Deep Learning–Based Surrogate Modeling of JULES-INFERNO for Accelerated Global Wildfire Prediction

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Background

Wildfires are increasing in frequency and intensity, creating a growing need for forecasting tools that are both accurate and computationally efficient. Physics based models such as the JULES-INFERNO wildfire model simulate complex interactions between climate, vegetation, and land surface processes to estimate burned area and fire behavior. However, these simulations are computationally expensive and often require high performance computing resources, limiting their accessibility and usefulness for rapid experimentation or real time forecasting. This research explores the use of deep learning surrogate models to emulate the behavior of the JULES-INFERNO system at a fraction of the computational cost. Two architectures, CAE-LSTM and ConvLSTM, are used to learn the relationship between climate inputs and wildfire outcomes. In addition to the standard environmental inputs used in prior work, this study evaluates whether incorporating additional climate variables such as precipitation and humidity improves predictive accuracy. Model performance will be evaluated using spatial similarity and error metrics to determine how closely the surrogate outputs replicate the original model. The goal is to create a faster and more accessible wildfire prediction framework while maintaining strong agreement with the physics-based system.

Figure 2

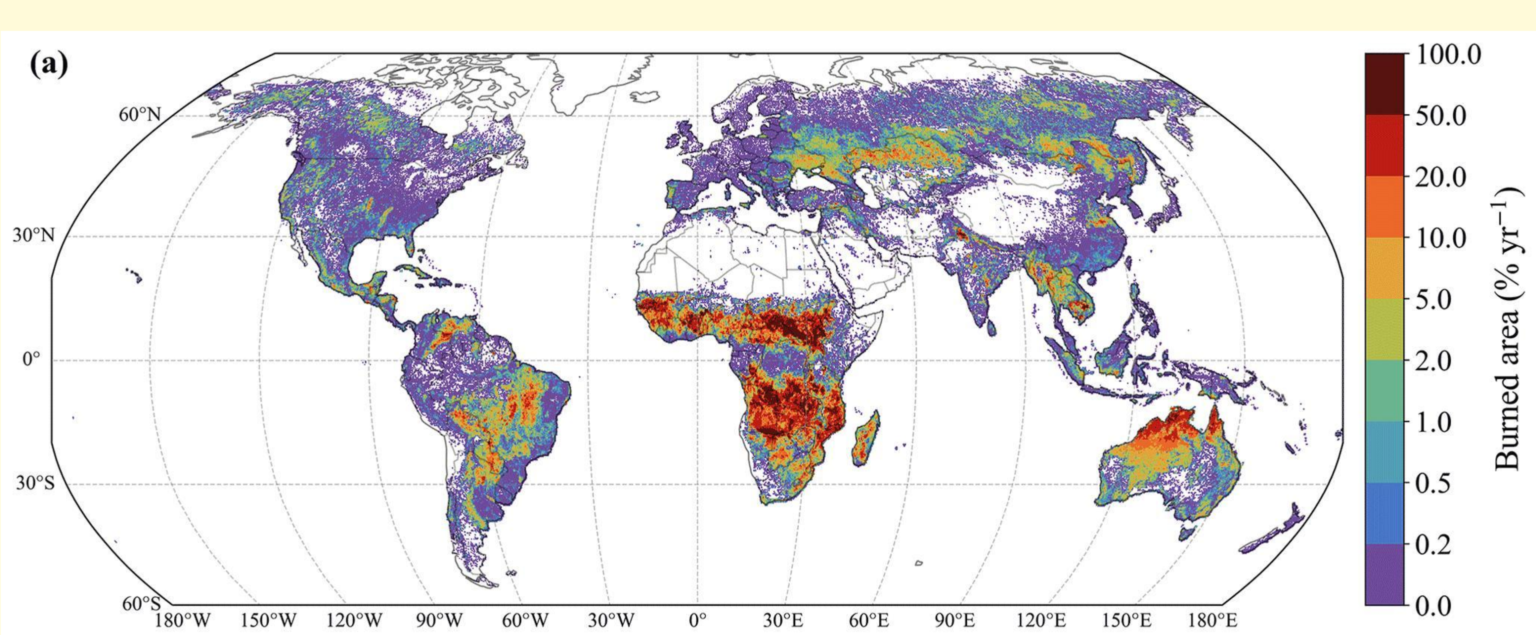

Figure 2. Example global wildfire outputs from the JULES-INFERNO model showing simulated burned area. *(adapted from Knorr et al., 2016)*

Figure 1

Surrogate Modeling Workflow

- Climate Inputs
- ↓
- Data Processing
- ↓
- Deep-Learning Models
- ↓
- Predicted Burned Area Maps
- ↓
- Evaluation Metrics

Acknowledgements & References

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References
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Best, M. J. et al. (2011). *The Joint UK Land Environment Simulator (JULES).* Geoscientific Model Development.
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Methods

This study develops deep learning surrogate models to emulate the behavior of the JULES-INFERNO wildfire simulation framework. Two neural network architectures are evaluated: a Convolutional Autoencoder Long Short-Term Memory model (CAE-LSTM) and a Convolutional Long Short-Term Memory model (ConvLSTM). These models are designed to capture both spatial wildfire patterns and temporal climate dynamics.

The models are trained on climate and environmental variables that influence wildfire activity. Standard inputs include vegetation density, soil moisture, surface air temperature, and previously simulated burned area outputs. To explore potential improvements in predictive performance, this study also introduces additional climate variables including precipitation and atmospheric humidity.
Model outputs are compared against the original JULES-INFERNO simulations. Performance is evaluated using Absolute Error per Pixel (AEP) to measure prediction accuracy and the Structural Similarity Index Measure (SSIM) to evaluate spatial agreement between predicted and simulated burned area patterns.

Expected Results

The surrogate models are expected to closely reproduce the spatial burned area patterns generated by the JULES-INFERNO wildfire model while requiring significantly less computational time. Previous research has shown that similar surrogate models can reduce simulation time from several hours on high performance computing systems to under a minute on standard hardware.
By incorporating additional climate inputs such as precipitation and humidity, this study aims to improve model sensitivity to environmental conditions that influence wildfire behavior.
Improved input representation may allow the models to better capture complex climate–fire relationships across different geographic regions.
Overall, the results are expected to demonstrate that deep learning surrogates can provide a fast and accurate alternative to computationally expensive wildfire simulations, enabling more accessible forecasting and rapid climate scenario experimentation.