A Modular Light-weight Voxel-Based 3D Wildfire Propagation Simulator in Python Using LiDAR Data, High-Performance Computing (HPC), and Immersive Scientific Visualization

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Abstract

Simulating fire spread and identifying potential propagation pathways in the Wildland–Urban Interface (WUI) are critical for wildfire prevention, emergency preparedness, and firefighting—especially in the wake of catastrophic events such as the 2025 Los Angeles wildfire, the 2019–2020 Australian bushfires, and the 2023 wildfires in Greece. Despite growing awareness of wildfire risks near urban boundaries, lightweight, high-resolution 3D simulation tools remain limited, hindering scenario-based planning and rapid response. To address this gap, we present a voxel-based 3D wildfire propagation simulator developed in Python. The simulator integrates LiDAR-derived voxel models of urban environments, GIS-informed fuel characterizations, and high-performance parallelism via the Taichi framework. Fire dynamics are modeled across 3D voxel grids using a hybrid of physics-based and empirical approaches, incorporating key parameters such as wind speed, fuel type, and moisture content. Critical processes—including inter-voxel heat transfer, crown fire spread, and surface fireline intensity—are captured to simulate realistic fire behavior. Simulation results are exported in standard 3D formats for immersive visualization in platforms such as Blender and Unity. A case study using LiDAR data from Newcastle, Australia demonstrates the tool's real-world applicability. Designed for modularity and extensibility, the simulator supports model replacement, parameter tuning, and integration with diverse spatial datasets. It also serves as a scalable framework for high-fidelity modeling of inter-voxel mass and energy transfer in complex urban environments, enhancing decision-support capabilities. Additionally, the tool generates synthetic fire spread data, enabling the training of generative AI models and integration with broader urban and environmental simulation platforms.

1. Introduction

The 2025 Palisades and Eaton wildfires in Los Angeles were among the most destructive urban fires in recent U.S. history, causing billions in damages, displacing tens of thousands, and devastating both urban and natural areas. Similarly, Australia's 2019–2020 "Black Summer" fires burned over 24 million hectares, killed an estimated one billion animals, and caused more than $4.5 billion in losses. Smoke traveled over 11,000 kilometers to Chile and Argentina, highlighting the global reach of extreme wildfire events.(Ahmed and Ledger, 2023, Natural Hazards Research Australia, 2023). Collectively, these disasters underscore the increasing frequency, intensity, and transboundary impacts of wildfires, reinforcing the urgent need for advanced predictive modeling, urban resilience planning, and ecosystem risk mitigation.

Fires originating near the Wildland–Urban Interface (WUI) can escalate rapidly due to dry vegetation, extreme weather, structural vulnerabilities, and strong winds. Wind-driven embers often jump miles ahead of the main front, creating spot fires that overwhelm emergency response efforts (Karels and Corbin, 2022). These events have destroyed thousands of structures, disrupted critical infrastructure, and caused long-term ecological damage. In WUI zones, firefighting and prevention are complicated by the tight coupling between natural hazards and the built environment (Alvis et al., 2025). Limited defensible space, flammable urban design, and the close proximity of structures to vegetative fuels hinder suppression efforts (Miller, 2017, Hakes et al., 2017, Baker et al., 2020). Under such constraints, even small ignitions can rapidly develop into large, destructive urban fires (Kendell et al., 2023), as seen in Portugal, Greece, and Chile (Bento-Gonçalves and Vieira, 2020, Alvis et al., 2025). Accessory structures, such as fences, gutters, roofs, and sheds, further act as ignition vectors that create continuous combustible pathways into primary residences (Hakes et al., 2017). These dynamics underscore the need for accurate fire propagation models that explicitly represent WUI-specific features—including 3D structure–fuel interactions, ignition sources, and ember transport—to support early intervention, resource optimization, and strategic firefighting operations (Hakes et al., 2017, Gonzalez and Ghermandi, 2024).

