The PRIMA Project: A Real-time Integrated Platform for Forest Fire Monitoring and Analysis

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Abstract

Wildfires represent an escalating threat with profound environmental and societal implications. Existing wildfire management strategies are often hindered by limitations in data integration, predictive accuracy, and operational usability. In response to these challenges, the PRIMA project (Piattaforma Real-time per l'Ingestion, il Monitoraggio e l'Analisi degli incendi boschivi) was developed within the framework of the Tech4You Program (PNRR, Mission 4 Component 2, Investment 1.5, Spoke 1 TR 4.1). PRIMA seeks to establish an advanced, integrated platform for the real-time monitoring and analysis of wildfires.

The system architecture is composed of two main modules: (1) Prediction and Propagation and (2) Satellite Monitoring. These modules enable the assimilation of heterogeneous data sources—including satellite imagery, drone observations, and terrestrial sensors—while leveraging real-time meteorological and hydrological inputs. The platform employs state-of-the-art technologies, including artificial intelligence, satellite data processing, and predictive modelling. Specifically, the Prediction and Propagation module simulates fire dynamics and the Satellite Monitoring module detects thermal anomalies and generates real-time alerts.

A distinctive feature of PRIMA is its user interface, which integrates LLMs and a real-time avatar to facilitate intuitive and efficient user interaction. With an initial Technological Readiness Level (TRL) of 5, the project aims to achieve TRL 7 through validation in real-world scenarios. Developed collaboratively by Revelis (AI and data analytics) and Easy City S.r.l.s. (aka "Dron-e", drone operations and imaging), PRIMA is based on the work of Department of Physics of University of Calabria.

Keywords

wildfire prevention, monitoring system, mathematical model, reaction-diffusion model, IoT, Wireless Sensor Networks, drones, satellite monitoring, artificial intelligence, big data, decision support system, user interface design, geo-visualization

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1. Introduction

In recent years, climate change has contributed to a rise in the frequency and intensity of catastrophic events, including wildfires. These events pose significant threats to human lives, forest ecosystems, and infrastructure. Data from Italy in 2023 showed that approximately 1073 km^2 of forest and non-forest areas were destroyed by wildfires, a 36% increase compared to 2022. The challenges persisted in following years with high temperatures and drought, leading to thousands of hectares burned across various Italian regions. Law enforcement efforts have also seen an increase in detecting fire-related crimes, although the number of individuals reported and arrests remain low compared to the number of crimes. Sicily and Calabria were among the most affected regions in terms of both crimes and burned area.

Given the increasing complexity of urban structures alongside forested areas, enhancing fire safety in urban and suburban areas has gained considerable attention [1]. While various fire propagation models exist to support emergency decision-making, many focus on single scenarios and struggle to balance accuracy and timeliness, limiting their application in large-scale, heterogeneous scenarios [2].

Current wildfire monitoring and management approaches often rely on isolated tools without effective data integration from diverse sources such as satellites, drones, sensors, cameras, and weather models. This fragmentation hinders a comprehensive, real-time understanding of the situation, leading to delayed detection, inaccurate assessments of fire intensity and propagation direction, and difficulties in coordinating response operations. Data incompatibility, interpretation challenges due to differing formats and resolutions, information overload for human operators, lack of accurate forecasting by integrating environmental data, response delays due to manual data collection and analysis, and decreased efficiency and increased costs are notable limitations [3].

To address these challenges, the PRIMA (Piattaforma Real-time per l'Ingestion, il Monitoraggio e l'Analisi degli incendi boschivi) project proposes an innovative, integrated platform for real-time monitoring and analysis of wildfires. PRIMA aims to provide comprehensive, real-time decision support for wildfire management by integrating multi-source data, advanced models based on Artificial Intelligence, and intuitive visualization tools integrating Large Language Models (LLM) and AI based real-time avatars. The platform is designed to improve prevention, rapid response, and post-fire management, thereby reducing the impact of fires.

2. The PRIMA Project Overview

The PRIMA project is a 12-month initiative structured under the Tech4You Program, Mission 4, Component 2, Investment 1.5 "Ecosystems of Innovation". The project's primary goal is the development of an integrated platform for the real-time monitoring and analysis of wildfires. The system is built upon three interconnected software modules:

1. Prediction and Propagation: This module focuses on the advanced real-time simulation of fire propagation. It integrates live weather and hydrological data with predictive models.

