Dynamic 3D Fire Spread Prediction via Visual Mapping: A Hybrid GNN and Cellular Automata Approach

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ABSTRACT

Wildfire damages in the United States exceeded $147 billion between 1980 and 2024, yet a critical gap exists between macro-scale fire spread prediction and micro-level visual detection. This mismatch is especially pronounced in Wildland-Urban Interface (WUI) environments, where fire propagates through fine-grained, structure-scale interactions. We present a micro-scale fire spread prediction methodology using Graph Neural Cellular Automata (GNCA), combining 3D voxel-based fire representation from multi-view video with a data-driven cellular automata framework that learns propagation rules directly from observations. To validate our approach, we conducted controlled burn experiments in Georgia with multi-angle video capture, binary fire segmentation labels, time-to-arrival annotations, and environmental measurements. Key contributions of this work-in-progress research include a WUI-representative benchmark dataset, a visual hull-based 3D voxel construction framework, and a GNCA predictive model for next-frame fire ignition at meter-scale resolution. This work establishes a foundation for fine-grained fire spread tools supporting tactical firefighting decisions.

Keywords

Wildfire Modeling, Digital Twin, 3D Spatial Computing, Graph Neural Cellular Automata, AI for Risk Reduction

INTRODUCTION

Wildfire is a devastating natural disaster that causes billions of dollars in losses and severe damage to ecosystems and infrastructure. According to the National Oceanic and Atmospheric Administration, wildfires have caused $147.6 billion in damages and resulted in 537 deaths in the U.S. between 1980 and 2024 (NOAA, 2024). Notably, $101.2 billion and 336 deaths occurred from 2017–2024 alone, representing over 68% of total damages from the past four decades concentrated in just the most recent seven years. This accelerating trend underscores the urgent need for intelligent wildfire monitoring systems to better support firefighting operations.

The most destructive aspect of fire lies not merely in its presence, but in its capacity to spread. Fire spread dynamics are inherently governed by complex spatial-temporal interactions among environmental factors including fuel load, wind speed, terrain, and fuel moisture content. This inherent spatial-temporal dependency makes fire spread fundamentally a dynamic phenomenon rather than a static event, and addressing it requires methods capable of modeling the evolving interactions between fire state and environmental conditions across both space and time. However, traditional fire progression and spread models are predominantly developed from a macro-scale perspective, focusing on landscape-scale wildfire behavior modeling and simulation. Consequently, they can only handle macro-scale inputs and outputs, which is insufficient for wildfire tactical response, where decisions must be made at the scale of individual structures and minutes rather than landscapes and days.

Furthermore, the scale mismatch between existing prediction tools and local fire management needs is particularly critical given the expanding Wildland-Urban Interface (WUI). In recent decades, WUI areas have been consistently increasing, posing a severe threat to human communities. According to Guo et al., global WUI expanded by more than 35% since 2000, with 85% of this growth occurring between 2010 and 2020 (Guo et al., 2024). Critically, while sharing the same underlying combustion physics, fire spread in WUI scenarios is shaped by localized interactions between structures, vegetation patches, and built infrastructure that wildland fire models are not designed to capture. This micro-scale spreading behavior, involving structure-to-structure ignition, fuel heterogeneity at building scales, and localized wind patterns around structures, requires fine-grained spatial-temporal analysis that traditional large-scale simulators cannot provide.

To address this critical gap in micro-scale fire spread understanding, particularly for WUI-representative scenarios, we propose a novel methodology that combines visual perception with spatial-temporal modeling: a Graph Neural Cellular Automata (GNCA) framework for micro-scale fire ignition prediction. Our approach constructs 3D voxel-based fire representations from multi-angle video inputs and leverages graph-structured learning to capture spatial relationships and propagation dynamics. We validate our methodology through a custom-designed controlled burn experiment that captures the localized fire dynamics characteristic of WUI environments. Our contributions span dataset collection, 3D fire representation, and a learning-based predictive framework, collectively bridging the gap between micro-level visual detection and spatial-temporal fire spread prediction.

