D2.10 IA2.1 brief: Improving data acquisition for landscape design based on novel remote sensing methods - Final

www.fire-res.eu

fire-res@ctfc.cat

Project Acronym: FIRE-RES

Project name: Innovative technologies and socio-ecological-economic solutions for fire resilient territories in Europe

Call ID: H2020-LC-GD-1-1-2020 (Preventing and fighting extreme wildfires with the integration and demonstration of innovative means)

Work Package: 2

Task Number: 2.1

Lead beneficiary: NIBIO

Contributing beneficiaries: NIBIO, ICGC

This document was produced under the terms and conditions of Grant Agreement No. 101037419 of the European Commission. It does not necessarily reflect the view of the European Union and in no way anticipates the Commission's future policy in this area.

Publication

Publication date: 28/11/2025

Authors: NIBIO, ICGC

Abstract: This report builds upon the foundations laid in Deliverable D2.1 and presents the advancements and implementation efforts carried out in subtasks "2.1.1 A dynamic high-resolution map of the state of the forest and fuel" and "2.1.2 Innovative methodologies for fuel structure assessment". For 2.1.1, the deliverable describes the improvements on the algorithms for detecting forest changes, their implementation in two Living Labs, and the successful near real-time automation demonstrated in the Norway–Sweden Living Lab. For 2.1.2, the delivery presents the application of the methodology developed in IA 2.1 for estimating fuel load within the Catalonia Living Lab. During the testing and validation phase, a field campaign was carried out to collect ground truth data and assess the performance of the model under regional conditions.

Key words: Sentinel-2, Automated Change Detection, Fuel Load, LiDAR

Quote as: de Lera Garrido, A; Hauglin, M; Ferràndiz, A, Corbera, J. (2025) IA2.1 brief: Improving data acquisition for landscape design based on novel remote sensing methods – Final. Deliverable 2.1 FIRE-RES project. 27 pages. DOI: 10.5281/zenodo.17724934

DOI: 10.5281/zenodo.17724934

Dissemination level

[X] PU- Public: must be available in the website

[ ] CO- Confidential: Only for members of the Consortium and the Commission Services

[ ] CI – Classified: As referred in to Commission Decision 2001/844/EC

Document history

Edition	Date	Status	Author
Version 0	19/09/2025	Draft/Outline	NIBIO, ICGC
Version 1	10/10/2025	Final version for Review	NIBIO, ICGC
Version 2	26/11/2025	Final version for submission	NIBIO

Table of Contents

List of figures

Acronyms

ALS: Airborne Laser Systems

CBD: Canopy Bulk Density

CBH: Canopy Base Height

CFL: Canopy Fuel Load

CTFC: Consorci Centre de Ciència i Tecnologia Forestal de Catalunya

D: Deliverable

dNBR: Differential Normalized Burn Ratio

GFW: Global Forest Watch

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

NBR+: Normalized Burn Ratio Plus

NIBIO: Norwegian Institute of Bioeconomy Research

NOR-SW: Norway-Sweden

WMS: Web Map Service

XGBoost: Extreme gradient boosting

1. Introduction

This document expands on the work started in D (Deliverable) 2.1, which delineates the endeavours undertaken within Task 2.1: *Improving data acquisition for landscape design based on novel remote sensing methods (IA 2.1)*.

This deliverable describes the services implemented and focuses on the improvements achieved up to month M47 in subtasks "*2.1.1 A dynamic high-resolution map of the state of the forest and fuel*" and "*2.1.2 Innovative methodologies for fuel structure assessment.*" Rather than repeating the detailed background and foundational information from Deliverable 2.1, this document builds upon those results, highlighting the progress and new developments that have occurred since then.

The section on subtask 2.1.1 focuses on refining the algorithms for forest change detection, detailing their implementation in two Living Labs (LL), and demonstrating the successful near real-time automation in the Norway–Sweden (NOR-SW) LL. Meanwhile, the section on subtask 2.1.2 focuses on the implementation of INRAE's fuel estimation methodology in the Catalonia LL. A dedicated field campaign was carried out to collect validation data, allowing the assessment of the model's adaptation for regional application.

2. Improved methodologies

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

2.1.1. Background and previous work

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 section 3.1 of the FIRE-RES report D2.1 "Improving data acquisition for landscape design based on novel remote sensing methods" (Corbera et al. 2024), the status and foundation for a dynamic high-resolution map of the forest and fuel was described. This concept has been developed further, and the improvements and lessons learned from a pilot implementation in the Norway-Sweden LL, as well as tests in the Greek LL, are described in the following.