In response to growing demand for fire spread simulation, academic researchers, government agencies, and fire management authorities have developed a variety of modeling tools (Gonzalez and Ghermandi, 2024, Hostikka et al., 2008). However, many of these systems remain inadequate for both proactive fire prevention and real-time emergency response—particularly within the complex conditions of WUI zones. Several critical limitations contribute to this shortfall. First, most models simulate fire propagation in two dimensions, rendering them incapable of capturing vertical dynamics such as crown fires in forests or fire spread along multi-story structures (Hostikka et al., 2008). Second, while some advanced 3D simulators do exist, they often rely on coarse spatial resolutions (typically 10–30 meters) and lack integration with detailed urban geometries or high-resolution datasets like 1-meter LiDAR point clouds (Comesaña-Cebral and Martínez-Sánchez, 2024, Moreno et al., 2012), limiting their usefulness for street-level prediction and tactical planning. Third, many tools are packaged as proprietary, GUI-based software, which restricts modularity, flexibility, and interoperability with smart city platforms such as urban digital twins, web-based decision support systems, and IoT-connected devices, including smartphones and virtual reality (VR) tools (Xu et al., 2023). Finally, the computational

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cost of high-resolution fire models often limits their scalability in large or densely built environments. These challenges underscore the need for a relatively high-resolution, fully three-dimensional modeling framework that leverages detailed spatial inputs—such as LiDAR-derived fine-scale 3D urban features—to accurately simulate fire behavior in both vertical and horizontal dimensions across WUI settings.

This paper presents a voxel-based 3D wildfire simulator for modeling fire behavior in complex urban and natural environments. Developed in Python and accelerated using the Taichi parallel computing framework (Hu et al., 2019), the simulator integrates LiDAR-derived voxel models with both physics-based and empirical fire spread models. It incorporates key variables such as wind, fuel type, and moisture content, while simulating inter-voxel heat transfer, surface fireline intensity, and crown fire dynamics. Simulation outputs are exported in standard 3D formats (e.g., OBJ and FBX) for immersive visualization in platforms such as Blender and Unity. A case study in Newcastle, Australia demonstrates the tool's effectiveness in replicating fire behavior using high-resolution LiDAR data. The remainder of this paper reviews existing 3D fire spread simulation approaches, highlights current limitations, and outlines the motivation for our work. We then describe the proposed methodology and present results from the case study.

2. Literature Review

This section reviews existing research on fire propagation simulation from multiple perspectives. We examine current fire spread simulation tools that model propagation in both 2D and 3D, and highlight recent advances in computational technologies with the potential to accelerate large-scale fire modeling.

2.1 Fire Simulation Tools and Software

Over the past few decades, a wide range of fire simulation tools have been developed to support wildfire prediction and real-time response. These tools vary significantly in dimensional fidelity, modeling approaches, and integration with geospatial datasets. In this review, we categorize existing fire spread simulators based on their ability to model fire propagation in 2 or 3D, with particular emphasis on tools capable of 3D simulation in complex urban environments. Commonly used 2D fire simulation tools and frameworks include *SPARK* and *Amicus*, developed by Australia's CSIRO (Sullivan et al., 2013, Miller et al., 2015); *FARSITE* and *BehavePlus* from the USDA Forest Service (Finney, 1998, Andrews et al., 2005); *Prometheus* from the Canadian Forest Service (Tymstra et al., 2010); and *WUI-NITY*, developed at Imperial College London (Wahlqvist et al., 2021). Many of these tools are integrated with GIS platforms and are actively used by fire management agencies worldwide to simulate wildfire spread across large 2D landscapes, supporting firefighting, rescue operations, and evacuation planning.