In this paper, we review the development of wildfire modeling tools, examine why they are intrinsically incapable of addressing micro-scale fire modeling, and explain why we believe a new approach can help resolve this long-standing challenge. We further describe the design of our modeling architecture, along with our experimental procedure, data collection, and data processing pipeline. The remainder of this paper is organized as follows: Section 2 reviews relevant background and prior work. Section 3 presents our controlled burn experiment setup and dataset structure. Section 4 describes our methodology for 3D fire representation and GNCA-based prediction modeling. Section 5 discusses limitations and future directions, and Section 6 concludes the paper.

BACKGROUND

The scientific foundation for fire spread modeling was established by Rothermel (1972), whose semi-empirical model remains the backbone of most widely used operational tools today, including FARSITE and similar landscape-scale simulators. Rothermel defined fire spread in terms of two fundamental components: a heat source and a heat sink. The heat source describes fuel that is actively combusting and releasing heat and thermal radiation into the surrounding environment, while the heat sink refers to adjacent unburned fuel that can be potentially ignited. The ease and rate of ignition across this interface depend on fuel-specific properties such as ignition threshold and heat-retaining capacity, which together determine how much effective heat transfer is required to propagate the fire front.

While the Rothermel framework has proven highly effective for landscape-scale operational planning, it was not designed to capture micro-scale flame dynamics. As noted by Cruz (2013), Rothermel himself acknowledged that modeling fire behavior at fine temporal and spatial scales was, for the foreseeable future, practically intractable. Micro-scale flame behavior is highly sensitive to turbulent flow structures, localized fuel heterogeneity, and rapidly changing environmental conditions. Compounding this challenge is a persistent sensor scale mismatch: environmental measurements such as wind speed are typically collected at coarse spatial resolutions that are poorly suited for resolving the localized interactions that govern micro-scale fire spread. As a result, these physics-based tools, though valuable for strategic resource planning and large-scale containment decisions, operate at resolutions fundamentally mismatched with the fine-grained, real-time demands of active firefighting, constraining fire spread prediction to macro-scale regimes.

Existing research on fire spread prediction has predominantly followed two approaches. The first is satellite-based burn area analysis, exemplified by Huot et al.'s Next Day Wildfire Spread prediction framework, which leverages remote sensing imagery to forecast large-scale fire progression (Huot et al., 2020). The second employs physics-based simulation methods, ranging from classic Rothermel-based simulators such as FARSITE to more recent cellular automata approaches such as Cell2Fire (Pais et al., 2021) and its validation on real landscapes (Kim et al., 2025). While these approaches provide valuable frameworks for understanding large-scale fire spread, they both face a fundamental limitation: an inability to scale down to the finer spatial resolutions needed for local fire dynamics analysis. Satellite-based methods, though effective for monitoring large wildfire events, suffer from limited spatial and temporal resolution, while simulation-based approaches rely on coarse-grained fuel maps, terrain data, and meteorological inputs, making them ill-suited for capturing localized dynamics. This creates a critical scale mismatch: existing macro-scale prediction methods operate at landscape or regional levels with satellite imagery at resolutions of tens to hundreds of meters, while early-stage visual detection and local fire management decisions require micro-scale understanding at meter or sub-meter resolution. These conventional simulators, designed primarily for wildland scenarios, also rely on assumptions grounded in large-scale forest fuel maps, terrain characteristics, and atmospheric weather conditions (Jain et al., 2020; Shaik et al., 2025), making them poorly suited for capturing the localized dynamics critical to WUI fire spread.

This limitation is compounded by the fact that existing WUI-specific research has primarily taken a static approach, focusing on how building materials, house design, and urban layout affect risk distribution among structures and communities (Zamanialaei et al., 2025; Wilkin et al., 2025). While these studies provide valuable insights for long-term planning and building codes, they cannot provide the dynamic, real-time information about fire spread behavior necessary for emergency response and tactical firefighting decisions at the micro scale.

