Some Facts on: The Wildfire Risk of California Residential Real Estate: Casualty Insurance, Risk Measurement, and Mitigation Policies

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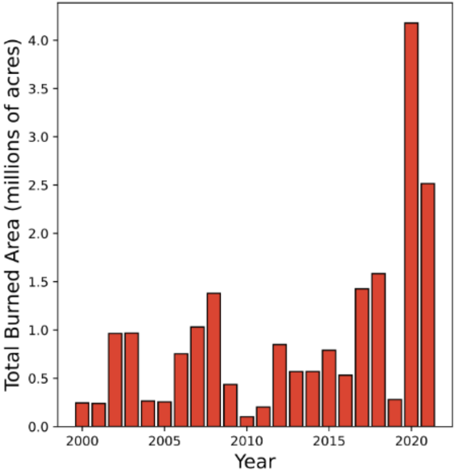
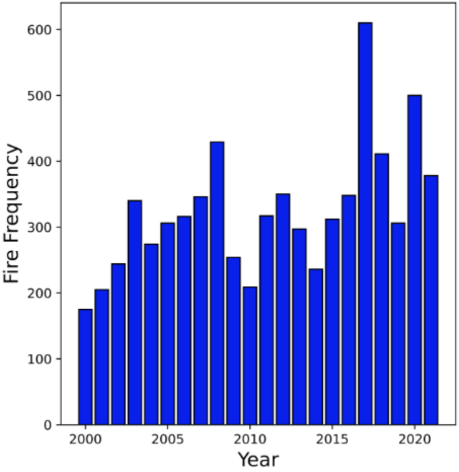
Frequency and size of California wildfires, 2000–2021



(a) Annual area burned (million acres)



(b) Annual wildfire counts

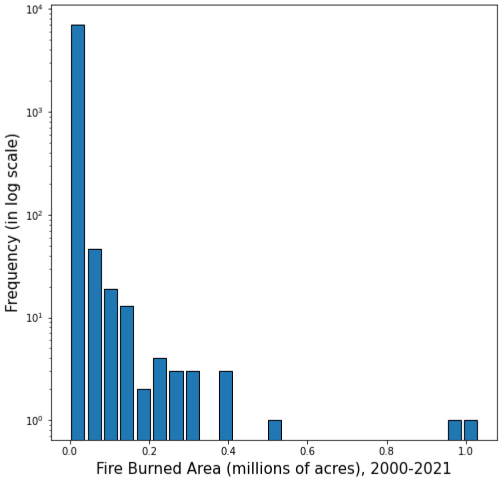
Potential distributional challenges

- Statistical forecasting of wildfire risk occurrence.

- Methods to diversify and securitize wildfire risks (micro-correlations, latent dependencies),

- Reserve strategies under Value-at-Risk management regimes,

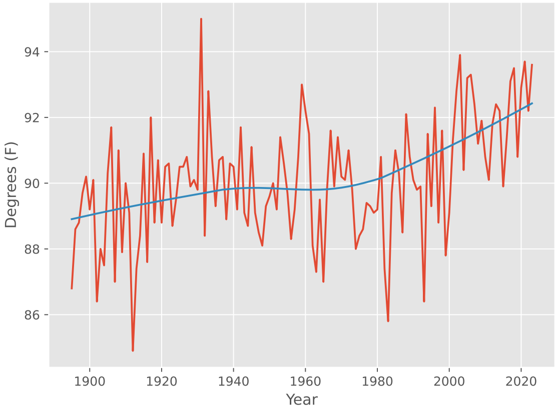
- Design of risk management strategies due to spatial dependencies that affect many people, properties, and insurance lines simultaneously



Annual Burn Areas, 2000–2021

Wildfire patterns in the West are driven by dynamic and nonlinear meteorological features

- **Wildfire probabilities increase non-linearly with daily maximum temperature.**
  - A 19%– 22% probability increase for a one-degree centigrade increase in the Sierra Nevada
- **Maximum temperature is highly correlated with other meteorological, vegetative, and topographic features.**

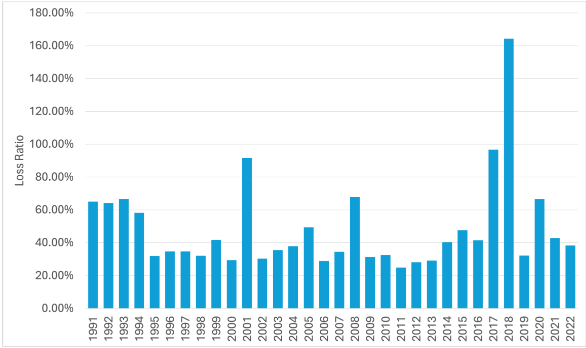


Maximum annual temperature West climate region

How do these dynamics threaten the provision of wildfire insurance in California?

