Actionable Fire Modeling in Firemap for Extended Attack Decision Support

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Abstract. The increasing frequency and severity of wildfires in the Western United States demand improved fire response tools. Initial Attack Fire Response within the first few hours of ignition is critical in preventing fires from escalating. WIFIRE Firemap has been instrumental in supporting early fire suppression efforts through real-time fire behavior modeling. However, wildfires often burn for days or weeks, necessitating longer-term predictive capabilities. To address this challenge, we extended Firemap to forecast fire spread from the first few hours to five days. This advancement integrates two long-term fire behavior models, ELMFIRE and GridFire, enabling real-time, data-driven decision support. The enhanced Firemap platform improves strategic wildfire response planning, allowing firefighters and emergency managers to anticipate fire spread on extended timelines. We present how these extensions were used during the Los Angeles firestorms of 2025, demonstrating their potential to mitigate wildfire risks, protect communities, and improve firefighting strategies, and make recommendations for effective use of extended attack tools for decision support.

Keywords: Wildfire Modeling · Decision Support · Workflows

1 Introduction and Motivation

The western United States, along with many other parts of the world, is facing a worsening wildfire crisis. Prolonged droughts and extreme weather conditions mean that even a small spark can lead to massive, fast-moving, or prolonged fires. The 2025 Los Angeles fires were a harsh recent example, overwhelming response teams and causing widespread damage. Although early detection tools for new fire ignitions and science-backed platforms for initial attack response were essential for fire management, these incidents demonstrated that more is

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needed to reduce risk, improve response times, and protect communities and ecosystems.

Initial Attack Fire Response refers to the actions taken by firefighters within the first few hours (3-5 hours) after the start of a fire, i.e., ignition time. The goal is to suppress or control the fire before it grows and becomes more difficult to manage. Firemap [9,5], an operational tool developed by WIFIRE [8,7], provides real-time information on the speed and direction of fire spread, affected structures, and population. Firemap uses the FARSITE fire model [14,15], which takes into account various factors such as weather conditions, fuel type, and topography to predict fire behavior. Adoption of Firemap by the fire response community has enabled better decision making for initial attack. However, as wildfires grow, response efforts take place over days, weeks, and even months, with growing risk to communities, ecosystems, and firefighters. A new approach to extended attack decision support using fire models is needed. To bridge this gap, we extended the Firemap platform to forecast fire behavior up to five days.

1.1 Actionable Fire Modeling for Extended Operations

Extended attack operations occur when a wildfire is not contained within the initial response window and requires ongoing management over days or weeks. Fire modeling for extended attack plays a crucial role in strategic decision-making by predicting fire behavior beyond the first operational period. Unlike short-term models which focus on immediate fire spread, long-term fire models such as ELMFIRE and GridFire integrate dynamic environmental data (e.g., weather patterns, fuel conditions, and topography) to simulate fire growth over multiple days. We collaborated with Spatial Informatics Group (SIG) and the Pyregence Consortium [2] to integrate two long-term fire behavior models into Firemap: ELMFIRE [11,4] and GridFire [1]. By incorporating real-time data and evolving fire conditions, extended attack fire modeling enhances situational awareness, allowing response teams to anticipate challenges and implement proactive measures to mitigate risk, protect communities, and optimize firefighting efforts.

Contributions. This paper outlines three key contributions:

1. Extentions to Firemap's Fire Simulator Workflow to support federated execution of long-duration fire models. This enhancement leverages containerized microservices, allowing seamless integration of current and future fire models. We incorporated ELMFIRE and GridFire to predict fire spread direction and speed on extended timelines, aligning with response planning.
2. Experiments with operational decision support workflows for effective actionable use of extended attack models. We deployed and tested the use of the extensions during the January 2025 Los Angeles firestorms, assessing model accuracy, usability, and effectiveness in real-time conditions. Insights from this testing informed further improvements in performance and scalability.
3. Lessons learned and recommendations for how fire modeling could be made applicable within extended attack fire response, after working with the fire management in experimental settings.