The rapid advancement of computer vision over the past decade offers a compelling new lens through which to revisit Rothermel's pessimistic assessment of micro-scale fire modeling, with computer vision serving as a complementary sensing modality capable of providing high-resolution, real-time observations of fire behavior at the local scale. Early computer vision research in wildfire focused narrowly on detection and classification tasks, as seen in the FLAME dataset and U-Net-based segmentation work of Shamsoshoara et al. (2021) and the multi-modal YOLO-based detection approach of Hu et al. (2025). While these detection and 2D segmentation methods play a vital role in modern wildfire management by providing early-stage warnings, they address only the first step in comprehensive fire monitoring. A critical next step remains largely unaddressed: once a fire has started, can we predict its subsequent spread behavior? Encouragingly, the field has since progressed substantially. Methods such as Metric3D (Yin et al., 2023) now enable zero-shot metric depth estimation from a single image, while SAM3D (Yang et al., 2023) demonstrates the feasibility of lifting 2D segmentation capabilities into full 3D scene understanding by projecting image-level masks into point cloud representations. Critically, these advances in visual 3D reconstruction are not limited to general scene understanding: Liu et al. (2025) demonstrated that 3D visual hull reconstruction methods can be directly applied to fire science, recovering accurate instantaneous flame geometries and radiative characteristics of fire whirls from multi-camera video inputs. Together, these developments show that the visual reconstruction of dynamic, geometrically complex phenomena such as fire is now within reach, and this shift toward fully visual, learning-based approaches opens a new pathway for addressing the sensor scale mismatch that long impeded micro-scale fire modeling. Rather than depending on coarse meteorological measurements, visual observations can serve as a surrogate sensing modality that captures the integrated effect of wind, fuel state, and thermal dynamics as they manifest in observed flame behavior.

Beyond visual reconstruction, the modeling of spatial-temporal propagation itself has also seen significant advances. The emergence of graph neural networks and neural cellular automata (Grattarola et al., 2021) provides expressive computational frameworks well-suited for modeling spatial-temporal propagation processes, and unlike physics-based simulators that require explicit parameterization of fuel and atmospheric properties, learning-based cellular automata can discover propagation rules directly from observed fire dynamics. Together, these developments suggest that the micro-scale fire modeling challenge that once seemed intractable may now be approachable through the integration of modern computer vision and graph-based learning, a hypothesis that motivates and underlies the methodology presented in this work.

DATA

Overview

This study utilizes a custom-collected dataset from a controlled burn experiment conducted in Columbus, Georgia, designed to capture micro-scale fire spread dynamics in a WUI-representative scenario. To support fire segmentation preprocessing, we additionally employed the FLAME dataset (Shamsoshoara et al., 2021) for segmentation model (U-Net) pretraining. This section describes the experimental design, data collection protocol, and annotation methodology.

Controlled Burn Experiment Design

We conducted the controlled burn experiment in cooperation with the Columbus Fire and Emergency Department in Georgia. The experiment was designed to mimic fire spread scenarios characteristic of WUI environments, where fires propagate between discrete fuel sources separated by non-combustible surfaces—analogous to structure-to-structure fire spread in residential areas.

Site Preparation: Prior to the burn, we surveyed the site and painted a ground reference grid with 36 × 36 inch cells in black. Each grid intersection coordinate was marked in orange to facilitate spatial registration and 3D reconstruction. Two stacks of wooden pallets were placed at separated positions, with grass fill material placed underneath and between the pallets (Figure 1). This configuration simulates isolated fuel sources (representing structures) with connecting combustible material (representing vegetation in WUI gaps).

Figure 1. Pallets and Grass Setup

Multi-Perspective Data Collection

To enable 3D fire reconstruction and spatial-temporal analysis, we deployed multiple synchronized recording devices capturing the fire from different perspectives:

Data Collection Equipment:

1. Aerial perspective: DJI M350 RTK Drone with GPS-enabled positioning for overhead view (Figure 2)
2. Stationary multi-modal: Mission Command Unit with co-located RGB and thermal cameras for fixed-angle observation (Figure 3)
3. Lateral perspectives:
    a. iPhone 14 for high-resolution lateral footage (Figure 4)
    b. JVC Recorder for secondary lateral perspective (Figure 5)

This multi-camera setup provides comprehensive angular coverage necessary for visual hull construction and 3D voxel mapping, while the ground grid enables spatial correspondence across viewpoints.