The overall concept is to use frequently updated remote sensing data to identify changes on the ground and, based on the detected changes, update existing map layers (*Figure 1).*

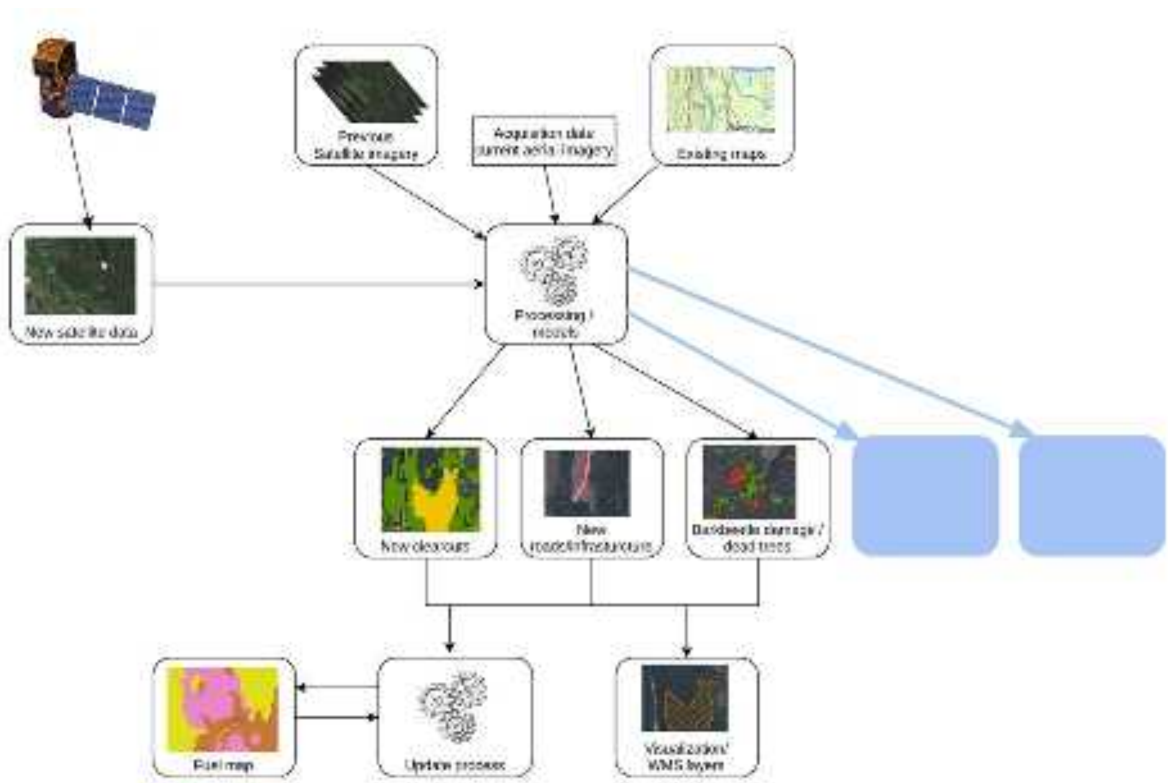

Figure 1. Conceptual overview. Dynamically updating map layers based on changes detected in satellite imagery.

In the pilot implementation, we have focused on using openly available data from the Copernicus programme of the European Space Agency, in particular data from the Sentinel-2 satellites. These satellites provide spectral data with a high spatial and temporal resolution. Several types of changes were pointed out in the previous report, namely clear-cut harvests, wind damage, drought stress, bark beetle damages, and new infrastructure. All these types of changes in the conditions on the ground will typically lead to changes in map layers too, for example, from one class to another in a fuel map. The produced map layers are then dynamic in the sense that detected changes are automatically incorporated into the maps.

2.1.2. Improvements in methodology and results

The improvements made from D2.1 have focused on enhancing the models and achieving full automation of the processing and map updating process.

Harvest

After comparing several methodologies and concluding that detecting harvests in single Sentinel-2 images was the overall preferred method in D2.1, we developed an Extreme Gradient Boosting (XGBoost) model to detect harvest areas. The process of predicting and postprocessing was fully automated for the pilot implementation area in the Norway-Sweden LL, so it runs whenever a new Sentinel-2 image is available.

