High-Resolution Urban Fire-Risk Mapping Using Low Altitude Drone Images

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Abstract

Wildfires are an escalating threat in the United States, posing increasing risks to lives, property, ecosystems, and critical infrastructure. One important challenge in wildfire science is estimating fuel mass, as the quantity and spatial distribution of available fuel play a fundamental role in fire spread and in the generation of fire-risk maps. Existing solutions commonly rely on satellite-derived vegetation solutions and standard fuel datasets such as LANDFIRE.

Although these tools are useful for regional and landscape-scale analysis, their spatial resolution is often too coarse to resolve the fine-scale heterogeneity that determines local risk, particularly in Wildland–Urban Interface areas where vegetation, terrain, and structures interact in complex ways. Here, we present a drone-based machine learning framework for fuel-mass estimation and mapping. Our goal is to enable more precise and geospatially consistent characterization of wildfire hazards, with the long-term aim of improving prevention, preparedness, and risk-informed decision-making in vulnerable communities.

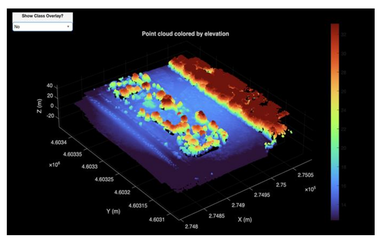
Problem Formulation and Challenges

- Limited spatial resolution of existing fire models & difficulty capturing micro-scale fuel variability
- Sparse availability of labeled aerial datasets for segmentation
- Mapping semantic classes → physically meaningful fuel models (FBFM40)
- Integrating: (i) 2D segmentation outputs, 3D terrain (point cloud / DEM), and Environmental factors (wind, slope)
- Computational cost of high-resolution fire simulation
- Ensuring realistic fire behavior (avoiding over-spread / instability)

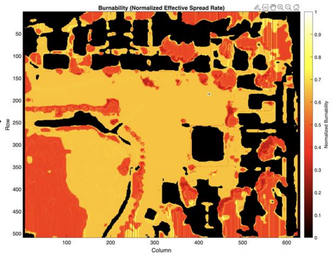
Proposed Solution

Flight Path
QGround Control is used to plan and automate Anafi 4K drone flights.

Point Cloud Colored by Elevation
The Orthophoto & point cloud are used to determine the Scott Burgan Fuel Assignment

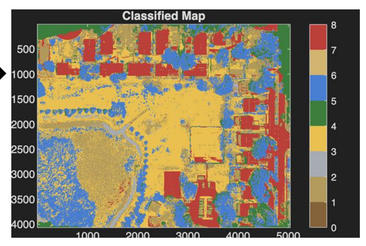


Effective Spread Rate
Effective Spread Rate calculated using the fuel assignment & point cloud density.

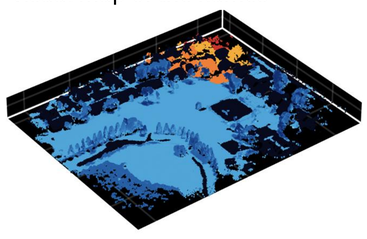


3D Geospatial Map
WebODM generates the orthophoto and point cloud.

Map of Pixels Classified by OpenEarthMap Class
The MLM is used to identify OpenEarthMap classes.

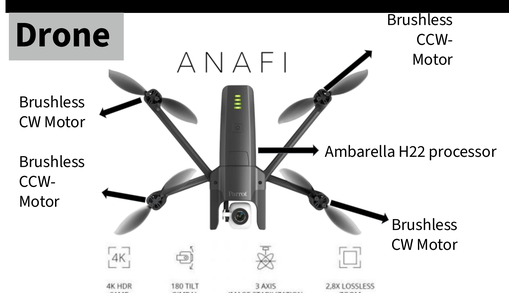


Fire Spread Visualization
Effective Spread Rate values are used to create a visual map of the flames

