SMAC-FIRE: Closed-Loop Sensing, Modeling and Communications for WildFIRE

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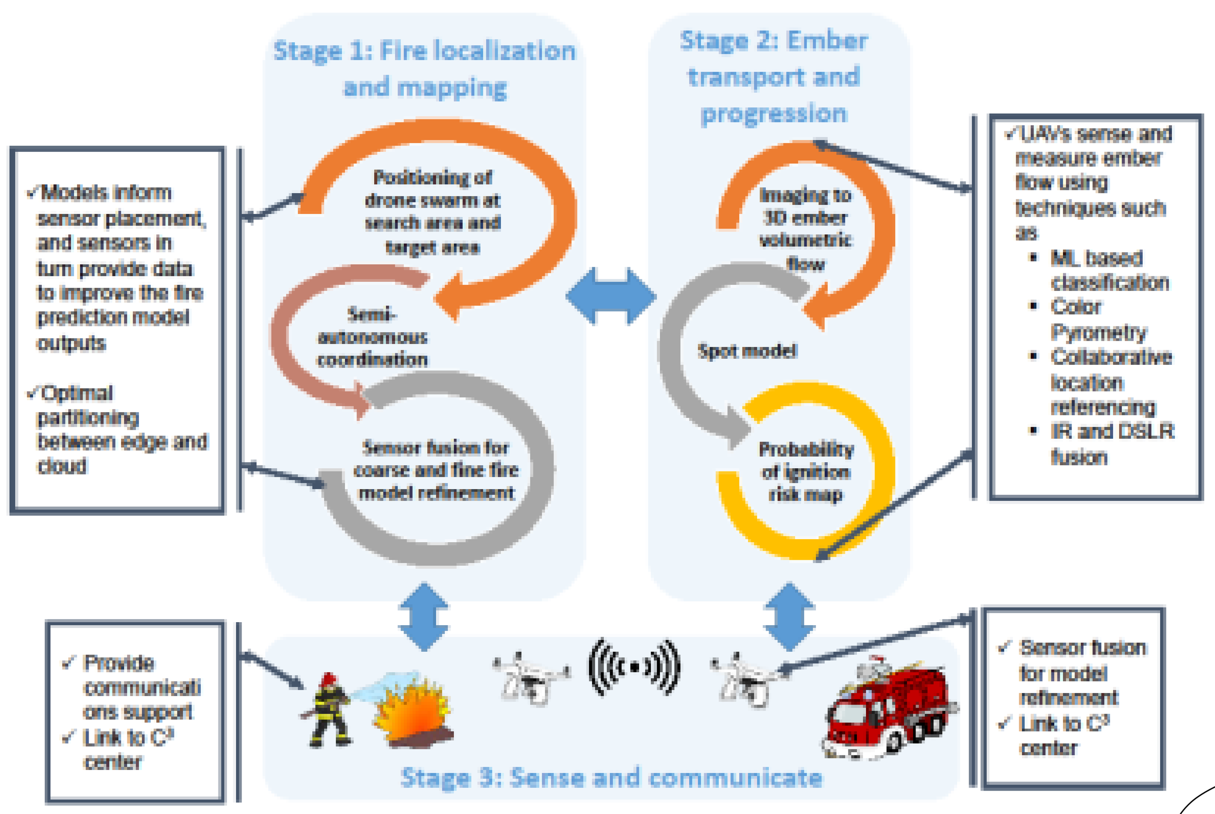
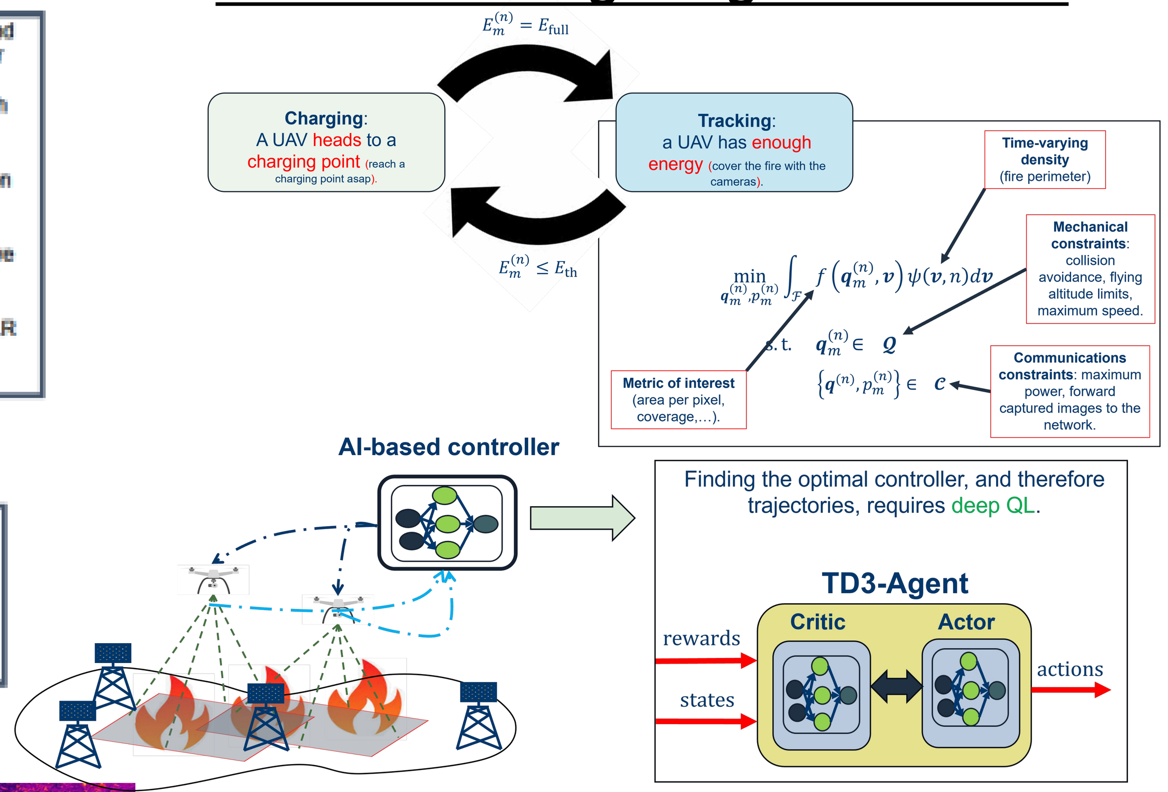
Challenge: Integrate UAVs, sensors, wildfire models, communications infrastructure for:
Solutions: Current fire models & communication needs $\Rightarrow$ sensor deployment, closed-loop UAV path planning.
UAV/sensor data (hot-spot localization, ember tracking, perimeter monitoring, etc) $\Rightarrow$ fire model updates.



