A Holistic Fire Management Ecosystem for Prevention, Detection and Restoration of Environmental Disasters

TREEADS D4.1 Live doc. TREEADS SOCIO-TECHNOLOGICAL Solution for Prevention and Preparedness. V1

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0.2	31/01/2023	USAL	Draft for internal review (first)
0.3	16/02/2023	USAL	Draft for final internal review
1.0	22/02/2023	USAL	Final submitted version

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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviation	Meaning
AAM	Alkali-activated material
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
GGBS	Ground Granulated Blastfurnace Slag
GSD	Ground Sample Distance
ISO	International Organization for Standardization
LiDAR	Light Detection and Ranging
LSTM	Long Short – Term Memory
ML	Machine Learning
NER	Named-entity recognition
NTUST	National Taiwan University of Science and Technology
OPC	Ordinary Portland Cement
PFA	Pulverized Fly Ash
PNOA	Spanish National Aerial Orthophoto Program
PRISMA	Hyperspectral Precursor of the Application Mission
PWA	Post-wildfire Wood Ash
RINA-C	Rina Consulting S.p.A.
SS	Sodium Silicate
SVM	Support Vector Machine
TDlib	Telegram Database Library
UniNa	Università degli studi di Napoli Federico II
WA	Wood Ash
WUI	Wildland Urban Interface
YOLO	You Only Look Once

Executive summary

This document defines the first version (D4.1, V1) of the TREEADS SOCIO-TECHNOLOGICAL solution for Prevention and Preparedness, based on the functional requirements of the Description of the Action (DoA), the technical meetings with TREEADS WP4 partners and the D2.3 for the Prevention and Preparedness Understanding and Technical Requirements.

In this document, all tasks of WP4 detail their development process, thanks to which the building of a demonstrator to showcase the TREEADS Technology Solutions for Prevention and Preparedness has started. The tasks of WP4 are listed as follows:

- T4.1: TREEADS Socio-technological toolset for secure incident-management, decision-making and communication – **Fire Daily Forecasting**

  The objective of this task in the first deliverable is to provide the first comprehensive review of the anthropogenic causes of forest fires. In this way, it provides a framework for future analyses and discussions for the TREEADS consortium, which will develop a European fire risk forecasting service with daily updates.

- T4.2: TREEADS high-fidelity fire and smoke propagation forecasting system – **Fire Simulation Models**

  The aim of this task is to model the spread of forest fires in an approximate way in order to increase the knowledge of forest fire dynamics, and to create useful tools for the daily work of forest fire managers.

- T4.3: TREEADS early warning system and landscape management though an enhanced Common Operation Picture and coordination and command systems – **Early Warning System**

  This task is being built upon an early warning system by utilising a four layered approach that will provide a more detailed and better understanding in the European EFFIS systems. TREEADS early warning system will take advantage of additional data sources to enrich the information available and provide added value functionalities that allow prompter detection of fires, a more accurate analysis of the situation, and better decision support for the response phase.

- T4.5: TREEADS Agroforestry index for enhanced land requalification and reinforcement learning – **Detailed Forest Mapping**

  This task will provide a highly detailed forest mapping with information about plant and tree species in the forest and their physical characteristics. Digitizing variables related to the territory, terrain, vegetation (fuel) and meteorology is key for forest fires prevention and preparedness through the use of current technology. Therefore, a previous evaluation of the available technologies, their capabilities and limitations according to the proposed goals and objectives is carried out in this deliverable.

- T4.6: TREEADS Big Data Analytics and Artificial Intelligence powered fire danger index and near event enablers – **Social Media Analysis**

  The purpose of this task is monitoring fire events expressed on social media by individuals, including online users who detect a fire or potential fire, such as smoke. To

do this, specific search criteria like keywords, accounts, and bounding boxes are used to collect social media data in real-time. The data is then analyzed to remove irrelevant information in order to reduce the noise, assess the relevance of a post by using classification techniques, and add geographic information by automatically identifying location-related words in the textual content of a post and associating them with exact coordinates.

- T4.7: TREEADS Fire-resilient materials for buildings and infrastructures – **Fire Resilient Materials**

  This task evaluates the valorisation potential of selected secondary raw materials using alkaline activation technology for the development of building materials with improved fire resistance properties. Suitable sets of secondary raw materials, such as wood from forest fires and other types of industrial or natural by-products, will be identified and appropriately tested. Fire resistant construction elements or materials will also be reproduced.

- T4.4: TREEADS Integrated fire Management systems, practices and Services – **Fire Prevention and Management System** / **Fire Risk Analysis**

  This task builds the TREEADS integrated fire management systems (IFMS). The Integrated Fire Management System is the main element to integrate the different capabilities described above for prevention and preparedness. This ensures that wildfires are managed in a way that the safety of people, housing, economic growth and ecosystem services are maintained or increased.

The Common document approach with all partners reporting on the same document provides a better understanding of all Partners' work on the WP. Furthermore, the integration of the different tools (T4.1, T4.2, T4.3, T4.5, T4.6, T4.7) in the Integrated Fire Prevention System (T4.4) shows how this prevention module is integrated in the TREEADS platform in a holistic way.

For the next version of this deliverable (D4.2, V2), all tasks of WP4 will be further detailed, and the full demonstrator will be developed.

Introduction

Purpose and scope

In this deliverable all tasks of WP4 detail their development process. As a result, this deliverable **establishes a clear and unified vision** for **prevention and preparedness** of wildfires in the TREEADS project. In addition, this deliverable stablishes the roadmap for showcasing the TREEADS Technological Solutions for Prevention and Preparedness through a demonstrator that will be developed in the second version (D4.2, V2 planned for October 2023). Last but not least, the integration of the prevention and preparedness module within the TREEADS platform is clarified in this deliverable.

The goal of this deliverable (D4.1, V1) is focused on developing a theoretical-practical approach for the different tasks within WP4 under a common connected thread for the prevention and preparedness of wildfires.

Overview

The approach adopted for prevention and preparedness relies on the technologies developed in the different tasks of WP4 as well as on their connection and integration within the TREEADS platform. Thus, the main core of the document D4.1 is **describing a theoretical-practical approach for the different tools developed in tasks involved (T4.1-fire forecasting; T4.2-fire simulation models; T4.3-early warning system; T4.5 detailed forest mapping; T4.6-social media analysis; T4.7-fire resilient materials), as well as their integration within a prevention module (T4.4-fire integrated prevention system)**. Additionally, the deliverable details the integration of the prevention and preparedness module within the TREEADS platform. Finally, some preliminary conclusions of the first version of the prevention and preparedness module have been included.

Document structure

The deliverable is structured based on the Guidelines on FAIR Data Management in Horizon 2020, Version 3.0, 26 July 2016, and contains the following information:

- Executive summary
- Section 1 – Introduction: provides the goals, scope and overview of this deliverable.
- Section 2 – Technological innovations: establishes a brief state-of-the-art of the different technologies associated within each task as well as the main contributions beyond the state-of-the-art that will be developed in TREEADS.
- Section 3 – Solution for prevention and preparedness: describes in detail the theoretical-practical development for each task (T4.1-fire forecasting; T4.2-fires simulation models; T4.3-early warning system; T4.5-detailed forest mapping; T4.6-social media analysis; T4.7-fire resilient materials), as well as their integration within a prevention module (T4.4-fire integrated prevention system).

- Section 4 – Integration within the TREEADS platform: presents the integration plan towards the initial development of the demonstrator (to be presented in October 2023, within D4.2, V2).
- Section 5 - Conclusions of the deliverable and brief presentation of the following steps towards the development of the demonstrator (to be submitted in October 2023, in D4.2, V2).

Relation with other deliverables

This deliverable is related to the following WPs, tasks and deliverables based on the Grant Agreement:

- WP2 Task 2.3- Prevention and Preparedness Understanding and Technical Requirement: Task 2.3 specific functional and non-functional requirements in the prevention and preparedness phase of wildfires were applied as input to the current deliverable.
- WP3 Deliverable D3.2- Live doc TREEADS Organisational Structural and Sociotechnical factors V1. Tasks 3.1, 3.2, 3.3, 3.4 and 3.5 will detail all organisational structural and sociotechnical factors including standards, interoperability and guidelines.
- WP3 Deliverable D3.1- Report on Ecological and environmental Models of Wildfires. Task 3.1. compiles and details the necessary studies about ecological and environmental models, thus providing a clear roadmap about the definition and implementation of the TREEADS models and services during the lifecycle of the project.
- WP3 Deliverable D3.5- Task 3.6 establishes the architecture of the TREEADS platform and particularly some back-end modules related with prevention and preparedness.
- WP5 Deliverable D5.1- Task 5.1 establishes a solution for detection and response based on the four-layer approach. In particular, Task 4.3 will advance on an Early Warning System based on satellites which will perform as input data in Task 5.1, that can be improved based on zeppelin and drones.
- WP7 Deliverable 7.1- Task 7.2 establishes an incremental deployment strategy that follows a step-by-step procedure adapted in this case to different demands in prevention and preparedness provided by end-users.

Technological innovations

This section presents a summary of the current technological innovations (state-of-the-art) for each task of WP4 in the prevention and preparedness phase as well as the expected technological innovations that will be developed in TREEADS.

State-of-the-art

FIRE DAILY FORECASTING [ANTHROPOGENIC CAUSES OF WILDFIRES] (T4.1)

Background

Wildfires are a significant ecological disturbance affecting the balance of ecosystems and their natural resources. They result from an ignition, a combination of fuel sources, and conditions that allow a fire to grow. Although wildfires may have natural causes, such as lightning and other geological processes, the current state of knowledge on the topic attributes to anthropogenic factors more than 90% of the fire occurrences (Ciesielski et al., 2022; Ganteaume et al., 2013; Mancini et al., 2018; Oliveira et al., 2017; Pozo et al., 2022; Rodrigues et al., 2016). These factors include accidental and intentionally ignited fires and the socio-ecological drivers that enable wildfires to occur.

To better understand the causes and circumstances driving wildfire occurrence and contribute to the development of the TREEADS Platform solutions, the present review reaches out to the literature of environmental management, sustainability, geography, and urban planning to identify factors that lead to wildfire occurrence from multiple sources. The preliminary results are presented in a two-fold categorization, with the socio-ecological factors presented in the first section and a list of practices that potentially lead to wildfires in the second. The categorization structure follows references in the literature and dialogues with present efforts by TREEADS partners to develop socio-technological solutions for wildfire prevention and preparedness.

The current version will be revised and complemented through iterations with WP4 partners. It will also be prepared for publishing in the coming months.

Objectives

The objective of this product is to provide the first comprehensive review of the anthropogenic causes of wildfires, providing a framework for the future analysis and debates of the TREEADS consortium. More specifically, the effort is part of the TREEADS Platform development. It intends to support the creation of a secure incident-management toolset that incorporates the relevant socio-technological factors in its decision-making and communication processes with stakeholders associated with the three phases of wildfire management: prevention and preparedness, detection and response, and restoration and adaptation.

Structure of this literature review

Following this introductory section, the second section of this report presents the literature review process conducted by the Copenhagen Business School team in 2022. The third section presents the main findings.

The causes of wildfires are presented into two broader categories. The first, presented as the socio-ecological drivers of wildfires, introduces the socioeconomic and geographical characteristics currently associated with higher wildfire occurrence. Factors listed in this first category are not per se direct causes of wildfires but have increasingly been known to enable activities that lead wildfires to occur. The second section, presented as human behaviour, lists social activities directly associated with wildfire occurrence. Activities listed in this section are known to cause wildfires directly and should be considered a fire hazard where they occur frequently.

The present literature review is an ongoing research effort and should be complemented through the TREEADS WP3, WP4, and WP8 iterations during the M13-22 months of the project.

<u>The process of Literature Review</u>

CBS conducted a literature review on socioeconomic factors and human behaviours that could potentially promote wildfire ignition. The purpose of the analysis is to identify the current state of research, collect the necessary knowledge, and build a secure incident management toolset that will consider all socio-technical factors. The tool will help the TREEADS Platform with decision-making and communication with all respective stakeholders.

The task began with the gathering of academic articles. Google Scholar was used for the search, and all the searches were conducted in English. To obtain a better overview of the results, there were no publication date or geography restrictions in our research. The search terms "socioeconomic factors" AND "wildfires" AND "Human behaviour" AND "wildfires" were used. An initial pool of 238 articles was created. Following an initial review of the abstract and conclusion sections, the most relevant articles were selected (which can be found in the reference section). The software NVivo was utilized to facilitate the in-depth analysis and identification of the most prevalent factors.

Despite the significance of the factors that predispose people to start fires, this preliminary analysis concludes that additional research is required.

Figure 1. World cloud of the most frequent words in the analysed literature

Socio-ecological drivers of wildfires

Wildland – Urban Interface

The Wildland–Urban Interface (WUI), which represents the border between the urban area and forests or open land, creates landscapes prone to forest fire ignitions. Its development in the Global North is associated with the desire of populations to be close to nature. It results in an increase in the fire hazard and the vulnerability of people and infrastructure (Vigna, Besana, Comino and Pezzoli, 2021).

Research estimates that the WUI area has expanded by 52 % between 1970 and 2000, increasing the risk that wildfire presents to communities and ecosystems (Theobald and Romme, 2007). These increases in WUI are associated with the 20th-century population expansion and the building of roads, railways, and tracks (Ciesielski et al., 2022; Keeley & Syphard, 2018; Lan et al., 2021; Mancini et al., 2018; Rodrigues et al., 2016). The number of vehicles can also potentially impact wildfire regimes due to the increased mobility of populations and forest penetration (Kolanek et al., 2021).

Rural Abandonment

Rural abandonment is recognized by research as a cause of exacerbated fire regimes. Abandoned agricultural land typically goes through a phase of fallow land, with a high level of flammable vegetation, before turning into stable forests (Vigna, Besana, Comino and Pezzoli, 2021). Over the past few decades, these processes have been observed in Europe's Mediterranean region, resulting in increased shrubland and woodland areas and decreased grassland and arable land. These processes simplify the landscape mosaic and increase the number of fuel loads. (Ganteaume et al., 2013; Pozo et al., 2022).

Inadequate Forest Management

Inadequate forest management policies such as fire exclusion, grazing practices, and not thinning out specific species can lead to an accumulation of flammable material close to populated neighbourhoods (McCool, Burchfield, Williams and Carroll, 2006; Lenart, 2010; Faulkner, MCFarmlane and McGee, 2011). Wildfire management should focus on "fuel management," removing burnable vegetation around residual areas to reduce the risk of communication in the WUI (Jakes et al., 2011; Lenart, 2010). Trust between citizens and authorities or fire operators plays a crucial role in the social acceptance of fire management activities. Similarly, trust in information and agencies influences the relationship between fire risked communities and fire-management operators (Sharp, Thwaites, Curtis and Millar, 2013).

Socioeconomic vulnerability

Different studies indicate that socioeconomically vulnerable regions with persistent unemployment, rural poverty, socioeconomic disparities, organized crime, and an aging population, or teenagers who are neither in employment nor education or training- are more likely to be associated with more frequent fire events (Canepa & Drogo, 2021; Dondo Bühler et al., 2013; Mancini et al., 2018; Oliveira et al., 2017; Pozo et al., 2022). These age groups appear to be less cautious with daily routines, making fires more likely to happen.

Populations with higher educational levels have better access to prevention information and knowledge of natural resource conservation and are more environmentally conscious.

Therefore, they may be more aware of fire hazards, develop safer habits, and behave more cautiously. (Canepa & Drogo, 2021; Dondo Bühler et al., 2013).

Population density

Research indicates that population density has two contradictory effects on fire behaviour (Dondo Bühler et al., 2013). On the one hand, a high population density suggests human presence and anthropogenic pressure, which increase the likelihood of human fire ignition (Ciesielski et al., 2022; Dondo Bühler et al., 2013; Keeley & Syphard, 2018; Kolanek et al., 2021). However, wildfires may occur less frequently when urbanization and population density exceed a certain threshold. This can be due to the loss of open spaces, restricted fuel availability, landscape homogeneity, or increases in local firefighting capabilities (Dondo Bühler et al., 2013; Mancini et al., 2018; Pozo et al., 2022).

Indigenous populations

Countries and regions with indigenous populations can potentially lead to accidental fires due to the vulnerability of these populations. Issues such as high unemployment rates, limited access to education, a prevalence of rural living, and a reliance on natural resources for food security are also associated. Also, indigenous populations reside close to natural and protected regions, using them as grazing grounds for livestock or harvesting natural resources like nuts and medicinal plants. In addition, indigenous populations tend to reside near popular tourist areas (such as national parks) that receive significant numbers of people and are likely to contribute to an increase in summer wildfire risk. However, definite conclusions cannot be drawn without further socioeconomic analyses. (Pozo et al., 2022)

Human behaviour

<u>Land Use change</u>

Although in the Global South, deforestation is often due to human-caused burning to convert land to agriculture (Vigna, Besana, Comino and Pezzoli, 2021). These practices have long-lasting cultural roots (Tedim, Leone and Xanthopoulos, 2016) and are associated with traditional cropping systems (Ciesielski et al., 2022; Mancini et al., 2018; Pozo et al., 2022).

In regions where the proportion of agricultural land remains high, one of the leading wildfire causes is the irresponsible use of fire in agricultural practices (e.g., burning stubble), which is also connected to the progressive loss of “fire culture” among rural populations (Ciesielski et al., 2022; Ganteaume et al., 2013; Pozo et al., 2022; Rodrigues et al., 2016).

<u>Tourism</u>

The recreational use of forests by tourists is a potential cause of wildfires. It is expected that the increased use of forests for recreation and the extended tourism seasons due to climate change will most likely increase the risk of forest fires. (Ganteaume et al., 2013; Mancini et al., 2018; Vigna et al., 2021).

The recent reduction of human activities due to local lockdowns during the COVID-19 crisis was correlated to a reduction in the occurrence of wildfires, highlighting the human factor related to wildfire occurrence (Bouguettaya et al., 2021).

<u>Deliberate fires</u>

Deliberate fire setting in areas close to residential areas (primarily by children – problematic fire setting and simply fire-play) (Willis, 2005).

Human-made hazards

Specific human-made hazards such as technological failures, pollution, and industrial by-products can increase wildfire potential (Victoria, 2003).

Evacuation planning

With the objective of supporting evacuation planning for a safer and more efficient evacuation, NCSRD investigated the use of machine learning techniques for anomaly detection in human trajectory data. Literature review shows many techniques in the field of anomaly detection that examine human as well as vehicular movement.

Anomaly detection using trajectory data can be achieved with several algorithms and can be applied in many types of data (video, GPS etc). There are standard Machine Learning and Deep Learning methods in the literature that resolved this problem efficiently. In a recent thesis (Moavinis, 2022), spatial outliers were detected using the combination of DBSCAN clustering algorithm with the Hausdorff distance, Support Vector Machine classifier and the Generalized Sequence Pattern algorithm. Methods were evaluated with the help of the Geolife dataset (Yu Zheng et al., 2008, 2009, 2010) to which an automatic labeling process was applied. The automatic labeling technique can be used in our method in order to perform some supervised Machine Learning techniques for anomaly detection. Although in this work the temporal outliers cannot be detected, that is why we have to modify or change the algorithms used.

A standard deep learning technique that is successfully used for anomaly detection in human mobility data is GANs. (Kathryn Gray et al., 2018) use a Bidirectional GAN (BiGAN), which is a GAN that inlcudes an encoder, coupled with an infinite Gaussian mixture model (IGMM) to generate synthetic human trajectories, find route-based anomalies etc. Synthetic data generation solves the problem of limited ground truth anomaly data and can be used for the generation of outliers' trajectories in a forest using GPS data. IGMM-GANs method also uses a generator to create routes trained on latitude and longitude as well as latitudinal and longitudinal velocity. The examination of velocity can be very useful in a real-time evacuation case because very high or very low velocity values may indicate a dangerous situation such as an injury or a state of panic. The IGMM-GANs method has also great results in anomaly detection in case the data used are multimodal.

Another method that is used in several research works is real-time anomaly detection of human trajectories using Sequence to Sequence Networks. (Bouritsas et al., 2019) proposed a model that uses a Sequence to Sequence auto-encoder to detect abnormal movement in crowded scenes. The method uses trajectories to analyze the spatiotemporal movement of humans in an airport. The data that are used to test the model are synthetic and created using the NCSRD iCrowd simulator (Kountouriotis et al., 2014, 2016). Even though the method is tested in indoors synthetic data, we believe that the idea of using an LSTM autoencoder to implement anomaly detection is something we can test in our model because it is successfully applied in high dimensional data. Also, the iCrowd simulator can be employed to generate the synthetic data we need.

Although the previous methods are not applied in case of wildfire emergency, they contain useful methodology and techniques that can be adopted by our model to perform anomaly detection in case of evacuation due to wildfire.

FIRE DAILY FORECASTING [CLIMATIC AND FUEL FACTORS OF WILDFIRES. USE OF BAYESIAN NEURAL NETWORKS TO THE WILDFIRE FORECASTING PROBLEM] (T4.1)

Wildfire is a natural phenomenon that is of uttermost importance for the global ecosystem, affecting the carbon cycle and shaping ecological development via disturbance and regeneration (Pausas & Keeley, 2009). However, wildfires affect negatively humans, posing a threat to human lives, the economy, and infrastructure (Pettinari & Chuvieco, 2020). Presently, global annual area burned is estimated to be approximately 420 Mha (Giglio et al., 2018), which is greater in area than the country of India. Thus, being able to model and understand the fire dynamics turns into a necessity, especially under the umbrella of climate change that threatens to inflate the negative impacts of wildfires on humanity in the next years (Pausas & Keeley, 2021). Moreover, as the climate warms, we are seeing increasing impacts from wildland fire (Coogan et al., 2019). In this context, accurate short-term wildfire forecasting is important for mitigating the negative effects of wildfires. However, the problem is extremely challenging as wildfires are a stochastic process that is driven by the complex interactions of various fire drivers, namely the climate, vegetation, and human activity (Archibald et al., 2013). Furthermore, fire activity can be examined across a vast range of scales — from ignition and combustion processes that occur at a scale of centimetres over a period of seconds to fire spread and growth over minutes to days from metres to kilometres (Taylor et al., 2013).

In order to mitigate the complexity of the problem several studies consider weather as a proxy for fire danger and are focusing on identifying the links between wildfires and fire weather. (Abatzoglou et al., 2019; Bedia et al., 2015). In this direction, several traditional fire indices are used operationally in many parts of the world for predicting fire danger. The most commonly used index is the Fire Weather Index (FWI) (van Wagner et al., 1974). FWI is an empirical index that relies on meteorological forecasts (temperature, humidity, wind speed, and precipitation) to derive fire danger predictions. It consists of different components that account for the effects of fuel moisture and wind on fire ignition and spread. The final outcome is the mapping of fire danger in 6 classes from very low to extreme. FWI consists of six components. The first three (Fine Fuel Moisture Code, Duff Moisture Code, and Drought Code) follow daily the moisture contents of forest fuel and are linked with the wind in pairs to form the two intermediate components (Initial Spread Index, Adjusted Duff Moisture Code). These intermediate layers represent the rate of spread and the amount of available fuel to be burnt. Finally, the last component (Fire Weather Index) is a combination of the two intermediate layers and represents the intensity of the spreading fire.

Following a different path, several works use Machine Learning (ML), trying to model the complexity of the problem in a data-driven way. Besides, the increasing amount of available data, related to wildfire ignition and spread, like the Remote Sensing data, facilitates the inception and growth of these methods. In the early years, Artificial Neural Networks and the Random Forest method were mostly used by the research community in order to forecast fire danger using meteorological and remotely sensed data (Jain et al., 2020). Other methods have also been used, like the MaxEntropy (De Angelis et al., 2015) method, Support Vector Machines

(Sakr et al., 2011), Deep Belief Networks (Dutta et al., 2016) as well as ensembles of different methods to predict the occurrence of wildfires in different temporal and spatial scales.

However, the recent growth of Deep Learning (DL) has started to penetrate the wildfire-related community. Camps-Valls et al. (2021), and Reichstein et al. (2019) have suggested DL as a well-suited methodology for modelling the complex interactions that occur in Earth System-related problems and especially wildfires occurrence and spread. Thus, there are several works that follow this direction using DL methods beyond classical Artificial Neural Networks for forecasting short-term wildfire danger. Particularly, Zhang et al. (2019) have used a Convolutional Neural Network (CNN) architecture in 5kmx5km spatial resolution for predicting the next day's wildfire danger in Yunnan province in China. The same authors (Zhang et al., 2021) extended their work and used again CNNs and Multilayer Perceptrons to produce seasonal fire susceptibility maps on a global scale. Following the same direction, Bergado et al. (2021) have used fully Convolutional Neural Networks to produce daily maps of the probability of a wildfire burn in the next seven days. Bjanes et al. (2021) used an Ensemble model based on two deep learning networks for wildfire susceptibility mapping in Chile. Moreover, Huot et al. (2020) treated wildfire forecasting as a segmentation task and used U-Net-inspired architectures to predict wildfire danger in the US in different temporal resolutions. Finally, Kondylatos et al. (2022) have used Long-Short Term Memory architecture to predict next-day wildfire danger in the Eastern Mediterranean and explainable AI to understand the decision behind the model's predictions. Furthermore, they compared their model's skill with the traditional FWI, demonstrating the superior performance of the former.

Another important field of study is the fuel properties since they are a required input in all fire behaviour models, whether it be a simple categorical vegetation type, as in the Canadian Fire Behaviour Prediction (FBP) System, or as physical quantities in three-dimensional space (e.g., FIRETEC model; Linn et al., 2002). Research to predict fuel properties has been carried out at two different scales: (i) regression applications to predict quantities such as the crown biomass of single trees from more easily measured variables such as height and diameter, and (ii) classification applications to map fuel type descriptors or fuel quantities over a landscape from visual interpretation of air photographs or by interpretation of the spectral properties of remote sensing imagery. Relatively few studies, however, have employed ML to wildfire fuel prediction, leaving the potential for substantially more research in this area (Jain et al., 2020).

By providing a measure of the wildfire danger for the next day(s), all the above works can contribute to better wildfire prevention and management and especially to better decision-making. However, all the methods only rely on the goodness of fit of Deep Learning methods to produce their outputs. Thus, the limitations of the DL methods like the lack of uncertainty of the predictions (Gal et Ghahramani, 2016), the miscalibration of the outputs, and the overconfident predictions (Srivastava et al., 2014) cascade to the wildfire danger forecasts. These limitations may be less significant in classic ML problems like image classification but are of uttermost importance in problems like wildfire forecasting, where a bad decision can put in danger human lives, properties, and the environment.

In order to surpass the limitations of Deterministic Deep Learning, we want to apply Bayesian Neural Networks (Jospin et al., 2020) to the wildfire forecasting problem. The stochastic nature of Bayesian Neural Networks, as well as the distributions that they put on the parameters, let them produce uncertainties for the predictions and induce better calibration. Moreover, BNNs can provide both aleatoric (uncertainty in the data) and epistemic (uncertainty in the model) uncertainty (Hüllermeier & Waegeman, 2021), which are both important in the current setting. Aleatoric uncertainty can provide a measure of the noise that is inherent in the data. In contrast, epistemic uncertainty can give us insights into the limitations of the model architecture and out-of-distribution data. Thus, these methods can provide more information about what the models know and what they don't know and go beyond mere forecasting. This can lead to the improvement of decision-making and ultimately to more trustworthy decisions, which are crucial for better wildfire management. For example, there could be a different treatment from the qualified authorities in cases where the model is sure that an area is highly vulnerable to being burnt than in cases where the model is highly uncertain about its predictions.

Therefore, the main contributions in the TREEADS project will be to:

- Use several Bayesian Neural Networks (BNNs) architectures for forecasting short-term wildfire danger. BNNs can provide uncertainties for the models' predictions, leading to the enhancement of the trustworthiness of the predictions and contributing to better decision-making. We want to try different BNN architectures and see how they compare to each other in terms of both accuracy and uncertainty estimates.
- Segregate between aleatoric and epistemic uncertainty. By measuring the aleatoric uncertainty of the models, we want to understand better how noisy the data we use is and try methods to mitigate the effect of this noise. In parallel, by measuring the epistemic uncertainty, we want to understand if the models are able to fit the data well and to acquire evidence about out-of-distribution data.
- Create a framework for using the uncertainty estimates provided by the BNNs in natural hazard forecasting settings. That means providing the metrics that are well-suited for these problems, the methods that can perform well in terms of accuracy, calibration, uncertainty estimation, and efficiency, and the best practices to perform BNNs in these scenarios.
- Check the uncertainty-accuracy trade-offs when testing in different temporal scales. That means examining how the uncertainty and accuracy change when we predict wildfire danger for the next day, the next two days, the next three days, etc.

Additionally, the use of neural networks such as U-NET for the segmentation of aerial and satellite images allows to achieve a classification of fuel types that can be used to improve the results obtained by the commented contributions.

FIRE SIMULATION MODELS (T4.2)

Understanding and predicting the complex process of wildfire spread is critical for those seeking to manage fire-prone ecosystems, particularly, in making prevention and preparedness decisions. The use of mathematical models to describe fire spread is not recent (Pastor et al., 2003), but the computational advances, the development of communication technology and the improvement in remote sensing information technology have exponentially increased the efficiency and applicability of wildfire modelling. There is currently a wide range of mathematical approaches and implementation of wildfire models and simulators applicable in forecasting wildfire spread. Generally, forest fire spread models can be divided in physical, quasi-physical, empirical and quasi-empirical models (Sullivan, 2009a, Sullivan 2009b). A *physical model* attempts to represent the physics and chemistry of fire spread; a *quasi-physical* model attempts to represent only the physics; an *empirical model* contents only statistical; and a *quasi-empirical model* uses some form of physical framework on which the statistical modelling is based. An amount of existing simulator models applicable in forecasting forest fire propagation can be found in Sullivan, 2009c and Papadopoulos et al., 2011. We must mention some of the most relevant existing systems: FARSITE (Finney, 1998), Prometheus (Tymstra et al., 2010), Bushfire (Johnston et al., 2005), and FIREMAP (Vasconcelos et al., 1992), among many others.

The historical evolution of fire propagation models begins with empirical models developed by engineers working with foresters and focused on the fire behaviour more than on the mechanisms of combustion and heat transfer. The next steps tried to incorporate in a simplified way some aspects of the combustion process such as the fire intensity, the effect of fuel moisture content, the mass lost during combustion, and the rate at which the fuel is fed into the flaming combustion, determined primarily by wind. This approach circumvented the more complex aspect of wildfire process and reduced mesoscale weather models to surface weather station data in a time when limited computing power was available.

The third-generation models use mechanistic combustion models and large-eddy simulation (LES) to define the flaming combustion and the mechanism of rate of spread (Bakhshaii et al., 2019). These wildfire models are then coupled to a computational fluid dynamic (CFD) or mesoscale weather model, allowing the simulation of substantial interaction between the fire and the atmosphere that occurs in extreme fire events such as those known as sixth-generation fires capable of modifying the climate and causing fire storms. The applicability of fire-atmosphere coupled models is still limited by their high computational cost. Some examples of fire-atmosphere coupled models are WRF-FIRE (Coen et al., 2012), ARPS/DEVS-FIRE (Dahl et al., 2015), and ForeFire/Meso-NH (Filippi et al., 2013), which use a multi-scale weather prediction model as a base, with quasi-physical fire spread and combustion models as an added module for the calculation of fire propagation, fluxes, and atmospheric variables.

