifer cover as the dominant type), Mix (greater than 10 percent tree cover and 20 to 90 percent hardwood cover) and Shrub (greater than 10 percent shrub cover as the dominant type);

[4] 1: 0-0.5%; 2: 0.5-2%; 3: 2-5%; 4: 5-10%; 5: 10-15%; 6: 15-30%; 7: 30-45%; 8: >45% ; http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/terrain-data-description/en/

[5] https://data.fs.usda.gov/geodata/edw/datasets.php

[6] Classification and Assessment with Landsat of Visible Ecological Groupings; https://www.fs.fed.us/r5/rsl/projects/classification/system.shtml

- Harvesting: layer "TimberHarvest", represents through polygons the harvesting activities undertaken as part of the Timber Harvest program of work;
- Fire treatments: layer "HazFuelTrt_PL" (Hazardous Fuel Treatments - Polygon), represents through polygons the activities for fuel reduction.

4.3.2.2 LiDAR data

The LiDAR scans were carried out using a Riegl® VZ-400i sensor, whose technical specifications are summarised in Table 6. The main area of interest was delimited setting a reflector (i.e. pole with atop a cylinder covered in reflective material) at each corner of the square and one at the centre, in order to facilitate the stitching of the collected scans and reduce as much as possible the error that could derive. This process was carried out with the proprietary software RiSCAN PRO (Riegl, Horn, Austria), using a semi-automatic procedure aided by manual fixing in case of misalignment. For what concerns the FPs, each area was scanned from three points surrounding the plot identified on the ground.

Table 6: Technical specifications of the RIEGL VZ-400i terrestrial laser scanner.

Ranging method	Time-of-flight
Wavelength	1550 nm
Angular resolution	≥ 0.0024°
Azimuth field of view	0° to 360°
Zenith field of view	-40° to 60°
Beam divergence	0.35 mrad
Beam diameter at emission	7 mm
Beam diameter at 100 m	42 mm
Pulse energy	0.48 ⇨J
Pulse length	3 ns
Sampling interval	1 ns
Peak pulse repetition rate	1200 kHz
Effective measurement rate	500 000 meas s^{-1}
Ranging accuracy	5 mm
Ranging precision	3 mm
Minimum range	0.5 m
Maximum range	120 m @ ρ = 20%
Resolvable targets per pulse	4
Weight	9.7 kg
Battery chemistry	NiMH
Laser safety classification	1 (Eye safe)

4.3.3 *Data processing*

4.3.3.1 Pre-processing

The single scans have been downloaded and stitched together using the proprietary software RiSCAN PRO software (Riegl, Horn, Austria). The stitching used a semi-automatic procedure in order to limit the operator input, providing an average error in the range of 2-3 mm. Finally, the data have been exported in LAS format in order to be analysed using the R package "lidR" (Roussel and Auty, 2017).

The extraction and analysis procedure for the FPs followed four main steps, as follows:

1. According to the coordinates based on azimuth and bearing from the plot centre, the fuelplots were extracted with a spatial query. In order to reduce the number of incomplete extractions derived from possible misalignment between field location and LiDAR, it has been necessary to set the radius of the circular plots to 4 metres.

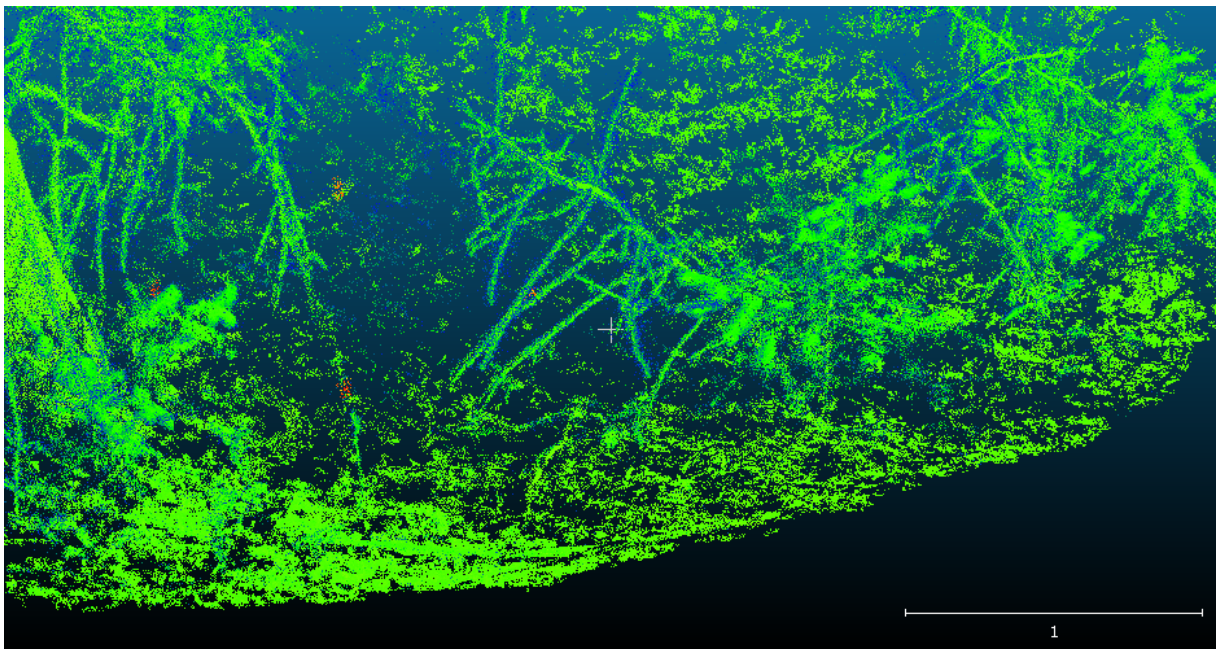

Figure 19: Overview of a fuelplot identified by four stakes (stakes in red; point cloud coloured according to Reflectance values).

2. Within the extracted point cloud, all the reflective materials (stakes + hardhats) were isolated by means of a filter on the reflectance values (Reflectance > 15dB) and the centre of these values was identified through a selection of the median X & Y coordinates. According to this corrected centre position, a further clip with smaller radius (R = 1.5 m) was applied in order to reduce the processed area for the ground classification. This is necessary due to the computational limitations related to the classification algorithm provided by the R package 'lidR'.

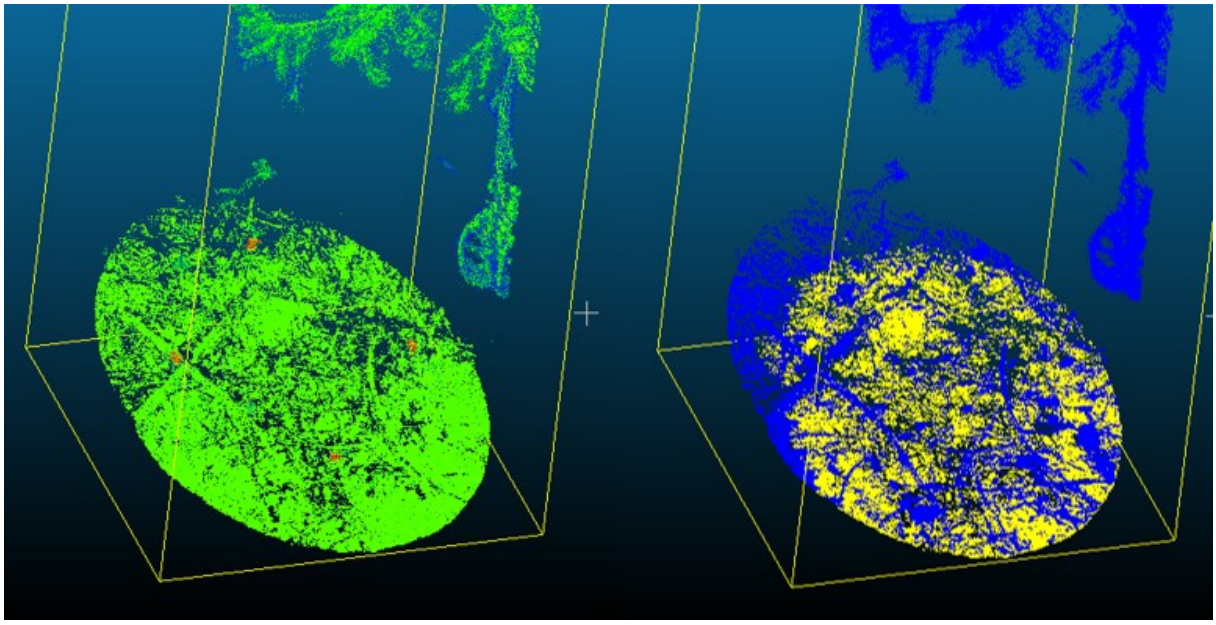

Figure 20: Re-centred clip and ground classification (coloured by Reflectance on the left and by Classification on the right).

