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

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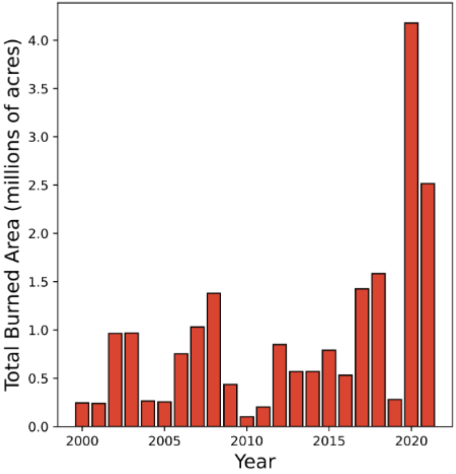
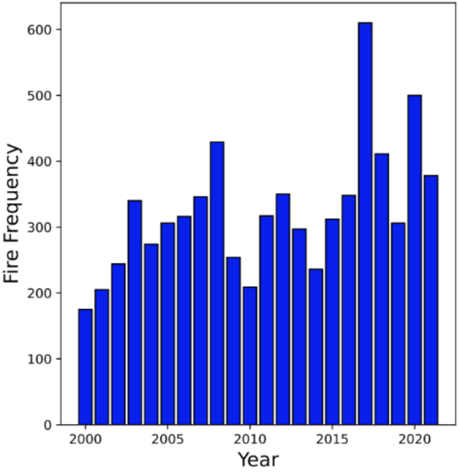
Overview of talk

1. The climate, economic, and regulatory drivers of increased CA wildfire risk.
2. New methods to measure wildfire propensity and housing losses given wildfire.
3. Wildfire mitigation policies and the risks of incomplete mortgage markets.
4. Conclusions

Frequency and size of California wildfires, 2000–2021



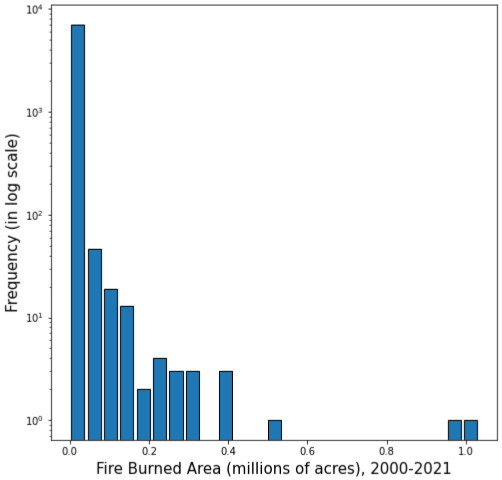
(a) Annual area burned (million acres)



(b) Annual wildfire counts

Potential distributional challenges

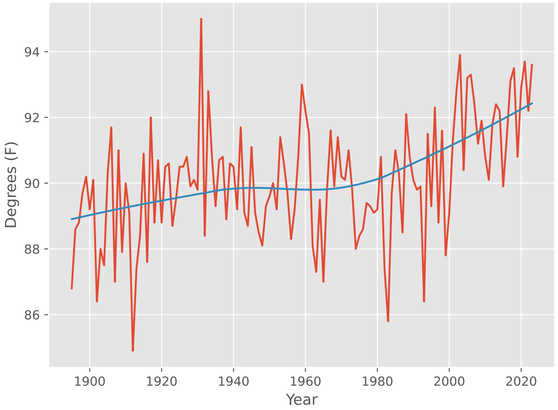
- Statistical forecasting of wildfire risk occurrence.
- Methods to diversify and securitize wildfire risks (micro-correlations, latent dependencies),
- Reserve strategies under Value-at-Risk management regimes,
- Design of risk management strategies due to spatial dependencies that affect many people, 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.**

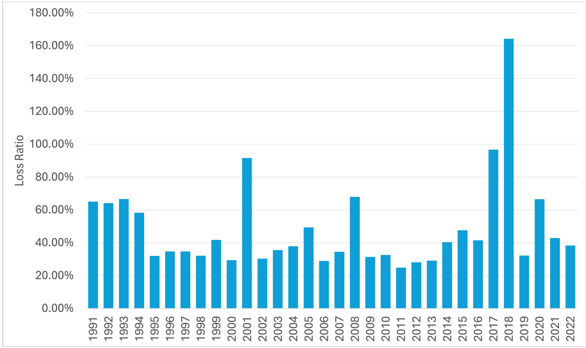


Maximum annual temperature West climate region

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.

