The Role of Lidar Systems in Fuel Mapping

Antonio Ferraz, Frédéric Bretar, Stéphane Jacquemoud, Gil Gonçalves

No. 13   2009

The Role of Lidar Systems in Fuel Mapping

Antonio Ferraz[1,2,3] , Frédéric Bretar[1], Stéphane Jacquemoud[2], Gil Gonçalves[3]

(1) IGN, Institut Géographique National, Laboratoire MATIS, 2-4 avenue Pasteur, 94165 Saint Mandé Cedex, France.
(2) IPGP, Institut de Physique du Globe de Paris, Géophysique Spatiale et Planétaire, Case 7011, 35 rue Hélène Brion, 75013 Paris, France.
(3) INESCC, Instituto de Engenharia de Sistemas e Computadores de Coimbra, rua Antero de Quental, n 119, 3000-033 Coimbra, Portugal.

Abstract : Wildland fire is a common threat in many European countries, especially in the Mediterranean Basin. Every summer in Portugal, Spain, Greece, Italy or France thousands of hectares of forests and shrub-land burn and even people are endangered. Since wildland fires represent a social and economic risk for the society, there is a compelling interest in understanding them to better control them or, at least, to weaken their impact. Providing accurate fuel maps is critical to study fire behavior, assess fire hazard, and quantify fire effects. Traditionally fuels had been mapped by field survey sampling, therefore a time and cost consuming task. Thus, there is a total interest in study the potential of remote sensing technologies to mapping fuels. In this report we review the standard methods and techniques to mapping fuels using airborne LiDAR (Light Detection and Ranging) systems data.

Acknowledgements

Outline

List of abbreviations and acronyms

CBD	Crown Bulk Density
CBH	Crown Base Height
CC	Canopy Closure
CHM	Canopy Height Model
CHP	Canopy Height Profile
DBH	Diameter at Breast Height
DSM	Digital Surface Model
DTM	Digital Terrain Model
FARSITE	Fire Area Simulator
FM	Fuel Model
FMC	Fuel Moisture Content
FT	Fuel Type
FTCS	Fuel Type Classification System
GIS	Geographic Information System
GPS	Global Position System
INS	Inertial Navigation System
LiDAR	Light Detection and Ranging
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
SHEI	SHannon Evenness Index
SLICER	Scanning Lidar Imager of Canopies by Echo Recovery
RADAR	RAdio Detection And Ranging
WAF	Wind Adjustment Factor

Introduction

This report aims to review standard methods and techniques dedicated to the production of fuel maps using airborne LiDAR (Light Detection and Ranging) systems and to evaluate the fusion of LiDAR data and aerial multispectral imagery. Providing accurate fuel maps is critical to fire behavior studies, hazard assessment, and quantification of effects. These are the three main topics of fire research programs but we emphasize here fire behavior, the key variables of which are based on the identification of key variables in fire models. FARSITE is one of the most popular semi-empirical model, which has eight input variables retrievable using LiDAR techniques. The first five ones – elevation, slope, aspect, fuel model and canopy cover – are required to simulate surface fires while the last three ones – canopy height, crown bulk density and canopy base height – are required to simulate crown fires. In this report, the topographic variables are mentioned because they impact on fire propagation, but the question of their determination using LiDAR data is not considered. Thus, we focus on fuel maps and review the methods, techniques and strategies that foresters and fire researchers have been applying for years to characterize forests. The know-how and the knowledge of the requirements of the other actors is crucial to model fire behavior using LiDAR. Therefore, the first part of this report is dedicated to the description of how specialists sample the forest environment. In the second part, we review the main LiDAR methods and techniques that can be applied to retrieve forest variables. Those are not necessarily used as inputs in fuel maps but direct extraction has been poorly studied so we wish to investigate the potential and limit of LiDAR systems for retrieving them. As far as fuel mapping methods and techniques are concerned, we divide them in two classes: direct retrieval of fuel variables and fuel classification methods.

1. Fire behavior

Wildland fire is a common risk in most European countries of the Mediterranean Basin, United States of America, Australia… Every summer, thousands of hectares of forests and shrublands burn and even people are endangered. Since wildland fires have a major social and economic impact, there is a compelling interest to better control them or, at least, weaken their consequence. Since they spread horizontally, ignite trees vertically, and progress with time, they can be viewed as a four-dimensional process. According to Finney (2004), this process depends on the ignition source (e.g., lightning, negligence), the fuel bed that is likely to burn (e.g., dry needles), and the environmental conditions that facilitate fire spread (e.g., wind, slope).

1.1. Types of wildfires and fuel strata

Fire scientists and managers generally consider three types of wildland fires according to the fuel stratum where flames spread: ground, surface, and crown fires. A ground fire spreads in ground fuels that burn very slowly and the fuel consumption can cause significant injury to trees and shrubs. A surface fire burns the surface fuel layer, which lies immediately above the ground fuel layer but below the canopy fuel. It is very variable depending on the nature of the fuel complex. Finally, a crown fire spreads in the elevated forest canopy that generally has higher moisture content and lower fuel load than surface fuels (Figure 1). Crown fires are more difficult to control than ground and surface fires, and their spread rate is several times faster than surface fires (Rothermel, 1983). Their effects are also severer and more lasting: after a crown fire, the mortality of several tree species is expected.
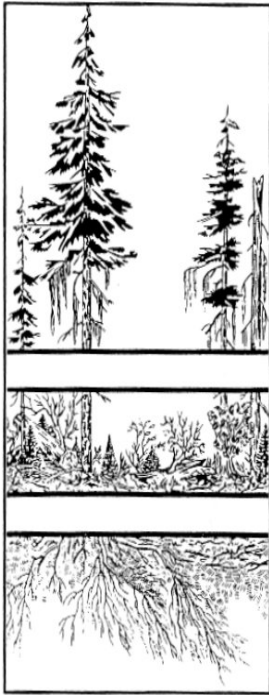
Figure 1. *Top: aerial fuels with all live and dead materials located in the upper forest canopy, including tree branches and crowns, snags, moss, and high shrubs. Middle: surface fuels with all materials lying on, or immediately above, the ground, including needles or leaves, duff, grass, small dead wood, downed logs, stumps, large limbs and low shrubs. Bottom: ground fuels with all combustible materials lying beneath the surface including deep duff, roots, rotten buried logs, and other organic material.*

According to Van Wagner (1977), there are three types of crown fires: passive, active, and independent. In passive crown fires (Figure 2a), often referred to as torching or candling, individual or small groups of trees torch out but solid flame is not consistently maintained in the canopy. In active spreading crown fires (Figure 2b), also called running or continuous, the entire surface/canopy fuel complex is involved but the crowning phase remains dependent on surface fuel heat for continued spread. In independent crown fires, canopy fuels burn without help from a supporting surface fire. There is no scientific evidence of such fire occurrence.

Figure 2. *Passive (left) versus active (right) crowning (Scott and Reinhardt, 2001).*

1.2. Environmental factors affecting wildland fire behavior

Wildfires arise and persist due to the coexistence of three elements: fuels, oxygen, and heat. They constitute the so-called fire triangle. If a single element ends, the triangle breaks and the fire goes out. We are interested here in three other elements influencing the spread rate of a wildland fire and acting as input variables in wildfire prediction models: fuel characteristics, topography, and weather (Figure 3). In the next sections, we briefly discuss the influence of topography and weather on fire behavior.

Figure 3. *Fire spread triangle.*

1.2.1. Topography
Landscape topography has an impact on the environmental conditions, the amount of certain types of vegetation, and therefore, has a direct influence upon fire propagation. In the following, we focus on the aspect, slope and elevation that are input variables of fire spread models and that can be retrieved using LiDAR.

a) Aspect: the aspect is the direction a slope is facing (Figure 4). The solar orientation generally determines the amount of heat provided by the Sun and therefore has high influence on the amount, condition and type of fuels. South-southwest slopes are more exposed to sunlight and often correspond to lighter and sparser fuels, higher temperatures, lower humidity and lower fuel moisture. They consequently are most critical in terms of start and spread of wildland fires. On the contrary, north-facing slopes are less subjected to fire activity than south-facing slopes. They are more shaded, which leads to heavier fuels, lower temperature, higher humidity and higher fuel moisture (Pyne et al., 1996).
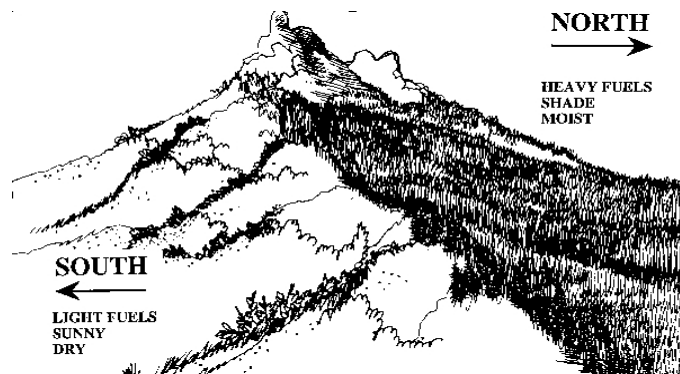

Figure 4. *North-facing vs south-facing slopes (NIFC, 2004).*

b) Slope: it is the degree of incline of a hill side (Figure 5). The steeper the slope, the faster the fire spreads, and it burns more rapidly uphill than downhill (NIFC, 2004). An explanation for these two phenomena is that the fuel above the fire is brought into closer contact with the upward moving flames. Another concern about steep slopes is the possibility that burning materials roll down the hill and ignite the fuel below the main fire.
A surface fire is primarily influenced by the amount of fuel and the wind speed, but a fire starting near the bottom of a slope in normal daytime upslope wind conditions should spread faster and over a larger area than a fire starting near the top of the slope (Linn et al., 2007).

c) Elevation: it plays a determining role in the state and amount of fuel. Fuel at lower elevation, where temperature is higher, dries out earlier in the course of the year than that at higher elevation (NIFC, 2004). High altitude landscapes are mainly characterized by grasslands or shrublands, which disappear beyond a variable elevation according to the latitude. Elevation affects fire behavior in several other ways, like the amount of precipitation or the wind exposure.
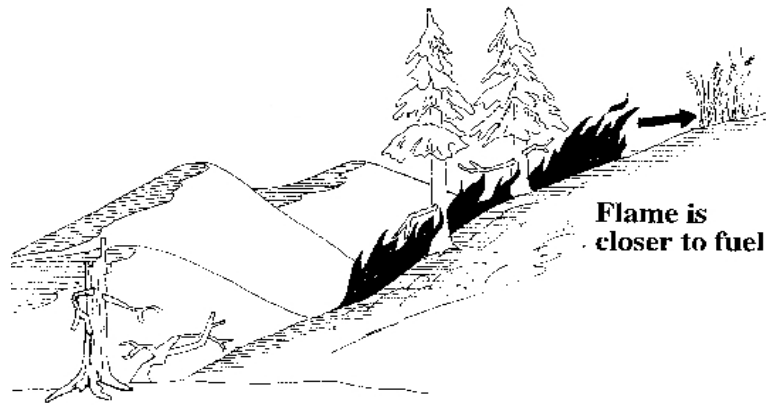
Figure 5. *Steep slopes causing rapid fire spread (NIFC, 2004).*

1.2.2. Weather

Of the three components of the fire triangle, the weather conditions are the most variable over time and the most difficult to predict. The fire weather parameters include air temperature and relative humidity, precipitation, atmospheric stability and wind. Air temperature varies with time, location and altitude. Changes in near surface temperature are caused by the alternation of seasons, night and day, and weather. Seasonal and diurnal temperature contrasts can be large or small, depending on latitude, elevation, topography, and on the proximity of oceans or lakes that smooth them. Surface and atmospheric temperature primarily results from solar radiation but, at a smaller scale, it may be caused by a wide fire (Pyne et al., 1996).

Relative humidity is the amount of water vapor that exists in a gaseous mixture of air and water. It is usually expressed in percent (1% corresponds to extremely dry air and 100% to extremely moist air). Air temperature and relative humidity are inversely related: when temperature increases, relative humidity decreases and vice versa. Firefighters can see or feel evidence of weather changes, such as wind intensification, rain or increasing temperatures but not changes in relative humidity that may have a significant impact on wildland fire behavior. Low relative humidity is indeed an indicator of high fire danger: atmospheric water content, whether in the form of water vapor, cloud droplets or precipitation, is the primary factor in wildland fuel moisture content (FMC) and its resulting flammability because the amount of moisture that fuel can absorb from or release to the air largely depends on it. FMC varies over time, location and fuel type. Light fuel such as grass quickly gains or loses moisture when relative humidity changes. Heavy fuel responds much more slowly to humidity changes. FMC is also affected by the amount and duration of a rainfall. Fine fuel reacts rapidly while heavy fuel gains or loses moisture more slowly. Intense and sudden showers generally don't raise FMC contrary to light and long rainfalls, when fuel has time to absorb water before it runs off (NIFC, 2004).

Wind is the most critical weather variable affecting wildland fire behavior, also the most unpredictable in time and location. This variability, especially in difficult terrain, can be a problem to firefighter life safety. The wind impacts the fire environment *i*) by increasing oxygen supply, *ii*) by determining the fire spread direction, *iii*) by increasing the fuel drying, *iv*) by canying sparks and firebrands ahead of the main fire front, causing new hot spots, *v*) by bending flames, which results in the preheating of fuel ahead of the fire spot, and *vi*) by influencing the amount of consumed fuel (NIFC, 2004). Indeed, a strong wind may affect the residence time of the fire front by shortening it, leading to a lower amount of consumed fuel. One considers two types of winds: general winds are caused by gradients between a high and a low pressure system and, as weak winds, they generally do not have great influence on fire behavior. Local winds, so named because they are caused by local conditions, are classified in

4

slope wind, valley wind, and sea and land breeze. They are induced by local differences in air temperature and pressure. The ground topography has direct influence in near surface air temperature, e.g., higher terrains or north-facing slopes warm less than lower terrain and have strong influence on local low-tropospheric winds.

To sum up, the most critical fire weather conditions are a strong and shifting wind, very low relative humidity, high temperature, unstable atmosphere and dry lightning (Millán et al., 1998).

2. Fuels

To predict fire behavior, it is convenient to describe vegetation as a fuel. Fuel maps are essential to compute spatial fire hazard and simulate fire growth and intensity across a landscape (Keane et al., 2001). Fuel is not the primary cause of fire, but it certainly changes its behavior, affecting the ease of ignition as well as the fire size and intensity. Correct description of fuel properties is then critical to improve fire danger assessment and fire behavior modeling. Mapping these properties requires knowledge of the vertical and horizontal vegetation structure (Chuvieco et al., 2003). Roughly, one can stratify the vertical distribution of fuel throughout the forest. As seen earlier, there are three types of wildland fires: ground, surface, and crown fires. Mapping fuels consequently requires to know fuel properties in each layer.

2.1 Surface fuel properties

Surface fuels are ground dead organic matter coming from the surrounding vegetation, grass, low shrubs and young trees. The physical properties of surface fuels include the surface-to-volume ratio, the specific gravity (or fuel particle density or mass-to-volume ratio), the load by size class, and the fuel bed depth. The chemical properties are the heat and ash contents.

2.1.1. Size and surface-to-volume ratio
Fuel particle size is critical in fire behavior. The smaller the size of a fuel particle, the larger the surface-to-volume ratio. The latter is an important fuel characteristic: the particles lose moisture and heat faster when the available surface area is large (Chuvieco et al., 2003). Traditionally, four size classes have been specified: 0-6 cm, 6-2.5 cm, 2.5-7.6 cm, and over 7.6 cm (Albini, 1976). They correspond to moisture timelags (Table 1, Figure 6), defined as the time necessary for a fuel component to reach two-third of its equilibrium moisture content (Allgower et al., 2004). Higher timelags, which do not influence fire behavior, must be considered when studying fire effect.

