Unraveling Fire and Plume Behaviors: A Multiscale Image Approach

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Daryn Sagel (dsagel@fsu.edu) & Bryan Quaife

Geophysical Fluid Dynamics Institute & Department of Scientific Computing at Florida State University

LI & Posters

Abstract

Understanding the variety of structures and behaviors that occur during fire spread and plume evolution is crucial. We explore fire spread and plume evolution by analyzing data across **diverse spatial and temporal scales** in **natural settings**, capturing interactions among **fire**, **plume**, **forest canopy**, and **atmosphere**. Our approach integrates **computer vision** and **graph theory** to track these dynamics from **visual** and **infrared** data obtained with ground-based instruments, unmanned aerial vehicles (UAVs), or satellites. Calculations that quantify **heat transport**, **fire spread**, **turbulent statistics**, and **near-field plume structures** contribute to our understanding of fire and plume behavior. A **statistical analysis** reveals patterns underlying fire and plume dynamics, energy transport, and fire-atmosphere coupling.

Methodology

- Images are **segmented** to isolate the **fire** and **plume**
  - **Visual** images are segmented using **hybrid RGB-HSV thresholding**
  - **Infrared** images are segmented using **temperature-based thresholding**
- An **α-shape boundary** is calculated around each region of interest
- **Boundaries** are **tracked** between **successive timesteps**, yielding **spread velocities** and **statistics** for the fire and plume

Optional Pre-Processing

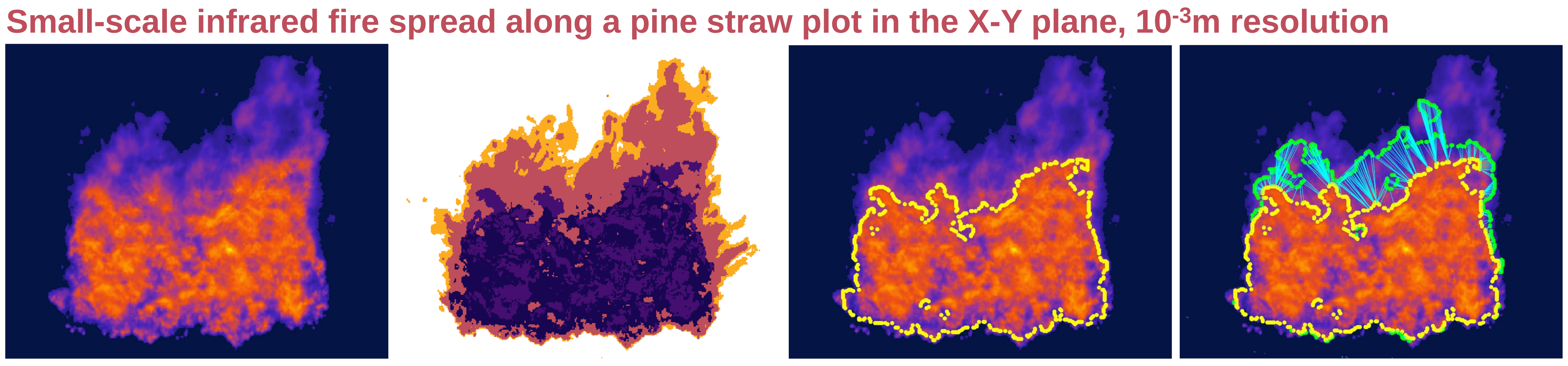
- Data collected from a UAV or other **non-stationary framework** undergo **stabilization**
- **Image inpainting** modifies individual images to generate a **spatially continuous dataset**

Sample Data & Results

The images below demonstrate how our methodology is applied to visual and infrared videos of fires and plumes at various spatial scales. Each row represents a different dataset and is arranged as follows:

