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Detection and Characterization of Plume-Dominated Wildfires

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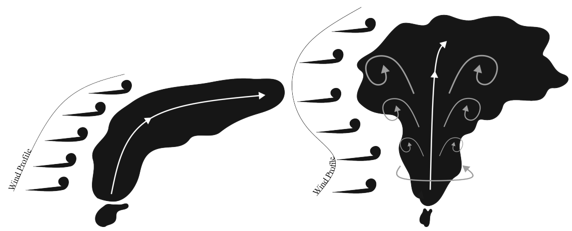
Abstract. Extreme wildfires are increasingly hazardous, particularly plume-dominated fires, which exhibit unpredictable behavior due to their self-sustaining convective columns. Despite their significance, these fires remain poorly understood, hindered by limited observational data and fragmented remote sensing approaches. This paper proposes an Artificial Intelligence-based method adaptive framework for real-time detection and characterization of plume-dominated wildfires using satellite and aerial imagery. The framework focuses on three critical aspects: fire intensity, vertical plume development, and rotational motion. Leveraging satellite data, alongside aerial datasets, the methodology dynamically adapts to available data to ensure accurate assessments. The final output is a risk-graded map identifying zones of active or potential plume-dominated activity, and a deeper characterization of the plume internal mechanisms. The proposed framework has significant potential for improving wildfire prediction, management, and mitigation strategies, contributing to improved safety and resource allocation in wildfire-prone regions.

Keywords: Fires · Risk assessment · Remote sensing · Multispectral imagery · Geoscience

1 Introduction

Extreme wildfires are increasingly intensified by climate [1] and land-use trends [48,6]. Understanding their mechanisms is crucial for effective mitigation. Wildfires are influenced by topography, fuel, and weather—the wildfire triangle [9]. Weather, particularly wind, significantly impacts fire spread, intensity, and longevity [54,17]. Rothermel [55]identifies two distinct mechanisms through which wind influences wildfire behavior: wind-driven and plume-dominated fires. A transverse view of these two fire types is illustrated in Figure 1.



(a) (b)

Fig. 1. Transverse representation (a) wind-driven and (b) plume-dominated wildfires. Adapted from [55].

In wind-driven fires, strong ambient winds push the fire front forward, driving rapid and directional spread. These fires typically exhibit predictable behavior, with the rate of spread largely determined through wind speed, fuel type, and topography.

Plume-dominated fires, on the other hand, generate self-sustaining convective columns, creating localized wind systems that override external winds. These fires, often extreme, exhibit unpredictable behavior, including fire whirls and rapid growth. Collapse of the convective column can cause erratic, multidirectional fire spread via embers.

Despite being the most hazardous, plume-dominated fires are also the least understood, to the extent that reliably and accurately predicting them remains unfeasible. Although it is widely accepted that the associated self-sustaining wind events exist and heavily influence fire behavior, the finer details regarding how and when this process initiates and is maintained remain poorly understood, hindering validation efforts for novel modeling, simulation, and prediction solutions. Furthermore, remote sensing solutions specifically for plume-dominated fire assessment are limited, often focusing on singular aspects of these fires [5].

This proposal aims to: (1) identify components of plume-dominated fires using satellite/aerial imagery; (2) assess and delineate zones of active/potential plume-dominated dynamics; and (3) achieve (2) in real or near-real time. The paper is structured as follows. Section 2 elaborates on the significance of this research within the broader landscape of innovation in AI-powered Cyber-Physical Systems. Section 3 reviews literature on real/near-real-time identification of plume-dominated wildfires. Section 4 outlines the proposed methodology. Section 5 analyzes risks and contingency strategies during the framework's development. Finally, Section 6 discusses the potential contributions and implications of the proposed framework.

2 This Research Within the Context of Technological Innovation for AI-Powered Cyber-Physical Systems

This research leverages advanced remote sensing, computational methods, and Artificial Intelligence (AI) to develop a cyber-physical system for real-time wildfire monitoring and analysis. Integrating satellite and aerial imagery with AI-driven data processing, the framework bridges physical environmental phenomena and digital intelligence, improving decision-making and response strategies. An innovation is the use of AI to dynamically adapt methodologies based on data characteristics, addressing the variability and unpredictability of wildfires.

3 Literature Review

The earliest works recognized that large wildfires could create intense vertical air currents, or plumes, due to the heat generated through combustion [22], which could transport heat and particulates high into the atmosphere [23]. It was also understood that under hot and dry conditions, the massive release of smoke into the atmosphere could give rise to pyroconvective clouds [18]—heat-driven clouds formed above intense heat sources—which have the potential to form fire-induced thunderstorms [34,49].