Timelag class	Woody fuel size class, cm	Duff depth class, cm
1 hr	0-0.6	0 – 0.6
10 hr	0.6 – 2.5	0.6 – 1.9
100 hr	2.5 – 7.6	1.9 – 10.2
1000 hr	> 7.6	>10.2

Table 1. *Correspondence between timelags class, fuel size and duff depth (Deeming et al., 1977).*

Figure 6. *Three different size classes.*

2.1.2. Fuel particle density
The fuel particle density is its mass per unit volume. For the BEHAVE fire model, Albini (1976) specifies a value of 51.25 kg m^{-3}. This is a standart value for the USA but it must be calibrated again for other zones.

2.1.3. Fuel load

Fuel load, expressed in kg m^{-2} or in t ha^{-1}, is the amount of fuel potentially available for combustion. In the particular case of fire behavior, it corresponds to the elements that directly influence fire spread and intensity. Its effects however may be antagonistic. As a heat source, the fuel availability tends to magnify the reaction intensity. Spread rates may however decrease as load increases because the extra fuel becomes an important heat sink, and the ignition temperature is not raised (Chuvieco et al., 2003). Much of the response depends on the fuel size class, its packing ratio, and whether it is dead or alive. Fuel load is first divided into dead or live fuel and second in size classes.

2.1.4. Fuel bed depth

The fuel bed depth is the average height of surface fuels contained in the combustion zone of a spreading fire front. In grassy or shrubby vegetation, it corresponds to plant height (Figure 7). In the litter bed, its measure is critical when litter and duff coexist, since litter has influence in fire behavior and duff not (Brown, 1981). The fuel bed depth directly affects the fuel bed bulk density, which is the total amount of fuel potentially available, defined as the weight per unit volume of loosely tipped fuel.
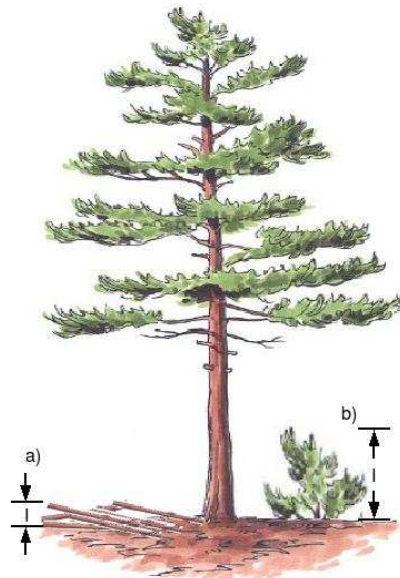

Figure 7. *Fuel bed depth: a) litter and b) shrubs.*

2.1.5. Heat content and ash content

The heat content is the amount of energy per unit weight contained in a fuel particle. It drives the energy of combustion. Some fire behavior models use a constant value, e.g., 18.61 MJ kg^{-1} in the BEHAVE fire system (Albini, 1976). It is determined in the laboratory with a bomb calorimeter or by near infrared reflectance spectroscopy. It is species dependent and it directly increases the rate of fire spread. The total mineral ash content of a fuel particle is the unburned fraction. It is also often considered as constant in fire behavior models and is usually retrieved by chemical analysis (Allgower et al., 2004).

2.2. Crown fuel properties

Crown fuels are those that burn when fire leaps from one tree crown to another. Their properties, which determine the spread rate and intensity of crown fires, include: canopy closure, canopy height, crown base height, and crown bulk density (Chuvieco et al., 2003).

2.2.1. Canopy closure

Canopy closure (CC) is defined as the progressive reduction of space between crowns as they spread laterally, increasing the canopy cover (Figure 8). CC influences the fire behavior because it affects the amount and proximity of fuel available for a crown fire. It also drives the moisture of shaded fuel above ground. A complex cover tends to reduce the wind below the canopy, influencing surface fires. Wind adjustment factors (WAF) are required to run the BEHAVE fire behavior modeling system. WAF is calculated from CC but also from canopy height.

Figure 8. *Canopy closure(CC)*

2.2.2. Canopy height

Canopy height (CH) affects fire spread: the higher the canopy the greater the wind speed. It also contributes to the amount of crown fuel. The fuel available in a tree crown is often estimated from tree height. It affects the lofting of embers from a torching tree (Albini, 1976), that is, an ember from a taller tree will travel further than one lofted from a shorter tree.

2.2.3. Crown base height

Crown base height (CBH) is defined as the vertical distance between the ground and the base of the live crown. Finney (2004) reports that dead branches, shrubs or small trees connecting the surface fuels to the crown fuels, may effectively reduce the nominal CBH value (Figure 9). It determines the threshold for transition from a surface fire to a crown fire.
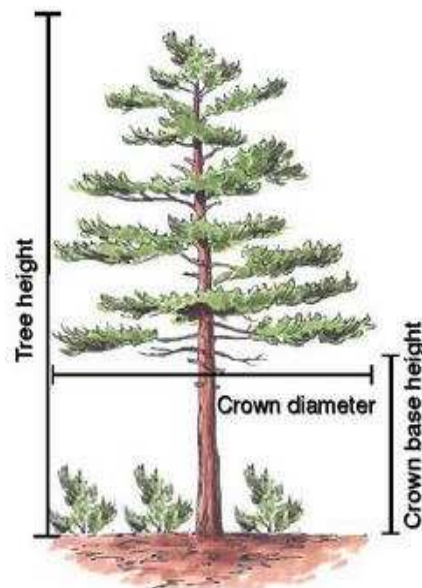

Figure 9. *Tree metrics: tree height, crown diameter and crown base height.*

2.2.4. Crown bulk density

Crown bulk density (CBD) is the amount of fuel per unit volume of forest canopy. Different species have different CBD depending on branching and foliage characteristics (Chuvieco et al., 2003). The overall bulk density of the forest depends on plant species and CC.

2.3. Classification schemes

Fuel properties are complex and the combination of vegetation species is almost infinite. It would be tedious to inventory all fuel properties every time it is necessary to predict an event or make a management decision. Fuel beds are also structurally complex: fire behavior, hazard and effects vary widely as a function of their physical attributes. Fuel bed characteristics result from the expression of ecological processes, natural disturbances, and human manipulation, thus they are difficult to model. Mapping fuel requires consistent, scientific, orderly classification methods as well as fuel bed properties inferring methods (Sandberg et al., 2001). Fire managers defined different classes of fuel types (FT) corresponding to "an identifiable association of fuel elements of distinctive species, form, size, arrangement, and continuity that will exhibit characteristics fire behavior under defined burning conditions" (Merril and Alexander, 1987). In practice, fuel stratification is difficult to handle so it is often accomplished by identification of FT, i.e., forest stands where similar association of fuel properties are expected. The most common fuel type classification systems (FTCS) have been developed in the USA and Canada. Usually, they are supported by a photo guide which facilitates field reconnaissance of vegetation types and percentage cover (Figure 10).
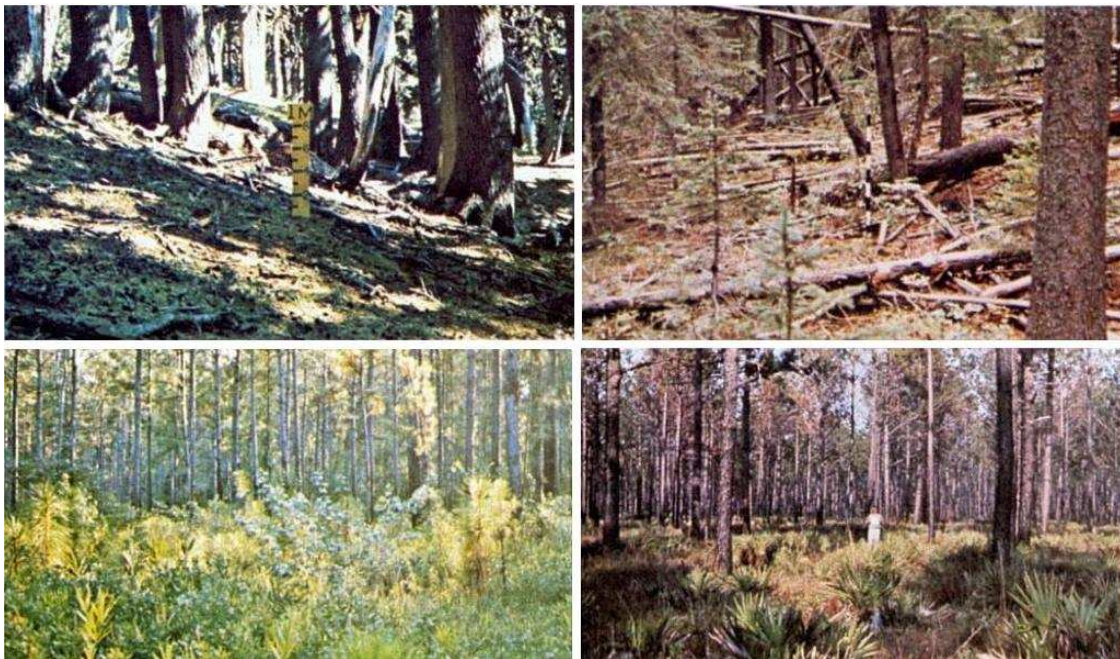
Figure 10. *Photo guide: fuel models 8 (upper left), 10 (upper right), and 7 (bottom) (Anderson, 1982).*

To characterize the North American forests, Anderson (1982) developed a FTCS that is applicable to a wide range of vegetation types. Recent systems propose to better describe national or regional forest reality. For instance, Table 2 presents the system dedicated to central Portugal (ADAI, 2000). And FTCS like Prometheus better suit Mediterranean ecosystems (Figure 11).

Group	ID	Description
Herbaceous	HER01	Herbaceous fuels
Shrubs	MAT01	Shrubs with mean height less than 0,5 m
	MAT02	Shrubs with mean height between 0,5 and 1,5 m
	MAT03	Shrubs with mean height higher than 1,5 m
Stands	PPIN02	Young pine plantation, without silvicultural intervention
	PPIN03	Pine plantation without understorey
	PPIN04	Pine plantation with understorey
	PPIN05	Overstocked pine plantation
	EUC01	Young eucalyptus stand (<3 years)
	EUC02	Eucalyptus plantation without understorey
	EUC03	Eucalyptus plantation with understorey
	FOLC01	Broadleaf deciduous trees
Logging slash	RESE01	Logging slash

Table 2. *Fuel types identified in the central region of Portugal (ADAI, 2000).*
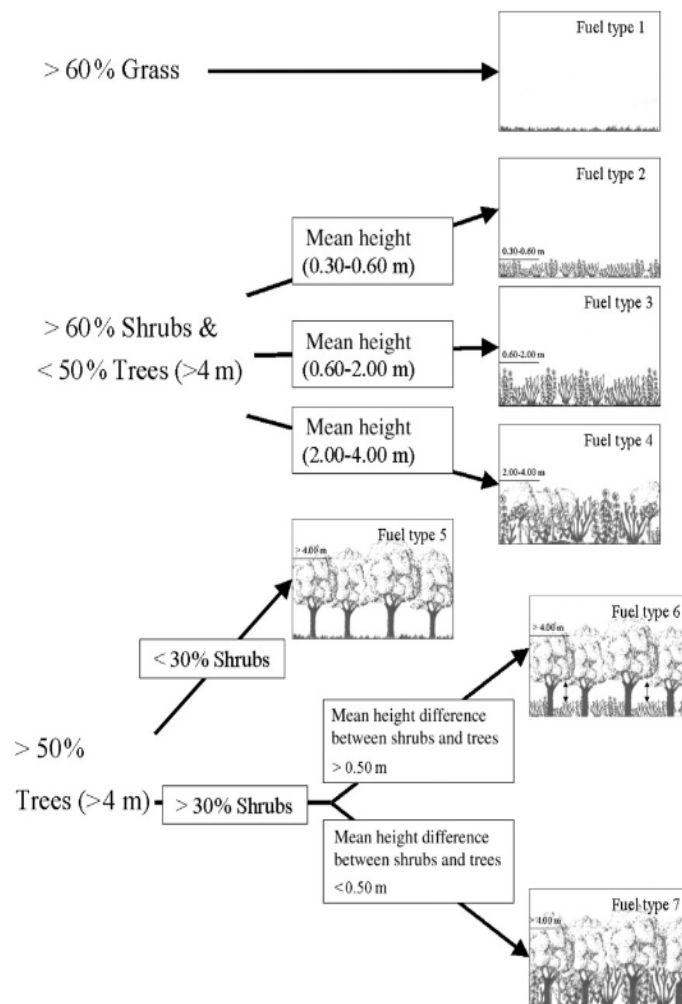
Figure 11. *Prometheus fuel type classification system (Riaño et al., 2002).*

The most complete fuel stratification was published by Sandberg et al. (2001) who assigned fuel characteristics to several combinations of categories of cover types and stand structures. Figure 12 shows the fuel layers and categories considered in this FTCS. It distinguishes six strata or fuel beds, each characterized by the presence of certain FT. This system aims to be more dynamic than the classical FTCS and helps to standardize the way FT are established, which opens new possibilities for non-specialists. Here, the different FT can be friendly

customized by the user who chooses the type of vegetation and the percentage cover in each stratum. According to these authors, it "simplifies the complexity to a reasonable degree, but does not oversimplify the description of wildland fuel beds".

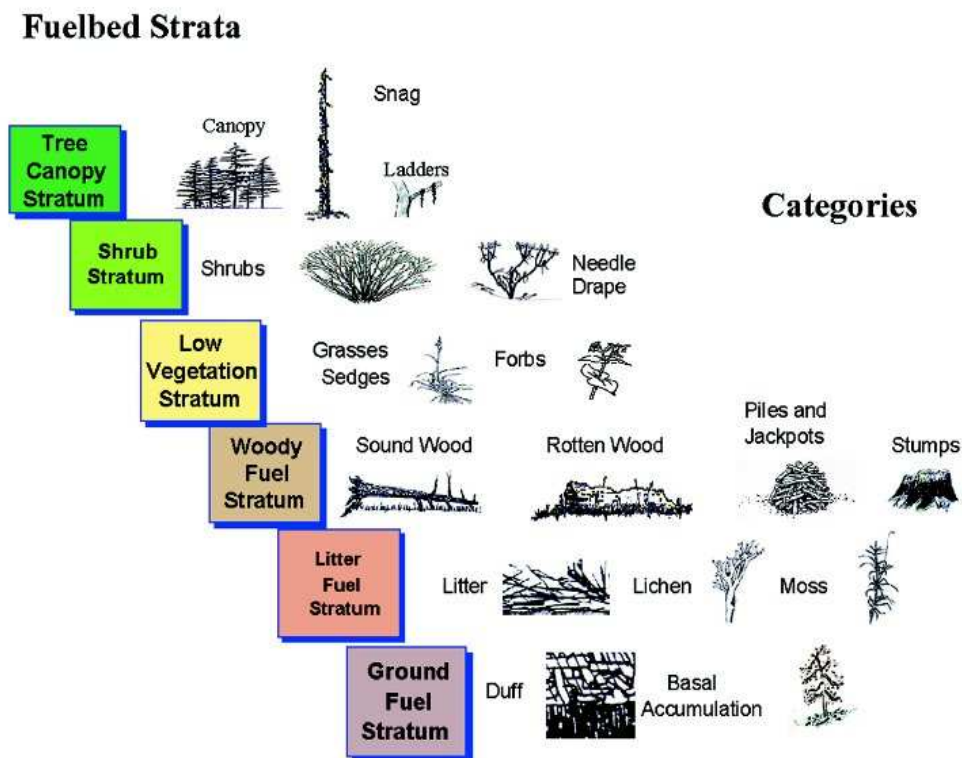**Figure 12.** *Fuel bed strata and categories (Sandberg et al., 2001).*

2.4. Fuel models

By itself, information about the spatial distribution of vegetation is not sufficient to characterize fire behavior. Quantification of all relevant fuel properties is required: canopy height, canopy base height, percentage cover, fuel load, surface-to-volume ratio… Within a fuel type, the aerial and surface fuels are estimated by different approaches. To calculate crown fuel properties, all trees within a stand are first identified. Second, their individual size or the mean size of several specimens is measured (height, DBH, crown diameter...). Then published allometric equations allow the calculation of crow fuels.

