Wildfire Spread Prediction Using Deep Learning

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Abstract

In this work, we explore deep learning-based fire spread prediction using the previously developed WildfireSpreadTS dataset, collected by a different research team prior to our study. Our primary goal is to accurately model the dynamics of wildfire propagation by leveraging Convolutional Neural Networks (CNNs) and U-Net architectures. We conduct extensive experiments that involve systematic hyperparameter tuning to find optimal configurations for capturing complex spatial features of fire progression. To handle the inherent challenges of segmentation and reduce prediction errors, we use the Intersection over Union (IoU) loss function, providing a robust measure for target-object overlap. Preliminary results demonstrate that this integrated approach effectively identifies fire-prone regions while maintaining strong predictive performance, highlighting the potential of deep learning methodologies for supporting timely wildfire management and resource allocation decisions.

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1 Introduction

Wildfires continue to pose a severe threat to ecosystems, infrastructure, and human communities worldwide. Over recent decades, climate change, population expansion, and land-use practices have contributed to more frequent and larger fire events [1]. These increasingly catastrophic blazes not only damage ecological habitats but also cause significant socio-economic losses. While traditional simulation approaches, such as FARSITE and Prometheus, have been widely adopted for modeling fire behavior, they often require extensive domain knowledge and manual tuning to reflect real-world complexity. As a result, machine learning (ML) and deep learning (DL) approaches have garnered substantial attention in wildfire spread prediction due to their ability to learn complex, non-linear relationships directly from data [2].

Among various DL architectures, U-Net has emerged as a popular choice for segmentation tasks because of its encoder–decoder structure and skip connections, enabling the capture of both high-level semantic features and low-level spatial details [2]. In this context, U-Net's capacity to handle pixel-wise predictions makes it particularly useful for modeling fire propagation, as it allows for fine-grained segmentation of prospective fire-perimeter regions. Recent work demonstrates that architectures based on convolutional neural networks (CNNs) often outperform purely physics-based methods by effectively leveraging large-scale remote sensing, meteorological, and topographic data [1].

In this study, we use a U-Net architecture to predict wildfire spread based on the WildfireSpreadTS dataset—specifically focusing on the 2018 subset [3]. This dataset's multi-temporal, multi-modal nature offers a valuable benchmark for deep learning algorithms, as it includes spatial resolutions that facilitate image-like representation of fire spread dynamics over consecutive days. Our aim is twofold: first, to demonstrate how U-Net can accurately learn the progression of fire fronts from historical satellite observations and weather variables; and second, to highlight the significance of proper loss functions—particularly Intersection over Union (IoU)—in improving predictive accuracy when dealing with highly imbalanced fire masks. By leveraging IoU, we directly optimize the overlap between predicted burned regions and ground-truth data, thereby addressing the class imbalance inherent in wildfire segmentation tasks [4].

Additionally, recent advances in multimodal data fusion have demonstrated the benefits of integrating satellite imagery, topographical features, and real-time climate indicators to capture the spatial and temporal complexity of fire behavior [5]. The breadth of data available from Google Earth Engine and other remote-sensing platforms allows for daily updates of environmental conditions—such as humidity, wind, vegetation indices, and land cover—that critically influence fire expansion.

This paper is structured as follows. Section 2 presents our data sources and describes the WildfireSpreadTS dataset, focusing on the 2018 fire season. Section 3 details the methodology, including data preprocessing, model architecture, and training strategies. In Section 4, we provide experimental results, analyzing model performance using IoU. Finally, we conclude by summarizing our findings, discussing limitations, and suggesting future directions for scaling this approach to broader geographic regions and longer forecast horizons.

2 Data

2.1 Data Collection

We obtained wildfire data through repositories curated using Google Earth Engine and GRIDMET (the Gridded Surface Meteorological dataset). The raw geospatial data was transformed and stored in TIFF files, used in the final training for predicting fire spread. Ultimately, the data was preprocessed into clean input tensors.

From the final dataset, we took the wildfire data from the year 2018 and specifically looked at VIIRS (Visible Infrared Imaging Radiometer Suite) bands, which are satellite-based images providing data on fire detection, vegetation, and burned areas [6]. The data from GRIDMET includes wind speed and direction, temperatures, and humidity data. From MODIS, there is information about elevation and land cover. All components were compiled into TIFF images keyed by the date of the fire data, offering a distinct, multi-parameter view of fire spread.