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1.2 Related Work

ELMFIRE (Eulerian Level set Model of FIRE spread) [11,4] is an advanced computational tool designed to simulate wildland fire behavior. ELMFIRE employs Eulerian level set methods to model the spread of fires across landscapes. It integrates various fire spread models, including the Rothermel surface fire spread model [13] and the Cruz crown fire model [10], to provide accurate predictions of fire behavior under different conditions.

GridFire [1] is a raster-based fire behavior model designed to simulate the spread of wildland fires across landscapes. The model can be used for individual fire simulations or Monte Carlo simulations over space and time, providing valuable insights into fire behavior under different conditions.

FSPro [12] calculates the spatial probability of fire spread, accounting for weather uncertainties. This tool is used to assess a fire's growth potential from an active fire perimeter and to prioritize firefighting resources.

2 Extensions to the Firemap Architecture and Data Workflows for Extended Attack Fire Modeling

Firemap [9,5] allows users to analyze and predict fire spread through fire behavior modeling, forecasting, and scenario analysis. Users can visualize and share the progression of the fire over time for better situational awareness and decision making. To support real-time fire modeling and visualization, Firemap is built on a scalable and modular architecture that integrates multiple data sources, computational fire modeling workflows, and user inputs. Figure 1 depicts parts of the system architecture for processing environmental data, running fire behavior simulations, and delivering interactive visualizations to users.

2.1 Input Layer for Data and Fire Modeling Service Access

The input layer serves as the foundation for Firemap's modeling and visualization capabilities by integrating multiple data sources and user-defined parameters.

- **WIFIRE Commons:** WIFIRE Commons [6] supports scientific and operational wildfire applications by organizing and sharing data and models. It provides access to curated datasets and models used in fire simulation, prediction, and response. It serves as the source of multiple data sources and models that Firemap ingests, such as real-time data, historical datasets, and external APIs, providing inputs for data-driven fire simulations.
- **User Input Interface:** Firemap's run configuration window enables users to define simulation parameters, configure environmental conditions, and fire model to customize runs.

2.2 Fire Simulator Workflow

Figure 2 illustrates the Fire Simulator Workflow for executing fire models on the Nautilus (NRP) Kubernetes cluster [3]. When a user initiates a model run by selecting "Run," a sequence of backend processes are executed as a part of

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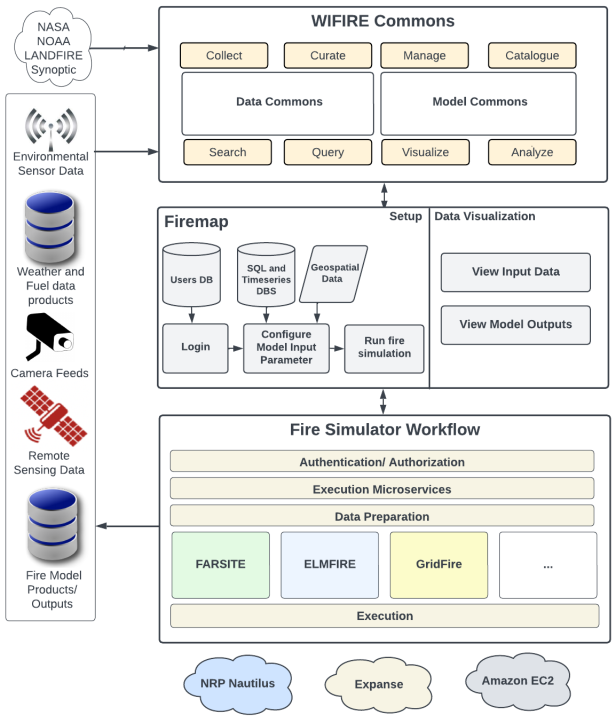

Fig. 1: Firemap's Architecture and Workflows integrate a suite of open-source fire modeling tools with multimodal input data and user-provided parameters.

the workflow. Specifically shown in Figure 2 is for execution of ELMFIRE is a workflow in which Firemap sends a request to the Execution Microservice with user-defined model parameters, which then forwards the request to the ELMFIRE REST API running on NRP for fire simulation execution. The ELMFIRE REST API processes the request, gets input data, runs the fire model, and stores the generated simulation results (raster files) in NRP Object Storage. The processed raster data is copied from NRP Object Storage to the Firemap storage. Firemap then retrieves the processed simulation results from storage, allowing users to visualize fire spread predictions.