Such an approach cannot be used to map surface fuels. To quantify them, Fuel Model (FM) have been designed. They aim at estimating the expected surface fuel loads under specific covers. These quantitative parameter sets are determined by sampling each FT: such procedures involve fuel description at the particle or element level (leaf, spine, branch, stem…), physical (length, width, volume, mass-to-volume ratio, surface-to-volume ratio…) and chemical (moisture, heat content…) characteristics that are assessed by different techniques (Allgower et al., 2004). Cohen et al. (2003) reviewed fuel properties for all species studied in the Mediterranean Basin. This work that is integrated in the Fire Star project (http://www.eufirestar.org/) aims to record information about the FT of the usual Mediterranean vegetation covers (Figure 13). The most classical FM were designed by Albini (1976) who defined 13 FM providing standardized FT properties and by Anderson (1982) who sampled the North-American environment into 13 FM. Table 3 displays the FM dedicated to Central Portugal for each FT listed in Table 2.

Figure 13. *Input GUI of the Wildland fuel particles characterization database structure (Cohen et al., 2003).*

Model	Load (kg/m^2)				S/V Ratio (cm^2/cm^3)		Depth	Heat Content	Extinction Moisture
	Dead Fuels			Live					
	1-hr.	10-hr.	100-hr.	(Ø<6 mm)	1-hr.	shrubs	(cm)	(kJ/kg)	(%)
HER01	1.17	-	-	-	80	-	28	18000	30
MAT01	0.22	-	-	1.27	60	60	51	22500	40
MAT02	0.74	-	-	22.3	60	60	94	22700	40
MAT03	0.92	-	-	57.4	60	60	130	22700	40
PPIN02	1.3	0.1	2	-	50	-	11.6	21000	35
PPIN03	0.6	0.1	0.1	-	50	60	6.5	21000	35
PPIN04	1.7	0.2	0.2	1.8	50	60	62	22000	35
PPIN05	0.35	0.1	0.25	0.1	50	-	5	21000	35
EUC01	0.35	-	-	-	55	-	3	20000	25
EUC02	0.3	0.46	0.3	-	55	-	8	20000	25
EUC03	0.7	0.3	0.5	0.9	55	60	30	22000	25
FOLC01	0.8	0.3	0.74	-	55	-	10	20000	25
RESE01	0.25	0.18	0.1	-	79	-	5	18500	21
HER01	0.7	0.72	0.4	-	55	-	12.2	22000	30

Table 3. *FM for Central Portugal (ADAI, 2000).*

A forest typology was developed for the Portuguese National Forest Inventory (NFI) and translated into FM (Table 4): it combines the cover type of the dominant overstory species and the forest structure (closed/open, low/tall). The wind adjustment factor (WAF) is another parameter that is crucial to determine whether open and low stand fuels are drier or not when exposed to the wind, and how the plant canopy modifies the wind acting on a surface fire. That kind of approach, where more significance is given to the horizontal and vertical spatial continuity, can be important because it has an effect on the environmental thresholds (fuel load, fuel moisture, wind speed), allowing horizontal and vertical fire development or spread in a given vegetation type.

To describe fuel properties, a new trend consists in merging data from different sources. The second-generation FTCS of Sandberg et al. (2001) that calculates fuel properties at different scales is now operational. A FT prototype is first selected (Figure 12). Second, the gradient and physiognomic variables are adjusted using local data found in the literature or in databases (Figure 13).

11

Cover and structural type		Depth, cm	Fine fuel load, t ha[-1] 1-h	Fine fuel load, t ha[-1] live	SVR, m[-1]	HC, kJ kg[-1]	Mx, %	WAF
Acacia spp.	CL	43	5.17	3.47	5214	20236	32	0.17
Eucalyptus globulus	OT	16	1.10	0.49	3645	19865	27	0.14
	OL	51	0.83	1.18	5764	21080	30	0.23
	CT	28	5.16	2.15	5752	20908	28	0.10
	CL	57	3.73	4.02	5579	20969	30	0.13
Quercus pyrenaica	CL	69	1.60	2.48	5497	20894	26	0.12
Diverse	OT	17	2.05	0.42	7119	19826	26	0.19
	OL	39	1.73	1.17	4720	20535	28	0.36
	CT	39	2.55	1.41	4772	20494	28	0.13
	CL	58	1.91	3.56	5318	20448	32	0.17
Other deciduous oaks	CL	43	6.37	4.89	5039	20436	25	0.14
Pinus pinaster	OT	8	4.32	0.90	4551	19608	38	0.17
	OL	36	1.36	2.36	4303	21189	36	0.44
	CT	24	7.36	3.04	4986	20223	37	0.12
	CL	46	6.66	6.35	4950	21379	36	0.16
Quercus suber	OT	41	1.38	0.56	5994	21475	28	0.16
	OL	50	1.28	1.00	5304	21225	32	0.36
	CT	17	3.29	1.19	5583	21280	22	0.12
	CL	39	4.75	4.39	4666	20406	25	0.15

Table 4. *Fuel model parameters for the 19 Portuguese forest types. CL: closed and low stands, CT: closed and tall stands, OL: open and low stands OT: open and tall stands, SVR: surface-to-volume ratio, HC: heat content, Mx: dead fuel moisture of extinction, WAF: wind adjustment factor (Fernandes et al., 2006).*

2.5. Fire models

Fuel characterization and fire models grew in parallel and were mainly developed by the American, Canadian, and Australian scientific communities. The concept of fire model was actually developed in the USA to accommodate the detailed and complex fuel inputs required to simulate surface fire spread using the so-called Rothermel model. Embedded in a variety of fire behavior modeling systems, these equations became very popular and a quasi-standard model in the wildland fire behavior research. The input variables are listed in Table 5. Three other input variables are also required in the Rothermel model: fuel moisture, topography, and wind.

Particle properties			
Particle classes		**Fuel load [kg/m²]**	**Surface-to-volume[m²/m³]**
Dead	0.0 < 0.6 cm	measured/estimated	measured/estimated
	0.6 < 2.5 cm	measured/estimated	constant
	2.5 < 7.6 cm	measured/estimated	constant
Live	Herbs	measured/estimated	constant
	Woody	measured/estimated	constant
Fuel bed properties			
Depth [m]		measured/estimated	
Moisture of extinction [%]		measured/estimated	
Particle density [Kg/m³]		constant	
Total mineral content [%]		constant	
Effective mineral content [%]		constant	
Heat content [Kj/kg]		constant	

Table 5. Fuel inputs in Rothermel (1972) fire spread equation.

FARSITE (Fire Area Simulator) is a fire behavior and growth simulator (Finney, 2004) that uses spatial information on topography and fuels along with weather and wind files. It incorporates the existing models of surface fire (Rothermel, 1972), crown fire (Van Wagner, 1977; Rothermel, 1991; Van Wagner, 1993), spotting (Albini, 1976), post-frontal combustion, and fire acceleration, into a two-dimensional fire growth model. Inputs are required in a raster format (Table 6) and the simulation outputs can be either in a vector or raster format (Figure 14). Since FARSITE uses the Rothermel equation, the input variables required to simulate surface fires are already known. For the simulation of crown fires, the quantification of the crown fuel properties is also needed.

| Raster theme	Units	Usage
Elevation	m, ft	Used for adiabatic adjustment of temperature and humidity from the reference elevation input with the weather stream.
Slope	percent, °	Used for computing direct effects on fire spread, and along with Aspect, for determining the angle of incident solar radiation (along with latitude, date, and time of day) and transforming spread rates and directions from the surface to horizontal coordinates.
Aspect	° Az	See Slope.
Fuel model		Provides the physical description of the surface fuel complex that is used to determine surface fire behavior (see Anderson 1982). Included here are loadings (weight) by size class and dead or live categories, ratios of surface area to volume, and bulk depth.
Canopy cover	percent	Used to determine an average shading of the surface fuels (Rothermel and others 1986) that affects fuel moisture calculations. It also helps determine the wind reduction factor that decreases windspeed from the reference velocity of the input stream (6.1 m above the vegetation) to a level that affects the surface fire (Albini and Baughman 1979).
Crown height	m, ft	Affects the relative positioning of a logarithmic wind profile that is extended above the terrain. Along with canopy cover, this influences the wind reduction factor (Albini and Baughman 1979), the starting position of embers lofted by torching trees, and the trajectory of embers descending through the wind profile (Albini 1979).
Crown base height	m, ft	Used along with the surface fire intensity and foliar moisture content to determine the threshold for transition to crown fire (Alexander 1988; Van Wagner 1977).
Crown bulk density	kg m^{-3} lb ft^{-3}	Used to determine the threshold for achieving active crown fire (Van Wagner 1977, 1993).

Table 6. *FARSITE inputs (Finney, 2004).*
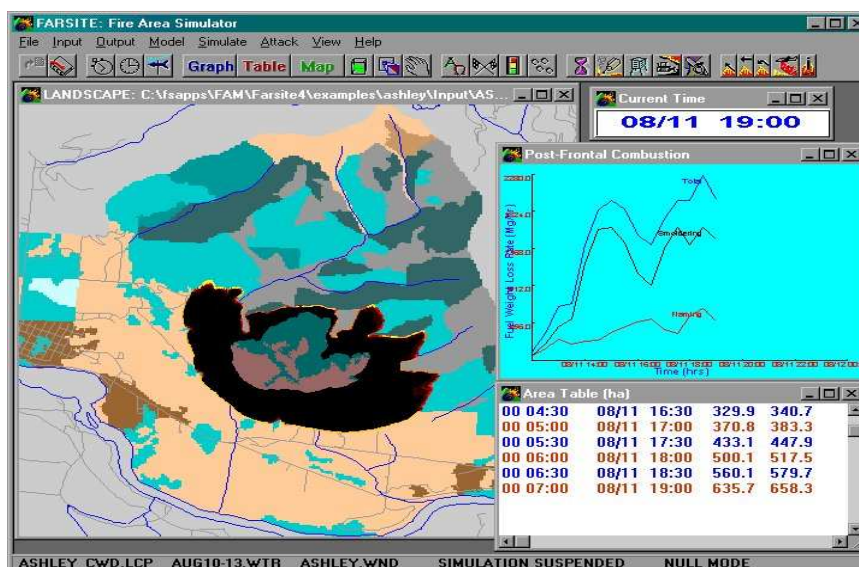
Figure 14. *Output FARSITE software.*

NEXUS, another crown fire hazard analysis software, uses the Van Wagner (1993) crown fire transition criteria to link surface fire behavior models with crown fire behavior models and to compute a crown fire potential index (Scott, 1999). CBD and CC determine the likelihood of active crowning, and CBH determines the risk that a surface fire is transformed into a crown fire.

To fit the requirements of several users and specialists, a flexible and customized system called BehavePlus was designed by Andrews et al. (2005). It can be used for several applications like the projection of an outgoing fire, the planning of prescribed fires, and training. Primary modeling capabilities include surface and crown fire spread and intensity, safety zone size, size of a point source fire, fire containment, spotting distance, crown scorch height, tree mortality, wind adjustment factors, and probability of ignition. BehavePlus provides the 13 standard fire behavior FM of Anderson. Because they may have different requirements, users can introduce their own parameters to build and save a FM closer to reality (Figure 15). Thus, the BehavePlus software allows customization, offering several options for inputs and outputs (graphical or GIS based, dynamics, vector and raster) and independent models for several calculations (wind adjustment factor, dead fuel moisture contents…). The software and its documentation can be downloaded at http://www.fire.org/.
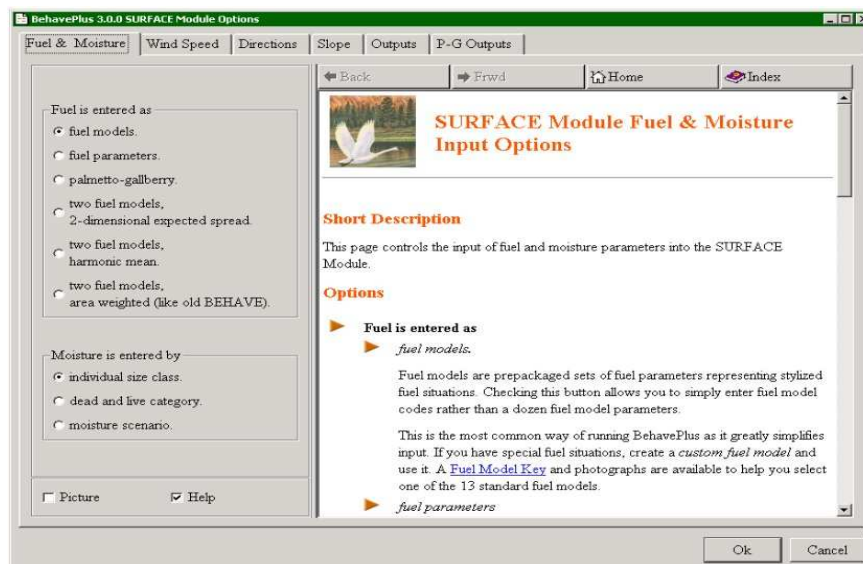

Figure 15. *Main GUI of BehavePlus software.*

3. Airborne LiDAR systems – Review of applications in forests

3.1. Basic principles

Airborne LiDAR systems provide information on the three-dimensional position of any spot at the Earth's surface by measuring the return time of laser pulses. They require accurate information on the location and altitude of the platform, which are provided by combining differential GPS and INS measurements (Figure 16).

A large number of airborne systems are available both for commercial and scientific use. A review of all available systems, as well as the basic relations and formulas, can be found in Baltsavias (1999). Airborne laser altimetry provides reliable elevation data with high altimetric (< 0.15 cm) and good planimetric (< 0.40 cm) accuracy (Ahokas et al., 2003).
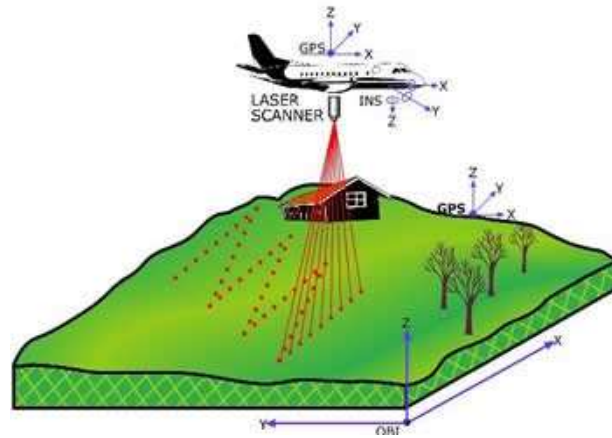
Figure 16. *Airborne LiDAR systems (http://www.fs.fed.us/pnw/olympia/silv/lidar/).*

For continental surface altimetry, the laser operates in the near-infrared region of the spectrum (1064 nm) to maximize the return signal and minimize the background noise. LiDAR systems can be classified on the basis of *i*) the footprint size (small from 0.2 to 0.8 m or large from 8 to 70 m); *ii*) the sampling rate *vs* the scanning pattern; and *iii*) the digitization sampling (multi-echo or full waveform). The footprint size depends on the divergence of the laser beam and the altitude of the sensor.