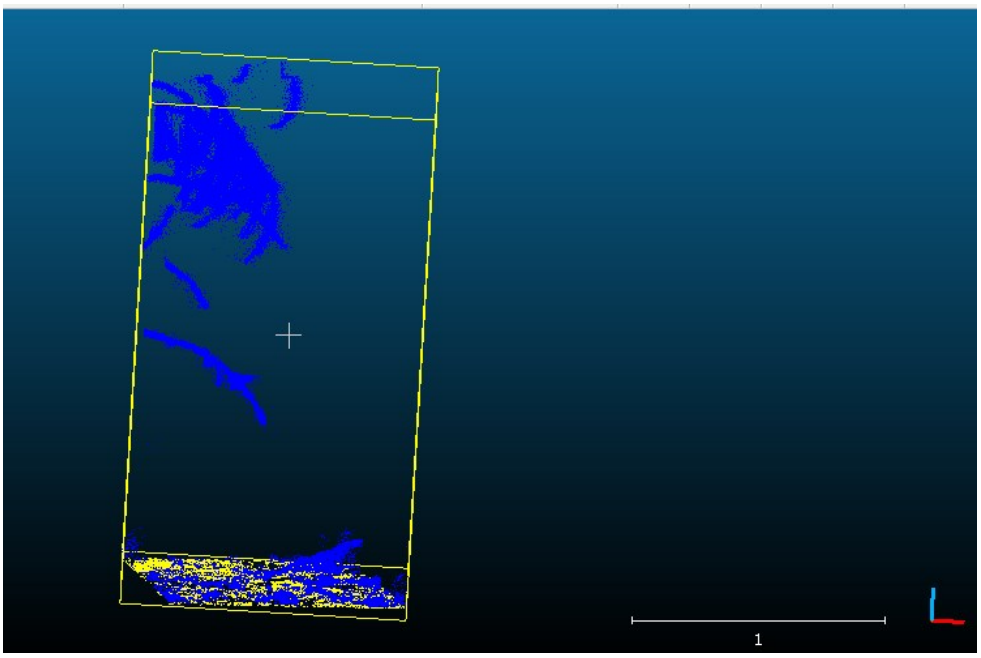

Figure 21: Side view of a classified and height-normalised fuelplot (coloured by Classification: ground in yellow, non-ground in blue)

3. The new clipped point cloud is classified in "ground" and "non-ground" with the use of a modified version of the Progressive Morphological Filter (Zhang et al., 2003). The algorithm implemented in "lidR" is applied directly at a point-cloud level with the possibility of sub-metric window sizes and allowing to skip the

intermediate ground rasterization step. The parameters used are a height threshold between 1 and 50 cm and a window size equal to 0.5, 1 and 2 metres. The point cloud with the reflectors is height-normalised as well in order to apply an additional filter on the height (Z < 1 m) and keep only the selection of points related to real stakes.

4. The point cloud was clipped according to the convex hull of the stakes and then analysed following the "layer cake" structure described above. Further data were extracted using several metrics from the point cloud and calculating some dispersion indexes on the voxelised (see Paragraph 4.3.3.2).
5. Finally, each point cloud was visually checked in order to assess the quality and remove noise.

4.3.3.2 Data processing

General statistics related to the distribution of height and intensity values were calculated for each FP point cloud.

For what concerns the evaluation of the cover percentage per each height layer, it was calculated through the rasterization of the values using a minimum mapping unit (i.e. pixel) equal to 5 mm. The distinction between live and dead material was done thresholding the Reflectance information, assigning to the former group all the values less than -10 dB and to the latter group all the ones above. This decision has been taken due to the peculiar technical specifications of the Riegl scanner VZ-400i, which laser is emitted at 1550 nm frequency. This wavelength gets partly absorbed by water and, therefore, it results in lower values of reflectance. The threshold was identified through a process of trial-and-error on specific elements of the scene (stem, leaves, ground) manually separated from the available point-clouds.

In order to characterise the horizontal and vertical distribution of the points within the fuel point-cloud, it was used a voxel-based approach, applying some of the dispersion indexes proposed by Lecigne et al. (2017). The selected functions describe the Euclidean distance of the voxel from a defined point (*point.distance*) or Cartesian axis (i.e. the "stem"; *axis.distance*) and the angle that is formed by each voxel from a user-defined X-, Y- or Z-axis (*axis.angle*). The last one allows also a projection of the data on a 2D space to describe the radial dispersion of voxels.

4.4 Results

4.4.1 Field data

A quick overview of the field data (Figure 19) shows that the majority of plots are located at an altitudinal range between 1000 and 2500 m.a.s.l. but they are quite equally

distributed for what concerns both aspect and slope steepness. In relation to forest type and management, there is a neat prevalence of plots in conifer stands, a slight majority of which were not treated, while the few available mixed stands are almost equally split into treated and non-treated. Only one case was part of a shrub (SHB) category.

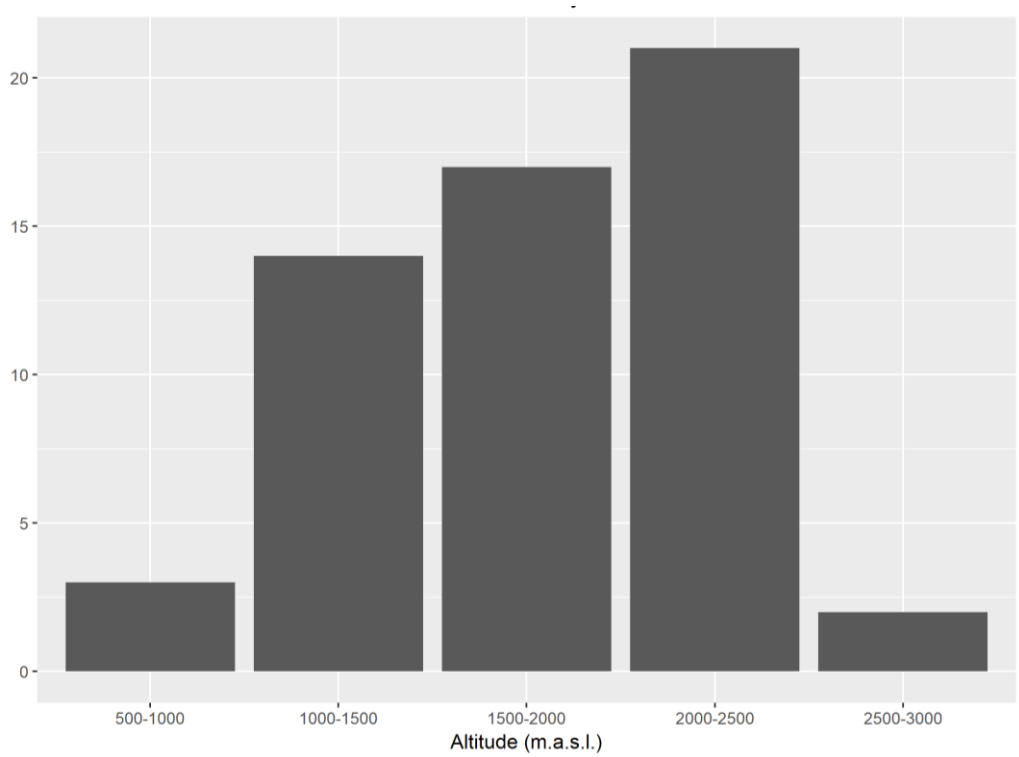

Figure 22: Distribution of the study plots by altitude range.

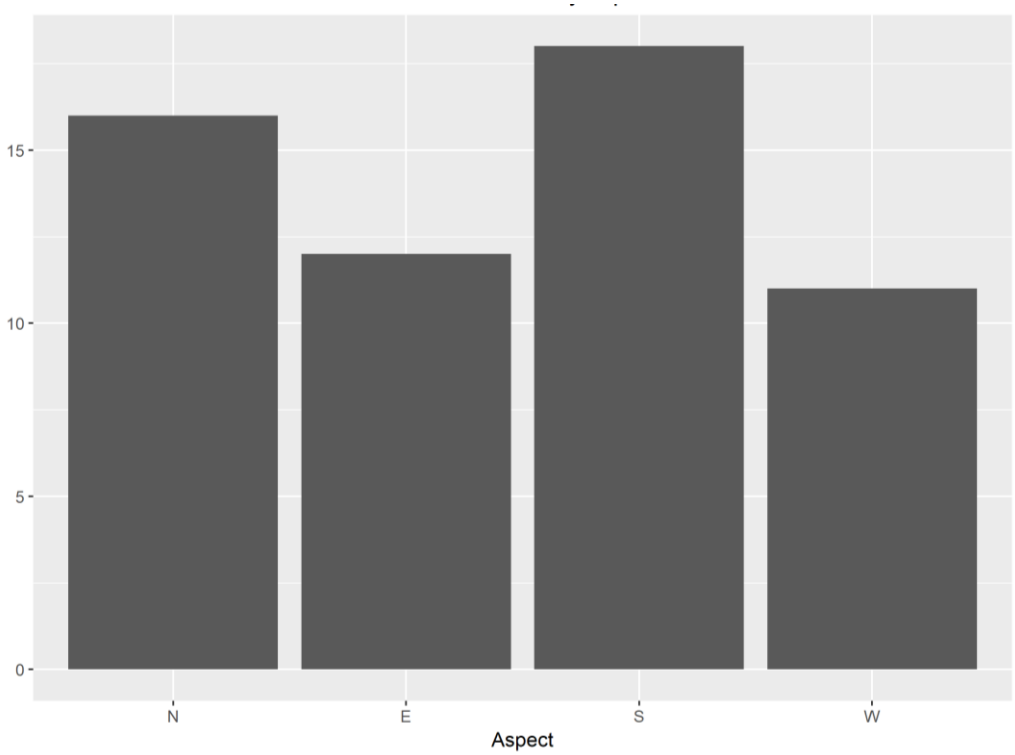

Figure 23: Distribution of the study plots by aspect
(N: North, E: East, S: South, W: West).

