Learning Wildfire Dynamics for Ignition Inversion

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Context

- Injuries, deaths, billions of USD in damages each year
- Want to visualize QoIs and sensitivities accessibly to front-line decision makers
- Complex physics inhibit rapid simulations
- Need computationally cheaper surrogate

Outline

1. Wildfire model
2. Neural-network surrogate
3. Inverse problem with surrogate
4. Inversion results

Governing physics

- Fire front propagates by level-set equation:[2]

$$\psi_t + S\|\nabla\psi\| = 0,$$

where $S = S(\boldsymbol{x}, t)$ is the spread rate.

  - $\psi > 0$: unburned
  - $\psi = 0$: burning
  - $\psi < 0$: burned

- $S(\boldsymbol{x}, t)$ depends on fuel, terrain, and atmospheric wind
  - ... which depends on the heat flux from the fire

- Implementation in WRF-SFIRE (Fortran)
  - Atmosphere: Finite differences and RK3; Navier–Stokes
  - Fire: Finite volume and RK2
  - Operator splitting to couple atmosphere and fire

[2] J. Mandel, J. D. Beezley, and A. K. Kochanski. "Coupled Atmosphere–Wildland Fire Modeling with WRF 3.3 and SFIRE 2011." *Geosci. Model Dev.* 4.3 (2011), pp. 591–610. DOI: 10.5194/gmd-4-591-2011.

Surrogate dynamics

- **Data-driven:** Collect ensemble of level-set trajectories

$$\{\boldsymbol{\psi}^i\}_{i=1}^M \subset \mathbb{R}^{d\times(N+1)}, \qquad \boldsymbol{\psi}_n^i = \boldsymbol{\psi}^i(t_n),\ n = 0,\dots,N$$

- Project snapshots into low-rank subspace:

$$\tilde{\boldsymbol{\psi}}_n^i = \boldsymbol{U}^\top \boldsymbol{\psi}_n^i \in \mathbb{R}^r, \qquad r \ll d$$

where $\boldsymbol{U}$ comes from an SVD of all snapshots.

- Learn flow map $\hat{\boldsymbol{F}}$ with DNN [Gulian; Day 2, Sess. 1]:[3]

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{M}\sum_{n=0}^{N-1}\sum_{p=1}^{P} \|\tilde{\boldsymbol{\psi}}_{n+p}^i - \hat{\boldsymbol{F}}^p(\tilde{\boldsymbol{\psi}}_n^i;\boldsymbol{\theta})\|_2^2$$

where $\hat{\boldsymbol{F}}(\tilde{\boldsymbol{\psi}}_n;\boldsymbol{\theta}) = \tilde{\boldsymbol{\psi}}_n + \boldsymbol{\mathcal{N}\mathcal{N}}(\tilde{\boldsymbol{\psi}}_n;\boldsymbol{\theta})$

[3] J. Hart, M. Gulian, I. Manickam, and L. Swiler. "Solving High-Dimensional Inverse Problems with Auxiliary Uncertainty via Operator Learning with Limited Data." *J. Mach. Learn. Model. Comput.* (2023).

Inversion

- Want to invert for point-source ignition $\boldsymbol{z}$ (deterministic)
- Optimize full-dimensional loss:

$$J(\boldsymbol{z}) = \frac{1}{2}\sum_{n=0}^{N} \|\boldsymbol{U}\hat{\boldsymbol{\psi}}_n(\boldsymbol{z}) - \boldsymbol{\psi}_n\|_2^2 + R(\boldsymbol{z})$$

where $\hat{\boldsymbol{\psi}}_n(\boldsymbol{z})$ comes from DNN flow map starting at parameterized IC

- Form of $\psi(\boldsymbol{x}, 0)$ known explicitly:

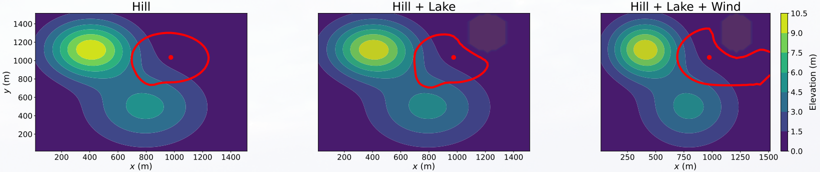
$$\psi(\boldsymbol{x}, 0; \boldsymbol{z}) = C + \|\boldsymbol{z} - \boldsymbol{x}\|_2$$

- Useful for computing gradients:

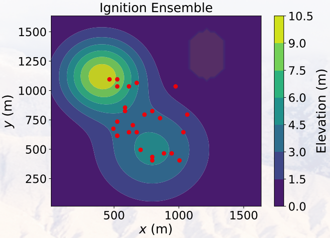
$$\nabla_{\boldsymbol{z}}\, \psi(\boldsymbol{x}, 0; \boldsymbol{z}) = \frac{\boldsymbol{z} - \boldsymbol{x}}{\|\boldsymbol{z} - \boldsymbol{x}\|_2}$$

Experiments

- Different regimes of synthetic/real terrain, and windy/still conditions
  - Real terrain and fuel east of Pagosa Springs, CO
  - $\Delta x = \Delta y = 30$ m; integrate up to $t = 3$ hr



- Generate 25 trajectories corresponding to different ignition points



Results

- 15/5/5 split for training, validation, and testing
- $\sim 1\%$ L^2 validation error for forward simulation with flow maps
- Inverse problem with testing data

Experiment	Abs err (mean)	Abs err (max)
Still, synthetic (no lake)	$0.15\Delta x$	$0.27\Delta x$
Still, synthetic (lake)	$0.20\Delta x$	$0.32\Delta x$
Windy, synthetic (no lake)	$0.71\Delta x$	$2.48\Delta x$
Windy, synthetic (lake)	$1.01\Delta x$	$3.76\Delta x$
Windy, Colorado	$0.24\Delta x$	$0.44\Delta x$

Table: Ignition-point inversion for real/synthetic data and windy/still air.

SciML-based digital twins

- Wildfire as test case for digital twins
- Surrogate-enabled inversion is one piece of the outer-loop
  - *Sub-mesh inversion error when applied to real data!*
- Additional methods/algorithms:
  - Reinforcement learning for wildfire suppression
  - Post-optimality sensitivities
  - Model-discrepancy update
- Physical system in real-time
  - Data acquisition
  - Meteorological/fire data assimilation