european Network on Extreme fiRe behaviOr

COST Action CA22164

Navigating the fire environment to ignite preparedness and readiness for extreme wildfires

CASE STUDY MANUAL (D2.1)

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1. Introduction

1.1. Why conduct a wildfire case study?

Wildfire case studies are indispensable to advancing fire science and informing fire management. By describing the evolution of a wildfire event, case studies play a crucial role in enhancing our understanding of fire spread and behavior, while also shedding light on phenomena that remain poorly understood. For instance, a high-quality case study may pave the way to increasing the availability of wildfire measurements or enhancing the predictive capabilities. More importantly, a well-conducted case study **fosters the uptake** of knowledge by practitioners and policymakers through effective science communication.

1.2. Purpose, Objective, and Scope

This document comprises Deliverable D2.1 ("Case Study Manual") of the COST Action NERO, CA22164. The overarching objective of the NERO Case Study Manual (CSM) is to **lay the groundwork for the systematic analysis of past wildfire events**, using established methods and tools while encouraging the integration of new techniques. The manual introduces guiding principles that should be considered in the design and implementation of high-quality wildfire case studies while recognizing that some flexibility is needed to accommodate the unique characteristics of each event.

1.3. Target Audience

Wildfire **researchers**, fire behavior **analysts**, and **modelers** who wish to conduct scientifically rigorous case studies of historical wildfires shall use the NERO CSM. **Young researchers and innovators**, in particular, will find the information presented in this manual highly valuable for developing the craft of their wildfire research. Individuals involved in **operational fire management**, **decision-makers**, and **trainers** who seek to improve preparedness and response for extreme wildfire events will also benefit from this manual.

2. Designing a wildfire case study

In the previous Section, we touched on the significance of high-quality wildfire case studies. But how might one approach designing such a study?

2.1. Well-defined Purpose

Before diving into data collection and method review, take a moment to ask yourself: "**What drives me to study this wildfire event?**". A catastrophic fire event or an interesting fire behavior observation can often motivate a wildfire case study. Alternatively, the case study may exemplify a fire behavior phenomenon that has long challenged researchers and practitioners but has yet to be thoroughly documented or adequately addressed. Regardless of the reason, a wildfire case study–particularly one conducted within the context of NERO–shall aim to **uncover, describe, and characterize the physical processes driving wildland fire behavior**, whether they relate to fuels, topography, weather, or a combination of all three. However, this is too broad a research topic for a single case study. The most common mistake at this stage is to rush into a data dump. Instead, concentrate on refining the research topic of NERO by framing a more **specific and compelling question**. Your question should highlight specific aspects of wildland fire behavior that remain unclear and aim to uncover insights through the case study. **Defining a good question is essential for a wildfire case study that goes beyond fact-grubbing**. For instance, your indirect question may look like this:

"I am investigating the drivers behind the rapid spread of the X wildfire during a specific period of the event because I want to find out, for instance, how live fuel moisture content may have contributed to the large fire rate of spread."

By including the because-I-want-to-find-out clause, you clarify the purpose of your case study and frame it in a way that goes beyond simply collecting and reporting data, a common pitfall in some research. As soon as you can, add another indirect question–a broader, more general one that **explains the purpose behind your first question**. Introduce this second implied question with "*in order to help the reader understand how/why/whether*". Building on the previous example:

*"I am working on the X wildfire event **because** I want to find out how the live fuel moisture content contributed to the large fire rate of spread, **in order to** help the reader understand how live fuel moisture measurements can be used for anticipating extreme fire behavior."*

The final step may be challenging, but it helps you assess whether your question is not only intriguing to you but also potentially significant to others. **This evaluation is particularly important for NERO, which aims to translate scientific knowledge into actionable practices in the field of wildfire operations**.

In summary, **to accurately define the purpose of a wildfire case study, you need to explain**:

- What you do not know – your question: “*because I want to find out…*”
- Why you want the readers to know about it – your rationale: “*in order to help the reader understand…*”

2.2. What to Avoid

At all costs, **avoid conducting a wildfire case study that merely describes what happened**. Simple documentation of a fire event often leaves the reader without a clear take-away message. What should the reader learn from this event? How can they apply the lessons learned? Instead of providing an event briefing, aim for a fire event discussion – an in-depth, engaging investigation of specific aspects of the event that critically and scientifically addresses questions aimed at achieving a deeper understanding of wildland fire behavior. Also, it is important to remind that the scope of the guiding questions highlighted herein is to stimulate the learning process for both practitioners and researchers to go in depth as much as possible in the fire behavior understanding. In this context, it’s important for both practitioners and researchers to **use both data/models and field observations**, working together to understand, explain, and validate the case study for the chosen fire. This can help to bridge researchers and practitioners, asking the correct questions while writing a case study and then stimulating cross-collaborations and exchange of data and expertise.