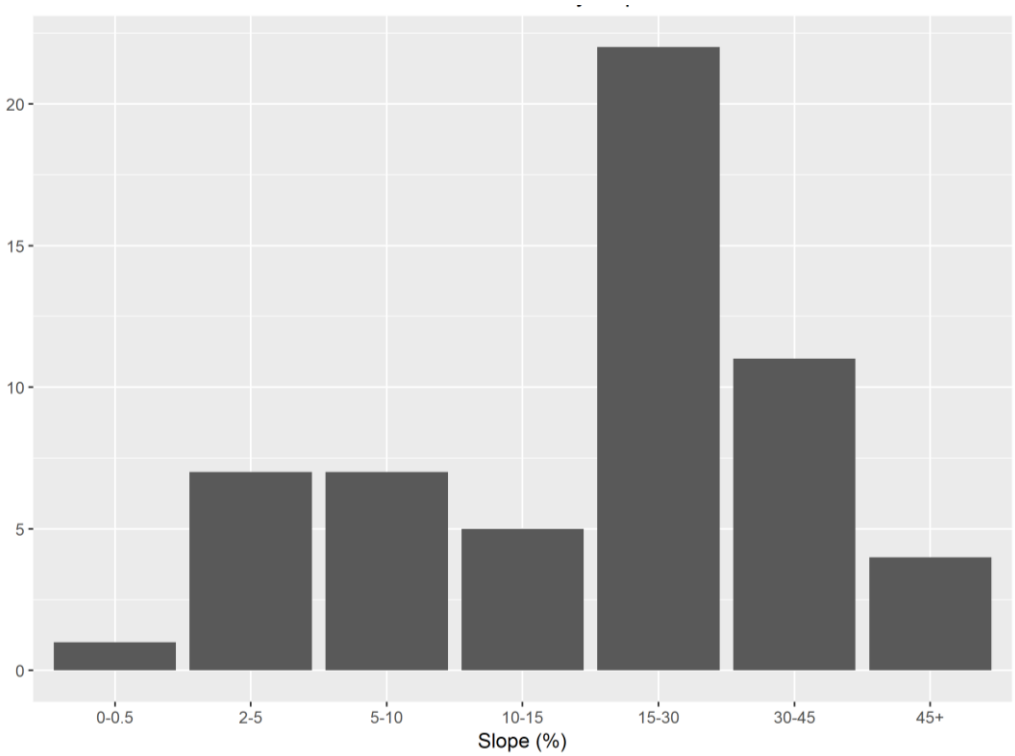

Figure 24: Distribution of the study plots by slope categories
(1: 0-0.5%; 2: 0.5-2%; 3: 2-5%; 4: 5-10%; 5: 10-15%; 6: 15-30%; 7: 30-45%; 8: >45%).

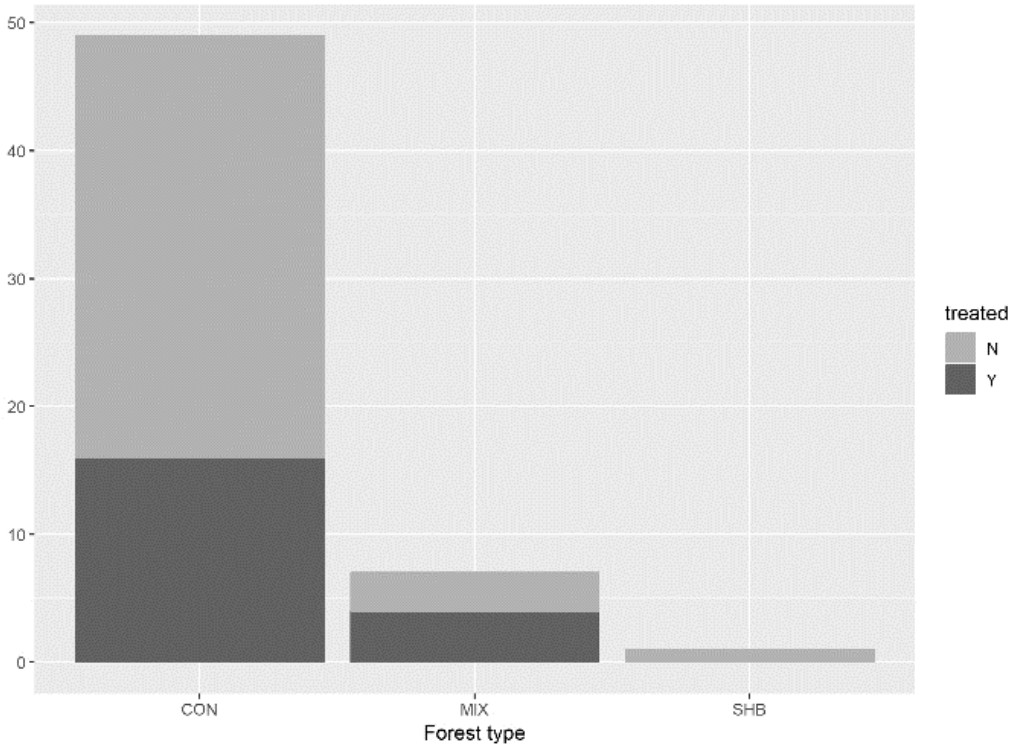

Figure 25: Distribution of the study plots by forest type and management (CON: Conifer, MIX: Mixed, SHB: Shrub).

4.4.1.1 Volume

As summarised in Table 7, volume values show a great variability among the plots, especially for what concerns CWD abundance.

Table 7: Volume values per hectare summarised by component and total amount (CWD: Coarse Woody Debris, FWD: Fine Woody Debris).

	Vol/ha (m^3)		
	CWD	**FWD**	**Tot.**
N.	46	57	42
Mean	54.90	4.29	61.95
Median	23.91	2.98	26.30
Std. Deviation	125.2	3.85	131.1
Minimum	0.11	0.18	0.94
Maximum	771.6	16.26	778.3

The description of the collected data focussed specifically on the volume distribution of FWD and CWD components according to the main topographical, environmental and management variables (Figure 26-Figure 29). For a purpose of representation, one plot belonging to the shrub cover category and values above 400 m^3 were removed.

The distribution across the elevational gradient does not show any particular trend (Figure 26).

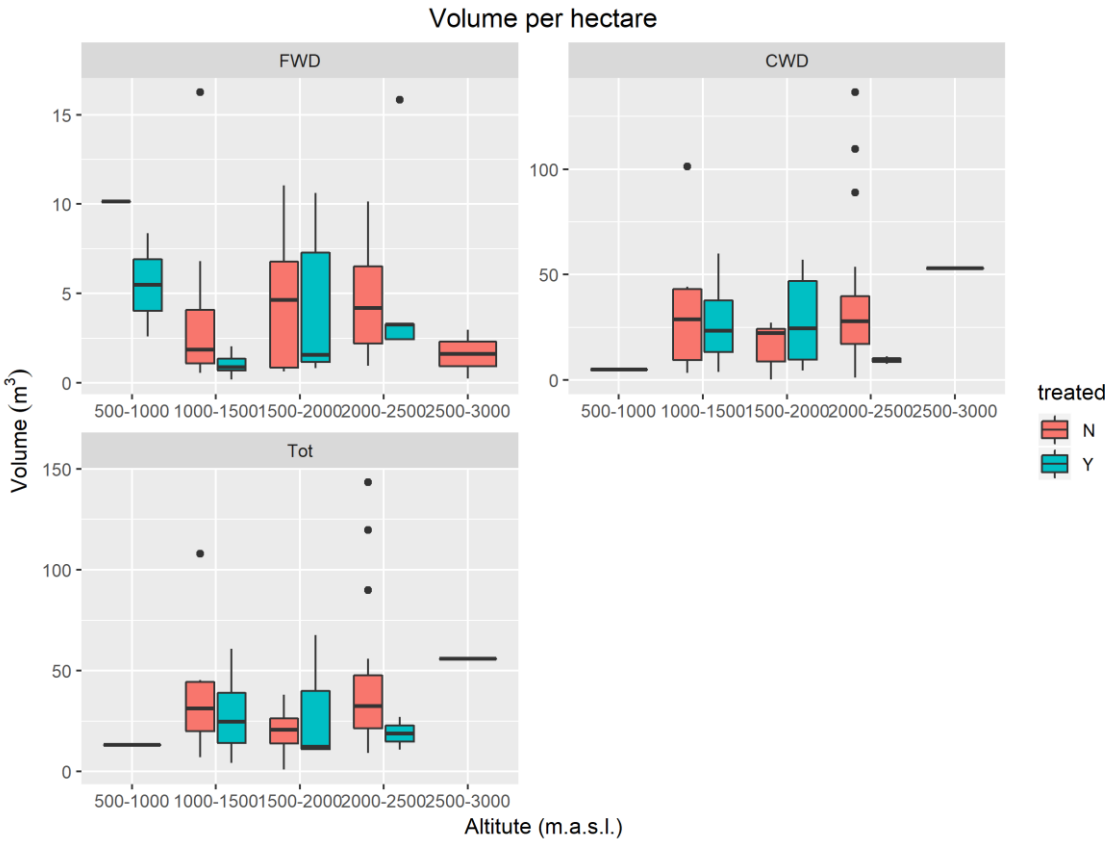

Figure 26: Volume distribution by altitude classes and treatment.

The volume distribution among aspect classes shows slightly higher quantities of deadwood on wetter slopes for non-treated stands, while for the same aspect classes within treated stands the CWD amount is considerably lower.

