

# PyTorchFire: A Differentiable Cellular Automata-Based Wildfire Simulator with GPU Acceleration

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## Motivation of this study

- **Timely wildfire prediction** is essential for informed decision-making in evacuation, firefighting, and long-term risk assessment.
- **Existing wildfire models** are often CPU-based, slow, and cannot handle large-scale or high-resolution simulations in real-time.
- **Data-driven ML models** suffer from poor generalizability across different geophysical regions.
- **Parameter calibration** in wildfire models is computationally intensive, unstable, or impractical for real-time use.

## Cellular Automata modelling

Following [1], the probability of fire propagation in the cellular automata is computed as:

$$p_{\text{propagate}} = p_h(1 + p_{\text{veg}})(1 + p_{\text{den}}) p_w p_s$$

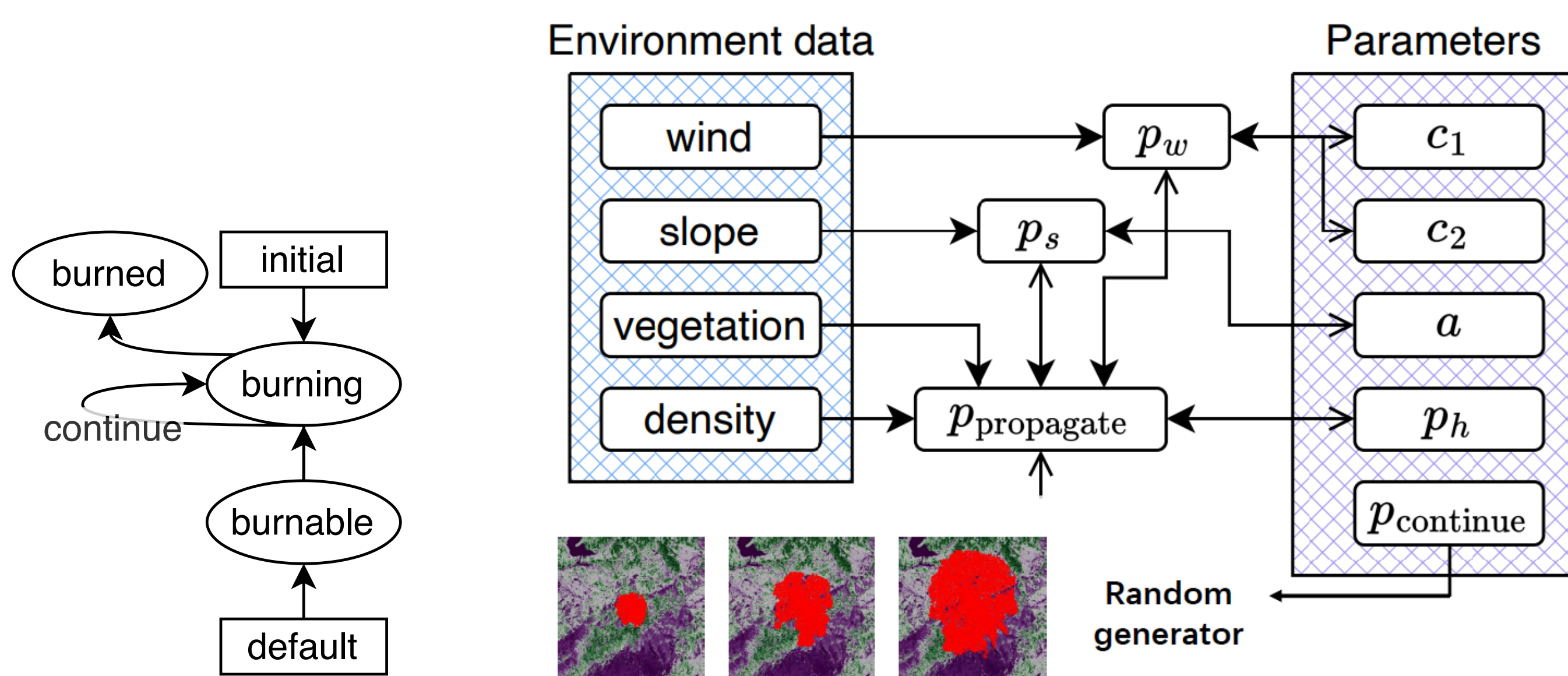
where  $p_h$  is the base ignition probability, and  $p_{\text{veg}}$ ,  $p_{\text{den}}$ ,  $p_w$ , and  $p_s$  are vegetation, density, wind, and slope factors. The wind factor is:

$$p_w = \exp(c_1 V_w) \cdot \exp(c_2 V_w (\cos \theta_w - 1))$$

where  $V_w$  is wind speed and  $\theta_w$  is the wind direction relative to neighbors. The slope factor is:

$$p_s = \exp(a \theta_s)$$

with  $\theta_s$  the slope angle and  $a$  a slope coefficient from data.

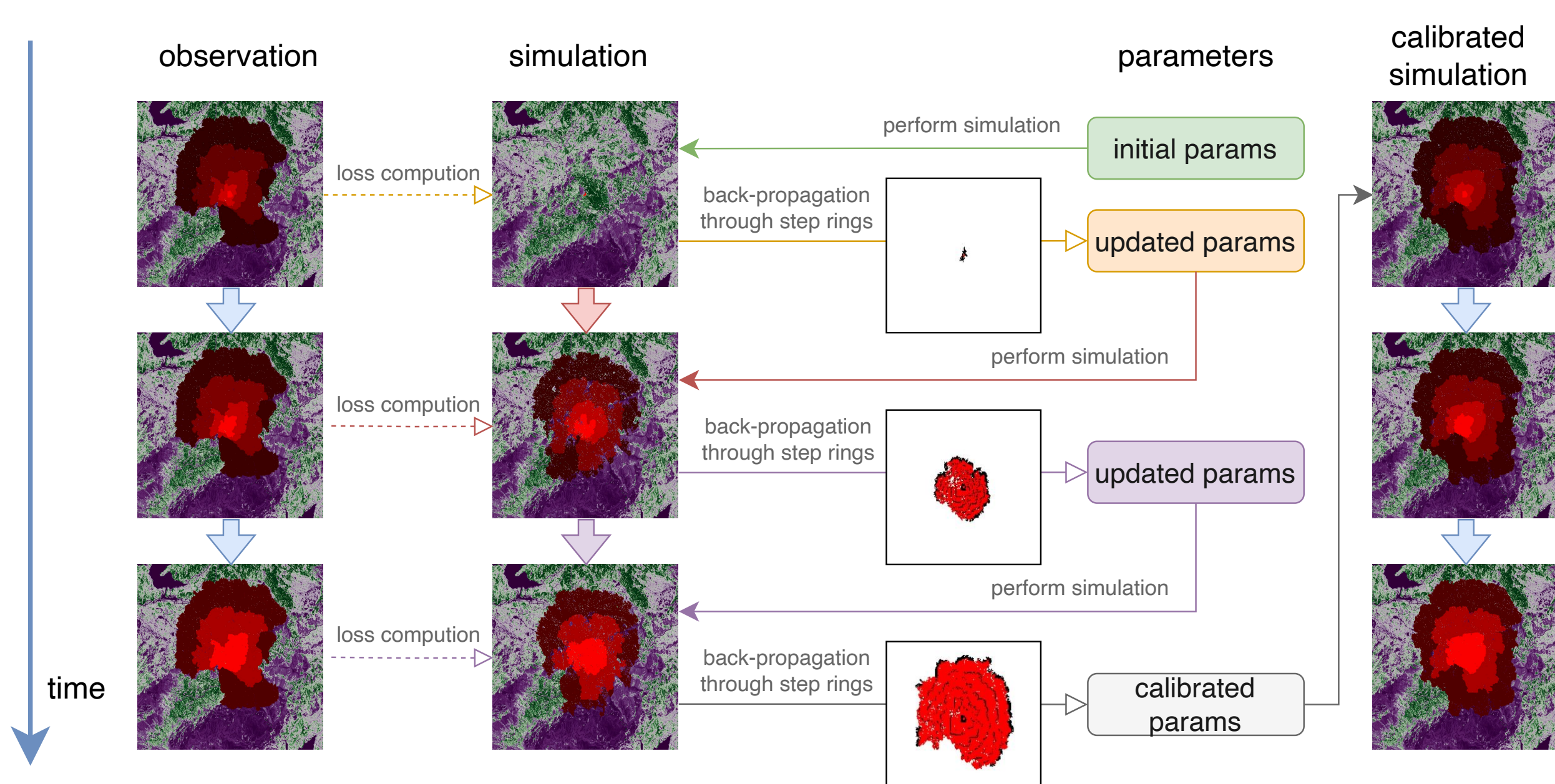


**Figure 1:** Illustration of the Cellular automata mechanism and the model parameters.

**Table 1:** Overview of selected wildfire datasets, including coordinates, dates, and areas.

| Dataset name  | Latitude | Longitude | Start date | Duration | Area                  |
|---------------|----------|-----------|------------|----------|-----------------------|
| Bear 2020     | 39.8173  | -121.0893 | 2020-08-19 | 23 days  | ≈ 107 km <sup>2</sup> |