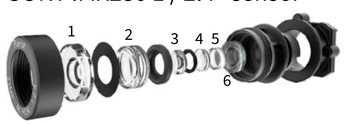


Results

Drone

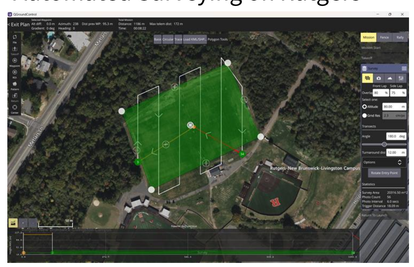


Optical Unit
SONY IMX230 1 / 2.4” sensor



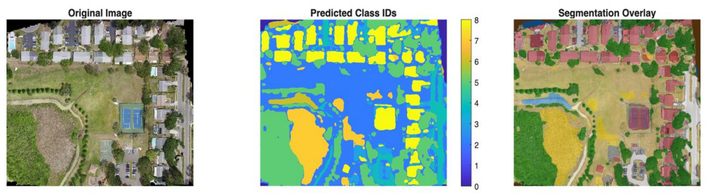
- Low dispersion aspheric lens architecture
- 6 lenses to minimize parasitic light
- HDR: 4K UHD video. Wide: 21MP (5344x4016) / 4:3 / 84° HFOV

QGroundControl
Automated Surveying on Rutgers

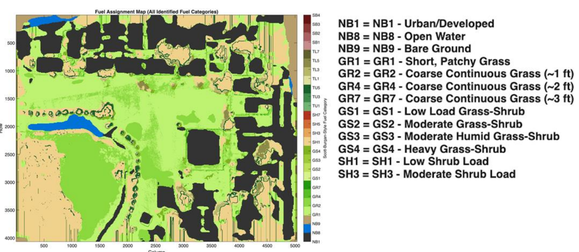


Machine Learning Model

- MLM used to identify OpenEarthMap classes
- DeepLab v3+ with ResNet 50 used for feature extraction.
- We used prelabeled public datasets & manually labeled ones



- Segmented orthophoto is divided into a uniform grid
- Point cloud is used to estimate vegetation density and
- to assign fuel categories to each grid cell.



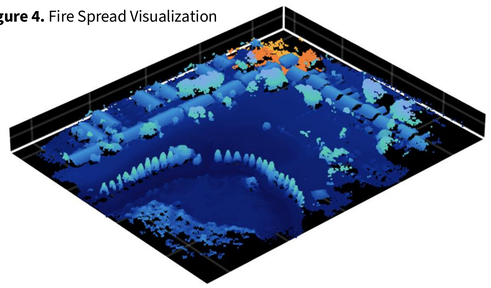
Fire Spread Map

XIII. Effective Spread Rate

$$R = R_0 \cdot \phi_{\text{wind}} \cdot \phi_{\text{slope}}$$

Spread rate is calculated where R_0 is the fuel initial spread rate, ϕwind speed and angle are given by the user, and ϕslope is derived from point cloud elevations

Figure 4. Fire Spread Visualization

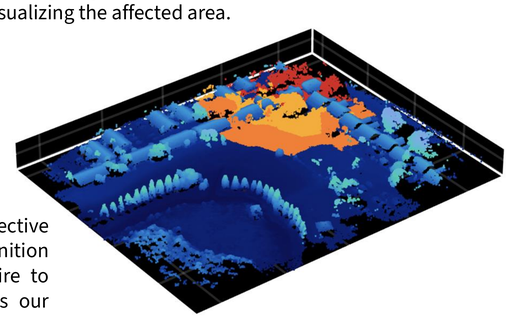


XIV. Fire Propagation

$$T_{\text{new}} = T_{\text{current}} + \frac{L}{R}$$

Propagation is calculated with R being the effective spread rate, L being the distance from the ignition point, and T_{current} being the Time for the fire to potentially spread to that cell. This creates our visual.

In **Figure 4.** the 3D fire spread map shows the progression of the flame from a designated ignition point, giving an estimated spread time as well as visualizing the affected area.



Future Direction

- Enhance model realism and accuracy by integrating real-time environmental data, and thermal imagery.
- Improve robustness and scalability through expanded, diverse training datasets and optimization for real-time onboard UAV deployment.
- Strengthen decision support for emergency response by coupling fire-spread predictions with evacuation mapping and actionable risk outputs.

References

[1] J. Wang, Z. Zheng, A. Ma, X. Lu, and Y. Zhong, “LoveDA: A Remote Sensing Land-Cover Dataset for Domain Adaptive Semantic Segmentation,” in Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks (NeurIPS Datasets and Benchmarks), 2021.

[2] J. Xia, N. Yokoya, B. Adriano, and C. Broni-Bediako, “OpenEarthMap: A Benchmark Dataset for Global High-Resolution Land Cover Mapping,” in Proc. IEEE/CVF Winter Conf. Appl. Comput. Vis. (WACV), 2023, pp. 6254–6264.