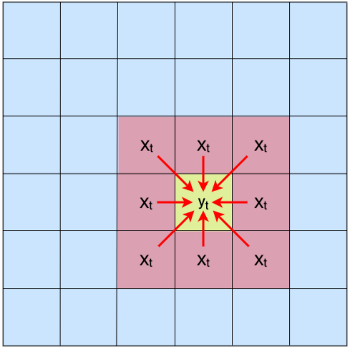


Realized loss rates (fire peril) for California Property and Casualty insurance companies

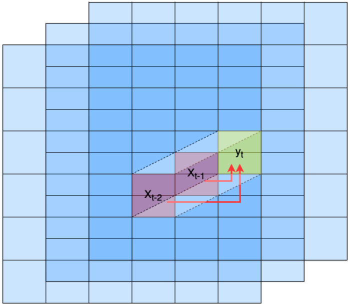
Accurate wildfire prediction is key to pricing: statistical modeling choices

- The dependent variable in this study is a binary indicator reflecting whether a wildfire occurs within a 365-day period.
  - Data are resampled into annual aggregates matching the annual prediction window.
  - For each climate variable, model focuses on aggregates of extreme-quantile realizations over the fire season.
  - Geography measured at 2×2 kilometer grid cells over state.
- Daily measured features at grid cells:
  - Specific humidity and maximum temperature (Gridmet).
  - Thirteen vegetative types (Calfire)
  - Counts of high voltage transmission lines (Arcgis U.S. Electric Power Transmission Lines),
  - Utility identity (Arcgis California Electric Utility Service Territory)
  - Tree and vegetation density (USGS)
  - Counts of dry lightening strikes (NOAA)
- Hourly measured features (ERA5-Land): Daily counts for Santa Ana and Diablo winds for grid-cells:
  - Winds measured for direction, speed, and relative humidity

Adding spatial and temporal dependence



(a) Spatial dependence



(b) Temporal dependence

Why Spatiotemporal Convolutional Neural Nets?

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

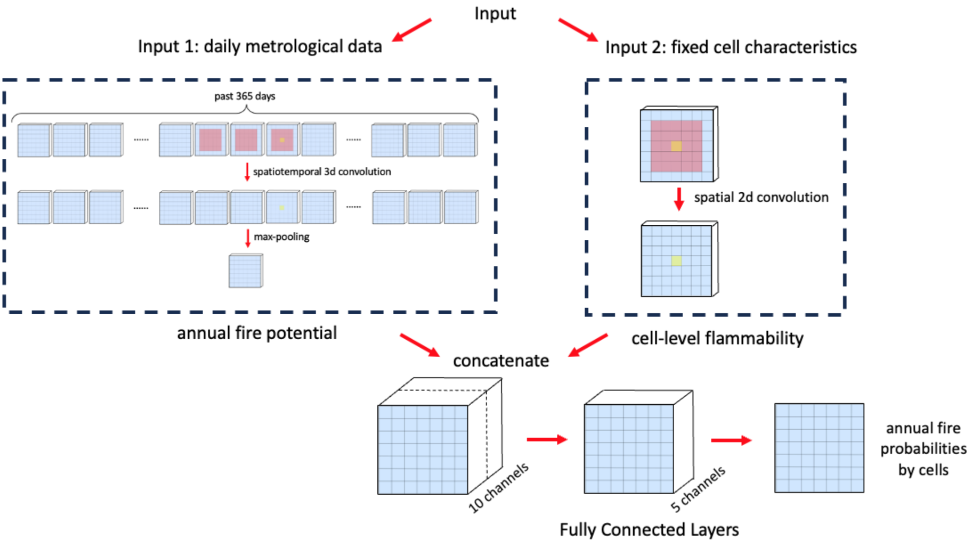
- They can learn the motion patterns in time-series data and fully use those patterns to account for how past values influence future predictions.

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

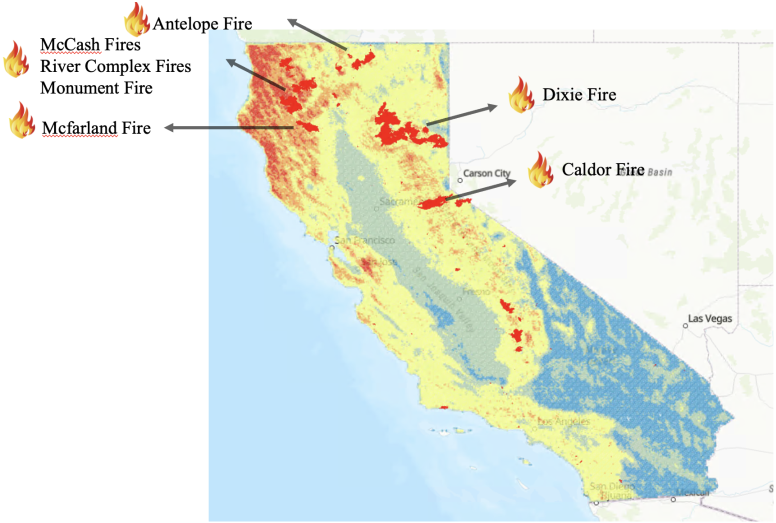
- They can easily handle the cell adjacency correlation structure of wildfire and temporal aggregation of some wildfire features by accounting for the cumulative effects of phenomena.