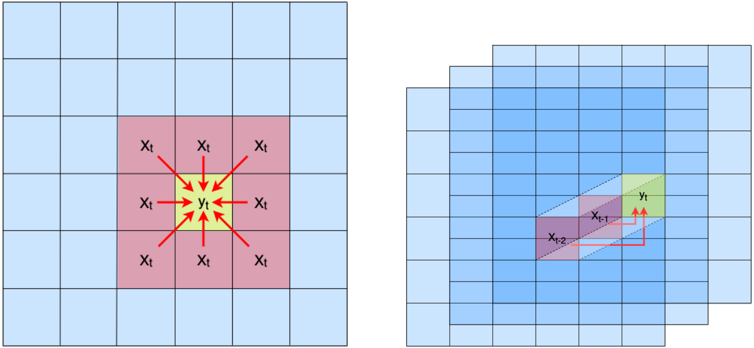
- Underwriting performance 2012 – 2021:
  - **Direct incurred loss ratio:**
    - 59.7% in the U.S.
    - 73.9% in California.
  - **Direct underwriting profit:**
    - 3.6% in the U.S..
    - −13.1% in California.

- Annual pattern of losses has led to an intertemporal smoothing problem for casualty insurers.



Realized loss rates (fire peril) for California Property and Casualty insurance companies

New forecasting strategies: Spatiotemporal CNN – Adding Spatial and temporal dependence



(a) Spatial dependence (b) Temporal dependence

Figure: Visualizing the potential dependence structure in a spatiotemporal dataset

Why Spatiotemporal Convolutional Neural Nets

- They can automatically extract important spatial and temporal features from data without relying on hand-crafted features.

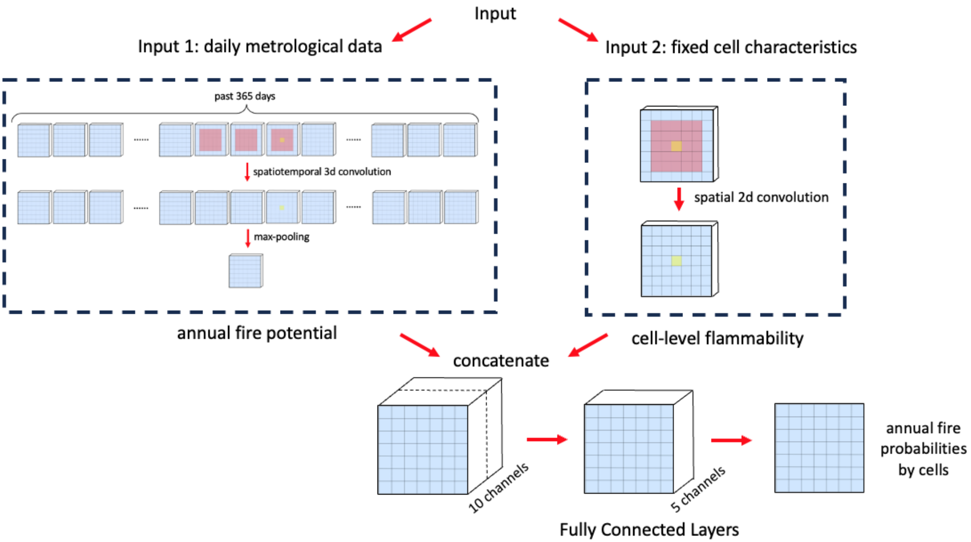
- They can learn the motion patterns in time series data and fully use those patterns to account for how past values influence future predictions.

- They allow for the complex functions that are needed to accurately model the joint spatial correlations and temporal dynamics of wildfire prediction.

- They can easily handle the cell adjacency correlation structure of wildfire and temporal aggregation of some wildfire features by accounting for the cumulative effects of phenomena.

- Handling correlations in both space and time helps to prevent over-fitting even with a high-dimensional nonlinear parameter space.

Out-of-sample one-year ahead model



CNN one year ahead out-of-sample wildfire prediction to 2021 (using 2000 – 2020 panel)