Convolutional Non-homogeneous Poisson Process with Application to Wildfire Risk Quantification for Power Delivery Networks

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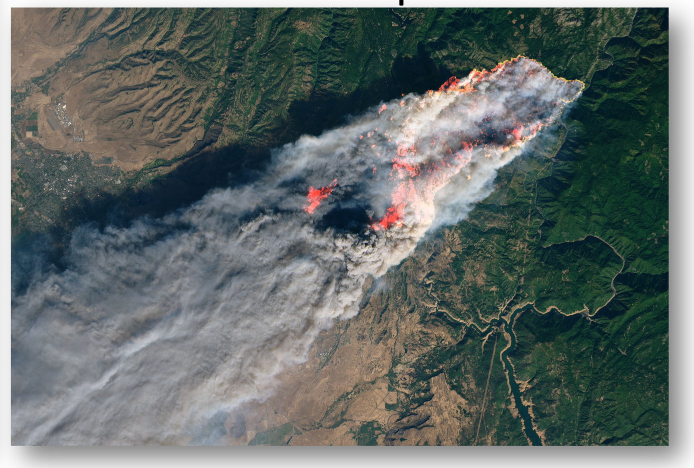
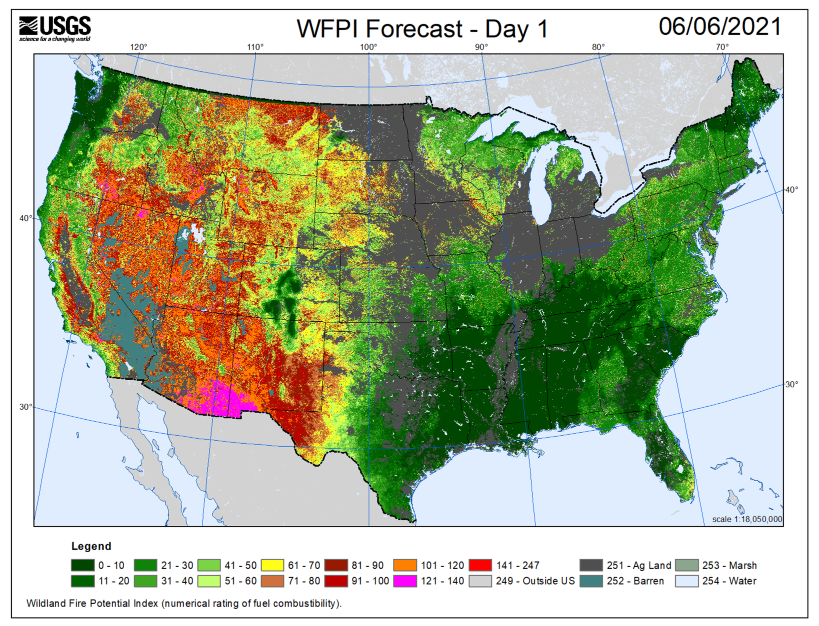
Background & Objective

2018 Camp Fire

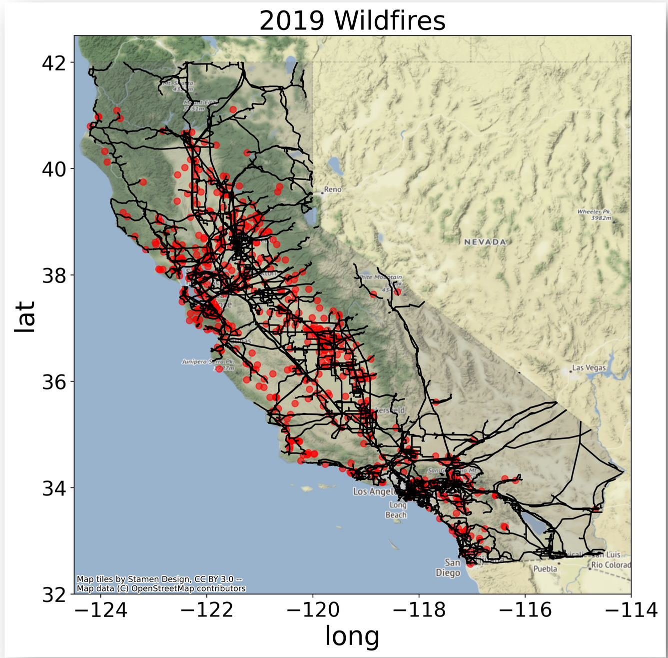


- Overhead power lines across forests and grasslands are especially vulnerable to wildfires. For example, the 2018 Camp Fire caused by the faulty electric transmission line killed 85 people, destroyed over 15,000 structures.

Currently used Fire Potential Index



- Only reflects the long-term trend of wildfire risks on a large scale.
- Does not consider the wildfire incident data and the power grid topology.



Research Objective

To propose a data-driven approach that can be applied to quantify wildfire risks on power delivery networks considering the dynamic environmental factors.

Methodology

- The proposed structure of the intensity function for the underlying spatio-temporal point process.