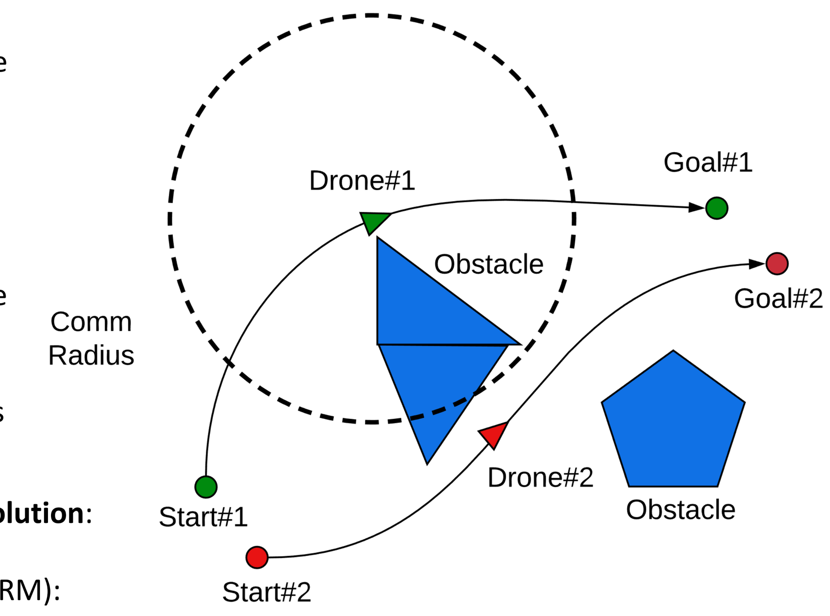
A Reinforcement Learning Approach for Wildfire Tracking using UAV Swarms



