

INTEGRATED MULTIMODAL APPROACH FOR ASSESSING TREE DELAYED MORTALITY TO PROMOTE SMART AND SUSTAINABLE MANAGEMENT OF FOREST POSTFIRE SITES (MAP4FIRE)





PARTICIPANTS





Research Institute on Terrestrial Ecosystems CNR- IRET

- Department: Department of Earth System Sciences and Environmental Technologies
- Mission: research, both basic and applied, on the study of structure, functioning and productivity of terrestrial ecosystems, biotic and abiotic components and their interactions, with a specific focus on global change and anthropogenic pressure;
- https://www.iret.cnr.it/en/
- Labs: Dendrobiology (Sesto Fiorentino)



National Institute of Optics CNR - INO

- Department: Physical sciences and technologies of matter
- Mission: pure and applied research in the field of Optics, accompanied by technological transfer, consulting for public institutions and businesses, metrology measurements and testing services and training activities;
- https://www.ino.cnr.it/?page id=15732
- Labs: Biomedical Optics (Florence)





THE BACKGROUND TO IDEAS: THE PNRR RELATED PROJECTS



NBFC – spoke 4 – Activity 4.5.2

'Monitoring, functional characterization and traceability of resilient forest reproductive material for reforestation of forest sites subject to extreme events'

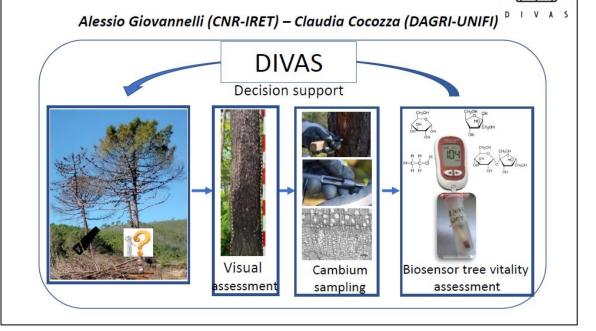


• Living labs: flooding, storms and post wildfire



PNRR_PRIN_2022 Project 'DIVAS'

'Developing of innovative methods to assess tree vitality after a wildfire through analyses of cambium sugars metabolism'







THE DIVAS PROJECT APPROACH: THE ROLE OF PIVOTAL SITES FOR ECOSYSTEM RESTORATIONS



Wildfire intensity;

Damage level;

Site selection based on ecosystem services and human health and safety;

Degree of vulnerability of the sites











THE 'TREE BY TREE' SAFETY STRATEGY: THE FATE OF SCORCHED TREES



Alive



Class A



Class B



Class C



Is the tree's state compatible with the ecosystem functions it must fulfil over the medium and long term?



The issue relates to the delayed death of the scorched trees





VS

WHY ARE SCORCHED TREES DYING? FIRE EFFECT ON TREE PHYSIOLOGY



Bar et al. (2019). Fire Effects on tree physiology. *New Phytologist 223:1728-1741*

Patrelli-Feltrin al. (2023). Death from hunger or thirst? Phloem death, rather than xylem hydraulic failure, as a driver of fire-induced conifer mortality. *New Phytologist* 237:1154-1163

Kelsey et al. (2017). Physiological Stress and Ethanol Accumulation in Tree Stems and Woody Tissues at Sublethal Temperatures from Fire. *Bioscience* 67, 5, 443–451



60°C 15 min



Irreversible damage of phloem and cambium

Proxy of tree vitality and latent mortality





Non structural carbohydrates

Ethanol





USING BIOSENSORS AS SMART TOOLS TO DETECT PROXIES OF TREE LATENT MORTALITY







Review

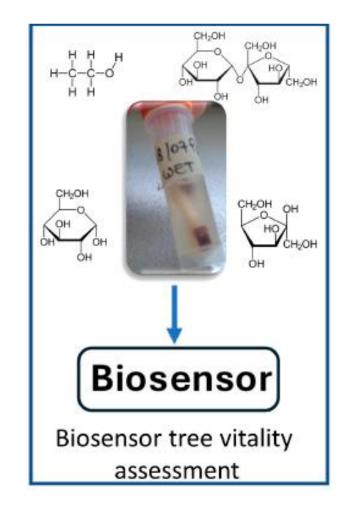
Fire up Biosensor Technology to Assess the Vitality of Trees after Wildfires