Small footprint systems differ from large ones by the surface area illuminated by the laser beam (Figure 17a). They provide high point density, allowing a detailed description of the illuminated area. They only sense individual elements or portions of forest elements (e.g., the side or the top of a tree crown, a portion of a shrub...) thus individual trees can be sampled. As a consequence, they also often miss the tree top and, in forests having high CC, they have some difficulty reaching the underlying ground. Derivation of accurate DTM and tree height maps consequently highly depends on the sampling rate, i.e., the pulse frequency and the footprint size.

Large footprint systems provide information on the forest structure rather than on individual trees (Figure 17b). The return waveform records the vertical distribution of intercepted surfaces within a wide area. By increasing the footprint, the ground is generally reached, even in dense media, avoiding the disadvantages of small footprints. Since the point density decreases, the information (crown volume, biomass, etc.) is provided at the stand level and it is impossible to describe individual forest elements such as trees. The separation of the vertical layers and the estimation of their height are coarser.
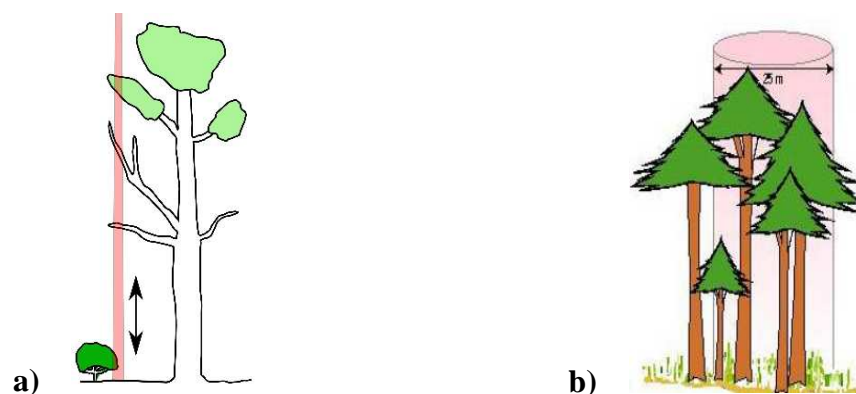

Figure 17. *a) Small and b) large footprint laser beam.*

In forestry, multi-echo and full waveform systems differ in the way they sample the forest three-dimensional structure. Multi-echo LiDAR systems record at least the first and last returns (Figure 18). Pulse detection is applied on the backscattered signal by an on-line system detector that extracts several time-stamped pulses from the continuous waveform, which gives the position of the target.
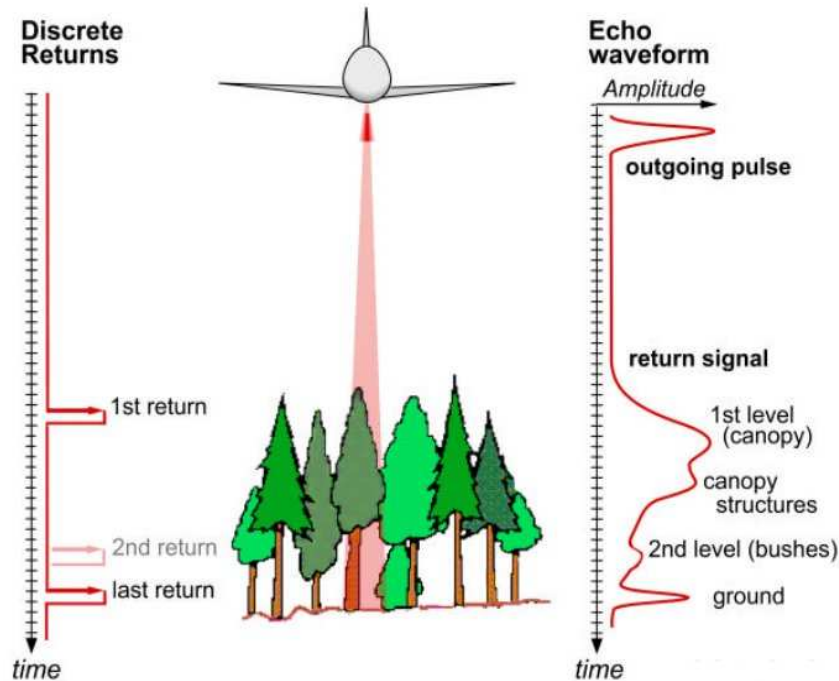

Figure 18. *Conceptual differences between discrete (left) and full waveform (right) LiDAR systems. The middle figure shows the laser illumination area within a forest.*

On-line peak methods vary according to the manufacturer who generally does not provide information about the implementation of its software. None is believed to be more accurate and reliable than another (Wagner et al., 2004). The standard pulse detection methods are: threshold, center-of-gravity, amplitude local maxima detection, detection of the zero crossing of the second derivate and constant fraction (Mallet and Bretar, 2007). They often take trigger-pulses due to noise (Figure 19).
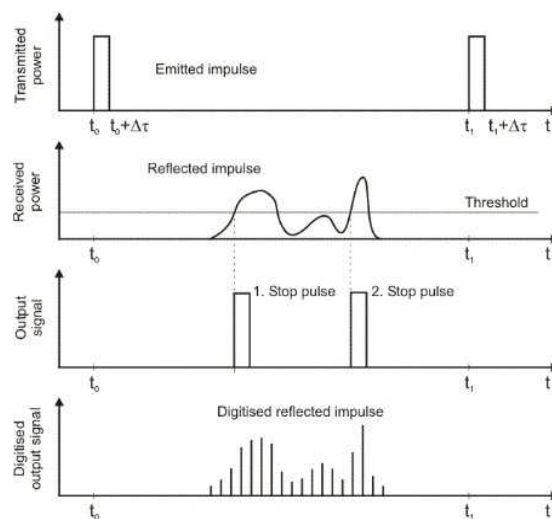

Figure 19. *Upper: emitted pulse. Middle upper: received signal. Middle bottom: peaks detected by a discrete system. Bottom: full digitized waveform (Wagner et al., 2004).*

Full waveform systems record the amount of energy returned to the sensor. This enables the user to analyze the waveform off-line in post-processing, and thus to use different detection methods or combinations of them to extract additional information from the data. This also partly solves the detection problem. The processing consists in decomposing the waveform into a sum of components, or echoes, with a parametric approach in order to characterize the different targets along the path of the laser beam. The aim is therefore to maximize the number of relevant peaks detected and to extract more information from the raw signal. The backscatter signal is often assumed to be a mixture of Gaussians (Figure 20), however, other mathematical functions have been proposed such as the generalized Gaussian function (Chauve et al., 2007a).
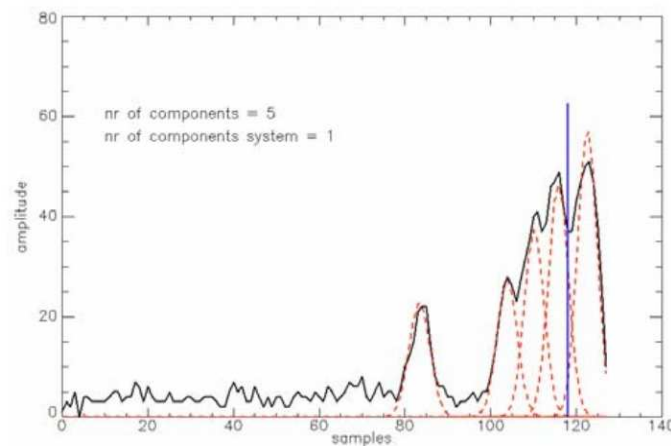

Figure 20. *Waveform data (black solid) and the Gaussian components (red dashed). The vertical line symbolizes the position of the point extracted by a multi-echo system. Persson et al. (2005) noticed that four points could be extracted in post-processing compared to a discrete system for this particular case.*

For the Gaussian model, the amplitude and the width can be obtained (Figure 21). They give information on the reflective properties of the target (Mallet and Bretar, 2007). These features can be seen as additional parameters for the purpose of classification. For instance, the backscatter signal on vegetation is wider than on the ground, but lower in intensity (Persson et al., 2005). The waveform registration also improves the vertical resolution (or multi-target resolution) of LiDAR systems, i.e. the minimum vertical distance between two targets likely to be recognized. In short, pulse peaks separated by about 0.5 m can be detected, which is impossible using conventional LiDAR (Hug et al., 2004).
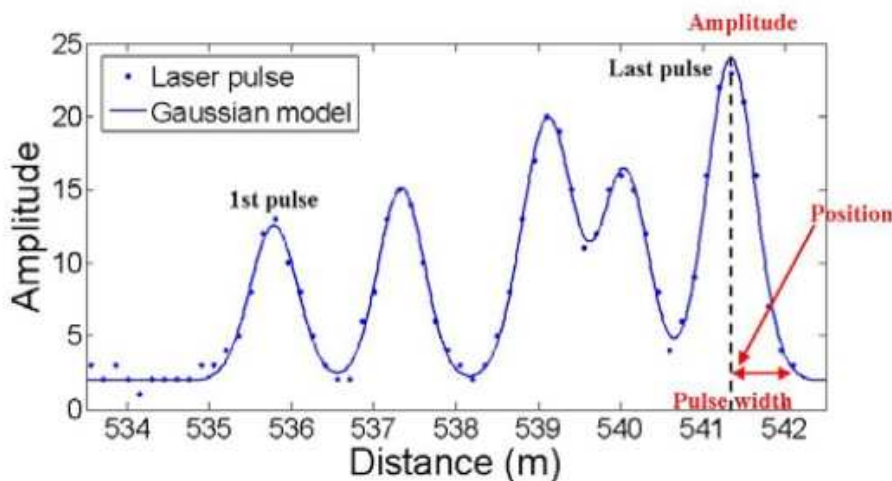

Figure 21. *Example of measured vs modeled waveform from a forest showing also the amplitude and width for a certain pulse (Wagner et al., 2006).*

3.2. Feature extraction techniques

Extraction of forest information from LiDAR data mainly involves distribution-based analyses and individual tree-based analyses. They make scale and accuracy requirement in the forestry information compatible with the LiDAR system acquisition mode. In the distribution-based analysis, the forest variables are assessed from the point cloud through predictive models. In the individual tree-based analysis, the neighborhood information of the point cloud is used to retrieve canopy biophysical characteristics (crown size, individual tree height, tree location…). A third hybrid analysis combines those two.

3.2.1. Distribution-based analysis

Based on the point cloud distribution at the stand or plot level, this method sets statistical relationships between tree characteristics measured in the field and LiDAR data. These correlations are often obtained by multiple regression. Both large and small-footprint metrics have been used as predictors in regressions or non-parametric models for the estimation of the mean tree height, the basal area, the stem number, the volume, the biomass (e.g., Næsset, 1997a, 1997b; Lefsky et al., 1999; Magnussen et al., 1999; Means et al., 1999; Lim et al., 2002; Næsset, 2002; Næsset and Økland, 2002; Maltamo et al., 2006b) and crown fuel properties (Riaño et al., 2003; Andersen et al., 2005; Peterson, 2005).

In this statistical approach, the distribution, shape, species and height of the trees directly impact on the construction of the models, thus local calibration is necessary. Stand delineation is another critical factor. Since high correlations are expected, these methods are sensitive to the sampling: the selected stands must be as homogeneous as possible. Working at fine scale has the advantage that information at coarse scale can be easily derived over a large area by simple aggregation of individual tree values or by extrapolation methods.

3.2.2. Individual tree-based analysis

If dimensional information on individual trees (height, crown size…) is accurately extracted, other canopy structure parameters can be derived using regression models or allometric equations (Hyyppä et al., 2001; Næsset and Økland, 2002; Persson et al., 2002; Riaño et al., 2004). These variables are determined with a consistent bias to avoid site-specific calibration (Hyyppä et al., 2008), therefore these methods are site independent. When the statistical analysis requires many plots or stands to set the regression models, the individual approach only involves a limited number of trees, which significantly reduces the cost and time of field work. The individual tree-based analysis seems to be a new direction in forest survey based on remote sensing and a powerful management tool for individual overstory trees (Brandtberg et al., 2003). Because results have been obtained on different experimental sites, a comparison of the distribution-based analysis and the individual tree-based analysis is still missing (Hyyppä et al., 2008) although a summary of the expected accuracy can be found in Næsset et al. (2004). Recent development in computer analysis of high spatial resolution images led to the semi-automated production of forest inventories based on individual tree crown information (Hyyppä et al., 2008). Extraction of such an information consists in finding the tree location and in delineating the full crown (Gougeon and Leckie, 2003). Algorithms developed for high and very high resolution aerial imagery can be used with LiDAR data by replacing the image by a digital surface model (DSM), a CHM or a normalized point cloud. Additionally, it is possible to improve these algorithms by using powerful ranging algorithms or knowledge-based approaches. For example, assuming that the tree height is known, the crown size can be roughly estimated by allometric equations or field based correlations.

a) Tree location: almost all the methods construct the CHM and find local maxima as best guests for tree location (Gougeon and Moore, 1989). The CHM is determined from the

first laser reflection and locally interpolated with special gridding methods. The interpolation of raw data to construct the CHM has a smoothing effect and, to some extent, it affects the success in finding tree tops (Reitberger et al., 2007). The sampling technique can fail in finding all trees in a forest: the number, position or height of tree tops are often erroneous. This misclassification occurs when some points are mistakenly assigned tree tops or when neighboring trees do not appear as two maxima (Figure 22). Since the local maxima method lacks accuracy, others approaches have been proposed. Reitberger et al. (2007) developed an algorithm that directly detects the stem position but that requires high density point clouds and high penetration rates through the canopy. Progress in similar techniques may increase the accuracy of tree location.
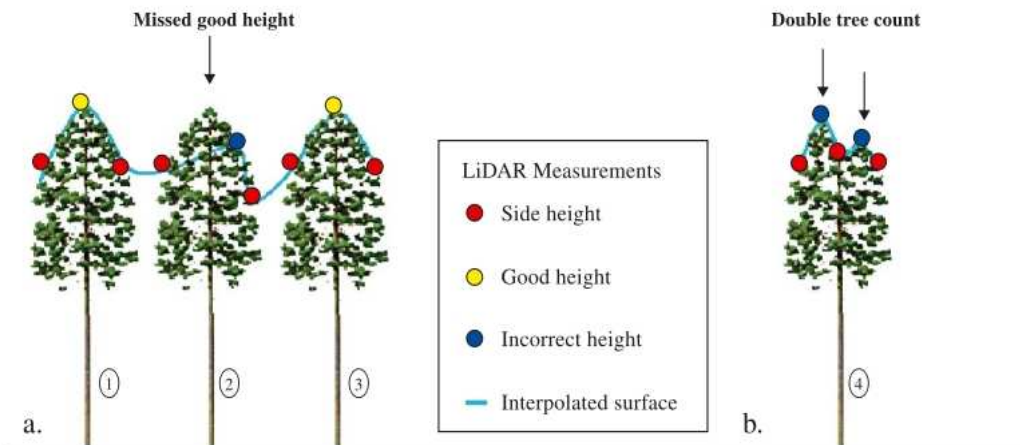