| Brattain 2020 | 42.6179  | -120.5761 | 2020-09-07 | 22 days  | ≈ 458 km <sup>2</sup> |
| Pier 2017     | 36.1226  | -118.7074 | 2017-08-29 | 31 days  | ≈ 250 km <sup>2</sup> |

## Differentiability regarding model parameters



**Figure 2:** Illustration of real-time parameter calibration thanks to the differentiability

Dynamic parameter calibration is enabled via a differentiable ignition model. The per-cell ignition probability  $p_{\text{ignite}}$  is computed using neighbor  $p_{\text{propagate}}$  values smoothed by tanh:

$$p_{\text{ignite},j}^t = 1 - \prod_{i=1}^8 \left(1 - \tanh\left(p_{\text{propagate},i,j}^t\right)\right) \quad (1)$$

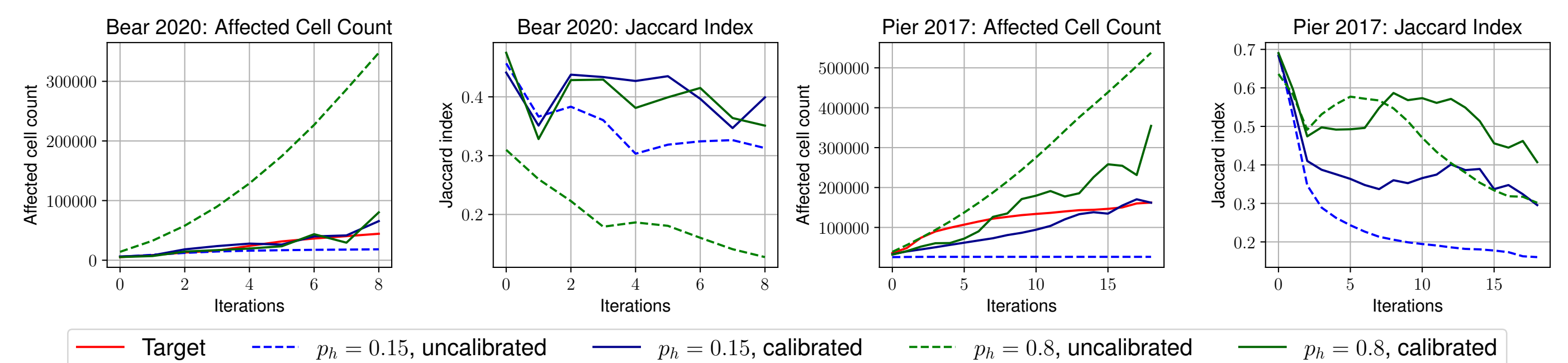
This could be extended to distant cells to model spotting in future work.