When working with single images, it is important to consider how predictions might vary from one image to another. The utility of the generated maps has always been a primary focus of this subtask. Maintaining consistency in the results is crucial, as we want to avoid predictions that fluctuate between "harvested" and "not harvested." Therefore, the post-processing of the projections has also been improved. Now, we check the time series and retain only those predictions that are consistent over time. Additionally, since some of the detected harvests were not new but had been harvested in previous years, we utilize Global Forest Watch (GFW) to mask out those previously harvested and show only the new ones. (*Figure 2*).

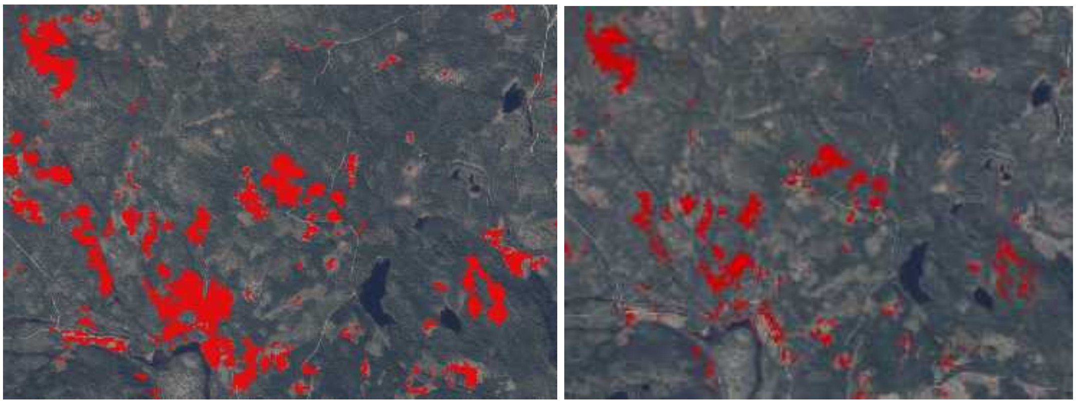

Figure 2. Differences in predictions from 2025 masking previous harvest using GFW (right) or without masking (left) over an orthophoto from 2022

Drought stress and bark beetle attack

From the several methods tested in D2.1, a ResNet convolutional neural network classification model was chosen as the detection algorithm. The model predicts the forest state for each pixel, using a series of Sentinel-2 images as input.

We increased the number of input channels to include most of the Sentinel-2 bands and included the possibility of including neighbouring pixels in the input. Although the algorithm can work for different time series lengths, the best results were obtained with a time series of 16 images going roughly a year back, using a 3 x 3 pixel neighbourhood. This model has been implemented to work autonomously in the NOR-SW LL.

New infrastructures

An UNet-like Transformer model using a CNN-based encoder and a Transformer-based decoder (Wang et al., 2022) was modified from https://WangLibo1995.github.io. This model was trained on Norwegian data to determine if it could improve the results obtained from the previous deep learning model. In this modified model, we increased the number of input channels to include most of the Sentinel-2 bands. The results improved and are promising; However, to demonstrate the importance and value of the tool, it is necessary to assess which detected roads and infrastructure are not represented already in other maps, and how long it takes for these features to be included in those maps. This assessment has not been implemented yet.

Burnt area

The algorithm to detect burned areas was slightly modified, and the prediction process has been fully automated for the NOR-SW LL. We transitioned from using the Differential Normalized Burn Ratio (dNBR) index to the difference in Normalized Burn Ratio Plus (NBR+) index, which helps reduce the number of false positives near water bodies and near clouds (Alcaras et al., 2022). We refined the threshold values based on the 2024 results, included a buffer for the cloud masking, and added a rule so that the detection of a burn area is not only based on a threshold from dNBR+ values but also on the NBR value of the latest image itself.

These criteria were added due to the small dimensions and low intensity of most fires in the Living Lab, which makes them more challenging to detect with satellite images. We aimed to maximize the number of fires that can be detected while minimizing false positives, such as those caused by clearcuts. An example of how different thresholds can affect the predictions of burnt area is shown in *Figure 3*.