In any case, **the use of wildland fire spread modelling and the tools developed around them has been relatively limited operationally due to the high level of uncertainty** (Rochoux et al., 2017). Despite the development of several models and simulation tools, all of them are by nature approximate, simplified versions of reality. Moreover, the huge complexity of wildfire behaviour due to the wide range of relevant spatial scales and to the multiple physical processes involved (biomass pyrolysis, combustion and flow dynamics, atmospheric dynamics, chemistry…), makes the task of its simulation an unsolved challenge. Available data to initialize and parametrize these models, such as fuels, topography, and weather, are also subjected to large uncertainties and limited resolution, both spatially and temporally.

A fourth approach to this problem is to couple existing models and real-time observations, with the objective of reducing the uncertainties in both model fidelity and input data by using real-time observations of the wildland fire dynamics. This approach is called “data-driven modelling” (or “data assimilation”) (Rochoux et al., 2015).

The ultimate aim of wildfire spread modelling, apart from increasing knowledge of wildfire dynamics, is to create useful tools for the day-to-day work of forest fire managers, as prevention and preparedness efficient tools. This involves the combined use of: (1) a realistic but sufficiently simple model, (2) numerical and computational techniques that lead to the most computationally efficient implementation, (3) the integration of the model into a

Geographic Information System (GIS) to provide a functional simulation tool, and (4) the availability of reliable and up-to-date cartographic and meteorological data.

The TREEADS approach will cover the following four items:

- We propose a simplified 2D wildfire spread model with some 3D effects, PhyFire, based on principles of energy and mass conservation.
- The numerical scheme and the computational code are optimized in order to give under real-time simulations.
- The PhyFire model is prepared to be integrated into a Geographical Information System in an optimized way. In fact, there exists a GIS-integrated prototype working on Spanish territory, through the use of corresponding topographic and fuel types and distribution cartography and can be easily extended to other areas of Europe.
- The input data of the PhyFire model includes all data of the fire behaviour triangle: topography (slopes and aspect), fuel (type, distribution and fuel moisture) and weather (wind, temperature, and relative humidity).

EARLY WARNING SYSTEM (T4.3)

Wildfires are not necessarily bad for the environment, some plant communities, the lodge pole pine and the Douglas fir among others, rely on high intensity fires for regeneration. Lodgepole pines have serotinus cones dependent on fire to open and disperse their seeds[1]. Although counterintuitive, forest fires are a natural process of keeping the ecosystem healthy. Wildfire suppression and prevention is necessary to prioritize public safety and protect property and economic activities.

Fire suppression comes with a heavy toll in terms of decline in biodiversity and forest resilience, and have also altered the way any fire would behave on the landscape.[2]

Losses by wildfires in Europe are conservatively estimated in about 2.700.000 Million Euro every year. It is thus essential to provide early warning to increase preparedness to prevent wildfires and to empower decision makers putting in place ecologically sound measures to limit the damage both to human activities and settlements and to the environment and biodiversity.

Effective early warning systems should embrace all aspects of emergency management, such as: risk assessment analysis, monitoring, predicting location and intensity of the fire event, communicating alerts to authorities and to potentially affected groups, and responding to the event. Effective communication is an important aspect of early warning systems as it gives the possibility to take prompt actions to initiate adequate response measures before the fire becomes a catastrophic event, thus protecting or reducing the loss of life and mitigating the damage and economic loss.

In spite of the existence of several early warning local systems, there is a need for a coordinated and wider action, as fires, likewise any natural catastrophic event, knows no boarders.

In support of EU forestry and civil protection policies, the Joint Research Centre (JRC) of the European Commission has developed the European Forest Fire Information System, known as

[1] "Fire Ecology" - Bureau of land management - US department of the interior (https://www.google.com/search?client=safari&rls=en&q=tree+species+that+rely+on+fire&ie=UTF-8&oe=UTF-80

[2] https://www.raincoast.org/2022/06/the-story-of-coastal-douglas-fir-forests-the-return-of-fire-to-the-landscape/

EFFIS[3], a system that enhances wildfire prevention, provides early warning and increases firefighting preparedness and efficiency, and finally monitors the impact of damages caused by wildfires. In order to monitor fire regimes and assess the impact of wildfires at the global scale, the JRC, in collaboration with European and international space agencies and research institutions, is developing a Global Wildfire Early Warning System, (GWFEWS[4]). In terms of functional and geographical coverage EFFIS represents the state of the art and reference platform in Europe.

EFFIS consists of a modular web-GIS that provides near real-time and historical information on forest fires and forest fires regimes in the European, Middle Eastern and North African regions. EFFIS addresses the full fire cycle - from the pre-fire conditions to assessing post-fire damages - through the following modules[5]:

- Fire Danger Assessment
- Rapid Damage Assessment (Active fire detection, Fire severity assessment, Land cover damage assessment)
- Emissions Assessment and Smoke Dispersion
- Potential Soil Loss Assessment
- Vegetation Regeneration

EFFIS Fire Database, which is the essential component supporting all features exposed by the platform, includes detailed information of individual fire records provided by the EFFIS network countries. Additionally, EFFIS platform includes the Fire News module, which geo-locates all the news related to forest fires that are published in internet in any of the European languages.

EFFIS uses data from satellites that comes in different formats, specifically:

- **VIIRS**, from the Visible Infrared Imaging Radiometer, a scanner that collects imagery and radiometric measurements of the land, atmosphere, cryosphere, and oceans in the visible and infrared bands of the electromagnetic spectrum including visible and infrared images of hurricanes and detection of fires, smoke and particles in the atmosphere, such as dust[6].
- **MODIS**, from the Moderate-resolution Imaging Spectroradiometer on board of two satellites operated by NASA that are designed to monitor the Earth's atmosphere, ocean, and land surface with a set of visible, NIR, MIR, and thermal channels take images for the entire Earth’s surface every 1 to 2 days.

Based on the above considerations, **TREEADS early warning system** will take advantage of additional data sources to enrich the information available and provide added value functionalities that allow prompter detection of fires a more accurate analysis of the situation and better decision support for the response phase.

Thus, on top of satellite data and weather forecast data, the early warning system will be able to use - through the features provided and orchestrated in TREEADS platform – real time data coming from surveillance and monitoring systems (i.e., zeppelin and drones), data coming from

3 http://effis.jrc.ec.europa.eu

4 https://gfmc.online/gwfews/overview.html

5 https://effis.jrc.ec.europa.eu/about-effis

6 https://www.nesdis.noaa.gov

social media, data coming from local systems, etc., which will allow a constant and near real time monitoring of forest environments. Additionally, the tool will provide a high degree of customization, for instance to decide which area to monitor, or which services of TREEADS offering to use, but also to execute simulations and what-if scenarios for a better assessment or better decision support.

The tool will be provided through user friendly, personalized, interactive, and secure dashboards that, besides providing an enriched user experience, will increase and improve the operational efficiency and control.

The objective of the Early Warning System to be developed and implemented consists on an improvement by means of the 4-layered approach of TREEADS. The European Forest Fire Information System, EFFIS, uses data that does not provide enough temporal or spatial resolution for the early detection of active forest fires at real or near-real time (Table 1 below summarizes the data sources used by the Copernicus service EFFIS, related to wildfire management in Europe and more specifically on the wildfire risk assessment). To assess this matter, several approaches can be assessed, such as the use of local data with higher spatial resolution. For example, the National Geographic Institute in Spain include thematic digital aerial orthoimagery derived from LiDAR and photogrammetric processes with a spatial resolution as low as 2,5 cm with a fixed update timeline of 3 years.

Table 1. Summary of data sources of Copernicus EFFIS service

<table>
<tr><td rowspan="4">Wildfire risk/
Danger</td><td colspan="2">Ignition</td><td>History of wildfires
Registry of active fires detected by satellite imagery (18 years, 30 ha)
Fuels
Meteorological data
Burned areas</td></tr>
<tr><td rowspan="3">Propagation</td><td>Fuel moisture</td><td>Drought codes calculated by Canadian FWI (FFMC, DMC, DC).
Weather forecast</td></tr>
<tr><td>Fuel types</td><td>Fuel Map of Europe (JRC)</td></tr>
<tr><td>Slope & wind</td><td>Digital Elevation Models:
SRTM
MERIT DEM
ASTER Global DEM
Wind:
ISI (FWI index): + FFMC</td></tr>
<tr><td rowspan="3">Wildfire risk/
Vulnerability</td><td colspan="2">Ecological value</td><td>Natura2000 Network of sites</td></tr>
<tr><td rowspan="2">Socioeconomic value</td><td>Environmental services</td><td>MAES report
WUI</td></tr>
<tr><td>Houses and human infrastructures</td><td>JRC Database
IDAS/KPMG</td></tr>
</table>

Fire hotspot detection is attainable by means of remote multispectral sensors equipped on ground, satellites or other aerial platforms. The sensitivity and frequency of the fire detection will depend on the satellite, its orbit and the specific characteristics of the instrument (Engel, et al., 2021). Active fire detection is based on sensors such as Advanced Very High-Resolution

Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Spectrometer (VIIRS) or Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR), amongst other instruments.

Table 2. Satellite systems related to active fire detection. Data directly from (Jones, 2017), adapted from (Fuller, 2000) and (LENTILE, 2006)

Satellite	Instrument	Temporal resolution	Spatial resolution (m)	Swath width (km)	VIS bands (µm)	MIR-TIR bands (µm)
Terra	ASTER	16 days	15-90	60	0.56, 0.66, 0.82, 1.65, 2.17, 2.21, 2.26, 2.33, 2.34	8.3, 8.65, 9.1, 10.6, 11.3
POES/MetOp	AVHRR	4 daily	1100	2400	0.63, 0.91, 1.61	3.74, 11.0, 12.0
Landsat 7	Landsat 7 ETM+	16 days	30 – 60	185	0.48, 0.56, 0.66, 0.85, 1.65, 2.17	11.5
Terra/Aqua	MODIS	4 daily	250 – 1000	2330	19 bands	16 bands (including 3.9, 11.0)
NOAA	VIIRS	2 daily	375 – 750	3000	14 bands	7 bands (including 3.7, 8.5, 11.45)

Sentinel constellation is not usually used for real or near-real time active fire detection systems as its temporal resolution is comparatively lower than the sensors included above (Barmpoutis, 2020). Overall, products relating active-fire detection derived from geostationary platforms perform better than those that follow sun-synchronous orbits (Marsha, 2022). Nevertheless, Sentinel-2 Multispectral sensor has been tested to complement active fire detection systems.

The techniques employed for detection of active fires from remote imagery are based on the observation the mid-infrared (MIR), thermal-infrared (TIR) and temperature brightness bands in relation to the surrounding environment (as could be known fuel loads), using different algorithms for the detection and characterization (location and size) of fire-related hotspots at pixel level or subpixel level. The active fire detection algorithms are classified in fixed threshold, contextual or multi-temporal categories. Fixed threshold algorithms use the energy emitted by a pixel and compare it against an empirical value, thus triggering and alarm if the energy is above or below this fixed value (threshold). Contextual algorithms are also called adaptative because the detection thresholds used to eliminate detection interferences such as clouds, haze or other phenomena are automatically adjusted to fit regional and temporal conditions. For example, Hu (Hu, 2021) used an adaptative algorithm on imagery taken by the Sentinel-2 multispectral sensor, which is based on detecting differences in the reflectance values of one pixel and the surrounding ones, accomplished by statistical investigation of the background characteristics of the local pixels. Finally, multi-temporal detection algorithms use changes in the radiance measured by the sensor for the threshold levels, and are especially effective for geostationary satellites, as they acquire images of the same area daily or even at higher frequency. For example, geostationary satellites also allow for the night-time detection of fires by adjusting the detection thresholds to the different environmental conditions (Engel, et al., 2021).

Deep learning architectures are also under research for the detection of hotspots/active fires by means of classification algorithms. To enable a rapid and efficient response, it is essential to detect wildfires as soon as possible after they have started and thus while they are still relatively small. By identifying smoke columns in the field of view directly from a fire tower or from a video feed from an aircraft, or the ground, human observers have traditionally been able to identify fires. Spatial or temporal coverage, human error, the presence of smoke from other fires, and the number of daylight hours can all impose restrictions on these techniques. Automated heat signature or smoke detection in infrared (IR) or optical images can increase the detection's spatial and temporal coverage, effectiveness in smoky conditions, and remove bias brought on by human observation. The task of analysing this data is basically a classification problem that can be solved automatically with good precision thanks to Machine Learning techniques.

For instance, Arrue et al. (2000) used fuzzy logic and ANNs to identify real wildfires in conjunction with IR image processing, visual imagery, meteorological data, and geographic information. Al-Rawi et al. 2001; Angayarkkani and Radhakrishnan 2010; Fernandes et al. 2004a, 2004b; X. Li et al. 2015; Soliman et al. 2010; Utkin et al. 2002; Sayad et al. 2019 are just a few researchers who have used ANNs for fire detection in a similar way. Additionally, Liu et al. (2015) built a fire detection system using ANNs on wireless sensor networks that used multicriteria detection on multiple attributes (such as flame, heat, light, and radiation) to find fires and sound alarms. SVM, another ML technique used in fire detection systems, can automatically identify wildfires from videoframes (Zhao et al. 2011), ANFIS (Angayarkkani and Radhakrishnan 2011; Wang et al. 2011), BN in a vision-based early fire detection system (Ko et al. 2010), GA for multi-objective optimization of a LiDAR-based fire detection system, and KM (Srinivasa et al. 2008) are examples of fire detection systems that use these techniques.

Recent work has focused on the problem of fire detection using CNNs (Deep Learning), which are capable of extracting features and patterns from spatial images and are widely used in object detection tasks. Several of these applications trained the models using images of fire and/or smoke taken from the ground, such as Zhang et al., 2016 ; B. Zhang et al., 2018 ; Q.X. Zhang, 2018 ; Yuan et al., 2018 ; Barmpoutis et al., 2019 ; Jakubowski et al., 2019 ; Sousa et al., 2019 ; X. Li et al., 2018 ; T. Li et al., 2019 ; Muhammad et al., 2018 ; Wang et al. 2019. In a related study, Q. X. Zhang et al. (2018) discovered that CNNs outperformed an SVM-based approach, and Barmpoutis et al. (2019) discovered that a quicker region-based CNN outperformed another CNN based on YOLO. CNN and optical flow were combined by Yuan et al. (2018) to include time-dependent data. Similar to X. Li et al. (2018), they were able to treat smoke detection as a video image segmentation problem by using a three-dimensional CNN to incorporate both spatial and temporal information. In a different method, Cao et al. (2019) used convolutional layers as a component of an LSTM neural network to detect smoke from a series of images (i.e., a video feed). They discovered that the LSTM method had 97.8% accuracy, a 4.4% improvement.

Fire/smoke detection models trained on GOES-16 (Phan and Nguyen, 2019), MODIS (Ba et al., 2019), or unmanned aerial vehicle (UAV) images (Zhao et al., 2018; Alexandrov et al., 2019) imagery may be more useful for managing fires. Comparing SVM, ANN, and three CNN models, Zhao et al. (2018) discovered that their 15-layer CNN model performed best, with an accuracy of 98%. In contrast, the accuracy of the SVM-based approach, which was unable to extract spatial features, was only 43%. In contrast to Barmpoutis et al. (2019), Alexandrov et al. (2019) discovered that YOLO was both faster and more accurate than their region-based CNN method.

The use of U-NET neural networks, originally developed by Ronneberger et al. (2015), for the segmentation of aerial and satellite images is proposed in TREEADS. The segmentation of aerial and satellite images to obtain better maps of vegetation and an adequate classification of fuel types will allow to complement the detection methods of hot spots and smoke columns by adding information that allows for a precise evaluation of risks.

DETAILED FOREST MAPPING (T4.5)

Digitizing variables related to the territory, terrain, vegetation (considered as fuel for forest fire) and meteorology is key for forest fires prevention and preparedness through the use of current technology. As for the variables related to the territory, terrain and meteorology, various dedicated applications provide elaborated representative geomatic products, even with different resolutions and precision. As for the variables that measure aspects related to the vegetation, such as forestry variables, no dedicated application exists that digitizes these variables with great detail.

The low profitability of forest exploitations (compared to other industries or exploitations) leads to focus the greatest efforts in forest management on fires. Therefore, the main contribution of advancing in digitizing forestry variables is in solutions for forest fires prevention and preparedness. The forestry variables of interest to achieve this goal consist of the three-dimensional structure of the forest masses and their fire response, where other environmental variables also interfere, such as the fuel humidity (Alvarado et al., 2019).

There are several studies focused on the application of machine learning to determine the relationships between agroforestry data and fuel types with wildfires. In an early study, in the Ispra region of Italy, Riaño et al. (2005) used an ANN to predict and map the equivalent water thickness and dry matter content of wet and dry leaf samples from 49 species of broadleaf plants. In order to create forest canopy fuel maps, Pierce et al. (2012) used RF to classify significant canopy fuel variables (such as canopy cover, canopy height, canopy base height, and canopy bulk density) related to a wildland fire in Lassen Volcanic National Park, California. Similar to Riley et al. (2014), who carried out fuel classification and mapping in eastern Oregon using RF with land fire and biophysical variables. For example, the authors of the aforementioned study were able to accurately model the forest at 97% of its height, 86% of its cover, and 84% of its existing vegetation group (i.e., its fuel type). In order to estimate aboveground biomass in the Sierra Madre Occidental, Mexico, López-Serrano et al. (2016) compared the performance of three common ML methods (SVM, KNN, and RF) and multiple linear regression. The authors discussed the benefits and drawbacks of each method and came up to the conclusion that for biomass estimation, nonparametric ML methods outperformed multiple linear regression. García et al. (2011) classified LiDAR and multispectral data using SVM in order to map different fuel types in Spain. Stochastic Gradient Boosting (SGB), an ensemble tree method that combines boosting and bagging, was found to have the highest overall accuracy when Chirici et al. (2013) compared its use with CART, RF, and other methods for mapping forest fuel types in Italy.

The capturing and estimation methods to retrieve these variables are diversified by all the opportunities offered by current technology to the scientific community. Spatial, radiometric and meteorological variables are measured with remote sensors of various kinds: cameras that are sensitive to the visible and infrared (near, mid- and thermal-) bands of the spectrum, hyperspectral sensors with a narrow differentiation between spectral bands, radar sensors or

LiDAR technology, among others. Sensors are carried on platforms that can be located at different distances from the point of study, from the ground to the space. In addition to direct measurements, some variables can be quantified using indexes computed as a combination of spectral bands, as for example: NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), NBR (Normalized Burnt Ratio), among others.

These wide range of data sources pops up the importance for an adequate prior analysis of needs and requirements. Therefore, a prior evaluation of the available technologies, their capabilities and limitations must be made according to the proposed goals and objectives. Specifically for forest environments, represented by extensive and heterogeneous landscapes where the smallest management unit is of the order of hectares, it is considered that the work resolution should be scalable according to the variables to be digitized and the entailed complexity (Aragoneses et al., 2022).

For instance, the FirEUrisk project (Aragoneses et al., 2022) has highlighted the need for a continuous fuel model map that covers the whole Europe and that is derived from such heterogeneous variables as the aforementioned. Therefore, segmenting the territory according to the fuel fire behaviour is needed, which depends on the vegetation type, its morphology and the environmental conditions (Krsnik et al., 2020).

On the one hand, some variables can be easily digitized. For instance, the vegetation height or canopy cover can be retrieved through RADAR systems, since the signal frequency allows for the penetration of the multi-return pulses that make it possible to reach the ground and the upper surface of the tree crowns at the same time. On the other hand, detailed geometry (and subsequent parameters such as tree density, presence and dimensions of firewalls, distance from buildings, dimensions and configuration of the urban – rural interface) can be obtained from laser scanning systems, such as the flights planned by the Spanish National Aerial Orthophoto Program (PNOA) (Botequim et al., 2019), Only when the point density of these clouds is at the limit of that for which they were initially planned (0.5 points/m^2), dedicated data acquisition flights may be needed, either a dedicated visible photogrammetric flight with a Ground Sample Distance (GSD) of several centimetres (intending to use the subproduct point cloud of this procedure) (Hartley et al., 2022) or a LiDAR flight with drones to obtain precise and detailed information on the soil, vegetation height and fraction cover (Fernández-Álvarez et al., 2019; Herrero-Huerta et al., 2016).

On the other hand, variables that are not perceptible in detail from nadiral shots, such as apparent density, minimum crown height or the fraction of area covered by bushes in very closed masses, should be measured on the ground (Cabo et al., 2018). The biggest drawback of these shots is their scanning performance compared to nadiral systems (Lin et al., 2022). Since it is not feasible to cover the same extension with both systems, the terrestrial one is usually estimated by means of statistical inference or dismissed when the objectives allow it (fire simulation, biomass quantification, etc.). Lastly, when applying statistical inference, it is more profitable to use manual sensors than to add other systems for digitizing spatial variables.

As for those variables that are obtained from radiometric data sources, mainly excepting those that are sensitive to the visible part of the spectrum, the tendency is to use satellite images (Bright et al., 2017; Shaik et al., 2022), given the data acquisition cost and processing of commercial multi- or hyperspectral sensors and the spatial and temporal resolutions of satellite sensors, which are suitable for digitizing forest environments. The use of drone flights highly depends on the weather conditions and has a high cost per surface unit. Still and all, drones are the most widely adopted solution to compensate for the deficiencies in the spatial and temporal resolutions of satellite images (Majlingová et al., 2018).

Surveillance or monitoring systems, which do not require a very high geometric quality, but roughly provide images or videos in visible or thermal image, can take advantage of the flight height, autonomy and stability of the platforms on-board zeppelins in comparison to drones (Belozerov et al., 2020). Regarding public satellites, their low spatial (between 10 and 90 meters, depending on the spectral band) and temporal resolution (from 5 to 16 days) does not allow them to be used solely as a preventive alert system, since the response time for obtaining the images or video makes it impossible to guarantee a prompt response from the means of extinction or civil protection (Oliver et al., 2022).

Given the above, TREEADS approach focuses its shot on an innovative and detailed forest mapping that takes advantage of all the aforementioned data sources at different levels, thus (i) satellites, such as Sentinel 1, Sentinel 2, Sentinel 3, PRISMA or Landsat 8, because of their freely availability and high spatial (10 to 90 m) and temporal resolutions (5 to 16 days), suitable for a constant and almost in near real time monitoring of forest environments; (ii) zeppelin and drones as surveillance and monitoring systems, to use solely on those areas that represent the higher levels of forest fire risk (identified in T4.1), so as to allow obtaining a more detailed characterization of the forest variables of interest (such as photosynthetic activity and fuel load) with a finer spatial and temporal resolution.

In this task, the segmentation using U-NET networks of aerial and satellite images to obtain better vegetation maps and an adequate classification of fuel types will also improve the obtaining of more detailed and precise forest maps.

SOCIAL MEDIA ANALYSIS (T4.6)

The vast amount of information contained in social media can be utilized for various purposes and applications. Especially with the rise of mobile phones, the social media users started to report frequently the various disaster incidents that affect their daily lives and enables the general public to contribute to the monitoring of disasters by reporting incidents related to disaster events (Saroj et al., 2020). Therefore, social media is a powerful tool for disaster prevention, response management, including enhancing situation awareness, promoting emergency information flow, predicting disasters and coordinating rescue efforts (Shan et al., 2019). More specifically, social media can be used for fire risk assessment, prevention, detection and management that lead to faster and more efficient aid from first responder, less casualties and reduced financial loses as a fire disaster is severe, costliest preventable and often results to many casualties. Below are presented various recent works that utilized social media data for fire management, analysis, prevention and event detection.

Yue et al. (2021) assessing wildfire risk in the United States by using social media data, by analysing geo-tagged tweets for the region of United States found a linear relationship between wildfire risk level which shows that larger population size result in significant increase in fire-inducing hazard level.

Additionally, Zamarreño-Aramendia et al. (2022) investigated the usage of social media posts by government authorities for the forest fires in Artenara and Valleseco, Canary Islands, Spain, during summer 2019. By using big data analysis and content analysis on tweets related to fires from several government Twitter accounts, they concluded that government authorities used the social media as a live-information channel and not as a preventive element. Additionally, they present recommendations for or the management of social media during natural disasters.

Furthermore, Fitriany et al. (2021) conducted a correlation analysis between meteorological, online newspapers, satellite and fire related Twitter data for the region of Riau, Sumatra for the timeframe of 2014–2019 in order to find out how they can contribute to early detection. The tweets were collected based on keywords and geolocated by the geoparsing algorithm TAGGS (de Bruijn et al., 2018). The results shown that crowdsourced data can be integrated in the fire management system and fire disaster mitigation effort.

Besides that, Loureiro et al. (2022) used natural language processing techniques and sentiment analysis to calculate a sentiment score that estimates the changes in happiness in Twitter about wildfires in Spain and Portugal during October 2017. They combined the sentiment scores with meteorological, socio-economical and air quality data to develop a hedonometer that estimates the impact of wildfires have on wellbeing. The results show that the closer to the wildfire the more increased was the fear sentiment and political discontent, on the other hand the further from the wildfires the fear sentiment decreases gradually. Also, in this work they input sentiment estimates into a standard utility framework in order to approximate the economic valuation from fire losses and welfare losses in terms of air quality.

Also, Tavra et al. (2021) used as an example a case study of a forest fire spread from the forests to the city of Split in Croatia in July 2017 to demonstrate an approach to better disaster management with the use of social media. They collected social data from Twitter and Facebook and combined them with other external data sources (e.g., Sentinel-2 satellite imagery) in order to reconstruct the event. By analysing the event they indicate that social media data can generate insights that can be incorporated into an emergency response with more reliable information that can be used for disaster management. Furthermore, the article emphasizes the importance of geo-referenced information from social media, as it allows combining data from different sources, which provides a different perspective for disaster management.

Over and above, George et al. (2021) proposed a real time event detection method that utilizes social media and is capable to detect social media events of a different spatial and temporal resolution. To combat the challenge of the unknown spatial resolution they used a quad-tree method to identify the diverse spatial coverage events and a statistical unsupervised approached of a Poison model to detect unseen events with different temporal resolution. The method was evaluated and achieved better results than the baseline algorithm on datasets from Twitter and Flickr for the cities: Paris, London, Melbourne and New York.

As well, Pekar et al. (2020) put forward a text classification approach that tries to detect crisis related messages from social media (storms, wildfires etc.) without prior knowledge of either specific events or their type. They overcome the data heterogeneity problem by proposing a new ensemble learning method that performed similar to the Gradient Boosting and AdaBoost ensemble learners on a benchmark Twitter data set comprising 26 disaster events and four classification problems.

Moreover, Lever et al. (2022) demonstrate that social media can be a predictor of wildfire activity. They combined geophysical satellite data and social data from Twitter with Sentiment

Analysis to build a machine learning model that predicts wildfire characteristics with high accuracy. This model can be considered useful by disaster management teams to identify areas of immediate risk and contributes to the development of more socially aware fire models.

On top of that, Papadimos et al. (2022) focusing in fire events on Twitter and they introduce an alert framework for real time fire detection in social media that was evaluated in a Twitter dataset for fire events in Spain. The framework aims to assist first responders in disaster management and decision making and includes a fire event detection methodology that fuses two modalities. The first modality calculates a Density Score (DS) from the timestamps of the tweet by applying a Kernel Density Estimation (KDE) that takes into account the number of Twitter posts for the examined time frame and also the sparsity and density of their publication time. The second modality calculates a Modularity Score (MS) by grouping the Twitter users in communities with a community detection algorithm. Finally, a fusion method considers the scores of the two modules (DS, MS) and decides if an event exists in the respective time period.

The above approaches are focusing on fire detection, management and analysis from social media. Twitter seems to be the more prominent platform to extract social fire data as it comes along with a public. Additionally, in these works are mentioned methods and techniques to extract u c AP useful and meaningful information from social media. Moreover, techniques such as sentiment analysis, geotagging of social media posts, community detection, text classification can be utilized from event detection algorithms and improve the performance of these algorithms.

Given the above the TREEADS social media analysis task focus on the monitoring of the fire events as they are expressed on social media by individuals, such as online users that are noticing a fire or indications of a potential fire, e.g., smoke. Based on well-defined search criteria (keywords, accounts, bounding boxes), social media data collected in a real-time manner and further analysed in order to filter out irrelevant information, reducing thus noise, and to enrich them with geo-information. The estimation of a post's relevance will be achieved with classification techniques that use textual and/or visual features, while the automatic geotagging involves the recognition of words that refer to locations and their association to exact coordinates. Moreover, this task includes density-based approaches for discovering user communities on social media and identifying key-players in these communities, i.e., user accounts that play an important role during a fire event and affect other users. Another subtask will be the fusion of social media data with alternative types of information, such as satellite images, aiming at a more sophisticated assessment of an incident's severity.

FIRE RESILIENT MATERIALS (T4.7)

Nowadays Alkali-Activated Materials (AAMs) manufactured using Wood Ashes (WAs) or Post-wildfire Wood Ashes (PWAs) as precursors or activators, and cement-based materials manufactured using WAs or PWAs as partial Ordinary Portland Cement (OPC) replacement are widely studied by several researchers. The main reason why this kind of topic took this hype is because it could be a big help to face one of the most important challenges of our society: the climate change issue.

The cement industry is responsible for 5-8% of the anthropogenic CO2 emission around the world (Andrew, R.M., 2018; Font A. et al., 2019). AAM can be produced without OPC. According to the literature, the CO_2 emission associated with the AAM production can be 55 -75% lower than those obtained for OPC (Font A. et al., 2019; Shirley R. et al., 2011).

Alkali Activated Material (AAM) is a binder system obtained by the reaction of an alkali metal source (solid or dissolved, i.e., activator) with a solid silicate powder (i.e., precursor). AAMs, which chemistry and reaction mechanisms are radically different from traditional binders based on OPC, have a high potential as alternative binder to OPC because of their excellent mechanical properties, durability and environmental benefits (lower CO2 emissions). These concretes are highly suitable to withstand with harsh environments related to extreme weather conditions and can overcome durability problems of traditional concrete when exposed to harsh environments thus reducing maintenance and retrofitting needs (Provis J.L. at al., 2014). WA has a substantial potential for use as a pozzolanic mineral admixture in cement-based materials and as precursor or activator in AAMs (Siddaque, R., 2012).

For documentation of reaction to fire properties of a material, there are small scale (e.g., ISO 5660-1, ISO 5658-2), medium scale (e.g., EN 13823) and large scale (e.g., SP FIRE 105) standardized test methods that are developed for land-based end-use. Here, different heat and fire exposure is used to document how the material behaves. In addition, there are experimental methods developed specifically to document reaction to fire properties of materials exposed to wildfires, such as the "NIST Dragon's LAIR " method in which the material is exposed to flying glowing embers.

