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FIRE-RES

Innovative technologies & socio-ecological-economic solutions for fire resilient territories in Europe

D2.1 Improving data acquisition for landscape design based on novel remote sensing methods

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Abstract: This report documents the work carried out in subtasks "2.1.1 A dynamic high-resolution map of the state of the forest and fuel", "2.1.2 Innovative methodologies for fuel structure assessment" and "2.1.3 Fire management models, adaptive landscape management strategies and operational management options, including machinery specifications". This work sets the specifications basis for the development of I.A. 2.1 "Improving data acquisition for landscape design based on novel remote sensing methods". This deliverable describes the methodologies and presents the main best practices in terms to apply it, with special dedication to document preliminary results as well as main advantages, limitations and recommendations.

Key words: Integrative System, Requirements, Architecture, EWE.

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Acronyms

AI: Artificial Intelligence
ALS: Airborne Laser Systems
CBD: Canopy Bulk Density
CBH: Canopy Base Height
CFL: Canopy Fuel Load
CHM: Canopy High Model
CTFC: Consorci Centre de Ciència i Tecnologia Forestal de Catalunya
D: Deliverable
DSM: Digital Surface Model
DTM: Digital Terrain Model
DNBR: Differential Normalize Burn Ratio
EO: Earth Observation
ESA: European Space Agency
FSG: Fuel Strata Gap
IA: Innovative Action
ICGC: Institut Cartogràfic i Geològic de Catalunya
INRAE: Institut national de recherche pour l'agriculture, l'alimentation et l'environnement
LiDAR: Light Detection and Ranging
LLs: Living Labs
LMA: Leaf Mass Area
MLS: Mobile LiDAR System
NDVI: Normalized Differential Vegetation Index
NIBIO: Norwegian Institute of Bioeconomy Research
NIR: Near Infrared
NRD: Return Density Index
ONF: French National Forest Service
PAD: Plant Area Density
RADAR: Radio Detection and Ranging
RS: Remote Sensing
SWIR: Short Wave Infrared
TLS: Terrestrial LiDAR System
WP: Work Package
WUI: Wildland User Interface

1. Introduction

The primary objective of this document, designated as D (Deliverable) 2.1 within the framework of the Innovative action *IA 2.1: Improving data acquisition for landscape design based on novel remote sensing methods*, encompasses two fundamental aspects:

- To summarize at high level the methodologies and Earth Observation data used
- To report main results and offer a set of recommendations and best practices to upscale the solutions proposed

This document delineates the endeavors undertaken withinTask “2.1.” and specifically delineates the following subtasksassociated with I.A. 2.1:

Subtask 2.1.1. A dynamic high-resolution map of the state of the forest and fuel: This initiative will leverage Copernicus satellite data along with forthcoming missions such as the ESAs “Living Planet Programme”. This will be combined with data from existing remote sensing-based forest resource maps. Transitioning from mapping to continuous monitoring, the action aims to establish a schedule for updates every 3to 5 days throughout the duration of the fire season. The resultant map will furnish fire fighters, decision makers, and other stakeholders with up-to-date information on the state of the landscape, particularly concerning fuel quantities (IA 2.1).

Subtask 2.1.2. Innovative methodologies for fuel structure assessment: Processing of LiDAR digital models encompassing elevation and surface data, in conjunction with point clouds and potentially waveforms (if available), will facilitate the computation of relevant metrics such as vertical and horizontal distributions of fuel bulk density, fuel availability/continuity, understorey amount, crown base height and canopy height models, or fuel mapping in WUI. The incorporation of various temporal layers will enable the detection of changes and forest recovery after fire events. Moreover, the trafficability of forest tracks will also be evaluated utilizing innovative Artificial Intelligence methodologies to optimize dispatch decisions and execute safe access to forested areas during fire events (IA 2.1)

Forest ecosystems provide a host of services and societal benefits. In a context of complex demands over forest land, comprehending long-term forest dynamics is imperative for sustainable planning and management, so precise tools with sufficient temporal frequency becomes paramount.

Accessing forested ecosystems can pose challenges, making field work a bit inconvenient. Conventional field-sampling-based long rotation (*e.g.*, 10 years) inventory of wood products, followed by statistical generalization, fall short of current information requisites for multifaceted sustainable management, particularly necessitating more frequent data acquisition, especially within the wildfire management framework.

Remote sensing approaches, spanning the spectrum from data acquisition to information and knowledge extraction, constitute a pivotal source of data and tools for monitoring forest dynamics, identifying change drivers, and determining main metrics essential for fostering resilient management practices to be fused with other geoinformation layers to provide decision support tools. These remote sensing techniques furnish data across a variety of spectral, spatial, and temporal resolutions enabling modelling forest condition and changes under diverse scenarios.

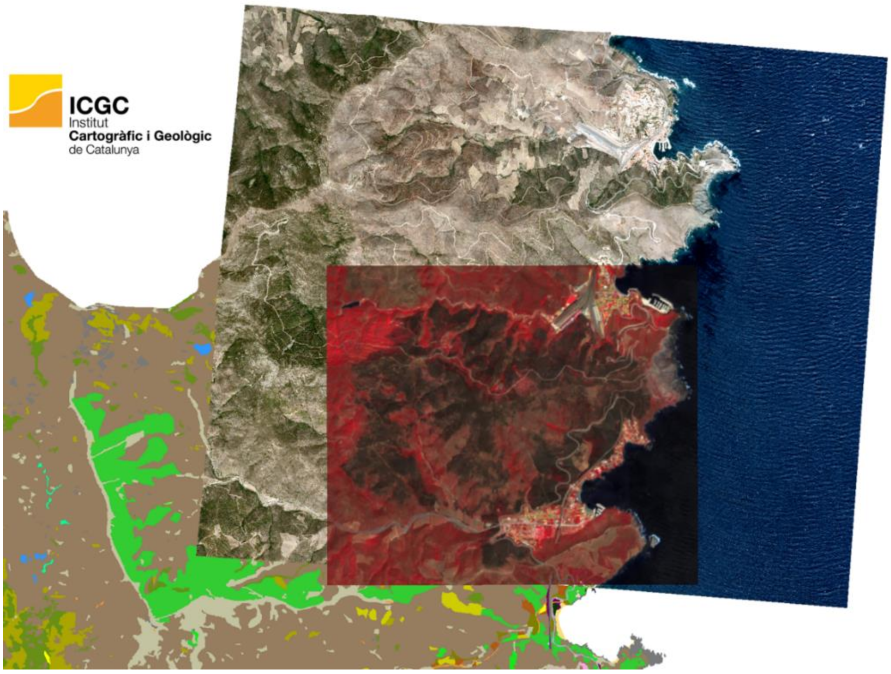


Figure 1: Combining high resolution and mid resolution (Sentinel-2 data) and land cover map over a wildfire at Living Lab Catalonia last August 2023.

Remote sensing techniques, incorporating both imagery and LiDAR (Light Detection and Ranging), have revolutionized the analysis of forest land ecosystems. By providing detailed spatial and spectral information, these tools have facilitated a comprehensive monitoring, assessment, and management of forest lands.

A summary, spotlighting the principal themes pertaining to the application of remote sensing over forest land ecosystems, is delineated as follow.

- Vegetation Mapping and Monitoring: Remote sensing data, notably satellite and airborne imagery encompassing multispectral and hyperspectral capabilities, enable accurate mapping and monitoring of vegetation cover, species distribution, and health status over large spatial extents. Advanced spectral analysis techniques aid in identifying vegetation types and the detection of temporal alterations.

- Forest Structure Assessment: LiDAR technology offers unparalleled capabilities in characterizing forest structure, including canopy height, biomass estimation, and vertical stratification. Coupled with ground-based measurements, LiDAR data facilitates the creation of high-resolution three-dimensional models of forests, enhancing our understanding of their structural dynamics.

- Fire Detection and Management: Thermal sensors onboard satellites enable early detection of forest fires, allowing for timely intervention and mitigation efforts. Additionally, remote sensing assists in post-fire assessment by quantifying the extent and severity of damage and aiding in the planning of rehabilitation measures.

- Biodiversity Conservation: Remote sensing data aid in identifying critical habitats, assessing habitat fragmentation, and monitoring wildlife populations within forested areas. Integrating multispectral and LiDAR data enhances species distribution modelling towards more sustainable habitats.

- Carbon Sequestration Estimation: A quantification of carbon stocks in forests is crucial for climate change mitigation strategies. Remote sensing, particularly LiDAR-based biomass estimation techniques, provides valuable insights into forest carbon dynamics, aiding in carbon accounting initiatives.

Remote sensing technologies have revolutionized our capacity to scrutinize and monitor forest ecosystems, proffering unparalleled insights into their structure, composition, and dynamics. Nonetheless, tackling emerging challenges such as data integration, scale mismatches, algorithm development, data accessibility, and interdisciplinary collaboration is imperative for advancing the field and effectively addressing contemporary environmental issues pertinent to forest lands.

2. Research and Innovation scenarios

Remote Sensing has become a key approach both at technical and research level to analyse and monitor forest land ecosystems, from local to national or continental scale. Unfortunately, the transformation of remote sensing into operational decision support tools, varies both at geographic and subject level.

The ideal innovation process is the trifecta of desirability, feasibility and viability. If your process meets all three criteria, then it contains these essential characteristics:

- A desirable solution, one that your customer really needs.
- A feasible solution, building on the strengths of your current operational capabilities.
- A profitable solution, with a sustainable business model.

But if you miss any one of these, implementing the idea becomes riskier and costlier.

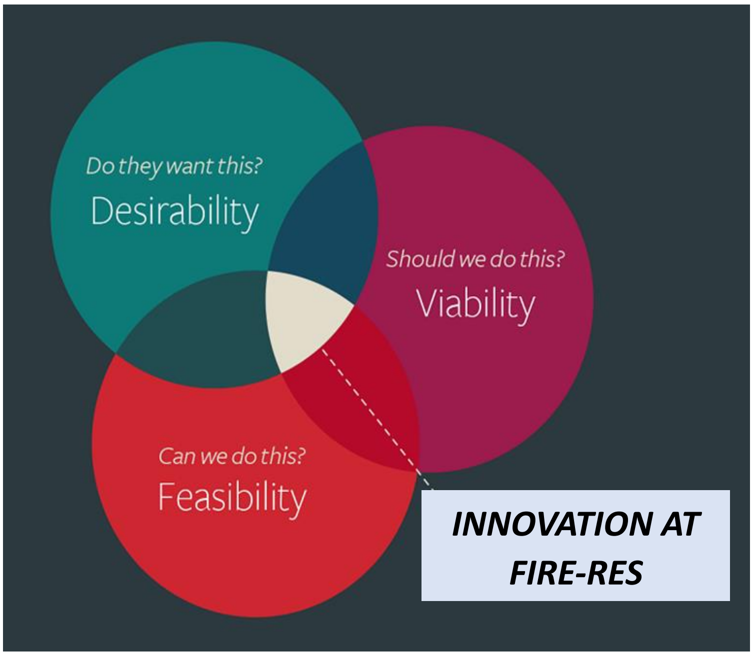


Figure 2: The main pillars of innovation at FIRE-RES at the context of this deliverable D2.1

It's not the purpose of this document to analyse in depth the main challenges or barriers that need to be overcome, but, as a summary, the main hurdles are itemized below, including how D 2.1 faces them and achieves the main characteristics to get an innovative process:

- Slow end user uptakes of remote sensing solutions

At FIRE-RES this challenge has been solved throughout close communication between scientist and end users, including stakeholders, regulators or firefighters among others based on a set of workshops and participate events. Key and innovative tools to refine and document expectations and limitations of remote sensing data to achieve the profitable balance to translate end user needs into remote sensing requirements into a feasible-viable solution. As a result, the main challenge to quantify the value proposition of new and emerging remote sensing approaches has been faced.

Assessing and understanding user requirements and finding ways to integrate new remote sensing technologies into innovative workflows, methodologies or architectures in order to minimize the adaptation needs required for end users and main stakeholders has a positive influence on the results and the potential to spatially upscale the innovation.