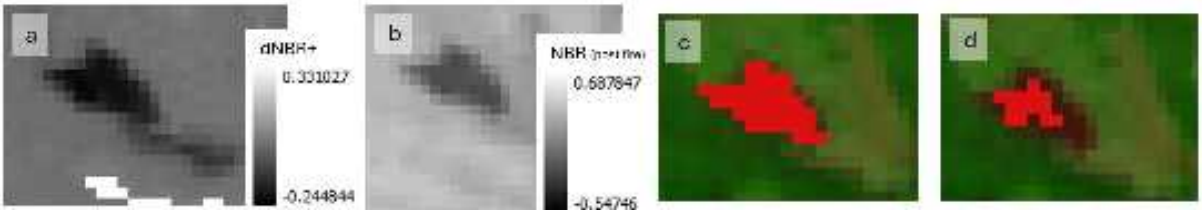

Figure 3. Example of how different thresholds of dNBR+ (a) and NBR values of the postfire S2 image (b), can produce different burnt area predictions (c & d). Burnt areas are shown in bright red over the S2 image visualization based on the bands B12, B8a & B4.

The algorithm requires a reference image to calculate the dNBR+ values, which we decided should be updated throughout the process. Therefore, we not only implemented an automatic process to run the algorithm on every newly available Sentinel-2 image, but also a method for automatically updating the reference cloud-free image and some rules to select appropriate ones, such as a limit on cloud cover and a time difference with respect to the new image.

Automatic updating of a high-resolution map

The goal of this subtask is to produce a dynamic, high-resolution map of forest and fuel conditions that is automatically updated whenever new information becomes available. All the models mentioned earlier were integrated into this process. Each day, we first check and download any new Sentinel-2 images that are available. After that, the different models are applied, and the results are stored and displayed as independent layers on a Web Map Service (WMS) server.

After each individual map is created, the maps are used to update the fuel map (*Figure 4*). Pixels that have experienced changes or disturbances are reclassified into a new fuel category, resulting in a dynamic high-resolution map that will show up-to-date information on the state of the forest and landscape.

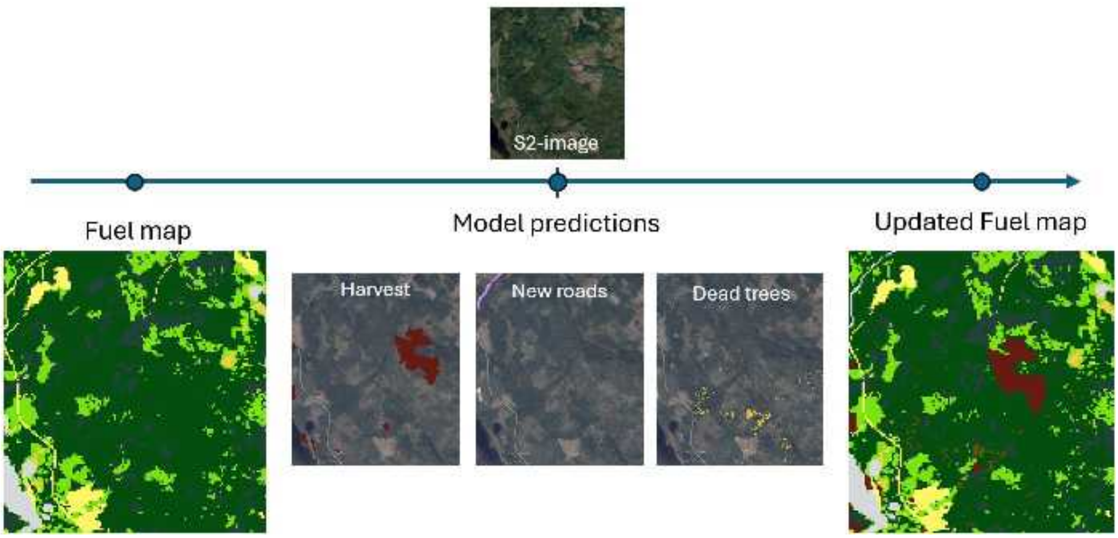

Figure 4. Representation of the updating process to create dynamic maps.

2.1.3. Implementation and replications in FIRE-RES Living Labs

NOR-SW

The innovation Action developed in subtask 2.1.1 has been implemented and tested in the NOR-SW LL in southeastern Norway (*Figure 5*) during the fire seasons (April to September) of 2023, 2024, and 2025.