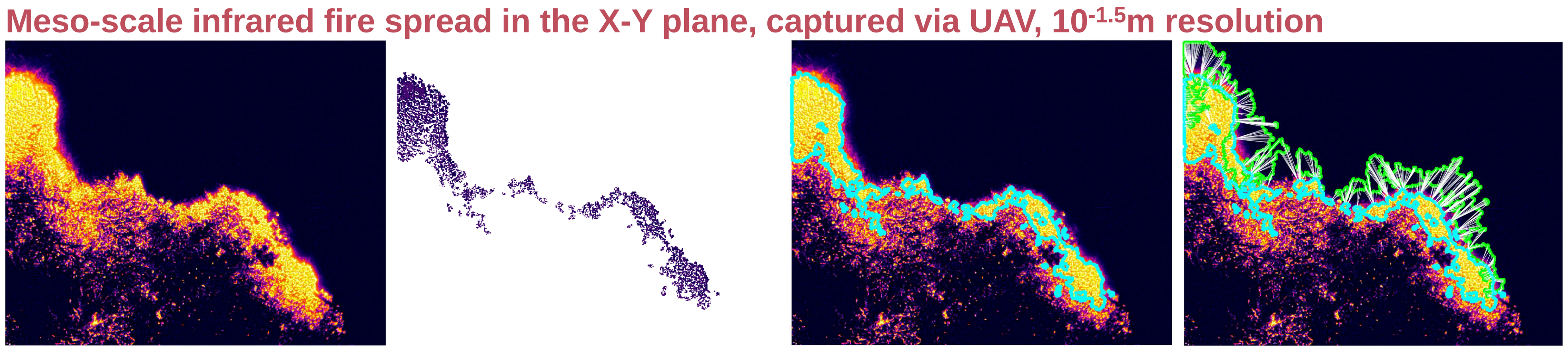
Original Image → Segmentation Mask → Resulting Boundary → Visualization of Matching with Subsequent Boundary

Small-scale infrared fire spread along a pine straw plot in the X-Y plane, 10^{-3}m resolution

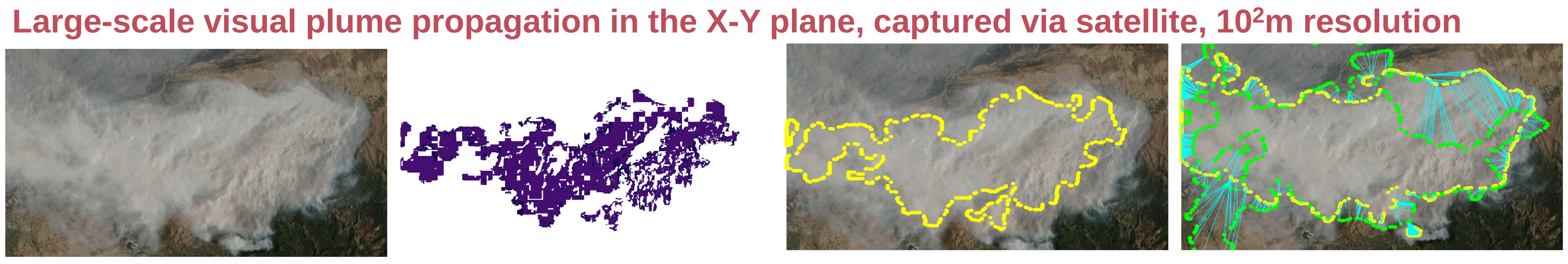


Meso-scale visual plume propagation in the X-Z plane, 10^{-2}m resolution

Meso-scale infrared fire spread in the X-Y plane, captured via UAV, $10^{-1.5}$m resolution



Large-scale visual plume propagation in the X-Y plane, captured via satellite, 10^{2}m resolution

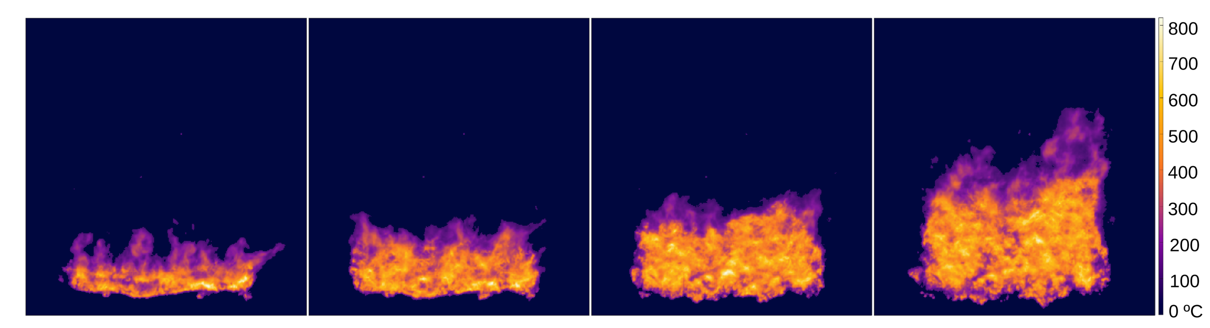


Data collected in collaboration with the Jones Center at Ichauway and Tall Timbers Research Station & Land Conservancy. Satellite images obtained through NASA Worldview.