In 3D space, advanced fire simulation systems such as *WFDS*, *FIRETEC*, *WRF-Fire*, and *QUIC-Fire* (Mell et al., 2013, Linn et al., 2020) offer robust capabilities for modeling both horizontal and vertical fire spread—critical for capturing dynamics like crown fires and flame propagation along multi-story structures in WUI zones (Ghaderi et al., 2020, Robinson, 2023). Despite their value, key limitations remain. Legacy tools like *FARSITE* are limited to 2D fire spread modeling, offering only simplified vertical representations focused on surface fire behavior (Ghaderi et al., 2020). Some 3D simulators support visualization in 3D space but simulate fire dynamics using 2D or 2.5D GIS data, reducing fidelity at fine scales—especially in urban settings with complex street and structure layouts (Moreno et al., 2010, Yun et al., 2011). Most advanced simulators rely on computational fluid dynamics (CFD) to model fire behavior under varying wind, fuel, and terrain conditions. While *WRF-Fire* and *QUIC-Fire* support fully coupled atmosphere–fire interactions, *WFDS* provides only limited coupling. *PyroSim* + *FDS*, though effective for structural fire modeling, lacks atmospheric integration and scalability for WUI scenarios (Robinson, 2023). In terms of geospatial inputs, *FARSITE* and *WRF-Fire* often use coarse-resolution data, such as 30-meter topographic maps and 111-meter atmospheric grids (Shamsaei et al., 2023), whereas newer tools like *WFDS* and *QUIC-Fire* can incorporate sub-meter LiDAR data, allowing detailed modeling of urban fuel structures and ember transport (Coen et al., 2024, Robinson, 2023). Notably, *QUIC-Fire* employs a LiDAR-based framework to simulate fire spread in heterogeneous urban environments using real 3D building data. Open-source access also differentiates these tools: WFDS and WRF-Fire are freely available and government-supported, while FIRETEC and *QUIC-Fire* typically require formal collaboration or permission for use (Moody et al., 2023, Robinson, 2023).

Most wildfire simulation tools are compiled, GUI-based applications that limit accessibility, extensibility, and integration with other platforms. Their lack of scripting support has driven growing demand for more flexible, programmable alternatives. Lightweight tools such as *simfire*, developed in Python, offer improved usability and automation, enabling batch simulations and integration with smart city systems and IoT-enabled fire detection networks (MITRE Fireline Initiative, 2022). However, these tools are restricted to 2D modeling and lack the scientific rigor to capture complex 3D fire dynamics—such as crown fires, ember lofting, and flame spread in multi-story structures—which are critical for accurate WUI fire modeling.

Together, these tools reflect an evolving landscape that prioritizes high-resolution, 3D-capable systems integrating GIS and atmospheric data to meet the complex demands of modern fire management. Nonetheless, several key limitations remain:

Resolution Constraints: Many 3D simulators still rely on coarse-resolution inputs (10–30 meters) and lack support for high-resolution urban geometries (Shamsaei et al., 2023), limiting their precision in modeling fire behavior at the street and building scale in urban environments (Xu et al., 2025).

Limited Interoperability and Modularity: Proprietary, GUI-centric designs restrict the integration of wildfire simulators with urban digital twins, decision support systems, broader urban and environmental simulation frameworks, and IoT ecosystems—including sensors, smartphones, and augmented reality (AR) tools.

Computational Challenges: Simulating large-scale urban fires using high-resolution 3D data demands significant computational resources. While tools like *simfire* offer modularity, they often lack parallelization or High-Performance Computing (HPC) support, resulting in performance bottlenecks in complex urban environments.

Given these limitations, there is a clear need for a flexible and efficient 3D fire propagation framework that leverages widely adopted scientific programming languages and HPC capabilities. To ensure broad applicability, the system should be modular, deployable as libraries or packages, and accessible via well-defined programming interfaces. Such a design would enable seamless integration with other scientific applications—including urban digital twins, 3D modeling platforms, and game engines —for use cases ranging from wildfire simulation and visualization to serious gaming and decision support.

2.2 Parallel Programming for High-Fidelity Simulation

Building a flexible 3D fire propagation framework that leverages high-resolution real-world data for large-scale urban simulations presents substantial computational challenges. Fine spatial granularity—particularly when using LiDAR-derived inputs —and complex fire–atmosphere interactions can quickly exceed the limits of traditional serial processing. To address these challenges, we review parallel computing frameworks commonly used in scientific computing to identify suitable technologies for scalable wildfire modeling.