Annotation and Label Generation

We developed a semi-automated pipeline for generating training labels at two levels of granularity:

Binary Fire Segmentation Masks:

We employ a U-Net architecture pretrained on the FLAME dataset for initial fire segmentation. The model generates binary masks indicating flame presence at the pixel level followed by manual review and refinement of segmentation masks.

Time-to-Arrival Labels:

For each grid cell and time step, we computed the time-to-arrival (TTA) as the temporal difference between the current frame timestamp and the timestamp when that cell first exhibits fire activity:

$$TTA(cell, t) = t_{ignition}(cell) - t_{current}$$

where $t_{ignition}(cell)$ is the frame timestamp when the cell first shows fire, and $t_{current}$ is the current frame timestamp. A positive TTA indicates the cell has not yet ignited, while a negative value indicates the elapsed time since ignition. These TTA annotations provide temporal information about fire progression dynamics across the spatial grid.

Figure 2. DJI M350 RTK Aerial Footage Sample

Figure 3. Mission Command Unit Stationary Camera Sample

Figure 4. Lateral camera footage sample - iPhone 14

Figure 5. Lateral camera second perspective sample - JVC recorder

METHODOLOGY

Our methodology comprises three key components: (1) 3D fire representation from multi-view video inputs, (2) feature space construction for spatial-temporal modeling, and (3) predictive modeling using Cellular Automata baseline and Graph Neural Network approaches. This section details each component and describes our experimental pipeline.

3D Fire Representation from Multi-View Videos

To obtain 3D spatial data for fire ignition prediction, we must first map 2D video observations from multiple cameras into a unified 3D voxel representation. Our data collection setup includes three stationary cameras capturing the fire from different angles and one aerial drone providing overhead perspective (as described in Section 2).

Traditional methods for 3D fire reconstruction have demonstrated feasibility and effectiveness in controlled scenarios. Ko (2014) proposed stereoscopic image-based 3D fire surface reconstruction. Matusik et al. (2000) developed image-based visual hulls, which serve as the foundation for voxel construction methods. Ciullo et al. (2018) successfully demonstrated 3D shape and surface reconstruction of fire in controlled burns, illustrating the capability of traditional approaches to capture fire geometry.

More recently, advanced learning-based techniques for fine-grained 3D/4D fire reconstruction have emerged (Nazarenus et al., 2025). Liu et al. (2025) further showed that visual hull-based 3D reconstruction can recover accurate instantaneous flame geometries directly from multi-camera video in indoor laboratory environment, demonstrating the feasibility of applying visual reconstruction methods to dynamic fire phenomena. These approaches address the inherent challenges of reconstructing turbulent fluids like fire, which violate the feature point assumptions of many classic computer vision algorithms. Such advances offer exciting opportunities for future high-resolution 3D mesh fire analysis.

For this work, we adopt the traditional perspective-based visual hull method. Given our research scope is validating the viability of predictive modeling for fire spread from video inputs, we prioritize stability and reliability in the 3D reconstruction component. Employing a well-established traditional method minimizes potential error accumulation at the reconstruction stage, allowing us to focus on demonstrating our core contribution: the GNN-based predictive framework. While fine-grained 3D reconstruction improvements are promising, they remain orthogonal to our current research objectives and represent a direction for future enhancement.

Using the painted ground grid as spatial reference, we construct a 3D voxel space where each voxel corresponds to a grid cell location and height layer. Binary fire segmentation masks from each camera view are projected into this voxel space using camera calibration parameters, and voxel occupancy is determined through visual hull intersection.