2. Satellite Monitoring: This module enables the early detection of thermal anomalies using satellite data, such as from Meteosat. It facilitates immediate alerts and continuous monitoring of fire evolution.
3. Post-Fire Analysis and Monitoring: This module handles the rapid processing of multispectral images acquired from various sources, including satellites and drones. It is used to assess fire severity, monitor natural regeneration, and analyze the structure of the affected territory.

The PRIMA project is a collaborative effort involving Revelis and Dron-e. Revelis specializes in Internet of Things (IoT) Analytics and data analysis, contributing expertise in managing and processing large datasets and AI/data analysis techniques. Dron-e specializes in using drones for environmental monitoring, providing expertise in aerial image acquisition, custom sensor development for drones, and training/consultancy on drone usage. This partnership leverages complementary expertise to cover the entire wildfire management cycle. The Laboratory of Modeling, Simulation and Visualization (LMSV) at the University of Calabria is also involved, providing expertise in modeling, simulation, and scientific visualization.

3. System Architecture

The PRIMA project aims to overcome the limitations of isolated systems by developing a Fire Monitoring Platform (FMP) that serves as a comprehensive and scalable solution for data acquisition, integration, analysis, and visualization, leveraging AI for improved efficiency and effectiveness.
The FMP is designed as a big data platform that integrates various data sources:

- **Satellite Data**: Includes multispectral images for vegetation analysis and risk estimation, thermal data for detecting temperature anomalies and active fire spots, and vegetation indices like the Normalized Difference Vegetation Index (NDVI). Satellites provide broad, constant coverage, essential for monitoring remote areas.
- **Drone (UAS) Data**: Provides detailed, flexible data from specific areas. Sources include RGB images for photogrammetry and 3D reconstruction (generating point clouds, 3D models, orthomosaics, contour lines, Digital Terrain Models (DTMs), and Digital Surface Models (DSMs), thermal images for identifying hotspots and monitoring fire evolution in real-time, Light Detection and Ranging (LiDAR) data for detailed terrain and vegetation mapping, especially in dense areas, and data from wind sensors on drones. Drones are valuable for inspecting specific zones, assessing flame intensity, and identifying critical points [4][5][6][7][8][9][10][11][12][13][14].
- **Terrestrial Sensor Networks**: Offer continuous and capillary monitoring with sensors for temperature, humidity (soil and air), smoke, particulates, and full weather stations. These networks enable early detection of small fire outbreaks. Specialized sensors can also provide a calculated wildfire probability index.
- **Camera Systems**: Fixed or mobile cameras (e.g., on watchtowers or vehicles) provide real-time visual monitoring of risk areas. AI can be used to automatically analyze images to detect smoke or flames and generate alerts.
- **Meteorological Data**: Essential for predicting fire risk and evolution, including temperature, relative humidity, wind speed and direction, precipitation, and lightning.

- **Fuel Data** (Corine Land Cover): Provides crucial information on land cover and use, essential for identifying risk areas, planning prevention strategies, and evaluating post-fire impact based on a standardized European classification system.

The platform utilizes a data-driven architecture for data acquisition, processing, and storage. Raw data are acquired and then structured for analysis. An event-driven model is employed for real-time acquisition, storage, and processing, particularly suited for IoT [15][16][17] and real-time analysis scenarios.
Key components of the data acquisition module include:

- Real-time Ingestion (Apache Kafka): Kafka is chosen for its ability to manage real-time data streams with low latency and high speed. It is a distributed, scalable, and fault-tolerant platform suitable for handling large volumes of data, organizing them into topics for consumption by different applications. Data from various sources are transformed into a standard JSON format (DeviceData) before being sent to designated Kafka topics.
- Storage (Elasticsearch): Elasticsearch serves as the storage and querying tool. It is a distributed, full-text search engine optimized for real-time analysis and capable of handling large volumes of big data. Its document-oriented nature (using JSON) makes it suitable for semi-structured and time-series data. Data are indexed rapidly for near real-time searching.
- Processing (Spring Boot Applications): Specific Spring Boot applications listen to Kafka queues for data ingestion and processing. An Ingester component specifically handles data ingestion into Elasticsearch.