In the Python ecosystem, *Taichi* and *Numba* provide *JIT*- compiled, high-performance numerical kernels with support for multithreading and GPU acceleration (Hu et al., 2019, Lam et al., 2015). *Ray* and *Dask* enable distributed computing across multicore systems and clusters, making them well-suited for large-scale simulations and batch processing workloads (Karau and Kimmins, 2023). For differentiable programming and vectorized parallelism, *JAX* and *PyTorch* offer GPU-accelerated computation and are increasingly adopted in hybrid modeling workflows (Sapunov, 2024). At a lower level, *Kokkos* provides an abstraction layer for parallelism in C++, supporting both CPUs and GPUs through backends such as *OpenMP* and *CUDA* (Incardona et al., 2023). In Julia, built-in support for threading, SIMD, and GPU computing makes it a performant and expressive alternative for developing high-efficiency simulation code (Besard et al., 2018).

These computing frameworks collectively provide a robust foundation for building a scalable, modular 3D fire simulation engine capable of meeting the real-time computational demands of wildfire modeling in complex WUI environments.

3. Methodology

We begin by outlining the study's motivation, target users, intended use cases, and core design requirements. Next, we present the simulator's conceptual architecture, detailing its scientific foundations and key geospatial inputs for 3D fire modeling in WUI environments. Finally, we describe the implementation, highlighting the use of advanced computing techniques to support time-critical emergency response.

3.1 Design Requirements

This study aims to develop a lightweight 3D fire simulator using widely adopted scientific computing techniques and programming languages, tailored for modeling fire propagation in WUI zones across Australia. The simulator is designed to support two primary user groups: (1) fire and rescue (F&R) teams conducting preventative hazard reduction burns in urban-adjacent areas, and (2) fire and rescue services (FRS) managing rural and large-scale bushfires. The tool is intended for both preparedness and real-time response, enabling simulation of fire behavior across complex urban and natural terrains. These users will benefit from mobile-accessible, high-resolution 3D modeling to inform operational decision-making, risk mitigation, and resource allocation. The simulator aligns with recent initiatives in Australia to improve bushfire management, including satellite-based evacuation messaging (Barton et al., 2024) and voxel-based fuel estimation using LiDAR data (Barton et al., 2020). These use cases define the core design requirements of the proposed simulation framework, summarized as follows:

3D Fire Spread Simulation: The tool must support fire spread modeling in both vertical and horizontal dimensions to capture realistic fire dynamics.

Flexibility and Efficiency: The framework must be lightweight, efficient, and capable of running across various computing environments, including mobile and HPC platforms.

High-Fidelity Geospatial Input: It should utilize accurate 3D geospatial data sources such as LiDAR, 3D GIS models, BIM, which have to be integrated in a uniform voxel-based representation to enhance simulation precision.

Modular and Deployable Architecture: The framework should adopt a modular design, allowing components to be reused, extended, or replaced for specific applications, and be deployable as reusable libraries or packages to enable seamless integration into broader workflows.

System Extendibility: The simulator should support integration with external systems—including urban digital twins, 3D modeling platforms, game engines, and environmental simulation tools—through standardized APIs and data exchange interfaces.

Scientific Language Compatibility: It should be implemented using commonly adopted programming languages (e.g., C++ and Python) to ensure ease of development, maintenance, and community adoption.

Based on these design requirements, we developed a Python-based framework that integrates high-performance parallel computing and supports high-resolution LiDAR data, enabling scalable simulations for wildfire visualization, serious gaming, decision support, and emergency planning.

3.2 Overall Framework Design

We developed a voxel-based modeling framework to simulate inter-voxel mass and energy transfer, forming the computational backbone for 3D wildfire behavior modeling—particularly in WUI environments where vertical interactions between vegetation and infrastructure are critical. The propagation model combines physical and empirical methods, building on established 2D simulators such as SPARK. To extend these capabilities into three dimensions, we integrated a crown fire module that captures vertical fire spread through canopies and multi-story structures, enabling realistic simulation of complex urban and peri-urban wildfire scenarios (Rothermel, 1972). Figure 1 illustrates the simulator's architecture, comprising four main components: (T1) Voxel Characterization, (T2) Inter-voxel Fire Spread Simulation, and (T3) Fire Propagation Visualization. At a conceptual level, fire spread is modeled as heat transfer across a voxel grid using 18-directional spatial connectivity.