- Gap between the potential of remote sensing and its real implementation

At FIRE-RES this challenge has been oriented to define a wide set of test areas or Living Labs across Europe with different realities, climates, species and challenges related to the management of the forest land. Proper remote sensing data sets over the Living Labs has been collected and analysed, according to current and near future availability.

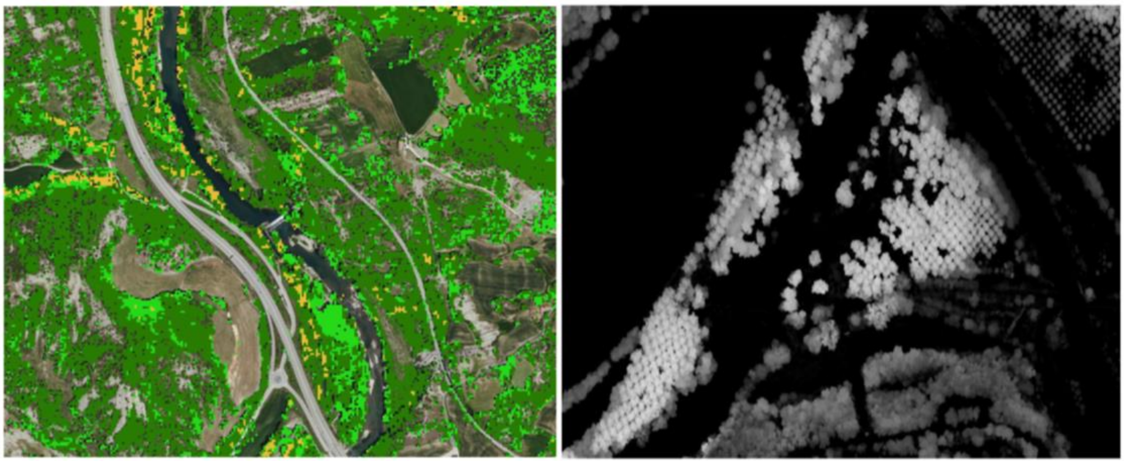


Figure 3: Derived forest land high density airborne LiDAR, Underwood and Canopy High Model.

It is expected that forest attributes, features etc from remote sensing data will increasingly be used to provide added value information in support to research and innovate products and services to implement actions and policies. However, to reach these goals, methodological challenges must be overcome so that the quality of results can be demonstrated. Therefore, clear and transparent validation approaches are required, and these have been defined in FIRE-RES subtasks related to this deliverable.

- Integrity and quality of products, services based on remote sensing data

As much as possible, remote sensing methodologies exposed at this deliverable have been based on open access, free of charge data provided by public stakeholders such as official mapping agencies or European space programs (Copernicus). The use of Copernicus data to be fused with local and regional information as well as the use of new high density LiDAR airborne sensors has offered us a new dimension of data to be interpreted in an innovative way as will be showed at the following sections.

With respect to the use of Earth Observation data, it is very important to validate the results with independent data to guarantee the integrity and quality of derived results. At this point, it should be pointed out that tasks carried out under subtask 2.1.2 take this approach as a paramount action.

Evaluation of the approach against field data at two steps of the chain, has been done at innovative processing chain to derive fuel load and structure metrics from LiDAR data and plant traits.

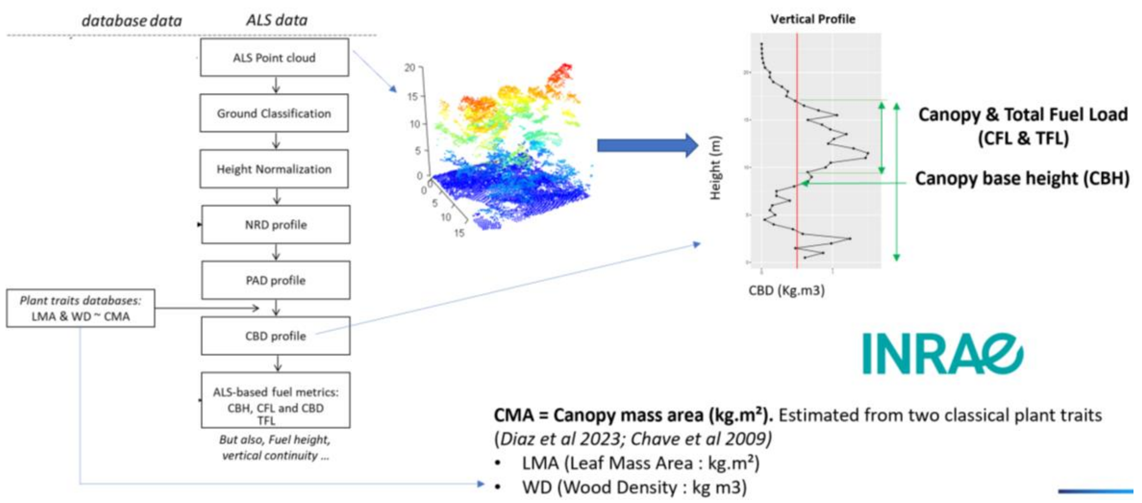


Figure 4: From the point cloud to Canopy Bulk Density (CBD) profiles and fuel metrics.

In parallel, in terms to estimate new vegetation morphological variables improving LiDAR point cloud classification and segmentation ICGC has subcontracted field inventory in Catalonia Living Labs to classify LiDAR data properly and train an AI model.

3. Developed methodologies

3.1 A dynamic high-resolution map of the state of the forest and fuel

3.1.1 State of the art and background

Maps and geographical information can play a vital role in all phases of wildfire management. It is important to know the state of the landscape and vegetation, and how relevant elements are connected. This can be essential information in order to make the right decisions in a variety of situations. Management of fuel, strategic allocation of firefighter resources and operational planning during a fire event are only a few examples. It is important that maps and geographical information reflect what is on the ground, i.e., it is important that it is as up-to-date as possible.

Today, maps are created with many purposes and a range of data sources. Remote sensing is, however, typically at the core of many map production pipelines. Automatic extraction of information from remote sensing data allows for rapid production of updated maps. This is particularly relevant for remote sensing data acquired from satellites, as this type of data is acquired frequently and systematically. Several publicly funded satellite programs provide open data, and in European context the Copernicus program from ESA is the most prominent one. With the Copernicus program, data from several satellites are provided openly, with a broad range of possible applications. In this subtask, primarily data from the Sentinel-2 optical satellites and Sentinel-1 radar satellites have been used. Data from the Sentinel satellites are ideal for rapid updating of existing maps, since the data are acquired frequently, and in a systematic way. The data are also made openly available shortly after the acquisition, facilitating a fast update process.

Maps can be used in many ways, and one general characterization can be to divide the use into two categories: maps intended for visual interpretation, and maps intended as input to computer driven analysis, such as fire simulations. Although these two uses are distinct, and pose different requirements for the maps, similar types of geographic data can be the basis for maps intended for both types of usage.

EWE puts a lot of stress on first responders and the tactical and operational planning. Unlike in the case of smaller wildfires, there will – in the case of an EWE – be more personnel involved that do not know the area. Without local knowledge of an area, it is vital that maps in the best possible way reflect what is on the ground. Having updated maps can therefore be even more important if a wildfire event develops towards an EWE.

Change estimation using satellite imagery is a fast-growing field of research encompassing a range of satellite data sources and methods (see e.g. Zhu et al. 2022 for a conceptual overview). Figure 5 gives a graphical overview of the process of updating maps using changes detected with satellite imagery.

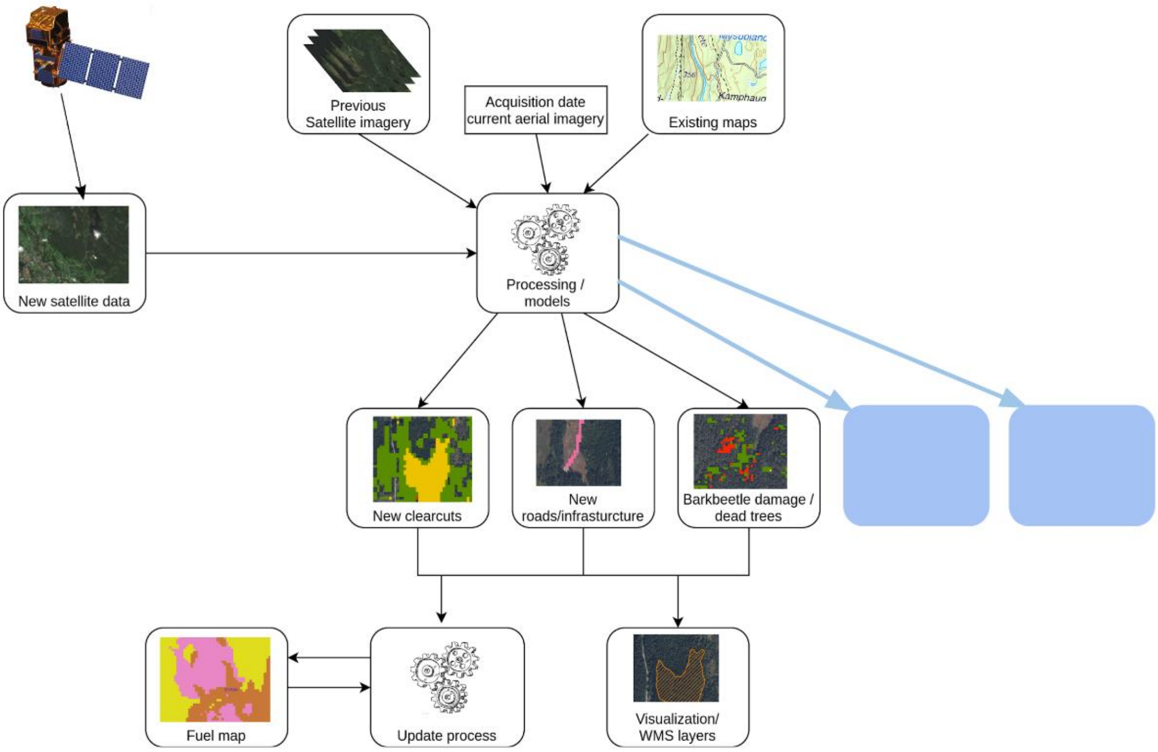


Figure 5: Conceptual overview of the process of updating map data using satellite imagery. The resulting maps are dynamic in the sense that they are continuously and automatically updated, to better reflect the actual conditions on the ground.

3.1.2 Progress achieved and results

One aim of subtask 2.1.1 was to develop and test an automatic implementation of the process illustrated in Figure 5. Through discussions with stakeholders and evaluation of other contributing factors, it was decided to focus on forest areas and the detection of the following changes – and how these can be used to update maps: clear-cut harvests, wind damage, drought stress and bark beetle attacks, burnt area and new infrastructure such as forest roads.

Harvest

In the boreal forests in Northern Europe clear-cut fellings are the most common harvesting method. In managed forests, a clear-cut is also the largest change in the forest structure that commonly occurs.

The difference between a clear-cut area and mature forest can be vital information, for example in operational planning during a fire event. The presence of a clear-cut instead of mature forest can also affect how a simulated fire propagates through an area.

Clear-cut fellings change the appearance of forest areas in satellite imagery and, as part of subtask 2.1.1, several methods for detection of harvest areas with data from satellite data have been compared and tested. The comparison was carried out with respect to two distinct criteria, namely 1) how well the method detects harvest areas, and 2) how long after the actual harvest it is reliably detected (Figure 6). A manuscript for a scientific paper describing the details in this comparison is under preparation.