Figure 22. *Trees erroneously retrieved through LiDAR data sample. a) Trees heights ① and ③ are correct because LiDAR returns intercept tree peaks (yellow). Tree height ② is incorrect because the LiDAR return is from the side of the crown (blue). b) Tree is counted as two stems (and heights) due to a forked or irregular tree crown (Zimble et al., 2003).*

b) Full crown delineation: crowns metrics are useful to accurately derive other tree and stand parameters. They are often used in allometric equations or in statistical analysis to estimate the biomass or the CBD. The full crown delineation can be divided in three major steps: *i*) the 2D crown delineation (projected maxima area); *ii*) the measurement of the crown length; *iii*) the modeling of the 3D crown shape or, at least, the assignment of its characteristics to a geometric object (cone, cylinder…). Two-dimensional crown segmentation usually involves a CHM and image processing techniques (Figure 23) such as the valley-following approach, the edge contour finding at multiple scales, the template matching, or the region growing (Persson et al., 2002; Brandtberg et al., 2003; Leckie et al., 2003; Popescu et al., 2003; Tiede et al., 2006).
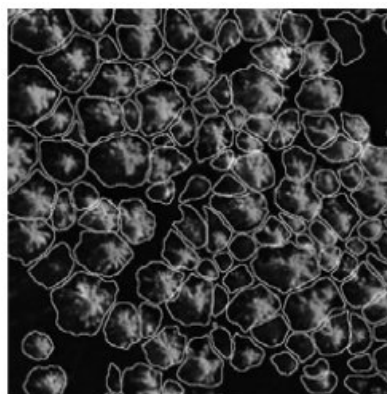

Figure 23. *Crown delineation superimposed on near-infrared image (Persson et al., 2002).*

CBH, a critical variable to define crown length, is discussed in section 4.3.2. In order to model tree crowns, Andersen et al. (2002) proposed to fit the point cloud by ellipsoidal models (Figure 24) and Korpela et al. (2007) adjusted it to a parametric surface determined using both the processed LiDAR data and allometric equations.
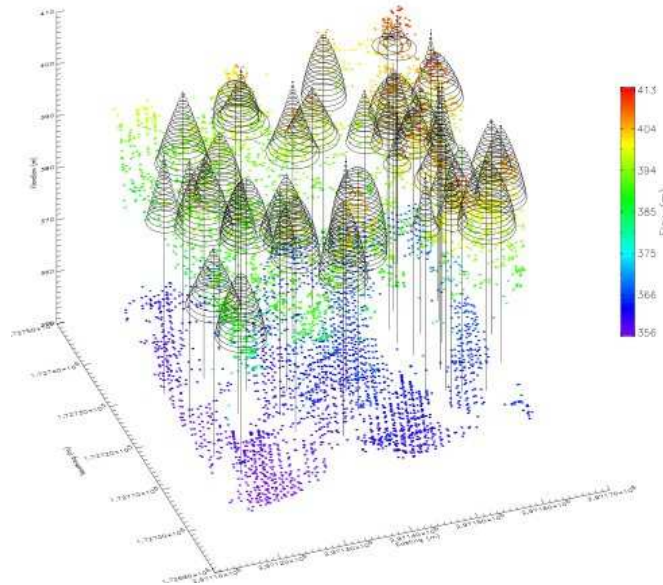

Figure 24. *Three-dimensional perspective view of three location and crown dimensions superimposed on LiDAR (Andersen et al., 2002).*

3.2.3. Hybrid analysis

Individual tree analysis can be used directly to predict information at the stand level. A series of plot or stand-level statistics (number of trees, maximum and mean tree height, mean crown size…) are first derived using the individual tree isolation approach. These statistical properties are then used to predict canopy structure at the plot or stand level (Holmgren, 2003; Popescu et al., 2003; Maltamo et al., 2004). Therefore, the method may improve the prediction accuracy of forest structural information but it cannot reduce the field work since the ground-truth is still needed. Hyyppä et al. (2008) reviewed the advantages and disadvantages of the distribution-based and individual tree-based analyses (Table 7).

Methods	Advantages	Disadvantages
Distribution-based methods	- Easy to integrate with present forest inventory practices due to common reference plots - Strong statistical approach - Laser scanning data relatively inexpensive	- Requires extensive, accurate, representative and expensive reference data - Without a large amount of reference data, strong possibility of large errors in operational inventories
Individual tree-based methods	- Good physical correspondence (existing models) with volume estimation - Low amount of reference data needed for calibration - Allows precision forestry and increased amount of information on the forest areas	- More expensive data - More complex system to implement

Table 7. *Distribution-based and individual tree-based analyses (Hyyppä et al., 2008).*

20

3.3. Synergy between LiDAR and aerial imagery

The synergy between laser scanning data and high-resolution optical imagery, whether they are acquired simultaneously or separately, should improve extraction of forest information. On one hand, LiDAR data contribute to the retrieval of height and crown shape, which are missing in non-stereo optical imagery. On the other hand, optical images provide information about spatial geometry and color, which are useful to vegetation species classification and health state diagnosis (Hyyppä et al., 2008). The need for data fusion has been reported by several authors (e.g., Baltsavias, 1999; Leckie et al., 2003). A strong criticism against LiDAR data is that they are not homogeneously distributed, i.e., there are gaps between two acquisitions especially when using small footprint LiDAR. Thus, crown 2D delimitation is more accurate in aerial images, in particular when crowns overlap (Leckie et al., 2003). In this case, more weight should be put in the optical data. However, they often treat low vegetation in canopy gaps as crown vegetation, when LiDAR data could easily remove that type of errors. Crown delineation is well established in boreal or managed forests, but over unstructured forests like in the Mediterranean countries, more research is needed (Hyyppä et al., 2008). Data fusion could also contribute to improve species identification. Persson et al. (2005) classified the Scandinavian forest: Norway spruce (*Picea abies*), Scot spine (*Pinus sylvester*), and deciduous trees. They combined LiDAR-derived metrics and optical spectral features, claiming a substantial improvement. Species identification can be very useful in the setting of allometric equations (Popescu et al., 2003; Korpela et al., 2007). For instance, Popescu et al. (2003) retrieved single tree crown diameters over the CHM by applying a filtering technique where the initial values were estimated using allometric equations. Those can be also very useful to detect erroneous segmentation. The coupling of optical imagery and LiDAR data could help to measure low vegetation because the latter often introduce a misclassification between ground and non-ground points. Riaño et al. (2007) calculated the NDVI (Normalized Difference Vegetation Index) on aerial images to detect vegetation and then decreased this misclassification. Fusion may also help to extrapolate forest spatial variables when LiDAR data are not available (Dubayah et al., 2000). In this case, however, a radiometric calibration is required. The correct horizontal and vertical segmentation of a forest obviously remains a challenge but data fusion seems to be very promising. Other methods can be found in Persson et al. (2004), Hyyppä et al. (2005), Suarez et al. (2005) and Maltamo et al. (2006b).

3.4. Tree species classification using LiDAR data

Tree species identification is particularly interesting in forest study, inventory and management. The spectral information contained in airborne or high-resolution spaceborne multi-spectral images generally provides good results (Brandtberg and Walter, 1998). Airborne laser scanning data have been also tested to classify tree species. One considers three steps: *i*) delineation of individual tree crowns by segmentation of the CHM and/or optical imagery; *ii*) extraction of individual tree characteristics (tree height, crown diameter and shape…); *iii*) classification of tree species based on the extracted features using an appropriate classifier. Holmgren and Persson (2004) tested species classification (Scots pine and Norway spruce) using an individual tree crown approach. They fitted a parabolic surface to the laser point cloud and could classify plant species by their crown shape with an accuracy of about 95%. Brandtberg et al. (2003) used LiDAR data under leaf-off conditions to segment individual trees. Classification of deciduous species with different indexes suggests a moderate to high degree of accuracy. Persson et al. (2006) identified species combining the tree features extracted from both high-resolution laser data and high-resolution multi-spectral images.

4. The Role of LiDAR in fuel mapping

Fuel properties influencing fire behavior are assessed at different scales. If fire scientists are interested by the particle level, fire managers prefer large scale maps. Knowledge about the vertical structure is critical to estimate fuel properties in forest environments. Passive remote sensing does not allow to penetrate deeply into plant canopies. This implies poor DTM retrieval over vegetated areas and consequently poor plant height estimation. LiDAR systems better deal with multi-layered forest reality. They often reach the ground, even in dense forests, and the backscatter signal is a function of the canopy structure. We identified two approaches to map fuels using LiDAR data: direct and indirect methods. The first ones intend to determine fuel properties directly from the point cloud. The second ones pretend to classify the forest environment in terms of FT. The disparity between the resolution of the LiDAR and the particle size of fine fuels (0 to 6 cm) and their horizontal arrangement on the ground, which does not allow its measurement, justify the indirect methods. Thus, direct methods are quantitative because they permit the retrieval of fire model input parameters using LiDAR metrics, and indirect methods are qualitative because the forest is first classified into pre-defined FT which can be then assigned to FM (section 2.5).

4.1. Fuel scales

Many people and research organizations are interested in fuel maps. Depending on the needs, different methods are available to study and describe fuel characteristics. Most of the time, it is very difficult to obtain an information that answer a specific question in a particular situation (Allgower et al., 2004). Moreover, fuels can be assessed at multiple scales, from the particle level to the landscape level (Table 8).

The physical, chemical and thermal fuel properties are determined at the cell, individual particle or element level (leaf, spine, stalk, twig, branch, stem…). Particle properties contribute to predict wildland fire intensity and severity. They have consequences on fire suppression and, therefore, are required to interpret the results of flammability laboratory experiments. Since collecting fuel properties at this level is costly and time consuming, databases like the one built by Cohen et al. (2003) are very useful. Moreover, that kind of work (section 2.4) helps to standardize fuel collection methods, describing the source, the reliability and protocols. The role of LiDAR in fuel mapping starts at the level of an individual tree: the different approaches to measure or estimate crown fuel properties have been reviewed in section 3.2.2. For instance, foliage biomass is usually achieved using allometric equations based on tree metrics. Note that CBD estimation requires prior knowledge, like the foliage biomass, at the particle level. At the plot level, even shrub fuel properties can be assessed using LiDAR. The description of that kind of surface is accomplished by retrieving shrub canopy mean height, percentage cover and, if possible, species identification. In a traditional forest inventory, percentage cover is determined visually, thus subjectively. Moreover, height measurements are critical since they are often heterogeneous. Other levels are however needed to fire management, ecological applications, experimental burns, risk maps, etc. There is a long tradition to use optical or radar imagery, but they cannot "see" through the canopy and the spatial resolution of radar images was, till recently, quite poor. Thus, LiDAR is still the most accurate way to map fuels at the stand level.

At the landscape level, the segmentation of forest environment in FT and their assignment in FM is the most elegant way to map fuels. However, operating small footprint LiDAR systems is still expensive, which limits their application over a large area. Spatialization techniques to

retrieve accurate fuel information at the landscape level are therefore necessary. They consist in searching correlations between optical images and LiDAR data and to extrapolate them where only optical (airborne or spaceborne) data are available.
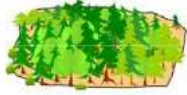
Fuel scale/level	Fire behavior model	Acquisition method	Intention
Landscape (2D/3D)	- BehavePlus - FARSITE - fire line rotation model	- Satellite images - Aerial photos - Imaging spectroscopy	- Fuel type maps - Ignition risk models - Risk maps - Spatial distribution of landscape elements
Stand (2D/3D)	- Behave - BehavePlus - FARSITE - NEXUS - Firetec - Canadian Model	- Stand inventory and mapping - Aerial photos - LiDAR - Imaging spectrometry	- Input parameters for fire behavior models - Fuel type characterization - Experimental burns
Plot (2D/3D)	- Firestar 2D (x,z) - Firetec 3D - CFIS	- Stand inventory and mapping - Aerial photos - LiDAR - Imaging spectrometry	- Input parameters for fire behavior models - 3D fuel structures - Biophysical parameters
Individual (3D)	- Firestar 2D (x,z)	- Cube method - Field sampling - Ground truth - Aerial photos - LiDAR	- Input parameters for fire behavior models - 3D fuel structures - Biophysical parameters
Particle	- Firestar 2D (x,z)	- Cube method - Field sampling	- Input parameters for fire behavior models - Structural and biophysical parameters
cell	...	- Biochemical analysis	- Input parameters for fire behavior models - Combustion behavior

Table 8. *Fuel scales, fire models, and fuel acquisition models (from Allgower et al., 2004).*

4.2. Direct methods – Mapping fuel properties with LiDAR

There are few studies using LiDAR to estimate fuel properties. With small footprint, we only identified the work of Riaño et al. (2003), Morsdorf et al. (2004) and Andersen et al. (2005).

4.2.1. Canopy closure
Vegetation cover is inversely related to the laser pulse penetration rate into the canopy. The laser-generated tree closure is the number of tree reflections divided by all reflections (from the trees, the understory and the ground). Means et al. (1999) and Riaño et al. (2003) showed a good relationship between CC and tree closure using, respectively, full waveform large footprint and first and last echo data. CC is well established with LiDAR taking advantage of its capacity to penetrate within canopies. It is more difficult to measure canopy cover with optical data because of the underlying grass or green shrubs that increase the misclassification. However, CC is the fuel property that is most easily determined by remote sensing (Chuvieco et al., 2003).

4.2.2. Crown base height

CBH is a fuel property used to estimate surface and crown fires. Although more emphasis has been put in the determination of tree height and crown diameter, CBH is a variable retrievable using individual tree-based analyses (Hyyppä et al., 2001; Næsset and Økland, 2002; Persson et al., 2002; Pyysalo and Hyyppä, 2002; Holmgren and Persson, 2004; Morsdorf et al., 2004; Riaño et al., 2004). Popescu and Zhao (2008) recently identified a trend to overestimate CBH, which was already noticed by other authors. To increase accuracy, they developed new methods such as the multiband height bins (voxel) to characterize the vertical structure of individual tree crowns.

Emerging small-footprint full waveform systems are promising to improve individual tree crown assessment because they permit extraction of additional points within the crowns. Chauve et al. (2007b) noticed an increase of more than 100% in dense canopies. Therefore, full waveform LiDAR improved the accuracy (Figure 25) of crown metrics measurements (Holmgren and Persson, 2004; Persson et al., 2005; Reitberger et al., 2007).
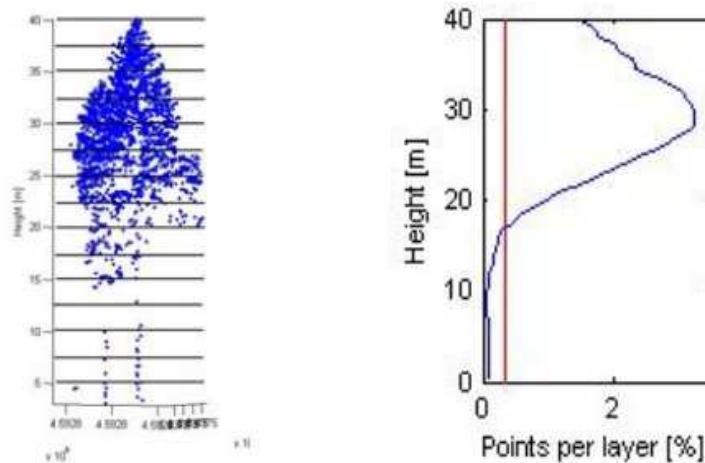

Figure 25. *Crown base height defined as the height that corresponds to 0.15% of the total number of points per segment (Reitberger et al., 2007).*

Despite some improvement in these approaches, CBH is not very useful by itself to fire behavior studies. As a fuel property, it is inseparable from the understory vegetation height. It means that it makes no sense to define CBH without accurate information on the fuel model below the canopy that may effectively reduce the nominal CBH value. Andersen et al. (2005) established predictive models between several LiDAR metrics and field inventory at the plot level. Riaño et al. (2003) did the same thing at the stand and tree levels with a clustering technique based on height percentiles. With large-footprint LiDAR, the estimation of canopy base height was performed either by analyzing or modeling the waveform or by regression models (Figure 26).