Path Planning in Wildland Burn Environments

For a specified target position and orientation of the UAS, the objective is to compute the shortest trajectory subject to:

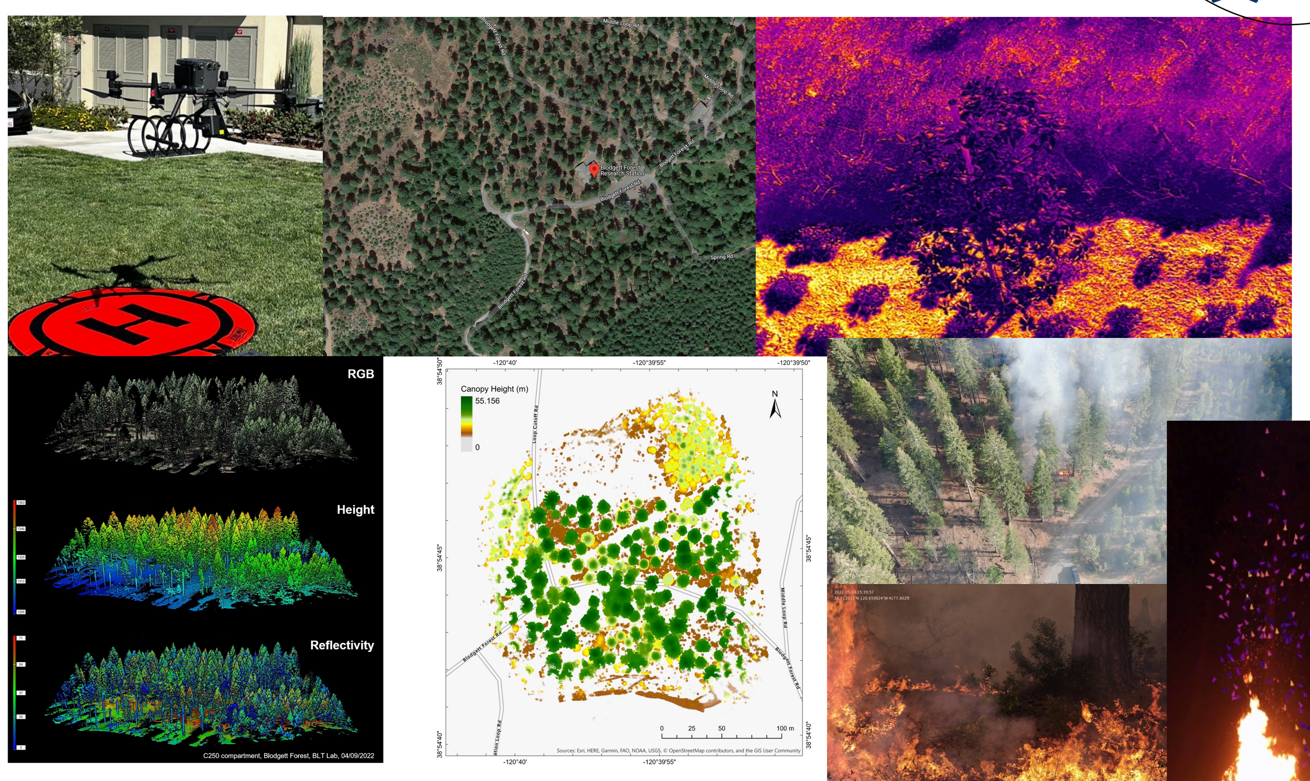
- Dynamics
- Actuator Constraints
- Safety Constraints (Obstacle Avoidance)
- Path Dependent Communication Constraints