The architecture shown in Figure 1 relies on specialized Gateways to integrate diverse, heterogeneous data sources into a unified format. These gateways act as the entry layer, designed with modularity and extensibility in mind. Two main types are implemented in Spring Boot:

- Polling Gateways: Actively query data sources at predefined frequencies, suitable for systems exposing REST APIs that need periodic polling. Examples include the Sensors Gateway (for terrestrial sensors connected to proprietary clouds) and the Environmental Sensors Gateway (for weather stations and ambient sensors).
- Subscription Gateways: Expose endpoints (e.g., REST) and listen for data pushed by sources, ideal for systems that send updates autonomously. The Drone Data Gateway is an example, exposing REST endpoints for receiving various types of drone data (images, LiDAR, telemetry).
- These gateways are responsible for data integration, transforming data into the standard JSON format, sending data to Kafka, and enriching data with metadata. For large data volumes like drone imagery, raw data is stored in an object storage, while metadata and analysis results are sent to Kafka with references. The system is designed for deployment in a Kubernetes containerized environment, ensuring auto-scaling, high availability, and robustness.

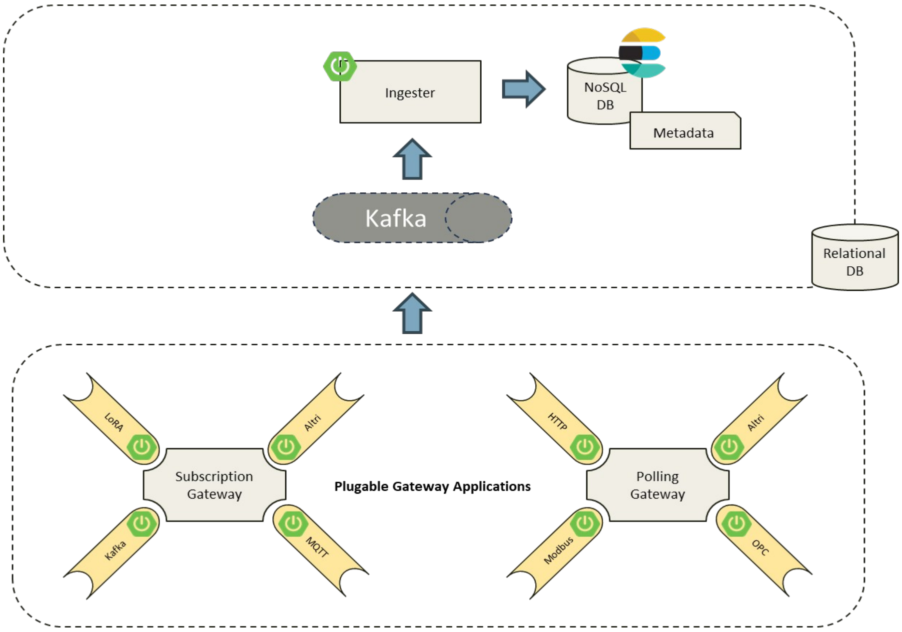

Figure 1: Architecture of Gateways used for data ingestion

4. Mathematical Modeling and Prediction

In past years some new models are introduced, [2] that combines forest and urban fire dynamics using a heterogeneous cellular automaton approach, making it well-suited for complex and expansive nature-urban boundaries. This model integrates fire behavior in both settings through thermal principles and real-world data, and with additional testing and validation, it has the potential to be developed into a software tool for fire prediction.

Other studies in the literature model wildfire spread using a convection-diffusion-reaction framework in two spatial dimensions, where temperature and fuel consumption are the main variables [18]. These variables change over space and time and are computed numerically using a semi-implicit method that simplifies the nonlinear convection-diffusion terms [19]. To address the reaction components, a Strang-type operator is used [20]. This modeling approach has been tested with different configurations and diffusion functions, showing that higher diffusivity leads to greater fuel consumption over time, while constant or minimal diffusivity produces comparable outcomes. These models account for changes in terrain that impact wind speed and direction, thereby influencing how fires spread and how much fuel they consume. The simulations enable the generation of risk maps, where the level of risk in specific areas is based on the rate of fuel consumption from fires ignited at various points within the modeled region.

Overall, numerical simulations indicate that risk maps incorporating uneven terrain reveal regions of both higher and lower fire risk when compared to models that assume flat landscapes [21][22].

A core component of the PRIMA platform is the mathematical modeling used for wildfire propagation prediction. The project leverages a preliminary mathematical model of reaction-diffusion, based on previous work [1], adapted for use with data from monitoring systems.