Eleftherios Touloupakis ^{1,*}, Isabela Calegari Moia ¹, Raffaella Margherita Zampieri ¹, Claudia Cocozza ², Niccolò Frassinelli ², Enrico Marchi ², Cristiano Foderi ², Tiziana Di Lorenzo ¹, Negar Rezaie ¹, Valerio Giorgio Muzzini ³, Maria Laura Traversi ¹ and Alessio Giovannelli ¹

Clark type O₂ electrode:

Ag anode,
$$4Ag + 4Cl^{-} \Rightarrow 4AgCl + 4e^{-}(4)Pt$$
 cathode, $O_2 + 4H^+ + 4e^- \Rightarrow 2H_2O$

Glucose +
$$O_2$$
 + H_2O \longrightarrow Gluconic acid + H_2O_2







GLUCOSE DETECTION IN SCORCHED TREES USING



Assessment

Methods

BIOSENSORS









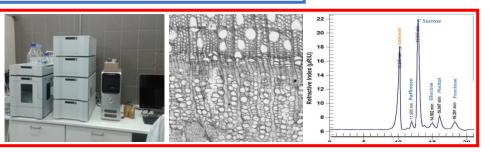
Article

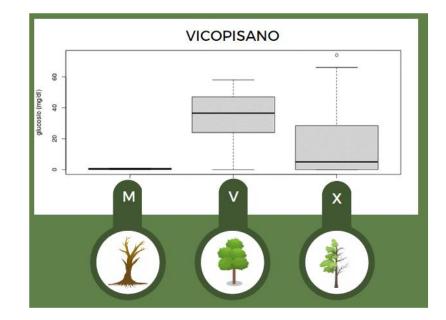
Detecting Glucose in the Phloem to Quickly Define Latent Post-Fire Mortality in Pinus Trees in Northern Italy

Niccolò Frassinelli 10, Claudia Cocozza 1,*0, Enrico Marchi 10, Cristiano Foderi 10, Eleftherios Touloupakis 20, Francesco Neri ¹, Maria Laura Traversi ^{2,3} and Alessio Giovannelli ^{2,3}













OPEN QUESTIONS: 'MAP4FIRE' PROJECT



Q1) What are the effects of high temperature on cell integrity and ethanol and glucose metabolism in the phloem and cambium of burned trees?



Optical and photonic approach (CNR-INO)

Q2) How could we identify new biochemical markers of delayed death trees in these stem compartments?



Optical and photonic approach (CNR-INO)

Q3) How could we predict the possible scenarios resulting from the release of burned-vital trees selected by biosensors and what are the implications for forest restoration planning in post-fire sites?



Post-fire delayed Tree death based model approach development (CNR-IRET)





OBJECTIVES: 'MAP4FIRE' PROJECT



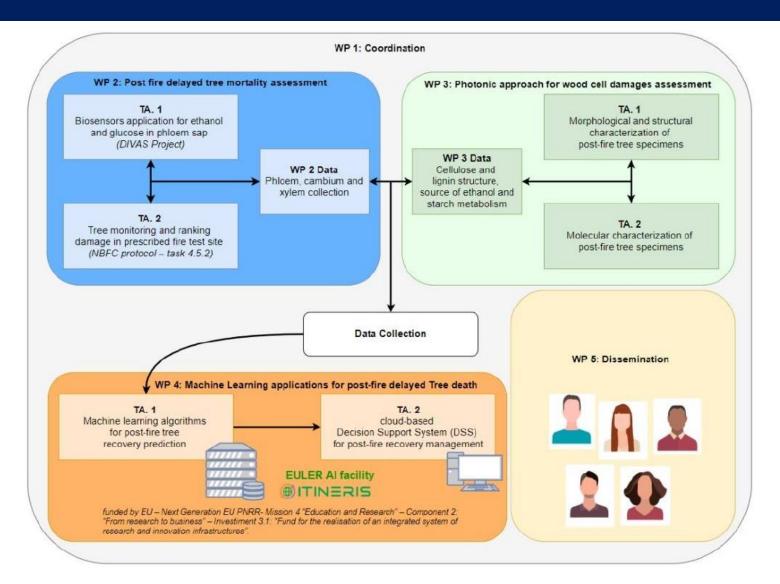
- a) assessing the fate of scorched trees by using ethanol and glucose biosensors (developed in DIVAS project);
- b) morphological/structural and molecular/functional characterisation of post-fire tree samples (xylem, cambium and phloem) by a multimodal approach using non-linear optical (NLO) microscopy techniques;
- c) develop a decision tree based machine learning model for:
 - i) estimating the fate of scorched trees (matching visual, optical and physiological data);
 - ii) predicting scenarios resulting from harvesting of scorched trees or their release based on visual assessment and biosensor approach in terms of fire risk and human safety.