Two-Phase Global Optimal Control Solution:

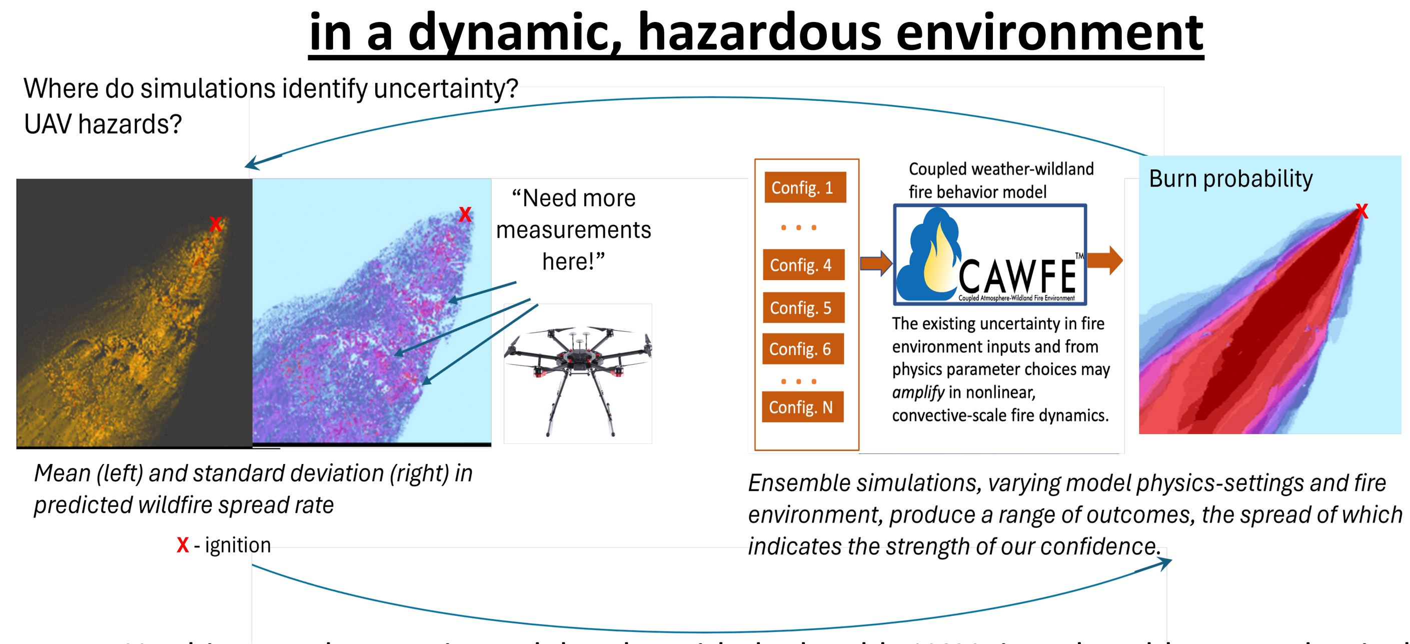
Construct a Probabilistic Road Map (PRM):
- Sample nodes across state space.
- Connect nodes via solving the optimal energy control problem tailored for the stated dynamics.

Determine Global Trajectory:
- Apply path-dependent communication constraints.
- Utilize combinatorial optimization on PRM.