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

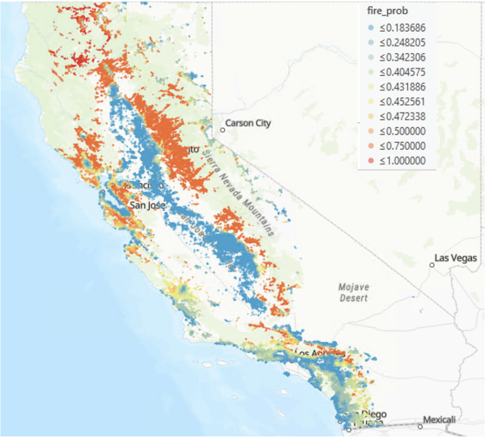
Out-of-sample one-year ahead model



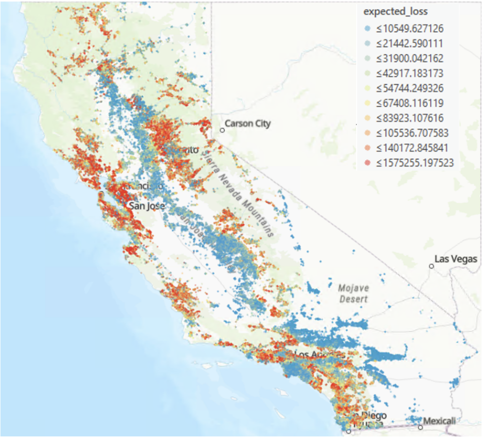
CNN one year ahead out-of-sample wildfire prediction: 2000 – 2020 panel to 2021 annual forecast



Expected annual wildfire probability estimates and wildfire structural losses for residential housing (out-of-sample 2021)



Probability of wildfire



Residential losses given wildfire

The economics of wildfire mitigation

- **Ehrlich and Becker (1972)** conclude under strong informational assumptions:
    - Self-insurance and market insurance both redistribute income toward hazardous states.
    - Self-protection does not redistribute income because the amount spent reducing the probability of a loss decreases income.
    - Market insurance and self-protection are complements in the sense that an increase in the productivity of self-protection or a decrease in the real cost of market insurance would increase the demand for both.

- **Boomhower, Fowlie, and Plantinga (2023)** conclude under weaker informational assumptions:
    - Premium discounts can increase private wildfire mitigation through two channels
        1. Discounts that allow household to internalize the benefits of risk mitigation associated with the reductions in insured losses.
        2. Premium discounts can generate additional value by communicating information about how investments in mitigation can reduce uninsured losses.

However, consumers have few options to fund mitigation investments

- **Lenders could expand mortgage product choices to second liens for mitigation:** (see Jaffee and Russell, 2013)

- **Jurisdictions could expand the use of Residential Property Assessed Clean Energy (R-PACE) for wildfire mitigation** (see Bellon, LaPoint, Mazzola, and Xu, 2024; Deason, Murphy, Issler, Wallace, and Schwartz, 2019)

Conclusions

- **Methods to diversify and securitize wildfire risk** face significant challenges, due to micro-correlations, latent dependencies, heavy-tailed event distributions.

- **Spatiotemporal CNN** can significantly improve wildfire occurrence prediction:
  - Handles the spatial adjacency correlations of wildfire,
  - Accounts for the cumulative effects of features over time,
  - Learns the motion patterns in time series data and fully uses those patterns for future predictions.

- **Improved property loss data and prediction models** allow:
  - More accurate measures of *Annual Average Losses* needed to evaluate the benefits and costs of property-level mitigation policies.

- **However**, there are few capital-market options for households to fund property-level mitigation investments.

References I

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Ehrlich, I., and G. S. Becker, 1972, Market insurance, self-insurance, and self-protection, *Journal of Political Economy* 80, 623–648.

Jaffee, D., and T. Russell, 2013, Catastrophe insurance, capital markets, and uninsurable risks, *Journal of Risk and Insurance* 64, 205–230.