3. Implementing a Wildfire Case Study

In the previous Section, we discussed how to refine the research topic of wildland fire behavior into a question that not only captivates your interest but also has practical implications for others. By doing so, you articulate a well-defined purpose for the wildfire case study you intend to conduct. As soon as you come so far, it is time to start planning how you will implement the case study. This Section offers some guidance for the datasets and analysis techniques you should consider in planning and conducting your study. The guidance provided is neither exhaustive nor definitive.

3.1. Datasets

In this Section we provide a list of variables/parameters and available datasets that could be used withing the frame of a case study focusing on Europe.

Variable/Parameter	**Available Dataset(s) and Link(s)**
Elevation	EU-DEM (30m) Copernicus GLO-90 DEM (90m) Copernicus GLO-30 DEM (30m)
Aspect	EU-DEM Aspect (30m)
Slope	EU-DEM Slope (30m)
Land Cover	CORINE Land Cover (100m) MODIS Land Cover Type (500m)
Fuel maps, models, and canopy variables	FirEUrisk European Fuel Map (1km) EFFIS Fuel Map (100m) Pan-European Fuel Map Server (100m) Fire-Res App
Live Fuel Moisture Content (LFMC)	Globe-LFMC 2.0 (800+ sampling sites)
Historical Canadian Forest Fire Weather Index System (CFFWIS)	Fire Danger Indices (Copernicus, 0.25° x 0.25°, Daily)
Historical fire perimeters, spread and behavior	EFFIS (20m–250m) FIREDpy (500m, Daily) ESA FireCCI (20m–250m, Daily-Monthly) GWIS/GlobFire (500m, Daily) GlobFire Portuguese Large Wildfire Spread DB (PT-FireSprd)

	Global Fire Atlas (500m, Monthly-Annual)
Surface atmospheric variables (e.g., temperature, humidity, wind)	ERA5 (0.25° x 0.25°, Hourly) ERA5-Land (0.1° x 0.1°, Hourly) CERRA (5.5 km, 3-Hourly) CERRA-Land (5.5 km, Daily)
Upper-tropospheric variables	ERA5 (0.25° x 0.25°, Hourly) CERRA (5.5 km, 3-Hourly)
Soil moisture	ERA5 (0.25° x 0.25°, Hourly) ERA5-Land (0.1° x 0.1°, Hourly) CERRA-Land (5.5 km, Daily) Copernicus Land Monitoring (1km, Daily) ESA Climate Change Initiative (0.25° x 0.25°, Daily-Monthly) EDO (5 km, 10-Day)
Snow cover	Copernicus Land Monitoring (20m–1km, Daily) MODIS Snow Cover (500m–4km, Daily-Monthly)
Drought conditions and Standardized Precipitation Index (SPI)	EDO (5 km, 10-Day)

3.2. Analysis Techniques

The choice of analysis techniques for fire behavior studies depends on the defined objectives of the case study as well as the data availability to implement those. The **analysis techniques** fall into **two broad categories**, which are the **data-driven modeling** and **numerical modeling**. Both categories have their advantages and disadvantages that we briefly discuss in the following Sections.

3.2.1 Data-Driven Modeling

Data-driven models are built entirely on data using machine learning and statistical algorithms [1]. The process involves analyzing historical data, examining the relationships between key variables, evaluating potential models, and selecting an algorithm to build the final model. These models serve classification, regression, or predictive tasks to support or automate decision-making in wildfire management, including tasks such as fire spread prediction, risk assessment, and resource allocation. Their success depends on the availability, quality, and spatial-temporal resolution of both environmental and fire dynamics data. Rather than relying on physical laws, these models employ various statistical and machine learning techniques—such as Logistic Regression (LR), Generalized Additive Models (GAMs), Genetic Algorithms (GAs), Self-Organizing Maps (SOMs), decision trees, neural networks, and deep learning methods (like Convolutional Neural Networks, CNNs, and Recurrent Neural Networks, RNNs)—to find relationships between variables. The models learn by identifying patterns, correlations, and key features that influence outcomes. Since data quality directly impacts model performance, only high-quality data can produce reliable results, a principle that holds true across most modeling approaches. These data-focused approaches are part of machine learning, a powerful tool for pattern recognition [2].