Blodgett Research Station Summer 2022 Measurements:
- UC Research Center in Sierra Nevada Mts.
- Flew quad-copter drone during controlled burns
- Collected data with thermal IR (hotspots), multispectral camera (fuel types & mapping), LiDAR (3D forest canopy)
- Issues: Visibility due to forest canopy, calibration/alignment of multiple LiDAR cameras
- pile burn data used for particle image velocimetry on embers
- ember tracking: one key to longer range fire spread
- characterized ember size, shape & density from real fuels
- identified shortcomings of **ember generation & lofting models**

Directing observations: Modeling a complex phenomena in a dynamic, hazardous environment

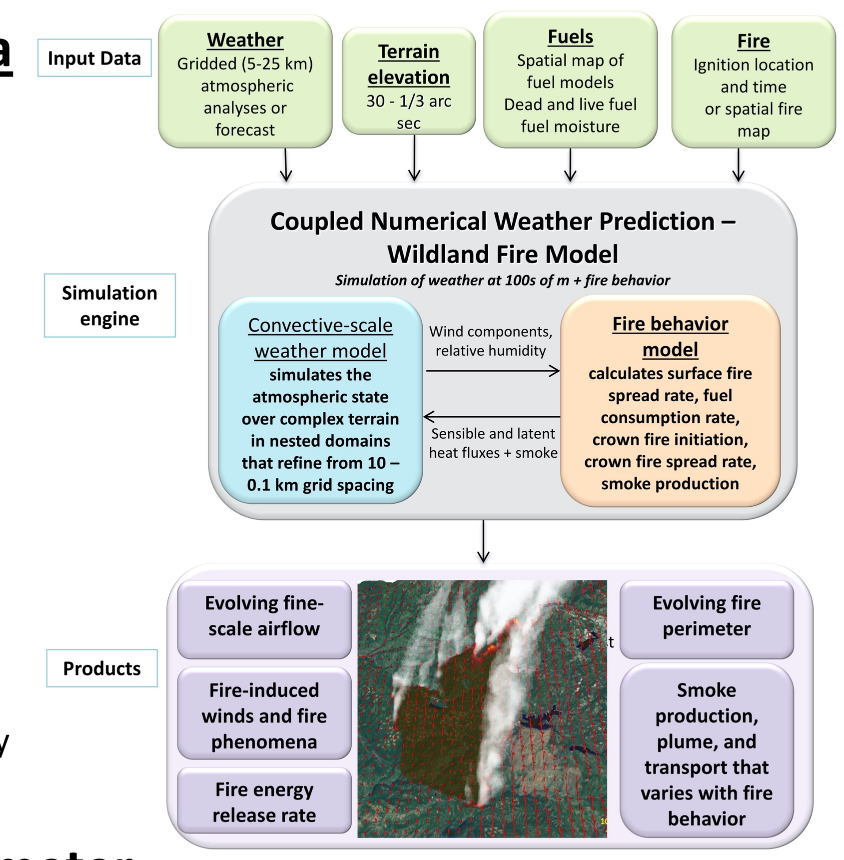


Mean (left) and standard deviation (right) in predicted wildfire spread rate

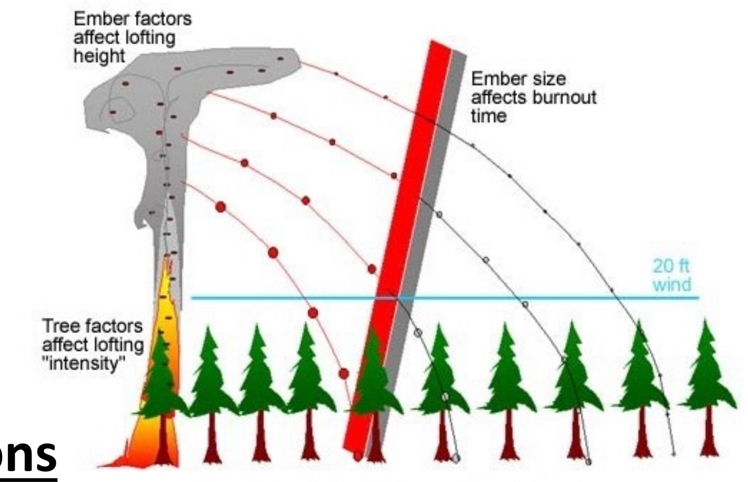
Ensemble simulations, varying model physics-settings and fire environment, produce a range of outcomes, the spread of which indicates the strength of our confidence.