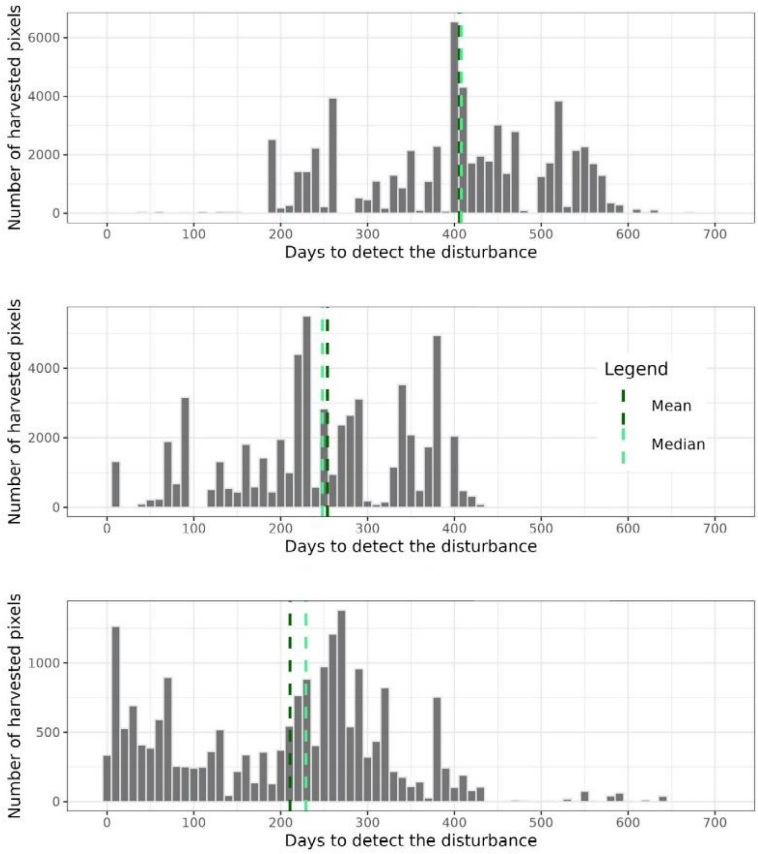


Figure 6: Comparison of detection time for Global Forest Watch (top), inter annual index comparison (middle) and BFAST time series analysis (bottom).

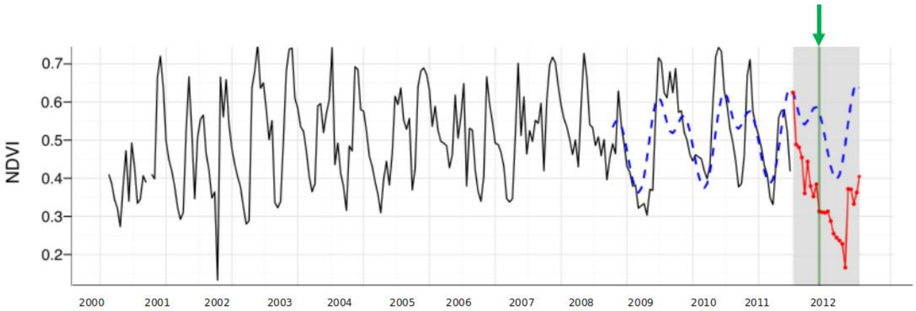


Figure 7: *Time series analysis can be used to detect abrupt changes, such as a harvest. In this figure the annual trend in the NDVI values for one pixel is analysed and the point where the NDVI deviates from this trend is indicated as a point of change.*

Our conclusion after comparison and assessment of methods for detecting harvest areas was that a detection of harvests in single Sentinel-2 images was the overall preferred method. A harvest will typically greatly affect the spectral values in the satellite imagery, and a method involving single images is simpler to implement than more sophisticated methods such as time series analysis (Figure 7).

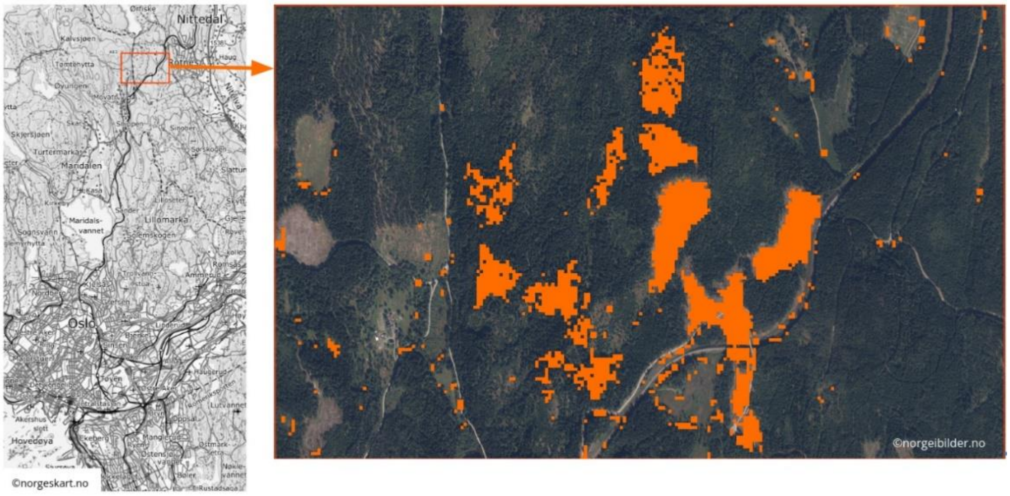


Figure 8: *Detection of harvested areas with machine learning and Sentinel-2 satellite imagery. Detection of harvests carried out both before and after the acquisition date of the aerial image (background)*

Wind damage

Extreme weather events might occur more frequently due to the expected climate changes, and in the past decade several storms have caused damage in the boreal forest in Northern Europe. As with a harvest, wind damage introduces an abrupt change in the structure of the forest. Severe wind damage will also create conditions which can strongly affect and hinder movement in the forest. If downed trees are not removed, they will change the composition of fuel present in the forest.

It can therefore be of importance for several activities that severe wind damage is located and incorporated in forest resource maps. In subtask 2.1.1, several methods to detect wind damage using Sentinel-1 radar satellite data were tested. However, the results were not good enough to be included in a dynamic updating of maps.

Drought stress and bark beetle attack

As with storm events, drought might also become more severe or frequent in the future. The weakening of trees by drought stress can in turn be linked to bark beetle attacks, which in boreal forest in Northern Europe leads to damaged and killed spruce trees. The presence of areas with many dead trees can be useful information in the operational planning during a wildfire event, and it can affect how a fire spreads through the forest which could be incorporated in fire simulations. Several methods to detect dead spruce trees using a machine learning approach and Sentinel-2 data were tested, with satisfactory results.

The detection algorithm will be included in the implementation in the Norway-Sweden Living Lab, and the developed methods will be documented in a scientific paper (in preparation).

New infrastructures

Regular topographic maps are used as base maps in many activities, and, typically, are the source of information on infrastructure, roads and buildings. The rate with which these topographic maps are being updated is generally good. Hence, newly built roads, buildings and other infrastructure are relatively rapidly brought into the official databases and underlying digital topographic maps. However, it can still take weeks, or even months before actual changes on the ground are reflected in the maps. In certain cases, it can take much longer. One example where this has been the case, is forest roads in rural areas in Norway. Any changes of land use from forest to roads or other infrastructure can potentially have a large impact on activities such as operational planning during a fire event. The change of land use away from forest will also affect the fuel properties and the risk of fire spread in an area.

In addition to topographic maps, aerial imagery is usually available, but this will reflect the situation on the ground at the time of the acquisition and will not contain changes occurring after the acquisition. Acquisition of aerial imagery happen at different frequencies depending on the location. In the Norway-Sweden Living Lab, where the task was developed, the acquisition of publicly available aerial imagery was done every 5-7 years.

A previous pilot study conducted for the Norwegian Environment Agency showed promising results for detection of new roads using a deep learning model with Sentinel-2 images (Trier et al. 2022). A similar detection procedure was implemented but the results obtained were not accurate enough to be useful in a visual indication of locations with new infrastructure.

Burnt area

A large wildfire will result in large areas affected by the fire, and these areas can be useful to show on maps. Typically, the perimeter of a fire will be registered as part of the reporting after a fire, with the extent of the burnt area registered either in the field or from drone or aerial imagery. There does however exist several methods for the identification of burnt area using satellite data, and it can be easily incorporated into a change detection process. An algorithm for the detection of burnt area was implemented. The algorithm is based on a burnt area index which is calculated from multiple spectral bands from Sentinel-2 imagery. This will be included as a separate map layer for visualization of burnt area.

Updating a high-resolution fuel map

Fuel maps can be important in several of the phases of wildfire management. Changes detected in satellite imagery may reflect changes in the characteristics of an area such that it belongs to a different fuel type class. A fuel map for the study area did not exist prior to the start of the FIRE-RES project, and as part of the work in this task a 16m resolution fuel map using the fuel models described by Scott & Burgan (2005) was created for the study area in the Norway-Sweden Living Lab. This was done to demonstrate the updating of the fuel map using satellite data. The development of the fuel map is a beneficial side-effect of the work done in this subtask. We aim to produce this fuel map at a national level in Norway and to investigate the harmonization of the fuel map with similar maps in Sweden.

Presentation of map layers

The detected changes were initially produced as a raster following the 10m resolution of the Sentinel-2 satellite imagery or resampled to 16m following the Norwegian forest resource map. To facilitate a fast and clear visualization of some of the map layers developed in subtask 2.1.1, a process was implemented to convert a binary raster detection to vector polygons. An example is given in Figure 9.

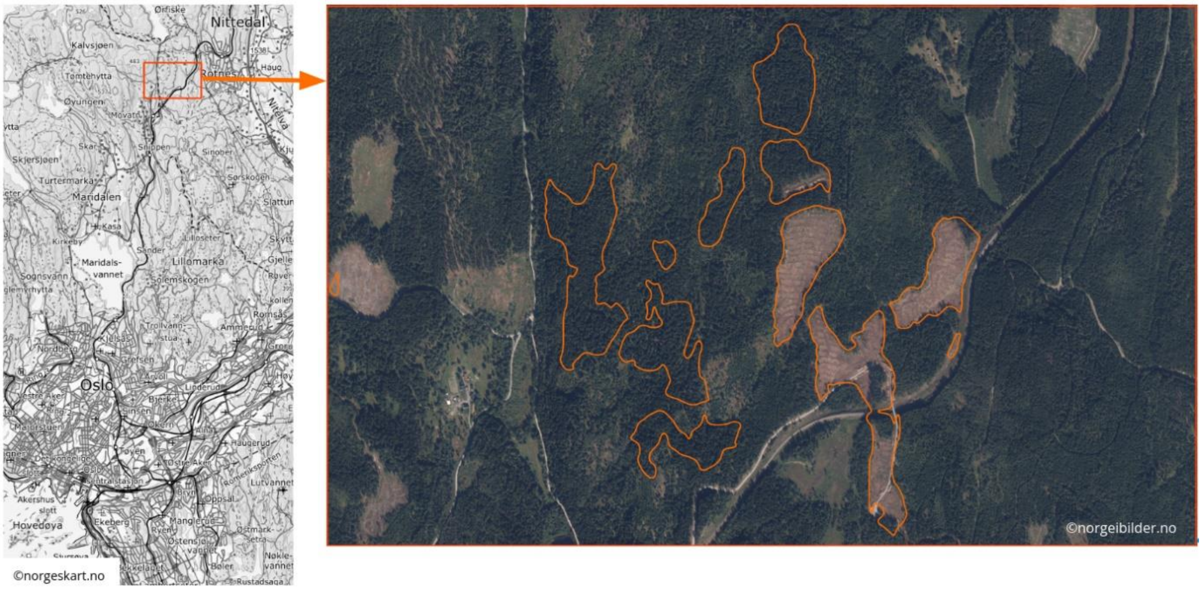


Figure 9: Example of generalization from raster to vector polygons for easy and clean visualization of the detected harvest areas on a map. The location is selected to show how the detected harvests correspond to the harvested areas before the acquisition of the image. And that there are detected harvests after the acquisition dates of the publicly available aerial imagery.

Implementation and replications in FIRE-RES Living Labs

The Innovation Action developed in subtask 2.1.1 will be implemented and tested in the Norway-Sweden Living Lab during the fire seasons (summers) of 2023, 2024 and 2025. A replication and adaption to other conditions will be done in the Greek Living Lab in 2024 and 2025. In the Norway-Sweden Living Lab the produced maps will be incorporated as WMS layers in the online map portal of the Norwegian Directorate of Civil Protection. The aim is to have the maps assessed in dialog with stakeholders in the Living Lab.