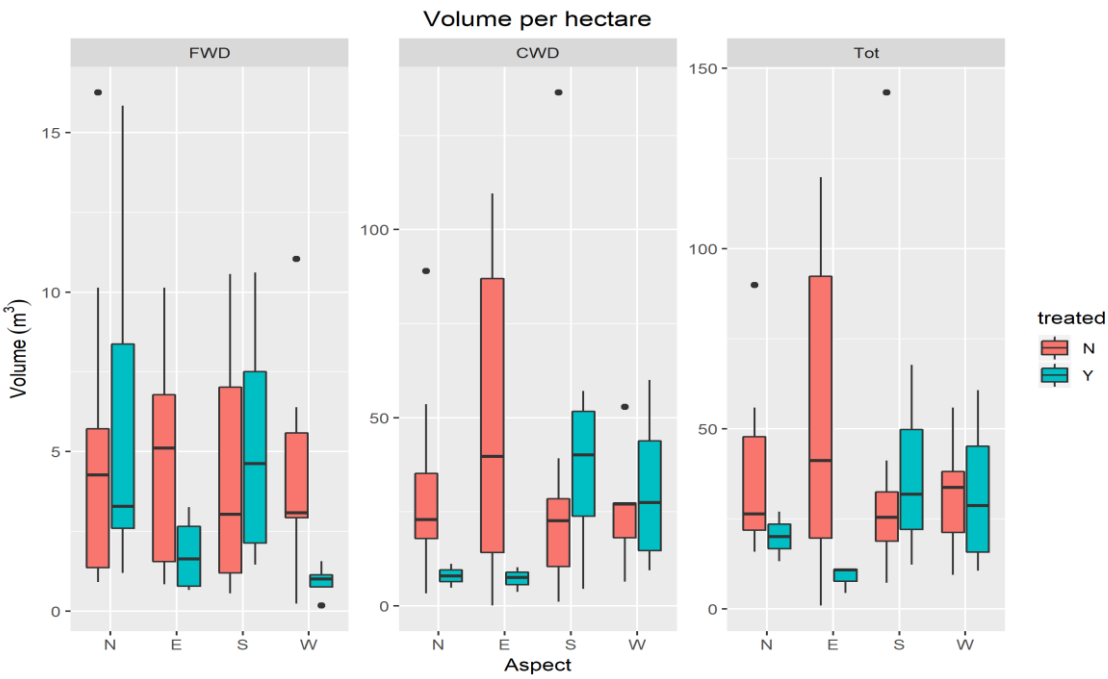

Figure 27: Volume distribution by aspect and treatment (N: North, E: East, S: South, W: West).

The volume of deadwood does not seem influenced by local slope even if FWD shows a positive trend.

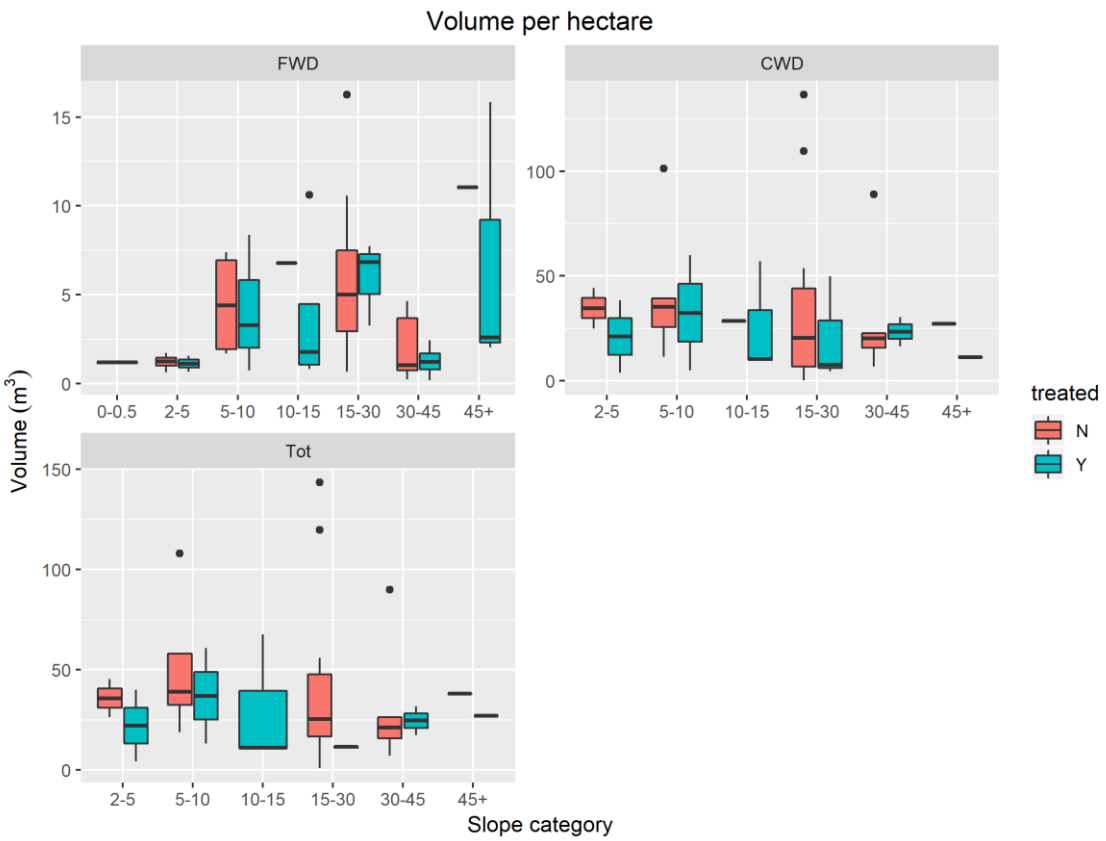

Figure 28: Volume distribution by slope and treatment.

Both CWD and FWD amount were lower in the treated MIXED stands compared to the untreated, while in the conifer stands the difference between treated and untreated is not so evident.

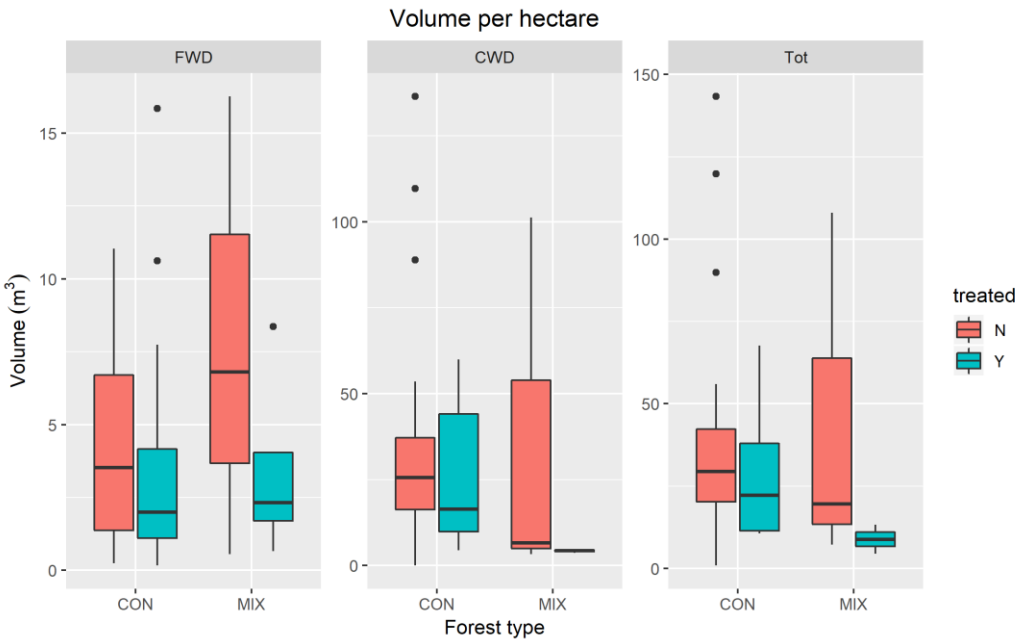

Figure 29: Volume distribution by forest type and treatment (CON: Conifer, MIX: Mixed).

4.4.2 LiDAR data

4.4.2.1 Ground cover estimation

Cover percentage values were estimated both for the total cover and the specific one related to living and dead material (Figure 30).

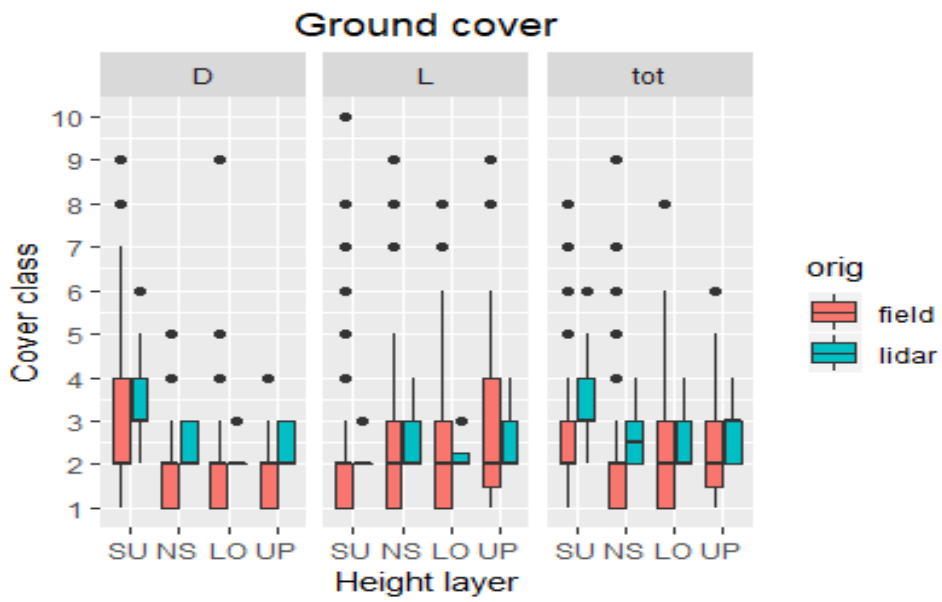

Figure 30: Comparison between field and LiDAR ground cover estimation
(SU: Surface layer, NS: Near surface layer, LO: lower layer, UP: upper layer).