Containerized Microservices for Extended-Duration Fire Models. Containerization provides a scalable and flexible approach to integrating fire models within Firemap. It ensures consistent execution across different environments by packaging models and their dependencies into isolated containers.

To extend Firemap's capabilities, we incorporated two long-duration fire models, ELMFIRE and GridFire, designed for multi-day fire behavior predictions—critical for wildfire response and planning. Containerized microservices were developed for these models, allowing integration into Firemap. The microservices expose an REST API, enabling model execution on the Nautilus Kubernetes cluster.

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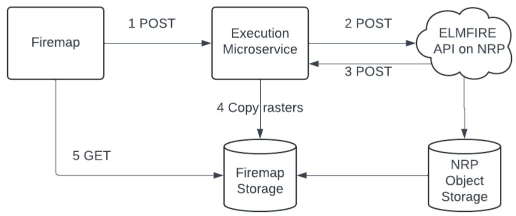

Fig. 2: Fire Simulator Workflow for Executing Fire Models on a Kubernetes Cluster

2.3 Output Visualization Layer

The generated fire simulation outputs (raster images) are stored in NRP Object Storage. Once the simulation is complete, the Firemap Execution Microserver retrieves the model results from NRP Object Storage and transfers them to a centralized storage of Firemap. Firemap retrieves the processed fire simulation results from Storage, displaying the fire spread predictions on its map interface for visualization.

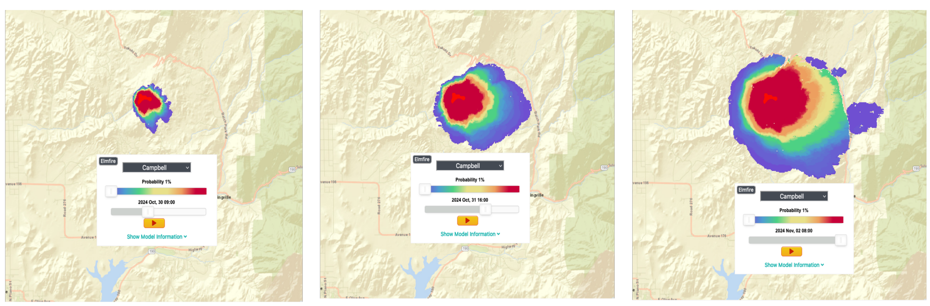

Fig. 3: Extended-Duration Fire Predictive Model Output at Different Time for a given Probability

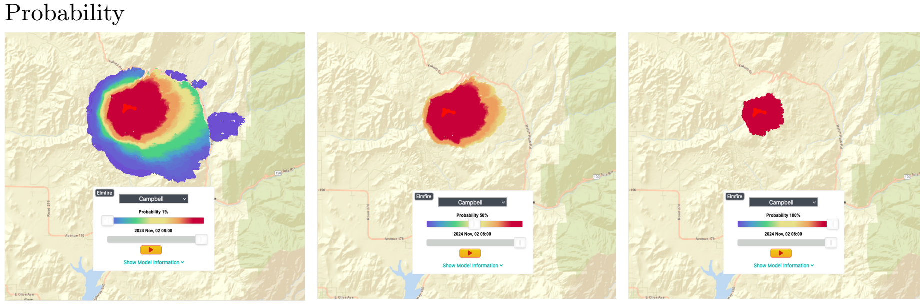

Fig. 4: Extended-Duration Fire Predictive Model Output at 1%, 50% and 100% Burn Probability

The outputs can be viewed using a manual time slider or using play capability to visualize fire growth over time as shown in the Figure 3. Users can also adjust a probability slider as shown in Figure 4 to display fire extents based on the minimum calculated probability, ranging from 1% to 100%. Probabilistic values per pixel are color-coded with a color scale displayed on the probability slider.