3.2 Innovative methodologies for fuel structure assessment

3.2.1 State of the art

The trends related to climate change and neglect in the rural world converge in the abandonment of forests, their growth, and the potential recurrence of major fires. For a better management of the forest space and, in particular, of the activities and infrastructures implemented, knowledge of the state of the areas of interaction with the natural environment are very important.

The forestry applications based on LiDAR can be considered one of the most important since it is the only sensor that is affected by multiple reflections, often with a range up to the surface of the ground, the LiDAR acquisition allows you to obtain valuable information from both the terrain and the canopy and therefore the possibility of generating metrics.

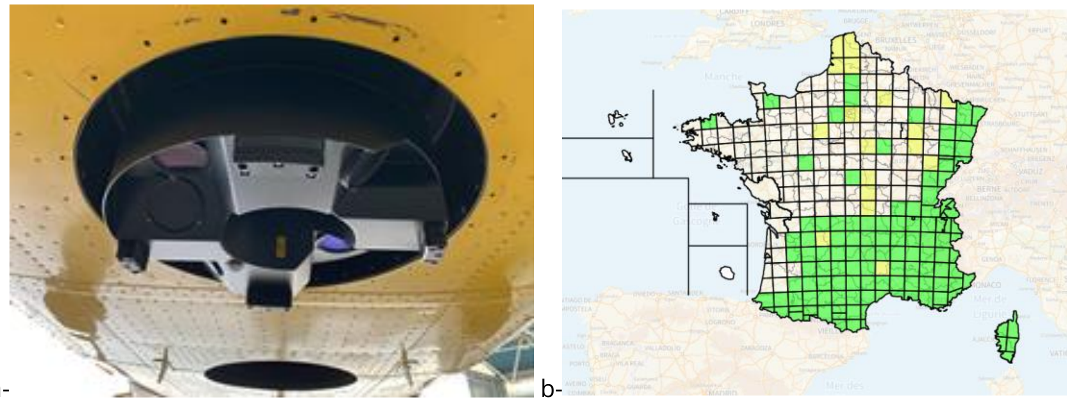
Operational methodologies, through analysis of LiDAR data, makes it possible to estimate indicators dealing with the state of the vegetation of the protection strip, mobility features of tracks inside forest land or morphologies at the unbuilt/humanized zones. This is achieved by dividing the protection strip into several sections depending on the state of the vegetation, by detecting individual trees within the unbuilt plots and sections, identifying trees that are too close near a built-up plot, calculating shrub and tree cover and obtaining distances between trees, majority slope, etc.

For a previous knowledge of forest land and in particular a good modelling of propagation and ignition, spatially explicit data of fuel quantity and distribution with sufficient accuracy is required to get reliable estimations. Fuel load and structure theoretically determine the intensity of fire and its ability to spread both in the surface layer and in the canopy layer of the vegetation depending on the horizontal and vertical continuity of fuel (Reinhardt et al., 2006). A long history of fire behaviour modelling has identified several fuel characteristics that simplify the complex three-dimensional arrangement of fuel and that are largely used for predicting fire behaviour (Finney, 1998; Wagner, 1977). The amount of fuel in the canopy that determines fire intensity and the rate of fire spread is often characterized by canopy bulk density (CBD) or canopy fuel load (CFL), which indicates the fuel weight in the canopy volume in kg/m3 or the fuel weight in the canopy per unit of ground area in kg/m^2. Quantifying the risk of fire spread in the canopy is of great importance because crown fires have the highest intensity and are the most difficult to control (Werth et al., 2016). The ability of a fire to spread from the surface to the canopy is determined primarily by the presence of vegetation in the mid-canopy which is the strata where the vertical propagation occurs (Cruz et al., 2006). Canopy base height (CBH) is often used in this context (Reinhardt et al., 2006; Wagner, 1977) because it is easy to measure in the field and is used in forestry well beyond wildfire studies.

Large-scale measurement of surface and canopy fuel characteristics using remote sensing data has been the subject of numerous publications and is becoming increasingly important for predicting fire behaviour, assessing fire risk, or making area management decisions. In this context, both passive (i.e., optical) and active (i.e., LiDAR and RADAR) remote sensing sensors are being used, with LiDAR proving particularly powerful for quantifying fuel load and structure (Gale et al., 2021). The ability of LiDAR instruments to describe the arrangement of vegetation in three dimensions gives them stronger predictive power for fuel loading and structure metrics compared to optical remote sensing products.

3.2.2 Progress achieved and results

At FIRE-RES context, high-density LiDAR flights under the same sort of parameters and in some cases, the same sensor, were carried out in France, Portugal and Catalonia Living Lab FIRE-RES areas, at a high density >= 10p/m2, what's a differential competence in terms of transferability of results and methodologies to derive fuel and vegetation metrics, were processed to analyse the main variables to define WUI zones and mobility issues for firefighters.



a- b-

Figure 10: a-Mechanization at ICGC airplane of LiDAR sensor-TerrainMapper_2). The same model of sensor LiDAR was used in certain region of Southern France. b- State of progress of the French national LiDAR campaign conducted by the geographic national institute (IGN) aiming at covering the whole territory by 2025. Coloured tiles are already available, most are already classified (green) and some are raw (yellow).

Compute relevant metrics such as vertical and horizontal distributions.

a-1: Canopy fuel metric estimation from ALS and evaluation against field data

While most of the study using ALS data to derive fuel metrics are based on classification approaches such as regression models (Marino et al., 2022) or machine learning (Arellano-Pérez et al., 2018), INRAE developed here an innovative method to directly retrieve fuel characteristics from the ALS point cloud, for any type of vegetation. The advantage of direct estimation of vegetation characteristics over classification approaches is that it does not rely on field data that are hard to obtain at large scale and not always suited to remote sensing data.

Moreover, this approach is highly generalist because it considers sampling heterogeneities (i.e variability in point cloud density), scanning pattern differences and occlusion and can therefore be applied no matter of LiDAR sensors devices used, flying patterns (i.e speed and trajectories) or vegetation types.

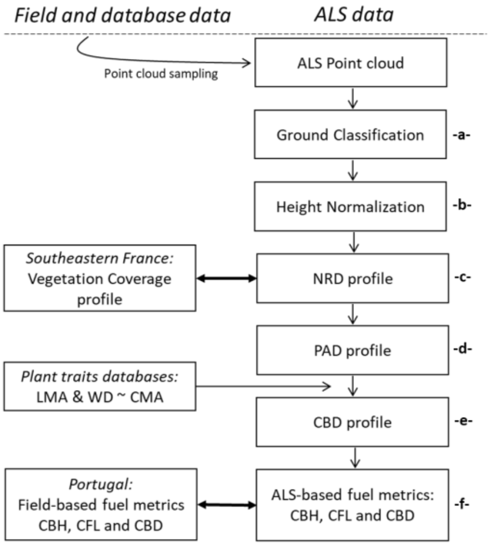


Figure 11: Summary of the workflow. The bold double arrows refer to the analysis for comparison between field and ALS data. The full processing chain is directly usable in the "lidR" R package.

The approach consists of several processing steps described in Figure 11:

1- The ALS point cloud is classified between ground and vegetation.

2- The point cloud height is normalised.

3- The vertical profile of vegetation density is estimated from the normalised return density index (NRD) (Campbell et al., 2018) in 0.5 m layers of the plot or pixel.

4- Plant Area Density (PAD in m^2/m^3) profile is estimated from NRD using an approach based on an inversion of the radiative transfer associated with laser scanning of vegetation.

5- Canopy bulk density (CBD) profile is estimated by crossing the PAD profile with species or vegetation type specific plant traits (leaf mass area (LMA) and wood density (WD)).

6- Fuel metrics (i.e. CBH, CFL and CBD) are extracted from the CBD profiles.

Steps -3- and -6- are evaluated using field data from France and Portugal respectively. It is important to note that the output of the processing chain at -e- is a complete vertical CBD profile. Therefore, it is possible to quantify several important fuel properties beyond those evaluated in this section (i.e. CBH, CFL and CBD), such as vertical fuel continuity, fuel strata gap (FSG) or fuel load at any height above one metre.

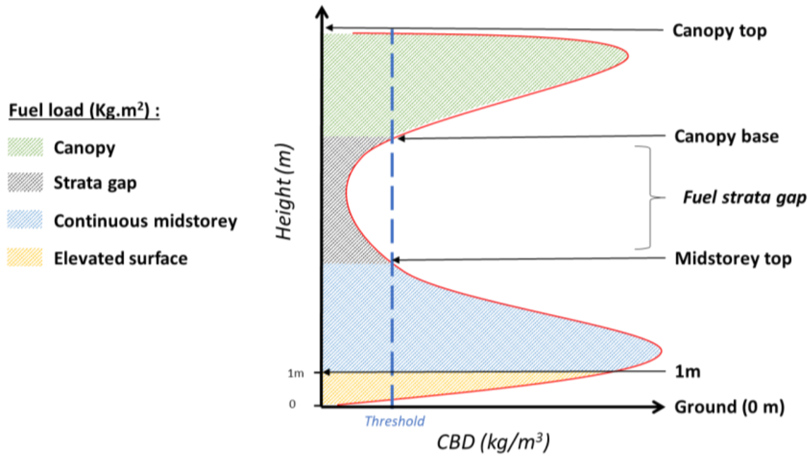


Figure 12: Schematic representation of canopy bulk density profile extracted from ALS point cloud illustrating the five potential strata's limits identified based on a bulk density threshold and the corresponding four fuel load metrics of the strata. The dashed blue line corresponds to a bulk density threshold used to identify the strata's limits.

Finally, it is worth noting that the entire processing chain has been implemented in R functions that can be easily used with the LiDAR package (Roussel et al., 2020) to perform large-scale analyses (see section 2 below).

In step -3-, the NRD profiles obtained from ALS were compared with field data collected in collaboration with the French National Forest Service (ONF) in South-East France on 183 plots. These field data consisted of a visual assessment of the vegetation cover in several vertical layers by a trained operator. We focus here on four vegetation layers: 1-2 m; 2-3 m; 3-4 m; 4-5 m. In step -f-, the ALS-based fuel metrics obtained from our innovative methodology were compared with field data collected in Portugal as part of a territory management project (áGiL TerFoRus - "*Piloto sobre produtos de análise, com recurso a LiDAR, para a gestão do território, da floresta e dos fogos rurais*").

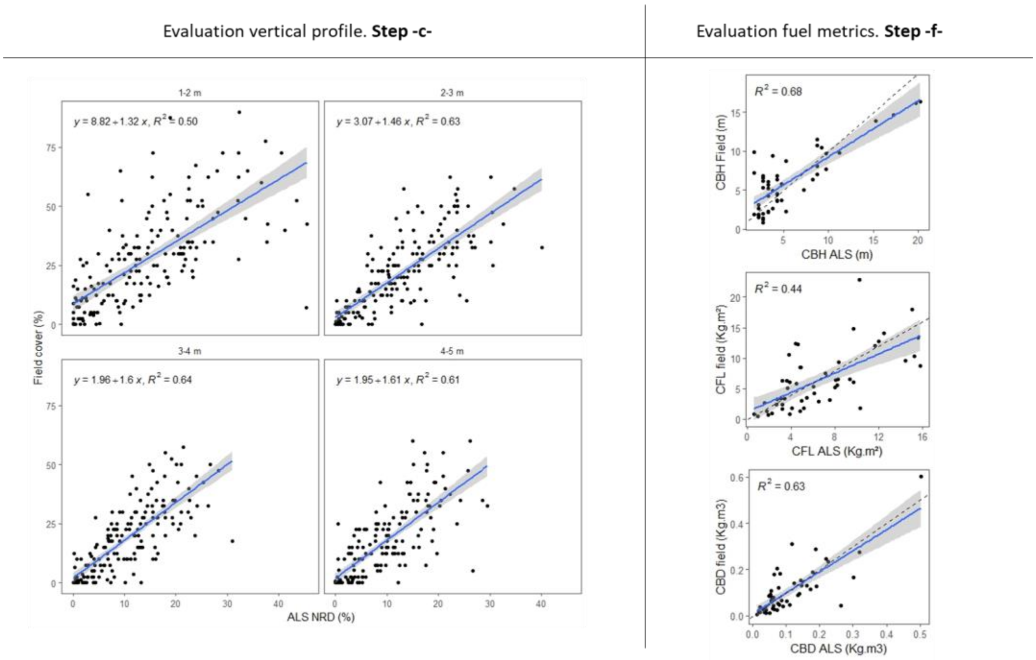


Figure 13: Results of the evaluation of the processing chain against field data at two steps (i.e. -c- and -f-). On the left is the evaluation at step c (i.e. vertical profile of vegetation cover). Each graph represents the linear relationship between field data and the ALS NRD index in a given vertical layer. On the right evaluation at step f. (i.e. quantification of fuel metrics). Each graph represents the linear relationship between field based and ALS based specific fuel metrics (CBH, CFL and CBD respectively). The blue line and grey area represent the linear regression and 95% confidence interval respectively. The dashed line is the 1:1 line.