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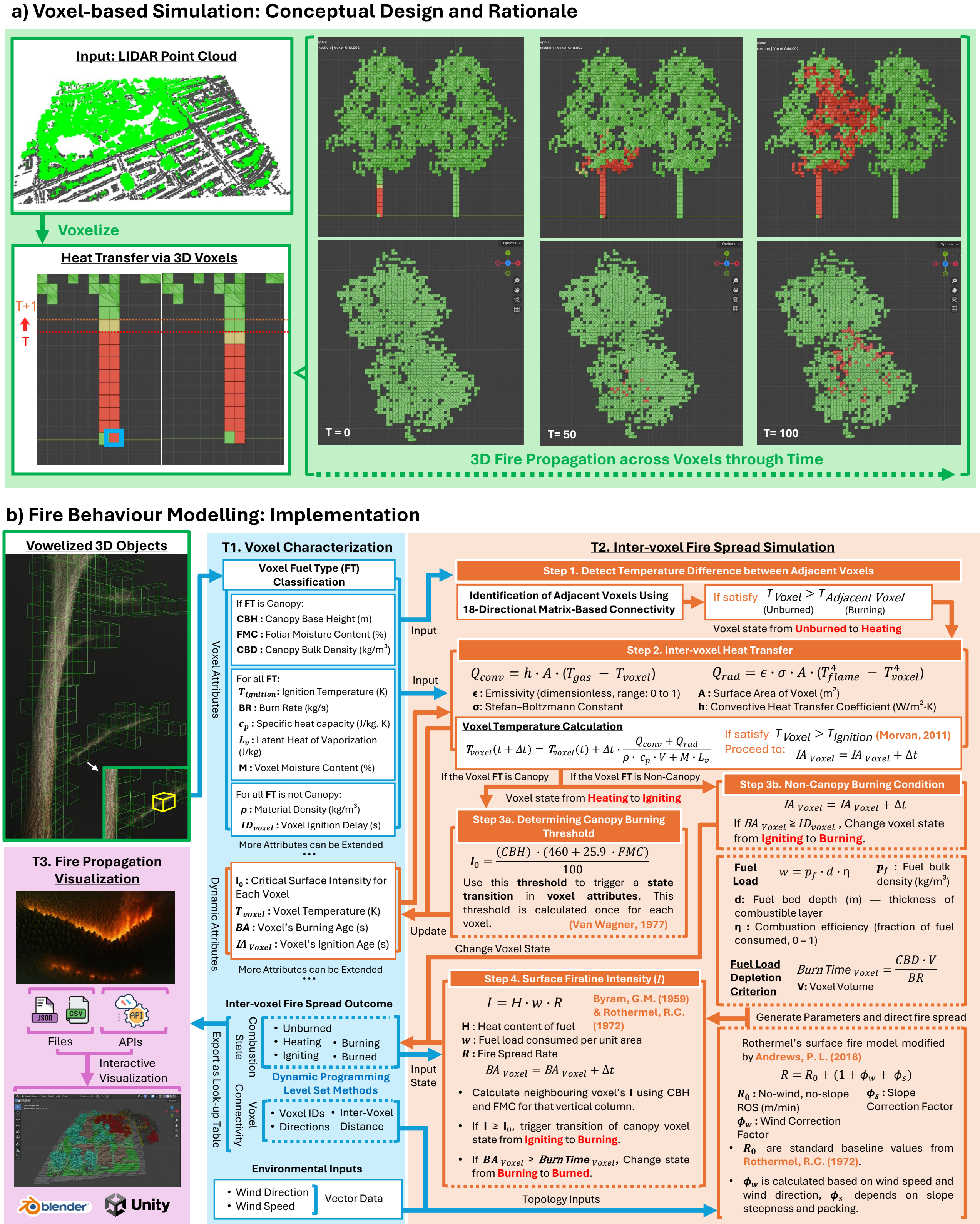

Figure 1. Overview of the simulator design, illustrating: (a) the rationale behind voxel-based fire simulation, and (b) the implementation of fire behavior modeling using a hybrid physical–empirical approach.