2.2 Data Cleaning

While a variety of data points are employed in different portions of the overall pipeline—as outlined in Section 3, 'Methods'—each compiled dataset goes through a standard cleaning process to ensure spatial and temporal consistency. TIFF files were checked to ensure that each pixel corresponds to the same physical location, and some files were cropped to zoom in on the actual burning area, with a buffer of a few kilometers. Lastly, continuous features were normalized to the [0,1] range and fire labels were made binary (fire vs. no fire).

3 Methods

3.1 Model Selection and Rationale

We chose a U-Net-based framework due to its proven success in segmentation tasks requiring precise boundary delineation [2]. By leveraging an encoder–decoder structure with skip connections, U-Net captures both high-level semantic features and low-level spatial details. Compared to traditional machine learning methods, convolutional neural networks (CNNs) can learn complex, nonlinear relationships directly from large-scale geospatial data [1]. Consequently, adopting a U-Net architecture provides a strong baseline for leveraging the multi-modal nature of the WildfireSpreadTS dataset [3].

3.2 Model Architecture

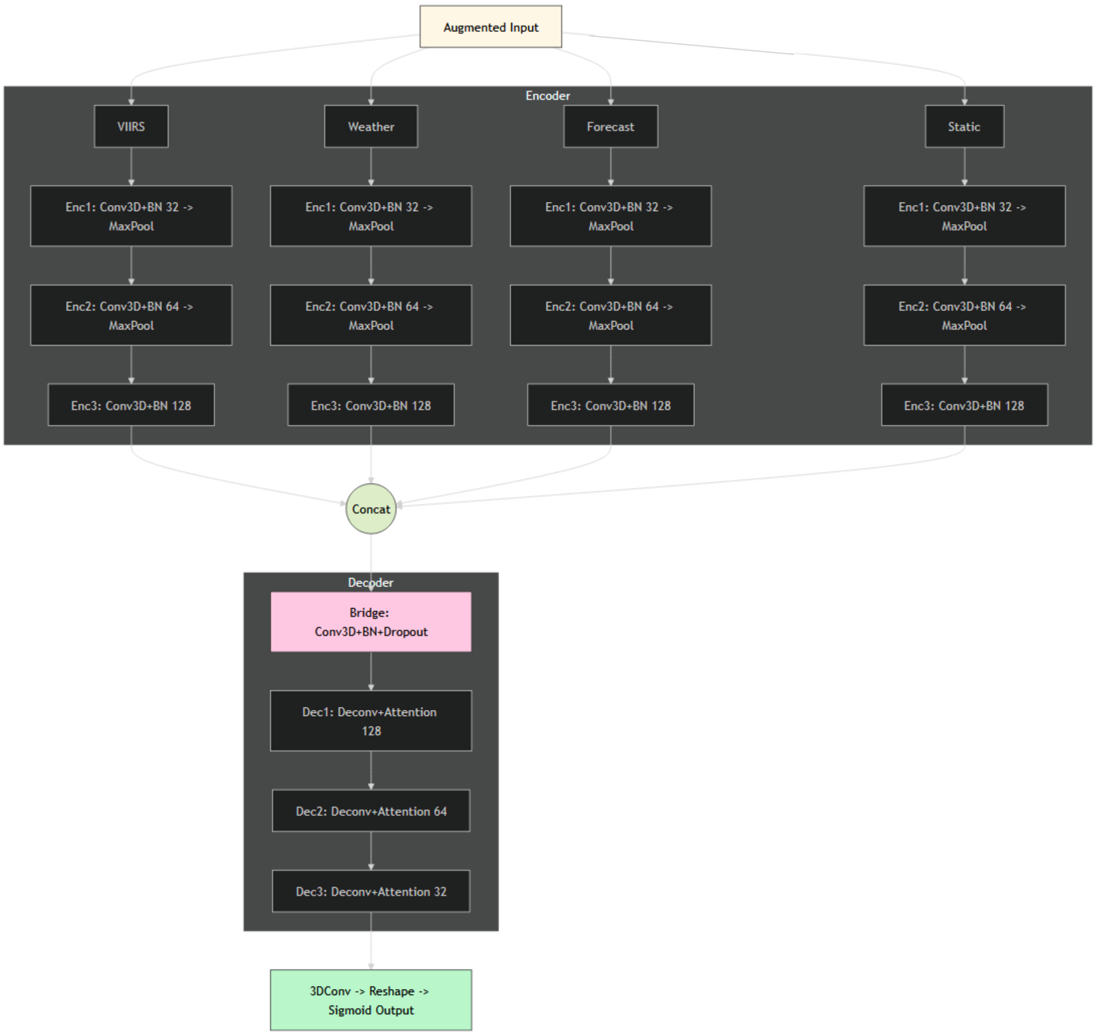

Figure 1: Diagram of our 3D U-Net model architecture.

As shown in Figure 1, our model employs a multi-branch 3D U-Net architecture that first separates the input tensor—representing three consecutive days of spatial data across 23 channels—into four modality-specific encoder branches (VIIRS, Weather, Forecast, and Static). Each branch processes its subset of channels through three sequential 3D convolutional blocks, each comprised of convolution + batch normalization layers followed by max pooling, capturing increasingly abstract features. The terminal outputs of these four encoder paths are concatenated and passed through a “bridge” layer, which further refines the merged feature representation via 3D convolution and dropout. On the decoder side, transposed convolutions progressively upsample the merged feature maps, and each stage integrates skip connections from the corresponding encoder blocks, gated by attention modules to focus on relevant spatial features. Finally, the last 3D convolution and reshape operation produce a single 2D fire-segmentation map, with a sigmoid activation to yield pixel-wise probabilities for fire vs. no fire.

3.3 Data Preprocessing

Before training our model, the 2018 WildfireSpreadTS TIFF files underwent a structured preprocessing pipeline. The goal was to transform raw geospatial data into a unified set of input tensors ready for segmentation. Key steps included:

Spatial Alignment and Resampling