For step -3- the results show good relationships from one to five metres height between the field estimate of vegetation cover and the ALS NRD index. This demonstrates that LiDAR data are consistent with a field expert analysis of vegetation vertical structure. Therefore, these results highlight the reliability of the ALS description of vertical vegetation profiles and its potential to accurately quantify fuel structure and loading at several heights.

The results of the evaluation of step -f reinforce the previous results by showing moderate to high goodness of fit (i.e. R^2) and very consistent values (in terms of order of magnitude) between ALS-based and field-based fuel metrics (CBH, CFL and CBD). Note that this methodology and results are the core of a scientific article in preparation[1].

a-2: Mapping fuel at large scale and evaluating existing European fuel map

[1] Martin-Ducup et al. (in prep) : Unlocking the potential of ALS data for direct assessment of fuel load and vertical structure.

Large scale operational fuel mapping for fire risk assessment and/or forest management decisions is usually based on groups of fuel typologies that greatly simplify the variability of fuel load and structure. The processing chain for extracting fuel metrics from ALS developed in Section a-1 has been applied to map fuel metrics at high resolution (i.e. 20 m pixels) in the Luberon Regional Park in South-East France (400 km²). The French national LiDAR campaign data were used to produce this map to demonstrate the potential of the approach to map fuel load and CBH quantitatively and at high resolution in an operational manner (Figure 14).

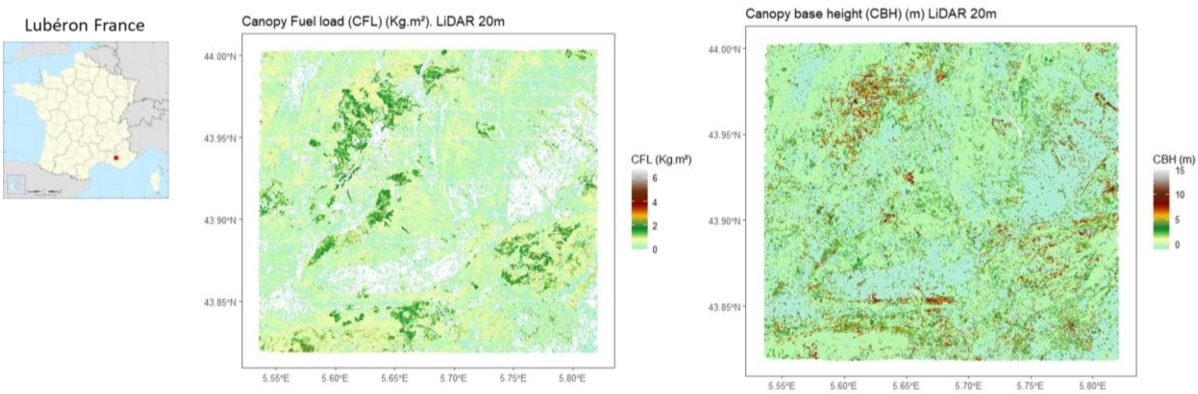


Figure 14; Maps of canopy fuel load and canopy base height based on ALS data at 20 m resolution in the Lubéron Regional Park (400 km²) in South-East France.

In addition, the approach was used to evaluate two recent European fuel maps developed in the context of the European FireEUrisk project (Aragoneses et al., 2023). The FireEUrisk fuel type map has a resolution of 1 km, while the FIRE-RES map has a resolution of 100 m and quantitatively estimates foliage biomass and CBH.

These evaluations were carried out on a sub-sample of 320 km² of the French national campaign LiDAR data, representative of the diversity of fuel types, to analyse the variability of fuel load and structure in each type for the FireEUrisk map and to compare biomass and CBH values with ours for the FIRE-RES map.

The results are presented in Figure 15 and show that the FireEUrisk fuel types are consistent in terms of mean values, but strong overlap between distributions highlighting the fact species-based fuel types correspond to a wide spread of actual fuel structure in terms of load and vertical distribution. Considering the importance of fuel load and CBH for fire behaviour (in terms of intensity and crown spread), these results suggest that this very large-scale fuel type map could take advantage of LiDAR fuel metric estimations (even if most validation at 5.6 (IA 5.10) was based on plots, this continuous lidar information becomes a powerful tool for validation), whenever available to re-segment fuel types or introduce new subtypes in the wildfire prone region. The FIRE-RES map of foliage biomass showed overall consistent values and a significant relationship when compared to ALS-based canopy fuel load. The Pan-European fuel map has done a great and new effort on implementing species specific allometries of canopy fuel characteristics.

Although those allometries are based on statistical models, will not show the same level of spatial variability that a direct measurement as LiDAR segmentation does.

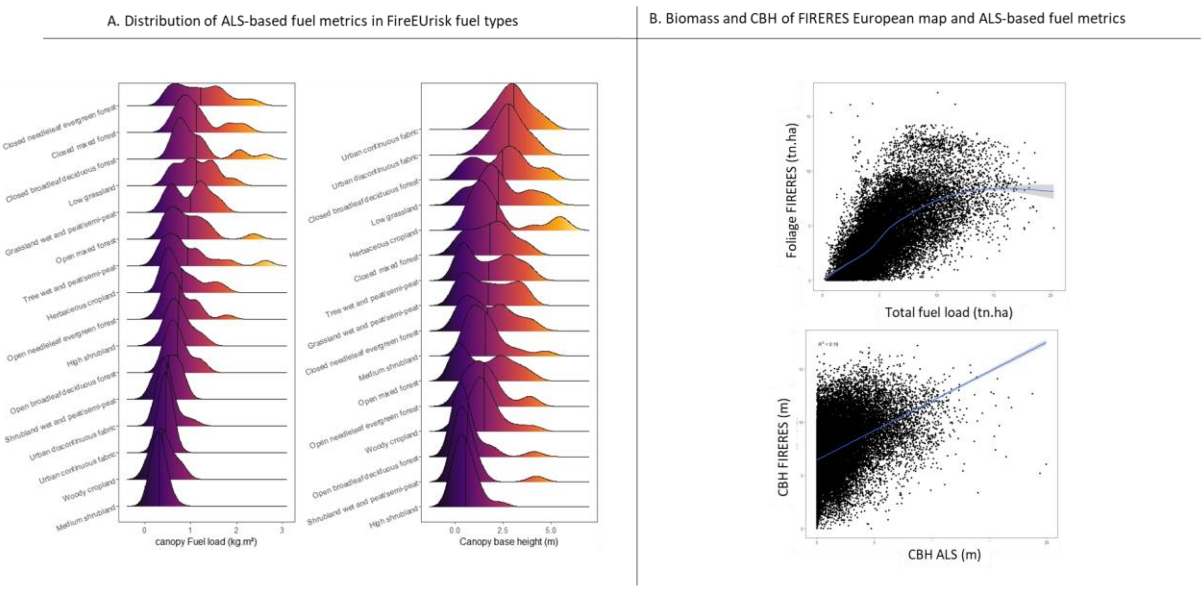


Figure 15: Evaluation of two European fuel map against ALS-based fuel metrics. A. FireEUrisk fuel type. B. FIRERES biomass and canopy base height map.

a-3: Vegetation morphology in the WUI

The Wildland-Urban Interface (WUI) is an area of transition between wildland and urban interfaces. Within the WUI a protection buffer/belt that encompasses both the urban and the wildland is defined at 25 metres from the urban limits, and it is expected to have low fuel loads. Analysing risk factors can help to manage the wildfire threat.

It is under discussion whether the WUI protection/buffer belt width should be expanded to 50 or 100 metres to decrease the wildfire risk. The methodology presented below analyses the morphology of the vegetation surrounding urban areas, up to 100 meters from its limit. For this purpose, we divided and studied independently 3 areas of vegetation influence from the edge of the urban area (from 0 to 25 meter, from 25 to 50 meters, and finally from 50 to 100 meters). It has been applied in a WUI located in Roses, in the LL Mediterranean northern coast (Catalonia).

The data used for the analysis come from the third LiDAR coverage flight of the ICGC, which density is 10pts/m^2 and are captured with a Terrain Mapper 2 system. LiDAR data in this WUI were flown in April and May 2021. Subsequently, data were classified to obtain ground, low, medium, and high vegetation, buildings, noise, powerlines and towers, and then the classified point cloud was height normalized no subtract the height of the vegetation above ground.

Each strip was segmented into 25-metre in length plots, with the aim of finding and then merging areas with similar vegetation morphologies.

In another WUI case study, the fuel load estimation with ALS data presented in section a.1 was applied by INRAE to three French municipalities in a fire prone region. The methodology is described in Figure 16 A and consists of:

1) extracting the point cloud around each building using the national cadastre with a defined buffer used (i.e. 20m in this example),

2) removing the point cloud classified as a building,

3) applying CBD profile estimation to the vegetation point cloud as described in section 1, and finally 4) extracting from the CBD profile relevant metrics for each building (i.e. fuel load in 0.5m-3m layers and total fuel load in this example).

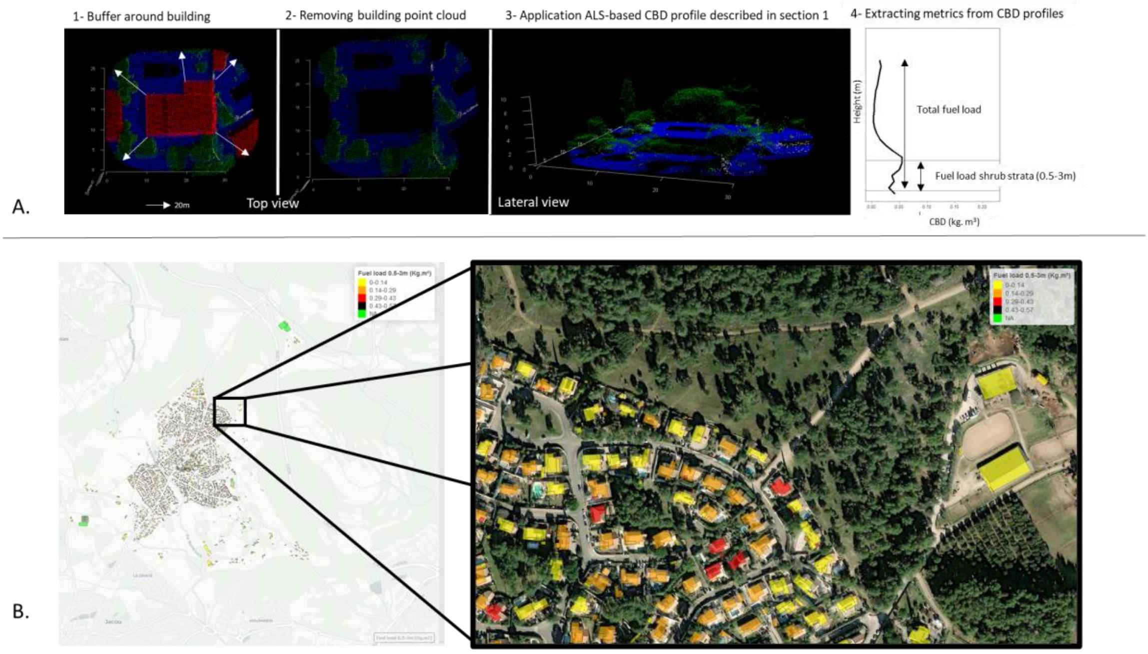


Figure 16: Application of ALS-based fuel metrics estimation (section 1) to the WUI with the French national LiDAR campaign. A. Summary of the workflow B. Screenshot of an interactive fuel load map for the shrub/mid-canopy layers generated for each building in the commune of Teyran (South-East France). The colour gradient corresponds to four fuel load groups (see legend at top right of map).