Subsequent studies revealed that, upon reaching a critical intensity, these fires could exert significant influence over their local wind systems [16]. The intense convection generated has the capacity to disrupt and modify local wind patterns, which, in turn, can accelerate the spread of fires [13]. This feedback mechanism became a foundation for the development of fire behavior modeling in simulations under plume-dominated conditions [8,32]. Nevertheless, despite these advances, predicting whether or when a fire becomes plume-dominated remains challenging, limiting the accuracy of real-world fire simulations [33].

Lareau et al. [33] highlight three fundamental characteristics of plume-dominated wildfires: high fire intensity, vertical plume development—i.e., the emergence of fire-induced updrafts and associated fire clouds—and rotational motion of the plume, discussed in the following subsections.

3.1 Fire Intensity

Wildfires are sustained through a process of combustion, where fuel reacts with oxygen in the atmosphere, releasing energy in the form of heat and light. The rate at which energy is released—fire intensity [22,30]—directly affects heat output and is closely related with the type and amount of fuel spent [38]. Consequently, the rate of spread [11] and the quantity and type of fuel burning [4,25] can serve as indirect estimators of fire intensity.

Thermal Infrared Remote Sensing (TIR) imaging is the most widely accessible method for measuring fire intensity, with satellite-based sensors—such as the Moderate Resolution Imaging Spectroradiometer (MODIS) [44] and the Visible Infrared Imaging Radiometer Suite (VIIRS) [45]—being the most employed tools in the literature for this purpose [42,36,2]. Airborne platforms equipped with thermal sensors can also be used effectively to achieve accurate results [63,57]. Fire Radiative Power (FRP) [29], which quantifies the rate of radiative energy released by a fire, is the primary metric derived from TIR imagery to estimate fire intensity and is mathematically expressed through the Stefan-Boltzmann law:

$$FRP = \sigma \cdot \epsilon \cdot A \cdot T^4 \tag{1}$$

where σ represents the Stefan-Boltzmann constant ($5.67 \times 10^{-8}\, W \cdot m^{-2} \cdot K^{-4}$), ϵ denotes the emissivity of the fire (typically between 0.85 to 1.0), A corresponds to the fire-affected area in square meters, and T is the absolute temperature of the fire in Kelvin.

3.2 Vertical Plume Development

Remote sensing solutions for studying the vertical development of wildfire plumes primarily focus on two areas: measuring *plume injection height* and detecting *fire clouds*. There are far fewer methods available for analyzing *fire-induced updraft* dynamics, and the existing approaches are mostly observational in nature. The limited research on detecting *fire-induced updrafts* relies on technologies such as infrared [14], radar [53], and Light Detection and Ranging (LiDAR) [7]. Although studies in this area are scarce, there is general agreement that these updrafts are extremely powerful and develop quickly as wildfires grow in intensity.

Accurate estimations of *plume injection height* have been achieved using active remote sensing technologies [31], such as radar [24] and LiDAR [62], which provide high-resolution vertical profiles of plume height. Satellite-based methods have also proven highly effective, particularly through satellite multispectral stereoscopic imaging. This technique uses the parallax effect—the apparent shift in the position of an object when viewed from different angles—between two or more sensor views of the same plume to estimate height. Studies employing this approach have demonstrated its ability to deliver spatially extensive plume height data [28,59]. Additionally, TIR imagery, such as that from the MODIS satellite, can be used for this purpose [37].

Satellite-based observations, such as those from MODIS and Geostationary Operational Environmental Satellite (GOES) [46], have been widely used to detect and analyze *fire clouds*. Studies have utilized multispectral and TIR imagery to characterize their development [20,50] and distinguish them from other cloud types based on their unique spectral signatures [51,12]. Additionally, radar and LiDAR-based techniques have proven effective in capturing the vertical structure and dynamics of fire clouds [39,35,62]. Advances in machine learning and automated algorithms have further improved the ability to classify these phenomena [52].

3.3 Rotational Motion

The literature suggests various relatively limited methods for studying the motion of wildfire plumes. However, most of these methods focus on general turbulence detection and localized flow mapping [10,60], failing to assess whole-plume rotation.

Several authors demonstrated the use of LiDAR to study vorticity (local rotation) and turbulence in wildfire plumes, providing high-resolution air velocity data [32,10]. LiDAR is advantageous for its ability to operate up to several kilometers, but it requires clear atmospheric conditions and can be limited by signal attenuation. Radar-based techniques have also been used to measure rotational motion in fire plumes [64], offering the benefit of operating in adverse weather conditions, though with a potentially lower spatial resolution.