Each of the 377 TIFF images was checked for coordinate system consistency. When necessary, data were reprojected or resampled to align with the baseline 375 m spatial resolution of the VIIRS active-fire product. This ensures that every pixel across different sources (e.g., weather raster layers, vegetation indices, topography) refers to the same ground location.

Region of Interest (ROI) Cropping

Fire events vary in their geographic extent, so many TIFF files covered large swaths of land. We cropped ROIs around known fire perimeters or ignition points, typically ensuring sufficient spatial context (e.g., a few kilometers buffer) beyond the actual burn extent. This step helps the model focus on relevant areas and reduces the computational load.

Temporal Consolidation

Because each daily TIFF captures a snapshot of conditions and active fires, we grouped consecutive days for each ROI into multi-day "stacks." This creates a sequence-like data structure that allows the downstream network to learn spatiotemporal patterns of fire spread over the course of consecutive days.

Normalization and Masking

During data preprocessing, all continuous bands (e.g., reflectance and temperature) were min–max scaled to the [0,1] range, ensuring a standardized input distribution. Any invalid pixels—for example, those occluded by smoke or cloud cover or corrupted by sensor issues—were tagged with a sentinel value (e.g., −1), enabling the model to learn how to handle or ignore these anomalies. Finally, the active fire labels were transformed into binary masks (fire vs. no fire), preparing the data for supervised segmentation tasks.

Train–Validation–Test Split

From the processed 3773 images, we allocated a portion for training, validation, and testing. Because fire behavior can be geographically and temporally distinct, we ensured that no single fire event was split across these subsets. Instead, entire events or contiguous ROIs were grouped to reduce spatial overlap among the partitions. A typical split ratio was used (e.g., 70–80% training, 10–15% validation, 10–15% testing), though exact percentages depended on the number of unique fire events available.

Batch and Patch Creation

Depending on GPU memory and model input constraints, large ROIs were sometimes tiled into smaller patches (e.g., 256 × 256 pixels) for batched training in the neural network. The "sliding window" or "tiling" approach ensures coverage of the entire burned area while making training feasible on standard hardware.

This end-to-end pipeline converts the multi-modal, daily TIFFs into uniform spatiotemporal samples for segmentation tasks, enabling our deep learning model to learn how wildfires typically progress under different environmental conditions. Further methodological details, including the specific network architecture and loss functions, are presented in the following subsections.