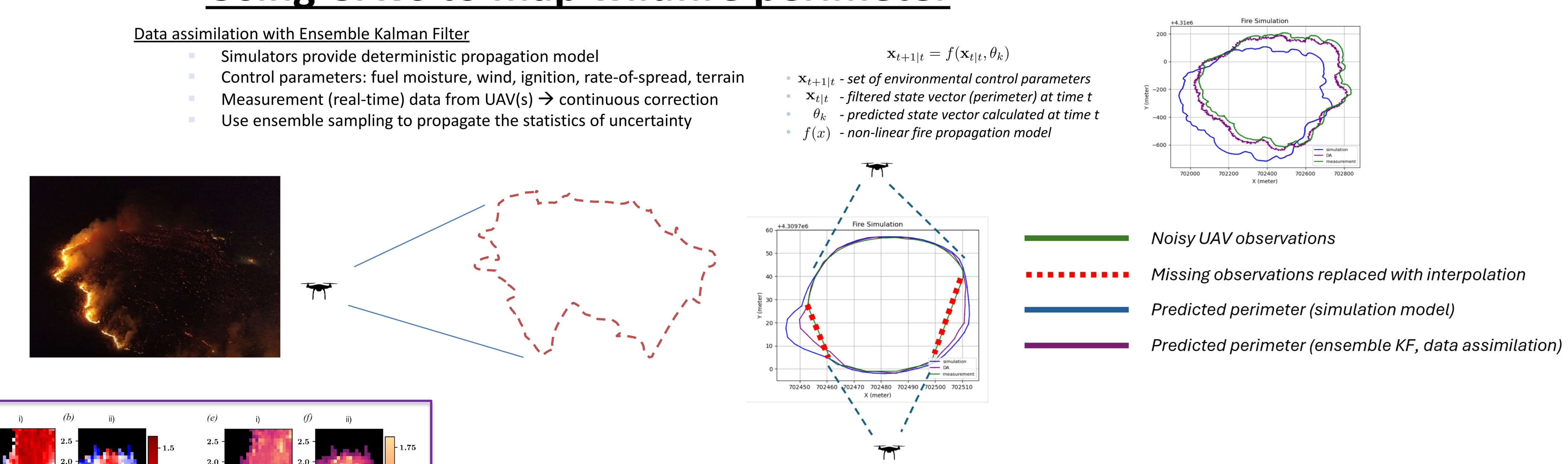
Use hi-res and strategic model scales with deployable UAVs in a closed-loop to adaptively enhance model fidelity *where needed*