Infrared thermography has been employed to infer flow patterns and rotational motion in fire plumes. In [60], the authors used infrared thermography to study plume dynamics, including the development of vortical structures. This method is non-intrusive and provides simultaneous temperature and flow data, but it is limited by its indirect measurement of velocity and the need for calibration.

Satellite-based remote sensing offers a wide perspective for studying large-scale fire plumes. Techniques such as multispectral and hyperspectral imaging can detect rotational motion by analyzing plume morphology and temperature gradients [43]. However, while satellite remote sensing provides global coverage, its spatial and temporal resolution may be insufficient for detailed studies of rotational motion if care is not taken when choosing the instrument and its specifications.

4 Methodology

This proposal aims to assess plume-dominated wildfire behaviors using satellite imagery and aerial imagery. It builds on the framework of Laureau et al. [33], which identifies three prime characteristics of plume-dominated wildfires: high fire intensity, vertical plume development and rotational motion of the plume. Figure 2 summarizes the proposal's architecture, including the planned data sources, supported methodologies, data fusion steps, and mapping of results.

4.1 Data Collection and Preprocessing

A selection of data sources was curated, covering both real-world and simulated datasets. The objective of using real-world data is to analyze actual patterns and behaviors in real environments, ensuring authenticity and relevance for decision-making. It reflects real-world complexities, though it may be noisy, biased, or incomplete due to limitations in data collection and privacy concerns. In contrast, simulated data is used to test hypotheses, model behavior under controlled conditions, and explore scenarios where real-world data is unavailable or difficult to obtain.

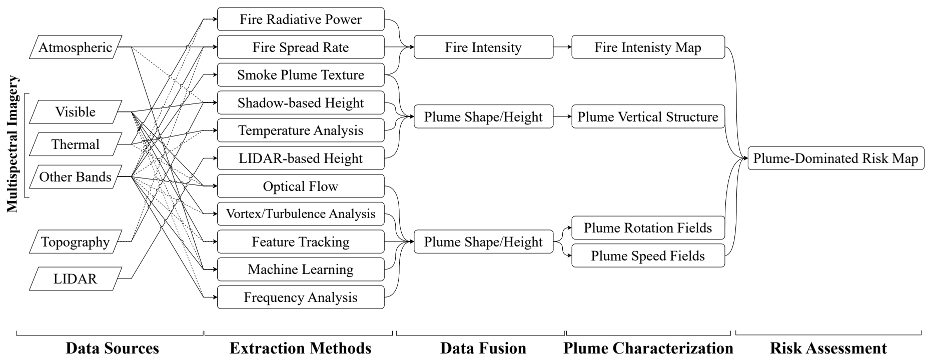


Fig. 2. High-level architecture of the proposed methodology. In the *Data Sources*' section, solid lines indicate primary sources, while dashed lines represent secondary (optional) sources. *Other Bands* include Near Infra-Red, Infra-Red and Red Edge.

Real-world data sources are categorized into satellite and aerial imagery. To enhance feature tracking, priority is given to satellite imagery with the highest available temporal resolution. Specifically, data from the GOES and Himawari-9 [26] will be utilized, offering temporal resolutions of 5 and 10 minutes, respectively. If necessary—should the data be of poor quality or insufficient for accurate feature tracking—supplementary imagery may be acquired from the VIIRS [45], Sentinel-3 [19], and the MODIS, albeit with lower temporal resolutions. In addition to satellite data, precompiled aerial datasets will be incorporated, including the FLAME dataset [56], the WIT-UAS dataset [27], and the UAVs-FFDB dataset [41]. Furthermore, the authors are developing their own dataset that will include multispectral imagery with fire and smoke masks, as illustrated in Figure 3.

(a) (b)

Fig. 3. Typical fire image sample in dataset under development: a) RGB image; and, b) the accompanying fire/smoke mask. In the mask, the background is represented in black, fire in white, and smoke in grey.

Simulated datasets are also considered, as their structured nature allows for controlled experimental conditions. Relevant sources include WildfireDB [58] and

PyroVision [15]. Additionally, the Fire Dynamics Simulator (FDS) [40] will be employed to generate high-precision datasets for analysis.

To ensure accuracy and consistency, all imagery will undergo several preprocessing steps. First, radiometric and atmospheric corrections will be applied to mitigate atmospheric interference. Next, cloud masking will be performed to remove pixels obscured by clouds, ensuring clear visibility of fire plumes. Finally, all data layers, including imagery, weather data, and topography, will be georeferenced to a common coordinate system to facilitate spatial alignment and analysis. All image processing tasks will be implemented using Python, using libraries such as Raster Forge [47], Rasterio [21], PyProj [3] for data handling and transformation.