Due to the similar distribution, these values were statistically tested with a Pearson's Chi-Squared test to assess if field and LiDAR data were significantly different (Table 8).

Table 8: Significance tests for cover percentage estimations
(SU: Surface layer, NS: Near surface layer, LO: lower layer, UP: upper layer).

	D			L			TOT		
	X^2	*df*	*p*	X^2	*df*	*p*	X^2	*df*	*p*
SU	59.58	7	<.001	36.19	7	<.001	67.94	7	<.001
NS	26.32	4	<.001	25.23	7	<.001	34.21	7	<.001
LO	16.5	3	<.001	29.22	7	<.001	27.44	6	<.001
UP	11.21	2	0.004	16.46	7	0.021	17.89	5	0.003

4.4.2.2 *Vertical structure*

The vertical structure of the "layer cake" was analysed both in terms of single-layer and total fuelplot connectivity. For what concerns the latter one, four connectivity levels have been defined depending on the relation between height layers containing fuels: "None" (discontinuity equal to three bins), "Low" (discontinuity equal to two bins),

"None" (discontinuity equal to one bin) and "High" (fully connected). The obtained frequencies show a comparable distribution between field and LiDAR data (Figure 31).

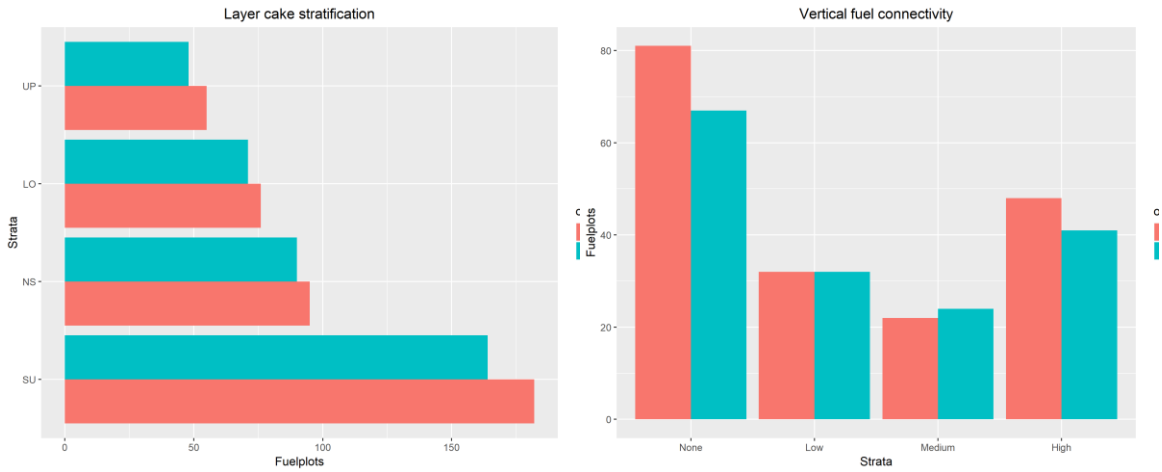

Figure 31: Comparison between field and LiDAR assessment of strata and strata connectivity.

The distributions of frequencies across strata and connectivity levels were tested using a Pearson's Chi Squared test in order to define the significance of the differences (Table 9).

Table 9: Results for the Pearson's Chi Squared test on the "layer cake" stratification and connectivity assessment.

	X^2	*df*	*p-value*
Origin x Stratum	0.14915	3	0.9853
Origin x Connectivity level	0.92427	3	0.8196

4.5 Discussion

4.5.1 Field data

An overview of the fuels' distribution does not show particular trends in relation to the main topographical variables investigated.

Volume quantities at the lowest and highest altitudes (Figure 26) should be considered with caution because they might be related to the low sampling number in the two altitudinal ranges (Figure 22).

Volume distribution across different aspects (Figure 27) does not show any marked behaviour, even if it is possible to notice a slight difference between eastern and western

slopes. This might be related to the different precipitation regime to which they are subjected due to the rain shadow effect that provides higher rainfall levels on western slopes. The results find support in the positive correlation that have been found between available moisture and deadwood abundance (Gould et al., 2008; Woodall and Liknes, 2008), specifically in the case of Ponderosa pine stands (Westerling et al., 2003), a pretty widespread forest type throughout the region. Nevertheless, further investigations are necessary to confirm such behaviour.

FWD presents higher abundances in steeper sites (Figure 28) but these sites are not so well numerically represented. A positive peak is present at lower elevations while a negative one can be found at western sites. These peaks might be related to the local drier conditions that affect the mortality process.

On a general perspective, non-treated sites have on average a higher volume of deadwood both in conifer and mixed stands disregarding the fuel type (Figure 29). Fuel treatments seem to be more pronounced within mixed stands, where the amount of fine and coarse woody debris is considerably lower. This might be related to the use of thinnings both for commercial and for fire hazard reduction purposes. Thinnings are indeed used to lower the tree density as a fuel reduction measure. Reconstruction of past forest structure on the Sierra Nevada often report a low stem density and frequent surface fires that reduced the FWD loadings and their continuity (Roccaforte et al., 2015; Van de Water and North, 2011). Nevertheless, the low number of plots included in the MIX category are not enough for a reliable comparison of the results.

4.5.2 LiDAR data

The preliminary results focussed on the capability of TLS to estimate ground cover and describe basic characteristics of the vertical structure of the FPs.

The estimation of ground cover took in consideration also a finer analysis trying to distinguish the cover typology into two groups: living and dead material. The use of a resolution equal to 0.5 mm did not prove to provide cover estimation values comparable with the ones from the field survey. This might be related to a wrong aggregation approach of the field data cover estimations that might lead to an overestimation of the total classes.

On the other hand, for what concerns the vertical structure, the statistical tests showed no significant differences for both the stratification procedure and the connectivity assessment (Table 9).

4.6 Conclusions

The project aimed at the development of a procedure for the identification, quantification and description of forest fuels using data from TLS. Field data was collected within square plots of 1 m by side and a corresponding point-cloud was isolated from a bigger 30x30 m scan. The extraction of the single fuel plots was done automatically thanks to the possibility of using the reflectance information coming from the four stakes that delimited the plot on the ground for the clip of the point-cloud.

The automatic extraction procedure worked fine in most of the cases but some limitations are still in place. One is the spatial constraint related to the manual need to enter the necessary information (distance and bearing) to locate the fuelplots and to proceed with a first clip. Another one is the necessity of a uniform scan cover of the plot area. Some of the missing stakes indeed were not excluded due to an insufficient search radius but due to the target occlusion that can take place in highly vegetated areas, as already noted in other studies (Loudermilk et al., 2009).

At the actual stage, it is only possible to say that TLS seems to provide consistent estimations at least for what concerns the ground cover percentages, also when the distinction between living and dead is applied.

Previous experiences showed the capability of TLS to reliably estimate of fuel characteristics , e.g. fuelbed height and volume (Loudermilk et al., 2009) and their variations across time using multi-temporal scans taken before and after a controlled fire event and two years later (Wallace et al., 2016). Our preliminary results, even if still limited to ground cover estimation and vertical structure description, open positive perspectives to further developments if evaluated in accordance with such studies.

Future perspectives may aim at applying the presented methodology for pre- and post-fire detection-change assessments within forested areas subject to natural or prescribed burning.

Possible noise in the correlation between the finer components of the FWD and the point cloud may derive from the amount of cones in the plot. Field evidence showed that especially within the plots with lodgepole pine or sugar pine, the presence of cones can be remarkable (in terms of number or size, respectively) and hence worth of deeper investigation. As already shown in the case of Sugar pine, indeed, recently deposited mature cones can constitute a relevant component of the burning material in terms of quantity and flammability (Gabrielson et al., 2012).

Within the Sierra Nevada forests the continuity of fuels is a known issues related to the extensive fire suppression policies that have been widely undertaken in the recent past (Knapp et al., 2005). This continuity may explain also the positive trend of wildfires in progressively increasing in size along with the general increase in temperatures of the last decades. The proposed procedure may offer an additional possibility of assessing the fuels spatial continuity in its vertical and horizontal components, a fundamental step for the refinement of available fire behaviour models.

Finally, appropriate quantification and characterisation of forest fuels loadings will help not only to focus the efforts for hazard reduction treatments but also for the evaluation of innovative local policies related to wildfires adaptation (Schoennagel et al., 2017) under a future temperature increase.

5 Post-fire regeneration dynamics following different restoration activities along a gradient of increasing human impact[7]

5.1 Keywords

Salvage logging; deadwood; regeneration; post-fire forest management;

5.2 Introduction

Post-disturbance conditions can be very harsh for vegetation recovery, especially for tree regeneration after high severity events. Limiting factors can act both at the establishment phase and on the subsequent survivorship, depending on species characteristics. The propagules availability can be guaranteed by a seed bank escaped the disturbance or by a seed rain from intact surrounding forest edges or green islands. For establishing, the seed should be viable, not subjected to post-dispersal predation, and landed on a suitable microsite. The microsite characteristics can act both at the germination stage, providing suitable seedbed and microclimate condition, and at the following survival. Several external elements can influence microsite conditions, enhancing the presence of safe site for seedlings, both directly and indirectly. Facilitative mechanisms between different species play an important role in degraded or harsh sites, when a net positive effect over competition mechanisms is found. Non-living elements can provide positive shelter effects without competing for resources (e.g. water, nutrients) in the short run (Castro et al., 2011; Martelletti et al., 2018; Marzano et al., 2013)and eventually constitute suitable substrate after decay process. After disturbances, among the biological legacies, deadwood elements are always present (Garbarino et al., 2015) and potentially can play a great role in shaping microsite availability and their quality. Any post-disturbance intervention removing, altering, displacing deadwood elements may therefore greatly alter microsite availability for seedling establishment.