CAWFE® Modeling System

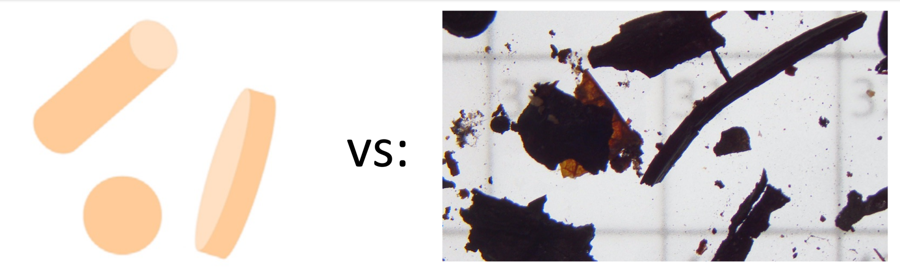


Using UAVs to map wildfire perimeter

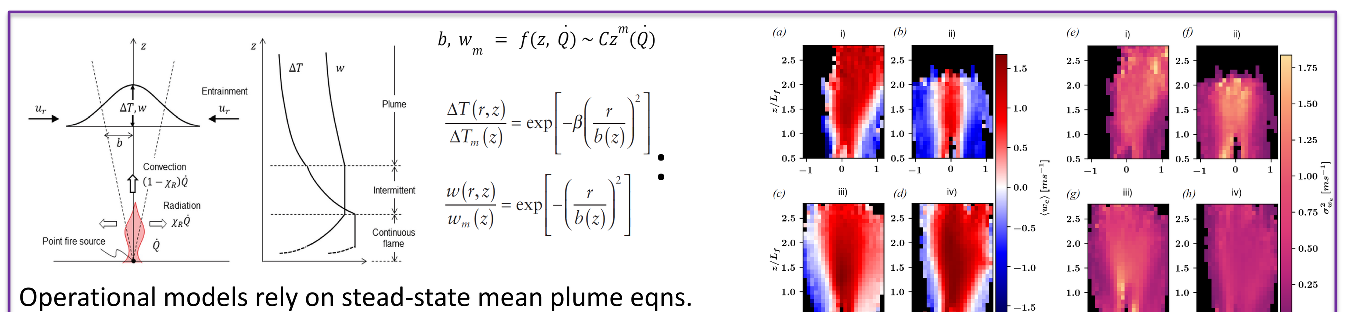




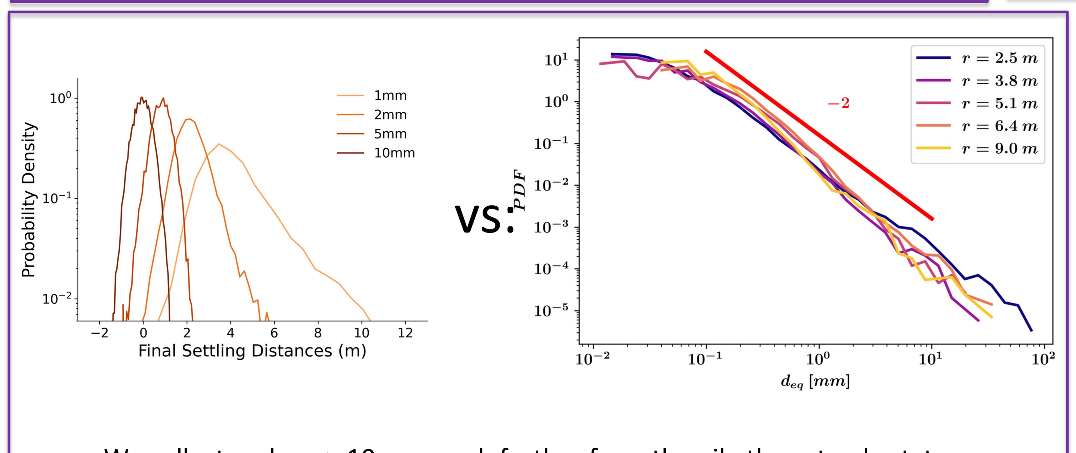
Operational Firebrand Models vs. Observations



Larger embers display a greater variation in shape
Large embers resemble irregular polygons with added noise
Ember shape models could incorporate a mixture of spheres, disks and cylinders