SCHEMATIC REPRESENTATION OF THE MAP4FIRE PROJECT





Researcher	Inst. affiliation	Professional	_
Alessio Giovannelli	CNR-IRET PI	Senior Researcher	WP1
Eleftherios Touloupakis	CNR-IRET	Researcher	WP2
Maria Laura Traversi	CNR-IRET	Technician CTER	_
Alessandro Montaghi	CNR-IRET	Lead Technologist TD	WP4
Riccardo Cicchi	CNR-INO COPI	Senior Researcher	WP3
Elisabetta Baldanzi	CNR-INO	Senior Technologist	WP5

Gantt

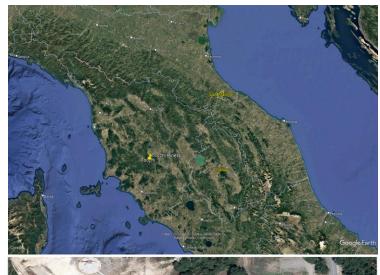
quarter	ı	П	III	IV	V	VI	VII	VIII
Coordination (WP1)								
Post-fire delayed tree death (WP2)								
Photonic mediated approaches (WP3)								
ML training and DSS prototyping (WP4)								
Outreach and dissemination (WP5)								





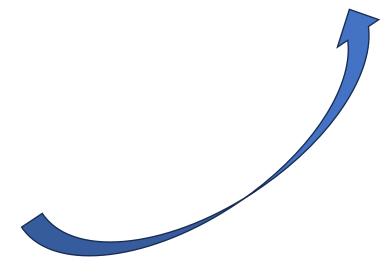
METHODS - WP2: ASSESSMENT OF THE FOREST STRUCTURE (CNR-IRET)







Forest structure analysis by Mobile Laser Scanner: *Pinus pinaster* forest (UNIFI_DAGRI)



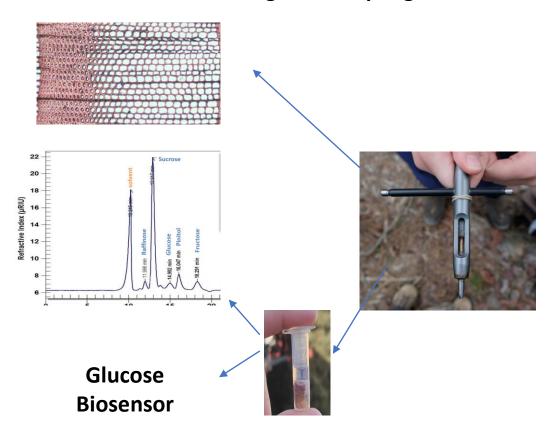




METHODS - WP2: TREE GROWTH MONITORING AND GLUCOSE-ETHANOL DETERMINATION (CNR-IRET)



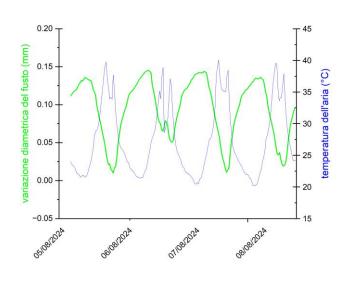
Monitoring and samplings







Real time monitoring



Tree ring analysis





METHODS - WP2: PRESCRIBED FIRE (CNR-IRET)



Test site 1: Prescribed fire (Pineta di Tocchi – Si)

Regolamento Forestale n° 2019/11/R

TITOLO II Tutela dell'area forestale

Prescribed fire is a planned fire; it is also sometimes called a "controlled burn" or "prescribed burn," and is used to meet management objectives.