Salvage logging, the practice of removing dead trees or trees damaged or dying because of injurious agents (Lindenmayer et al., 2008), is a widespread practice after severe large events, adopted for different reasons, mainly related to recovery economic value, safety, or risk reduction (i.e. fuel

[7] The present work is based on the following paper in preparation:

Lingua E, Marques G, Marchi N, Garbarino M, Marzano R, 2018. Post-fire regeneration dynamics following different restoration activities along a gradient of increasing human impact.

control, risk of insect outbreaks,…). However, this practice has been demonstrated to negatively affect ecosystems processes in different ways, with consequences potentially lasting for several years, also resulting from the unknown interactions between the natural disturbance and the anthropogenic one (Leverkus et al., 2012; Marzano et al., 2013).

The main aim of this research was to assess if the facilitative effects of deadwood is changing in time and if the intervention are playing an important role in affecting deadwood structure

5.3 Methods

5.3.1 *Study site*

The study site is located in the municipality of Verrayes (Aosta Valley - NW Italy) close to the Bourra pasture (45°46'21''N, 7°29'55''E). In March 2005 a stand-replacing fire severely affected the *Pinus sylvestris* forest, behaving as an active crown fire in 160 ha (total burned area 257 ha).

A post-fire salvage logging project was approved in December 2005 and logging operations started during autumn 2007 (Marzano et al., 2013). Within the salvaged area, five hectares of the burned forest were left untouched until 2009, when a sub-section of them (2 ha) was subjected to a cut and release intervention adopting two different procedures. In one area (1ha, Random Directions - RD) the standing dead trees were cut close to the ground and released on the site following random directions; in the other area (1ha, Fishbone - FB) the snags were cut at 1 m height, delimbed and the resulting logs were displaced on the ground according to a fishbone scheme and oriented at about 45° to the maximum slope. The remaining three hectares of the experimental area were passively managed with no human intervention (Passive Management - PM). In the surrounding area, the conventional salvage logging operations adopted in the region took place (Beghin et al., 2010), consisting in felling close to the ground all the trees, removing all trunks and large branches, and piling the slash. In order to reduce uncontrolled effects, in this study we considered only a 5 ha salvaged area (Salvage Logging - SL) adjacent to the other treatments with the aim of having an overall study area of 10 ha, characterized by similar pre-fire conditions and affected by a similar fire behaviour, resulting in the same fire severity.

5.3.2 *Field sampling*

Field surveys on the regeneration were conducted in summer 2016 adopting a two-scale approaches (site and microsite) according to Marzano et al. (2013).

At site-scale we repeated the survey in the same 60 circular sample plots (6 m radius; approximately about 113 m²). Twenty plots were located within the salvaged area (SL), 20 in the passive management (PM), and 10 each in both RD and FB (Figure 32).

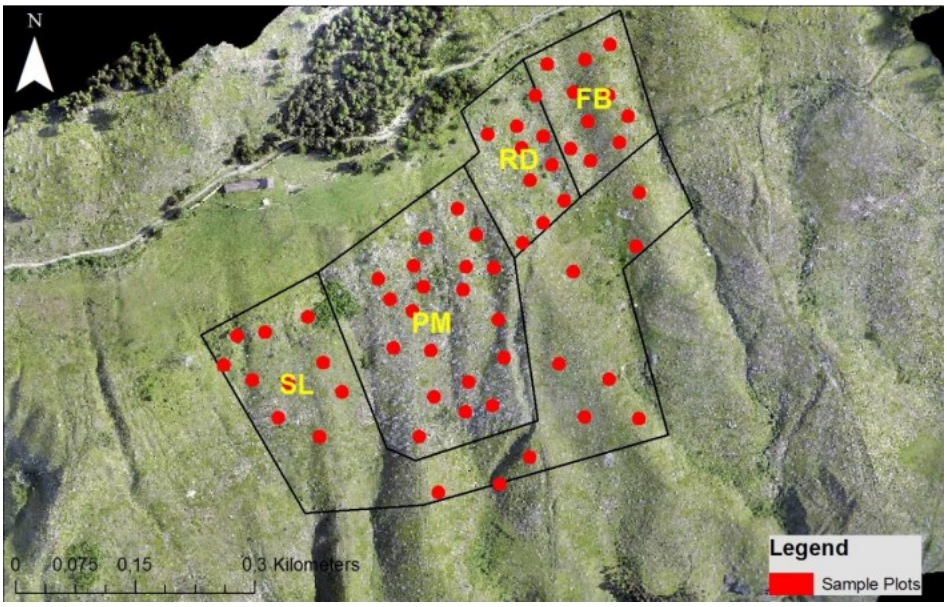

Figure 32: Distribution of sampling plots across the different treatment areas.

In these plots we recorded regeneration characteristics (species, seed or sprout origin, height), the presence of deadwood, and ground cover. This latter was visually estimated to the nearest 5% and comprised litter, lying deadwood, bare soil, grasses, forbs, shrubs, and gravel.

For each seed-origin seedling found in the plots, a microsite-scale survey was adopted (matched case-control design). A 20 cm × 20 cm quadratic plot was centred on each seedling and then matched with a microsite of the same size but without seedlings (control) located 1 m eastward from it on the same contour for comparison.

Besides collecting the seedling (if present) characteristics (species, height), the microsites were characterized according to Marzano et al. (2013) defining: (1) seedbed type (litter, rotten wood, bare soil, grasses, forbs, shrubs, and gravel); (2) presence and relative position (distance, azimuth) of standing or lying deadwood elements within one meter from the microsite centre; (3) presence and relative position of rock elements (height>10 cm).

In order to allow further monitoring, microsite position was recorded with a submetric GPS device.

5.3.3 *Data analysis*

For each plot, we derived topographic variables from LiDAR data acquired in June 2011. The use of LiDAR technologies for deriving deadwood parameters has proven to be an efficient

approach to obtain reliable data over large areas (Marchi et al., 2018). In order to acquire parameters related to the presence of deadwood on the ground we computed indices both directly from point clouds and from a LiDAR-derived DTM (1-m resolution). From the surface raster we computed the Terrain Ruggedness Index (TRI), that is the mean of the absolute differences between the value of a cell and the value of its 8 surrounding cells, and the Roughness index, that is the difference between the maximum and the minimum values of a cell and of its 8 surrounding cells (Wilson et al., 2007), using for both indexes GDAL (gdaldem). We further derived directly from the point clouds the Rumple index of roughness (R_3), which is the roughness of a surface computed as the ratio between its area and its projected area on the ground. If the input is a gridded object (lasmetric or raster) the function computes the surfaces using Jenness's algorithm (Jenness, 2004). If the input is a point cloud, the function uses a Delaunay triangulation of the points and computes the area of each triangle. Before running the algorithms, all the points higher than 3 m from the ground were removed in order to detect only the deadwood lying on the ground (Lingua et al., 2018).

In order to describe local environmental characteristics, we computed from the DTM the Heat Load Index (HLI) that combines both slope and aspect (McCune and Grace, 2002), averaging the value inside each plot.

To understand if the regeneration establishment and survivorship were affected by different parameters in the time-period analysed, we computed total and seed-origin regeneration density in 2010 and 2016 (Reg2010, Reg2016, Seed2010, Seed2016) and the differences in regeneration density between the two surveys (ΔReg; ΔSeed).

In order to define the influence of different factors on the regeneration we ran generalized linear models (GLM) considering treatment (T), Heat Load Index (HLI), deadwood presence (R_3), and distance from the seed source (DIST) as fixed parameters, along with their possible interactions. The GLM analyses were run using STATGRAPHICS centurion XVII (Statpoint Inc., USA, 2014). Model simplification was accomplished by computing the Akaike information criterion (AIC). Starting from the full model, the minimal adequate GLM was obtained by sequentially removing any non-significant model term until no further reduction in AIC was observed.

For the microsite analysis, only seedlings recorded inside the plots in the 2010 dataset were selected to capture environmental changes in the same sampling location.

5.4 Results

Total tree regeneration density slightly decreased between the investigated periods, but the number of seed-origin individuals was instead higher. The mean regeneration density in 2010 was 606 individuals ha^{-1} (±?), including 128 seedlings ha^{-1} (±?) considering only seed-origin individuals. In 2016 the mean regeneration density was 590 individuals ha^{-1}(±182), including 173 seedlings ha^{-1}(±30) originated from seeds. Agamic regeneration was the dominant strategy in both surveys, but

the percentage of sprouting was significantly different (χ^2 test; $p<0.001$), with higher values (78.6%) in 2010, while in 2016 the sprouts accounted for 70.8% of the whole regeneration.