Analysis

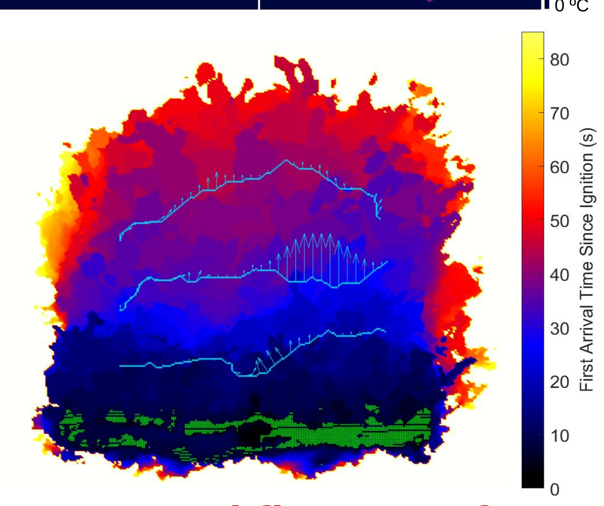
This section showcases statistical results that may be obtained by analyzing visual or infrared videos of fire environments. The examples shown are taken from the infrared pine straw plot dataset.

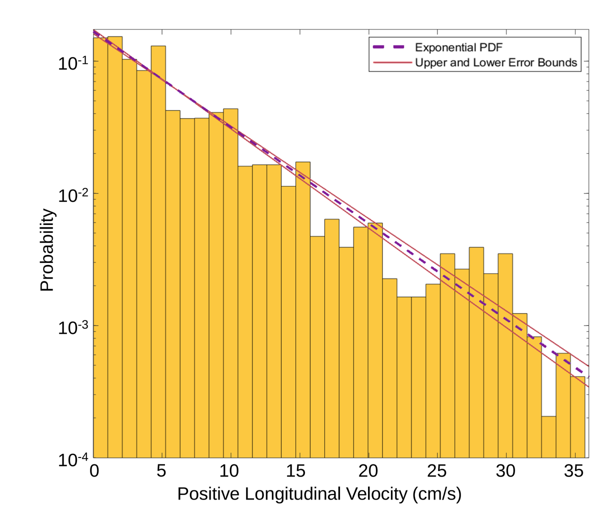
Infrared frame examples, sampled at 0.1Hz



First arrival time map

Map of the time each pixel exceeds ignition temperature with initial ignition pattern in green and sample isotherms in blue.



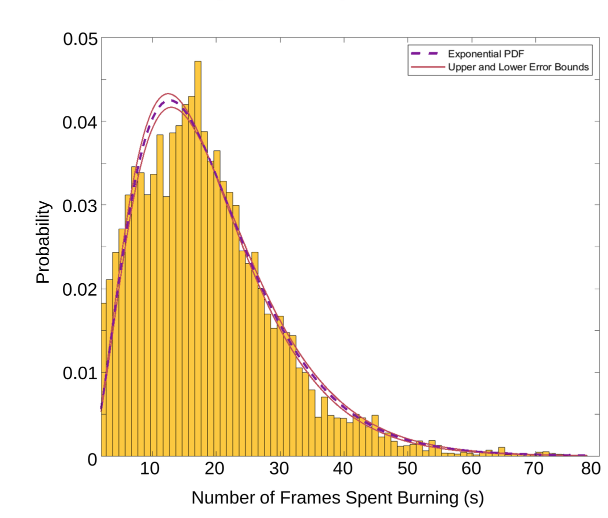


Forward fire rate of spread distribution

Velocities fit with an exponential distribution. Suggests that small-scale fire behavior can be modeled as a random, memoryless process.

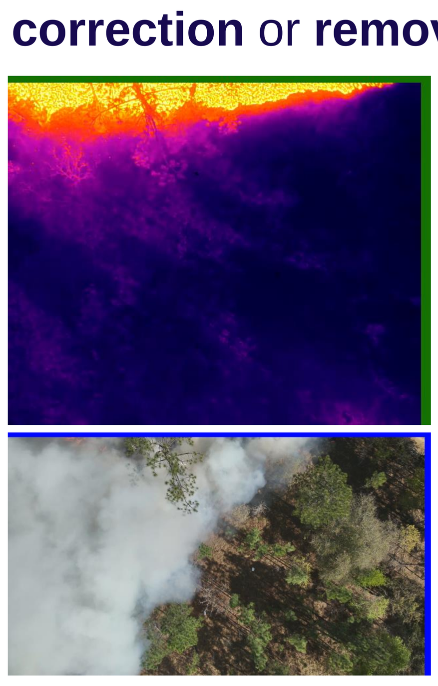
Burn time distribution

Per-pixel burn times fit with an Erlang distribution. Implies that burn time relies on multiple exponential factors, like the forward spread rate.