4.2.3. Crown bulk density

CBD is described as the foliage biomass divided by the crown volume. Therefore, large tree branch biomass is not included since it does not have influence on fire behavior. However, the laser beams target all material in the canopy, thus CBD cannot be directly assigned to the cloud point returned by tree crowns. CBD can be either empirically estimated from LiDAR metrics and field measurements or from the foliage biomass and crown volume. Empirical methods are common in large footprint data analyses (Drake et al., 2002; Hyde et al., 2005; Peterson, 2005). Andersen et al. (2005) estimated CBD by establishing predictive models between LiDAR heights and field survey measurements at the stand level in a coniferous

forest with Douglas fir (*Pseudotsuga menziesii*) and western hemlock (*Tsuga heterophylla*).
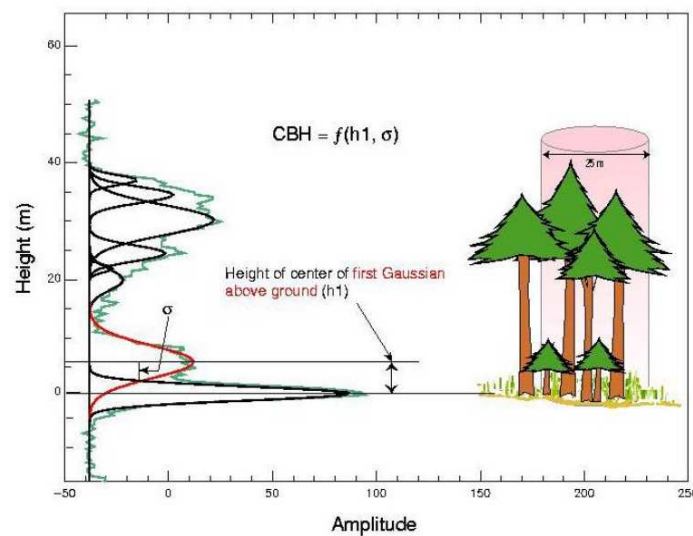

Figure 26. *Gaussian-fitting method used to derive CBH at the stand level from LVIS data. The lowest Gaussian above ground (red) is assumed to represent the lowest canopy return (Peterson, 2005).*

However, the calculation of the foliage and crown biomass separately, using allometric equations, led to better results. Several allometric equations are provided in the literature for different species as a function of tree characteristics (Figure 27). Riaño et al. (2004) used allometric equations to predict crown and foliage biomass. However, they studied an intensively managed homogeneous Scots pine forest where individual crowns were easy to segment. No model validation has been carried out in forests with a complex structure (Andersen et al., 2005). Popescu (2007) investigated the LiDAR accuracy to derive individual tree measurements (height and crown width) and their impact on individual tree components biomass estimations (foliage and stem biomass) using allometric equations. Instead of crown or foliage biomass, almost all works aim to predict total above ground biomass (Naesset, 1997b; Means et al., 2000; Hyyppä et al., 2001; Drake et al., 2002).
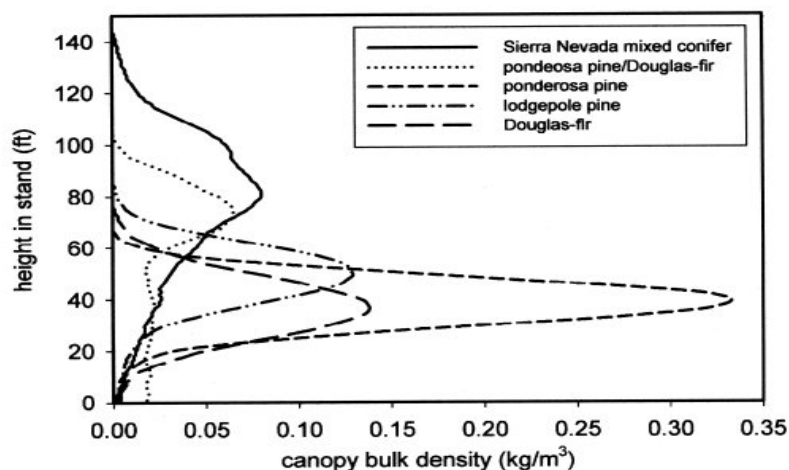
Figure 27. *Canopy bulk density allometric equations at the stand level as a function of tree height (Scott and Reinhardt, 2001).*

4.2.4. Low vegetation cover

Low vegetation is very important in fire hazard and fire behavior estimation since it dries very fast and regrows quickly after a fire, providing most of the new fuels for surface fires. Large fires also always start and spread in this layer. Even without upper vegetation, the height of

small vegetation – grass, shrubs, small trees – is not easy to retrieve by remote sensing. Contrary to optical imagery, LiDAR data can have serious difficulties to detect it and misclassification between ground and low vegetation often occurs. This variable is however crucial not only for fuel mapping purposes, but also to retrieve accurate DTM. Because the height is the primary characteristic of fuel load in this type of vegetation, there are different FT where the single difference is the vegetation height.

Naesset and Bjerknes (2001) estimated the mean height of a young forest using a small footprint LiDAR (first and last echoes) and found values ranging from 1.5 to 6 m with an average of 3.8 m. They compared the ground truth with laser-derived canopy height metrics and density. Riaño et al. (2007) subtracted the DSM and the DTM generated by the LiDAR data provider: they noticed a high misclassification degree between vegetation and ground in plots covered by low shrubs. This effect also occurred in higher but dense shrubs, fixing shrub heights unrealistically close to zero. For fuel mapping purposes, they calculated the DTM by removing the vegetation signal using airborne imagery and also improved the DSM: canopy heights ranged from 0.5 to 1.6 m with an average of 0.8 m.

Surface vegetation height is difficult to assess using large footprint LiDAR because ground and low vegetation signal are difficult to separate. Full waveform small footprint LiDAR processing methods offer new opportunities to measure low vegetation. They permit extraction of additional points within the understory. For instance, Chauve et al. (2007b) noticed an increase of more than 100% in this layer. Hug et al. (2004) and Persson et al. (2005) suggested to use the pulse width and intensity to detect the presence of low vegetation because the pulses reflected by plants tend to be larger than ground hits (Figures 28 and 29).
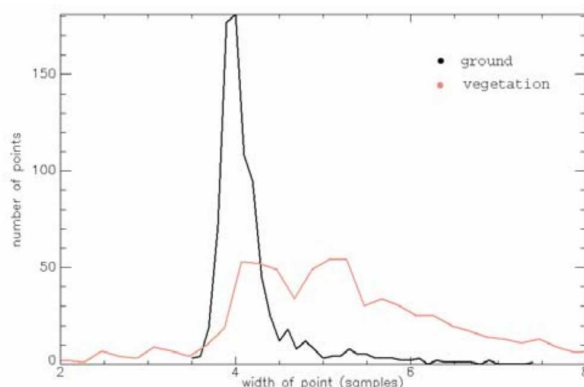

Figure 28. *Histogram of width points, ground (black) and vegetation (grey) (Persson et al., 2005).*
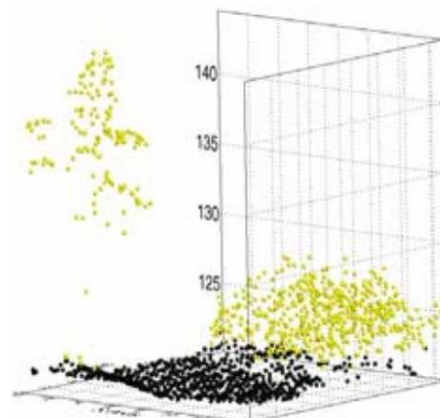
Figure 29. *Width based classification, ground (black) and vegetation (yellow) (Persson et al., 2005).*

Live vegetation is not the only factor influencing the width and intensity of the peaks: terrain slope, dead vegetation over the ground, etc. also induce wider peaks and decrease intensity. Point cloud segmentation using peak intensity and width is consequently still challenging. Such a classification has been performed in urban areas where the response of the different targets is easier to recognize. The application to natural environments seems to be a hard task since it is poorly stereotyped. However, improvements in vertical resolution introduced by full waveform systems can be useful to differentiate low vegetation from the ground (Figure 30). The waveform detection allows an accurate determination of the peaks of overlaid pulses down to a target separation of about 0.5 m only.
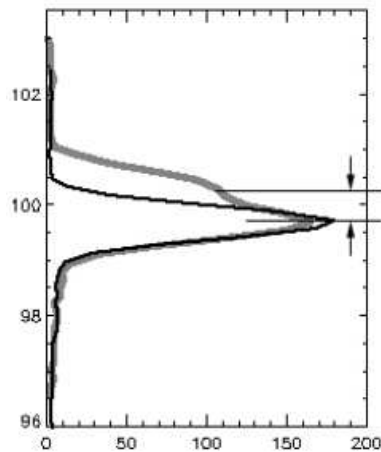
Figure 30. *Low vegetation and the limits of multi-target resolution (Hug et al., 2004).*

4.2.5. Understory canopy height

The structure and spatial distribution of understory vegetation (percentage cover and height) is critical in fire behavior models, but their parameterization is tricky. Besides all the problematics developed in section 4.2.4, the understory layer grows vertically underneath the overstory layer, increasing the difficulty in separating the two layers. The contribution of lower vegetation in the backscatter signal justifies further studies. Some authors maintain that LiDAR data need to be corrected from shading effects: it does not only concern the understory layer but also lower foliage and branches shaded in the same tree crown. This factor can also increase accuracy in CBH estimations.

The main effort has been put in depicting the vertical structure of trees using both large and small footprint LiDAR. The extraction of understory vegetation and their specific characteristics was poorly studied. Harding et al. (2001) used SLICER large full-waveform data to characterize multi-layered forests. They introduced an occlusion factor present in the backscatter signal due to the upper canopy and the ground noise. The goal was to retrieve a canopy height profile (CHP) that better describes a forest environment vertically (Figure 31). They applied an exponential transform to the waveform described in Lefsky et al. (1999). Calculation of CHP relies on assumptions about the rate of occlusion of specific canopy surfaces. In consequence, it is not applicable to all types of forests. When only discrete LiDAR are available, a similar correction must be performed. Riaño et al. (2003) used the same transform to retrieve CHP and simulated full waveform from discrete data. With a cluster analysis, they segmented the overstory and understory and then calculated the understory cover as the ratio of the number of laser beams that hit the understory to the total number of ground hits. Maltamo et al. (2006a) first calculated the cumulative proportional canopy densities to retrieve CHP and then analyzed whether the height distribution of laser hits were multimodal or not: if multimodal, the underlying canopy structure was considered as multi-layered. This work was performed to retrieve stands with cut trees. The number and size of logged trees were predicted using regression models.

No work was identified that extracts understory characteristics (height, percentage cover) using small-footprint full waveform. However, this type of data may increase the accuracy of such measurements. First, waveform processing methods appeared as a promising technique to detect understory, as noticed in section 4.3.5 (Hug et al., 2004; Persson et al., 2005, Chauve et al., 2007b). Second, the processing of large footprint full waveforms showed that its decomposition in three main Gaussian components (trees, underlying vegetation and ground) was possible.
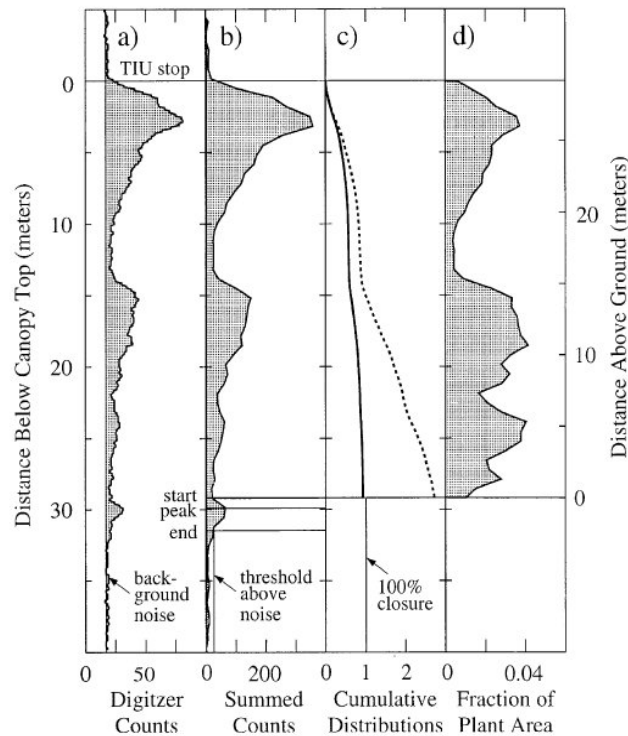
Figure 31. *Steps converting a raw SLICER waveform to a CHP:(a) raw waveform a single laser pulse; (b) waveform above mean background noise summed and start, peak, and end of the ground return; (c) cumulative distributions of canopy closure (solid), assuming that ground reflectance is half that of the canopy, and transformation to projected plant area (dashed); and (d) normalized, incremental distribution of plant area above the ground (Harding et al., 2001).*

4.2.6. Conclusion

There are few studies of fuel properties estimation. More emphasis has been placed in the extraction of forest variables. Most of the approaches only concern the estimation of tree characteristics. Despite this effort, fires do not only depend on tree crowns. More attempts are needed to improve the vertical segmentation of a forest environment. The height and percentage cover of the lower layers, whether an overstory is present or not, are of primary importance to predict fuel load.

In low vegetation, two approaches must be accounted for. The first one takes place when the laser trip does not find upper vegetation and the other one when aerial vegetation interferes with the laser beam. In both cases, small footprint full waveform offers a new perspective not yet explored. In the first approach, the main problem is the misclassification between ground and non-ground points. New classification techniques should be based on the features that can be extracted from the waveform: additional points against multi-echo systems, shape, peak width and intensity. The fusion with multi-spectral optical data may also help to identify whether the laser beam hits vegetation or not.

This misclassification also occurs when there is aerial vegetation. Moreover, one must take into account the influence of the upper vegetation in the backscatter signal. Although large footprints have been successfully analysed with exponential transforms, using the same technique on full waveform small footprints is still an issue.

4.3. Indirect methods – Fuel type classification

Most effort on classification methods over forest environments emphasized land cover maps that aim to identify tree species and their horizontal gradient along the landscape. This task

has been successfully performed using passive remote sensing, however its inability to penetrate in forest canopy increases the difficulties in fuel mapping. Rather than vegetation identification, a fuel map must deal with the horizontal gradient and mainly vertical forest structure. The classification through multispectral images can identify certain FT, usually those which can be assigned to land cover. For instance, it is possible to estimate some vegetation properties to derive fuel properties, such as the total living and dead biomass in grassland and shrublands. However, since height is the best predictor of total biomass in surface vegetation, these are coarse estimations. The vertical structural component is missing in the optical data, thus image classifications often just discriminate vegetation types more than fuel attributes. Recognizing the limitation of optical imagery to directly mapping fuels, some research works correlated FM with some vegetation characteristics. This approach assumes that some biophysical properties can be accurately classified from remotely sensed imagery and, after, assigned to fuel characteristics. However, fuels are not always related to land cover maps or vegetation characteristics, polygons with the same land cover can have more than four FM (Keane et al., 2001).