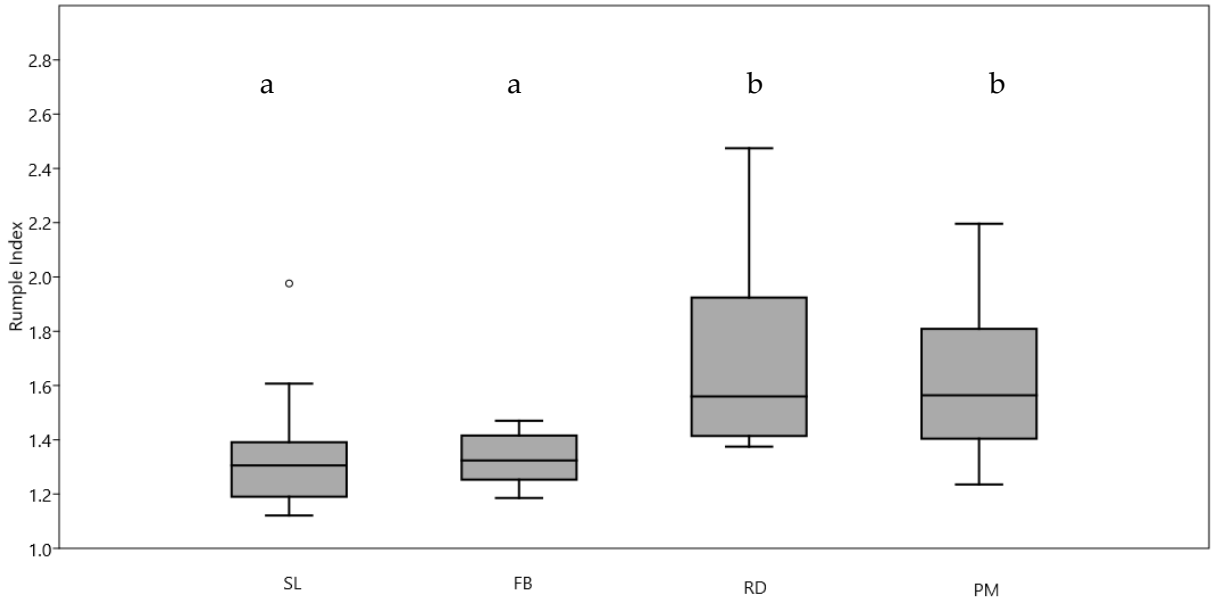

Figure 33: Deadwood availability and heterogeneity as defined by the Rumple Index of roughness for the first 3m above ground in the different treatments. (SL=Salvage Logging; FB=Fishbone; RD=Random Directions; PM=Passive Management). Different letters indicate significant differences ($p<0.01$).

Among the LiDAR derived indexes, the Rumple index (R_3) was the only one able to discriminate between treatments (Figure 33) and was significantly and positively correlated to deadwood presence on the ground (Spearman rho; $p>0.01$). The passive management and the RD treatments showed similar values with significantly higher deadwood heterogeneity/complexity compared to the FB and SL ones.

GLMs provided significant results only for Seed2010 and Seed2016. When sprouters were included (Reg2010, Reg2016) no significant models ($p>0.05$) were generated as well as considering differences in regeneration density (ΔReg; ΔSeed). The models showed that different factors affected regeneration in a complex pattern in both years (Table 10).The final model for Reg2010 ($F=2.22$; $p=0.0181$) showed that the treatments had a significant impact as well as several interactions, while for Reg2016 ($F=2.50$; $p=0.0072$) also the R_3 was important alone. In both cases (Seed2010 and Seed2016), the HLI and DIST were only important when combined with deadwood presence (R_3) and with treatments.

The conditional logistic regression analysis for matched-pairs on presence-absence of seedlings showed a significant role of deadwood elements (Table 11). The proximity to a deadwood element increased the probability of regeneration presence in both surveys of more than threefold (odds ratio 2010=3.7, $p<0.01$; odds ratio 2016=3.6, $p<0.01$). However, the anisotropic relationships changed among the surveys, reducing the importance of deadwood elements located southward in 2016 ($p>0.05$).

Table 10 Summary of the GLM for seed-origin regeneration in 2010 and 2016. T, treatment; R3, Rumple Index; HLI, Heat Load Index; DIST, distance from the living mature trees.

Survey	Source	df	F	P
2010	T	3. 31	4.75	0.008
	R3	1. 31	1.45	0.239
	HLI	1. 31	2.22	0.147
	DIST	1. 31	2.94	0.097
	T x R3	1. 31	4.81	0.008
	T x HLI	3. 31	4.15	0.015
	T x DIST	3. 31	3.34	0.335
	R3 x HLI	1. 31	3.58	0.069
	R3 x DIST	1. 31	5.55	0.026
	DIST x HLI	1. 31	3.81	0.061
	T x R3 x HLI	3. 31	4.23	0.014
	T x HLI x DIST	3. 31	3.77	0.022
	T x R3 x DIST	3. 31	3.74	0.022
	R3 x HLI x DIST	1. 31	5.40	0.028
	T x R3 x HLI x DIST	3. 31	4.12	0.015
2016	T	3. 31	3.86	0.019
	R3	1. 31	5.25	0.029
	T x R3	3. 31	4.19	0.013
	T x HLI	3. 31	3.91	0.018
	T x DIST	3. 31	3.81	0.019
	R3 x HLI	1. 31	7.63	0.009
	R3 x DIST	1. 31	6.39	0.017
	T x R3 x HLI	3. 31	4.10	0.015

T x HLI x DIST	3. 31	3.90	0.018
T x R3 x DIST	3. 31	4.15	0.014
R3 x HLI x DIST	1. 31	5.09	0.031
T x R3 x HLI x DIST	3. 31	4.15	0.014

Table 11: Results of the conditional logistic regression analysis. Rocks value for cardinal directions are not presented since no significant values were found.

	Explanatory variable	**Beta**	**S.E.**	**p-Value**	**Odds ratio**	**95% Confidence interval for odds ratio**	
	Proximity to:					Lower	Upper
Regeneration 2010	Rocks	0.707	0.548	0.197	2.027	0.692	5.934
n= 268	Deadwood	1.320	0.274	***0.000***	3.743	2.188	6.404
	Deadwood_N	0.865	0.318	***0.007***	2.376	1.2727	4.435
	Deadwood_E	1.394	0.354	***0.000***	4.029	2.0147	8.058
	Deadwood_S	1.311	0.335	***0.000***	3.709	1.9244	7.148
	Deadwood_W	0.037	0.402	0.926	1.038	0.4722	2.282
Regeneration 2016	Rocks	0.511	0.516	0.323	1.667	0.606	4.586
n= 147	Deadwood	1.299	0.651	*0.046*	3.667	1.023	13.143
	Deadwood_N	1.485	0.650	*0.022*	4.417	1.236	15.785
	Deadwood_E	1.343	0.657	*0.041*	3.829	1.057	13.875
	Deadwood_S	0.803	0.633	0.204	2.233	0.646	7.716
	Deadwood_W	0.861	0.624	0.168	2.366	0.696	8.045

5.5 Discussion

Right after the natural disturbance and the subsequent anthropogenic one, sprouter species were favoured. *Populus* root suckers production is induced by disturbances, even increasing in number after subsequent disturbances (Palik and Kastendick, 2009).

Obligate seeders, especially if the species are not well adapted to fire occurrence, need more time to establish. However, in our case study, dense patches of European aspen tended to self-thin quite early, relatively reducing the importance of sprout-origin individuals. Seed-origin regeneration increased its relative importance taking advantage of microsite amelioration during the 11 years since the wildfire.

The post-fire treatments affected seedling recruitments, both altering site conditions and affecting already established regeneration. Delayed intervention can rewind the succession processes and eventually diverge the pathways. Soon after the intervention, deadwood presence on the ground was not yet effective in promoting regeneration, but its effects start to be evident after some years.

The distance from seed sources, edges of the intact forest or the green islands, is typically an important factor in determining the speed of the recovery process. This is not particularly important when the species is not the target one for forest management or when it was not a native species or was a pioneer species.

When salvage logging is carried out in Mediterranean mountains, the seedling establishment is greatly affected by an increased water stress(Lingua et al., 2018; Moya et al., 2015). Salvage logging operations produce a general soil degradation, directly by compaction due to heavy machinery and indirectly by the vegetation removal (García-Orenes et al., 2017). In southern exposed slopes suffering for lack of precipitation, the herb layer and especially the shrub layer can ameliorate moisture availability (Smit et al., 2008). In the early post-high severity fire environment, bare soil is widespread, organic matter consumed and superficial erosion extensive. Grasses, herbs and shrubs colonize the site in the following years, enhancing the soil conditions and mitigating harsh conditions to the seedlings.

Standing burned trees are a starting point for post-fire regeneration, creating a heterogeneous habitat during the collapsing phases with both standing and lying deadwood of different size, type, and decay status (Lindenmayer et al., 2008; Molinas-González et al., 2017). The microsite enhancement is largely produced by the lying or suspended deadwood close to the ground, thus increasing when snags are beginning to break and fall down. Intermediate interventions are practically accelerating this process potentially creating a greater availability of safe sites for seedling establishment in a shorter period.

The post dispersal predation can be a limiting factor (Castro et al.1999) and deadwood manipulation can increase the predation rate creating safe sites for seed-predators (Martelletti et al., 2018).

The interaction between natural disturbances and salvage interventions can produce a cumulative effect that can limit ecosystem recovery, eventually defining new successional pathways (Leverkus et al. 2018b).

From the economical point of view, salvage logging was the most expensive options, as found also in other Mediterranean mountain areas where the income from the salvaged timber was low (Leverkus et al., 2012). Intermediate treatments can speed up the process of snag falling with reduced cost, especially if not involving delimbing or debarking operations. If there is no pressure from the socio-economical and political sides, or prescriptions for public safety reasons, and time is not a constraint, the passive management should be pursued at least partially in the disturbed sites.

6 Discussion and general conclusions

Although in the last decade numerous studies have been addressed to automatic deadwood parameters extraction using LiDAR data (Marchi et al., 2018), several issues still require to be tackled exhaustively.