4 Experiments

4.1 Formatting Input Data

To train on daily wildfire progression, we organized spatiotemporal features into 3-day windows, each containing 23 channels (e.g., reflectances, weather variables, land cover). These were concatenated into a (3,300,220,23) tensor, giving the model a coherent snapshot of evolving fire events. This arrangement preserves necessary spatial detail while enabling the model to learn from day-to-day changes without excessive overhead.

4.2 Why IoU loss?

Intersection over Union (IoU), also known as the Jaccard Index, quantifies how well a predicted segmentation overlaps with the ground-truth mask by dividing the size of their intersection by the size of their union. This is particularly suitable for wildfire tasks, where missed fire pixels or excessive false alarms have real-world consequences. IoU also helps mitigate challenges of class imbalance by focusing on the overlap of positive predictions rather than raw accuracy [4]. For these reasons, we employ IoU to robustly evaluate segmentation performance.

4.2 Experiments Conducted

In our experimental phase, we conducted numerous training runs with variations in batch size, learning rate, and focal loss hyperparameters. From these, we selected five representative configurations that achieved the highest IoU scores, as summarized in Table 1. All experiments in this table had 100 epochs and a focal gamma of 2.0. The chosen experiments highlight how small changes in hyperparameters can meaningfully influence convergence and segmentation quality, especially in the context of highly imbalanced wildfire data. By examining each configuration's IoU score, we can see that more conservative learning rates and moderate focal alpha values tend to capture burn perimeters more accurately, indicating that overly aggressive updates or inadequate weighting of minority classes can undermine performance.

Batch Size	**Learning Rate**	**Focal Alpha**	**IoU**
9	0.0001	0.75	0.4012
8	0.0001	0.75	0.3880
7	0.0001	0.75	0.2821
8	0.001	0.75	0.2539
8	0.001	0.65	0.2497

Table 1: Our top five best performing experiments.

Among these five experiments, the best run attained an IoU of 0.4012, demonstrating the inherent challenges of segmenting sparse fire pixels. Complete metrics for this model show that it achieves a Loss of 2.6033, an Accuracy of 0.9980, a Precision of 0.5232, a Recall of 0.6384, and an F1 Score of 0.5751. The high Accuracy largely reflects the abundance of non-fire pixels, illustrating why metrics such as IoU, Precision, and Recall are more meaningful in this domain. Although the Recall indicates the model succeeds in capturing around two-thirds of the true fire pixels, there remains room to reduce false negatives, as these can have serious consequences in real-world fire management scenarios.

To illustrate the predictions produced by our best-performing model, we provide sample outputs comparing the model's binary masks with ground-truth fire labels in Figure 2. In several cases, the model effectively delineates fire fronts and identifies multiple ignition points, though small or fragmented burn regions sometimes remain challenging to detect. The probability maps also reveal occasional overestimation in regions with noisy reflectances or extreme weather signals, highlighting the need for additional preprocessing steps or domain-specific regularization. Despite these limitations, the obtained IoU scores establish a promising baseline for wildfire segmentation using 3D U-Net architectures, pointing to future avenues for improvement in data curation, model refinements, and integration of physics-based constraints.