Vipo's polymer-based fire protection systems are generally known as the Firestop technologies. It includes a range of materials and products, but also well proven engineering and manufacturing techniques for protection of steel and concrete structures against hydrocarbon and jet fires.

Firestop is passive fire protection systems used to protect personnel and equipment by minimizing fire escalation by providing time to evacuate people, close down critical equipment and for responders to gain control of the fire. The certified systems protect structures from exceeding critical temperature limits.

Firestop can be tailor-made to suit any customer specific need. It can be coated or extruded on pipes or structures, hand-built or moulded as a component. The coated structure shall fulfil its load-bearing capacity throughout the fire exposure period with a surface temperature below critical value, 200–400 °C depending on project requirements. The system shall prevent spread of flames and hot fumes with a low generation of smoke.

Main application areas of Firestop today are oil & gas installations, supply ships and marine. A typical fire scenario is demanding. Existing material technologies are designed for resistance against the high heat flux fires with a highly erosive flame (jet fire) relevant for offshore application with risk of gas explosion followed by a fire. Wildfire characterization simulated during the Norwegian pilot is expected to be different, and the concepts can be tailormade for the actual applications with a reduced cost and weight.

As for Woodify AS, it offers a vast range of fire-impregnated wooden materials for use as claddings, construction materials as well as interior panels. Our fire-impregnated range "BrannpanelTM" consists of various wood species of high quality and grade from our own milling factory Backegårds List AB (BL), combined with fire-impregnation technology provided by Woodsafe Timber Protection AB (WS). WS impregnation facility, fire-retardants and expertise have provides the basis of Woodifys fire-impregnated wooden products for over 10 years.

Presently, in collaboration we have certified a large range of wooden species to comply with EU regulation for the use of wooded facades. Our ambition within this project is to review the current standards and testing parameters for the existing Euroclass system and evaluate if changes need to be made in order to provide more effective fire-impregnated facade systems in the future. This is particularly relevant for the use in rural areas, or areas bordering on woodlands / forests. Our objectives are to a) identify valid test parameters that is applicable for wooden materials in relation to wildfire risk, b) test wooden materials in accordance with these relevant test parameters (Cone calorimeter, SBI, Large scale, c) identify the best options for façade systems considering cost and sustainability.

Last but not least, a table with the **main technological innovations in TREEADS for prevention and preparedness** in comparison with the existing technologies is outlined in Table 3.

Table 3. Main technological innovations beyond the state-of the art in TREEADS during prevention phase.

Fire daily forecasting	The use of Bayesian Deep Learning to enhance the mere short-term fire risk forecasting with uncertainty estimates of the predictions. The use of segmentation with neuronal network as U-Net applied to aerial and satellite imagery to improve and/or complement predictions with a vegetation approach
Fire simulation models	The use of a realistic but sufficiently simple model, implemented in the most computationally efficient way possible using numerical and computational techniques, integrated into a geographic information system to provide a functional simulation tool, with access to reliable and up-to-date cartographic and meteorological data provided by the other technologies of the projects.
Early Warning System	The innovative aspects brought forward in TREEADS early warning system are the use of additional data sources that will allow enriching the information available. Data to be considered, on top of satellite data, is data coming from aerial means (drones, zeppelin) and other TREEADS tools, but also data coming from local sources and from social media, which are not currently available in EFFIS. Such data will allow the provision of added value functionalities for a constant and near real time monitoring of forest environments, which result in a prompter and more accurate detection of fires, and for a more accurate analysis of the situation leading to a better decision support for the response phase.
Detailed forest mapping	A downscaling approach for analysing the forest and its main variables regarding wildfires. In particular, this module will provide a coarse-to-fine approach for obtaining those cartographic products that are of paramount interest in prevention and preparedness of wildfires.
Social media analysis	Implementation of a social media crawler that uses fire related search criteria (keywords, accounts) for retrieving fire related social media posts in real time. For each retrieved post a series of analysis to extract higher knowledge is performed. The collected social media posts are getting geotagged by a NER implementation that detects location names in social media posts texts and queries the OSM API to retrieve the precise coordinates of those location names. Filtering out irrelevant to fires tweets by a machine learning model that automatically classify social media posts as relevant or not relevant. Discovering user communities and identify key-players that play an important role during a fire event and affect other users.

Fire resilient materials	The great availability of WA in a post-wildfire scenario opens a way on the possibility to reuse the waste of wood (post-wildfire wood ash – PWA) for the production of Alkali-Activated Materials (AAMs) manufactured using Wood Ashes (WAs) or Post-wildfire Wood Ashes (PWAs) as precursors or activators, and cement-based materials manufactured using WAs or PWAs as partial Ordinary Portland Cement (OPC) replacement. TREEADS project aims to explore new possibilities to reuse PWA into the above-mentioned construction materials, increasing their fire-resilient performances. Evaluation of data to form base of test parameters to improve the fire resilience of wooden facade systems for the use in high-risk wildfire areas. Wood species, wood thickness, levels of fire-retardant and the implications of the use of surface coatings will be evaluated against existing as well as new testing parameters. Development of fire resilient materials and concepts suitable for protection of critical infrastructure in high-risk wildfire areas. Reaction to fire properties of the materials will be evaluated against criteria defined relevant to withstand an exposure from a wildfire. The characterization of a wildfire is expected to be different compared to a jet fire which determines most of the requirements for passive fire protection applied for oil & gas installations. In the fire experimental scheme in task, the basis for the fire experiments will be relevant reaction to fire experimental methods, at different scales. It will be important that the relevance for wildfires under Norwegian conditions is taken into consideration when designing the experimental scheme. It will also be important that the chosen methods are evaluated to be the best suited to document the reaction to fire properties and fire resilience of the technologies (materials used in product for PFP protection of steel and concrete infrastructure onshore (VIPO) and materials used in product for improved fire resilience of wooden cladding for buildings (WAS) and that the chosen experimental schemes are relevant for the end-use of the materials and products.

Motivation

INTEGRATED FIRE MANAGEMENT SYSTEM

The **Integrated Fire Management System** (T4.4) is the main element to integrate the different capabilities described above for prevention and preparedness.

It integrates other WP4 components into a unified interface through custom common APIs that wrap the actual components exposing their inner functionality to end users.

This component interacts with middleware components, such as the security authentication and authorization component and makes use of integration services for implementing the enterprise-service-bus that will glue together the front-end and back-end components.

The following diagram presents the interactions of the TREEADS Main Portal component with the other components of the TREEADS system, using the Application Service Integration described further:

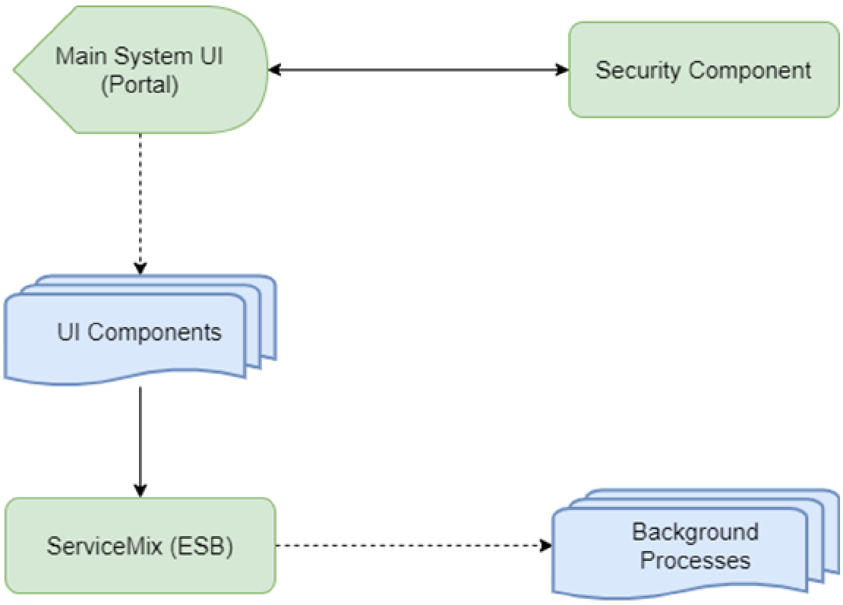


Figure 2. Main System User Interface - Component Interactions Diagram

APPLICATION SERVICES INTEGRATION

The integration of the various systems and components of WP4 will be done using the Apache ServiceMix integration platform.

Apache ServiceMix is an open-source integration platform that combines the features of Apache ActiveMQ, Camel, CXF, and Karaf to offer a powerful runtime environment for developing integration solutions. It provides an extensible enterprise service bus that is powered by OSGi solely.

Application integration is the process of interconnecting software applications and systems so that they can exchange data and functionality. Apache ServiceMix is an ideal tool for application integration since it enables developers to link and manage disparate applications and systems utilizing a wide range of protocols and technologies. It has support for messaging, Service-Oriented Architecture (SOA), and Enterprise Service Bus (ESB) capabilities, among other features and tools.

Apache ServiceMix's capacity to manage large-scale and complex integration projects is one of its primary advantages for application integration. It is based on the OSGi architecture, which permits modular and dynamic deployment of services and components. This makes it simple to add, remove, or update functionality as needed and guarantees that the integration solution stays flexible and adaptable as company needs evolve.

In addition, Apache ServiceMix offers numerous connectivity options, including support for JMS, HTTP, SOAP, and REST. This enables developers to effortlessly connect to a range of apps and services, regardless of their platform or technology.

Overall, Apache ServiceMix is a potent and versatile tool for the development of application integration solutions. Its open-source nature, extensive feature set, and OSGi foundation make it a popular choice among developers seeking to link and manage disparate corporate systems.

Application Services Integration will perform the following responsibilities:

- Integrate external systems and components in a loosely coupled manner
- Publish and describe interfaces that are exposed to other systems
- Describe the syntax and format used for exchanging data messages
- Utilize open standards for external system communication

The Application Services Integration component provides enterprise service bus services that ensure federation, clustering, and container-based failover. It will ensure:

- Rapid deployment and management of business object lifecycles
- Vendor autonomy with respect to vendor-licensed products
- Conformity with the JBI standard JSR 208

This component combines the following constituent elements:

- Apache Camel: is an open-source framework for message-oriented middleware with a rule-based routing and mediation engine that provides a Java object-based implementation of the Enterprise Integration Patterns by means of an application programming interface (or declarative Java domain-specific language) to configure routing and mediation rules.
- Apache CXF: is an open-source services framework that facilitates the construction and development of services using frontend programming APIs, such as JAX-WS and JAX-RS. These services can speak a variety of protocols, such as SOAP, XML/HTTP, RESTful HTTP, or CORBA, and operate over a variety of transports, such as HTTP, JMS, or JBI.
- Apache Karaf: is a modern and polymorphic container that can be used as a standalone container and supports a vast array of applications and technologies. It also supports "run anywhere" (on any machine with Java, cloud, or docker images) with its embedded mode.
- Apache ActiveMQ: is an open-source, Java-based message broker that includes a full Java Message Service (JMS) client.

The diagram below provides a summary of ServiceMix's components:

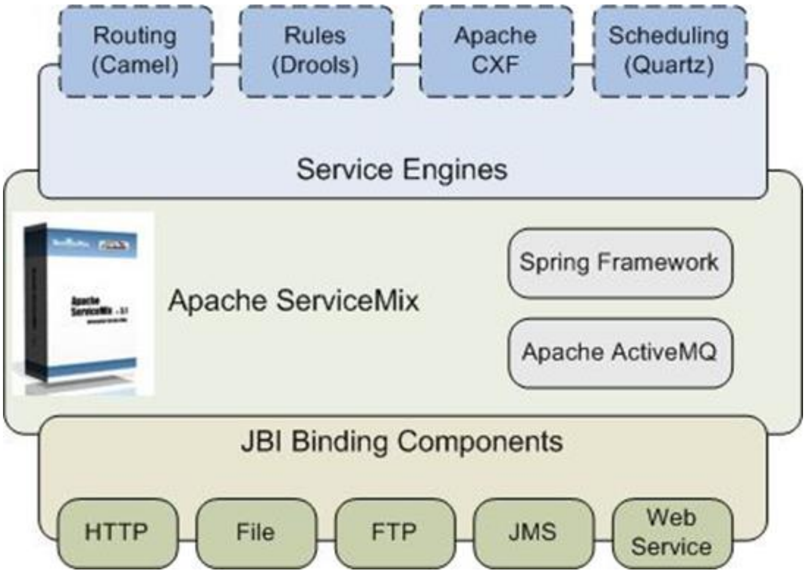


Figure 3. Application Integration Services – Components description

The diagram below illustrates a sample implementation of interactions between the Application Integration Services component and a generic TREEADS system component:

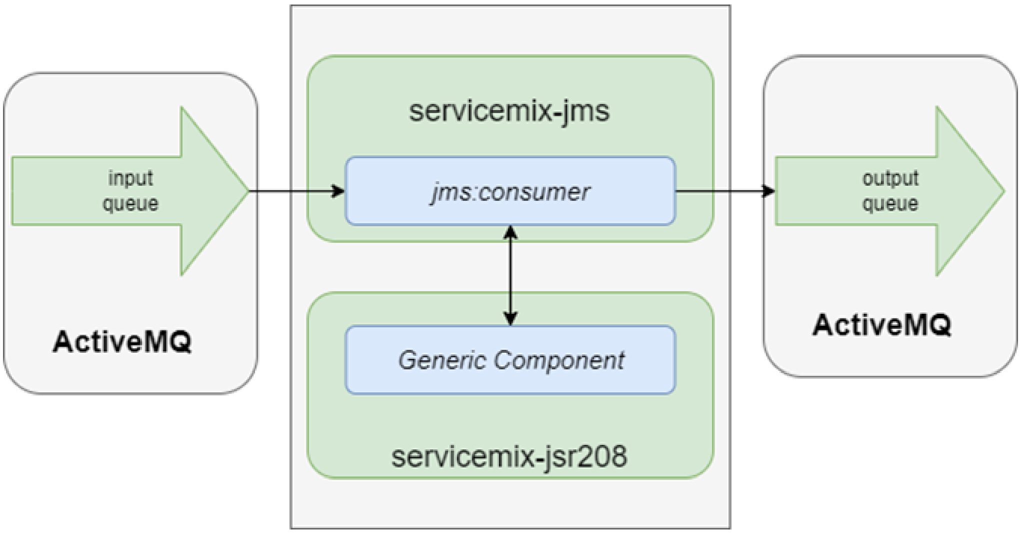


Figure 4. Application Integration Services – Interactions Diagram

ServiceMix, through the use of standards based inter-process messages, serves as the integration glue for all other TREEADS WP4 components.

TECHNOLOGICAL APPROACH DECISION

The decisions for the proposed tools were made based on an open technical questionnaire sent to the WP4 partners. The results of this questionnaire are highlighted below:

Table 4. Results of technological focus decision questionnaires

QUESTION	Yes	No	Maybe	N/A
Do your components / systems in WP4 already expose or plan to expose an integration API?	41.7%: REST – 50% SOAP – 50%	16.7%	8.3%	33.3%
Are your components / systems containerized?	16.7%	50%		33.3%
If not, do you consider containerizing them?	16.7%	33.3%	16.7%	33.3%
Is the data of your components / system saved in a database?	50%	16.7%		33.3%
Do you use / plan to use a logging or auditing mechanism activated to monitor the activity / performance of your components / applications?	16.7%: PostGIS – 8.3% OpenData Cube – 8.4% PostgreSQL – 8.3% MySQL – 16.7% MongoDB – 8.3%	25%	33.3%	25%
Do you use / plan to use Big Data in your components / systems?		33.3%	33.3%	33.3%

Do you use / plan to use event streaming platforms?		50%	25%	25%
Do your components / applications integrate with other external systems?	41.6% Google Earth Engine, OGC service, Google Street Maps, OSM, Copernicus	16.7%	16.7%	25%
Do you have / plan to use a logging or auditing mechanism activated to monitor the activity / performance of your components / applications?	16.7%	25%	33.3%	25%

INTEGRATION WITH THE TREEADS MAIN PORTAL

The TREEADS main portal incorporates both technical and user interface components. Technical integration refers to the ability to link and communicate with various systems and components, whereas user interface integration refers to the ability to deliver information to the end-user in a unified and coherent manner.

A key part of the integration is the portal's capacity to present the output from WP4 components in a consistent format. This means that the portal must be able to manage and present diverse output formats from WP4 components in a consistent and straightforward manner. This may involve presenting the results as charts, graphs, or maps, with the Integrated Fire Management System playing a key role in this.

The ability to link to existing GIS systems for displaying the visual output of WP4 components is another crucial part of the integration. This enables the portal to overlay output data on a map and provide a more contextual perspective of the results.

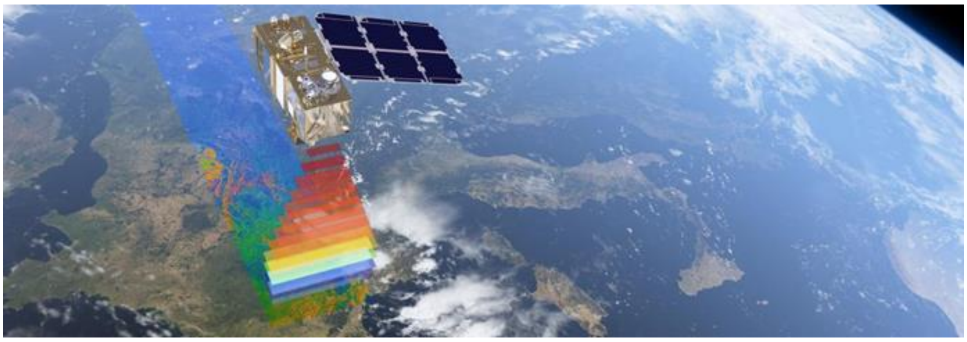


Figure 5. NDVI Satellite

The integration also provides the capacity to connect to NDVI suppliers, such as Copernicus Terrascope, which can provide additional data on vegetation and land cover. This enables the gateway to provide accurate and up-to-date information about the state of the land.

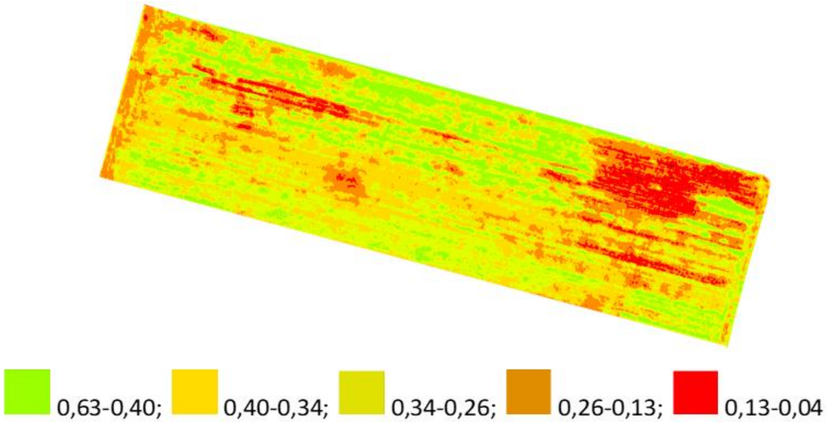


Figure 6. NDVI index

In addition, the integration offers the capability to link to weather forecast providers, such as OpenWeather, which can provide information about present and upcoming weather conditions. This enables the portal to display pertinent weather information and its potential impact on the output of WP4 components.

The integration offers the capacity to link to numerous land sensor values, which can provide data on a variety of parameters including soil moisture, temperature, and humidity. This enables the gateway to offer a more detailed perspective of the land and its circumstances.

Also, social network analysis will be a part of the integrated approach.

Integration in the main portal is a difficult and comprehensive process that requires the capacity to connect to numerous systems and components, handle diverse data types, and show the information in a consistent and user-friendly manner. These linkages are essential for providing the end user with an accurate and full view of the land and its circumstances.

Additional integration perspectives and proposals may include:

1. The primary gateway could interact with remote sensing systems, such as those utilized by WP4 components, to collect satellite imagery, aerial imaging, and other types of remote sensing data. This would enable the portal to display high-resolution photos of the land alongside the output from the WP4 components to provide a more comprehensive view of the area.
2. Integration with data storage and management platforms: the main portal might integrate with data storage and management systems, such as databases and data warehouses, in order to store and manage the output from WP4 components and other data sources. This would enable the gateway to retrieve and show historical data, in addition to performing data analytics and visualization functions.
3. Integration with machine learning and analytics platforms: the main portal could integrate with machine learning and analytics platforms, such as those used by the WP4 components, in order to perform complex data analysis and predictions based on the output from the WP4 components and other data sources. This would enable the gateway to deliver more precise and advanced information about the land and its status.
4. The main site could interact with reporting and dashboard systems, such as those used by the WP4 components, to generate and show reports and dashboards based on

output from the WP4 components and other data sources. This would enable the portal to give a more intuitive and engaging method of displaying facts and information.

5. Integration with alert and notification systems: the main portal could link with alert and notification systems, such as those used by WP4 components, in order to send notifications to users depending on certain occurrences or thresholds. For instance, if the output from the WP4 components detects a potential problem or anomaly, the portal might send an alert to the relevant users informing them of the problem.

Overall, these new platform interfaces would provide a more comprehensive and advanced perspective of the land and its circumstances, making it easier for the end-user to access, evaluate, and utilize the data.

Solution for prevention and preparedness

Methodology overview

Given the aforementioned, the methodology followed to develop the TREEADS solution undertakes the main goal of **delivering a tool for prevention and preparedness of wildfires as an efficient and tangible solution that is based on, and steps forward to, the best results captured from existing scientific literature**. In this sense, the TREEADS solution for prevention and preparedness will be developed to give response to **two storytelling** that capture the main stakeholders' needs highlighted in the workshops that have been held within the TREEADS project to date, and that are further explained in the following section.

Firstly, TREEADS solution will allow for **enhancing local forest management practices**, traditionally made randomly, by identifying and prioritizing the forest areas that need cleaning as a first and simpler measure to avoid wildfires. Secondly, the TREEADS solution will be developed as an **integrated platform ecosystem** (T4.4) that will allow for: (T4.1) identifying high fire danger areas where further analysis will take place, namely (T4.2) modelling of the fire spread to identify socioeconomic activities in danger, (T4.3) detecting hotspots and smoke columns, thereby serving as an early warning tool, (T4.5) characterizing forest properties with a high spatial, temporal and spectral resolution, such as fuel maps and drought indices, thereby allowing for delivering accurate and reliable results for prevention and preparedness, (T4.6) taking into account social media analyses and specifically posts from the main actors during a forest fire, (T4.7) delivering a guide of good practices in regard to fire resilient materials to be used, and lastly, (T4.4) performing an integrated fire risk analysis in the study areas (Figure 2).

To this end, the TREEADS solution will use the best up to date available data sources, such as Copernicus data, LiDAR data, very high-resolution data, weather data and socioeconomic data. Likewise, the TREEADS solution will use the modelling approaches and algorithms that have proven to deliver accurate and reliable results, such as Deep Learning and segmentation. Further details regarding each TREEADS solution component are given as follows (Figure 7).

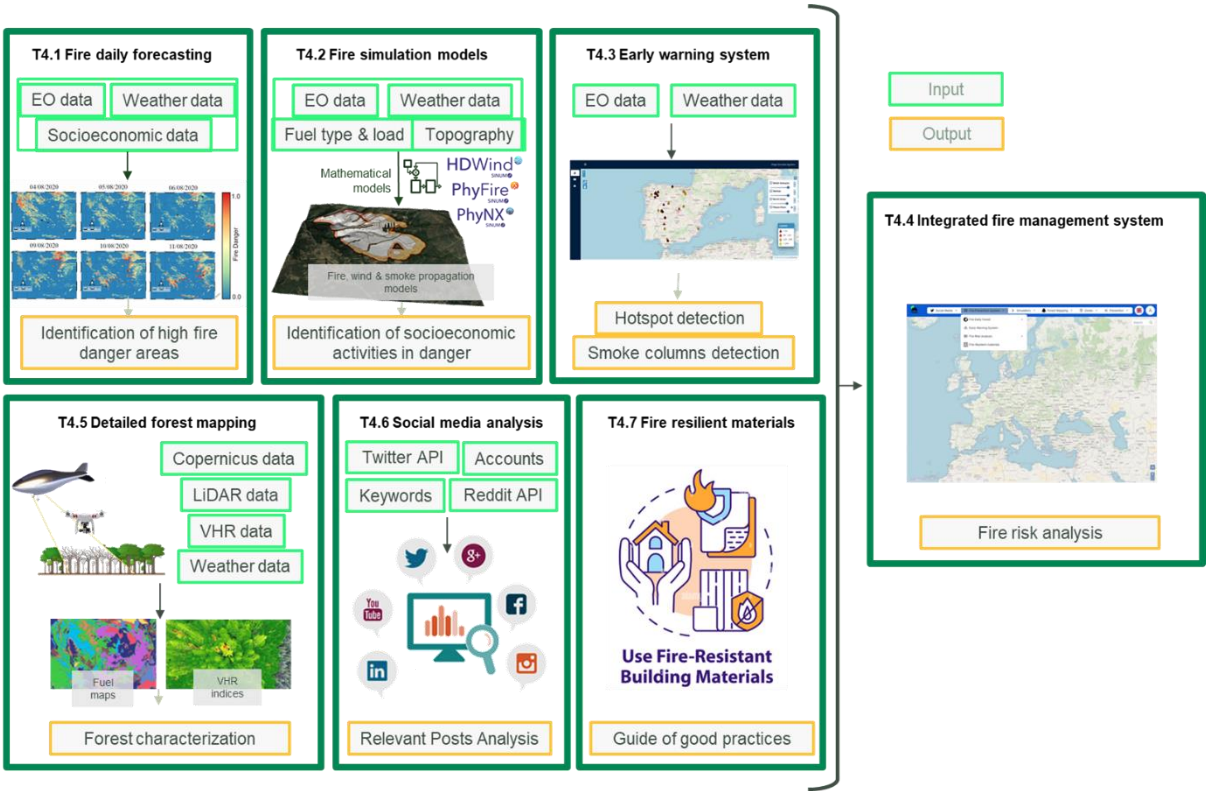


Figure 7. Example of a pipeline of the solution for prevention and preparedness in TREEADS.

Fire daily forecasting

As afore-mentioned, Deep Learning models fail in providing uncertainty estimates and suffer from overconfidence. In the context of TREEADS, to surpass these limitations and produce models that can improve decision making we are going to use Bayesian Neural Networks (BNNs) (Jospin et al., 2020). BNNs are Stochastic Neural Networks trained using Bayesian Inference. In contrast to Deterministic Neural Networks which provide point estimates of the model's parameters, BNNs set a distribution on them. Specifically, they produce the posterior distribution of the weights by setting a prior belief on them and use the training data as well as the Bayes' Theorem as an update mechanism. While this idea is intuitive there are certain challenges in training and predicting from these networks:

- Training BNNs with the classic Bayesian techniques like MCMC and Variational Inference is time-consuming and computationally expensive.
- Prediction in BNNs requires sampling from the posterior distribution which adds an extra amount of time during prediction, which may be a showstopper for some applications, where real-time response is necessary.

The main goal when training a BNN is to induce the Bayesian paradigm in Neural Networks so that on the one hand we could end up with good uncertainties of the model, while on the other hand, the model remains feasible to train. Several approaches have been proposed to train BNNs (Jospin et al., 2020). In TREEADS, we want to apply some of these methods for predicting short-term wildfire danger, being the first to apply BNNs in a natural hazard-related application. Specifically, **Bayes by Backpropagation** (Blundell et al., 2015) is a purely Bayesian method that leverages Variational Inference to perform the well-known Backpropagation algorithm for training the parameters of a Neural Network. Bayes by Backpropagation has been applied successfully to Artificial Neural Networks (Blundell et al., 2015), Convolutional Neural Networks (Shridhar et al., 2019), and Recurrent Neural Networks (Fortunato et al., 2017), but is computationally expensive as the network ends up having at least two times the number of parameters of a deterministic Neural Network. That's because a BNN trained with Bayes by Backpropagation has two trainable variational parameters for each weight which capture the mean and the variance of the weight's distribution.

The inefficiency of Bayes by Backpropagation has led to the creation of other less expensive approaches, that we also want to apply. Particularly, Dropout Methods are leveraging the well-known Dropout technique, which acts as a regulator in Deterministic Neural Networks, also during inference time. Monte Carlo Dropout (Gal et Ghahramani, 2016) is the most well-known method, where the variational posterior of the parameters is approximated by Bernoulli Distributions. Practically, in this method, the Neural Network is trained like a Deterministic Neural Network with Dropout layers, but the Dropout layers are also activated during inference, giving us in each forward pass, samples from the posterior. Other Dropout methods are Variational Dropout (Kingma et al., 2015) which applies Gaussian Dropout, and Concrete Dropout (Gal et al., 2017) which tries to learn the probabilities of the Bernoulli approximations in the Monte Carlo Dropout.

As has been discussed so far, the advantage of Bayesian Neural Networks is their ability to accompany their predictions with uncertainty estimates. While single Deterministic Neural Networks are generally unable to capture these uncertainties, Ensembling methods have been proven to provide good uncertainties of the model. Particularly, Deep Ensembles (Lakshminarayanan et al., 2017) are based on the idea of training multiple models with the same architecture but different initialization conditions and combining their outputs in order to get the mean of the predictions as the output of the model and their variance as a measure of uncertainty. While this method has been criticized as its uncertainties may lack in some ways (Gal, 2016), in practice they seem to provide very promising results, even better than some more rigorously formulated Bayesian Neural Networks (Ovadia et al., 2019, Fort et al., 2020), but on the expense of a significant extra computational cost, as Deep Ensembles require training the same model multiple times from scratch.

Although Deep Ensembles used to be criticized as non-Bayesian methods, the latest studies argue that they are a compelling approach to approximating the Bayesian Model Average (Wilson, 2020; Wilson et Izmailov, 2020; Pearce et al., 2018), stating that the success of Deep Ensembles is a strong motivation for following the Bayesian Approach. As has been pointed out (Ovadia et al., 2019; Fort et al., 2020) Deep Ensembles tend to find many different basins of attraction. Thus, the uncertainty of a prediction comes from the variance between point estimates of each separate network, each one belonging to a mode of the posterior distribution. On the other hand, Variational Inference Bayesian methods focus their modeling effort on a single basin of attraction and provide uncertainties based on the variance of the points around one mode of the distribution. Led by the idea of mixing these two approaches, MultiSWAG was proposed (Wilson et Izmailov, 2020), which combines an Ensembling of multiple independent SWAG approximations to create a mixture of Gaussians approximation to the posterior, adding no extra training time over standard Deep Ensembles. Moreover, other Ensemble methods have been proposed that expand the Deep Ensembles' idea. Specifically, Hyperparameter Ensembles (Wenzel et al., 2021) are using multiple Neural Networks with the same architecture but with different hyperparameters to approximate the Bayesian Model Average, Batch Ensembles (Wen et al., 2020) define each weight matrix to be the Hadamard product of a shared weight among all ensemble members and a rank-one matrix per member, thus decreasing both the computation and memory costs in training.