Feature Space Construction

Our feature space is designed to capture both observable fire characteristics and environmental factors relevant to ignition dynamics. Features are organized into three categories:

1. Observable Fire State Features:
    a. Ground fire front position
    b. Voxel fire intensity (derived from segmentation confidence)
    c. Spatial fire distribution across the 3D grid

2. Combustion and Environmental Parameters:
    a. 2D Rate of fire front spread (ROS)
    b. Flame dimensions (width, height, length)
    c. Environmental conditions (humidity, wind speed, wind direction)

3. Fuel Properties:
    a. Fuel type and size
    b. Fuel load parameters and moisture content
    c. Spatial fuel distribution

In this research, fuel properties are treated as known ground truth, as material selection and measurement were conducted prior to the experiment. However, in real-world deployment scenarios, these parameters would ideally need to be estimated from visual inputs through automated fuel recognition and characterization. We also implemented and tested a fully image-based 3D fuel reconstruction pipeline using the Segment Anything Model 3D (SAM3D) introduced by the Meta research team (Chen et al., 2025), with results shown in Figures 6 and 7. The resulting point clouds provide valuable information regarding fuel load distribution in 3D space. Furthermore, the single-image inference capability of SAM3D represents a strong practical advantage in real deployment scenarios where available camera views are limited.

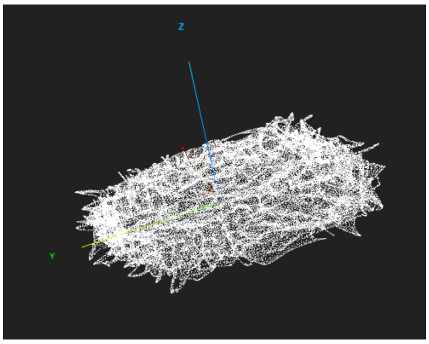

Figure 6. Point cloud of hay bales at the controlled burn site, reconstructed using the monocular 3D reconstruction model SAM3D.

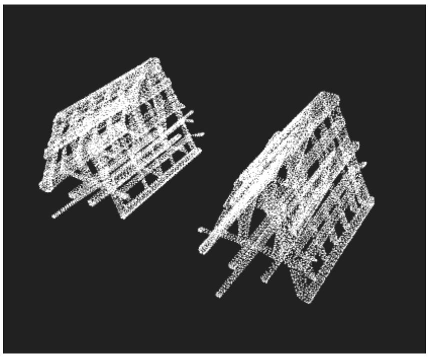

Figure 7. Point cloud of pallets at the controlled burn site, reconstructed using the monocular 3D reconstruction model SAM3D.

Predictive Modeling

We developed two modeling approaches for fire spread prediction: a traditional Cellular Automata (CA) with handcrafted rules as our baseline, and a Graph Neural Cellular Automata (GNCA) framework that leverages Graph Neural Networks to automatically learn propagation rules. This comparison allows us to evaluate the benefits of learning-based rule discovery over manual rule specification.

Cellular Automata Baseline

Cellular Automata is a classic simulation method naturally suited for grid-based state propagation. CA has proven effective for macro-scale wildfire spread simulation (Pais et al., 2021; Kim et al., 2025), making it a natural baseline for our micro-scale prediction task.

In traditional CA, the next state of each cell is determined by handcrafted rules based on its current state and the states of its neighbors. However, CA's primary limitation lies in its reliance on manual rule specification, which requires extensive domain knowledge and results in rigid, inflexible simulation logic. For our baseline, we implement a basic CA model with rules derived from fundamental fire spread principles: distance-based ignition probability, fuel consumption dynamics, and directional spread influenced by wind conditions.

Graph Neural Cellular Automata

Rather than handcrafting propagation rules, we propose a Graph Neural Cellular Automata framework that automatically learns fire spread dynamics from observed data. GNCA combines the structured propagation framework of cellular automata with the learning capability of Graph Neural Networks, enabling the model to discover complex, data-driven transition rules that may be difficult to specify manually.

Graph Neural Networks, introduced by Gori et al. (2005) and formalized by Scarselli et al. (2008), were originally designed to overcome the limitations of traditional machine learning algorithms that compress topological information into flat vectors. GNNs enable learning while preserving graph structure and spatial relationships. The key principle of GNN is learning node representations through iterative aggregation of information from neighboring nodes—a process known as message passing.