We consider the following two-dimensional energy equation [23][24]:

$$\rho C\left(\frac{\partial T}{\partial t}+w\cdot\nabla T\right)-\nabla\cdot\left(\left(k+4\sigma\delta T^3\right)\nabla T\right) + h(T)\left(T-T_\infty\right)=\rho Q\lambda Y \quad (1)$$

where ρ is the air density and C its specific heat; $T(x,t)$ is the average temperature at the position $x=(x,y)$ at time t; the drift velocity w is the sum of the average wind velocity and of the gradient of the topography height function, $w=\overline{w}+\nabla h_T$; $k+4\sigma\delta T^3$ is the turbulent diffusivity, with σ the Stefan-Boltzmann constant, δ the optical path length for radiation in the fuel bed; $h(T)=\left|T-T_\infty\right|^{1/3}$ is the heat transfer coefficient due to vertical convection, with T_∞ the atmospheric temperature; and $\rho Q\lambda Y$ is the heat source due to combustion, where Q is the heat of the combustion, λ the reaction rate, and Y the unitary concentration of solid fuel.

The model is solved numerically using techniques like a linearly implicit-explicit method to discretize nonlinear convection-diffusion terms, combined with Strang-type operator subdivision for the reaction term. Numerical integration is performed in a spatial domain with specified initial data and Neumann boundary conditions. The scaled equations for temperature $T(x,t)$ and fuel concentration Y are solved.

Environmental data collected by the monitoring system, such as temperature, humidity, wind speed (e.g., 1.5 m/s) and direction vectors, are integrated into the mathematical model. Furthermore, terrain topography data, derived from image processing techniques like drone photogrammetry and LiDAR to create detailed meshes, is used to influence the drift velocity in the model. The fuel matrix, identifying and classifying vegetation types using image segmentation methods such as K-means [25][26] and Otsu [27][28], provides data on the distribution and concentration of solid fuel Y for the model.

The numerical simulations based on these integrated data inputs illustrate the predicted progression of the fire, showing the distribution of fuel consumption and heat over time. For instance, simulations can show how fires initiated at specific points, with a fuel matrix derived from the actual terrain, might propagate and reach certain structures under given wind conditions. The ability to solve this model efficiently allows for the calculation of risk maps, quantifying the risk associated with a location based on the rapidity of fuel consumption by a fire starting there. Numerical simulations accounting for non-planar topography shows areas of both increased and decreased risk compared to models based on flat areas.

5. Real-time Monitoring and Visualization

A critical aspect of the PRIMA platform is providing real-time monitoring and effective visualization tools to support decision-makers in high-pressure situations [3][15][29]. The platform integrates real-time data from its diverse sources to provide a current view of the situation.

Designing a Decision Support System (DSS) for firefighting is challenging due to the complexity of the system and the need for usable and accessible information. Research has highlighted the lack of data usability as a main barrier in DSS, emphasizing the need for high-quality information design that is understandable by users of varying abilities and backgrounds. The PRIMA project adopts an interdisciplinary design-oriented process, combining mathematical physics with Human-Computer Interaction (HCI) [30][31] design principles and a User Experience (UX) [32] driven approach. This human-centered approach aims to tailor DSS interfaces to specific user needs and the operational environment.

Primary users of the Overworld FIRE DSS (the case study within PRIMA focusing on Calabria) have been identified as regional command room (SOUP) operators and firefighting team chiefs. These users make critical decisions that significantly impact the effectiveness of firefighting operations. The design process involved developing scenario-based representations, like journey maps, to visualize the decision-making process and information flow during a fire event intervention, highlighting key elements, actors, and required information. This also helped identify data needs, classifying them into evidence-based input data (e.g., weather, topography, location, vegetation) and simulated output data (e.g., predicted propagation, impact assessment).