Interactive fuel load maps are generated for each building and can be used to assess the risk of fire spread in each community. An example of a generated map is shown in Figure 16 B.

Individual tree detection was performed to find the crown and feet of the trees. Firstly, a methodology based on tree detection from segmented point clouds was developed, based on Terrasolid tree segmentation algorithms, and then finding segment limits to delineate treetops and the highest point inside the crown to derive the tree foot. The resulting tree detection had some errors, mostly clustered trees, so it was decided to try the method based on local maxima region growing from a Canopy Height Model (CHM), also generated with the same LiDAR data (Aragoneses, 2023). Raster-based region growing provided better results than those obtained with point cloud segmentation, so region growing method was used to analyse the WUI.

Several LiDAR metrics were calculated for each tree, such as tree maximum, minimum, mode and average height, area of the projected treetop, percentiles of height and intensity and point distribution statistics from elevation and intensity values like Skewness, Kurtosis, Canopy Relief Ratio, AAD (Average Absolute Deviation), MAD median, etc.

Other parameters were estimated based on the tree's position, such as the distance to the nearest tree or to a built-up plot.

Figure 17: Individual tree detection based on local maxima region growing from a CHM, and their estimated height. Special trees (in red) are those trees whose crown is located less than 2m from a built-up plot.

LiDAR metrics for each 25-metre plot of the WUI strip were calculated to obtain new parameters associated to the plot such as tree and shrub density and coverage, slope, number of trees and number of special trees, average and minimum distance between tree feet. In the point cloud vegetation classification, it was considered that returns below 3 metres belonged shrubbery and those above 3 metres to trees.

Figure 18: Strip 25-metre in length plots represented by tree density.

To foster the potential use of results, a classification was performed in each plot considering the three more relevant parameters: tree feet density, tree Fractional Canopy Cover (FCC) and shrub fractional cover. Neighbouring plots with the same class were merged to obtain a strip segmentation based on its vegetation morphology. This classification does not aim to indicate higher or lower risk nor priorities, it simply evidences the changes in vegetation morphology between adjacent plots and thus, the forest clearing work in the strip would be adjusted for each of the classes.

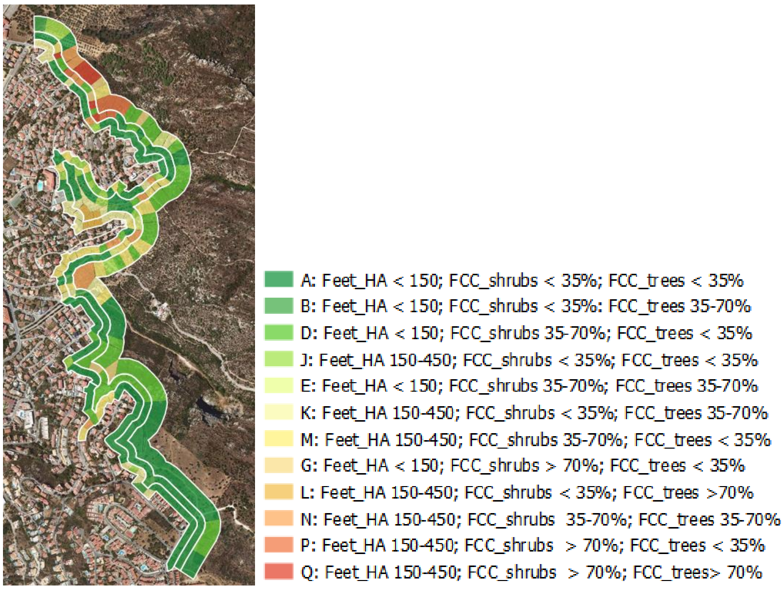


Figure 19: Example of plots of the areas defined. The classes (from A to Q), indicate different types of vegetation morphologies.

a-4: Improving LiDAR classification with AI to estimate new vegetation morphological metrics

The main goal at this section is to train an Artificial Intelligence model to enhance the vegetation classification and segmentation of LiDAR data. This will enable the derivation of new morphologic metrics as Canopy Breast Height (CBH), understory cover and height, fuel continuity, and more. The main purpose is a better forest land characterization to define levels of protection and prioritizing management in areas surrounding urban areas to avoid fire transmission.

To achieve this, field data collection was conducted in living Lab Catalonia. The fieldwork consists of 150 plots distributed throughout the LL of Catalonia whose forests have different morphological characteristics. The plots are grouped into 4 areas:

- Riparian vegetation area
- Mediterranean northern coast. Area with high recurrence of fires and with large expanses of scrubland.
- Inland Mediterranean southern coast. A forest-urban transition area affected by drought and a high availability of vulnerable vegetation.
- Pyrenees. High mountain area with a large accumulation of forest biomass.

Field data will be compared with high density LiDAR data (10pt/m2) from the 3rd Catalan LiDAR coverage, which has encountered some delays compared to the initial planning and is currently in the flight and processing phase. Additionally, there are hyperspectral images available in the same studied areas.

The LiDAR dataset in the plots will have an enhanced classification of scrubs and understory, medium vegetation, subdominant and dominant trees, as well as improved segmentation of the individual trees. Hyperspectral information will be a support to assign to each tree a functional group. Initially, each LiDAR point in the plot areas is automatically classified and segmented, followed by manual editing to refine the results.

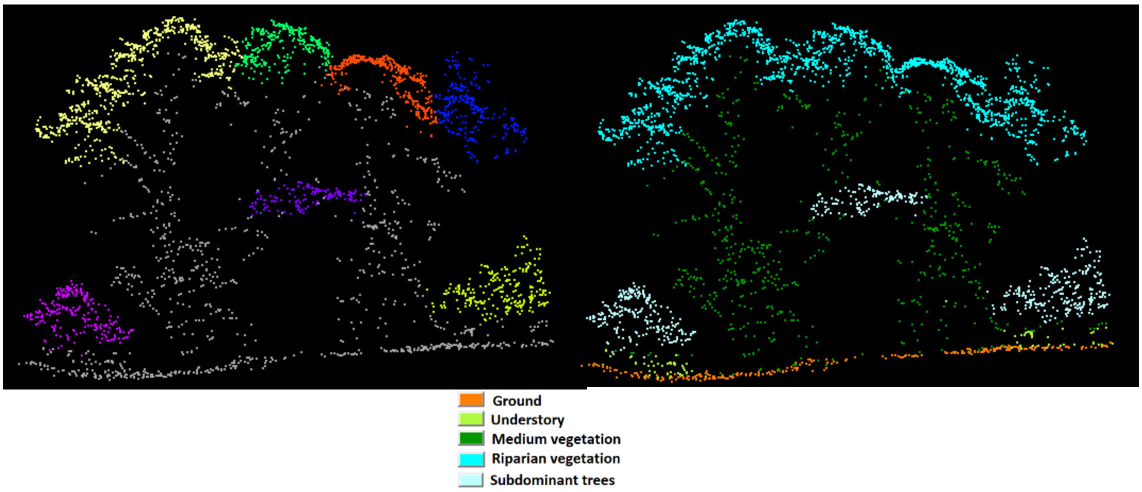


Figure 20: In the first image, point cloud segmented by individual tree. In the second one, point cloud classified according to ground, understory, medium vegetation, subdominant trees, and functional group.

Currently, a new method has been developed that enables the segmentation of small and large objects within a highly varying density point cloud scene using AI (Carós, 2023; Carós 2024). Parallelly, a LiDAR dataset of the riparian vegetation area has already been classified and segmented, and it is ready for training the AI model. This methodology will first be applied to the riparian vegetation area, and other plots will be incorporated as new high-density LiDAR data become available.

b) Combination of different temporal layers to detect changes and forest recovery after the events

Several geoinformation layers were produced in the area affected for the Sta Coloma de Queralt wildfire (24th-26th July 2021, 1680 ha), located in the Living Lab Inland Mediterranean, southern coast, in Catalonia. The combination of these layers enables the analysis wildfire affectations in the forested area. The description of the layers is listed below:

b-1: Photogrammetric Digital Surface Model (DSM)

The DSM is a raster layer at 1m pixel size containing orthometric heights. It represents the topmost height for every pixel position on the grid, be it the ground or features such as forest canopy and buildings.

It is generated using Trimble/Inpho's software package MATCH-T DSM. It works fully automatically using different image matching techniques like feature-based matching (FBM), cost-based matching (CBM) and least squares matching (LSM) to produce highly dense point clouds. The process follows a hierarchical approach starting from an upper level of the image pyramid and generating an approximate DSM for the next lower pyramid level. Different layers of smoothing can be applied as a function of terrain roughness to filter or reject outliers from the generated point cloud. Large point clouds (>5 million Points) are automatically split into a squared tile structure. From the final point cloud (tiles) a raster file with the selected 1-m grid size is interpolated. The same aerial photogrammetric images at 0.25m-0.35m used to produce the orthophoto are employed, thus guaranteeing a good consistency between these products.

The quality of the DSM was checked against a high number of independent check points. These points form a photogrammetric network available country wide. Only points located on the ground were selected (around one thousand points). From the check points, an empirical vertical accuracy value (Root Mean Squared Error – RMSE) better than 30cm was derived.

Since the DSM is automatically generated, their quality can be considerably decreased in areas where the matching algorithm did not achieve optimal results (e.g. in shadow areas). It should be also noted that in areas covered with some kind of forests and mildly sparse trees the DSM does not always represent the height of the canopy, depending on the tree density and the presence of foliage.

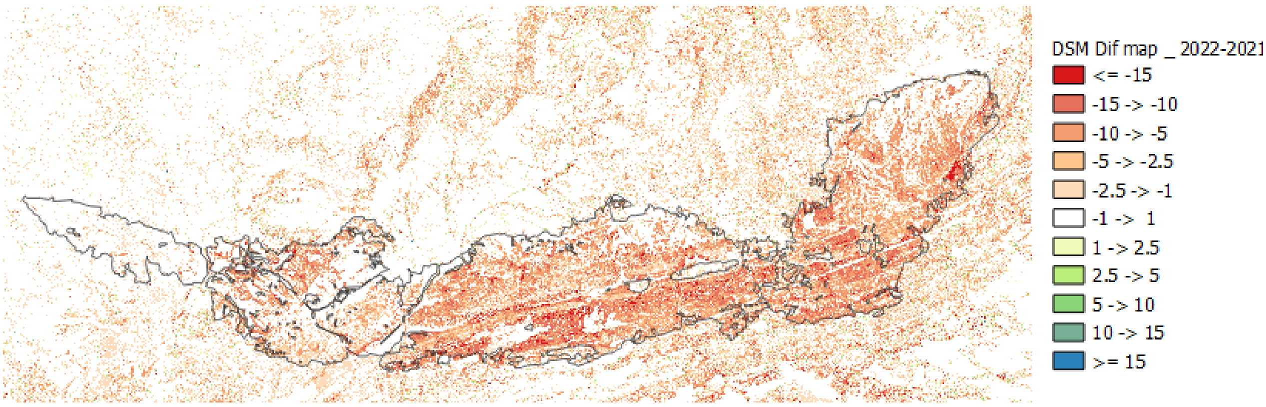


Figure 21: DSM difference map between 2022 (postfire) and 2021 (prefire) The greatest differences are associated with the disappearance of trees due to the fire severity

b-2: Canopy Height Model (CHM)

The CHM is a high resolution (1 m) raster that maps all the objects over the terrain as a continuous surface. It is advantageous to delineate the forest extent. Each pixel of this model represents the height of the trees above the ground topography. This layer was created through subtraction of the 2016-2017 LiDAR DTM from the 2018 photogrammetric DSM.