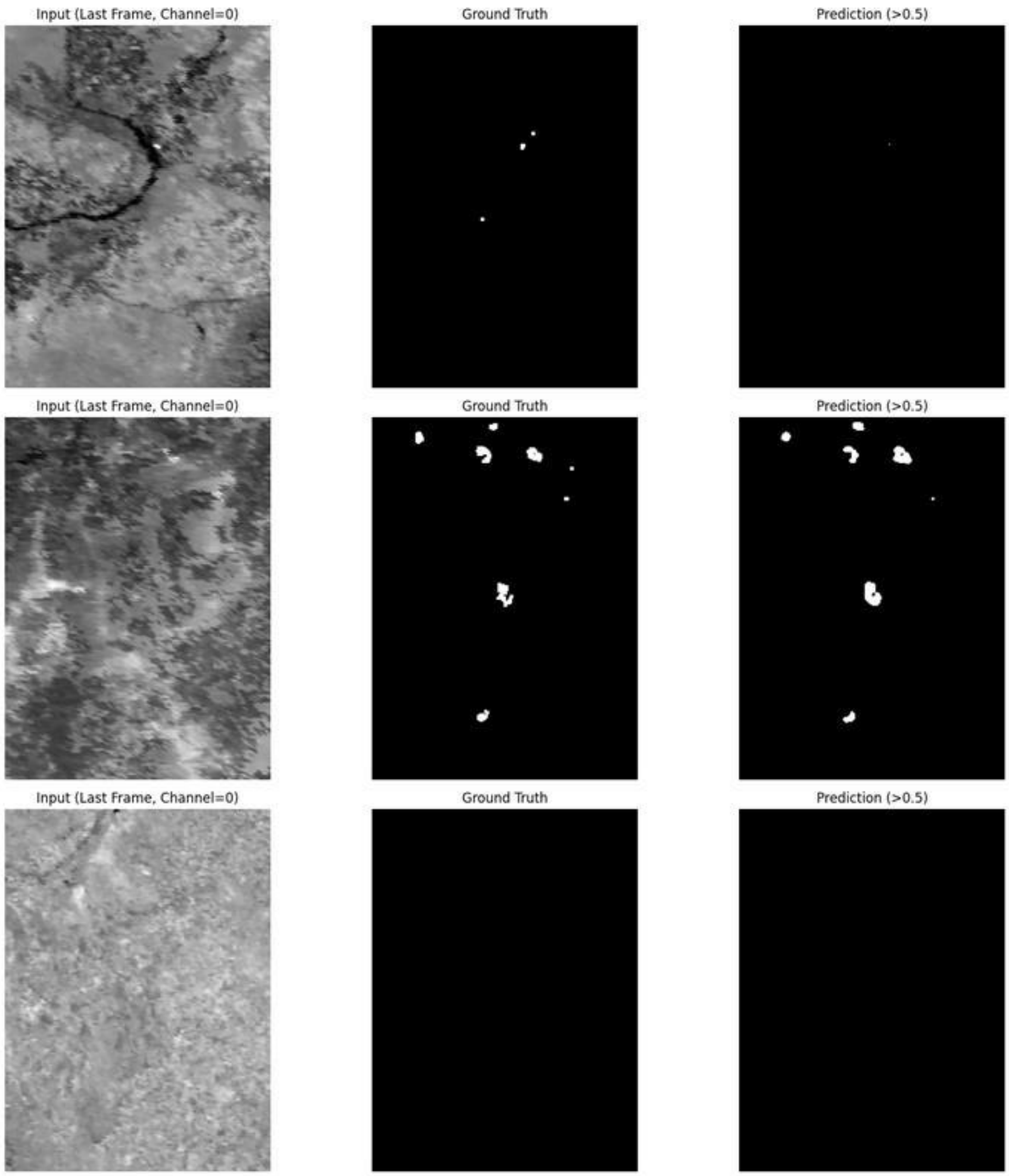

Figure 2: Example predictions from our best performing experiment achieving an IoU score of 0.4012.

5 Challenges

5.1 Data Acquisition and Preprocessing

Our first major challenge lay in acquiring and preparing geospatial TIFF files that contained the necessary information for accurately modeling wildfires. Despite the variety of available data sources—ranging from satellite imagery to governmental agencies—each source provided data in different formats, resolutions, and timeframes. This inconsistency required extensive effort to align and merge multi-layered TIFF files. We had to ensure that the temporal and spatial coverage overlapped, so our 3D U-Net would have comprehensive snapshots of environmental factors like temperature, vegetation density, and soil moisture.

Once obtained, the TIFF datasets went through several preprocessing steps to make them suitable for 3D U-Net input. These steps included reprojection (to ensure a uniform coordinate system), normalization (for consistent numeric ranges), and artifact filtering (e.g., removing clouds that could obscure ground data). Although time-consuming, meticulous preprocessing was essential to prevent biases or missing values from degrading the model's predictive accuracy.