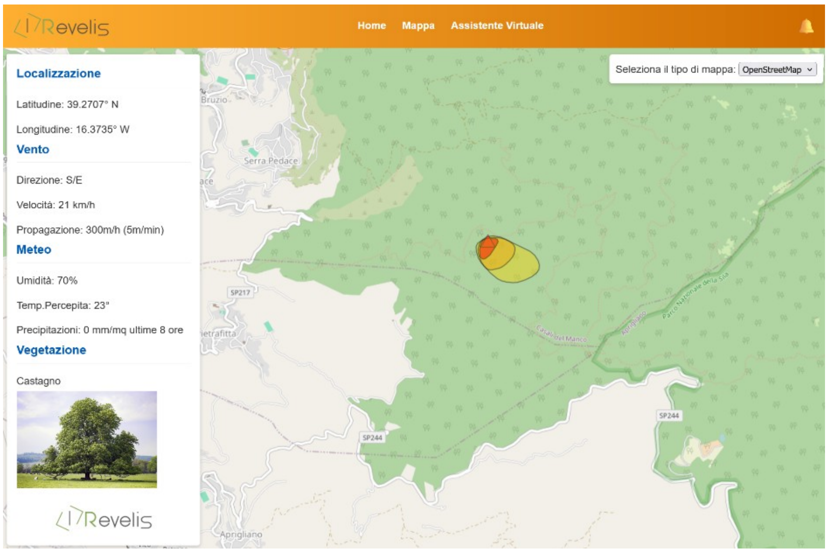

Figure 2: an example of a wildfire analysis using isochrone to show predicted propagation

Based on these insights and adhering to usability principles, user interface (UI) prototypes were developed for the primary user personas. The design incorporates strategies to address challenges in emergency management interfaces, such as avoiding cognitive overload, facilitating constant information exchange, and ensuring users feel in control. Key usability heuristics were applied, including visibility of system status (feedback, progress bars), user control and freedom (interacting with simulation timeline), consistency and standards (visual structure inspired by familiar interfaces like Google Maps, cross-UI consistency, use of standardized firefighting language and symbology), error prevention (optimizing readability, confirmation steps), and recognition rather than recall (using familiar terminology and visual language like SI.TA.C symbology, standardized isochrones, map legends).

Two distinct UI prototypes were designed:

SOUP Interface: Designed as a desktop-based application for use in control rooms. It allows operators to input fire location coordinates, view cadastral maps and road networks to assess potential impact on infrastructure and natural areas, determine necessary resources, visualize the nearest teams, and assess accessibility. This interface is also where fire propagation simulations are initiated and viewed. It integrates external data sources for weather parameters automatically once ignition data is entered. The simulation output, showing fire spread over time, is visualized using differently colored isochrones (Figure 2). The interface incorporates 2D/3D visualization with topography to provide a clearer perspective on potential critical issues.

Fire Chief Interface: Designed as a tablet-based application for use on-site. Fire chiefs receive simulation results from the SOUP, including location, wind direction, weather, and vegetation type. This interface enables them to organize teams and plan interventions by strategically placing resources (e.g., fire trucks, helicopters) on the map and visualizing how fire propagation might change based on these actions. It allows for keeping a record of decisions made. Similar to the SOUP interface, it uses 2D/3D visualization with topography to aid planning, especially for less accessible areas. The interface utilizes standardized icons for resource allocation.

The interfaces aim to make complex fire dynamics more comprehensible and manageable by providing an intuitive visual representation of real-time data, simulation outputs, and planning tools.

6. AI and Decision Support

Artificial Intelligence (AI) [33] is a fundamental technology underpinning the PRIMA platform, contributing to various aspects from data processing to forecasting and decision support.

AI and Machine Learning (ML) techniques are applied in the FMP for:

- Data Analysis and Processing: AI is used to analyze and process data from various sources, including Wireless Sensor Networks (WSNs) and multispectral images. This includes identifying distinct vegetation clusters using algorithms like K-means for the fuel matrix and image segmentation using methods like Otsu.
- Early Detection and Monitoring: AI algorithms analyze images from cameras to automatically detect the presence of smoke or flames and generate real-time alerts. Thermal anomalies detected via satellite are also key for early fire identification.
- Forecasting and Risk Assessment: AI algorithms, integrated with meteorological and environmental data, are used to forecast fire risk with significant advance. The platform aims to identify areas at higher risk. Mathematical models, supported by the processed data, also contribute to predicting fire propagation and creating risk maps.

- Post-Fire Analysis: AI is applied to process multispectral images for assessing fire severity, monitoring natural regeneration, and analyzing the structure of the affected territory.
- Resource Optimization: The platform aims to optimize the allocation of resources for prevention and intervention.