A prescription is a set of conditions that considers the safety of the public and fire staff, weather, and probability of meeting the burn objectives.













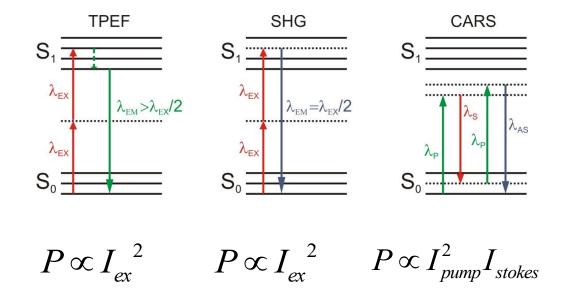






METHODS - WP3: NON LINEAR OPTICAL (NLO) MICROSCOPY TECHNIQUES (CNR-INO)





Advantages of non-linear interactions

- High intrinsic spatial resolution
- High selectivity of excitation
- Low photobleaching and photodamage
- Reduced scattering
- 3D optical sectioning capability

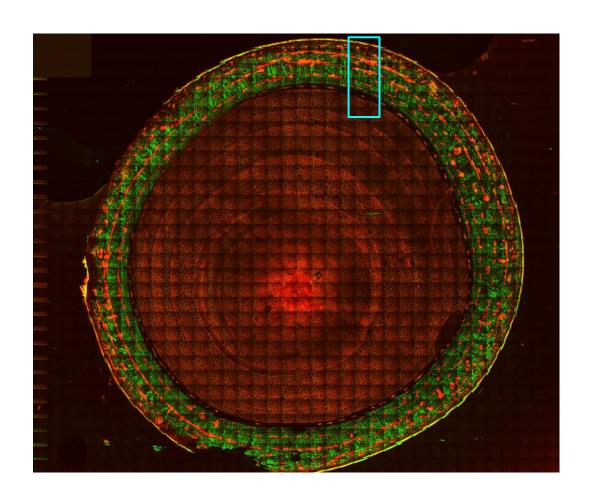
- TPEF (two-photon excited fluorescence)
- SHG (second-harmonic generation)
- CARS (coherent anti-stokes Raman scattering)

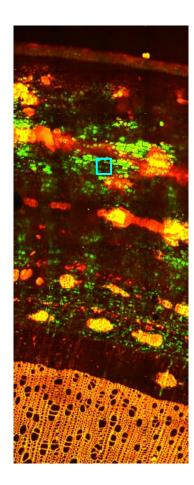


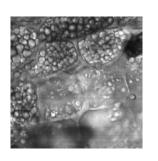


METHODS - WP3: NON-LINEAR MULTIMODAL IMAGING OF TREE STEM (CNR-INO)

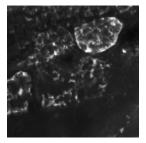




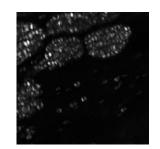




CARS
Lipid membranes



TPF
Lignin and cellulose



SHG
Starch and cellulose





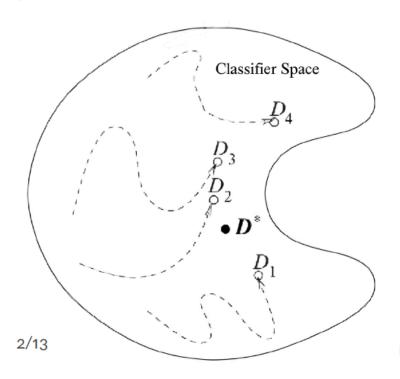




Ensemble learning

Theoretical background

Ensemble learning is a **machine learning paradigm** where multiple models, typically called *base learners*, are combined to solve the same task in order **to improve predictive performance and robustness**.



The computational reason for combining models: D^* is the optimal (*hypothetical*) models (e.g., classifier) for the problem, the closed space shows the space of all models, the dashed lines are the hypothetical trajectories for the models during training.

The **objective** of the ensemble is that aggregating the models (e.g., by some voting strategy) will produce a combined classifier closer to D^* than one randomly chosen from the classifier space.