The work done reviewing the available literature material was fundamental to define the state of the art on the use of LiDAR for deadwood identification and then to figure out the actual knowledge gaps and research opportunities. The large availability of remote sensed data allowed to address several specific needs for the forestry sector, trying to provide new tools easily transferable at an operational level. Research often addresses its objectives making use of very innovative tools or techniques not widely available, resulting in many cases as a limitation for their spread on the market until the price becomes economically affordable. It is the case of the LiDAR systems, which saw a progressive decrease of costs thanks to a wider commercial use. Nevertheless, when it comes to the forest sector, the availability of LiDAR datasets refers almost completely to ALS data and it is often represented by scans with point densities lower than 10 pts/m^2. With this aim, the assessment of canopy damages presented in Chapter 3 was tested at different point densities in order to offer an overview on the application possibilities. The proposed procedure properly quantified the entity of the damage through a multi-temporal approach, making use of scans taken before and after a heavy ice storm event. The best performance was provided by the dataset with the highest point density (200 pts/m^2) but similar results were achieved with the intermediate one (10 pts/m^2). Nevertheless, the inefficacy of the dataset with low point density (5 pts/m^2) should be considered a consequence of the constant pixel resolution (0.5 m) used in order to keep the trials comparable. This does not affect the feasibility of the procedure using coarser resolutions (i.e. 1 m) more appropriated for the point density.

Further studies may take in consideration the single-tree approach to assess and quantify the damage at individual level. The abovementioned study took in consideration only one segmentation method, that could provide information on the single individuals, using a widely available data format (i.e. raster CHM) and low-computational requirements. Results showed a scarcely reliable estimation of tree density within all the plots, demonstrating the inefficacy of the selected method independently from the point density. The main hypothesis for such an error is the missing identification of dominated trees. Several segmentation algorithms that could improve the delineation of trees in the understory have been proposed in the last years. Among the main ones, some of them maintains the top-down approach (Kandare et al., 2014; Li et al., 2012), other methods take advantage of a vertical stratification approach (Ayrey et al., 2017; Hamraz et al., 2017) or invert the perspective starting from the identification of the stem first (Lu et al., 2014; Vega et al., 2014). Nevertheless, till now research focussed more on the creation of new algorithms more than comparing the efficacy of the existing ones, also due to the low availability of software implementing them. Only few recent studies, indeed, benchmarked some of the mentioned methods (Eysn et al., 2015; Pirotti et al., 2017; Vauhkonen et al., 2012).

Better segmentation algorithms may also improve the characterisation of the surface fuels' layer from ALS data. Being able to isolate the tree component from the scan without removing useful data from the lower layer, relevant information could be extracted and described through the means of roughness indexes, such as in the case study in the Aosta valley (Chapter 5), where the layer between 0 and 3 metres was required for the study purposes.

Indexes proved to be an important source of information being capable of capturing and summarising specific details related to point distribution. At the author's knowledge, the studies presented above are the first ones making use of the recently proposed LAD and Rumple indexes. The Leaf Area Density index (Bouvier et al., 2015) showed to be able to describe the changes taking place along the vertical profile of a forest stand. Its application on three monospecific stands provided additional information on species-specific response to ice damages, characterising the damages in the upper canopy for European beech and stem break for Norway spruce. No evident differences were visually found across the different datasets but further research should be carried out to assess the sensitivity of the index to a variation in point density or bin height. In the case of the Rumple index, the specific implementation available in the R package "lidR" was found statistically significant for the characterisation of the abundance of lying deadwood in a post-disturbance (i.e. wildfire) scenario. This result may allow the assessment of favourable conditions for natural regeneration processes over areas affected by wide scale disturbances. Further developments are expected to come from the application of the Vertical Complexity Index (Van Ewijk et al., 2007) for the description of the vertical heterogeneity of fuels in combination with the voxel approach applied within the plots set on the Sierra Nevada (Chapter 4).

For what concerns the exploitation of the radiometric information, a direct application to support the identification of dead material was conducted in the case study in Chapter 4. In the specific case, the absorption of the wavelength of the TLS was pretty significant when the laser beam was hitting objects with high water content. On the contrary, in the case of the trees damaged by the ice-storm in Slovenia, no specific tests were made because all the derived dead material was thought not old enough to show the changes in reflectivity that are usually associated with the aging of deadwood, characteristics that sometimes were used for its identification (Wing et al., 2014).

Positive developments can be expected with the introduction of new LiDAR sensors capable to exploit the radiometric information. As recently reviewed by Eitel et al.(2016), among these new systems, two main alternatives were presented in the last years: multi-wavelength LiDAR and Single-Photon LiDAR (SPL). The weakness points related to the difficult use of the intensity data in the single-wavelength systems are widely known and possible improvements were easily displayed using a dual-band LiDAR for the estimation of the forest vegetation moisture content (Gaulton et al., 2013). Further insights were offered for the description of forest structural and physiological characteristics (Woodhouse et al., 2011) using multi-wavelength (or multispectral) LiDAR, with possibility of mapping the normalized difference vegetation index (NDVI) variations within the canopy. The other recent possibility that was presented on the market is the Single-Photon LiDAR, a sensor that offers many advantages from the system technology side (e.g. requires less energy and

produces less heat) to the technical one. Using a visible green wavelength (532 nanometres) is capable of penetrating semi-porous surfaces like fog, low clouds and vegetation. The few available studies refer mostly to its application to space-borne platforms (i.e. ICESat II) suggesting interesting perspectives for the forest monitoring purposes and related analyses (Awadallah et al., 2014; Kim et al., 2015; Rosette et al., 2011).

Dealing with close-range assessments, (handheld) Mobile Laser Scanning has already proved to be a fast and efficient tool for collecting data for forest inventory purposes (Bauwens et al., 2016; Ryding et al., 2015). Nevertheless, at the actual stage, TLS data results still an innovative technology for what concerns the application on deadwood identification and characterisation. Only few studies indeed took in consideration its use for the characterisation of the decay process on snags (Putman et al., 2018; Putman and Popescu, 2018), the fuelbed characteristics (height, volume; (Loudermilk et al., 2012, 2009)) or the identification and segmentation of downed logs (Polewski et al., 2017). The preliminary results obtained in Chapter 4 show promising perspectives for the description of the spatial distribution of surface fuels, providing further insights for forest wildfire management.

Finally, some considerations should be made in relation to the economical aspects connected to LiDAR acquisitions. The few available experiences are reported mostly through agencies' technical reports (e.g. USDA-FS, USGS, etc.) or online publications dedicated to practitioners. The distribution of literature resources follows the three main areas of scientific interest for LiDAR technology: North America, Europe and Australia.

Benefits are mostly related to the abovementioned technical improvements (e.g. canopy penetration, high precision mensuration, etc.) when compared to other technologies (i.e. photogrammetric surveys) and, hence, they refer to the several multi-purpose outputs that can be obtained. An overview made for the USA, money savings related to flood-risk mapping at state level accounted for more than two times the cost of the LiDAR acquisition, reaching in some cases a benefit to cost ratio equal to 3.5 $ (Hallum and Parent, 2008). Nevertheless, LiDAR technology still constitute an expensive tool for smaller areas or multi-temporal scans due to the high initial fixed costs connected to the flight itself, that can achieve prices equal to 20.000 $ (Erdody and Moskal, 2010). More in general, costs are often reported as ranges and not always accompanied from the specifications of the included products. For North America, a first analysis was carried out on 2000 by range of acquisition extent (Renslow, 2000), while a comparison of accuracy and costs between LiDAR and field survey is available for 2005 (Tilley et al., 2005) and 2007 (Hummel et al., 2011). Briefer overviews from U.S.A and Canada are offered for more recent years (2008-2015) for landscape-wide acquisitions (Asner, 2009; Frazer et al., 2015; Hallum and Parent, 2008; Sorensen, n.d.). Finally, only few sources refer to Australia and Europe finding an overall agreement with the other areas.

The retrievable information, summarised in Table 12, is not easily comparable due to differences in acquisition parameters (technology, point density, extent, etc.), currencies and period, but it is possible to identify a decreasing trend through the years that should be necessarily interpreted in relation to the corresponding technological progress involved.

Table 12: Costs of LiDAR acquisitions per area range (based on Renslow, 2000; modified).

Extent range	Cost per hectare								
(ha)	2000 *(USD)*[1]	2005 *(USD)*[2]	2007 *(USD)*[3]	2007 *(AUD)*[4]	2008 *(USD)*[5]	2009 *(USD)*[6]	2010 *(€)*[7]	2014 *(CAD)*[8]	2015 *(CAD)*[9]
< 1,000		31							
2,000 – 4,000	9.0	4.5							
4,000 – 12,000	7.5		3				4-6		
16,000 – 24,000	7.0								
24,000 – 40,000	6.0	0.7-1	2						
40,000 – 100,000	5.0								
> 100,000	4.5				0.3-0.5	0.05-0.2		1.5-2.5	
n.d.				0.5 - 12	0.8-3.9				3-10

[1] Renslow, 2000; post-spacing of 3-4 metres
[2] Tilley et al., 2005
[3] Hummel et al., 2011
[4] Turner, 2007
[5] Hallum and Parent, 2008
[6] Asner, 2009
[7] Barilotti, 2010; point density of 5 pts/m^2
[8] Sorensen, n.d.
[9] Frazer et al., 2015

While for the ALS surveys there is enough material for an approximate estimate of what is available on the market, the same information could not be found for TLS surveys. The variables that affect such an estimation are indeed quite many, as reported in Liang et al (2016) such as equipment, scan type (single-scan/multi-scan), data accuracy and hence time consumption of data acquisition and post-processing of the data.

Nevertheless, it is common opinion that the main advantages are related to the possibility of creating time-series of data sets, providing the ability to reproduce objective analyses. In addition, the possibility of developing allometric models from non-destructive measurements with millimetric accuracy may lead to the update of existing equations and a rapid growth of those related to the less studied species (Liang et al., 2016).

In conclusion, the results obtained in the three case studies showed the capability of LiDAR data to capture important structural information about different elements of deadwood. This information can be useful to describe local and global processes for the study of ecological dynamics related deadwood in the context of natural disturbances.

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