Voxelization transforms high-resolution point clouds—collected from low-altitude flights or UAVs via LiDAR or photogrammetry—into a 3D voxel grid representing buildings, infrastructure, and vegetation in WUI areas. To construct a voxel-based model, various data sources can be used, including LiDAR, imagery, video, existing 3D models, and building information modeling (BIM) data. For real-time bushfire response, LiDAR point clouds are considered the most suitable for capturing the current state of vegetation. These data can be further processed to estimate fuel type and fuel load (Barton et al., 2020). The resulting voxel grid preserves spatial density and topological connectivity, forming the foundation for simulating heat transfer and combustion dynamics.

3.2.1 T1. Voxel Characterization Following voxelization, each voxel is assigned material and environmental properties that influence its ignition and combustion behavior. Using GIS-linked datasets, voxels are classified by fuel type into two categories: ”canopy” and ”non-canopy.” Environmental variables such as wind, temperature, and moisture are incorporated to capture dynamic fire behavior. Each voxel is associated with a standardized set of parameters based on its classification. For canopy voxels, key parameters include canopy base height (CBH), canopy bulk density (CBD), and fuel moisture content (FMC). For non-canopy voxels, relevant parameters include ignition temperature (T_ignition), fuel load (p_f), material density (rho), fuel bed depth (d), combustion efficiency (eta), specific heat capacity (c), and burn rate. Many of these values are derived from LiDAR point density to capture spatial variability in fuel distribution. To ensure interoperability, our schema aligns with the SPARK model and the Amicus Fire Database, enabling integration with existing wildfire modeling workflows.

3.2.2 T2. Inter-voxel Fire Spread Simulation This module simulates fire propagation by updating each voxel's combustion state—*Unburned, Heating, Igniting, Burning*, or *Burned* —based on thermal gradients, heat transfer mechanisms, fireline intensity, and physical fuel characteristics. The simulation proceeds in four key steps:

Step 1: Detect temperature differences between adjacent voxels. Neighboring voxels are identified using 18-directional matrix-based connectivity. A voxel transitions from *Unburned* to *Heating* if its temperature is lower than that of an adjacent burning voxel, indicating potential heat influx.

Step 2: Inter-voxel heat transfer. Thermal energy is transferred from adjacent burning voxels through convection and radiation. The voxel's temperature is incrementally updated based on these inputs (Morvan, 2011). Once the temperature exceeds the ignition threshold, the voxel transitions to the *Igniting* state.

Step 3: Ignition and combustion transitions. Voxels are classified as either *canopy* or *non-canopy*, with distinct criteria governing the transition from the *Igniting* to *Burning* state for each category:

Step 3a (Canopy Voxels): A critical fireline intensity threshold is calculated based on canopy base height (CBH) and fuel moisture content (FMC) (Wagner, 1977). If this threshold is exceeded, the voxel transitions to *Burning*.

Step 3b (Non-Canopy Voxels): For non-canopy voxels, ignition depends on whether the burned area exceeds a predefined threshold. Key parameters such as fuel load, bulk density, fuel bed depth, and combustion efficiency determine the rate and duration of burning.

Step 4: Surface fireline intensity and burn completion. Fireline intensity is calculated using established empirical models (Rothermel, 1972, GM, 1959), with the rate of spread adjusted according to wind, slope, and other environmental factors. These estimates are based on equations, coefficients, and empirical parameters derived from prior studies and field observations (Rothermel, 1972, Andrews, 2018). Once a voxel reaches its predefined burn duration, it transitions to the *Burned* state.

This process generates a time-resolved fire spread simulation, with each voxel annotated by its combustion state and corresponding timestamp. Outputs are organized into lookup tables containing voxel IDs, directional spread vectors, and travel distances—enabling seamless integration with real-time planning tools, 3D visualization systems, and decision-support platforms.