LiDAR allows three-dimensional measurements of multi-layered forests. Section 4.2 reviews the potentials and limits to estimate crown and surface fuels. The measurements of some surface fuels properties as those of litter are an unattainable goal. First, the particle size influencing fire behavior (0-6 cm) is incompatible with LiDAR spatial resolution. Second, the horizontal disposition over the bare soil and the low porosity make it impossible to measure their depth or even their presence.

Indirect methods to differentiate FT are classification techniques like those used in optical imagery. Since the backscatter signal is a function of the forest structure − describing the spatial arrangement − and the metrics of the FT are well established by fuel modelers, one expects that LiDAR data be a major factor in the classification of FT. In Figure 32 that presents full-waveform amplitudes distributed in space for four different zones, one can recognize some patterns that are likely to be assigned to the FT of Figure 33.

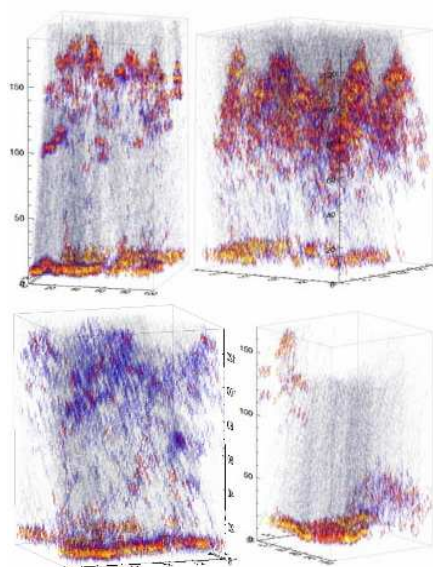
Figure 32. *Waveform samples inserted in a 3D volume consisting in small 3D cells (voxels). The amplitude of the waveform is assigned to each voxel. Upper left: pine trees; upper right: spruce trees; bottom left: deciduous trees, bottom right: road surrounded by grass and some trees (Persson et al., 2005).*
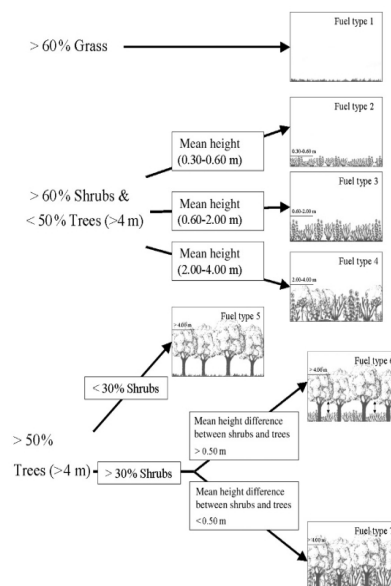
Figure 33. *Prometheus classification fuel types system (Riaño et al., 2002).*

Figure 34 shows the extracted points corresponding to the same waveforms in the upper left and bottom left displayed in Figure 32. A similar and complementary analyze could be tried here.
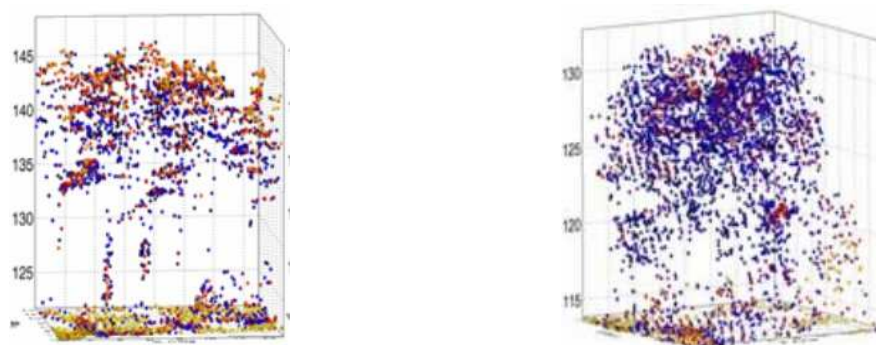

Figure 34. *Extracted points from LiDAR waveform data corresponding to upper left and bottom left of Figure 33.*

4.4.1. Methodology

Indirect methods aim to study the correlation between the LiDAR backscatter signal and the forest metrics well established in terms of FT. This subject has been poorly studied. Mutlu et al. (2008) fusionned LiDAR metrics (discrete system with 2.58 points/m²) with multispectral QuickBird imagery to classify FT. They also compared the accuracy of fuel maps classification using the imagery alone, the LiDAR alone and the two data together. The derived metrics were eleven height bins normalized (number of points per volume unit by total number of points) with the same horizontal dimension of images pixel (2.5 m × 2.5m). With an average of 2.5 points/m² they had 16 points par cell. The fusion was made with three techniques: LiDAR-multispectral stack, principal components analysis and minimum noise fraction. They identified seven FM in the study area: models l, 2, 4, 5, 7, 8 and 9 described in Table 9. A total of 27 regular polygons, each with a radius of 11 m, were selected. The supervised classification was performed using parametric decision rules (through maximum likelihood and Mahalanobis distance) in a per pixel characterization of fuels. The accuracies retrieved were 76.52% for the QuickBird image alone and 90.10% for the best fusion method. Therefore, using LiDAR derived metrics obviously increases the accuracy.

Fuel Model (FM)	
Grass and grass dominated	
FM 1 – Short Grass (0.30 m)	Short live and dead grass, grass-tundra, grass-shrub combinations (1/3 brush)
FM 2 – Timber (grass-understory)	Open shrubs lands and pine or scrub oak stands which cover 1/3 to 2/3 of the area
Chaparral and shrub fields	
FM 4 – Chaparral (1.82 m)	Stands of mature shrubs 1.82 m or more, live and dead fine woody material in the crowns of a nearly continuous secondary overstory
FM 5 – Brush (0.60 m)	Young and short shrubs, little dead material and grasses, in the understory, light surface fuels loads
FM 7 – Southern rough	Stands of shrubs between 0.60and 1.82 m high, Palmetto-gallberry understory-pine overstory sites, occasionally black spruce-shrub combination
Timber litter	
FM 8 – Closed timber litter	Closed canopy stands of short-needle conifers or hardwoods. Needles, leaves, and occasionally twigs in the understory
FM 9 – Hardwood litter	Long-needle conifer and hardwood stands, closed stands of long-needle pine like ponderosa, Jeffrey, red pines, and southern pine plantations

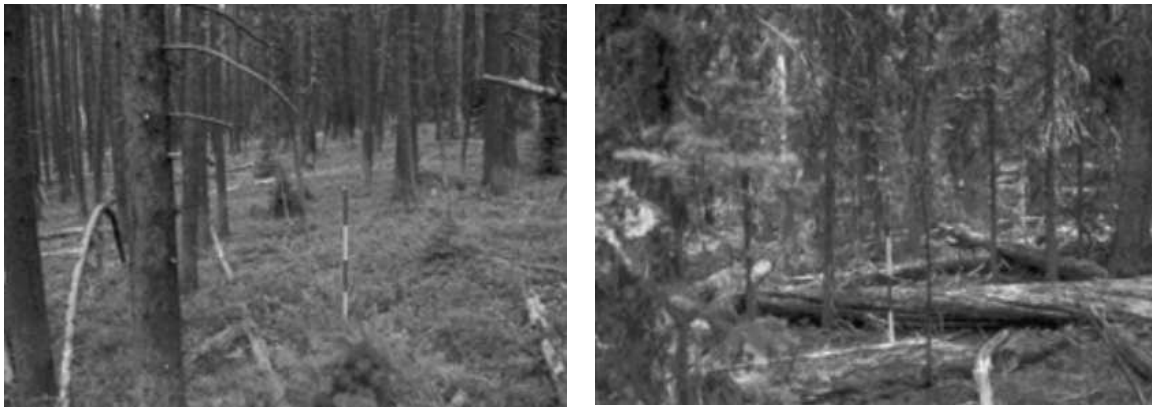**Table 9.** *Description of Anderson (1982) fuel models.*

Figure 35. *(left) FM 8 and (right) FM 10 Seielstad and Queen, 2003).*

They conclude that obstacle density is characterized by a unimodal distribution in FM 8 and by a multimodal distribution in FM 10 (Figure 36). Therefore, the obstacle density allows to differentiate surface roughness. Based on field survey, they suggest other analyzes such as the linear relationship between total fuel load and obstacle density. They claim that large logs and branches in forest floor dominate the roughness signal even in plots with significant shrubs and seedling-sapling components, and that the obstacle density is primarily a function of coarse woody debris. However Seielstad and Queen (2003) clipped the ground points by hand because their separation from coarse wood on the forest floor was critical.
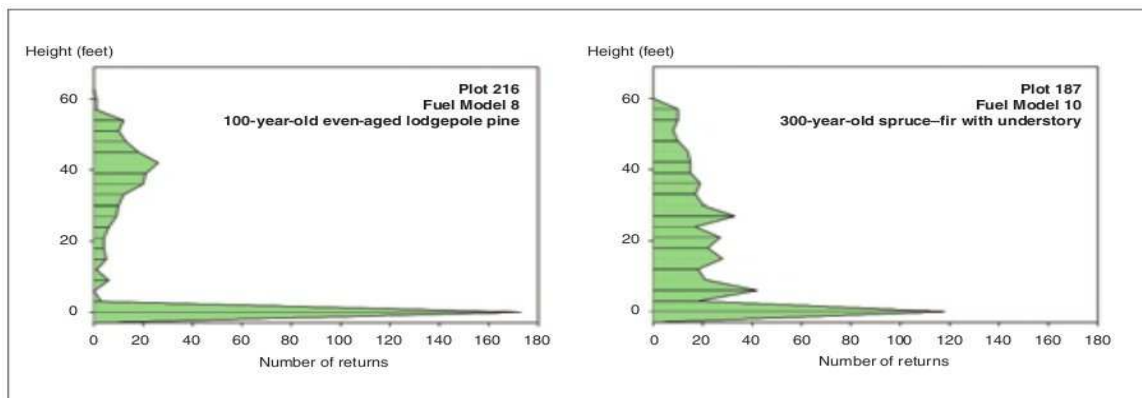

Figure 36. *Laser Height Profiles for two plots representative of FM 8 and 10, respectively (Seielstad and Queen, 2003).*

4.4.3. Conclusion

The measurement of surface fuel properties is not expected using this approach. We emphasized the disparity between the LiDAR resolution and the particle size of fine fuels, their horizontal arrangement near the ground, and the poor porosity of litter which do not facilitate the separation from the ground. However, these works suggest that it is possible to find LiDAR-derived metrics, associated or not with multispectral imagery, to distinguish some FT. For instance, surfaces covered by long-needles and short-needles are classified as two different FM even if they have similar CH. The litter depth is not retrieved by LiDAR, but LiDAR metrics can depict the canopy conditions that are specific for a certain type of FM. In brief, LiDAR metrics are better suited to describe the overall forest canopy condition that is optimal to feed a FM. This technique is actually similar to field reconnaissance using photo guides. Moreover, Seielstad and Queen (2003) suggested that laser-derived estimations of FM were more consistent than field reconnaissance. New LiDAR metrics and stoical analyzes deserve to be developed to establish robust classification methods. These metrics can be achieved by a direct approach (CBH, CBD, biomass, DBH…), canopy height variances (Blaschke et al., 2004; Zimble et al., 2003), more consistent ecological and spatial indexes

(connectivity, proximity, neighborhood of forest structure…). Among others, one can cite the SHEI or the DIVI. The robustness of classification methods can be also increased with gradient modeling proceeding from different sources. For example, a north-facing aspect has more chance to develop a specific FT than another.

Fuel type classification also deals with segmentation of forest environment into stands. Their delimitation can be ambiguous in field reconnaissance or by image interpretation (Naesset, 2002). The segmentation accuracy increases when using regression models to estimate the others forest variables (mean height, stem number, basal area, volume, biomass…). The success of this type of analysis is very dependent on the stand delineation. Naesset (2002) noticed that the use of digital image and laser data in automated segmentation procedures should be considered to take full advantage of the structural properties inherent to laser data.

Conclusion

Fuels have been traditionally mapped by field survey sampling, their spatialization achieved by field or imagery reconnaissance. It is therefore a time and cost consuming task. Thus, there is a great interest in studying the potential of remote sensing to map fuels. Due to their capacity to describe the horizontal and vertical forest structure, LiDAR are the most powerful tool to achieve it, specially when other remote sensing techniques are ineffective (e.g., radar, optical imagery). For instance, we showed their capacity to directly retrieve fuel properties, which is a great improvement in fuel mapping. Large areas can be also processed, reducing the time and effort spent in this task. Finally they increased the accuracy compared to field measurements that are subjective and not always easy to implement.

Moreover, LiDAR is recognized as the most accurate technology to retrieve the DTM over forests, thus providing the other variables used by fire behavior models: elevation, aspect and slope. Despite these innovations, LiDAR systems are limited. For instance, the separation of ground from low vegetation returns is still difficult. Therefore, DTM extraction is directly related to the measurement of low vegetation and vice versa, thus improvement in these two layers is a challenge in fire behaviour studies. This is actually more critical in the Mediterranean reality. Here, the environment is characterized by shrublands and complex forest structures, with understory, therefore more exposed to fire events. However, most of the methodologies have been tested over boreal, deciduous and managed forest with little lower vegetation. Thus, more emphasis has been given to the tree canopy characterization and it is unclear whether these methodologies still work or not in such complex forest structures.

FT classification should be taken into account due to the LiDAR inability to measure some fuel properties. New LiDAR metrics and more robust classification methods must be studied to increase the accuracy in the whole set of FT existing on the studied area. Another limitation of LiDAR data is the poor spatial and temporal cover. Fire management and suppression need fuel maps at the landscape level. Moreover, vegetation is a dynamic target. Correlations between LiDAR metrics and satellite images (vegetation indexes, texture...) have been poorly studied, although they are complementary. On one hand, the limit of passive optical measurement to penetrate in the canopy can be plugged by LiDAR data. On the other hand, the lack of high spatial and temporal cover of laser technology can be found in satellite images.

The dialog with foresters and fire researches should occur more often. It is necessary to have better and specific knowledge of their needs, difficulties and limitations. Moreover, to map fuels, directly or indirectly, accurate field measurements are needed to validate the results.

References

ADAI (Associação para o Desenvolvimento da aerodinâmica Industrial) (2000), *Guia fotográfico para a identificação de combustíveis florestais – Região centro*, Universidade de Coimbra, 26 p.

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

Albini F. (1976), *Estimating wildfire behavior and effect*, USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-30, Ogden (UT, USA), 74 p.

Allgower B., Calogine D., Camia A., Cuiñas P., Fernandes P., Francesetti A., Hernando C., Kötz B., Koutsias N., Lindberg H., Molina D., Morsdorf F., Ribeiro M., Rigolot E. & Séro-guillaume O. (2004), *Methods for wildland fuel description and modelling - A state of the art*, EUFIRELAB: Euro-Mediterranean Wildland Fire Laboratory, Contract number EVR1-CT-2002-40028.