Ultimately, the application of AI enables the platform to generate insights, predictions, and alerts that support decision-makers. The goal of the DSS design, enhanced by AI, is to empower operators to make better decisions, rather than feeling controlled by the technology. The platform provides tools for visualizing prediction results, evaluating potential outcomes of different intervention strategies (via simulation tools), and optimizing the deployment of resources.

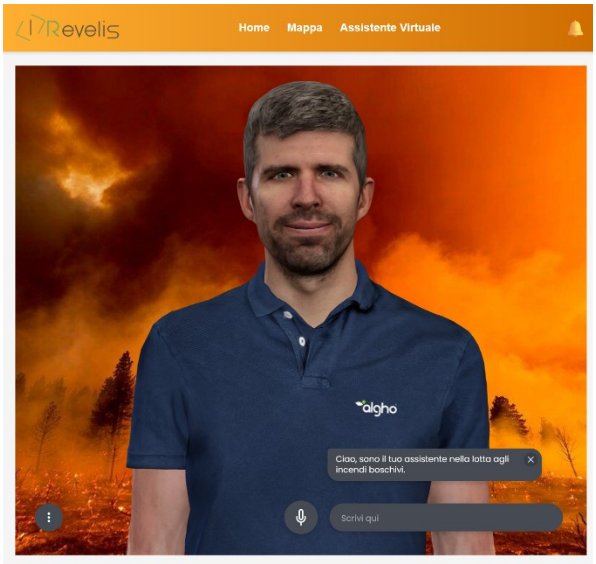

Figure 3: the AI based real-time avatar used to interact with the platform.

The platform usability can be significantly enhanced by integrating large language models [34] (LLMs) and real-time avatars [35] to present simulation results. LLMs can interpret complex simulation data, generate natural language summaries, and answer user queries about fire behavior, risk levels, and recommended actions, thereby making technical insights more accessible to a broad audience. Real-time avatars like the one shown in Figure 3 can serve as interactive agents that visually and verbally communicate simulation outputs, such as predicted fire spread, affected areas, or evacuation alerts, in a more engaging and intuitive format. By combining data-driven modeling with AI-powered interaction, the platform can support decision-making for emergency responders, policymakers, and the general public, improving situational awareness and response effectiveness during wildfire events.

7. Conclusions and Future Work

The increasing threat of wildfires necessitates advanced, integrated solutions for monitoring, prediction, and management. The PRIMA project addresses this need by developing a comprehensive Fire Monitoring Platform that integrates data from multiple sources, leveraging sophisticated mathematical modeling and AI/Big Data analytics. It contributes exploiting sustainability-oriented artificial intelligence techniques primarily by reducing the environmental impact of wildfires and optimizing resource use in their management. The platform's architecture, built on Kafka and Elasticsearch with specialized gateways, ensures scalability, robustness, and the ability to handle diverse, real-time data flows.

The application of a reaction-diffusion mathematical model, fed by environmental data, topography, and fuel characteristics derived from techniques like drone imaging and remote sensing, provides crucial predictive capabilities regarding fire propagation. The interdisciplinary design approach, incorporating HCI and UX principles, is vital for translating complex data and model outputs into usable and intuitive visualizations for primary decision-makers like SOUP operators and fire chiefs. The designed interfaces, featuring geo-visualization, interactive simulation visualization with isochrones, and standardized symbology, aim to enhance situational awareness and support effective decision-making in critical, high-pressure environments.

AI plays a central role in PRIMA, enabling advanced data processing, early fire detection, forecasting of risk areas, and supporting post-fire analysis. The use of LLM and real-time avatars for consulting the outputs provide a greater usability of the user interface.

The PRIMA platform represents a significant advancement in wildfire management technology, demonstrating how the integration of diverse data sources, advanced modeling, and AI can improve the efficiency and effectiveness of response operations. The project aims for broad transferability and replicability of its results, utilizing modular and flexible design, open standards, and promoting knowledge sharing. Future work may involve scaling the platform to other regions and integrating new data sources and more sophisticated algorithms as technology evolves. Ultimately, solutions like PRIMA contribute significantly to reducing the environmental and social impact of wildfires, protecting communities, and optimizing resource utilization in confronting these challenging natural disasters.

Declaration on Generative AI

The authors utilized ChatGPT and Grammarly to enhance language clarity and readability. The authors, who take full responsibility for the final version of the manuscript, carefully reviewed and refined all content generated by these tools.

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