GNNs have demonstrated success across diverse domains, including bioinformatics (Zhang et al., 2021), natural language processing (Besta et al., 2024), and material science (Reiser et al., 2022), establishing their capability to model complex relational dynamics. This message-passing mechanism naturally parallels many physical propagation processes, making GNNs particularly well-suited for modeling phenomena where each entity's future state depends on information exchange with neighboring entities.

In fire spread scenarios, this alignment becomes especially compelling. Each cell's future ignition state depends on heat transfer, flame propagation, and environmental influences from neighboring cells—a process that directly corresponds to GNN's message-passing paradigm. Recent work has begun exploring GNNs in wildfire contexts, including satellite-based next-day wildfire spread prediction, active fire detection, and burned area prediction (Zhao et al., 2024; Cassimon et al., 2025; Das et al., 2025), demonstrating the potential of GNN architectures for capturing fire dynamics.

Beyond domain-specific applications, Grattarola et al. (2021) developed a pioneering general framework that combines GNN methodology with cellular automata to create self-learning CA systems. Their work demonstrated that GNNs can effectively learn cellular automata transition rules from data across various domains, replacing manual rule specification with learned propagation dynamics. This approach bridges the interpretability and structure of CA with the learning capacity of GNNs, providing a principled method for discovering complex spatial-temporal propagation patterns—applicable to any CA-based simulation task.

We apply this general GNCA paradigm to the specific domain of micro-scale fire spread prediction with 3D voxel representations. In our implementation, the graph structure captures the spatial relationships and dependencies within the fire scene. Each node represents a grid cell/voxel with associated features including:

- Observable fire state (fire intensity, presence)
- Combustion parameters (ROS, flame dimensions)
- Environmental conditions (wind speed, wind direction, humidity)
- Fuel properties (type, moisture content, load)

Edges encode spatial adjacency relationships, enabling information flow between neighboring cells. Through the GNN's message-passing mechanism, each node aggregates information from its neighbors and updates its state prediction, effectively learning the cellular automata transition rules directly from our controlled burn data rather than through manual specification. This data-driven approach allows the model to capture subtle propagation dynamics that may be difficult to encode in handcrafted rules, while maintaining the interpretable grid-based structure of traditional CA.

Experimental Pipeline

Our complete experimental pipeline consists of the following stages:

1. 3D Voxel Construction: Multi-view video inputs → fire segmentation → visual hull-based 3D voxel occupancy
2. Feature Extraction: Compute spatial-temporal features from voxel representation and environmental sensors, constructing node features for graph representation
3. Model Training: Train both traditional CA baseline (rule calibration on validation data) and GNCA model (learning propagation rules through GNN message passing)
4. Prediction Task: Next-frame fire ignition prediction—binary classification of whether each voxel/cell will exhibit fire in the subsequent time step
5. Evaluation: Assess prediction accuracy, precision, recall, and spatial agreement metrics, comparing handcrafted CA rules against learned GNCA rules

DISCUSSION, LIMITATIONS AND FUTURE WORK

This work represents an ongoing research effort. The methodology and experimental framework presented here establish the foundation for fire spread prediction at micro-scale, with full quantitative evaluation and result analysis currently in progress. The ultimate goal of this research is to provide time-to-arrival prediction capabilities for fire spread. This paper provides experimental proof-of-concept for short-interval fire ignition prediction, establishing the foundation for longer-horizon temporal prediction. By developing iterative forward simulation where predicted states serve as inputs for subsequent time steps, the framework could evolve toward a coarse-grained fire digital twin. Such a system would predict the highest-probability fire positions in upcoming time frames, enabling proactive suppression strategies and informing analysis of which ignition locations along the burn path contribute most significantly to fire spread extent.