Kuncheva, L. I. (2014). Combining pattern classifiers: methods and algorithms. John Wiley & Sons.





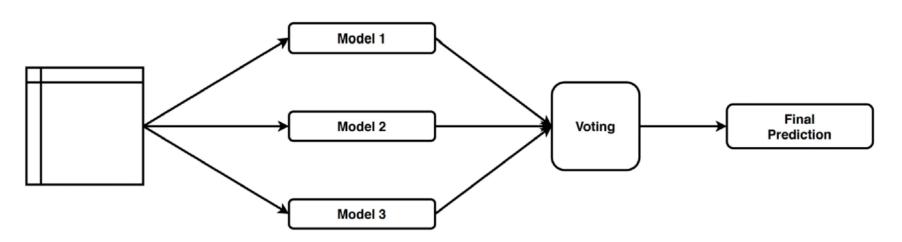




Ensemble learning: software architecture

Theoretical background

In practical terms, the above can be translated into the following software architecture. Suppose we are given a set of T=(2n+1) individual classifiers ("base learners") $\{h_1\cdots,h_T\}$ and our tasks is to combine h_i 's to predict the class label from a set of l possible class labels $\{c_1\cdots,c_l\}$.



Kuncheva, L. I. (2014). Combining pattern classifiers: methods and algorithms. John Wiley & Sons.









Ensemble learning: voting

Theoretical background

For a given instance \mathbf{x} , the output labels $h_i(\mathbf{x}) = (h(x)_i^1, \dots, h(x)_i^l)^\top$, with $i = 1, \dots, T$ are combined using a **voting strategy**. Popular voting methods include:

1. **majority voting**: the final class label is the one that receives more than half of the votes;

$$H(x) = \begin{cases} c_j & \text{if } \sum_{i=1}^T h_i^j(x) > \frac{1}{2} \sum_{k=1}^l \sum_{i=1}^T h_i^k(x), \\ \text{rejection} & \text{otherwise.} \end{cases}$$

2. **plurality voting**: the final class label is the one that receives the largest number of votes;

$$H(x) = c_{\arg\max_{j} \sum_{i=1}^{T} h_{i}^{j}(x)}$$

3. **weighted voting**: similar to plurality voting, but each classifier h_i is assigned a weight w_i .

$$H(x) = c_{\arg\max_{j} \sum_{i=1}^{T} w_i \cdot h_i^j(x)}$$

Kuncheva, L. I. (2014). Combining pattern classifiers: methods and algorithms. John Wiley & Sons.

4/13









Machine Learning Algorithms (ML) models

Theoretical background

Model diversity within an ensemble is a critical factor for enhancing both accuracy and generalization performance.

In the first phase of **WP4** (*Task 1*), various supervised machine learning algorithms will be identified to form the ensemble. To avoid indecision scenarios, the total number of selected algorithms will be odd (2n + 1). The selection will be guided by the following criteria:

- The algorithms may be based on rule-based "IF-THEN" learning algorithms (e.g., decision trees, rule lists, ensembles with rule extraction capability);
- 2. for completeness, the set of algorithms should cover the main families of supervised methods, in order to explore the classifier space as thoroughly as possible;
- 3. The algorithms must have been successfully applied in previous scientific studies.

Kuncheva, L. I. (2014). Combining pattern classifiers: methods and algorithms. John Wiley & Sons.









Explainable Artificial Intelligence (XAI)

Theoretical background

Explainable Artificial Intelligence (XAI) aims to make the behavior and decisions of machine learning models transparent, interpretable, and understandable to human users.

- In the context of a rule-based Decision Support System (DSS), XAI techniques are crucial to ensure that the recommendations generated by the system can be traced back to understandable reasoning steps.
- XAI methods support transparency by presenting each decision as a set of interpretable rules, allowing users to verify which input conditions led to a specific output.
- By exposing the logic behind both individual rules and aggregated decisions (e.g., through voting), XAI ensures accountability and builds trust in the DSS among non-technical stakeholders.