3.2.3 T4. Fire Propagation Visualization Simulation outputs from Task T3 are exported as structured lookup tables that record voxel state transitions and attributes at each timestep. Results are saved in standard formats (e.g., CSV, JSON) and can be mapped to 3D voxel objects (e.g., OBJ, FBX). For real-time integration, data can also be streamed via web APIs (e.g., HTTPS, WebSockets) to IoT devices and external simulation platforms, including traffic, flood, urban planning, and air quality models. This interoperability enables seamless visualization in tools such as Blender, Unity, and Unreal Engine, supporting immersive simulations on platforms including holographic tables, VR headsets, and AR interfaces. These visualizations enhance the simulator's utility for decision support, emergency response training, public education, and community engagement.

3.3 Implementation Using Python Parallel Programming

The simulator is implemented in Python and accelerated with the Taichi parallel programming framework to support high-resolution, large-scale 3D wildfire simulations. Combining Python's flexibility with Taichi's performance ensures scalability and portability across desktop, cloud, and edge environments for wildfire analysis and decision support. Taichi enables efficient parallel execution on CPUs and GPUs, allowing voxel-level operations—such as heat transfer and combustion state updates—to run concurrently across the simulation grid. The simulator's modular design, covering voxelization, fuel characterization, fire spread, and visualization, is optimized for parallel processing. Core simulation loops are handled by Taichi, while NumPy supports preprocessing tasks like point cloud voxelization and GIS-based fuel classification.

4. Result and Discussion

We conducted a case study to demonstrate the effectiveness of our voxel-based wildfire propagation framework in capturing complex three-dimensional fire dynamics across diverse WUI environments.

4.1 Study Area

The study area is a residential community along Bayview Street in Newcastle, New South Wales, Australia (Figure 2). The 3D point cloud, sourced from the dataset *Newcastle201-409-LID1-C3-AHD_3746350_56_0002_0002.las*, was collected in September 2014, referenced to the Australian Height Datum (AHD), and projected in UTM Zone 56S. With a typical density of 4–8 points/m^2.