4.2 Plume Detection and Characterization

As discussed in Section 3, the proposed methodology builds on the observations of Laureau et al. [33]. The primary philosophy underpinning the design of this architecture is to maximize adaptability. Specifically, the system is designed to dynamically adjust its methodologies based on the available data for a given region of interest using AI, with the goal of extracting the most accurate assessment possible. This approach inherently involves a data fusion step, where results from multiple methods are integrated to provide a unified evaluation of the same characteristic. This process not only enhances the robustness of the output but also offers a unique opportunity to evaluate the performance of individual methods within the context of specific regions of interest.

Given a dataset, the system will employ a AI-driven approach—e.g., random forests or gradient boosting machines—to identify and apply the most appropriate methodologies based on the inherent characteristics of the data (type, resolution, format, etc), which aims to optimize efficiency and usability. Following the application of these techniques, the results are integrated, after which a preliminary statistical evaluation of results is conducted. Spatial representations of the three main attributes are subsequently derived, enabling a detailed assessment of plume-dominated activity. This analysis facilitates the identification of areas with the highest likelihood of exhibiting or developing extreme fire behavior dynamics. The final output is presented as a risk-graded map, which spatially delineates zones according to their probability of plume-dominated wildfire activity.

4.3 Validation

To ensure the robustness of the results, this study will employ multiple validation techniques. The limited observational data available on plume-dominated wildfire events will serve as a foundational basis for validation. Additionally, specific isolated characteristics of the phenomena will be validated using established tools and datasets. For instance, plume height estimates will be cross-validated using data from the Cloud-Aerosol LiDAR and Infrared Pathfinder Satellite Observations (CALIPSO) [61] instrument, which provides independent measurements of aerosol vertical distribution. This multi-faceted validation approach ensures the reliability of the findings and enhances the credibility of the analytical outcomes.

5 Contingencies

In any research study, anticipating challenges and developing mitigation strategies is crucial. One primary risk is the unavailability or poor quality of satellite and aerial imagery, which could hinder the analysis of plume-dominated wildfire behaviors. This risk, with a moderate to high probability depending on the region, will be mitigated by relying on multiple data sources for redundancy.

Another potential risk is computational limitations, as processing high-resolution imagery and large datasets may overwhelm available resources, leading to delays. This risk has a moderate probability of occurring and can be mitigated by processing only a subset of the data while ensuring the viability of the proposed framework is maintained. Furthermore, in the event of local computational failure, cloud computing can serve as a viable solution to safeguard processing capabilities.

Methodological limitations, with a low to moderate probability, may arise if plume detection and characterization methods perform inconsistently across regions or datasets. To address this, the methodology will undergo rigorous testing and validation in diverse environments to ensure its generalizability. In cases of under-performance, alternative or complementary techniques will be explored to enhance the robustness and accuracy of the extraction methodology. Additionally, the framework will be designed for seamless integration of alternative data sources and methods, which will not only help mitigate this risk but also improve the general usability of the framework.

Finally, unforeseen external factors like changes in satellite missions or geopolitical issues, though with low but increasing probability, could disrupt data access. To address this, the study will maintain flexible data sourcing and periodically update contingency plans to adapt to changing circumstances.

6 Conclusions

This research proposal aims to make several significant contributions to the field of wildfire research and remote sensing through a novel methodology for assessing plume-dominated wildfire behaviors.

The study will introduce a framework for analyzing plume-dominated wildfires, focusing on three critical aspects: thermal assessment, vertical development, and rotation of the plume. In addressing these dimensions simultaneously, the proposed methodology aims to provide a more comprehensive assessment of plume dynamics than previous studies, which often focus on isolated aspects.

The four primary potential contributions of this study are as follows. First, it advances the understanding of plume-dominated wildfires, addressing the current gap in knowledge by providing a structured, data-driven approach to analyze their complex dynamics. Second, the adaptive nature of the framework ensures its applicability across diverse regions and datasets, making it a versatile tool for global wildfire monitoring. Third, the risk-graded maps generated by the framework offer actionable insights for emergency responders and land managers, facilitating more effective resource allocation and mitigation strategies. Finally, the study's emphasis on real-time or near-real-time assessment addresses a critical gap in current wildfire monitoring capabilities, paving the way for improved early warning systems and predictive modeling.

By bridging the gap between remote sensing technology and plume-dominated fire understanding, this study has the potential to significantly boost our ability to monitor, predict, and manage plume-dominated wildfires, contributing to reduced risks and improved safety in wildfire-prone regions.

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