Supervided dataset

Explanable Rule-Based DSS

Given a supervised dataset $mathcalD = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$, where:

- $\mathbf{x}_i \in \mathbb{R}^d$ is a **feature vector** representing the attributes collected for instance i, derived from activities performed within other Work Packages (WPs);
- $y_i \in \mathcal{Y}$ is the **label** manually assigned by a **domain expert** in the forestry sector, representing a suggested intervention based on observed symptoms of **tree vitality**. These annotations may have been supported by **visual inspections** and **professional judgement**. The labels y_i can be either:
 - Discrete classes (e.g., "urgent intervention", "monitoring", "no action required"), or
 - Structured decisions involving multiple dimensions (e.g., intervention type + urgency level).

Note: manual annotations by experts must be consistent and well-documented to ensure generalizability of the extracted rules.









Global rule set

Explanable Rule-Based DSS

Train a rule learning algorithm, such as **RIPPER** (Repeated Incremental Pruning to Produce Error Reduction), on the labeled dataset $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$, to **generate a global rule set**:

$$\mathcal{R} = \{r_1, r_2, \ldots, r_m\}$$

Each rule r_i is of the form:

$$r_j$$
: IF $c_j(\mathbf{x})$ THEN y_j

where $c_j(\mathbf{x})$ is a conjunction of feature-based conditions, and $y_j \in \mathcal{Y}$ is the associated class label.

This rule set \mathcal{R} is stored and forms the basis for the DSS inference.





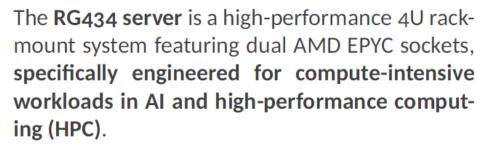




Models Traning

Explanable Rule-Based DSS

The computational operations will be carried out using the computing infrastructure acquired through the ITINERIS project funded by EU - Next Generation EU PNRR.



In this configuration, the system includes the 5 X NVIDIA H100 NVL 94GB GPUs are designed for:

- large-scale AI training;
- high-throughput inference;
- memory-intensive HPC workloads.











Objective

Explanable Rule-Based DSS

The goal of the proposed Explanable Decision Support System (DSS) is to support human decision-making by providing interpretable rule-based suggestions derived from a labeled dataset.

Given a new input instance \mathbf{x} , the system must identify a return a set of k decision rules that are relevant to the instance and **present them to the human operator as justifiable recommendations**.

Given a new instance \mathbf{x} , the **DSS** aims to:

- 1. Apply an ensemble of interpretable models (e.g., rule-based learners) to the input instance \mathbf{x} , generating a set of activated or predicted rules;
- 2. Aggregate the outputs of these rules (e.g., via majority voting or weighted voting) to produce a preliminary decision $\hat{y} \in \mathcal{Y}$;
- 3. Retrieve the top k most similar rules to \mathbf{x} from a precomputed global rule set (e.g., using k-NN), and present them as interpretable justifications to the human operator.





METHODS - WP5: DISSEMINATION AND COMMUNICATION ACTIVITIES



- The results of the project will be communicated through a specific press campaign
 - ✓ press release
 - ✓ websites and official portals of partner institutions
 - ✓ social media campaign
 - ✓ webTV
- Interviews and videos will be distributed through all communication channels of the CNR and partner institutions
- Communication initiatives related to CNR exhibitions and outreach projects
- Specific professional partership with press agency and services will be evaluated





OUTPUT/OUTCOME/IMPACT



MAP4FIRE: multidisciplinary approach in which traditional forest competences are merged with biotechnology, imaging and AI technologies with the aim to develop a user-friendly protocol able to support the decision of the technicians in the field.

- Technological innovation and/or industrial applications.
 - integration of innovative technology (KET, Key enable technologies);
 - green technology as a tool to reach carbon neutrality within 2050 (European Green Deal).
- Scientific community reinforcement.
 - new model development of restoration ecology based on nature-based solution;
 - contribution to EU 2030 Biodiversity strategy and New Biodiversity Future Centre (NBFC);
 - support the strategy 'One Health'
- Level of research internationalization.
 - European Union priorities such as forest restoration (EU Forest Strategy, COM (2013) 659);
 - minimization of water pollution (Water Framework Directive, 2000/60/EC);
 - recovery of carbon sinks (2050 EU Low-Carbon Economy Roadmap, COM (2011) 112).







Grazie per l'attenzione arrivederci!

A cura di Alessio Giovannelli