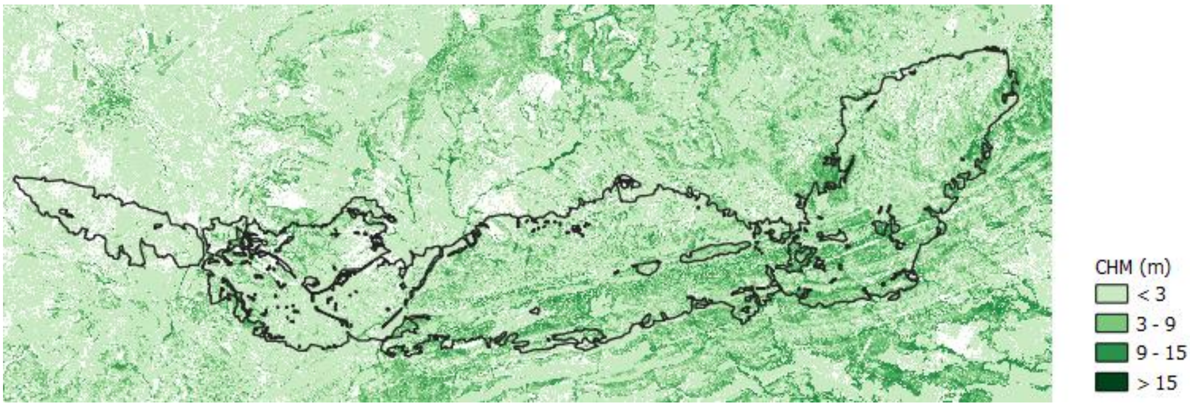


Figure 22: CHM (Canopy Height Model) from May 2021 (prefire)

While LiDAR coverage temporality is over 5 years, photogrammetric flights are performed annually in order to update the orthophotos. This enables to obtain an annual monitoring of the changes in the forest heights through the extraction of these models (DSM and CHM).

The DSM from 2023 is not generated yet, but when available, it will allow to monitor forest recovery after the wildfire.

In this case a large wildfire was analysed, but these models can be used to detect smaller changes due to wildfires or other perturbations, to monitor areas of fire prevention such as firebreaks or WUI, etc.

In this use case, DSM and CHM were complemented with other layers, such as other topographic information and severity index detailed below:

- Digital Terrain Model (DTM)

The DTM is a topographic model of the bare earth. This is a standard layer freely distributed by ICGC and built upon the classified information of the LiDAR wide-scale coverage.

- Aspect map

The aspect map yields the orientation of the maximum slope between adjacent pixels. It contains values from 0 to 360 expressing the slope direction, starting from North (0º) and moving on clockwise.

- Relief map

The relief map represents the height of the land surface showing by colour raised areas, valleys, etc.

b-3: Severity Index map (dNBR)

Fire severity is a measure of the magnitude of the immediate wildfire impacts on vegetation. The methodology is performed by using Sentinel-2 data as close as possible to pre and post wildfire. NIR and SWIR bands of Sentinel-2 (Bands 8A and 12) were used to calculate the Normalized Burn Ratio (NBR) for the pre and post-fire images, after applying cloud masks procedures.

$$NBR = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}}$$

The dNBR is determined through the difference between the pre and post-fire NBR composites. Finally, dNBR is classified according to the severity thresholds adopted by Key & Benson (2006).

Class	dNBR range
Unburned of regrowth	< 0.1
Low severity	0.1 - 0.27
Moderate low severity	0.27 - 0.44
Moderate high severity	0.44 - 0.66
High severity	>= 0.66

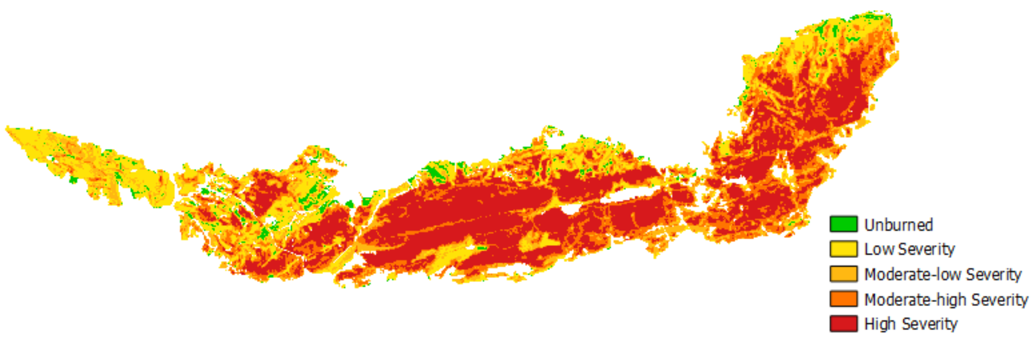


Figure 23: Severity Index, dNBR calculated as a difference between Sentinel 2 pre fire and post fire image (18th August 2021)

The DSM differences map was reclassified to extract only those pixels with a change detected upper to -1m. These pixels were considered forested areas burnt, allowing to estimate some metrics like forest cover affected in the wildfire. We can assume that the forested area burnt in the Santa Coloma de Queralt wildfire is the 57% of the total burnt area and corresponds to 959ha.

The comparison between CHM and severity map shows that those areas with higher vegetation had higher severity index, so this indicates a larger impact of the wildfire.

CHM was not used to derive volumetric information such as biomass because it does not allow to know the vertical distribution of the vegetation. It is considered that LiDAR data would be more adequate for this purpose.

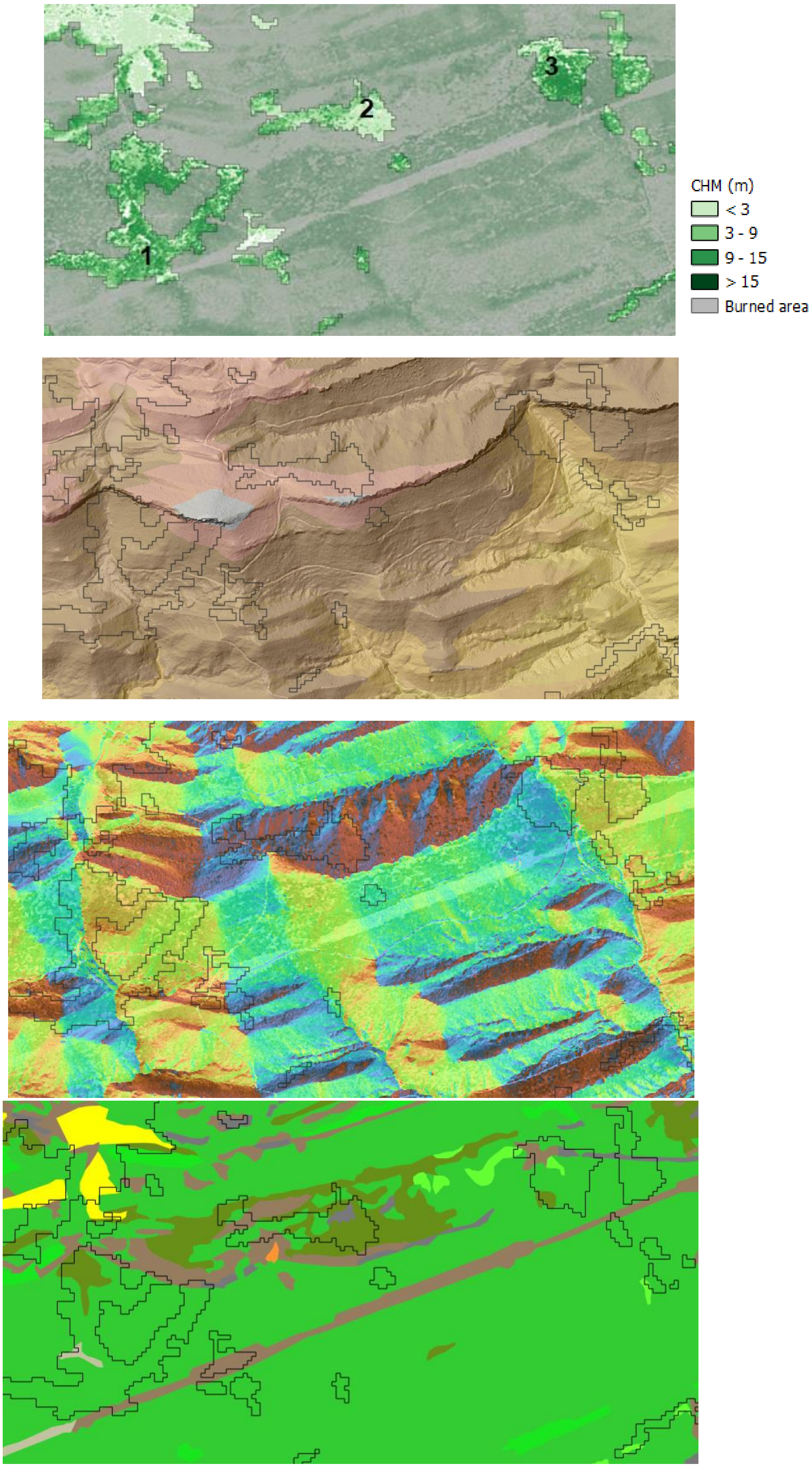


Figure 24: From top to bottom, CHM, relief map, aspect map and land cover map. Analysis of the not burnt areas inside the wildfire area. Gaps 1 and 3 have a high density of vegetation and corresponds to the top of the hills. Gap 2 have a lower presence of vegetation and its terrain has a different orientation from the closer burnt areas with similar vegetation densities. Gap 2 has also different forestry cover (mainly sclerophyll and laurisilva).

Other gaps in the wildfire area have a high correspondence with the terrain orientation.

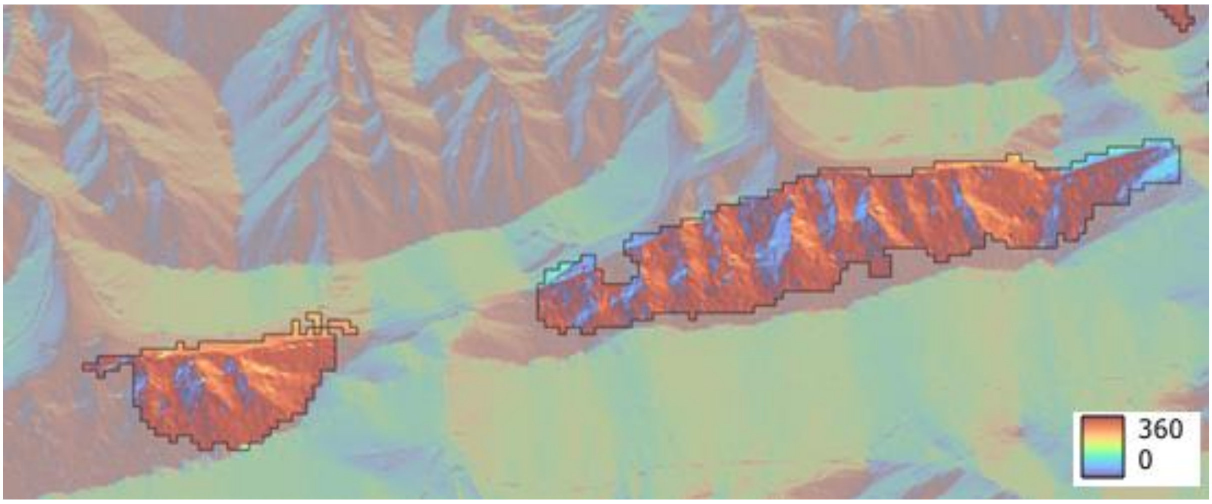


Figure 25: Aspect map. Area not burned inside the wildfire area.

Severity Index and DSM differences maps show small areas inside the burnt area where the fire did not reach. Analysing the CHM, it can be appreciated that some of these areas had a significant presence of high vegetation. Taking into account topographic and vegetation layers, it could be concluded that topography had played an important role in the fire dynamics. These gaps are usually on the top of a hill, on a different face of the mountain or they coincide with areas with low density of vegetation. There are also other aspects not taken into account in this analysis and that must have relevant influence in the fire dynamics like firefighters works and climatological aspects.