5.2 High-Performance Computing Constraints

Even with the extensive preprocessing, running a 3D U-Net on these large-scale geospatial datasets demanded more computational power than anticipated. While we utilized Rosie, our high-performance computing (HPC) cluster, memory and GPU availability remained bottlenecks. The multi-gigabyte size of individual TIFF stacks often pushed system limits, especially when we attempted to process multiple time snapshots or geographic regions in parallel. Despite parallelization strategies and optimized frameworks, scheduling workloads at scale required careful coordination to prevent gridlock in the HPC queue.

Moreover, adapting our 3D U-Net to handle geospatial data introduced complications like varying spatial resolutions and heterogeneous input structures. These adaptations further taxed system resources by increasing the complexity and size of intermediate tensors. As a result, thorough experimentation and resource management were critical to prevent crashes, optimize training efficiency, and fully leverage Rosie's capabilities.

6 Future Work

6.1 Physics Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) have demonstrated strong potential for improving the accuracy and generalization of predictive models by embedding physical laws directly into the learning process. Studies such as "Physics-informed neural networks for parameter learning of wildfire spreading" [7] and "Physics-Informed Machine Learning Simulator for Wildfire Propagation" [8] highlight the capability of PINNs to integrate governing equations of wildfire behavior, such as reaction-diffusion equations and wind-driven fire spread models. The integration of these equations allows predictive models to be more general than their training data as a portion of the decision is based on the equations.

Integrating a PINN into our UNet framework could improve key metrics, including prediction accuracy and generalizability across diverse terrains and weather conditions. One possible approach is incorporating a physics-informed loss function at the neural net "bridge" of the UNet architecture, ensuring that predictions adhere to known physical constraints. Alternatively, an independent PINN model could replace the UNet for fire spread prediction, leveraging physics-based regularization instead of purely data-driven learning. However, further experimentation is required to determine the trade-offs between a hybrid approach and a standalone PINN implementation.

6.2 Sentiment Analysis

Sentiment analysis of social media has emerged as a promising tool for disaster response and early warning systems. Research such as "Sentimental Wildfire: A Social-Physics Machine Learning Model for Wildfire Nowcasting" [9] and "Investigating Disaster Response through Social Media Data and the Susceptible-Infected-Recovered (SIR) Model: A Case Study of the 2020 Western U.S. Wildfire Season" [10] suggest that analyzing social media posts can provide critical situational awareness, potentially improving wildfire response times. Using social media posts to understand where people are and where the fire is spreading could help advise disaster response.

While sentiment analysis could enhance our model by incorporating real-time reports from affected individuals, several challenges must be addressed. The primary difficulty lies in obtaining and curating relevant data, as wildfire-related social media posts are often unstructured and sparse. Developing an effective dataset would likely require collecting and labeling data manually. Furthermore, integrating sentiment analysis into our wildfire spread prediction model would require treating it as an additional input parameter, contributing to uncertainty quantification and alerting mechanisms. Previous solutions used a separate AI that had access to APIs to pull, parse, and sort posts for relevance and use that curated list as an input into the fire prediction model. This could be replicated in our work but would be a lot of effort for another input parameter that hinges on live social media coverage of the fire.

6.3 Optimizing Firefighter Response

Beyond predicting wildfire spread, a natural extension of our model is optimizing firefighter response strategies. By leveraging our predicted fire spread as an input to another decision-support model, we could provide actionable insights for resource allocation and evacuation planning. Such an approach could involve reinforcement learning or optimization-based methods tailored to minimize fire damage while ensuring firefighter safety.

However, real-time integration of firefighter location data presents legal and logistical challenges. Regulations on real-time GPS tracking of emergency personnel vary by jurisdiction, and ensuring secure data sharing between agencies remains a key concern. Overcoming these hurdles may require partnerships with firefighting agencies and the development of privacy-preserving data-sharing protocols. Future work should explore the feasibility of integrating geospatial firefighter deployment data with our predictive framework to enhance operational decision-making.

7 Conclusion

We presented a multi-branch 3D U-Net for wildfire spread prediction, showing how spatiotemporal stacking, IoU-driven segmentation, and attention-based skip connections can accurately delineate fire fronts. Our experiments on the WildfireSpreadTS dataset demonstrate both the promise and limitations of such deep learning methods, suggesting that integrated data streams and physics-informed constraints are likely to push performance further. Continued refinements in model architecture, data preprocessing, and HPC strategies will aid practical deployment in real-time fire-management scenarios.

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