UAV Video Stabilization

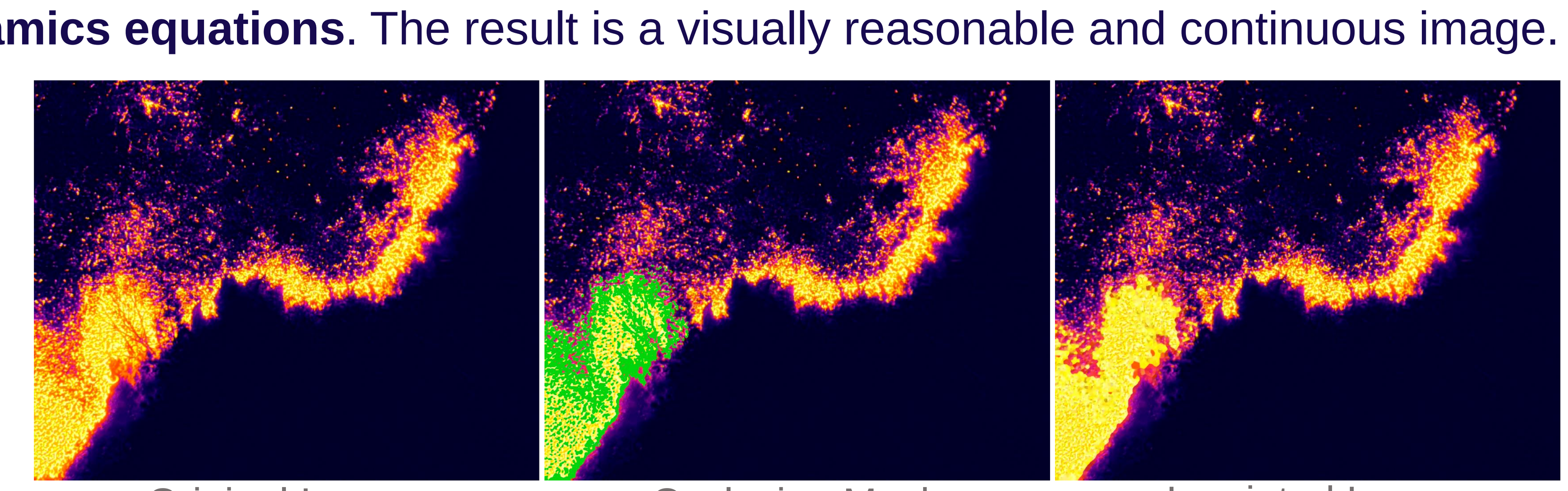
Videos recorded by UAVs and other **non-stationary frameworks** encounter **distortion** beyond the standard rolling shutter effect. Frames affected by slight positional adjustments or gusty winds require **identification** and subsequent **correction** or **removal**.



- UAV videos commonly contain a ground control point or other recognizable structure
  - For videos with a **continuously recognizable object**, the object is **detected** and frames are **translated** to maintain the object's original position
  - Rotation and scaling are not currently accounted for
- If a pair of images experiences translation beyond a user-defined threshold, that pairing is **discarded**
  - Motions that are **too large** between frames have a **high risk** of additional error from **motion blur**

Inpainting Example

Some models require **spatially continuous** datasets as input. For images with **occlusions**, such as trees in UAV imagery, gaps in data may lead to the calculation of **false velocity vectors**. We isolate gaps using segmentation and employ an image inpainting algorithm developed by Bertalmio et al. to fill them. This algorithm **propagates isophote lines** inward from the gap exterior **according to fluid dynamics equations**. The result is a visually reasonable and continuous image.



Original Image | Occlusion Mask (Green) | Inpainted Image

Current & Future Work

- In-depth comparison of statistics derived from visual and infrared images of the same dataset
- Investigation of dynamics within the plume
- Incorporation of datasets with applications beyond physics (e.g., fire ecology)
- Algorithmic verification and improvements, namely for stabilization

References

- Sagel, D. & Quaife, B. (2024). Fire Dynamic Vision: Image Segmentation and Tracking for Multi-Scale Fire and Plume Behavior. In progress.
- Sagel, D., Speer, K., Pokswinski, S., & Quaife, B. (2021). Fine-Scale Fire Spread in Pine Straw. Fire, 4(4), 69.
- Sagel, D. (2020). A New Way to Look at Fire: Computer Vision Applied to Fire Dynamics. The Florida State University.
- Bertalmio, et al. (2001). Navier-Stokes, Fluid Dynamics, and Image and Video Inpainting. IEEE CVPR, Vol. 1.