In the context of TREEADS, we want to use at least one method from each of the aforementioned categories (Bayes by Backpropagation, Dropout, Ensembles). Specifically, as a first step, we want to apply the more classical Bayes by the Backpropagation algorithm, the MC Dropout, and the Deep Ensembles to predict short-term wildfire danger along with uncertainties for the predictions. If time permits, other methods will be examined. The final goal will be to measure the quality of the uncertainty estimates and to understand how the uncertainties can enhance decision-making. To this end, the uncertainties should be measured both quantitatively and qualitatively by examining both the appropriate metrics and the fire danger maps produced by the BNNs.

In this work, we want to calculate both the aleatoric and the epistemic uncertainties of the predictions and measure their quality. Regarding the epistemic uncertainty, we will use the outputs of the multiple forward passes that are needed during inference for approximating the posterior and either use the mutual information or the variance between the different samples as a measure of the model's uncertainty. For the aleatoric uncertainty, we want to follow the works of Kendall & Gal (2017) and Collier et al. (2020). The Gaussian (or another simple distribution e.g., Gumbel) distribution is placed on the logits of a standard softmax classification model, making the logits latent variables. In order to compute gradients with respect to the stochastic model, the reparametrization trick is applied. The mean and standard deviation are computed as a linear function of a shared representation outputted by the final layer of a neural network before passing it from the softmax. Then, the output is written as a deterministic function of a standard normal distribution using the mean and the standard deviation that have been calculated from the network. The standard deviation that has been learned from the network for each sample can then be used as a measure of the aleatoric uncertainty.

With the two uncertainties calculated, we need to find a way of declaring how good they are and how they can help towards better decision-making. For this, we will follow the work of Mukhoti & Gal (2019) in order to calculate the appropriate metrics that can shed light on the uncertainties' quality and practicality. As a first step, we will calculate the mean aleatoric and epistemic uncertainties for the validation set in order to have a baseline of the level of uncertainties that the model has for the predictions. This baseline can also be used as a threshold for identifying if a sample should be considered certain or uncertain during inference. Using this threshold, we can then calculate the probability of being accurate given the fact of being certain and the probability of being uncertain given the fact of being inaccurate. These two probabilities should be high for the model to be considered trustworthy. Except for the aforementioned metrics a visual representation will be produced. That means that a visual map will be produced with both the predictions and the uncertainties of the model, giving a qualitative overview of the outputs.

Finally, as BNNs are known for producing better-calibrated predictions than Deterministic Neural Networks, the calibration of the models will be also measured. For this, we want to use the Expected Calibration Error (ECE) which simply takes a weighted average over the absolute accuracy vs. confidence difference. Practically, we divide the probability interval [0,1] into multiple bins. Then, the ECE is calculated as a weighted average of the prediction errors across the bins, weighted on the relative number of samples in each bin. In addition, reliability graphs of the ECE will be presented for identifying if the model is underconfident, overconfident, and where it fails.

In the previous lines, we described in detail the methods that will be used to investigate the scientific questions of Task 4.1 in TREEADS. In the next lines, we will describe the input data, the experimental setup as well as the final outcomes of this work. In a summary, the ultimate goal of the work is to use data that are related to fire ignition and spread, train a Deep Learning model that also quantifies the uncertainties of the predictions, and produce an output that represents the next day, or next two days, etc. wildfire danger along with the uncertainty about the predictions.

Regarding data, in the context of Deep Cube (H2020 program), several variables will be collected which are known to influence the ignition and spread of fire in the Mediterranean region covering a temporal span from years 2002 to 2022. All the data will be post-processed, curated, harmonized, and stored in a 1km x 1km x daily spatial-temporal datacube. The data that will be collected are:

- **Satellite data** from MODIS: Land Surface Temperature (LST) Day/Night (Wan et al., 2021), Leaf Area Index (LAI) (Myneni et al., 2021), Normalized Difference Vegetation Index (NDVI) (Didan et al., 2021).
- **Meteorological Variables** from ERA5-Land (Muñoz Sabater, 2021): maximum temperature of the day, maximum dewpoint temperature of the day, maximum wind speed of the day, minimum relative humidity of the day, average solar surface radiation downwards of the day, maximum surface pressure of the day.
- **Soil Moisture** from JRC European Drought Observatory (Camallerri et al., 2017).
- **Distance to Roads, Population Count** from worldpop.org (Tatem, 2017).
- **Land Cover** from Copernicus Climate Change Service (https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab=overview, DOI: 10.24381/cds.006f2c9a)
- **Elevation, aspect, slope, and curvature** from Copernicus Digital Elevation Model (Bashfield et al., 2011)

The aforementioned data will be used as input data to the DL model. As predictand, the EFFIS burned areas will be used (San-Miguel-Ayanz et al., 2012), after being pre-processed by the MODIS hotspots product for correcting the errors regarding the dates and duplication of fire events. In the context of TREEADS, the aforementioned data cube will be used and expanded by fuel loads that will be produced by CARTIF as well as by local data that can be made available by Pilot Leaders.

As noted by Kondylatos et. al (2022) the temporal component is significant for forecasting wildfire danger. That is why we will begin using the Long Short-Term Memory Architecture (LSTM) for the experiments. The LSTM will be trained on past events, using as inputs a times-series of the variables described above in order to predict the burned areas that will occur the next days. The Deterministic LSTM will be used as a baseline model, while Bayesian LSTM will enhance the forecasting task. The setup (training/validation/test splits, number of negative examples, etc.) cannot be rigorously defined yet but some already known issues should be taken into consideration:

- Negative samples are far more than the positive ones (highly imbalanced dataset); thus, a clever sampling strategy should be followed in order to acquire good samples for training the models. We should be very careful in choosing the negative samples, as, on the one hand, we want the distribution of positives vs negatives to be as close as possible to the real distribution and on the other hand to not make it too difficult for the model to be trained.
- Wildfire occurrence is stochastic. That means that a lack of fire occurrence does not mean a lack of fire danger. Thus, negative sampling should be done in a way to decrease as much as possible this stochasticity.
- The split in training/validation/test datasets should be temporal. Dealing with a forecasting task we should train in the past and evaluate the performance in later years (Oliveira et al., 2021).

In order to measure the skill of the models, classic metrics used in DL will be used (e.g., Precision, Recall, F1-Score, Area under Precision-Recall Curve), while for measuring the quality of BNNs the metrics that were described above will be used (mean epistemic/aleatoric uncertainty, probability of being accurate given the fact of being certain, being uncertain given the fact of being inaccurate, ECE). The final outcome of the model will be a probability, representing the wildfire danger for the next day(s). Moreover, wildfire danger maps with predictions as well as uncertainties will be presented for the area of interest.

As stated above, the final outcome of the model will be a map of the area of interest presenting the wildfire danger probability of each pixel catching fire in the next day(s). Along with this, two other maps will present for the same area the aleatoric and the epistemic uncertainty of the predictions. The spatial resolution of the maps will be 1km x 1km and these maps will be produced daily. The inputs that are needed for the model in order to predict the danger will be collected daily automatically from the various data sources and pre-processed in order to have the same format as the input of the models. After, the pre-processed variables for each pixel will be forward passed through the model and the outputs will be produced for each pixel. The outputs for every pixel will then be concatenated in order to create the final maps. This process is intended to run automatically and a separate georeferenced .tif file will be produced daily for each one of the maps. This will run in an online service and both an API and a WMS server will be available for anyone to access both the inputs and the outputs of the models.

Furthermore, one of the main improvements proposed in this module is the use of semantic segmentation applied to satellite and aerial imagery in order to complement the use of the aforementioned variables. There are different computer vision tasks. One of the most common applications is image classification, which involves the computer identification of the main object of an image and assigning it a label to classify it. Object classification is limited to a single object per image. Object detection is even more complex and requires the computer to detect and locate different objects within the same image.

Semantic segmentation consists of labelling each pixel of an image with a class corresponding to what is being represented. This is also known as "dense prediction" since every pixel has to be predicted. Unlike other computer vision tasks, semantic segmentation is not limited to producing labels and bounding boxes. It generates a high-resolution image, in which each pixel is classified.

Instance segmentation goes a step further, classifying each instance of the same class separately. For example, if an image shows three buildings, each building is an instance of the "buildings" class. Each of them will be classified separately, for example, using different colours.

Through these different tasks, the computer "understands" the content of the images with an increasingly precise level of granularity. Semantic segmentation makes it possible to distinguish, for example, the different types of terrain in an automated way.

There are different methods to solve semantic segmentation problems. Traditional approaches consist of detecting points, lines, or edges. It is also possible to be based on morphology or to gather groups of pixels.

Deep Learning convolutional neural networks are now widely used and can tackle more complex problems thanks to image segmentation. One of the most widely used neural networks for image segmentation is U-NET. It is a fully convolutional neural network model. This model was originally developed by Olaf Ronneberger, Phillip Fischer, and Thomas Brox in 2015 for medical image segmentation.

The U-NET architecture consists of two "tracks". The first is that of contraction, also called the encoder. It is used to capture the context of an image. Actually, it is a set of convolution layers and layers of "max pooling" that allow you to create a feature map of an image and reduce its size to reduce the number of network parameters. The second way is that of symmetric expansion, also called decoder. It also allows precise localization using transposed convolution.

In the field of Deep Learning, it is necessary to use large series of data to train models. Gathering such volumes of data to solve an image classification problem can be difficult in terms of time, budget and hardware resources. Data labelling also requires the knowledge and experience of various developers and engineers. U-NET allows to solve these problems, since it is effective even with limited series of data. It also offers higher precision than conventional models.

A classical autoencoder architecture reduces the size of the input information and the subsequent layers. Decoding starts later, the linear representation of features is learned, and the frame size gradually increases. At the end of this architecture, the output size is equal to the input size.

This architecture is ideal for preserving the initial size. The problem is that it compresses the input linearly, which prevents the transmission of all features. This is where U-NET comes into its own with its U-shaped architecture. The deconvolution is done on the decoder side, which avoids the bottleneck problem that occurs with an autoencoder architecture and thus avoids loss of features. The purpose is to define and implement a forest fire risk assessment for fire risk mapping with the combination of different inputs as shown in the following figure.

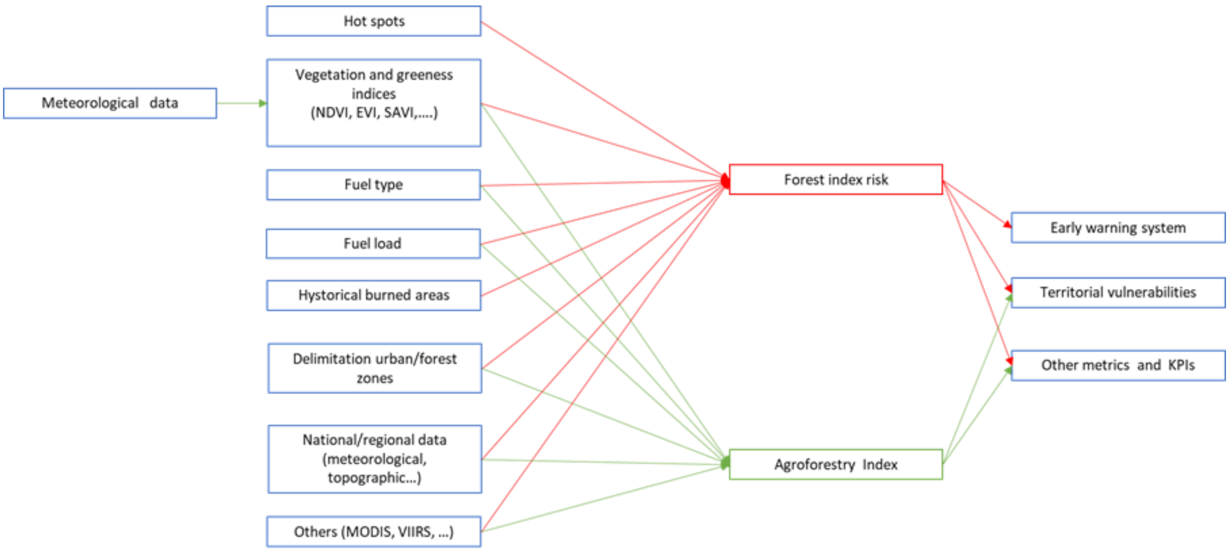


Figure 8. Different inputs used to calculate the vegetation indices

The use of segmentation using U-NET networks of aerial and satellite images to obtain better vegetation maps and an adequate classification of fuel types will complement the FireCube dataset in order to improve the fire forecasting.

The main goal is creating a classification model and then repurpose this learning in a segmentation model. As a starting point to create a classification model, we will study the use a model previously trained on ImageNet, like ResNet-50 or ResNet-101, applied to satellite and aerial imagery datasets as BigEarthNet.

A first approximation with a few classes can be seen in the following figure that shows the segmentation of an area in the Spanish pilot, Casillas (Ávila).

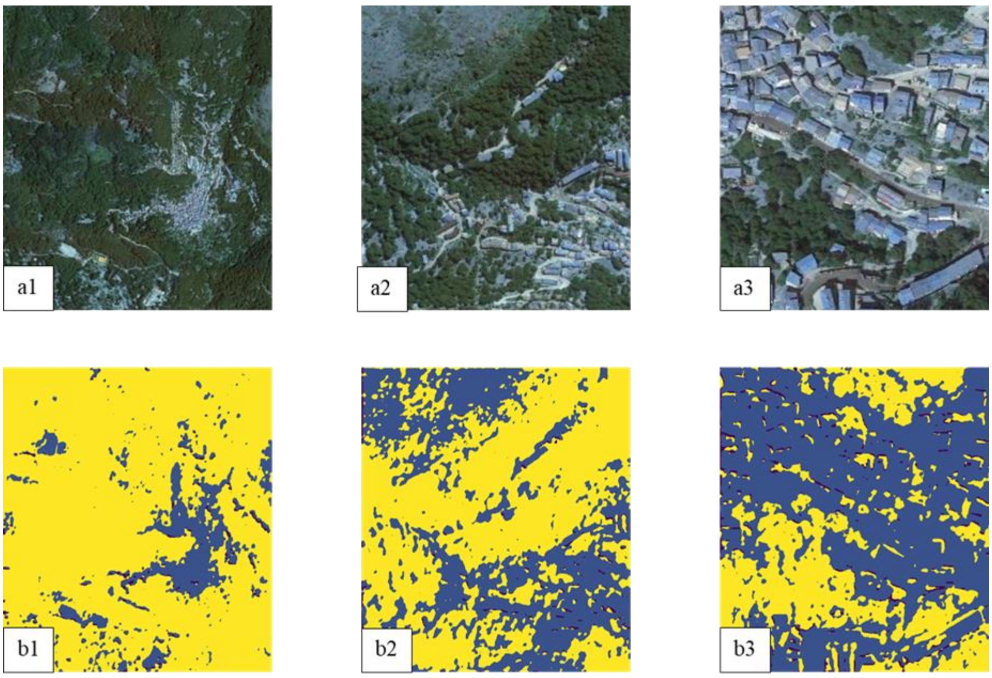


Figure 9. First segmentation approach of an area in Spanish pilot, Casillas (Ávila).

The classification model will be use as a pretrained encoder in a modified U-Net model to generate pixel level land cover classification maps, using smaller datasets with training images from the pilot areas. After the study of the main factors affecting fire risk and the determination of the weight for each factor influencing forest fire risk, the final outcome of the model will be georeferenced .tif files presenting the forest index risk of each pixel. The output periodicity is not clearly defined yet, but even if it will be daily some of the features considering do not vary periodically as vegetation types.

Forecasting connected with evacuation preparedness and planning

Evacuation preparedness is a topic of high significance posing many challenges due to its criticality and real time nature. In light of this challenge the TREEADS solution will offer a mobile application for forest rangers, first responders, and site visitors alike. The solution will involve the use of machine learning techniques in order to improve site visitor evacuation by analyzing visitor paths while being able to support evacuation planning and relevant decision support, being also able to offer real time notifications related with evacuation and movements within the monitored area.

The architecture of the application will involve a main backend service which will be responsible for the following:

- Exchanging information with sensor systems in real-time
- Storing necessary information in the database such as user data and sensor values
- Communicating with the mobile application for providing necessary information
- Communication with the machine learning module in evacuation scenarios and decision support functionality for visitor evacuation paths
- Distribute manual/automatic notifications to users

The architecture will make use of latest technologies employing best practices for efficiency and security. Information exchange will be carried through various channels including REST APIs, MQTT broker and Apache Kafka. The mobile application will be designed with simplicity and ease of use being the top priority.

Fire simulation models

For the simulation of the complex fire spread and smoke dispersion process we proposed three simplified physical models that works in a coupled way, solved using effective numerical and computational techniques and GIS integrated. For the fire spread process we propose the **PhyFire** model, for the dispersion of the smoke cloud we propose de **PhyNX** model, and for improving wind input data for both models, we propose the high- definition wind field model **HDWind**.

The three models can be improved to respond to new needs that arise during the development of the project since the developers of these models are part of the consortium, and therefore these models are not external tools working as black boxes, but are tools with a very advanced development, fully functional but that can be improved and adapted responding to the arising requirements of the project. Although they are all fully operational models, an intense process of parameter adjustment must be carried out through the simulation of historical fires, for which access to the greatest amount of relevant information is essential. The uncertainty of the simulation results can also be reduced by improving the accuracy of the model input data, using the other technologies involved in the project.

The numerical solution of the equations of the three models are implemented in C++ using an own Finite Element library, Neptuno++, and they are adapted to parallel computing, using OpenMP. The numerical schemes and the computational codes are optimized in order to provide simulations in less than real time, and they can be adapted to different levels of spatial resolution. Techniques of reduced basis have been incorporated to numerically solve the wind model, enabling a much more efficient resolution of the corresponding optimal control problem. Adaptive Finite Element Method with characteristics in the horizontal directions and Finite Differences in the vertical direction and splitting techniques are used for the dispersion model.

The fire spread model **PhyFire** is a simplified 2D wildfire spread model with some 3D effects. It is based on principles of energy and mass conservation (Asensio et al., 2002). The model considers the energy lost in the vertical direction due to natural convection, and the two main heat transfer mechanisms in a wildfire, radiation and convection. Radiation from the flames above the surface, considers the effect of wind and slope over flame tilt. It is a one phase model: only solid phase considered, gaseous phase is parameterized through flame temperature and flame height in radiation term (Ferragut et al., 2007, 2014, Asensio et al., 2020). The convective term is critical as wind is one of the most influential factors in the spread of a fire. Surface slope is also considered in the convective term of the energy conservation equation. Fuel moisture content is considered by using a novel idea, an enthalpy multivalued operator. The model includes some random phenomena as fire spotting (Asensio et al., 2021). The model can be adapted to different fuel classifications and scenarios. If updated information on the evolution of a real fire is available, this data can be assimilated by the model to improve the results of the simulations (Ferragut et al., 2015). The model is also prepared to update meteorological and cartographic input data during the simulation process, for example the use of firebreaks can be included in the simulation by the modification of fuel distribution data. This allows to study the effect of prevention works in possible fire events.

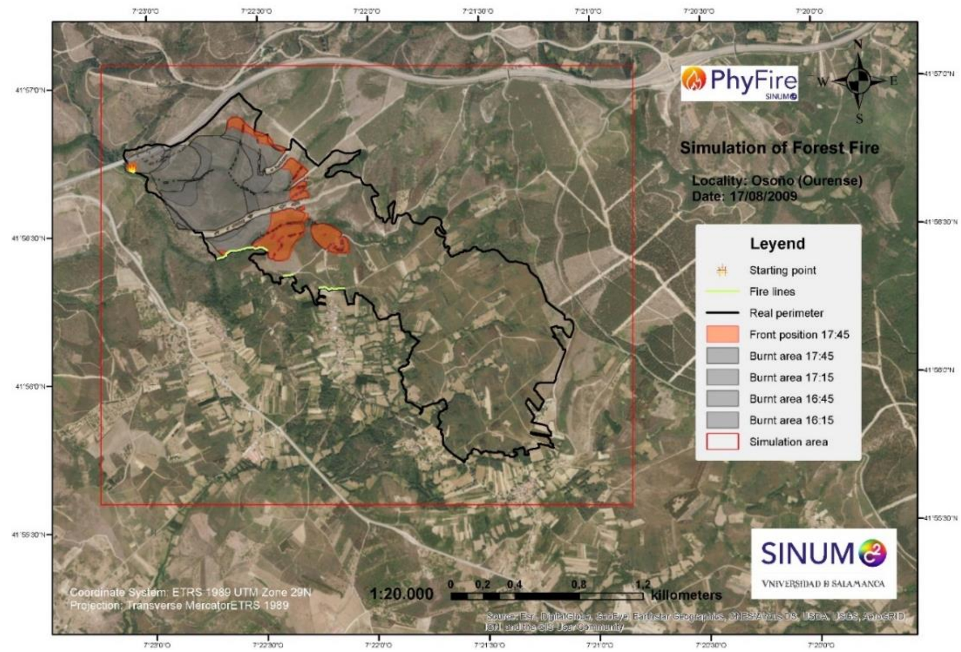


Figure 10. Fire spread simulation with PhyFire, including fire spotting and firebreaks (yellow lines).

As wind is one the most relevant factors in fore spread, and accurate information is often not available in areas near the fire, the PhyFire model includes its own wind model, HDWind. Both models work in a coupled way, improving meteorological wind data to feed the fire spread simulation model.

HDWind is a mass consistent vertical diffusion wind field mode that arises from an asymptotic approximation of the Navier-Stokes equations. The most salient feature of this asymptotic approach is that it provides a three-dimensional velocity wind field (which satisfies the incompressibility condition in the air layer) governed by a two-dimensional equation, so that it can be coupled with the temperature surface distribution in order to consider surface thermal effects. In addition, the terrain elevation information is also considered by the model, as well as surface roughness (Asensio et al., 2005). HDWind only requires meteorological wind measures at a small number of points in the simulation area, adjusting these data by solving an optimal control problem in which the wind flow on the surface boundary is the parameter to be controlled (Ferragut et al., 2011). This wind model can be coupled with mesoscale forecasting weather models to improve at a local level wind forecasting (Prieto et al., 2021)

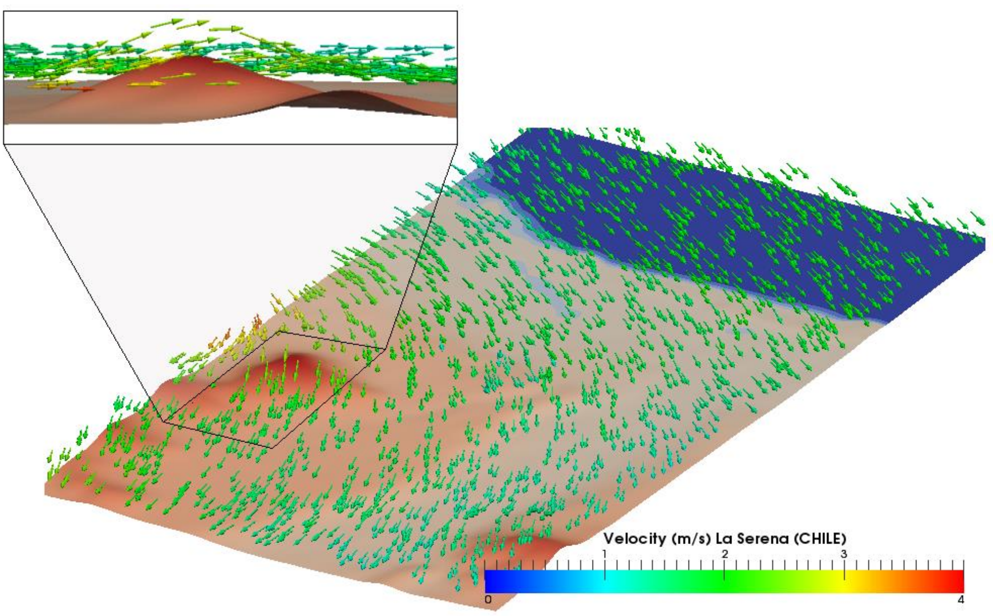


Figure 11. Wind field simulated with HDWind, the effect of local orography can be observed.

The outputs of the PhyFire model are: burning area (fire edge and fire thickness), burned area, main spread direction and rate of spread. PhyFire model is prepared to provide the heat release rate and smoke emissions, and work in a coupled way with the atmospheric pollutants dispersion model PhyNX.

PhyNX is an urban scale Eulerian non-reactive multilayer air pollution model, describing convection, turbulent diffusion and emission (Ferragut et al., 2013). The wind field data used in this air pollution model is provided by the HDWind model. The model provides pollutant concentration and hazards levels values at different air layers above ground. The PhyNX model uses a dataset called PAC (Protective Action Criteria), which are indices or guide levels of exposure during emergencies, designed to protect the population from the health effects of exposure to hazardous chemical compounds for short periods of time. The PAC dataset used is a compilation of three types of chemical exposure indices or limits: Acute Exposure Guide

Levels (AEGLs) from the United States Environmental Protection Agency (EPA), Emergency Response Planning Guidelines (ERPGs) from the American Industrial Hygiene Association (AIHA), and Temporary Emergency Exposure Limits (TEELs) from the U.S. Department of Energy (DOE). The model allows predicting the areas under risk to human health due to the effect of smoke from a hypothetical fire so that it can be used as a tool to help in the decision making of evacuation plans.

In order to adapt this air pollution dispersion model to the smoke cloud dispersion, coupled with the fire spread model PhyFire, it is necessary to do an intense work of adjusting the following parameters: combustion efficiency coefficients, emission coefficients and dispersion coefficients. This work must be addressed in collaboration with other members of the consortium.

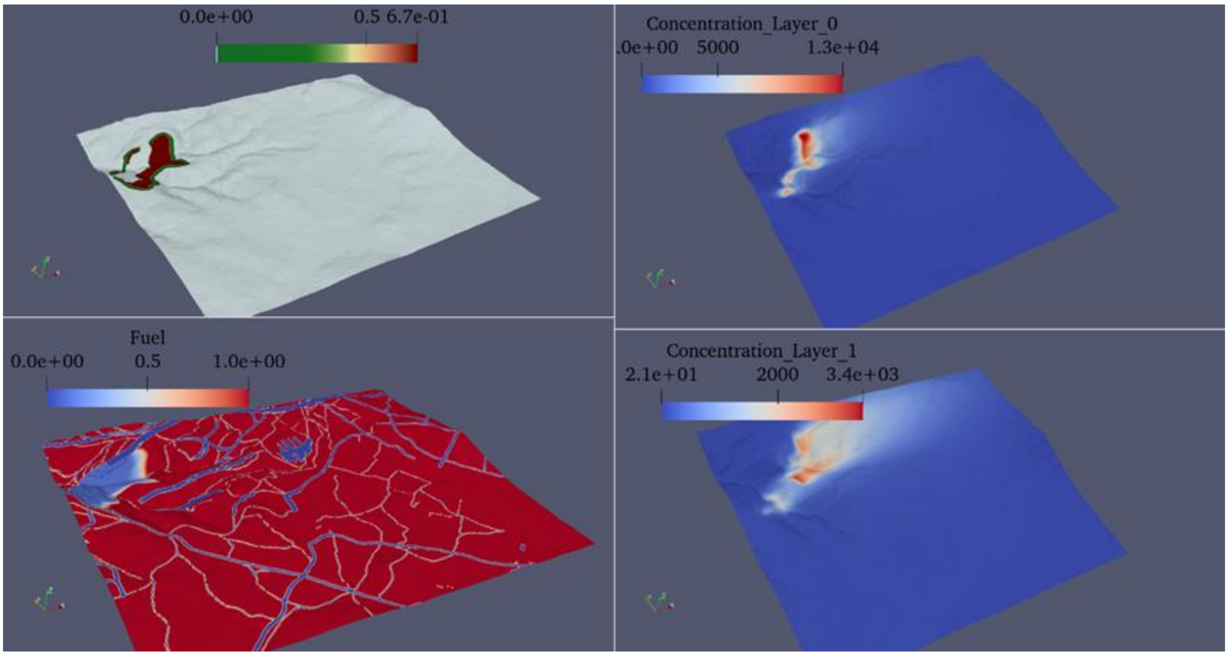


Figure 12. Fire front, burned area and smoke concentration at two different air layers, simulates using the coupled system PhyFire-HDWind-PhyNX.

The three model are prepared to be integrated into a Geographical Information System in an optimized way. In fact, there exists a GIS-integrated prototype (Prieto et al., 2017) working on the Spanish territory, using corresponding topographic and fuel types and distribution cartography. This can be improved and extended to other areas of Europe.

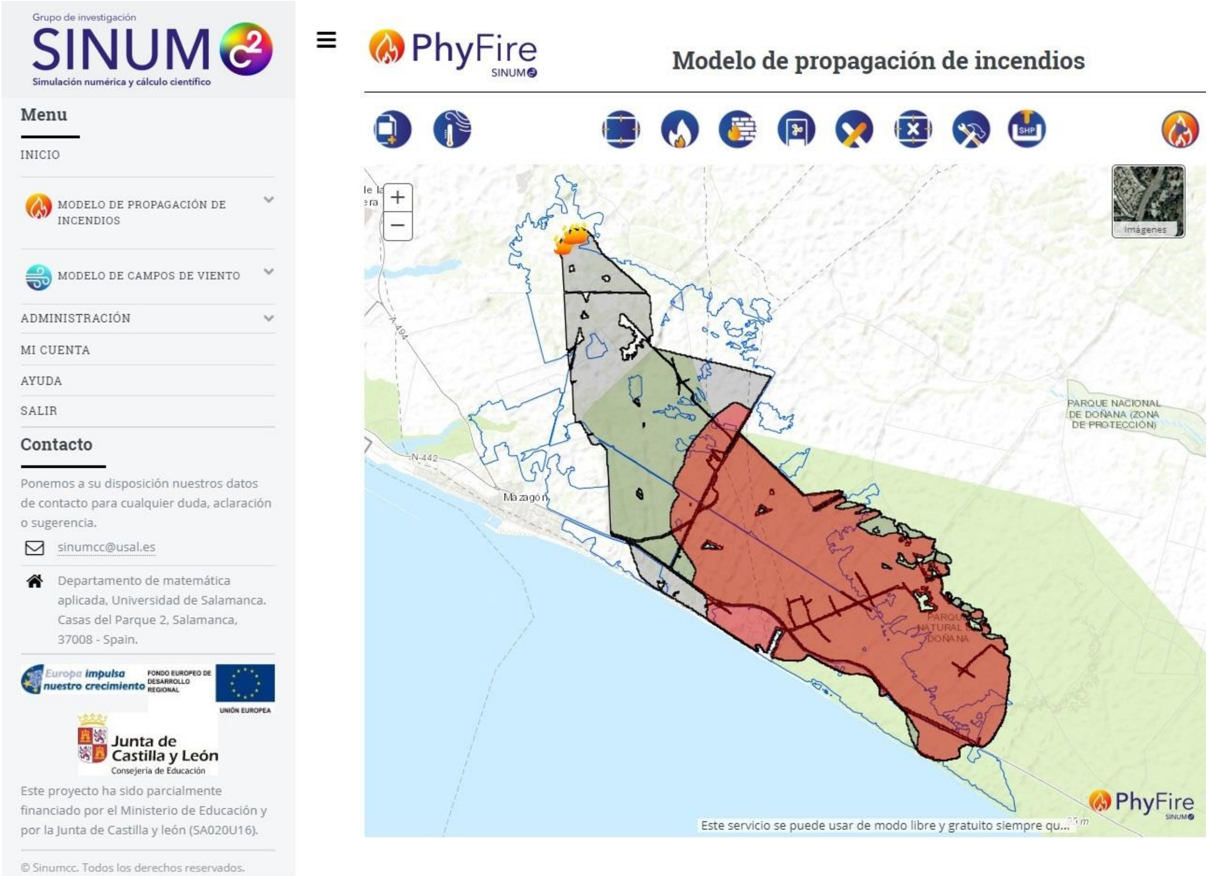
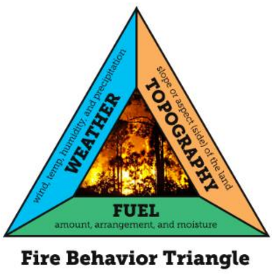


Figure 13. GIS-integration of PhyFire and HDWind over the Spanish territory.