Andersen H.E., Reutebuch S.E. & Schreuder G.F. (2002), Bayesian object recognition for the analysis of complex forest scenes in airborne laser scanner data, in *Proceedings of the ISPRS Technical Commission III*, Graz (Austria), 9-13 September 2002.

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

Anderson H. (1982), *Aids to determining fuels models for estimating fire behavior*, United States Department of Agriculture, Forest Service - Intermountain Experiment Station, 22 p.

Andrews P., Bevins C. & Seli R. (2005), *BehavePlus fire modeling system, version 3.0: User's Guide*. Gen. Tech. Rep. RMRS-GTR-106WWW Revised, Ogden, UT: Department of Agriculture, Forest Service, Rocky Mountain Research Station, 132 p.

Baltsavias E. (1999), Airborne laser scanning: basic relations and formulas, *ISPRS Journal of Photogrammetry and Remote Sensing*, 54:199-214.

Blaschke T., Tiede D. & Heurich M. (2004), 3D landscape metrics to modelling forest structure and diversity based on laser scanning data, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* Freiburg (Germany), Vol. XXXVI-8/W2, pp. 129-132.

Brandtberg T. & Walter F. (1998), Automatic delineation of individual tree crowns in high spatial resolution aerial images by multiple-scale analysis, *Machine Vision and Applications*, 11:64-73.

Brandtberg T., Warner A., Landenberger E. & McGraw B. (2003), The influence of the forest type on the design of an autonomous system for individual tree-based analysis of lidar data, in *Proceedings of ScandLaser Scientific Workshop on Airborne Laser Scanning of Forests*, Vol. 112, pp. 213-222.

Brown J. (1981), Bulk densities of nouniform surface fuels and their application to fire modelling, *Forest Science*, 27:667-683.

Chauve A., Mallet C., Bretar F., Durrieu S., Pierrot-Deseilligny M. & Puech W. (2007a), Processing full-waveform LiDAR data : modelling raw signals, in *Proceedings of ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007*, Espoo (Finland), 12-14 September 2007, pp. 102-107.

Chauve A., Durrieu S., Bretar F., Pierrot-Deseilligny M. & Puech W. (2007b), Processing full-waveform LiDAR data to extract forest parameters and digital terrain model : validation in an alpine coniferous forest, In *Proceedings of ForestSAT O7*, Montpellier (France).

Chuvieco E. (ed.) (2003), Fuel Loads and Fuel Type Mapping, In *Wildland fire danger Estimation and Mapping. The Role of Remote sensing Data* , Singapur, World Scientific Publishing.

Cohen M., Cuinas P., Diez C., Fernandes P., Guijarro M. & Moro C. (2003), Wildland fuel particles characterization database content. Deliverable D6-03-A1, Fire Star: a decision support system for fuel management and fire hazard reduction in Mediterranean wildland – urban interfaces, Contract no. EVG1-CT-2001-00041.

Deeming J.E., Burgan R.E. & Cohen J.D. (1977), *The National Fire-Danger Rating System*, USDA Forest Service general technical report INT 39, 63 p.

Drake J., Dubayah R., Knox R., Clark D. & Blair J. (2002), Sensitivity of large-footprint lidar to canopy structure and biomass in a neotropical rainforest, *Remote Sensing of Environment*, 81:378-392.

Dubayah R., Knox R., Hofton M., Blair J. & Drake J. (2000), Land surface characterization using lidar remote sensing, In *Spatial Information for Land Use Management* (M. Hill and R. Aspinall, eds), International Publishers Direct, Singapore.

Fernandes P., Luz A., Loureiro C., Ferreira-Godinho P. & Botelho H. (2006), Fuel modelling and fire hazard assessment based on data from the Portuguese National Forest Inventory, in *Proceedings of the 5th International Conference on Forest Fire Research* (D.X. Viegas, ed.), 27-30 November 2006, Figueira da Foz (Portugal).

Finney M. (2004), *FARSITE: Fire Area Simulator-model development and evaluation*, USDA Forest Service, Research Paper RMRS-RP-4, 47 p.

Gougeon F. & Moore T. (1989), Classification individuelle des arbres à partir d'images à haute résolution spatiale, *Télédétection et Gestion des Resources*, 6:185-196.

Gougeon F. & Leckie D. (2003), *Forest information extraction from high spatial resolution images using an individual tree crown approach*, Information report BC-X- 396, Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, 26 p.

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

Holmgren J. (2003), *Estimation of forest variables using airborne laser scanning*, PhD thesis, Acta Universitatis Agriculturae Sueciae, Silvestria 278, Swedish University of Agricultural Sciences, Umea (Sweden).

Holmgren J. & Persson A. (2004), Identifying species of individual trees using airborne laser scanning, *Remote Sensing of Environment*, 90:415-423.

Hug C., Ullrich A. & Grimm A. (2004), LiteMapper-5600 - A waveform-digitizing LIDAR terrain and vegetation mapping system, in *Proceedings of the ISPRS Workshop on Laser scanners for Forest and Landscape Assement*, Friebourg (Germany), Vol. 36, pp. 24-29.

Hyde P., Dubayah R., Peterson B., Blair J., Hofton M. & Hunsaker C. (2005), Mapping forest structure for wildlife habitat analysis using waveform lidar: validation of montane ecosystems, *Remote Sensing of Environment*, 96:427-437.

Hyyppä J., Schardt M., Haggrén H., Koch B., Lohr U., Scherrer H., Paananen R., Luukkonen H., Ziegler M., Hyyppä H., Pyysalo U., Friedländer H., Uuttera J., Wagner S., Inkinen M., Wimmer A., Kukko A., Ahokas A. & Karjalainen M. (2001), HIGH-SCAN: The first European-wide attempt to derive single-tree information from laserscanner data, *The Photogrammetric Journal of Finland*, 17:58- 68.

Hyyppä J., Mielonen T., Hyyppä H., Maltamo M., Yu X., Honkavaara E. & Kaartinen H. (2005), Using individual tree crown approach for forest volume extraction with aerial images and laser point clouds, in *Proceedings of ISPRS Workshop Laser Scanning 2005*, Enschede (Netherlands).

Hyyppä J., Hyyppä H., Leckie D., Gougeon F., Yu X. & Maltamo M. (2008), Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests, *International Journal of Remote Sensing*, 29:1339-1366.

Keane E., Burgan R. & van Wagtendonk J. (2001), Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling, *International Journal of Wildland Fire*, 10:301-319.

Korpela I., Dahlin B., Schäfer H., Bruun E., Haapaniemi F., Honkasalo J., Ilvesniemi S., Kuutti V., Linkosalmi M., Mustonen J., Salo M., Suomi O. & Virtanen H. (2007), Single-tree forest inventory using lidar and aerial images for 3D treetop positioning, species recognition, height and crown width estimation, in *Proceeding of the ISPRS Workshop on Laser Scanning 2007 and SilviLaser*, Espoo (Finland).

Leckie D., Gougeon F., Hill D., Quinn R., Armstrong L. & Shreenan R. (2003), Combined high-density lidar and multispectral imagery for individual tree crown analysis, *Canadian Journal of Remote Sensing,* 29:633-649.

Lefsky M., Cohen W., Acker S., Parker G., Spies T. & Harding D. (1999), Lidar remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests, *Remote Sensing of Environment*, 70:339-361.

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

Linn R., Winterkamp J., Edminster C., Colman J. & Smith W. (2007), Coupled influences of topography and wind on wildland fire behaviour, *International Journal of Wildland Fire*, 16:183-195.

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

Mallet C. & Bretar F. (2007), Le Lidar topographique à retour d'onde complète : état de l'art, *Traitement du Signal*, 6:441-465.

Maltamo M., Eerikäinen K., Pitkänen J., Hyyppä J. & Vehmas M. (2004), Estimation of timber volume and stem density based on scanning laser altimetry and expected tree size distribution functions, *Remote Sensing of Environment*, 90:319-330.

Maltamo M., Eerikainen K., Packalen P. & Hyyppä J. (2006a), Estimation of stem volume using laser scanning-based canopy height metrics, *Forestry*, 79:217-229.

Maltamo M., Malinen J., Packalen P., Suvanto A. & Kangas J. (2006b), Nonparametric estimation of stem volume using airborne laser scanning, aerial photography, and stand-register data, *Canadian Journal of Forest Research*, 36:426-436.

Means J., Acker S., Harding D., Blair J., Lefsky M., Cohen W., Harmon M. & Mckee A. (1999), Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the western cascades of Oregon, *Remote Sensing of Environment*, 67:298-308.

Means J., Acker S., Fitt B., Renslow M., Emerson L. & Hendrix C. (2000), Predicting forest stand characteristic with airborne scanning lidar, *Photogrametric Engineering and Remote Sensing*, 66:1367-1371.

Merril D. & Alexander M. (eds) (1987), *Glossary of forest fire management terms*, National Research Council of Canada, Canadian Committe on Forest Fire Management, Otawa (Ontario). Publication NRCC No. 26516.

Millán M., Estrela M. & Badenas C. (1998), Meteorological processes relevant to forest fire dynamics on the Spanish Mediterranean coast, *Journal of Applied Meteorology*, 37:83-100.

Morsdorf F., Meier E., Kötz B., Itten K. & Allgöwer B. (2004), LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management, *Remote Sensing of Environment*, 92:353-362.

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

Naesset E. (1997a), Determination of mean tree height of forest stands using airborne laser scanner data, *ISPRS Journal of Photogrammetry and Remote Sensing*, 52:49-56.

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

Naesset E. & Bjerknes K. (2001), Estimating tree heights and number of stems in young forest stands using airborne laser scanner data, *Remote Sensing of Environment*, 78:328-340.

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

Naesset E. & Økland T. (2002), Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve, *Remote Sensing of Environment*, 79:105-115.

Naesset E., Gobakken T., Holmgren J., Hyyppä H., Hyyppä J., Maltamo M., Nilsson M., Olsson H., Persson A. & Soderman U. (2004), Laser scanning of forest resources: the Nordic experience, *Scandinavian Journal of Forest Research*, 19:482-499.

NIFC (National Interagency Fire Center) (2004), Introduction to Wildland Fire Behaviour S-190 Student Workbook, National Wildfire Coordinating Group.

Persson A., Holmgren J. & Söderman U. (2002), Detection and measuring individual trees using an airborne laser scanner, *Photogrammetric Engineering & Remote Sensing*, 68:925-932.

Persson A., Holmgren J., Söderman U. & Olsson H. (2004), Tree species classification of individual trees in Sweden by combining high resolution laser data with high resolution near infrared digital images, in *Proceedings of the International Conference NATSCAN Laser- Scanners for Forest and Landscape Assessment – Instruments, Processing Methods and Applications*, Freiburg (Germany), Vol. 36, pp. 204-207.

Persson A., Söderman U., Topel J. & Ahlberg S. (2005), Visualization and analysis of full-waveform airborne laser scanner data, In *Proceedings of the ISPRS Workshop on Laser Scanning*, Enschede, (The Netherlands), Vol. 36, pp. 103-108.

Persson A., Holmgren J. & Söderman U. (2006), Identification of tree species of individual trees by combining very high resolution laser data with multi-spectral images, *In Proceedings of the International Workshop on 3D Remote Sensing in Forestry* (T. Koukal & W. Schneider, eds), pp. 102-107.

Peterson B. (2005), *Recovery of forest canopy heights using large-footprint LIDAR*, M.A. Thesis, University of Maryland, College Park (MD, USA).

Popescu S., Wynne R. & Nelson R. (2003), Measuring individual tree crown diameter with LIDAR and assessing its influence on estimating forest volume and biomass, *Canadian Journal of Remote Sensing*, 29:564-577.

Popescu S. (2007), Estimating biomass of individual pine using airborne lidar, *Journal of Biomass and Bioenergy*, 31:646-655.

Popescu S. & Zhao K. (2008), A voxel-based lidar method for estimating crown base height for deciduous and pine trees, *Remote Sensing of Environment*, 112:767-781.

Pyne J., Andrews P. & Laven R. (1996), *Introduction to Wildland Fire*, 2nd Edition, John Wiley & Sons (New York).

Pyysalo U. & Hyyppä H (2002), Geometric shape of the tree extracted form laser scanning data, *International Society for Photogrammetry and Remote Sensing – ISPRS Commission III Symposium*, Graz (Austria).

Reitberger J., Heurich M., Krzytek P. & Stilla U. (2007), Single tree detection in forest areas with high-density lidad data, In *Proceedings of Remote Sensing and Spatial Information Sciences (U. Stilla et al., eds),* International Archives of Photogrammetry, 36 (3/W49B).

Riaño D., Chuvieco E., Salas J., Palacios-Orueta A. & Bastarrika A. (2002), Generation of fuel type maps from Landsat-TM images and auxiliary data in Mediterranean ecosystems, *Canadian Journal of Forest Research*, 32:1301-1315.

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

Riaño D., Chuvieco E., Condés S., Gonzalez-Matezans J. & Ustin S. (2004), Generation of crown bulk density for *Pinus sylvestris* L. from lidar*, Remote Sensing of Environment*, 92:345-352.

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

Rothermel C. (1972), *A mathematical model for predicting fire spread in wildland fuels*, Res. Pap. INT-115. Ogden, UT: U.S. Department of Agriculture, Forest Service, Inter-mountain Forest and Range Experiment Station, 40 p.

Rothermel C. (1983), *How to predict the spread and intensity of forest and range fires*, Gen. Tech. Rep. INT-143. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 161 p.

Rothermel C. (1991), *Predicting behavior and size of crown fires in the Northern Rocky Mountains*, Res. Pap. INT-438. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 46 p.

Sandberg D., Ottmar R. & Cushon G. (2001), Characterizing fuels in the 21st Century, *International Journal of Wildland Fire*, 10:381-387.

Scott J. (1999), NEXUS: a system for assessing crown fire hazard, *Fire Management Notes*, 59:20-24.

Scott J. & Reinhardt E. (2001), *Assessing crown fire potential by linking models of surface and crown fire behavior*, Res. Pap. RMRS-RP-29, Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 59 p.

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

Suarez J.C., Ontiveros C., Smith S. & Snape S. (2005), Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry, *Computers and Geosciences*, 31:253-262.

Tiede D., Lang S. & Hoffmann C. (2006), Supervised and forest type-specific multi-scale segmentation for a one-level-representation of single trees. In *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Salzburg (Austria), Vol. XXXVI-4/C42.

Van Wagner C. (1977), Conditions for the start and spread of a crown fire, *Canadian Journal of Forest Research*, 7:23-24.

Van Wagner C. (1993), Prediction of crown fire behavior in two stands of jack pine, *Canadian Journal of Forest Research*, 23:442-449.

Wagner W., Ullrich A., Melzer T., Briese C. & Kraus K. (2004), From single-pulse to full-waveform airborne laser scanners: potential and practical challenges, in *Proceedings of the Forestry International Archives of Photogrammetry, Remote Sensing and spatial informations systems*, 35(B3):201-206.

Wagner W., Ullrich A., Dudic V., Melzer T. & Studnicka N. (2006), Gaussian decomposition and calibration of a novel small-footprint full-waveform digitizing airborne laser scanner, *ISPRS Journal of Photogrammetry and Remote Sensing*, 60:100-112.

Zimble D., Evans D., Carlson G., Parker R., Grado S. & Gerard P. (2003), Characterizing vertical forest structure using small-footprint airborne LiDAR, *Remote Sensing Environment*, 87:171-182.

http://www.fire.org (home page of Systems for Environmental Management in cooperation with the Fire Sciences Laboratory of the USDA Forest Service Rocky Mountain Research Station).