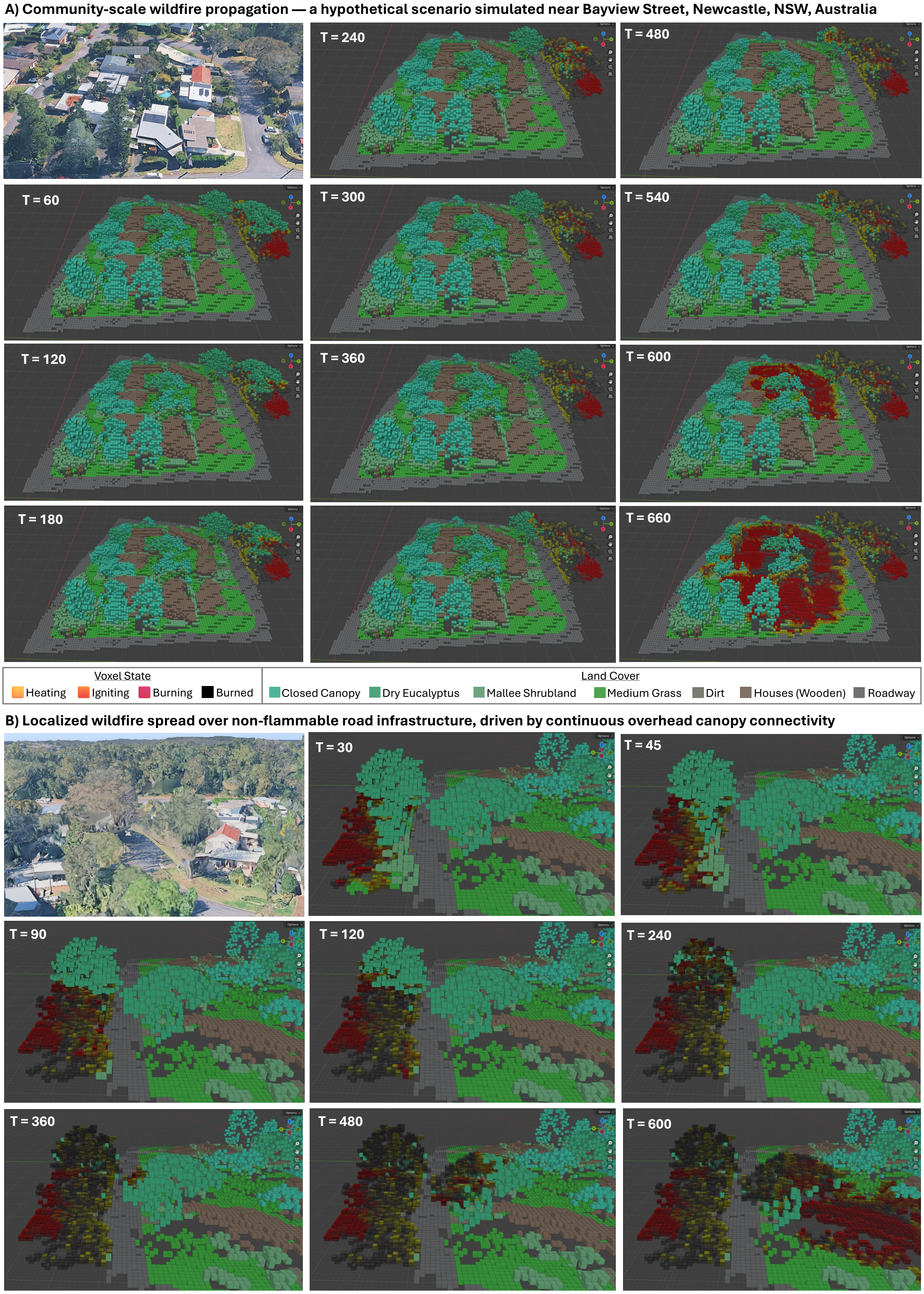

Figure 2. Simulated 3D fire propagation in a hypothetical residential area near Bayview Street, Newcastle, New South Wales, Australia.

The dataset enables detailed terrain reconstruction, vegetation analysis, and urban fire simulation. It is voxelized at a 1-meter resolution into a 130 × 128 × 35 grid, totaling 582,400 voxels. Fuel load properties are assigned based on ALUM land use/land cover data and SPARK fuel classifications, with manual validation conducted via Google Earth Engine.

4.2 Fire Spread Visualization and Interpretation

The simulated scenario is configured with a westward wind at 5 m/s and an environmental temperature of 298.15 K (25°C). The simulation spans 4,500 seconds from ignition. Figure 2A shows a global view of fire progression, with the fire crossing the road at $T = 600$ s and eventually engulfing the residential block. Figure 2B provides a close-up, illustrating how fire traverses non-burnable road surfaces via continuous tree canopy, reaching an otherwise isolated community as early as $T = 90$ s and $T = 120$ s. The simulation is visualized in a 3D environment, highlighting critical fire spread pathways, including breaches across firebreaks such as roads. These insights can inform emergency strategies, such as pruning overhead canopy or applying fire retardants to protect defensible zones. The simulation, spanning 16,640 m^2 with 582,400 voxels over 4,500 seconds, was completed in 92.4 seconds, including a 5.4-second compilation time.

4.3 Limitations and Future Work

While the simulator effectively models wildfire spread using a hybrid physical–empirical approach, its parameterization and underlying fire dynamics require further refinement. The current model has not yet been validated against real wildfire observations, and several parameters remain uncalibrated. Future work will focus on validating the model with real fire datasets and controlled burn experiments, as well as conducting a systematic performance comparison with other 3D wildfire propagation models. We also aim to incorporate generative AI methods to accelerate prediction and support scaling to larger spatial domains without compromising fidelity.

5. Conclusion

In this study, we presented a voxel-based 3D wildfire simulation framework designed to model the complex dynamics of fire behavior in WUI environments. The simulator integrates high-resolution voxel grids, environmental data, and a hybrid physical–empirical fire spread model, providing a scalable and adaptable platform for simulating wildfire propagation and inter-voxel mass and energy transfer. Implemented using the Python-based Taichi parallel computing framework, the system delivers high computational performance while maintaining the flexibility required for diverse modeling tasks. The framework functions not only as a wildfire simulation engine but also as a scientific computing tool capable of real-time data integration, fire spread simulation, and immersive 3D visualization—making it a valuable asset for decision support, emergency response, urban planning, and educational applications.

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