The input data of the PhyFire model includes all data of the fire behaviour triangle: topography (slopes and aspect), fuel (type, distribution and fuel moisture) and weather (wind, temperature, and relative humidity). The PhyFire model can be adapted to different resolution levels through data interpolation techniques, as well as the other two simulation models. The PhyFire model can also be adapted to different fuel classification as the Northern Forest Fire Laboratory (NFFL) system (Anderson, 1982), the Fire Behaviour Fuel Models (FBFM) (Scott and Burgan, 2005), or the Mediterranean-European Prometheus system (European Commission, 1999).

The following scheme provide a general vision of the input data needed, and initial map suggested with the corresponding resolution and the technology that can provide the corresponding information.

- **Base Map:** Open Street Map (Global level)
- **Topographic Map** (Digital Elevation Model, DEM): several options
    - EU-DEM v1.1 (Copernicus) [25 m] (European level)
    - DEM ALOS PALSAR [12.5 m] (Global level)
    - MDT02 [2 m] (Spanish pilot)
- **Fuel Map** (No fuel areas, fuel type distribution, fuel type properties): need of the following layers
    - Open Street Map (Global level): To determine no fuel areas.

    - FirEUrisk_Europe_fuel_map [1km] (European level) (Includes fuel type 0, no fuel) (Aragoneses et al., 2022)
    - EFFIS Fuel Map (European level but not completed)
    - MFE25 & IFN4 (2008-now) or MFE50 & IFN3 (1997-2007) (Spanish pilot)
    - Satellite derived indices, such as NBR, EVI and NDVI for no fuel areas and fuel type distribution.
- **Other layers:**
    - Fuel moisture content, for example using MODIS.
    - Surface temperature, for example using MODIS.
- **Meteorological data:** from service with API (European level).

With the three models proposed (PhyFire, HDWind, PhyNX) we can predict and explore how fires and smoke clouds may spread through computer simulation. We can explore scenarios and test different fire management strategies under different weather conditions. Using updated and improved cartographic data and the wildfire toolset proposed we can simulate several wildfire scenarios and test different configurations of firebreaks under different weather conditions and evaluated their effectiveness. This serves as a tool to help decision-makers in the design of prevention plans, through the location of the most hazardous areas and weather conditions.

Early warning system

Early Warning is "the provision of timely and effective information, through identified institutions, that allows individuals exposed to hazard to take action to avoid or reduce their risk and prepare for effective response".

An Early warning system is a (digital) *tool that comprises the capacities needed to generate and broadcast timely and meaningful information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately to reduce the possibility of harm or loss*.

In line with the United Nations' International Strategy for Disaster Reduction[1], TREEADS early warning system will integrate four main elements:

- Risk Knowledge (forecast and assessment)
- Monitoring and Prediction location and intensity of the natural disaster waiting to happen This information gives the possibility of taking action to initiate mitigation or security measures before a catastrophic event occurs.
- Dissemination Information (timely / reliable) communicating alerts to authorities and to potentially affected; and responding to the disaster.
- Response Capability, to enable fire managers and decision makers to assess the fire-weather development at locations where wildfires or land-use fires are currently burning.

TREEADS early warning system builds upon and uses the capabilities of TREEADS digital infrastructure (holistic platform and digital representation of the landscape) to provide authenticated users the following main features:

Definition of users and roles: it is an administrative function that allow to define the user, which process and/or which data he/she can execute/view.

Definition of the area of interest: this is another administrative function that the end-user uses to define the territory to be monitored and analysed. The result is a polygonal area on the map and represents the territory that is under the responsibility of the user.

Selection of the services to use: the next step is select the services and TREEADS technologies that the user wants to use in order to monitor the area and detect risky situations. This is also an administrative function.

Examples of services/technologies could be:

- Monitoring missions (UAVs/Zeppelin)
- Execution of TREEADS services (e.g., Risk assessment/ Fire propagation simulation, risk prediction, etc)
- Receiving / sending alerts
- Broadcast of information through different and most appropriate communication channels.
- Management of resources (ensure prompter response)

Additionally, TREEADS early warning system will provide mechanisms to incorporate data coming from different sources following TREEADS 4-layered approach (satellite data, Zeppelin, UAVs, social media), and data from other TREEADS services (e.g., hot spot detection, risk assessment etc), and the possibility to define and assess relevant indicators (KPIs).

[1] https://sdgs.un.org/statements/un-international-strategy-disaster-reduction-unisdr-8377

The detection of hotspots or incipient fires still in its early stages when they are still small and their temperatures relatively low is an interesting tool to be implemented in the TREEADS early warning system. Satellite imagery alone is not enough for time-sensitive fire detection due to the low spatial, temporal and radiometric resolution, uncapable of measuring the energy emissions of incipient fires. To overcome this issue, satellite imagery can be combined with relevant data such as fire fuel maps that will also be developed to support the fire risk assessment module and the simulation modules. Moreover, the TREEADS 4-layered approach can enhanced both the spatial and temporal resolution, as suitable sensors (like multispectral cameras or others) can be equipped on the platforms to perform surveillance activities in the area of interest like fire prone areas such as Spain or Greece during the summer months, when the fire risk will be dramatically high, as properties and even human lives can be destroyed. The images taken by these aerial platforms can be merged with georeferenced data to increase the accuracy of the early warning system, as they will also be leveraged by the calculation of typical vegetation indices derived from multispectral sensors (the most used being NDVI of NDWI), other cartography data like Corine Land Cover or Natura 2000 to detect fire in vegetation areas or areas with high ecological value or other places where the vulnerability towards fire risk is higher. Also, the use of human settlement data could be used to determine wildland-urban interfaces: these areas are especially sensitive since fire effects can be the most catastrophic.

4-layered approach relies on cameras and sensors equipped on TREEADS aerial platforms, which will permit surveillance and monitoring of the area of interest in relation to forest fire management. A number of radiometric vegetation indices derived from remote observations are based on the spectrometric behaviour of vegetation in the infrared band of the electromagnetic spectrum. However, cameras installed in drones are limited to the visible bands of the spectrum, thus the radiometric vegetation indices become impossible to compute. Nevertheless, these indices can be adapted so they can be calculated when the infrared/near-infrared band is not available. Some examples of vegetation indices for visible bands only are the following:

- GRVI (Green-red Vegetation Index)
- RGBVI (Red-green-blue Vegetation Index)
- GLI (Green Leaf Index)
- VARI (Visible Atmospherically Resistant Index)
- NGRDI (Normalized Green-Red Difference Index)

Detailed forest mapping

Forestry and orographic variables of interest for forest fires prevention and preparedness consist mainly of aspects related to the landscape and the state of the vegetation cover. These are spatial and radiometric variables related to the photosynthetic processes and the vegetation cover temperature. Digitizing and representing these variables as geomatic products of various kinds (different dimensions and spatial, temporal, spectral and radiometric resolutions) allow for identifying forest fire risk scenarios. In this way, the most up-to-date computer and technological tools together with the constant availability, almost in near real time, of remote sensing data pop up opportunities for helping in preventing forest fires by detecting the risks, minimizing the damage and increasing the resilience of a territory and its population.

Four types of data sources are considered in order to acquire the variables of interest, which are listed as follows:

- **Anthropic variables**: Firstly, the forest areas (all areas covered with vegetation) must be delimited, and the means and infrastructure available in the territory must be located. Therefore, an approximation with geographic information on land uses and coverage is needed, such as CORINE Land Cover (CLC). CLC allows for segmenting those areas that are likely to contain vegetation, thereby locating the analyses and efforts in them (for instance, there is no place for a forest fire in a sea area). These anthropic variables are obtained from data of various kinds and always require supervision to ensure that the use/coverage assigned to a specific location or space is accurate.
- **Spatial variables** provide information about the forest mass structure (i.e., canopy height and canopy cover) and represent the terrain relief (i.e., slope, and orientation). Moreover, these variables allow for typifying and quantifying the vegetation in terms of fuel models and fuel loads. In this case, it is remote sensors, such as laser scanner, LiDAR technology and radar sensors, that capture this three-dimensional information.

- **Radiometric variables** mainly provide information about the state of the vegetation coverage through measuring sunlight used for photosynthesis. Quantifying the photosynthetic performance of a plant is directly related to the amount of biomass produced, and therefore, with the amount of living fuel present in that area. Monitoring the presence or absence of photosynthetic activity can support the segmentation of areas covered by vegetation whereas monitoring the occurrence of sudden drops in the photosynthetic activity can support the detection of an increasement in the availability of burning fuels in that area.
  Moreover, radiometric variables provide information about the temperature of the vegetation cover when thermal bands are used in the electromagnetic spectrum. This data allows for calculating the evapotranspiration rate of plants, and consequently the amount of humidity contained, and their level of water stress, thereby allowing for estimating the soil water content. Most of the sensors dedicated to capturing this data dump the information on images.
- Lastly, **meteorological variables** can be implicit in the state of the vegetation, so they must be known not only as indicators of atmospheric conditions, but also as to estimate in advance the vegetation response to fire. These data are usually captured in a timely manner, at weather stations, or estimated and interpolated with satellite images and atmospheric measurements.

It is to note that all these variables are represented in cartographic products which extension covers as much surface as proposed to be digitized. Geographic information systems are the most appropriate tools to handle this information. In particular, when using images captured by satellite missions, Google Earth Engine and Sentinel Hub platforms allow for executing the complete flow of downloading, processing and exporting the data, thus easing the process for the entire scientific community.

In the following Table 5, the variables of interest have been listed (rows) together with different geomatic products (columns) and their suitability as a data source according to a numerical criterion from 1 to 3:

1. **Main**, as a main and sometimes unique data source.
2. **Complementary**, as a data source that provides information that complements the main source.
3. **Minor**, as a possible data source that, depending on the capturing conditions, can provide some improvement to the previous ones.

Table 5. Variables of interest for detailed forest mapping, possible geomatic products as data sources and their level of suitability.

	Information about:	LiDAR	RADAR	Visible image	Near / Infrared image	Thermal image	Not remote sensing	Land Use	Manual input
Digital Terrain Model	territory	1	1						
Digital Slope Model	territory	1	1						
Digital Aspect Model	territory + canopy	1	1						
Urban-Forest Interface	territory			2	2			1	3
Civil protection resources	territory			1				1	1
Firefighting resources	territory								1
Canopy Height Model	canopy	1							1
Canopy Base Heights	canopy	2							1
Canopy Bulk Density	canopy	2		3	3				1
Fuel models	canopy	1		2	2			1	3
Fuel loads	canopy	1		2	2			1	1
Humidity	meteorology		1			2	1		2
Temperature	meteorology					2	1		2
Precipitation	meteorology		1				1		2

The following Figure 14 illustrates the variables of interest to be mapped and their origin as data sources and geomatic products.

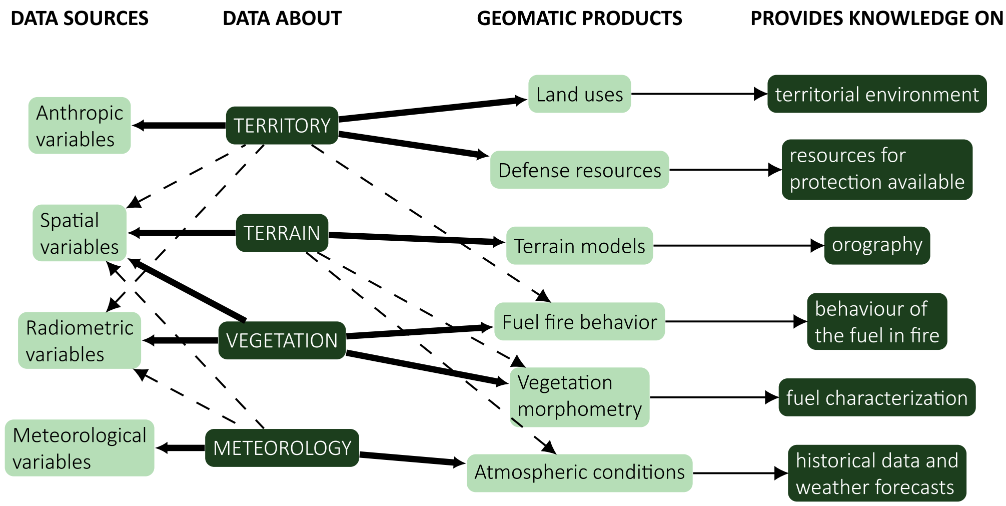


Figure 14. Data sources, data type, geomatic products and knowledge provided.

The use of multitemporal analysis of satellite imagery allows monitoring the evolution of the vegetation data mentioned before. These indices are based on the reflectance of light in the electromagnetic spectrum and are a combination of spectral bands register by satellite (as Sentinel 2). Vegetation indices have their own specific formula and could be used to map and monitor vegetation cover and distribution, and to identify areas of vegetation damage or stress.

There are many different vegetation indices that will be considered in these tasks. The vegetation indices expected to be used in TREEADS are shown in the next table.

Table 6. Vegetation indices.

Index	Description	Formula
NDVI	Normalized Difference Vegetation Index uses the visible and near-infrared bands of the electromagnetic spectrum to measure the amount of green vegetation in an area. It is used to assess the health of vegetation and to monitor changes in vegetation over time	NDVI = (NIR-RED) /(NIR+RED)
EVI	Enhanced Vegetation Index is a measure of the density and health of vegetation. It is similar to NDVI, however, EVI corrects for some atmospheric conditions and canopy background noise and is more sensitive in areas with dense vegetation.	EVI = G*(NIR-RED) /(NIR+C1*RED-C2*BLUE+L)
GLI	Green Leaf Index is a measure of the density of green leafy vegetation in an area. It is calculated from measurements of reflected light in the red and NIR bands of the electromagnetic spectrum.	GLI = ((GREEN-RED) +(GREEN-BLUE)) /(2*GREEN+RED+BLUE)
SAVI	Soil Adjusted Vegetation Index is a modified version of the NDVI that is used to correct for the effects of soil brightness on vegetation measurements	SAVI = ((NIR-RED) /(BUR+RED+L)) *(1+L)
GCI	Green Chlorophyll Index is used to estimate leaf chlorophyll content in the plants based on near-infrared and green bands	GCI =NIR/GREEN - 1

RGRI	Red-Green Ratio Index is used to estimate the course of foliage development in canopies. It is an indicator of leaf production and stress, and it may also indicate flowering in some canopies	RGRI=RE/GREEN
SIPI	Structure Insensitive Pigment Index is used as an indicator of the health and productivity of plants, as well as a measure of the amount of photosynthesis that is occurring. Higher SIPI values are generally associated with healthier plants	SIPI = (NIR-BLUE) /(NIR-RED)
ARVI	Atmospherically Resistant Vegetation Index is a modified version of the NDVI that is used to mitigate atmospheric scattering by doubling the red spectrum measurements and adding blue wavelengths	ARVI = (NIR-2*RED+BLUE) /(NIR+2*RED+BLUE)
NBRI	Normalized Burn Ratio Index is used to highlight burnt areas in large fire zones.	NBRI = (NIR-SWIR) /(NIR+SWIR)
OTCI	OLCI Terrestrial Chlorophyll Index is a measure of the amount of chlorophyll in plants. OTCI is a specific indicator for Sentinel 3 images and is often used as an indicator of the health and productivity of plants, as well as a measure of the amount of photosynthesis that is occurring.	OTCI = (B12-B11) /(B11-B10)

As an example, Figure 15 shows some vegetation indices in the Spanish pilot obtained from Sentinel 2 using Google Earth Engine.

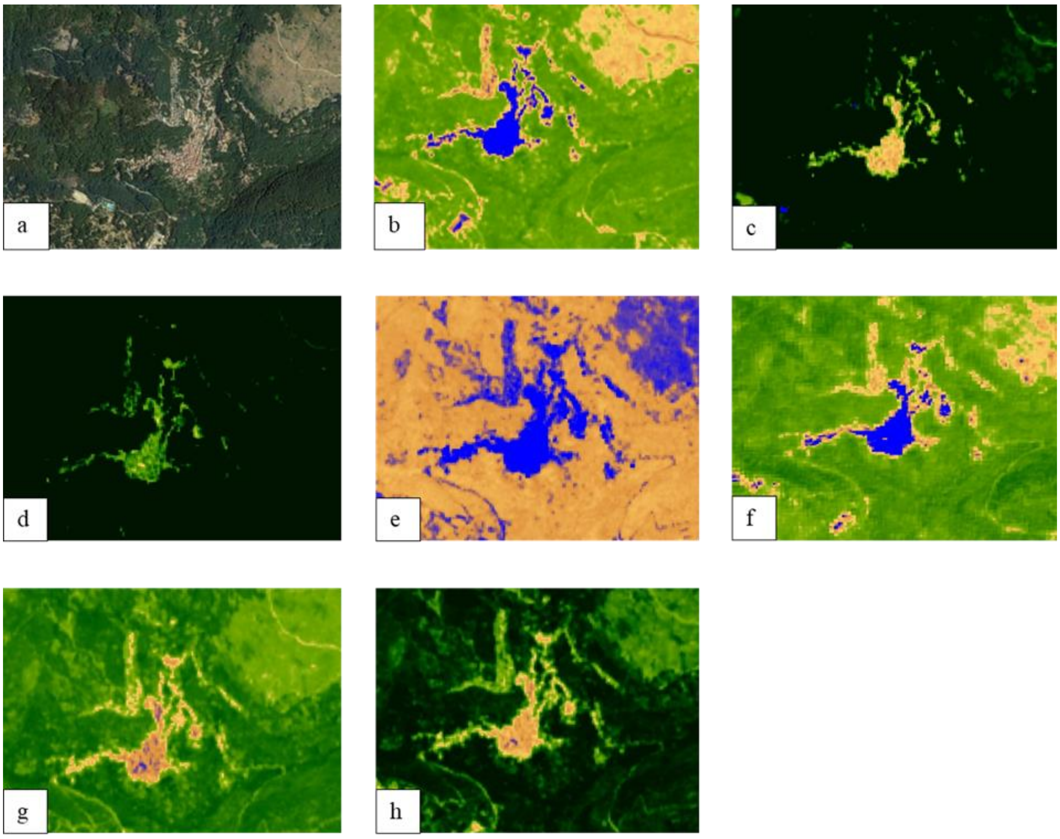


Figure 15. Vegetation indices from Spanish pilot (Casillas area, Ávila) (a) Original image (b) ARVI (c) EVI (d) GCI (e) GLI (f) NBRI (g) NDVI (h) SAVI

On the other hand, the distance at which each sensor captures the data is a very significant factor since the sensors’ sensitivity has been designed for each specific platform. TREEADS project uses four kinds of platforms: satellites, airships and drones (in three different altitude levels), which characteristics in terms of capabilities to estimate the forest variables of interest are defined as follows.

Satellite

The spatial resolution is of the order of tens of meters in free products and submeters in commercial products acquired on request. The spectral resolution offered is wide along the electromagnetic spectrum (with wavelengths from the visible to the microwaves band) since the sensors on-board are designed to maximize the capabilities for digitizing the Earth's surface and to be operated remotely. The temporal resolution is from 5 days to 1-2 weeks in free products and can be improved up to a few days in paid products.

The technological offer of satellite products makes available to users a large amount of information with a fine spatial and temporal resolution, allowing for a constant monitoring of variables related to the state of the vegetation and the atmosphere.

Zeppelin

Since the data is captured at around 150 m above the ground, sensors on-board airships allow for a considerable improvement in the spatial resolution (up to centimetres) compared to satellite images. In addition, since there are hardly any elements interfering between the sensor and the Earth's surface (as happens with the atmosphere in the case of satellite sensors), the need for corrections is significantly reduced.

As a shortcoming, the manoeuvrability of these platforms does not allow for very complex flight plans to be executed. Therefore, they are not used to execute photogrammetric flight plans but to capture independent images or videos which are not orthorectified afterwards (surveillance, observation, etc.).

As for the temporal resolution, it increases but is constrained to the possibility of capturing the data with favourable weather conditions.

Drones (low-medium and low altitudes)

Drones flight at around 100 m above the ground and both the multirotor and the fixed-wing equipment are well manoeuvrable, which allows for executing photogrammetric flight plans. A requirement for the sensors on-board drones is their miniaturization, which allows to minimize their weight and bulk. Drones’ main limitation is their flight autonomy, which forces to optimize the weight carried and thus the sensors and batteries.

Orthoimages and point clouds from photogrammetric processes are obtained when images are captured whereas mono or multi-return point clouds when LiDAR sensors are on-board. As for images in the visible and non-visible regions of the electromagnetic spectrum (i.e., thermal, multispectral or hyperspectral), the spatial resolution can be improved from tens of meters to centimetres (Figure 16). As for the temporal resolution, even though it depends on favourable weather conditions for the flight, it also improves regarding satellite temporal resolution. However, both improvements mean a considerable increase in the data acquisition costs, especially when dealing with extensive landscapes.

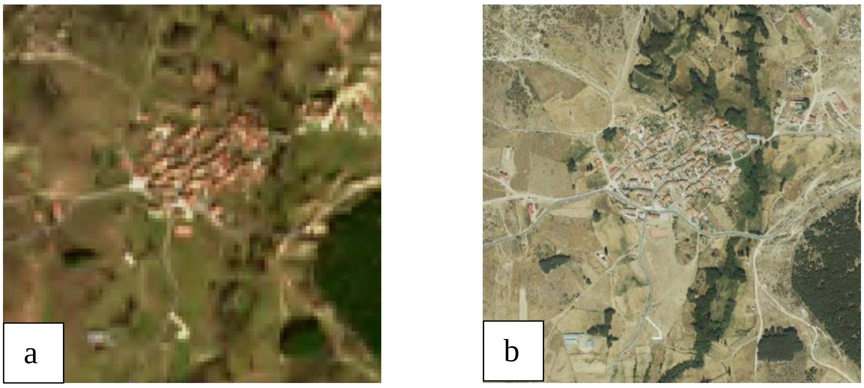


Figure 16. (a) Sentinel 2 image, with a spatial resolution of 10 m. (b) Orthophoto from the Spanish National Orthophoto Program (PNOA) with a spatial resolution of 0.25 m.

The following Table 7. Analysis of the different platforms that will be used in TREEADS. shows the main differences between the aforementioned platforms, clarifying the strengths and weaknesses of each the data acquisition needed to map the forest variables of interest.

Table 7. Analysis of the different platforms that will be used in TREEADS.

GEOMATIC PRODUCT	SATELLITE	ZEPELLIN	DRONE	OBSERVATIONS
Land uses (Urban-Forest Interface, ...)	Supports the initial segmentation of the territory	Can provide confirmation from the observation view	Excessive costs and resolutions	Product elaborated with semi-automatic processes, supervising the accurate classification.
Defence resource (Civil protection and	It can only provide an overview. insufficient resolution	Can provide confirmation from the observation view	Can provide confirmation when the elements are perceptible.	The product elaboration entails a very manual process.
Terrain models (and derived)	Low spatial and temporal resolutions	Provides only observation view	Suitable when high spatial or temporal resolutions are required	Product preferably obtained from pre-existing geographical information sources
Fuel fire behaviour (fuel models, fuel loads, ...)	Allows monitoring of the state of the vegetation with high spectral resolution.	Can provide confirmation from the observation view	Suitable when high spatial, or temporal resolutions are required	Variables derived from spatial and radiometric information using semi-automatic processes and costly produced.
Vegetation morphometry (CHM, CC, ...)	Supports the initial segmentation of the territory. Allows monitoring the state of the vegetation with high spectral and	Can provide confirmation from the observation view when the variable is perceptible.	The most suitable when high spatial, spectral or temporal resolutions are required.	Variables derived from spatial and radiometric information with semi-automatic processes and costly produced, thus

	temporal resolution (automated).			preferably extracted from pre-existing cartography (i.e., National LiDAR flights).
Atmospheric conditions (weather, smoke, …)	Very suitable for studying the Earth's surface from images.	Can provide confirmation with specific sensors on-board	Not applicable	Meteorological stations or forecast services supplemented with satellite information are preferably used.

Additionally, to the aforementioned platforms, it is to note that some flights are carried out with manned aircrafts within the framework of national observation plans for the territory, dedicated to the digitization of geographic information. These flights are photogrammetric (visible) and/or LiDAR (such as PNOA in Spain). The main advantages are that their products are usually available to society and present a decent spatial resolution (decimetres). Also, they are significantly valuable because of its extension, covering the entire country, and temporal coverage of many years.

As an example, Figure 17 shows various layers of geographic information obtained from an automatic process of PNOA LiDAR point clouds and SIOSE land use map that TREEADS will consider.

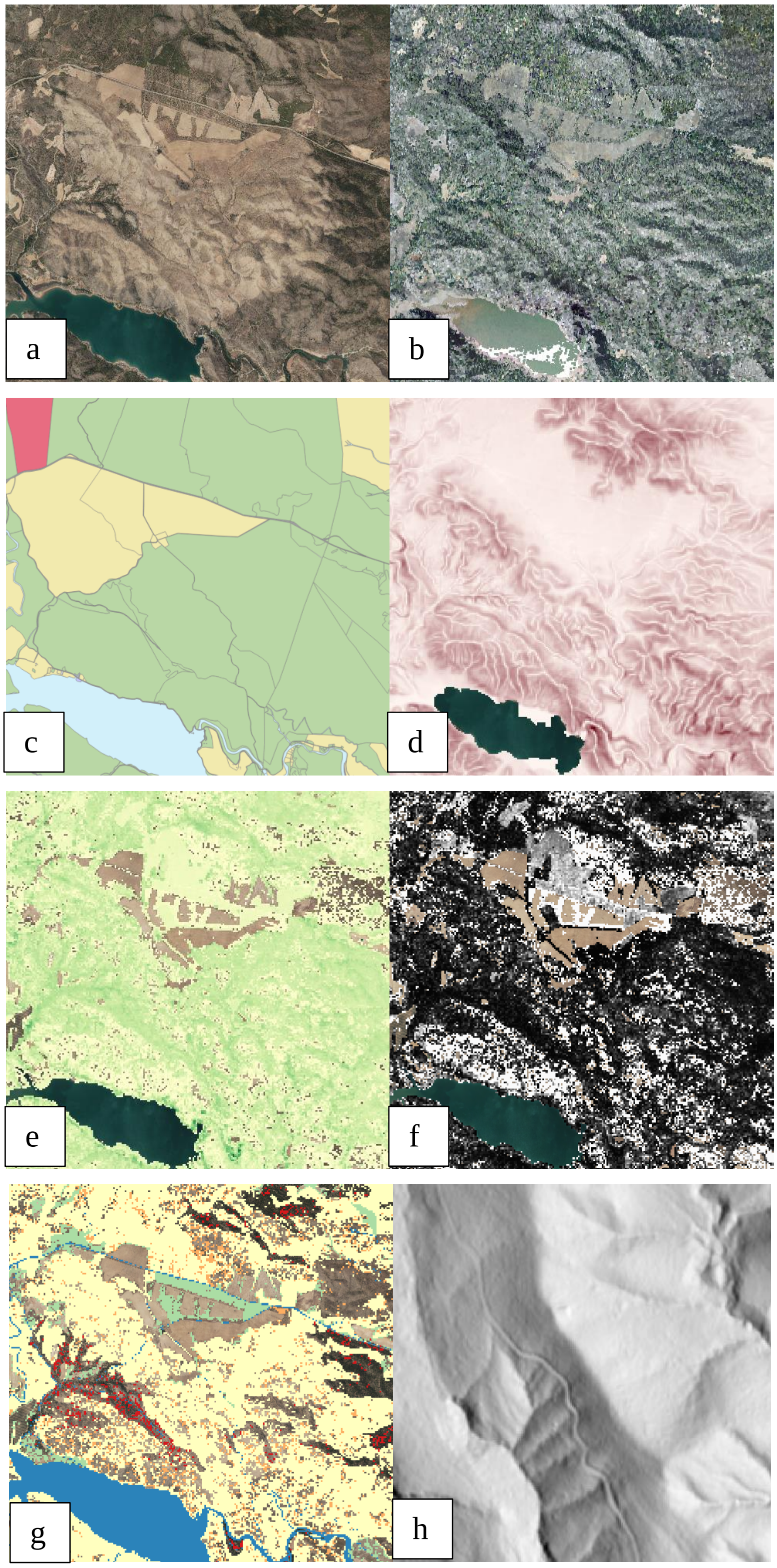


Figure 17. (a) Orthophoto from PNOA with 0.25 m spatial resolution. (b) Point clouds from PNOA. (c) Land uses from the Spanish Land Cover / Land Use Information System (SIOSE). (d) Terrain slope map. (e) Canopy Height Model (CHM) map. (f) Canopy Cover (CC) map. (g) Fuel model map. (h) Detail of the shadow map of the digital elevation model with 2 m spatial resolution.

Social media analysis

This subsection must define the solution in TREEADS for **social media analysis (T4.6)** from a theoretical point of view (method) and from a practical point of view (with results and datasets, not necessarily from the pilots).

Overview

This module focuses on the collection of social media posts in almost real from social media platforms based on pre-defined search criteria (keywords, accounts, bounding boxes) about fires for the early detection and monitoring of fire events. In order to reduce noise and filter out irrelevant information the collected social media data posts are analysed with classification techniques to estimate the post's relevance using the textual or visual content of the post. Furthermore, the posts are getting geotagged by a NER algorithm that detects words in the social media text that refer to location and queries these to the OpenStreetMap API to retrieve the exact coordinates. Additionally, this module utilizes density-based community detection algorithms in order to discover user communities on social media and identifying key-players in these communities, i.e., user accounts that play an important role during a fire event and affect other users. Finally, sentiment analysis is explored to identify and group the positive/negative sentiments of social media posts regarding the occurrence of a wildfire.