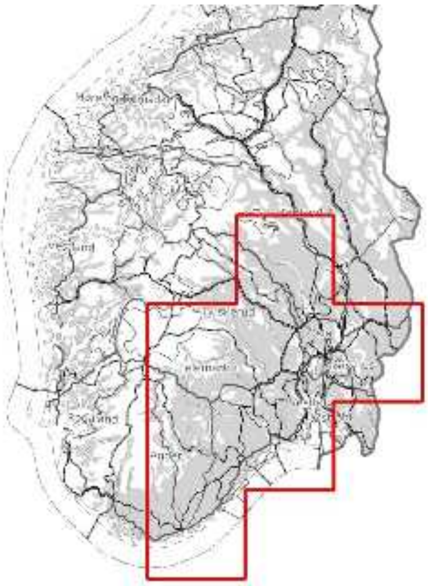

Figure 5. Area of implementation in the NOR-SW LL

In 2023, most of the work involved developing and testing the different models. In 2024, the models were improved, and the first tests for monitoring were conducted and evaluated upon completion of the fire season (*Figure 6 - Figure 7*).

Figure 6. Comparison of Sentinel-2 RGB image from 2024 (left), results from Global Forest Watch loss for 2024 in blue *(middle) over a 2022 orthophoto, and predictions of harvested areas using the XGBoost in red (right)*

Figure 7. Example of the product's utility. Orthophoto from April 2024 (left), and predictions for Sentinel-2 images on 21st May 2024 for harvest (middle) and on 26th May 2024 for burn area (right).

Finally, in 2025, the process was fully automated and made available to selected stakeholders via a WMS. The Service displays multiple layers (*Figure 8*), including predictions of new clear-cut harvests, bark beetle attacks, burned areas, and newly constructed forest roads. These layers also serve as inputs for daily updating the fuel map, supporting near-real-time monitoring.

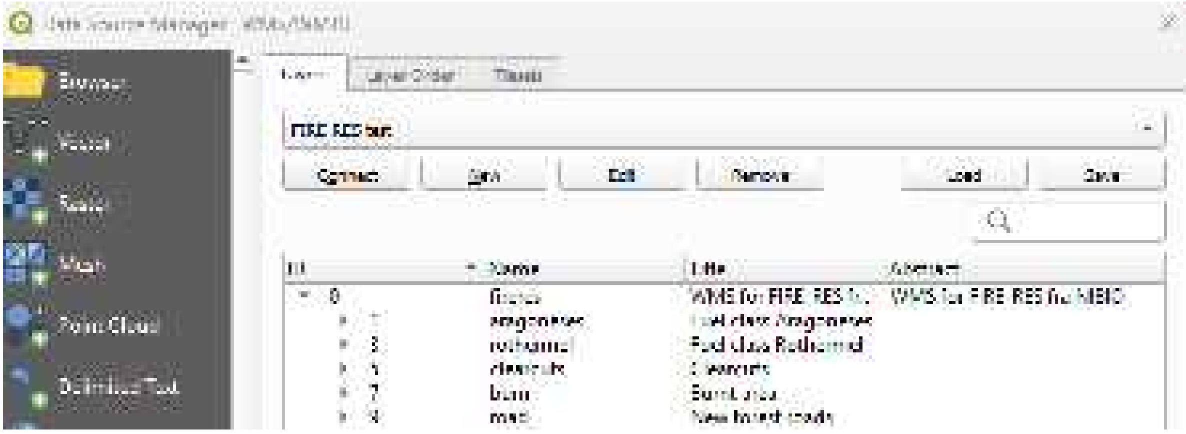

Figure 8: WMS access through QGIS and the different accessible layers.

Greece

The transferability of two models developed using Sentinel-2 imagery in the Nordic LLs was tested in the Greek LL, specifically on Lesvos Island. The ResNet convolutional neural network, trained to classify dead trees due to bark beetle infestations, and the XGBoost model for detecting harvested forest areas.

The ResNet model was applied to detect attacks by *Dendroctonus micans* and *Tomicus piniperda.* The evaluation was conducted using a shapefile provided by the Greek LL. The models showed limited performance when applied directly on data from Lesvos.

The model did not accurately detect all beetle-affected areas in the shapefile, particularly in areas with sparse forest cover; however, it identified other regions with visible tree mortality (confirmed via Google images) (*Figure 9*).

Figure 9. Reference shapefile data over a Google map (left), where ill trees are outlined in red and a coniferous forest mask in light green. Prediction with the ResNet model (right) with predictions of forest in green, dead trees in orange, and non-forest in blue.