To calibrate model parameters, we minimize the discrepancy between simulated ( $\mathbf{x}^t$ ) and observed ( $\hat{\mathbf{x}}^t$ ) fire spread. To achieve this, we define a loss function  $L(\mathbf{x}^t, \hat{\mathbf{x}}^t)$  that captures differences in both **fire shape and size** on the specific cells covered by the step rings (see Figure 4).

$$\sum_{q,k} \left\{ \underbrace{-\left[x_{q,k}^t \log(\sigma(\hat{x}_{q,k}^t)) + (1 - x_{q,k}^t) \log(1 - \sigma(\hat{x}_{q,k}^t))\right]}_{\text{BCE Loss for shape matching}} + \underbrace{\left(\text{AvgPool2d}(x_{q,k}^t) - \text{AvgPool2d}(\hat{x}_{q,k}^t)\right)^2}_{\text{MSE Loss for size matching}} \right\}, \quad (2)$$

where  $\sigma(x) = \frac{1}{1+\exp(-x)}$  and AvgPool2d is a spatial downsampling operation.

## Results & Interpretability



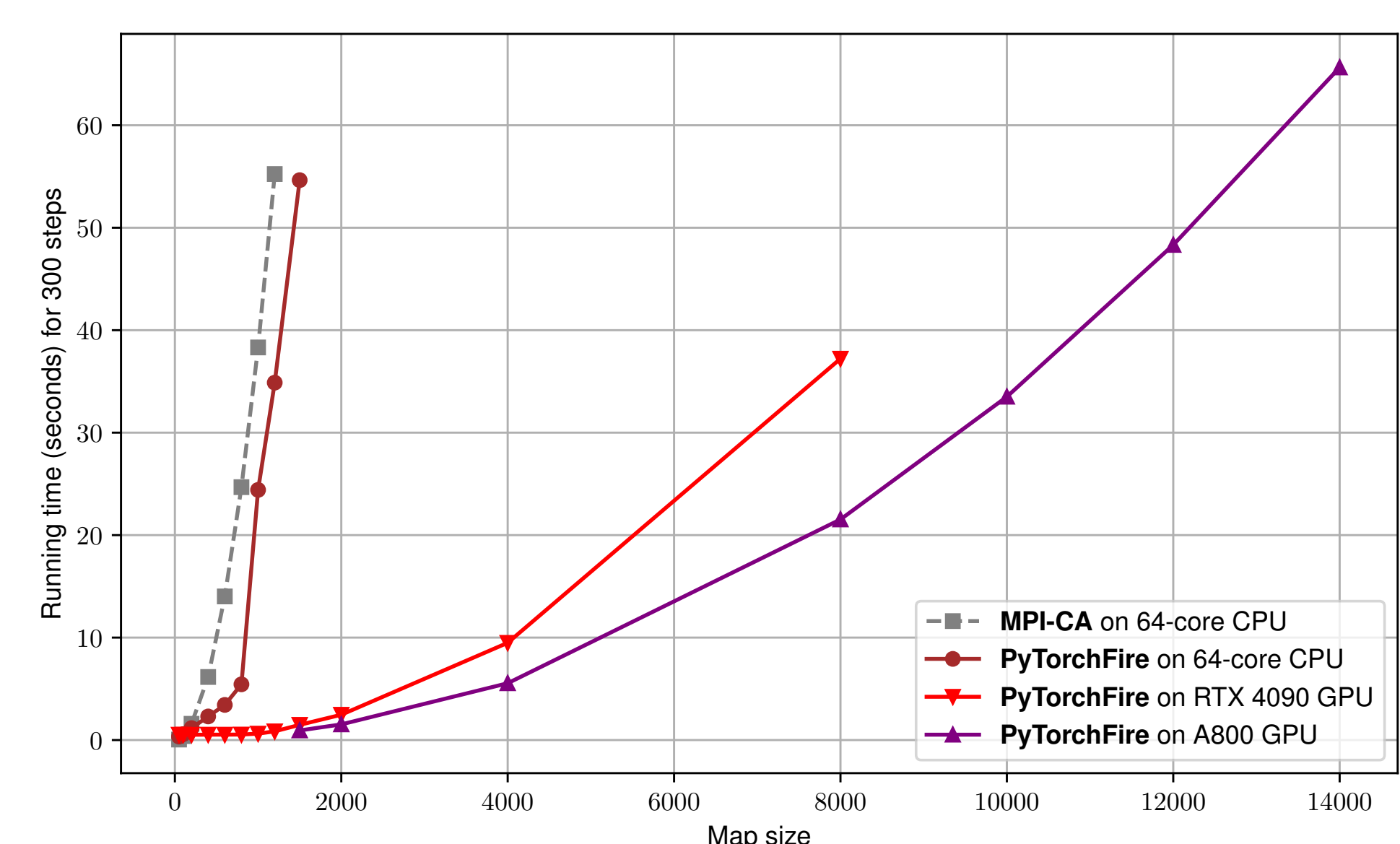
**Figure 3:** Statistical results for simulation and parameter calibration in the Bear and Pier fires in California