Our current approach relies on traditional visual hull-based 3D reconstruction, which provides coarse-grained voxel representations. While sufficient for demonstrating our predictive modeling framework, the 3D reconstruction resolution fundamentally limits the spatial granularity of fire state representation. There exists a trade-off between voxel resolution and reconstruction accuracy: increasing voxel resolution without corresponding improvements in reconstruction quality may introduce noise and degrade prediction performance. Future work should investigate the integration of advanced learning-based 3D reconstruction methods (e.g., Nazarenus et al., 2025) to achieve finer-grained fire representations, balanced against reconstruction accuracy and computational efficiency. Additionally, the controlled burn scenarios used in this study are relatively constrained in scale and scene diversity. While this setting is appropriate for establishing cell-based fire spread prediction as a proof of concept, generalization to larger-scale scenarios involving multiple structure types and varied environmental conditions will require richer experimental datasets and broader validation. Moreover, as this is an emerging area, and computer vision research in wildfire dynamics is itself still relatively nascent, the availability of datasets necessary for broader research remains highly limited. Future efforts should focus on expanding dataset richness and diversity, and on establishing standardized protocols and broader scope for wildfire data collection, so as to support the development and scaling of a wider range of modern learning-based models.

A second challenge concerns prediction uncertainty and fuel observability. Fire spread prediction inherently involves high uncertainty due to turbulent fluid dynamics, environmental variability, and incomplete observability. For iterative multi-step prediction, where predicted states serve as inputs for subsequent time steps, error accumulation becomes a critical concern as the prediction horizon extends. Future research should develop uncertainty quantification methods that provide confidence bounds on predictions, enabling informed operational decision-making and supporting the transition from experimental validation to deployment. In our controlled experiment, fuel properties are treated as known ground truth, whereas in real-world deployment, automated fuel recognition and characterization from visual inputs would be necessary for end-to-end prediction. Our dataset, which includes both raw footage and ground-truth fuel annotations, provides a foundation for future research on visual fuel type classification and parameter estimation. In addition, further research should investigate a dynamic algorithm for determining when and how to update the fuel digital twin reconstruction as the burn progresses, so that changes in fuel geometry and state during the event can be reflected in the prediction pipeline.

The multi-camera requirement for 3D reconstruction adds a third challenge. The methodology presented in this work requires multiple camera inputs to reconstruct 3D fire representations. However, as the first work to introduce fire dynamic perception from video inputs, our focus is on establishing proof of viability: demonstrating that fire spread dynamics can be predicted given reliable 3D fire representations. Recent progress in monocular 3D reconstruction and neural rendering suggests that single-camera 3D fire reconstruction may become feasible, potentially enabling end-to-end deployment pipelines for practical firefighting applications.

Looking forward, we envision this methodology as foundational to operational fire monitoring systems in WUI environments. Consider a deployment scenario where fixed multi-view cameras monitor critical WUI locations from tower installations. With cameras capturing the same area from different angles, the system could reconstruct 3D fire behavior in real time, with pre-generated material property databases serving as a digital twin foundation and meteorological stations providing wind and weather conditions. Such an integrated system would serve as the backbone of multi-scale WUI digital twin infrastructure, providing fire departments, residents, and stakeholders with continuous situational awareness during wildfire events.

CONCLUSION

In this research, we introduce a novel methodology for micro-scale fire spread prediction that bridges the gap between visual detection and spatial-temporal fire dynamics modeling. Our key contributions include: (1) a custom-designed controlled burn experiment with multi-view video capture and a 3D grid reference system, providing a benchmark dataset for micro-scale fire spread analysis; (2) a 3D voxel-based representation framework that maps 2D video observations into unified 3D fire states; and (3) a Graph Neural Cellular Automata approach that learns fire propagation rules from data rather than manual specification, demonstrating the viability of learning-based methods for micro-scale fire spread prediction.

Our approach addresses a critical gap in current wildfire research: the scale mismatch between macro-level satellite-based prediction systems and micro-level visual detection capabilities. By focusing on WUI-representative scenarios where fire spreads between localized structures, this work provides a foundation for developing fine-grained fire spread prediction tools relevant to tactical firefighting and community protection. Beyond the specific technical contributions, the dataset and methodology provide a testing bed for evaluating alternative approaches to micro-scale fire dynamics modeling, and this research direction aligns with emerging trends toward next-generation sensing solutions and comprehensive digital twin systems for wildland environment monitoring and fire management.

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