From a post-fire restoration perspective, areas of high severity with steep and extensive slopes may require restoration actions, depending on pre-fire vegetation characteristics. The unburned islands may facilitate seed dispersal up to a certain distance.

It is not the goal of this study to perform a complete analysis of fire dynamics or to propose post-fire restoration actions. Instead, its purpose is to provide geoinformation layers that can be used for decision-making and post-fire management, after conducting more exhaustive studies.

b-4: Trafficability of forest tracks

The trafficability of forest tracks was assessed by using innovative methodologies to enhance dispatch decisions and faster and safer access to the forest in case of fire events.

Trafficability of forest tracks becomes a paramount geoinformation because the importance of knowing status of tracks in terms of accessibility of firefighters, evacuation or facilitate fuel/forest management actions, among others.

Two methodologies were developed to delineate the forest tracks. The first one is based on AI methods. However, foreseeing that due to delays in the implementation of the methodology results would not be obtained within the timelines of this task, a second methodology based on GIS analysis was developed. This was done with the expectation of improving the results later on with AI techniques. Subsequent analyses are common to both methodologies.

The objective was to acquire updated cartography of the forest tracks to assess if emergency vehicles could traverse through it. In the first methodology, this cartography was manually generated with the aid of terrain morphological layers derived from LiDAR, including terrain slopes and shadow maps and LiDAR ground intensity. This data will be the basis for training an AI model for automatic track delineation.

The second method also relies on terrain morphological layers. To narrow down the search area, an initial position of the tracks is required. This could come from cartographic databases, user’s GPS tracks, among others. A user-defined buffer around the track determines the search area. Within this area, low-pass filters are applied to the terrain morphological layers, resulting in a smoother ground surface.

A preliminary statistical analysis was conducted on the terrain morphological layers of the tracks delineated by the first method to understand the defining characteristics of the terrain within these tracks. The findings indicated that the slope inside the tracks typically stayed below 20%, while the ground surpassed a value of intensity of 45. Meanwhile, the terrain irregularity index was found to be redundant with the slope map and was thus excluded from the study.

A vegetation mask is created using LiDAR returns for heights above the ground less than 3 metres.

In the search area, pixels that meet the criteria of having a slope less than 20% and either ground intensity values greater than 45 or devoid of vegetation below 3 metres are classified as a track. Subsequently, the track is vectorized and its geometries are smoothed to delineate the track's boundaries.

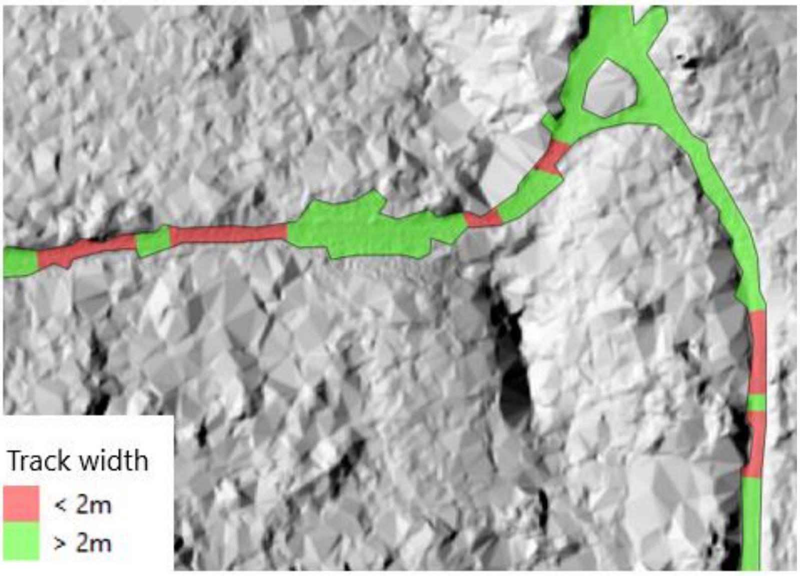


Figure 26: Results of the automatic track detection.

From this vectorization, the width of the track is extracted at 2-metre intervals. The segmentation of the tracks allows a more in-depth examination of the distinctive characteristics of each section.

For each 2-metre interval, the following parameters are determined: average slope, coverage of vegetation below 3 metres and maximum and minimum track widths.

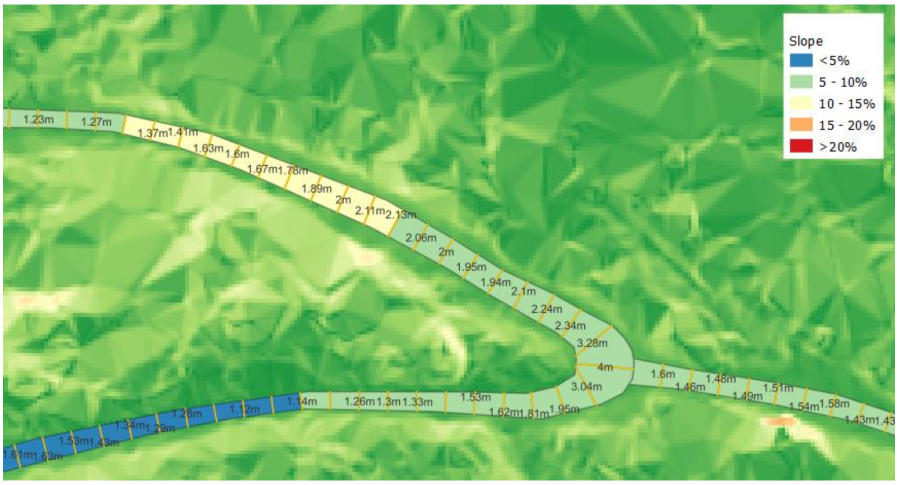


Figure 27: Map showing the average slope and the minimum width of the forest tracks.

Track widths help us to determine whether an emergency vehicle can travel along it, whether two vehicles can pass alongside each other, if a vehicle has manoeuvrability, and to identify potential parking areas for vehicles. The vegetation coverage helps identify any vegetation that might be obstructing the track.

Figure 28: Map of the forest track trafficability.

4. Closing remarks

4.1 A dynamic high-resolution map of the state of the forest and fuel

The operationalization of change detection utilizing satellite imagery presents inherent challenges. One notable issue encountered during the operationalization of the processes within this subtask by NIBIO was the effect of prediction accuracy, particularly concerning the occurrence of false positives. The perception of a map as inherently accurate poses a challenge in effectively integrating or conveying, uncertainty in a good way.Excessive false positives not only obfuscate the interpretation of a map layer for end-users but also fail to enhance comprehension of ground-level situations, despite the underlying change detection model exhibiting satisfactory overall accuracy.

NIBIO has chosen to regard the change features and models as mature for operationalization using both prediction accuracy and visual appearance of resulting map layers as key factors. Certain features subjected to testing were deemed unsuitable for incorporation into maps intended for stakeholder presentation. This was notably observed in the context of wind damage detection and identification of new infrastructure. Subsequent research could improve the methods used, and potentially integrating these features into a process of updating maps utilizing satellite imagery.

Transitioning from a research-oriented phase to an operational testing phase posed considerable challenges, with an underestimation of the intricacies involved in implementing a live working automated process. Key lessons learned from this experience underscore the necessity forall code and infrastructure components to be conducive to autonomous execution without intervention. Additionally, the operational process must incorporate mechanisms to automatically handle encountered errors without halting the whole process.

4.2 Innovative methodologies for fuel structure assessment

The LiDAR-based processing chain developed by INRAE has demonstrated its reliability in measuring the vertical profile of vegetation and fuel metrics commonly utilized in fire behaviour models, such as canopy base height, canopy fuel load or canopy bulk density. In addition, exploratory cases were conducted to map fuel characteristics at high resolution and large scale and to apply the approach in WUI scenarios.

The added value of ALS data for assessing the quantity and structure of fuel biomass in forest canopies has been clearly demonstrated. This approach enables accurate determination of this structure accurately at the dates of LiDAR acquisition.

Furthermore, LiDAR based results allow for an assessment of the effectiveness of forest fuel maps based on alternative remote sensing techniques,which offer less accuracy but allow high-frequency temporal monitoring of canopies. This is exemplified in the preparation of a forthcoming article (foot note 2), where our estimate of fuel load and CBH serve as reference data for a Pan-European fuel map.

The results obtained from the development, evaluation and application of the approach, as summarized in the preceding sections, represent a significant advancement towards an operational fine description of fuel at large scale. These findings have prompted several research questions and raised development perspectives. Some of them, critical to our opinion, are briefly discussed in the following paragraphs.

While the results presented here primarily focused on vegetation above one metre in height, it was observed that field data and ALS-based metrics were less consistent below this height, with no correlations observed below 0.5m (results not shown). The challenge in describing the lowest layer systems from occlusion effects (the highest vegetation element obscuring the lowest) and, more importantly, soil classification issues, particularly in areas with complex topography. Given the importance of surface vegetation for fire ignition and spread, efforts are underway to enhance our ability to describe surface fuels. INRAE is currently conducting research to improve the characterization of this first layer by testing alternative soil classification algorithms. Encouraging preliminary results (not presented) suggest that a fine-tuned ground classification approach enhancesvegetation characterization in the lowest layers when the terrain slope is high. Additionally, INRAE plans to investigate the combination of ALS with passive remote sensing data (e.g. Sentinel-2) to improve the description of surface fuels. More importantly, thanks to the methodology developed and described in section 1, which enables accuratefuel structure description, it is possible to target specific locations for fieldworkto improve our understanding of the interaction between LiDAR data and surface fuel strata.

The evaluation of methodologies such as the one developed here requires enough reliable field data comparable to those obtained with LiDAR technology (i.e. fine vertical profiles).

In this context, additional field data from the French National Forestry Service are currently being analysed to expand our sampling and to examine various factors that may influence ALS-based fuel characteristics (i.e. terrain slope, vegetation types, season of LiDAR acquisition and field data collection…). Moreover, accurate fuel load estimates based on field data from the Living Lab Aquitaine will soon be available as another source of validation data.

Terrestrial (TLS) and mobile (MLS) LiDAR combined with species-specific plant characteristics offer a promising approach to validate and calibrate the approach developed with ALS.

Thesedata provide a highly accurate representation of the local environment, and methods have been developed to estimate woody and leaf area based on fine-scale (10 cm resolution) voxelization, considering various biases associated with the nature of LiDAR data and its acquisition (Nguyen et al., 2022; Pimont et al., 2018). INRAE plans to utilize plot-scale TLS data for the validation/calibration of ALS-based vegetation profiles.

The analysis of vegetation distribution around WUI is crucial for forest management and enhancing the protection of individuals and buildings within WUI against potential wildfires threats. The developed techniques represent another valuable tool for agents managing this forested space. Once again, LiDAR has proven to be the optimal technology for conducting such analyses, as it provides comprehensive insights into the vertical structure of vegetation.

There is an ongoing debate surrounding the width of the WUI, particularly given the severity of sixth-generation wildfires. While the current standard designates a 25-meter buffer from the perimeter of the urban area, discussions are underway about expanding this area to 50 or even 100 metres. Although this study does not directly simulate fire behaviour to assess the potential benefits of expanding WUI width, it endeavours to provide tools that could facilitate such assessment in the future.

Photogrammetric canopy and surface models offer high spatial resolution and multi-temporality, given their acquired more frequently than LiDAR data. However, they are highly dependent of illumination conditions. In general, photogrammetric digital models are crucial sources for change detection due to the recurrence of data capture and for training at this case A.I approaches.

Finally, LiDAR technologies emerge as the preferred approach for detecting the morphology and evaluating the trafficability of the forest tracks. Nevertheless, their limitations in providing updates due to the limited recurrence of LIDAR coverages must be considered. The current methodology relies on an initial track position to calculate its morphology and trafficability. Efforts are underway to leverage AI techniques to detect tracks without the reliance on preliminary cartography, with promising prospects for uncovering old and unused tracks, as well as to scale it to other areas without the need to have cartographic databases that include forest tracks.

These studies have engendered opportunities for the implementation AI techniques in change detection, refining LiDAR point cloud classifications to derive new and improved vegetation structural metrics and identify tracks that are not currently included in the databases.

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