Definition of the search criteria

The social media content collected by the Twitter API utilizes filtering parameters that are used as input queries to APIs i.e., the search criteria. Before the development of the crawler, it is important these search criteria to be meticulously defined in order the retrieved data to be relevant with the topic of the use case. The search criteria should be defined with the collaboration of the pilot leaders as much as possible, as their expertise in their scientific domain and their native language offers better understanding of the task, resulting in more precise searching criteria.

The first step was to prepare a questionnaire Table 8 for the end users of TREEADS to collect the search criteria (keywords and accounts) for crawling the Twitter and to indicate some past fire events in order to be collected by Twitter's API historic endpoint, to conduct a community detection experiment to discover user communities and identify the key players in the communities of these past events that were reported in the social media by the users.

Table 8. Area of interest for each pilot.

1. Contact Information	
1.1. Name	
1.2. E-mail	
1.3. Pilot Use Case	
2. Involvement of social media data	

We aim to collect tweets from Twitter in real-time, analyse the textual and visual information they carry, and promptly detect early signs of a fire based on social data.
2.1. Do you already use/monitor the platform of Twitter as a source of information?
2.2. How do you imagine exploiting the collected Twitter data in the TREEADS project?
3. Crawling Twitter **We aim to develop a Twitter crawler that retrieves tweets in real time according to user-defined search criteria. Twitter offers two options: (1) collect tweets that contain a keyword or a phrase and (2) collect tweets that are posted from a specific Twitter account. The tweets can be in English and/or in the language of the PUC's area of interest.** **Furthermore, we have the ability to crawl historic data from Twitter. We are highly interested in past fire events in order to identify the most involved Twitter users (key players) in these events.**
3.1. What keywords/phrases would be of interest for your pilot use case? **(Examples: "smoke", "hot windy day", "burning smell", etc.)**
3.2. Which Twitter accounts would be of interest for your pilot use case? **(Examples: @FireNewsEurope, @WildFires, @BCGovFireInfo)**
3.3. Please indicate some past fire events of interest. **One example:** • **Location: Serra da Estrela** • **Dates: August 6-14 2022** • **Relevant keywords: "Serra da Estrela blaze/wildfire", "Portugal Fire", "Forest fire", "Firefighter injured", "natural park fire" etc.**

For the definition of the search criteria for the Social Media Crawler, a questionnaire was circulated to the Pilot leaders. The area of interest for each Pilot is shown in Table 9. The initial search criteria are defined for the pilots PO1, P02, P04, P05, P06, P07. In the future, further discussions with the end users will continue for clarifications and refinements of the search criteria as some keywords from the initial search criteria tend to be broad and generic and some accounts irrelevant. These keywords and accounts will be removed as they are bound to bring a lot of noise during the several rounds of communications with the pilot leaders.

Table 9 Area of interest for each pilot.

Pilot	Area of Interest
P01	Norway
P02	Italy
P04	Spain
P05	Austria
P06	Germany
P07	Greece

Finally, based on the provided keywords and user accounts (Table 10) from the questionnaire Table 10. (Table 8), which the users are interested in tracking, a Social Media Crawler was developed that retrieves in real time from Twitter any post that match the user-defined search criteria by performing complex queries to Twitter API.

Table 10. Twitter search criteria.

Twitter Keywords						
P01		**P02**	**P04**	**P05**	**P06**	**P07**
English	**Norwegian**	**Italian**	**English**	**German**	**German**	**English**
forest fire	Skogbrann	incidendio	fire	Feuer	Vegetation sbrand	Samaria
heather fire	Lyngbrann	fuoco	wildfire(s)	Rauch	Waldbrand	hot windy day
burning forest	Brenner skog	sterpaglia	smoke	es brennt	WUI	burning smell
smells like smoke	Lukter røyk	alte temperature	hot day	alarm	Dürre	
		piromani	windy day	alarmiert		
		Cause dolose	burning smell	Einsatz		
		costiera	dry weather	Feuerwehr		
		penisola	arsonist	Waldbrand		
			pyromaniac	#Feuer		
			fire started	#Brand		
			forest fire			
			burned area			
			ash			
			lit cigarette butts			
			firelighters			

			combustion fire			
			propagation			
			fire intensity			
			firemen			
			fire brigade			
Twitter Accounts						
@brannvern		@vigilidelfuoco	@bomberosdeavila	@gollnerfire	@gollnerfire	@Pyrosvestiki
FRICfirecentre		@DPCgov	@dipuavila	@GuillermoRein	@GuillermoRein	
@risefr		@crocerossa	@Avilared	@DWD_presse	@DWD_presse	
@brannfaglig		@CampaniaSma	@INFOCYL	@PeterWohlleben	@PeterWohlleben	
		@Reg_Campania	@naturalezacyl		@USDA	
		@TurismoCamp	@noticiascyl			
			@IncendiosES			
			@abc_es			
			@elmundoes			
			@proteccioncivil			
			@AT_Brif			
			@FireNewsEurope			
			@WildFires			

Development of the Twitter crawler

A Twitter crawler was developed with Python programming language in order to collect social media posts from Twitter API. The crawler establishes an open connection to the Twitter filtered stream endpoint[7] by utilizing the Python library Tweepy[8]. The Tweepy library provides easy connection with the Twitter API endpoints. The established connection grants access to the Twitter's public stream of data and the crawler can begin retrieving tweets in almost real time that are matching a set of rules[9] that are applied to the stream and performing complex queries to filtered stream endpoint.

[7] https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream/introduction

[8] https://www.tweepy.org/

[9] https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream/api-reference/post-tweets-search-stream-rules

In order to gain access to Twitter's filtered stream endpoint, a Twitter account, a developer account in the Twitter portal[10] , at least Essential access (lowest level of Twitter API access) and a bearer token[11] is required. In the Twitter API v2 a bearer token allows developers to have a more secure point of entry for using the Twitter APIs. A bearer token can be generated from the Twitter portal by having a developer accounts and at least Essential access. Additionally, CERTH applied and gained Elevated access (Twitter API access level) by Twitter in order to have higher limits[12] in Twitter API.

The Tweepy Python client uses the bearer token in order to authorize and open a connection to the Twitter filtered stream endpoint. When the connection is established, the client inserts various sets of rules based on the predefined search criteria (keywords or phrases, accounts), inserts the request parameters and fetches tweets that matching those rules and query parameters[13].

The crawler uses four query parameters:

- **tweet.field**s*:* This parameter enables the crawler to select specific tweet fields
- **media.fields:** This parameter allows the crawler to select specific media fields
- **user.fields:** This parameter authorizes the crawler to select specific user fields
- **Expansions:** This parameter permits the crawler to request additional data objects that relate to the originally returned Tweets in each returned tweet object from the Twitter API.

Table 11Table 11 shows the parameters fields that has been selected to been returned in each tweet.

Table 11. Query parameters used by Twitter Crawler.

Query Parameter	Fields	Description	Type
tweet.fields	id	Unique identifier of this Tweet.	String
	created_at	Creation time of the Tweet	Date (ISO8601)
	lang	The language of the tweet	String
	text	The text of the tweet	String
	attachments	Specifies the type of attachments (if any) present in this Tweet (image,video)	JSONObject
	referenced_tweets	A list of Tweets this Tweet refers to. For example, if the parent Tweet is a Retweet, it will include the related Tweet referenced to by its parent.	Array
	possibly_sensitive	Indicates if this Tweet contains URLs marked as sensitive	Boolean
	entities	Contains details about text that has a special meaning in a Tweet.	Json Object

[10] https://developer.twitter.com/en/portal/dashboard

[11] https://developer.twitter.com/en/docs/authentication/oauth-2-0/bearer-tokens

[12] https://developer.twitter.com/en/docs/twitter-api/getting-started/about-twitter-api

[13] https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream/api-reference/get-tweets-search-stream

	in_reply_to_user_id	If this Tweet is a Reply, indicates the user ID of the parent Tweet's author.	String
Media.fields	type	Type of content (animated_gif, photo, video).	String
	url	A direct URL to the media file on Twitter.	String
	media_key	Unique identifier of the media content.	String
User.fields	id	The unique identifier of this user.	String
	username	The Twitter screen name, handle, or alias that this user identifies themselves with	String
	name	The name of the user, as they've defined it on their profile	String
Expansions	attachments.media_keys	List of unique identifiers of media attached to this Tweet	Array
	referenced_tweets.id	The unique identifier of the referenced Tweet.	String
	entities.mentions.username	The part of text recognized as a user mention.	String
	referenced_tweets.id.author_id	A list of referenced Tweet authors	Array

A rule can contain at least one operator[14]. The crawler utilized four rule operator types to define the rules based on the search criteria.

- **keyword:** operator that matches a word within the body of a tweet (e.g. “wildfire”)
- **exact phrase match:** operator that matches the exact phrase within the body of a Tweet (e.g., "forest fire")
- **from:account:** operator that matches any Tweet from a specific user (e.g., from:User1)
- **lang:code:** operator that matches Tweets that have been classified by Twitter as being of a particular language (e.g., lang:”en”)

Additionally, multiple operators can be stringed together in a single rule. The parentheses group the operators together. A space between the operators will result in boolean "AND" logic. An OR between them will result in boolean “OR” logic. Prepend a dash (-) to a keyword (or any operator) t will result in boolean “NOT logic”. For example, the rule (hot windy day OR "forest fire") (from:User1) (lang:en) will fetch tweets from User1 in English language and contains the keywords "hot”, "windy”, “day” in or the exact phrase “forest fire” in the tweet text.

The crawler retrieves newly published tweets from the Twitter API as a JSON strings. Each tweet is represented by a JSON string with the attributes shown in the Table 11. For every tweet, the crawler passes through all these attributes and extract the useful information and creates a new JSON string with the attributes displayed in Table 10. For example, the attribute *created_at* in the initial tweet JSON is transformed to the attribute *timestamp* in the new JSON or from the attribute *referenced_tweets* in the initial tweet JSON the crawler can infer if the tweet is a reply, a quote or a retweet that are represented by the attributes *is_reply is_quote*, *is_retweet* in the new JSON. This action filters the excess and unnecessary information. Thus,

[14] https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream/integrate/build-a-rule

the new JSON is smaller and needs less storage, which enhances the database's query retrieval speed.

The geolocation of the tweets is a critical information that can be utilized in many versatile ways such as the combining of data from different sources, the visualization of tweets in a map or the clustering of tweets by location etc. Twitter API mostly lacks geolocation information, only few tweets provide it. This is also apparent in the already collected data in Table 21. Moreover, the coordinates of the geolocated tweets from Twitter are based on the location of the user and not the location mentioned in the text.

The localization web service attempts to answer this problem. For every newly fetched tweet the crawler attempts to geotag it by using a localization web service that have been developed in two other H2020 projects: EOPEN[15] for English, Italian and CALLISTO[16] for German. The results of which are stored in the attribute *extracted_locations.*

The Twitter crawler sends the tweet text in a HTTP GET request to the localization service. The localization web service accepts the tweet text pre-processes and feeds it in a Long Short-Term Memory (LSTM) network. Afterwards Named Entity Recognition labels are assigned in words or phrases that are detected as location in the social media post text. The, localization uses these labels to query the OpenStreetMap API[17] which returns the exact coordinates and the placename for each queried label. The output of the localization web service is a JSON string with name of the place, the longitude and longitude coordinates. An example of an output JSON string of the localization service is shown below:


```
"extracted_locations" : [
        {
           "placename" : "Canary Islands, Spain",
           "geometry" : {
              "type" : "Point",
              "coordinates" : [
                -16.6214,
                 28.2935
                ]
            }
         }
      ]
```


Finally, the tweets that are retrieved from the Python client are stored in a MongoDB database (Table 12) in JSON format. The JSON format is chosen because it is easy to parse and flexible to add or delete attributes. Also, an example tweet collected from the Twitter stored in JSON format in the database is shown below:

[15] https://eopen-project.eu/

[16] https://callisto-h2020.eu/

[17] https://wiki.openstreetmap.org/wiki/API

```
{
  "id" : "1608347075418419206",
  "platform" : "Twitter"
  "is_retweet" : true,
  "is_quote" : false,
  "is_reply" : false,
  "text" : "RT @user1: SA Bushfire Watch &amp; Act for Bramfield, Old Coach Road. #bushfire #fire #ausfires
#ewnalerts #wildfire #SA #safires https://t.co/V22bg3qcsY https://t.co/UXfbt8IPJf",
  "media_url" : [
    "https://pbs.twimg.com/media/FlH_JFDaAAQP-oC.png"
  ],
  "media_type" : "image",
  "mentioned_users" : [
   {
    "id" : "28356819".
   }
],
  "replied_user_id" : [],
  "quoted_user_id" : [],
  "retweeted_user_id" : [
{
"id”:"28356819”
}
],
  "userid" : "428356819",
  "username" : " User2",
  "language" : "en",
  "timestamp" : "2022-12-29T06:19:59.000Z",
  "extracted_locations" : [
   {
     "placename" : "Saudi Arabia",
     "geometry" : {
       "type" : "Point",
       "coordinates" : [
         42.3528328,
         25.6242618
       ]
     }
   }
  ]
}
```


Table 12. The fields of a stored tweet in the mongoDB

Fields	Description	Type
id	The id of a tweet	String
is_retweet	A value that shows if the tweet is a retweet	Boolean
is_quote	A value that shows if the tweet is a quote to another tweet	Boolean
is_reply	A value that shows if the tweet is a reply to another tweet	Boolean
media_url	The media URL or an array of media URLs from a tweet	Array
media_type	The type of media that is included in the tweet	String Possible Values: **“image”**

		Note: null when empty
platform	The source of the data	String Possible Values: **“Twitter”**
mentioned_users	Array of JSON objects that contains the mentioned user(s) id	Array
replied_user_id	Array of JSON objects that contains the replied user(s) id	Array
quoted_user_id	Array of JSON objects that contains the quoted user(s) id	Array
retweeted_user_id	Array of JSON objects that contains the retweeted user(s) id	Array
userid	The id of the user that posted the tweet	String
username	The username of the user that posted the tweet	String
language	The language of the tweet	String Example: **“en”** for english
timestamp	The date and time when the tweet was published	String Example format: **”2023-01-21T13:16:41+0000”**
extracted_locations	An array of JSON objects that contains the locations detected in the text	Array
placename	A value with the location name as defined in OpenStreetMap	String
geometry	A JSON object that contains the type of the value of the location coordinates	JSON
type	The type of the location coordinates	String Possible Values: **“Point”**
coordinates	An array with the location coordinates using the (WGS84) projection (longitude, lattitude)	Array

DEVELOPMENT OF THE FACEBOOK, INSTAGRAM, TELEGRAM, YOUTUBE CRAWLERS

Social media refers to the use of the internet to facilitate communication in open or semi-open settings by means of techniques, technologies, and applications. Social media examples include social networking platforms (like Facebook), microblogs (like Twitter), chat and messaging apps (like Telegram), and photo and video sharing platforms (such as Instagram and YouTube).

Social media analytics research typically focuses on three main areas:

- Analysing content (such as popular topics and sentiment)
- Studying groups and networks (such as identifying key users within a group and how they interact)
- Predicting real-world events based on online behaviour and usage patterns

In addition to issues with data access, storage, and processing, social media research must contend with misinformation and deception. In addition, the infrastructure required to manage large amounts of data is expensive, and there are legal considerations for data storage. There have been few attempts to integrate multiple types of social media data and traditional data into a single analytical environment, despite the abundance of social media data.

FACEBOOK CRAWLER

A Facebook crawler is developed with NodeJS[18] in order to collect social media posts from Facebook API. The collected data is stored in a MongoDB database.

Facebook provides developers with the Graph API[19] to access and manipulate data on the social network. It is based on the HTTP protocol and permits applications to query data, create new posts, manage advertisements, and upload images.

The Graph API is named after the concept of a "social graph," which is a representation of Facebook's information. It is made up of:

- **nodes** - essentially individual objects such as Users, Photos, Pages, and Comments
- **edges** - connections between a group of objects and a single object, such as Photos on a Page or Comments on a Photo
- **fields** - information about an object, such as the birthday of a User or the name of a Page

Nodes are used to get data about a specific object, use edges to get collections of objects on a single object, and use fields to get data about a single object or each object in a collection.

The endpoints used for crawling purposes are described below:

POST ENDPOINT

A post is an individual entry in a Facebook[20] profile's news feed. The profile may be of a user, page, application, or organization. The /{post-id} node delivers an individual post.

Following is a list of the most valuable properties returned by the Facebook Graph API for a post.

Table 13. Facebook's Graph API - User Attributes

Fields	Description
id	The post unique ID.
caption	Link caption in post that appears below name. The caption must be an actual URL.
created_time	The time the post was initially published.
description	A description of a link in the post (appears beneath the caption).
icon	A link to an icon representing the type of this post.
message	The status message in the post.
place	Any location information attached to the post.
shares	The shares count of this post.
type	A string indicating the object type of this post.

The following table summarizes the edge endpoints exposed by the Graph API to retrieve relationships from a given post.

Table 14. Facebook's Graph API - Post Endpoints

18 https://nodejs.org/en/
19 https://developers.facebook.com/docs/graph-api/overview
20 https://developers.facebook.com/docs/graph-api/reference/post

Fields	Description
/comments	Comments on given post.
/insights	Insights for given post (posts on pages only).
/likes	People who like given post.
/private_replies	Reply to given visitor type post (only) with a private message.
/reactions	People who have reacted to given post.
/sharedposts	Shares of given post.

USER ENDPOINT

On Facebook, a user represents a person. The /{user-id} node returns an individual user.

The table below lists the most important attributes returned by Facebook's Graph API for a user account.

Table 15. Facebook's Graph API - User Attributes

Fields	Description
id	The id of this person's user account. This ID is unique to each app and cannot be used across different apps.
address	The User's address.
birthday	The person's birthday. This is a fixed format string, like MM/DD/YYYY.
email	The User's primary email address listed on their profile.
name	The person's full name.
first_name	The person's first name
last_name	The person's last name
gender	The gender selected by this person (male, female or custom).
hometown	The person's hometown.
location	The person's current location as entered by them on their profile. This field is not related to check-ins.
link	A link to the person's Timeline.

INSTAGRAM CRAWLER

An Instagram crawler is developed with nodeJS in order to collect social media posts from Instagram API. The collected data is stored in a MongoDB database.

Instagram's Graph API is based on Facebook's Graph API. It functions identically and supports the same features; the primary distinction is authentication. The Instagram Graph API is the primary method for transferring data into and out of the social network.

The Graph API is named after the concept of a "social graph," which is a representation of Instagram's information. It is made up of:

- **nodes** - essentially individual objects such as a User, a Hashtag, a Media, or a Comment
- **edges** - connections between a group of objects and a single object, such as Media on a Page or Comments on a Media
- **fields** - information about an object, such as User's birthday, or a Hashtag's name

Typically, nodes are used to get data about a specific object, use edges to get collections of objects on a single object, and use fields to get data about a single object or each object in a collection.

The endpoints used for crawling purposes are described below:

HASHTAG ENDPOINT

An Instagram hashtag is represented by a hashtag. The /{ig-hashtag-id} node returns the name of the hashtag.

The following table details the hashtag-related attributes returned by Instagram's Graph API.

Table 16. Instagram's Graph API - Hashtag Attributes

Fields	Description
id	The hashtag unique ID.
name	The hashtag name

As shown in the below table, the Graph API additionally supports a set of edge endpoints for extracting associations based on a given hashtag.

Table 17. Instagram's Graph API - Hashtag Endpoints

Fields	Description
/recent-media	Returns a list of the most recently published photo and video media objects published with a specific hashtag
/top-media	Returns the most popular photo and video media objects that have been tagged with the hashtag

TOP MEDIA ENDPOINT

Top media is a group of the most popular photos and videos that have been tagged with a hashtag on IG Media.

Utilizing the same algorithm that selects the top posts when searching for a hashtag on instagram.com, popularity is determined by a combination of views and viewer interaction.

This edge provides only publicly available photographs and videos that do not include personally identifiable information and does not return promoted/boosted/ads media.

The following table details the Instagram Graph API properties returned for a media asset.

Table 18. Instagram's Graph API - Media Attributes

Fields	Description
caption	Caption of media object. Captions that @mention an User will not include the (@) symbol unless the request is made by the User that owns the Media object upon which the caption was made.
children	The list of media objects included in an album
comments_count	The number of comments.
id	The unique id of the media object.
like_count	The number of likes.
media_type	The type of media object.

media_url	The URL of media object.
username	The name of the user that created the media object

TELEGRAM CRAWLER

A Telegram crawler is developed with nodeJS in order to collect social media posts from Telegram API. The collected data is stored in a MongoDB database.

Telegram gives developers two types of APIs. The Bot API[21] makes it simple to construct applications that use Telegram messages as an interface. The Telegram API/TDLib[22]enables the development of bespoke Telegram clients.

TDLib (Telegram Database Library) was chosen for our project since it is meant to assist third-party developers in building apps on the Telegram platform by enabling keyword-based queries on public channels and handling all networking, local storage, and data consistency concerns.

When an application is using TDLib, it can start a request by calling the Client.send method and get the response through the Client.receive method as soon as it's ready. The TDLib interface can change the names of these methods and how they are used, but the overall process stays the same.

An application not only responds to requests, but also receives a lot of important information through updates. These updates are used to send new information from TDLib to the application. They also often control how the application works, which eliminates the chance of errors.

Telegram is a messaging app, and a message is its main thing. Each message belongs to a certain chat and has a unique number within that chat. Identifiers should be used to sort messages in a chat. Telegram lets you send different kinds of messages with different kinds of content. There are currently more than 35 different types of message content, such as messageText for text messages, messagePhoto for photos, and messageScreenshotTaken for alerts about screenshots taken by the other party.

"User" is the word for a person who uses Telegram. For example, if you know who sent a message, that person is a user. Each user has a unique identifier and a first name. They can also have a last name, a username, and a profile photo, but these are not required. On the other hand, each chat has "members," which are users who get all messages sent to the chat. Each chat has a unique name, a title, and a chat photo, if you want to use one. Chats are put into lists that are shown to the user, usually in the order of when they were last used. Files can be in messages, chat photos, and many other things. Each file has a unique name and can be kept on a hard drive or on a cloud server. Most of the time, these files can be saved to the local hard drive or sent to Telegram's cloud servers.

Telegram also lets you search for messages based on keywords using the messages.search method[23]. You can search for messages in all chats except secret chats, and the results are

[21] https://core.telegram.org/bots/api

[22] https://core.telegram.org/tdlib

[23] https://core.telegram.org/method/messages.search

shown in reverse chronological order. In the table below, you can see all of the useful parameters that the messages.search method can accept.

Table 19. Telegram's Messages Search – Input Parameters

Fields	Description
peer	User or chat, histories with which are searched, or (*inputPeerEmpty*) constructor for global search
q	Text search request
from_id	(*optional*) Only return messages sent by the specified user ID
filter	(*optional*) Filter to return only specified message types
min_date	(*optional*) Only return messages with a sending date bigger than the given one
max_date	(*optional*) Only return messages with a sending date smaller than the given one

YOUTUBE CRAWLER

An Youtube crawler is developed with nodeJS in order to collect social media posts from YouTube Data API. The collected data is stored in a MongoDB database.

With the YouTube Data API, the YouTube website features can be used in own app. It can be used to get different kinds of resources, like videos, playlists, and subscriptions, which are represented as JSON objects.

The API also includes ways to add, change, and remove these resources. The API has a search endpoint that returns information about YouTube videos, channels, and playlists that match the search parameters.

The search result takes you to a unique resource, but it doesn't have any of its own information. The search result can be set up to only show a certain kind of resource, and its JSON structure is shown.

The following JSON structure shows the format of a search result:


```
{
   "kind":                                   "youtube#searchResult",
   "etag":                                                     etag,
   "id":                                                          {
     "kind":                                                 string,
     "videoId":                                              string,
     "channelId":                                            string,
     "playlistId":                                           string
   },
   "snippet":                                                     {
     "publishedAt":                                        datetime,
     "channelId":                                            string,
     "title":                                                string,
     "description":                                          string,
     "thumbnails":                                                {
       (key):                                                     {
         "url":                                              string,
         "width":                 unsigned                  integer,
         "height":                 unsigned                 integer
       }
     },
     "channelTitle":                                         string,
     "liveBroadcastContent":                                 string
   }
 }
```


The following table provides a list of the properties that appear in a search result.

Table 20. YouTube search result attributes

Fields	Description
kind	Identifies the API resource's type. The value will be youtube#searchResult.
etag	The Etag of this resource.
id	The id object contains information that can be used to uniquely identify the resource that matches the search request.
id.kind	The type of the API resource.
id.videoId	If the id.type property's value is youtube#video, then this property will be present and its value will contain the ID that YouTube uses to uniquely identify a video that matches the search query.
id.channelId	If the id.type property's value is youtube#channel, then this property will be present and its value will contain the ID that YouTube uses to uniquely identify a channel that matches the search query.
id.playlistId	If the id.type property's value is youtube#playlist, then this property will be present and its value will contain the ID that YouTube uses to uniquely identify a playlist that matches the search query.
snippet	The snippet object contains basic details about a search result, such as its title or description. For example, if the search result is a video, then the title will be the video's title and the description will be the video's description.
snippet.publishedAt	The creation date and time of the resource that the search result identifies.
snippet.channelId	The value that YouTube uses to uniquely identify the channel that published the resource that the search result identifies.
snippet.title	The title of the search result.
snippet.description	A description of the search result.
snippet.thumbnails	A map of thumbnail images associated with the search result.
snippet.channelTitle	The title of the channel that published the resource that the search result identifies.
snippet.liveBroadcastContent	An indication of whether a video or channel resource has live broadcast content. Valid property values are upcoming, live, and none.

REDDIT CRAWLER

This Reddit Crawler module is based on specific key-words for retrieving relative to wildfire disaster posts from Reddit. It aims to focus on collecting posts of fire events as recorded by individual posts on the Reddit platform, emphasizing on selected groups of online users that systematically provide instant notices on wildfire or indications of such an event (smoke seeing, potential risks etc). The main criteria utilized are the same as described in the Twitter tool equal to well-defined search criteria (keywords, users/groups accounts etc).

Reddit data will be collected in almost real time based on Reddit limitations. At this point, needs to be mentioned the fact that there is no ability to search subreddits that are private or quarantined, so these posts are excluded.

The Reddit API will utilize filtering parameters that are used as input queries to APIs i.e., the search criteria defined with the partners, in collaboration with the stakeholders, through the questionnaire process. The definition of the keywords and the search criteria is crucial for the overall process since only meticulous parameters need to be defined for the optimal collection of Reddit posts relevant to the occurrence of a wildfire event, or the detection of a high-risk event. The tool will be language agnostic, since the input blogs, will be translated into all languages of the pilots, which could cover the needs and expectations of all stakeholders.

More analytically, the parameters defined for the Reddit crawler are the following:

- main keywords: main keywords for search (main search terms)
- additional keywords: additional keywords aligned with the main keywords
- fields: One returns specific fields (comma delimited)
- sorting: Sort results in a specific order
- author: Restrict to a specific author
- subreddit: Restrict to a specific group of interest
- time filter: will return posts from a specific time phase
- limit: the total number of posts to be returned

FIRST SAMPLE OF COLLECTED DATA

Twitter data

The Twitter crawler has been running since 23 December 2022 and has collected about 85,000 fire-related tweets as of 11 January 2023. As the definition of search criteria is not finished for all pilots, the crawler retrieves tweets for the pilots P01, P04, P06, P07. The pilots P02, P05 search criteria has not been defined completely yet, but are planned to be added in the future.

Table 21 presents the initial results for the Twitter crawler. It is apparent that there is a big difference in retrieved tweets between the P04 and the other pilots. This is attributed to the fact that the P04 search criteria (keywords and accounts) are more extensive. On the other hand, the P07 search criteria seem to not perform as expected as only 279 tweets are collected. Additionally, in P01 the tweets that are gathered for the Norwegian language are very few. From the above, it is obvious that a refinement of the search criteria for the P01, P06, P07 pilots is required in order to increase the rate of tweets fetched from the Twitter API.

Moreover, location coming directly from Twitter’s initial JSON is very scarce in our data and only 0.4% to 1.8% are geolocated from Twitter. In contrast 17.5% to 35.4% of tweets become geolocated with our Localization web service. Geotagged social data are very useful as they can been combined from other extra source (e.g., satellite data). It is evident that Twitter does not contain a lot of geotagged tweets for that reason the localization web service is used to geotag the tweets. Finally, it is worth mentioning that 7.1% to 10.9% of the tweets contain at least one image. It may not seem a significant number but it is a considerable amount of visual information.

Table 21. Statistics for the collected tweets

PILOT	Language	Collected Tweets	Location from Twitter	Localization from Twitter	Contain image
P01	English	3,260	39 (1.2%)	571 (17.5%)	270 (8.2%)
	Norwegian	2	0 (0%)	0 (0%)	0 (0%)
P04	English	86,889	1,564(1.8%)	18,501 (21.2%)	9505 (10.9%)

P06	German	1,754	7(0.4%)	622 (35.4%)	125 (7.1%)
P07	English	279	0 (0%)	70 (25.0%)	37 (13.2%)

SENTIMENT ANALYSIS

Sentiment analysis is a technique applied in Natural Language Processing (NLP), for the determination of the existence of emotional undertones within any statement. Within the TREEADS context sentiment analysis will be applied to social media inputs as a common method to identify and group the positive/negative sentiments regarding the occurrence of a wildfire. To this extent several alternate techniques could be involved, either machine learning based or not.

Sentiment analysis techniques that are expected to be leveraged, will be both rule-based and machine learning methods. The rule-based methodology uses pre-set lexicons to identify, categorize, and score certain terms. Lexicons are collections of words used to convey the intention, feeling, and tone of the author. It is simple to put up a rule-based sentiment analysis system, but it is challenging to scale. For instance, you'll need to continue adding new terms to the lexicons as you find new ways to express purpose in text input. Additionally, this method might not be reliable when analysing statements that have been impacted by several cultures. On the other hand, Machine learning techniques use sentiment classification algorithms, such as neural networks, to teach computer software to recognize emotional sentiment from text. A sentiment analysis model must first be constructed and constantly trained on existing data in order to be able to properly predict the sentiment. ML sentiment analysis is useful since it accurately analyses a wide range of text data. If the machine learning algorithm is sufficiently trained with examples, sentiment analysis may accurately forecast the emotional tone of messages. However, a trained ML model is targeted and optimized for a certain sector, means that cannot generalize on others. Fo the scope of TREEADS some of the below state-of-the-art techniques (both rule based and machine learning) will be examined:

Vader (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon-based algorithm for analysing the sentiment of text data. It was developed specifically for social media text, which tends to be informal and often contains slang, emoticons, and other non-standard languages. The algorithm works by analysing the words in the text and assigning them a score based on the valence (positive or negative sentiment) of the word.

BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art natural language processing (NLP) model developed by Google. It has been widely used for a variety of NLP tasks including language translation, question answering, and text classification. For sentiment analysis, BERT can be used to classify the sentiment of a given piece of text as positive, negative, or neutral. It does this by learning to predict the sentiment of a given text based on the words and phrases used in the text and their context within the sentence.