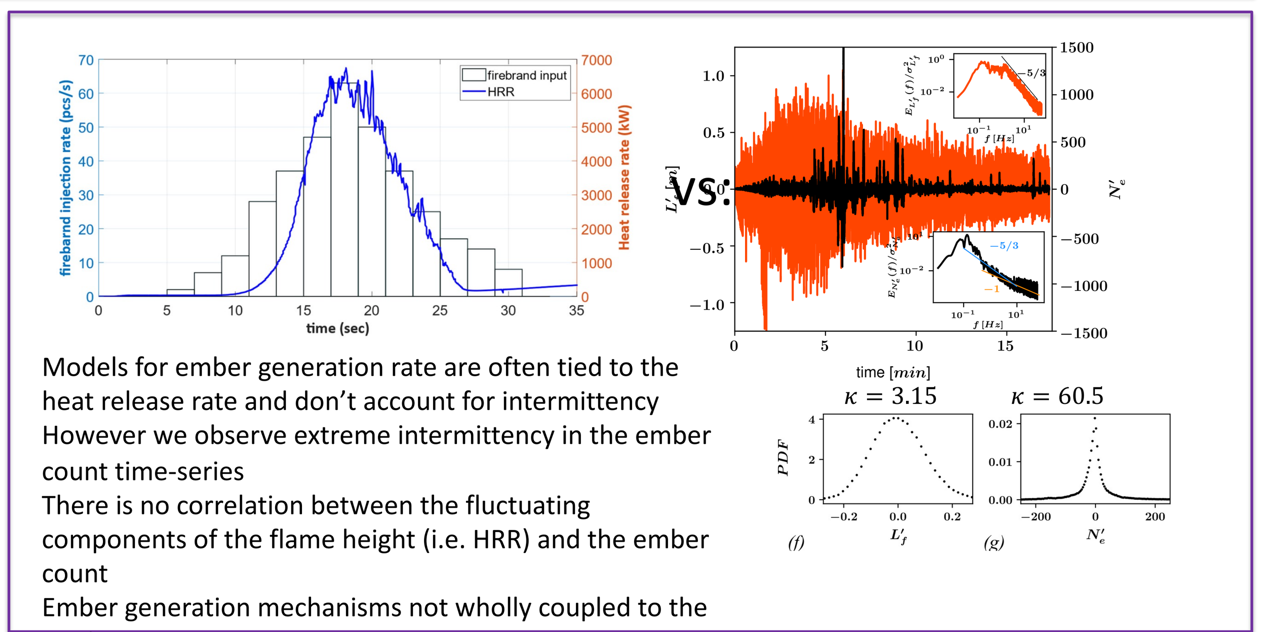


Operational models rely on stead-state mean plume eqns.
We measure high intermittency in ember velocities, especially early in the fire—turbulence and plume time-dependence is important



We collect embers > 10mm much further from the pile than steady-state models might suggest

Using such models seem to drastically underpredict lofting height and settling distance for > 1 mm embers



Models for ember generation rate are often tied to the heat release rate and don't account for intermittency
However we observe extreme intermittency in the ember count time-series
There is no correlation between the fluctuating components of the flame height (i.e. HRR) and the ember count
Ember generation mechanisms not wholly coupled to the fire/turbulence

Broader Impacts:
- CPS tools developed here can support disaster management for other applications in remote, harsh environments
- Wildfire management & incident response is a huge problem in the western U.S., better communication connectivity and more accurate fire prediction models can save hundreds of lives and millions of $$ in property damage
- K-12 "Game of Drones" activity

Outreach Activities:
- Boulder County Firefighter refresher course
- Orange County Firefighter Association drone training

Future Directions: Autonomous coordination of multiple drones, maintaining connectivity, handling large data volumes, real-time data flow to command center
Optimizing UAV trajectory, power allocation, and sensing while keeping communication interference at bay and minimizing energy consumption
What is the best mechanism for using UAV/sensor data to inform fire behavior model?
Parsing the large data sets is a challenge, as is calibration especially for optical (LiDAR) cameras
Ember generation & flow model must be incorporated into fire behavior models
Localized measurement of wind speed and direction is important for fire prediction, how to do this over a large area with few drones?

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