|                                             | Under estimation<br>$p_h = 0.15$<br>(initial) | Step Rings | Over estimation<br>$p_h = 0.8$<br>(initial) | Step Rings | Under estimation<br>$p_h = 0.15$<br>(calibrated) | Over estimation<br>$p_h = 0.8$<br>(calibrated) | Target |
|---------------------------------------------|-----------------------------------------------|------------|---------------------------------------------|------------|--------------------------------------------------|------------------------------------------------|--------|
| Iteration<br>$it = 0$<br>Date<br>2020-08-20 |                                               |            |                                             |            |                                                  |                                                |        |
| Iteration<br>$it = 3$<br>Date<br>2020-08-23 |                                               |            |                                             |            |                                                  |                                                |        |
| Iteration<br>$it = 5$<br>Date<br>2020-08-25 |                                               |            |                                             |            |                                                  |                                                |        |
| Iteration<br>$it = 8$<br>Date<br>2020-08-28 |                                               |            |                                             |            |                                                  |                                                |        |
| Jaccard index                               | 0.35                                          |            | 0.196                                       |            | 0.408                                            | 0.397                                          |        |
| Manhattan distance ( $\times 10^4$ )        | 9.35                                          |            | 113.96                                      |            | 4.93                                             | 7.06                                           |        |

**Figure 4:** Comparison of wildfire simulations with satellite observations over time on the Bear 2020 map

**Table 2:** Comparison of various fire simulators' capabilities.

| Simulator              | GPU-acceleration | Generalizable | Differentiable | Real-time calibration | Test on real fire event |
|------------------------|------------------|---------------|----------------|-----------------------|-------------------------|
| Flammap [2]            | ✗                | ✓             | ✗              | ✗                     | ✓                       |
| MPI-CA [1]             | ✗                | ✓             | ✗              | ✗                     | ✓                       |
| ML Models [5]          | ✓                | ✗             | ✓              | ✓(expensive)          | ✓                       |
| FCA [3]                | ✓                | ✓             | ✗              | ✓(unstable)           | ✗                       |
| <b>PyTorchFire [4]</b> | ✓                | ✓             | ✓              | ✓                     | ✓                       |



**Figure 5:** Prediction time (in seconds) for completing 300 steps of simulation across various map sizes.

## Highlights & Conclusion

- The first differentiable cellular automata wildfire spread prediction model
- Ultra-fast, GPU-accelerated wildfire simulator using PyTorch
- Real-time parameter calibration, accurately mimicking real-world fire events
- Superior generalizability compared to supervised learning surrogate models

## Future work

- Hybrid physics-data-driven model for complex fire behavior, including phenomena like fire spotting
- More realistic CA modeling with additional climate and geological inputs
- Incorporating various human interventions such as firebreak placement
- Call for collaborations in AI for wildfire and machine learning for dynamical systems

## References

- [1] A. Alexandridis, D. Vakalis, C. I. Siettos, and G. V. Bafas. A Cellular Automata Model for Forest Fire Spread Prediction: The Case of the Wildfire That Swept Through Spetses Island in 1990. *Applied Mathematics and Computation*, 204(1):191–201, Oct. 2008.
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