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3 Using Modeling and Visualizations for Decision Support for Extended Attack

Extended attack operations require decision support tools that integrate fire modeling and visualization to anticipate fire growth and support response efforts. Probabilistic models like ELMFIRE and GridFire simulate multiple fire spread under varying conditions, providing scenario-based insights (see Figures 3, 4). When integrated into platforms like Firemap, these models enable real-time updates for planning, resource allocation, and risk assessment. Our field deployments with fire management partners have revealed key lessons and opportunities for making these tools more effective in operational settings.

3.1 Results and Impact

Long term fire modeling is useful for gauging resource needs across multiple large fires happening in the state simultaneously. On January 7th, WIFIRE supported the Palisades and Eaton Fires with initial attack models. By the afternoon of January 7th and again January 8th, the long term ELMFIRE models were executed from FIRIS aircraft perimeters, and Cal OES Fire and Rescue shared the probabilistic forecast to the Advanced Planning Unit of OES for strategic decision support. They were provided to have the forecast (Palisades Jan 7 figure) which shows the highest probability outcomes in red and the lowest probability forecast extent in blue running through January 12th. Rates of spread were faster than forecasted and the lowest probability came to fruition by the early hours of January 8th.

The first Eaton Fire probabilistic model was run on January 8 (Eaton Jan 8 Figure) and run through January 13th. Effective suppression prevented the fire from continuing as far northwest as forecasted in the model, however, the rest of the model extent remained representative to the final fire extent.

Cal OES found that the long-term models provided insight to what could happen in ways they did not have access to before. WIFIRE is now customizing the execution of the long-term models to run on near-term 12-24 hour time frames for localized mid-term response and planning on demand.

3.2 Lessons Learned and Recommendations

Fire modeling is not actionable unless it is integrated into existing decision-making chains within existing workflows or through the development of new workflows. Early engagement with fire management partners in the design and development phase results in better usability and user-centric interfaces that align with existing fire management decision-making processes. Clear customizable visualization, documentation, training, and real-world validation through case studies improve user trust and interpretability of of fire models.

When it comes to computational needs for fire model, one size does not fit all. Extended attack modeling requires longer running probabilistic models compared to initial attack. The development of readily available and deployable

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microservices for multiple fire models is useful for rapid deployment of detailed simulations. This approach can also scale to more complex landscapes in which fire modeling requires more computing resources. In addition, establishing robust data pipelines that continuously feed live observations and fire updates into fire models, ensuring that predictions remain updated and responsive to changing conditions, improves model confidence and the trust of the stakeholders in actionable nature of model outputs. Effective visual communication strategies, such as interactive probabilistic fire spread maps, risk zones, critical infrastructure overlaps, and scenario analysis, are needed to better convey uncertainties to decision makers. New operational processes are needed for effective interpretability of visualizations throughout the decision chain. Standardizing data formats and model output visualizations as demonstrated in this paper can improve interpretability of model outputs, ensure ability to use multiple models when possible, ad facilitate interoperability between decision support platforms, emergency management systems, ultimately leading to effective collaboration and fire management decisions.

4 Conclusion

Fire modeling must incorporate multi-source inputs—such as real-time field reports, satellite imagery, and weather data—and align with the decision-making timelines of fire managers to enable actionable strategies throughout all phases of a wildfire incident. Different phases of fire response—initial attack (first few hours), extended attack (hours to days), and prolonged management (weeks or more)—require models that provide relevant forecasts on appropriate timescales. Short-term models, such as FARSITE, focus on immediate fire behavior to guide rapid suppression decisions, while longer-term models like ELMFIRE and GridFire extend predictions to support ongoing containment strategies. Effective decision-making relies on models that not only forecast fire spread accurately but also deliver insights within operationally useful timeframes.

This paper presented computational science extensions to the existing Firemap tool for extended attack decision support. We have described the design considerations to enable decision workflows for extended attack and provided example uses both in experimental and operational settings. In future work, we plan to create enhanced data assimilation techniques for real-time fire behavior updates, improve model interoperability to support additional fire modeling frameworks, use AI methods for model explainability and interpretability, and refine uncertainty visualization for better risk communication. We also invite collaborators to work with us on AI-driven generative techniques and predictive analytics to optimize firefighting resource allocation and strategic planning.

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