GPT-3 (Generative Pre-trained Transformer 3) is a state-of-the-art natural language processing (NLP) model developed by OpenAI. It is a large-scale machine-learning model that has been trained on a massive amount of data and is capable of generating human-like text. GPT-3 has been used for a variety of NLP tasks, including language translation, question answering, and text generation.

Undoubtedly, one of the main challenges of Sentiment Analysis is the language recognition. Having input from various languages makes the task of sentiment analysis complicated, when the majority of models were fine-tuned on English language. Especially, for the needs of TREEADS, and as the input could be in any language of the participating partners the below 2 alternatives will be examined:

Multilingual Sentiment Analysis: The practice of extracting emotional insights from data that may be in numerous languages is known as multilingual sentiment analysis. This is typically true when analysing customer feedback data from diverse audiences or from various geographic places with a consistent customer base.

Pipeline creation with a translation engine: Simply use a translation engine for translating every language to English language and perform the sentiment analysis there. On the other hand, a machine learning model could be used to translate everything in English language. A great alternative here could be Helsinki Neural Machine Translation system (HNMT) which is a full-featured system for neural machine translation, with a particular focus on morphologically rich languages.

User communities & influencers

Community detection aims to discover communities of social media users, i.e., Twitter accounts that are interlinked through their online behaviour and interactions on the platform. Communities are formed from users mentioning, quoting, retweeting, responding to one another in regards to an event.

The identification of the so-called influencers, meaning the users that have been the most interacted with or have initiated the most interactions, is the main focus of this task.

Community detection on Twitter data

The methodology adopted is based on EOPEN's "Community detection in Social Media". More specifically, the approach based on the user interactions detects communities and follows up with the identification of the influencers in those communities.

The first step is to denote a social network G as G (N, L), with N nodes that represent a Twitter user account and L links, where a link between to users (i, k) exists if user ni has interacted with user nk. The interaction used in the EOPEN model is only user mentions. In the current approach in order to gain a more thorough network of users, additional relationships will be considered. Those relationships include retweets of a user's post, replies to a user's post and quotes from the user's post. Following the collection of the user relationships EOPENS community detection algorithms will be applied to divide the network into groups of users more densely connected to each other within the group than to the rest of the network outside the group, resulting in an output containing all the detected communities and the set of nodes that belong to each of those communities. Finally, EOPEN's key-player identification procedure takes place in order to extract the most influential users within that network, making use of the Mapping Entropy Betweenness (MEB) centrality measure, which takes into consideration the betweenness centrality of nodes.

An experiment focuses on identify the main key players (top influencers) for past fire events and analysing their impact during the duration of those events. The data used for the experiment is an extract of the twitter API for past Tweets. The incidents covered in this experiment focus on fire events from Spain, Germany and Norway. The locations, dates and relevant keywords for each country are represented in Table 22.

Table 22. Fire events information for each country

PILOT	Event location	Search date	Relevant keywords	Number of tweets
Spanish	Cepeda de la Mora. Parameras	14/08/2021 – 19/08/202	"Parameras wildfire", "Parameras wildfires", "Avila fires","Avila fire", "Avila wildfire", "Avila wildfires", "Incendio Forestal Parameras", "Tiétar Valley Forest fire", "Incendio Forestal Avila", "sosavila"	3560
	Poyales del Hoyo	22/07/2019 – 24/07/2019	"Poyales del Hoyo wildfire", "Poyales del Hoyo wildfires", "Avila fire", "Avila fires", "Tiétar Valley Forest fire", "Tiétar Valley Forest fires", "Avila wildfire", "Avila wildfires", "Poyales del Hoyo", "Poyales del Hoyo, Ávila", "Incendio Forestal"	437
Germany	Meppen, Lower Saxony	18/09/2018 – 21/09/2018	"Moorbrand in Meppen", "Moorbrand Meppen", "Moor fire Meppen", "Brand in Truppenübungsplatz"	1929
	Treuenbrietzen, Brandenburg	23/08/2018 – 26/08/2018	"Treuenbrietzen fire", "Treuenbrietzen forest fire", "Treuenbrietzen evacuated", "Waldbrand Treuenbrietzen", "Evakuierung von Ortschaften"	2823
Norwegian	Frøya, Trøndelag region	27/01/2014 – 31/01/2014	"lyngbrann", "Frøya skogbrann", "brannrøyk", "røyklukt", "Frøya", "Trøndelag skogbrann", "Frøya wildfire", "Frøya forest "fire", "Trøndelag wildfire", "Trøndelag forest fire"	480
	Flatanger, Trøndelag region	26/01/2014 – 29/01/2014	"lyngbrann", "skogbrann", "brannrøyk", "røyklukt"	489
	Lærdal, Vestlandet region	23/01/2014 - 28/01/2014	"bebyggelsesbrann", "storbrann", "verneverdig",	490

			"skogbrann", "brannrøyk", "røyklukt", "Lærdar", "Laerdal"	

The data were extracted from a full-archive search endpoint of the Twitter API with academic access, which allowed us to search for past tweets dating back to tweets from 2006.

For each incident the tweets are parsed and user ID pairs are extracted, where each user ID pair symbolizes the relationship between 2 user ID's. The relationships that are taken into consideration are:

1. **Retweets:** The ID of the user whose tweet is retweeted and the ID of the user responsible for the retweet.
2. **Mentions:** The ID of the user who tweeted and the ID of the user mentioned.
3. **Replies:** The ID of the user who made the original tweet and the ID of the user replying to it.
4. **Quotes**: The ID of the user responsible for the tweet and the ID of the user that has been quoted.

This list of ID pairs is extracted and fed to EOPEN's community detection R script to extract the communities and top influencers. In this deliverable the Twitter user names are encoded and not the actual user names for the protection of the user and to be in line with ethical regulations of GDPR.

Spanish fire events

Firstly, we looked at the Parameras wildfires, the largest fire to hit Castilla y León since 1984. The wildfire had a perimeter of 130 kilometres and razed more than 20,000 hectares of land. The dataset consists of 3560 past tweets within a period of 6 days (14/8/2021 – 19/8/2021). The most influential users in that period of time are listed in Table 23.

Table 23. Parameras fire event top Influencers

#	Encoded Twitter user name	Description
1	1JliXjJvE7GZi3tzL	Educational page about the environment
2	YhNm4yil3zWZKhYeR72DEJ	Food charity
3	guitbWvLH9rAP5j69v0cYTDE4d	Chef and founder of Kitchen
4	0n4i8qhu8q2WtMAWJoO	Citizen
5	sVHWntJzFAUYEHtdWWdn71UU1Ic	Non-Governmental and Nonprofit fire prevention and extinguishing organization
6	Dm8VTnEcJ6pPfMVSpvxbcMHEEfzkP	Citizen
7	mMruACp8lchKp1pl3x9aCrs0	Emergency Management Service provides mapping products based on satellite imagery.
8	gl3eZZVgn4N9MjcKrphMAciAT	Workers Association of BRIF (Reinforcement brigade forest fire)
9	ZLWgDQcNKIAGdHYpcexcY2hHuL8	Spanish branch of a French news organization.
10	ZLWgDQcNKIAGdHYpcexcY2hHuL8	French news organization.

In Table 23, the most influential accounts are a chef (#3), who is also the founder of a charity that offers food to people struck by natural disasters; (#2) is a public figure who was active on twitter covering this event. Accounts that covered this event on Twitter as we can see were mostly environmental and crisis related organizations (#1, #2, #5, #7, #8) and news organizations (#9, #10).

It is also noteworthy that some of the top influencers for the Parameras fire event were regular users (#4, #6), e.g citizens, with the distinction that #4 is a user who delves into commentary about different topics and #6 being a regular twitter user.

The second region we looked out for the Spanish fire events was Poyales del Hoyo. The fire event took place in July 2019. The tweets collected were 437 and range from 22/07/2019 to 24/07/2019. The top influencers for that period of time are listed in Table 24.

Table 24. Poyales del Hoyo fire event top influencers

#	Encoded Twitter user name	Description
1	cz2cQzRHVR56B1ddAOiy	Page that focuses on forest fires in Avila region.
2	vdciHKX800oJxbyjNen5Jx1D8jC	Workers Association of BRIF (reinforcement brigade forest fire)
3	FZjzEyebNfryztAso2fCY	Reinforcement brigade for forest fires.
4	IH0IRHmNg9pOxlYrq3	Reinforcement brigade for forest fires.
5	LXha0QWS0LLy4O2	Page that focuses on information and dissemination of the work of firefighters
6	rCiBS8ZuWFT7vduPUWvyHvP	Digital newspaper of Avila.
7	UQ3ivo5Uc2FlS3PRPncTJPuPUBlKp	News agency
8	UQ3ivo5Uc2FlS3PRPncTJPuPUBlKp	News agency
9	rGr7lzvocNeNBlD	Citizen, ex-BRIF
10	2Cco0qhIezAjSkMP2uQIIDLM1o3	Environmental Agency focusing on forest fires.

Similar to Parameras fire event no public figures appear to have been actively involved in covering the fire event in Poyales del Hoyo. By looking at the type of users that were most influential we do not see any regular twitter users (Citizens) being active contributors for that event. The most influential accounts seem to be accounts of firefighting organizations (#2, #3, #4, #5, #9), news agencies (#6, #7, #8) and environmental agencies (#1, #10).

German fire events

Regarding the fire events in Germany, the first incident we focused on was the one Meppen, Lower Saxony. Reportedly the cause of the fire were rocket tests carried out by the military. The dataset that we analyzed consists of 1929 tweets between 18/9/2018 and 21/09/2018 and the top influencers for the event can be seen in Table 25.

Table 25. Meppen fire event top influencers

#	Encoded Twitter user name	Description
1	ejYReY2n72D9YoICoHyQqecKRos5	Journalist
2	s37YTUTB0fla4KoXe53p1krms5prP	Meteorological agency
3	9TeiO9YU6MR6LWf	Environment protection non-governmental and non-profit organization

4	phRW71m0ACWEZ6uHTjExQM	Citizen / blogger
5	MYW7lZuvgGEixaedehaAu	Environment protection non-governmental and non-profit organization
6	4svOoZ5FbtvYhVfJ2YDWQ	Citizen
7	hx09u1LRQZherSBG7XcrGWyoOF671	News agency
8	tq9BosudDcT3F8QC5oY1ttMM	News agency
9	hipQfCLO46s4fIWrSr5C	German Official

The results indicate that the most involved twitter accounts were journalistic and news accounts (#1, #7, #8) as well as Environmental and Meteorological organizations (#3, #5, #2). Contrary to the Spanish events, a political official has also been in the center of many tweets regarding the event (#9). Also, we ca see regular twitter accounts/ Citizens (#4, #6). Finally, the 10th most influencing user on this fire event was a banned account on Twitter for that reason we decided not to included it into the results.

The forest fire at Treuenbrietzen, Brandenburg, burned an area the size of 400 football fields. Three villages in the region were evacuated and a large amount of emergency forces were needed to contain the fire. The 2823 tweets collected between 23/08/2018 and 26/08/2018 produce the results shown in Table 26.

Table 26. Treuenbrietzen fire event top influencers

#	Encoded Twitter user name	Description
1	CnMpWp7JYh7Q2IPbBW0	News agency
2	1zYBh0EZN0MffZGefHql9jS	Police
3	lLR7fzxAGHj97cNISh7tUv	Firefighter
4	l7F386ep0S05UfXRJcdLMfOuWEM	Police
5	dSpZpnGilXqlx10ut9emotB	Citizen
6	dSpZpnGilXqlx10ut9emotB	News agency
7	MBxteGyp764sMFLr8fAnEZ	Newspaper agency
8	MBxteGyp764sMFLr8fAnEZ	Citizen
9	pL2Wq5oYMuMjNuLJx5eTcTJXc4	Citizen
10	41ygiMHyyi40htPA8yW0	Citizen / blogger

Here we see the citizens playing a greater role in the online interactions when it comes to this event (#5, #8, #9, #10). This was probably due to the fact that the fire was next to a populated area for that reason there was many witnesses of the event. It is also the first event where official accounts of police departments (#2, #4) are taking part in the social media coverage of fire events. Finally similar to the other fire events we can see those accounts representing news and newspaper agencies (#1, #6, #7) and firefighters (#3) are more often major contributors to massive fire events.

In 2014 Norway was struck by winter wildfires. One of the regions struck by the winter flames was Frøya, Trøndelag. Within the period of 27/01/2014 and 31/01/2014, a total of 480 tweets was amassed and the most influential accounts for that timeframe can be seen in Table 27.

Table 27. Frøya fire event top influencers

#	Encoded Twitter user name	Description
1	idqSuQBdX9Lqn4rvbsxzZ	Police
2	LeKHcLHpsgnqe8nBh5	Citizen
3	e0SBAFq6WWgytAIFXg	Red cross – Search and rescue
4	U9DX6V2ehDaKBYQV2Qp	Red cross – humanitarian organization
5	ucGtFeu13pXLSe6	Journalist
6	oZiqoZ9JGyZ9NOBN9PQkSTsnN	Citizen
7	7YHJmnljPq60sBb	Voluntary rescue organization
8	7MaMvOkh6ajIhGtZ	Page tracking police tweets
9	zB3NCMGnBG3PQSICdvTY	Citizen
10	tPvUtjWvjYI4Ou19hHxfmPP198k	News page

Similar to the German events Citizen (#2, #6, #9) as well as police involvement (#1, #8) is more pronounced in this region. Additionally, many emergency, rescue and humanitarian organizations (#3, #4, #7) played a great role during the wildfires.

*Norwegian fire event*s

Another Norwegian fire in the Trøndelag region razed an entire peninsula in Flatanger. In the timeframe between 26/01/2014 and 29/01/2014, 489 tweets were collected. The most influential accounts from the aforementioned collection of tweets can be seen below in Table 28.

Table 28. Flatanger fire event top influencers

#	Encoded Twitter user name	Description
1	dNMEliptk11vfGGyH3rRn4H	Citizen
2	uEucmaRy1DqdjxFEIjsPjIxPhx6	Police
3	XPvs29dycJPiCbYlZG5TSIDUm7	Red cross – Search and rescue
4	cOREp0ZrCf8PjzDDLg	Red cross – humanitarian organization
5	fpX4cLoCqBOLM5GHHtvrAVKLXZt	Helicopter rescue
6	iI48iEVabkdISjURfcGd	Page tracking police tweets
7	yIZH9HTJCsDFC5V36YM3Y2tSI1K	Police
8	Ric7hrNGxeJvxVGHZWmdSbu	Citizen
9	lWR7jkVEsspNl0U1WiM9i03	Citizen
10	lWR7jkVEsspNl0U1WiM9i03	Norwegian newspaper agency

Considering the timeframe and the proximity of the Norwegian events that we analyzed, the top influencers are similar. We can see heavy citizen (#1, #8, #9), police (#2 #6, #7) and humanitarian and rescue organizations (#3, #4, #5).

During the same timeframe Norway experienced one of the worst city fires in its history. A fire in a residential building quickly spread to other houses in the area resulting in many buildings being burned down or damaged, citizens being evacuated and hospitalized. The collected 490 tweets between 23/01/2014 and 28/01/2014 produced the following top influencers in Table 29Table 29.

Table 29. Lærdal fire event top influencers

#	Encoded Twitter user name	Description
1	vUhMxbP1luc3CKE7jp3AFlj40	Journalist
2	2Oenq1uLUzjFWyhHrjv	Freelance author, social debater, speaker and columnist
3	0LBzNEbvGcNO84Y	Lawyer, Ex-city councilor
4	QMm3BXnmr1DyoBW5UcLZU	Citizen
5	yefrmGEaiWDIzPWZeouBA0SF1q4H	Editorial manager of new agency
6	mXs7ME3AGXEUEhMW	News agency
7	nGdBa8sfayhMeFT6vF8tJcH7bln	News page
8	W4Shh1t1EuSWjd78y	Citizen
9	W4Shh1t1EuSWjd78y	Citizen
10	eGs4kFnR2Xoqp7gaqMR0dNDi6	Citizen

Citizen involvement (#4, #8, #9, #10) is the most we have seen in all the events covered. This could be attributed to the fact that the fire event took place in a residential area. Public figures (#2, #3) also took part in the online interactions regarding the occurrence. It should be noted that unlike the last 2 Norwegian fire events, no emergency services or the police accounts were part of the top influencers.

Additionally, from fire events on Spain, German and Norway, we observe that the closer the event it is into a residential area the more citizens are actively playing a main role into the reporting of the fire incident and the more public figure, politicians are talking about it. On the other hand, in cases where the fires are occurring in forests or remote areas the citizen coverage of the event is less and the journals, news and emergency agencies are talking the lead in broadcasting the fire events

Next steps

An important future task, is the refinement of the search criteria with the collaboration of the pilot leaders in order to increase the amount of fire related social media posts that are collected and decrease the amount of irrelevant social media posts (noise) by extending the crawler to support a wider range of keywords, accounts and languages. Another future work, will be the implementation of a relevance classification machine learning mode that will automatically classify social media posts as relevant or not relevant. Additionally, the localization web service module that geotags the tweets will be extended for other languages. Moreover, a community detection algorithm will be implemented that discovers user communities and identify key-players that play an important role during a fire event and affect other users. Finally, another future task will be the fusion of social media data with other sources of information such as satellite images aiming at a more sophisticated assessment of an incident's severity.

Fire resilient materials

Fire resilient materials play a crucial role in the prevention and preparedness phase of the TREEADS project. Different technologies to protect different kind of structural materials (e.g., concrete, wood, steel) are being developed in **task 4.7 TREEADS fire-resilient materials for building and infrastructures**. Table 30 gives an overview of the cited fire resilient materials.

Table 30. Fire resilient materials of TREEADS project

Fire resilient material	Material to be protected	Partner
Alkali-Activated Materials (AAMs) manufactured using Wood Ashes (WAs) or Post-wildfire Wood Ashes (PWAs) as precursors or activator	Concrete	RINA-C, UniNa, NTUST
Cement-based materials manufactured using WAs or PWAs as partial Ordinary Portland Cement (OPC) replacement	Concrete	RINA-C, UniNa, NTUST
Polymer based fire resilient materials developed to be used in tailormade products for protection of the underlying structure from a critical temperature increase during a fire	Steel/Concrete	VIPO
External wooden claddings for building manufactured using fire-impregnation through vacuum-pressure process	Wood	WAS

This section summarizes the different approaches used in the development of these fire-resilient materials by the TREEADS partners.

Wood ash used as replacement in AAM and cement-based materials

The potential for the valorisation of some selected secondary raw materials through the alkali activation technology is being assessed for the development of construction materials with improved fire-resistance properties. Suitable sets of secondary raw-materials have been properly identified and they are being tested; this may include post-wildfires wood ashes (PWA) and other types or industrial or natural by-products (e.g., pulverized fly ash - PFA, ground granulated blast furnace slag – GGBS, rice hush). Sodium silicate (SS) and sodium hydroxide will be used as alkaline activator. Raw materials will be tailored to fully exploit the fire resistance behaviour of the alkali activated construction materials made thereof. Mechanical strength and workability of developed mixes will be utilised as performance indicators. Durability properties will be also investigated and the influence of PWA on the fire resistance of AAM will be assessed at different curing times. Building elements/materials (e.g., blocks, plasters) will also be reproduced for demonstrating the feasibility of the technology for future industrial applications.

Since the wood type and the combustion conditions have a great influence on the chemical composition of the WA (PWA) it is appropriate to define a PWA production protocol to be used. Thus, the controlled burning conditions ensure the achieve of WAs (PWAs) with similar chemical composition and properties in all the production lots.

The detailed description of the process and the results related to the mechanical characterization of the proposed materials will also be available for future analysis to evaluate the trade-offs between the use of PWA for concrete production and its effects in the natural forest regeneration.

The PWA used for the development of the fire-resilient material for buildings and infrastructures are obtained following a standard fabrication protocol. A summary of this process is reported below.

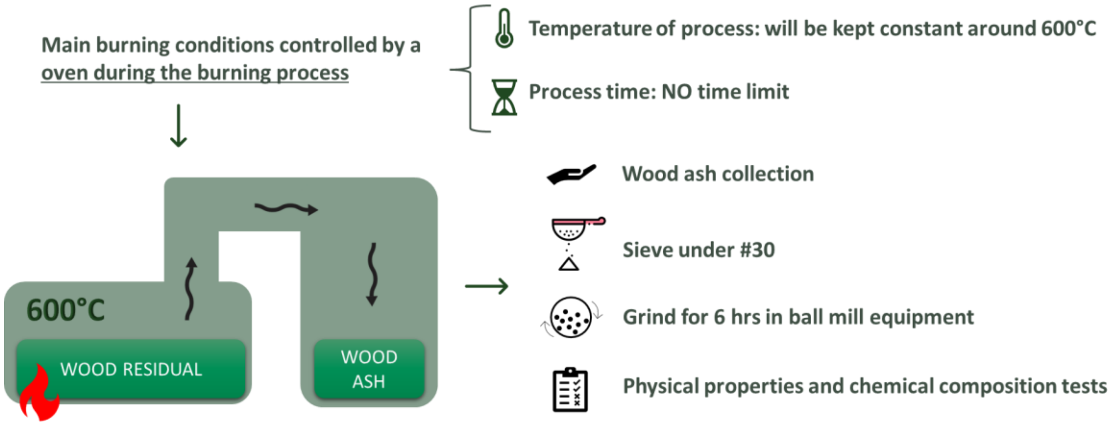


Figure 18. PWA production protocol

Physical properties and chemical compositions tests of wood ash shall be conducted as same with Portland cement following the ASTM and/or equivalent EN standards (Table 31).

Table 31. Standard for test on the mineral filler powder

Measured parameters	Standard	Notes
Physical properties: grading	ISO 13320:2020	Particle size analysis - Grading of wood ash shall be determined by laser diffraction methods or similar (e.g., using Mastersizer 2000)
Physical properties: mean particle size d50	ASTM C136, C33	Particle size analysis - Particle size distribution of wood ash shall be determined by laser diffraction methods or similar (e.g., using Mastersizer 2000)
Physical properties: specific gravity	ASTM C188-17	Standard Test Method for Density of Hydraulic Cement
Physical properties: finesses	ASTM C204-18e1	Standard Test Methods for Fineness of Hydraulic Cement by Air-Permeability Apparatus
Chemical composition	ASTM E1621-21	Standard Guide for Elemental Analysis by Wavelength Dispersive X-Ray Fluorescence Spectrometry

The results of the raw material characterization are reported in Table 32.

Table 32. Raw material characterization

Items		Wood Ash (Taiwan)	FA (Taiwan)	FA (Italy)	GGBFS (Taiwan)	GGBFS (Italy)	OPC
Physical Properties	Specific gravity	2,51	2,17	-	2,98	-	3,15
	Mean particle size d50 (µm)	10,08	14,61	-	-	-	16,82

	Fineness (cm2/g)	8219	3110	-	-	-	3310
	LOI	-	-	4,53	-	1,78	-
Chemical Composition (%)	SiO2(S)	14,56	64,09	53,70	~ 35	35,16	20,20
	Al2O3(A)	3,76	22,58	28,10	~ 10	10,76	4,13
	Fe2O3(F)	5,53	4,55	6,99	~ 0,5	1,40	2,98
	S+A+F	23,85	91,22	89,39	~ 45,5	47,32	27,31
	CaO	25,37	1,00	4,32	~ 40	41,91	61,64
	MgO	3,56	0,66	1,59	~ 6	7,68	4,92
	SO3	3,39	0,23	-	~ 1	1,92	2,55
	K2O	8,86	1,46	1,89	~ 0,5	0,14	0,44
	Na2O	-	0,43	0,87	~ 0,5	0,11	0,39
	TiO2	0,15	-	-	-	-	0,59

The results achieved in the development of AAM and cement-based materials which involve wood ash as replacement of activators (in the AAMs) or of OPC (in the cement-based materials) will be exploited in the Italian pilot (T8.3).

Jotne will contribute to the creation of fire-resilient materials by offering the use of their_PLM software EDMtruePLM to act as a repository for the test results from the RISE test labs to facilitate accessibility and interoperability of the data. Jotne will develop new functionality for EDMtruePLM if needed.

The following steps will be performed by TREEADS partners:

1. Survey and evaluation of relevance of test methods (FRN).
2. Integrating the field measurements into the test methods (FRN).
3. Development of realistic test methods relevant for wildland fires (based on input from step 1 and 1) in different scales. Focus will be on reaction to fire testing methods. For the large-scale method, known façade testing methods and known wildland exposure methods will be considered and adapted.
4. Execution of experiments to document and evaluate the reaction to fire properties and performance of the fire resilient materials and products (FRN/WAS/VIPO).
    a. Small and medium scale experiments (part of T4.7)
    b. Medium scale classification tests (part of T8.2)
    c. Large scale experiments (part of T8.2)

The materials and products will be demonstrated as part of the Norwegian pilot campaign (task 8.2).

A survey of available technologies for fire resilient materials and market potential for protection of steel and concrete infrastructure onshore, will give input to the design of material concept to be developed. Fire resilient materials consists of a base polymer with a flame-retardant filler system incorporated.

Selection of polymer type will modify properties of the final system in terms of resistance against our door environment including UV radiation, humidity and temperature variations. Our door climate, in particular in Nordic areas with temperatures below -20°C, will influence the service life of a product if a polymer with limited flexibility at low temperatures is selected. For a product designed for a dynamic application, typically a seal or a polymer coated fabric, this is of high importance. But even a static design like a protective panel or coating assembled onto a rigid surface, should withstand possible impacts without cracking. Service life of a polymer-based product for outdoor climate, is highly dependent of the ability to resist exposure from sun / UV radiation in combination with humid conditions. Different polymers will have variable inherent resistance against UV attack.

Selection of type and level of flame-retardant additives will determine the reaction to fire properties and the ability to protect the underlying structures. A high level of insulative fillers is beneficial when it comes to insulation from dangerous temperature increase, but a highly filled material will typically suffer from reduced mechanical strength and flexibility. The necessary level to obtain sufficient resistance against a wildfire will be selected.

As part of the initial development phase, a set of in-house screening tests is established to be able to distinguish between materials and select the best way forward. The methods are used evaluate typical parameters for reaction to fire like ignition oxygen index, self-extinguishing properties and visual appearance and strength after fire exposure.

The material composition will influence process behaviour. Type of production process will be selected to match the concept design. Injection moulding, extrusion, calendaring of sheets followed by compression moulding or coating of a fabric layer are parameters to investigate to be able select a cost-effective process depending on the design of the product. Input from the measurements documented during the Norwegian pilot and further simulation of wildfire properties will be used to design necessary layer thickness, geometry and if additional reinforcement is needed. These are all parameters which are critical to explore to be able to design a cost effective, low weight system with sufficient properties.

3 series of small and medium scale fire experiments will be completed at RISE to document properties. Samples of existing materials are prepared and ready for testing to establish a baseline for evaluation. Finally, output from large scale fire experiments on selected prototypes will be used to give input to the guideline development for protection from wildfires.

Through survey and evaluation of existing test methods and the collection of data from previous forest fires we will identify a testing range as well as valid fire testing methods for wooden materials relevant to the protection of infrastructure / buildings in areas at risk of wildfires.

The study of data from own library as well as data provided by other partners (Woodsafe and Woodsafe allies) of fire tests deemed relevant to acquiring knowledge that will assist us in setting a quality assured fire testing schedule. The study will focus on the differences between wood species, wood thickness, the use of surface coating systems, impregnation type and more.

Development of product used as PFP protection of wooden buildings (WAS):

- Fire testing in accordance with findings established by studies (M13-19), results of phase 1 will be applied in testing schedule (SBI, large scale fire-testing in collaboration with FRN/RISE). Testing in accordance with SP Fire 105 or preliminary guides for new test standard if warranted).

- Test parameters:
    - Identify differences between wood species (reaction to fire performance indicators, cost implications – density and impregnation saturation, and wood-thickness)
    - Implication of using various surface coating systems (non-fire solutions, standard systems only)
    - Use both Woodsafe impregnation products (PRO, Exterior WFX) to identify the most cost effective and durable solutions

Identifying one or more solutions that will qualify within the desired set of parameters for fire in combination with durability, sustainability and cost efficiency for large scale testing and commercializing.

Several updates from 16/12/2022 (Internal Treeads meeting Woodify + Linked Third Parties) are listed as follows:

- Baseline fire testing (CC) in collaboration with RISE (FRN) is due to start 01/23 and continue throughout 2023. Approximately 8 product variations and 80 samples (Week 7+8).
- The small pressure tank in which our test-samples will be impregnated with fire-retardant Is due for completion in February 2023 (Woodsafe Factory). This entails a much more time efficient schedule for producing test samples for testing from Q2 at the latest.
- During the course of Q2 we are scheduled to start SBI testing at Backegårds List AB. This will increase our efficiency in relation to the testing schedule.
- A third fire-retardant option will be added to the testing regime.

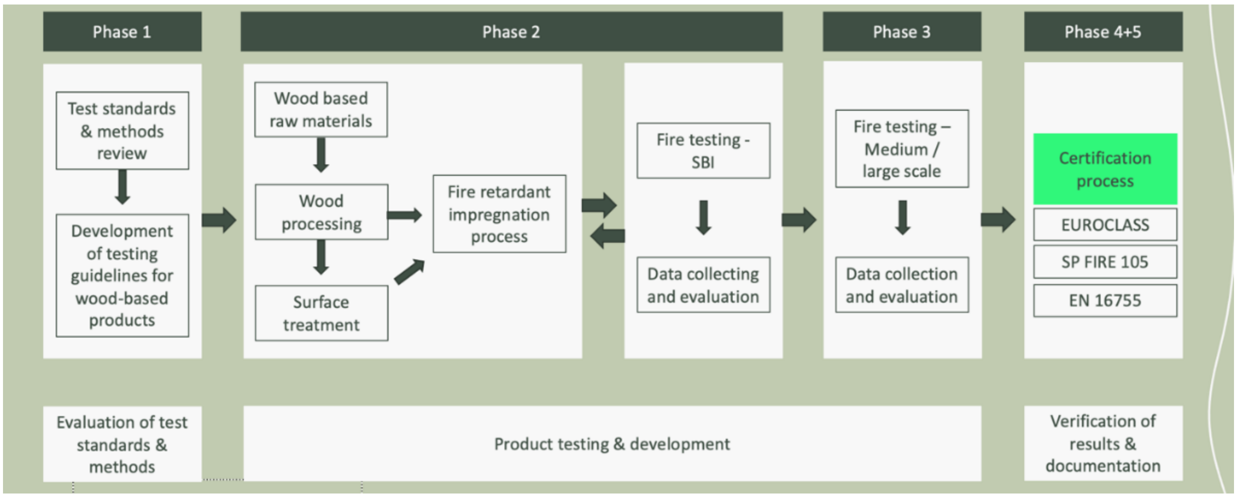


Figure 19. Overview of project phases

Integration within the TREEADS platform

In WP7 all toolsets and solutions built in each phase of TREEADS shall be considered, in order to come back with an optimisation solution for the use of every technological service and solution. The concept is about thinking and working with a holistic approach. A holistic approach in computing and of course in service management, means that each hardware or software component, each tool, each application, each service must always be thought of as an element of a whole, which will contribute to globally achieving the worth. Therefore, a simple and practical strategy is to produce simple solutions that lead to an added value or at least an integral part.