Data-driven models in wildfire management analyze weather, fuel characteristics, topography, and historical fire patterns to predict fire behavior descriptors (e.g. rate of spread, intensity). These models can identify complex, nonlinear relationships in wildfire data that traditional physical models might overlook. This capability makes them valuable for both improving our understanding and guiding tactical decision-making. For example, deep learning models are especially effective at recognizing spatial and temporal patterns in wildfire behavior, often outperforming traditional prediction methods.

For example, LR has been widely used in wildfire studies—from fire danger assessments (e.g., [3, 4]) and ignition probabilities (e.g., [5]) to risk estimation (e.g., [6]). ANNs and CNNs have proven effective in predicting fire behavior, including flame height, angle, and rate of spread [7-9]. GAs have enabled fire spread simulation in both real and idealized scenarios, offering a dynamic data-driven framework that reduces uncertainties and computation time [10, 11]. These algorithms have also shown value in optimizing fuel models using experimental field data [12]. Additionally, researchers have combined Geographic Information Systems (GIS) with machine and deep learning techniques to study fire spread dynamics using satellite, weather and vegetation data (e.g., [13-15]). For a comprehensive review of machine learning applications in wildfire science, readers are referred to [16] and [17].

Data-driven modelling offers two key advantages: they typically run faster than physics-based models and can integrate large, diverse datasets. However, these models face significant challenges. They often lack interpretability, making it difficult to understand which variables drive their predictions. In addition, they require extensive historical data for training, calibration, and validation [18], and tend to perform poorly when encountering data outside their training dataset.

3.2.2 Numerical Modeling

Numerical models include physics-based, empirical, and semi-empirical models that simulate wildfire perimeter growth and behavior. These models have served as invaluable tools for managing wildfires for decades. Since their development in the early 1970s, numerical models have helped experts understand past fires, predict spread patterns, and assess environmental influences on fire behavior. Today's models range from advanced 3D computational fluid dynamics models like FIRETEC [19] and WFDS (Wildland-Urban Interface Fire Dynamics Simulator) [20] to empirical models such as FARSITE [21] and BehavePlus [22]. Each type has distinct strengths and limitations regarding computational demands, data requirements, accuracy, robustness, and transferability [23].

Purely physical models offer high theoretical precision by simulating combustion processes and fire dynamics at fine spatial resolutions. However, their intensive computational demands make them impractical for large-scale studies and operational use, limiting them to small areas or coarser landscape representations. Even with sufficient computing power, these models require extremely high-resolution input data (e.g., fuel type and condition, topography) that is rarely available. Additionally, their practical application is often constrained by the complexity of real-world fire-atmosphere interactions.

On the opposite end, empirical and semi-empirical models are computationally efficient and can produce accurate spread predictions—even in scenarios beyond their initial training datasets [24-26]. Between these extremes lie coupled fire-atmosphere models, which balance capability and practicability by integrating numerical weather prediction (NWP) models with 2D fire spread models. This approach enables realistic physical process representation while remaining suitable for real-time use. Coupled models, such as WRF-Fire/SFIRE [27-32], Meso-NH/ForeFire [33, 34] and ACCESS-Fire [35], can simulate fire spread [27-37], smoke dispersion [38, 39], and dynamic phenomena like convective plumes, fire-induced winds, pyroconvection, and horizontal roll vortices [40-44].

The most commonly used models in the community are empirical models driven by external meteorological data [45-48], despite their limitations and uncertainties [25]. For instance, external meteorological models typically provide wind data at resolutions too coarse to capture local topographic effects. While diagnostic models based on mass conservation can generate finer wind data [49-50], they cannot enhance the temporal resolution of the primary meteorological data, which typically updates hourly. More importantly, external meteorological forcing does not account for two-way interactions between fire and atmosphere, missing the dynamic "fire-weather" feedback where fires create their own localized atmospheric conditions. Regardless of the chosen modeling approach, users must recognize the importance of model calibration and validation using fire environment observations to achieve reliable results.

4. Best Practices

Coming soon! The NERO CSM is a dynamic, evolving document, and this Section will soon be updated to offer a set of best practices for conducting wildfire case studies.

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