The technological solutions for prevention and preparedness proposed for each tool (T4.1, T4.2, T4.3, T4.5, T4.6, T4.7) must act as an independent component with interaction designed to be integrated holistically in TREEADS. Without interconnected services or without an integrated vision (T4.4), there is no solution in prevention and preparedness, but only solutions or tools in an environment without storytelling for Prevention.

The increasing introduction of heterogeneous technologies in the production process makes such processes more complex and thus more difficult to control (Nikolakis et al., 2020). From a computing point of view, considering the design of each component, tool and/or solution through the adoption of container technologies, will allow the creation of a hierarchical structure enabling the holistic production plan, supervision, and control. In addition to helping each stage of the WP Socio-Technological Solutions (WP4 - WP7), the role of the platform is to package the applications together with their corresponding dependencies (data models, processes, libraries, etc.) within standardized units known under the software container term. In fact, **it allows software to be encapsulated or packaged within such a container using a microservices architecture**. This design allows the tool to be scaled, replicated, versioned and adapted to the different pilot areas, being the communication of services and/or processes managed by a system orchestrator that offers solutions and narrative to each phase and zone.

The following figures show how each tool is encapsulated independently, containing its specific inputs and outputs:

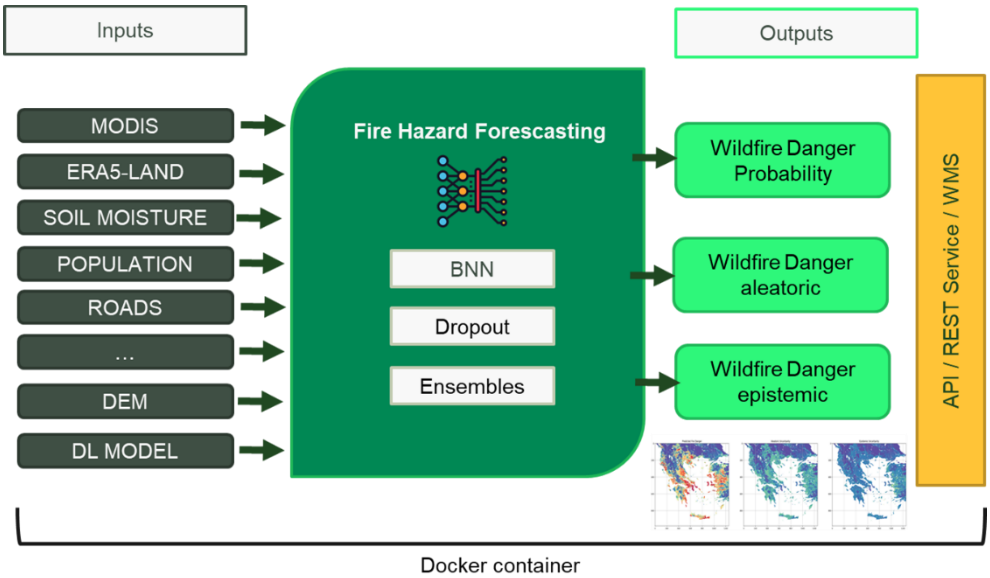


Figure 20. Fire daily forecasting (T4.1) Inputs and Outputs.

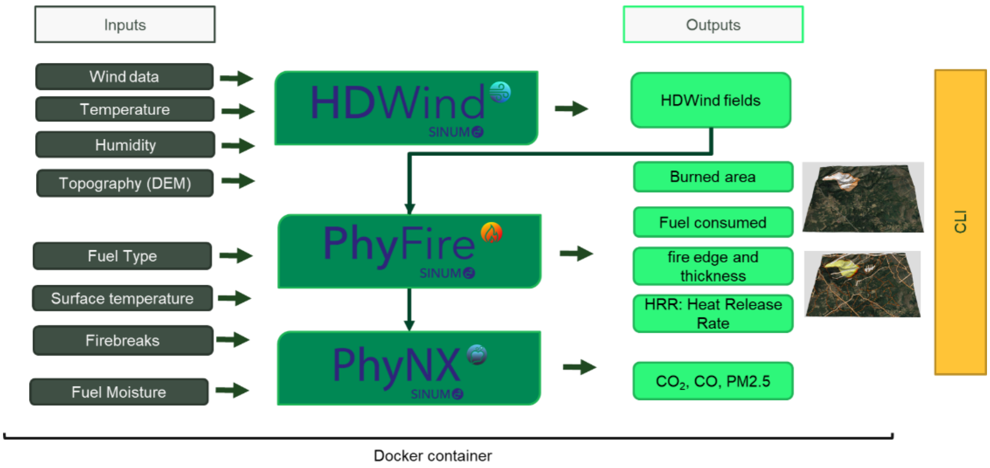


Figure 21. Fire and smoke propagation forecasting system (T4.2) Inputs and Outputs.

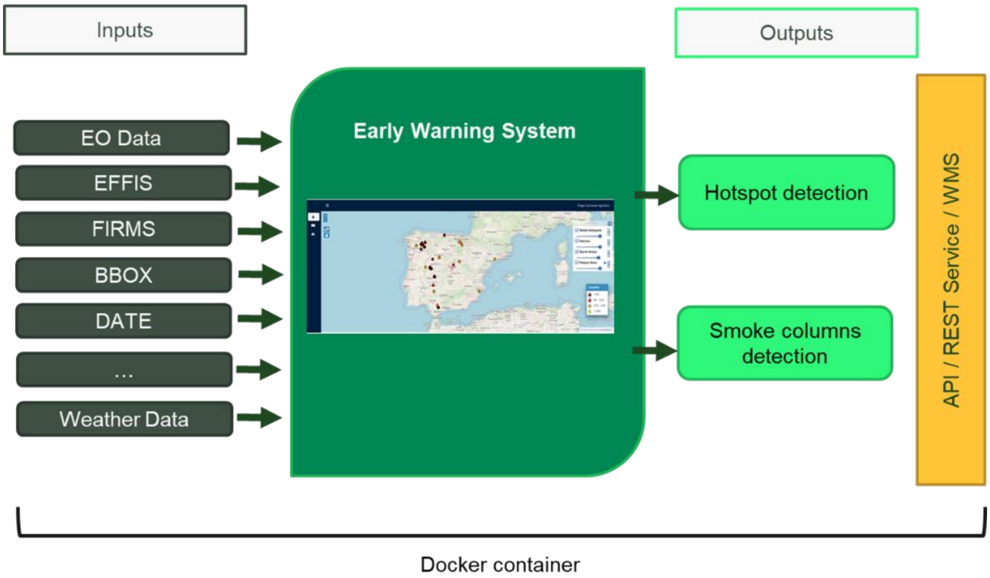


Figure 22. Early Warning System (T4.3) Inputs and Outputs.

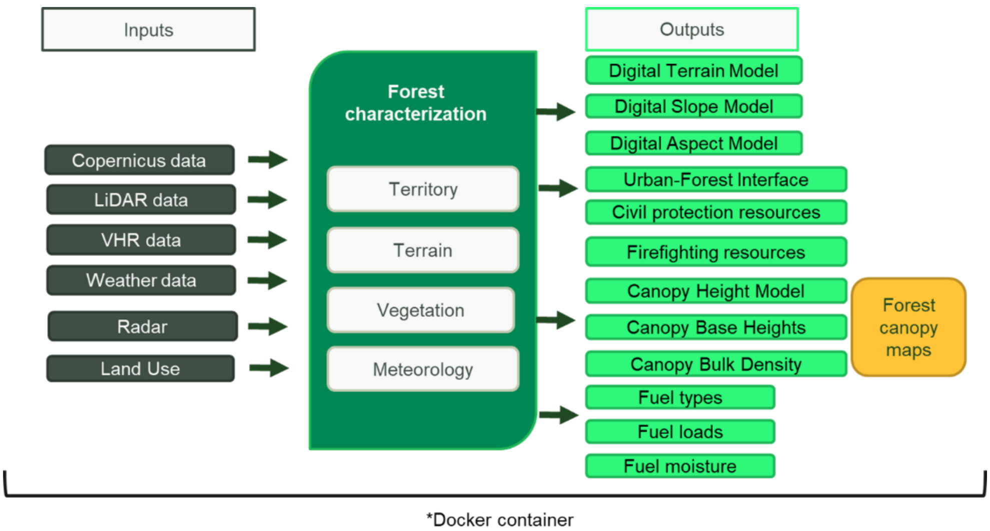


Figure 23. Detailed forest mapping (T4.5) Inputs and Outputs.* Some of the processes are not dockable.

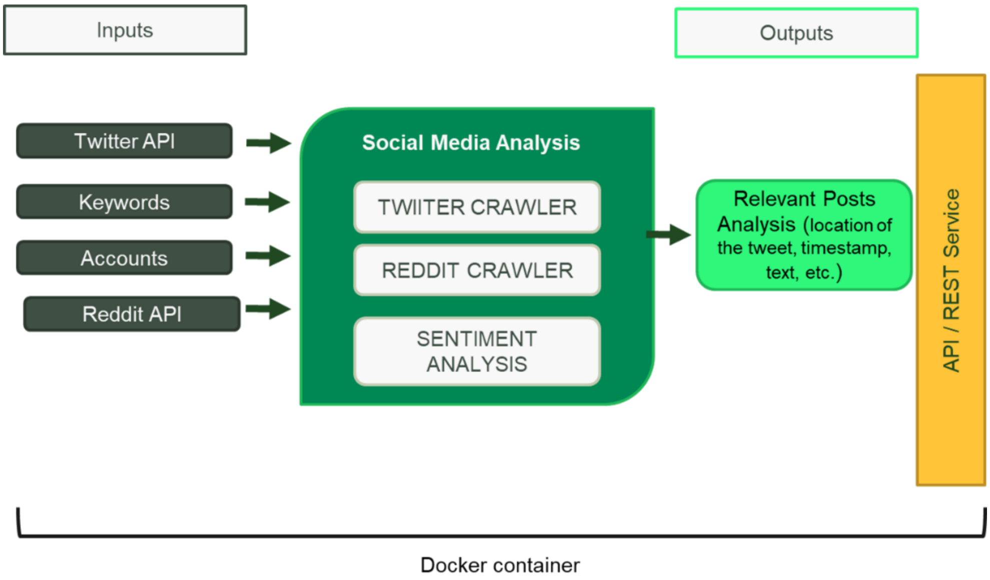


Figure 24. Social media analysis (T4.6) Inputs and Outputs.

The different tasks and technologies involved in WP4 will be integrated in the TREEADS platform within a module dedicated to Prevention and Preparedness as follows (Figure 25).

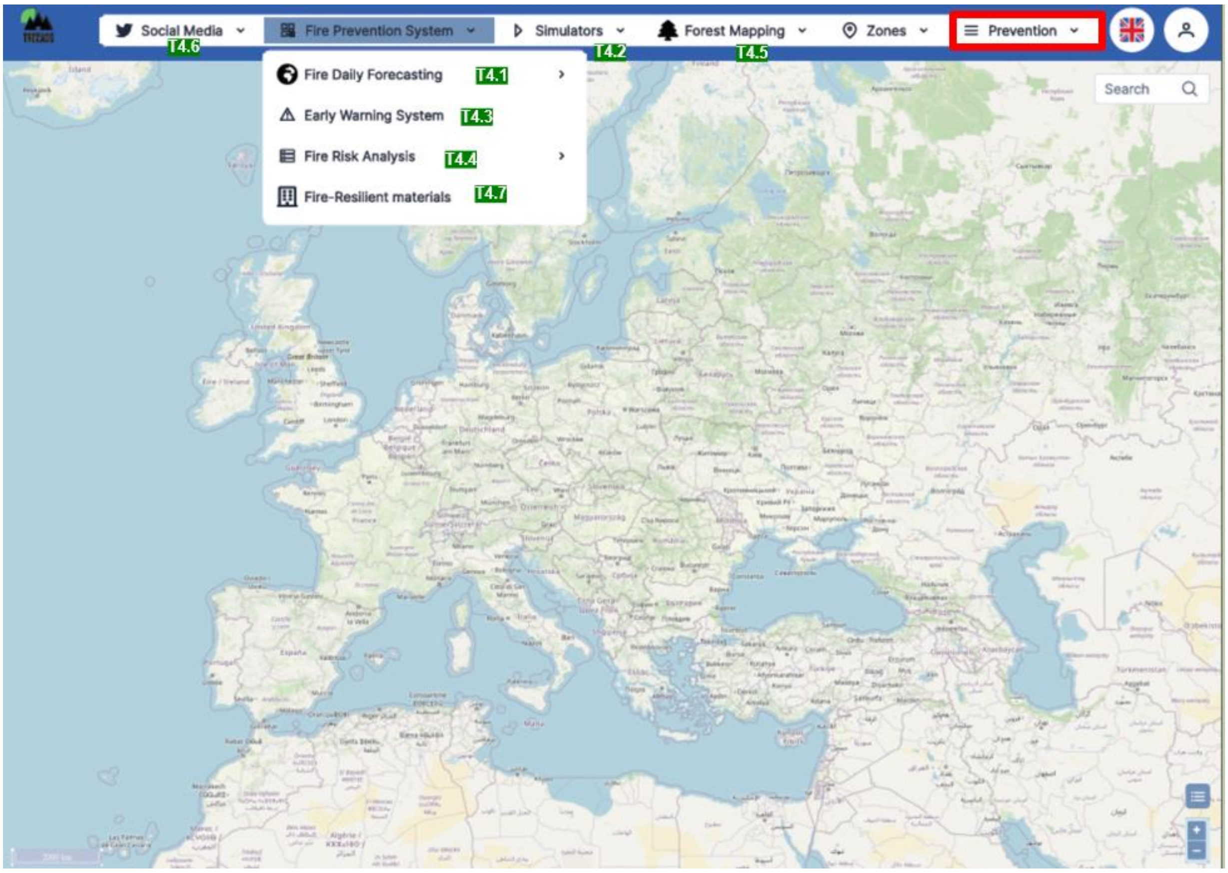


Figure 25. Mock-up with the integration of the different tasks and technology for prevention and preparedness.

Depending on the weight and importance of these tasks/techniques along the value chain of wildfires (Prevention, Response, Restoration), some tasks will be integrated as main menus (e.g., social media, Simulators, Forest Mapping), while others will be allocated within the Fire Prevention System (e.g., Fire Daily Forecasting, Early Warning System, Fire Risk Analysis, Fire Resilient Materials).

Regarding simulators, the different simulation models for fire spread, smoke and wind will be integrated within the Simulators menu (Figure 26), allowing a comparison among models and predictors.

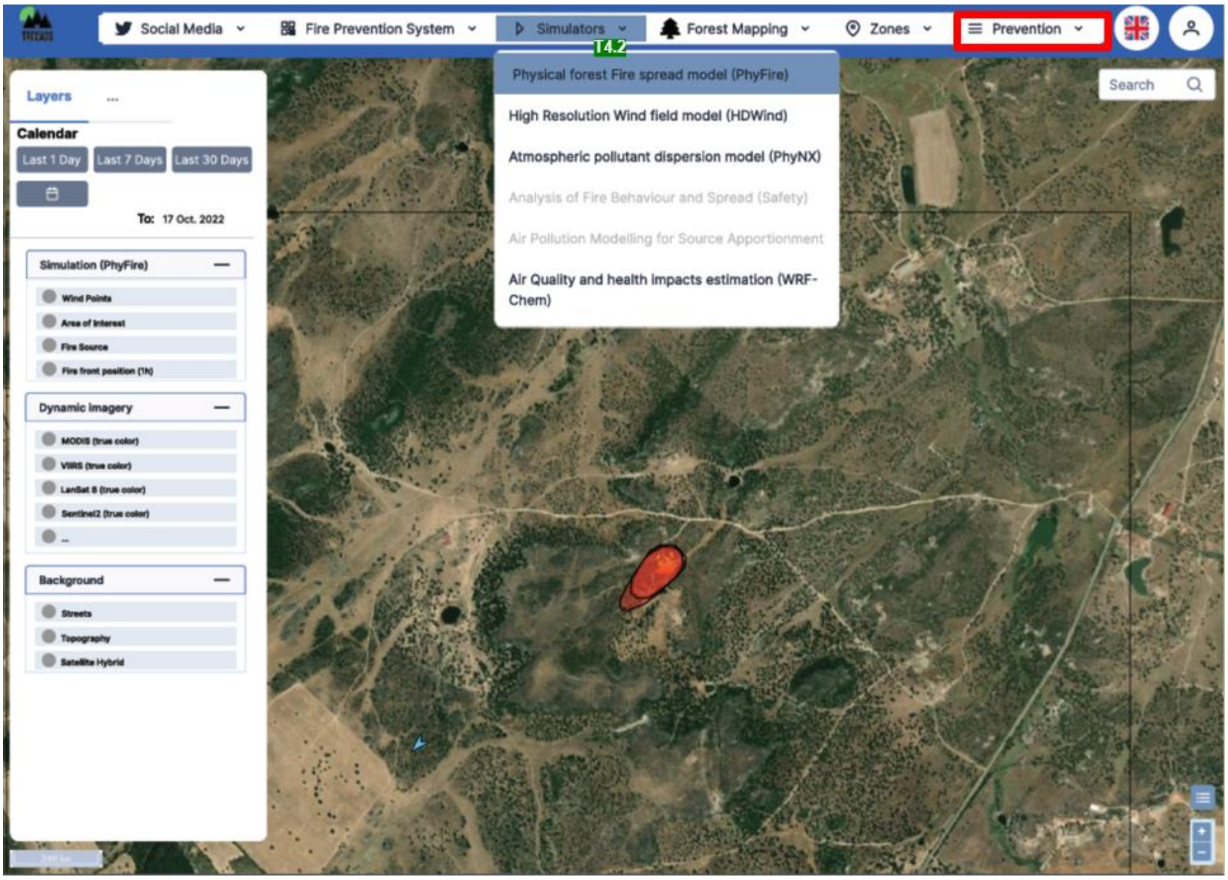


Figure 26. Mock-up with the integration of the different simulation models.

Last but not least, Forest Mapping will include those variables of interest to be mapped and their origin as data sources and geomatic products. As a result, different layers and geomatics products will be provided, so we can perfectly know the territory, the environment, the orography, the behaviour of the fuel in fire, as well as the resources for protection available (Figure 27).

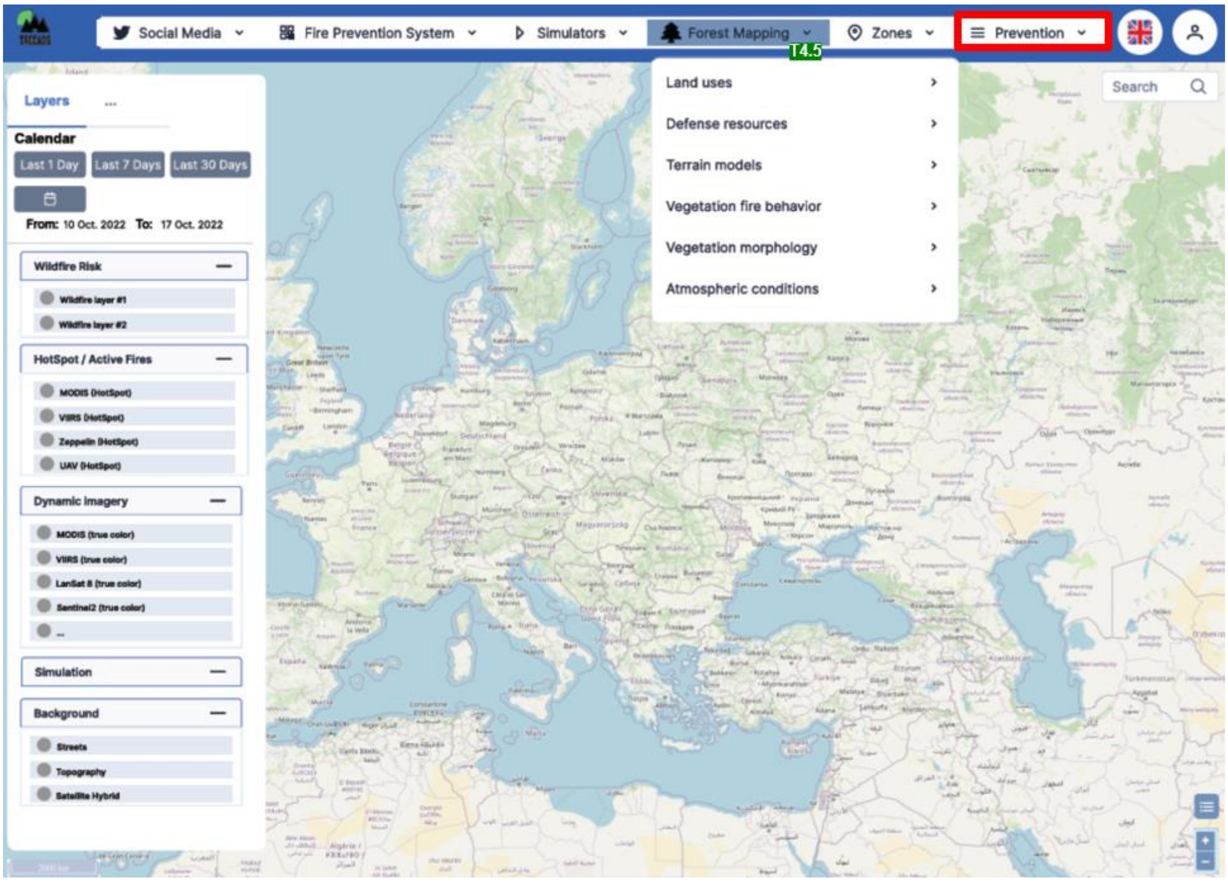


Figure 27. Mock-up with the integration of the different layers for forest mapping.

Finally, to have a clear picture of the "Prevention and Preparedness" module in TREEADS and thus about the functionality of the TREEADS platform, the following two storytelling can be developed as examples of possible applications:

1st storytelling: non-seasonal approach for the smart cleaning of the forest

Currently the Administrations have to face important investments in their budgets for cleaning the forests, and up to now there is not a tool which allows to generate reports which priorate and characterize those forest areas that should be cleaned. Therefore, TREEADS could provide a solution for this non-seasonal period (i.e., autumn and winter) generating these cleaning reports of the forest areas (Figure 28).

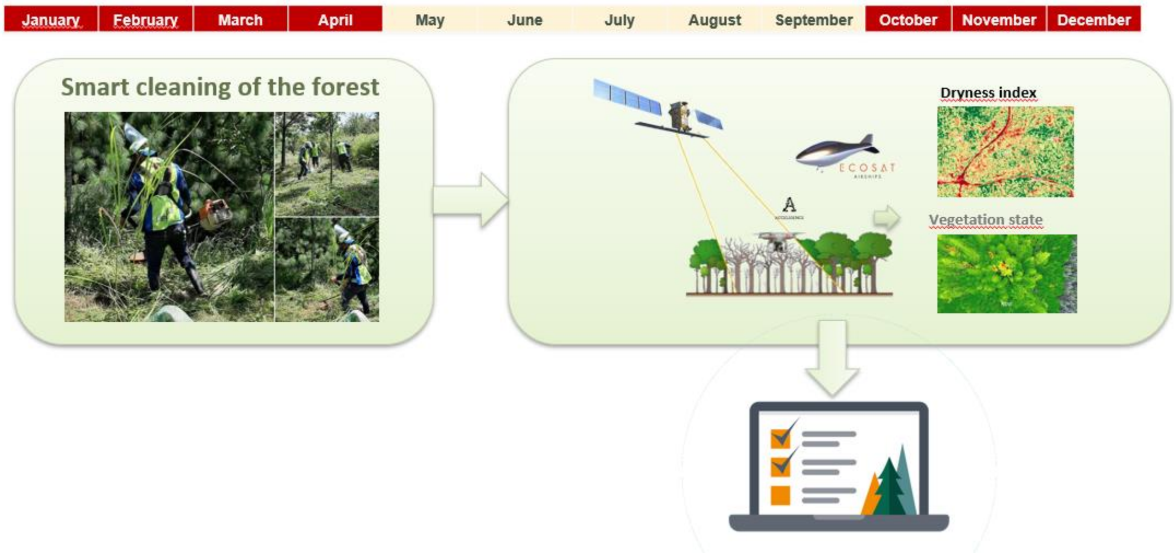


Figure 28. 1st storytelling: non-seasonal approach for the smart cleaning of the forest.

2nd storytelling: seasonal approach for the risk analysis of the forest

Currently the Administrations only receive daily forecasting about fires based on climatological data during seasonal period (i.e., spring and summer). In particular, the Fire Danger Forecasting (EFFIS) used in Europe, takes into account only meteorological data as input. However, wildfires are the result of complex interactions between humans, climate, and vegetation, which are difficult to model. To this end, TREEADS will use the last advances in artificial intelligence together with detailed forest mapping, early warning system, fire simulations and social media analysis to provide a better risk analysis related with wildfires (Figure 29).

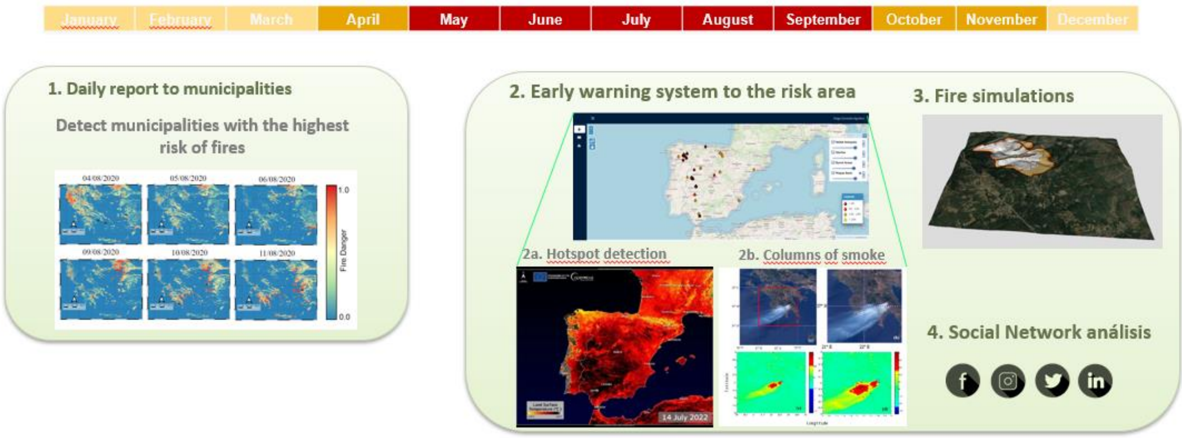


Figure 29. 2nd storytelling: seasonal approach for the risk analysis of the forest.

Conclusions and implications

To sum up TREEADS D4.1 V1, **TREEADS solution for prevention and preparedness will deliver an efficient and reliable system based on, and upcoming, the best available data sources and technologies for prevention and preparedness of wildfires.**

To this end, the TREEADS solution for prevention and preparedness will be an **integrated system** consisted of **six interdependent components** which outcomes and innovations provided are summarized as follows:

1. **Fire daily forecasting:** a deep learning-based model that uses satellite data from MODIS to retrieve vegetation and energy indices, meteorological variables from ERA5-land, soil moisture indices from JRC European Drought Observatory, distance to roads and population count from worldpop.org and products of land cover, elevation, aspect, slope and curvature from the Copernicus Climate Change Service and the Copernicus Digital Elevation Model to create a **datacube at EU scale** that will be used and expanded by fuel loads that will be produced by CARTIF by means of the segmentation approach, as well as by local data that can be made available by the Pilot Leaders. A forest risk index and an agroforestry index will be retrieved and will feed the early warning system component to identify territorial vulnerabilities. The **main outcome** from this component will be the **identification of areas of higher fire danger** where the subsequent analyses from the other TREEADS platform components will be performed.
2. **Fire simulation models:** three simplified physical models that work using effective numerical and computational techniques and GIS will be integrated within the TREEADS ecosystem, namely (i) PhyFire, for the **fire spread process**, (ii) PhyNX, for the **dispersion of the smoke cloud**, and (iii) HDWind, for **improving wind input data** for both models. The input for these models is very similar to that from the previous component of the TREEADS platform, thereby consisting of satellite data from the Copernicus program, weather data and fuel maps and load data from the firEUrisk project with whom TREEADS has stablished a collaboration. Last but not least, it is to note that the three models can be adjusted according to evolving needs and demands that arise during the development of the project.
3. **Early warning system:** this component will benefit, as well as the bellow mentioned, of the innovative **4-layered approach** of TREEADS solution, which relies on not only satellite data but also sensors on-board drones (low-medium and low altitude) and airships (zeppelin). The higher resolution of this data will allow for **detecting hotspots and smoke columns** as an early warning system for **identifying incipient fires on their early stage** to proceed accordingly as soon as possible with the subsequent response phase of the project.
4. **Detailed forest mapping:** this TREEADS component will rely on the 4-layered approach to offer an **accurate characterization of the forest at the highest possible resolution**. Anthropic variables, spatial variables, radiometric variables and meteorological variables calculated from LiDAR, multispectral, hyperspectral and ancillary data will allow for the detailed mapping of variables that are key in the prevention and preparedness of wildfires, namely terrain variables (digital terrain, slope and aspect models), urban forest interface, available resources (i.e., civil protection and firefighting) and the accurate modelling of vegetation and soil properties (i.e., canopy height and density, fuel models and load, humidity, temperature and precipitation). The

main outcome of this component will be very **high-resolution maps and the detection of drought areas**. These maps will also serve for the **non-seasonal monitoring of the forest to allow for smart cleaning practices**.

5. **Social media analysis:** this innovative component of the TREEADS solution will monitor fire events as they are expressed on social media. Based on well-defined search criteria and relevancy filters, **social media data will be collected in real time to enrich the geo-information outcomes** from the other TREEADS modules, targeting specially users that play an important role during fire events.
6. **Fire resilient materials:** a **guide of good practices** will be provided as an outcome of this component, indicating materials to be used in the prevention and preparedness phases of wildfires. A detailed description of the proposed materials' chemical composition and properties, process and results related to their mechanical characterization will be provided as well as future analyses of their effects in the natural forest regeneration.

These components will be integrated and articulated so that their performance is coordinated for the different applications considered, named as storytelling. This integration will be performed within the Integrated Fire Management System, also taking into account the different levels of expertise of the potential users and the tools they would be interested and able to manage.

Last but not least, thanks to the use of the best available data sources and most accurate modelling and processing technologies and integration systems, the **TREEADS platform will be an efficient and tangible solution that will allow for the further validation and evolvement of Copernicus products and services in the field of the monitoring and management of the environment and, more particularly, in the prevention and preparedness of wildfires.**

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Fire Forecasting

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TREEADS

A Holistic Fire Management Ecosystem for Prevention, Detection and Restoration of Environmental Disasters

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