The intensity function (wildfire risk) $\log\lambda(i,t)$

$$c(i,t) = \boldsymbol{x}^T(i,t)\boldsymbol{\beta}$$ — Incorporate key environmental factors

$$h(i,t) = \xi \sum_{i'\in\Omega_i} w_{i,i'} \log\lambda(i', t-\Delta)$$

The spatio-temporal dependency among networks.

Cumulative effects from the historical covariate information

- $c(i,t)$ incorporates the current effect of covariates at time t for segment i through a linear model. $\boldsymbol{x}^T(i,t)$ denotes the covariates associated with segment i at time t, $\boldsymbol{\beta}$ is a vector of covariate effects.
- $h(i,t)$ explains how historical covariate information (before time t) associated with the neighboring segments of segment i ($\log\lambda(i', t-\Delta)$ for $i' \in \Omega_i$) affects the intensity of segment i at time t.

Convolutional Non-homogeneous Poisson Process

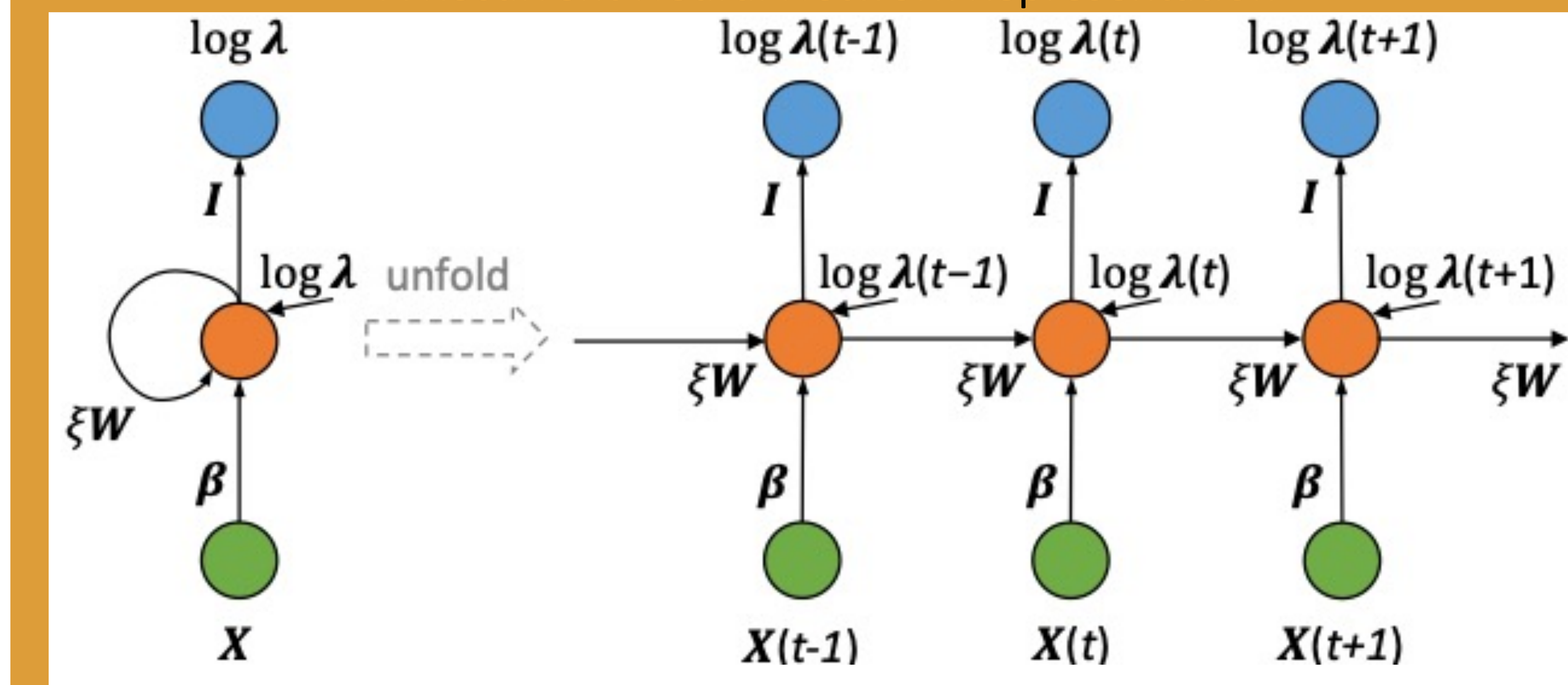
Consider a linear network $L = \cup_{l=1}^{N} l_i$ with N segments. The event process on each segment I is modeled as a Non-homogeneous Poisson Process (NHPP) with is log intensity being given by an infinite series:

$$\log\lambda(i,t) = c(i,t) + h(i,t)$$
$$= \sum_{i=0}^{\infty} \xi^n \mathcal{N}\mathcal{C}^{(n)}\{c\}(i, t-n\Delta)$$

More flexible structure
Lower computational cost

Less training dataset required

A Recurrent Neural Network Representation



$$h(t) \triangleq \xi \boldsymbol{W} \boldsymbol{h}(t-1) + X(t)\beta, o(t) \triangleq Ih(t) = \log\lambda(t)$$

Application: Wildfire Risks on Power Transmission Lines

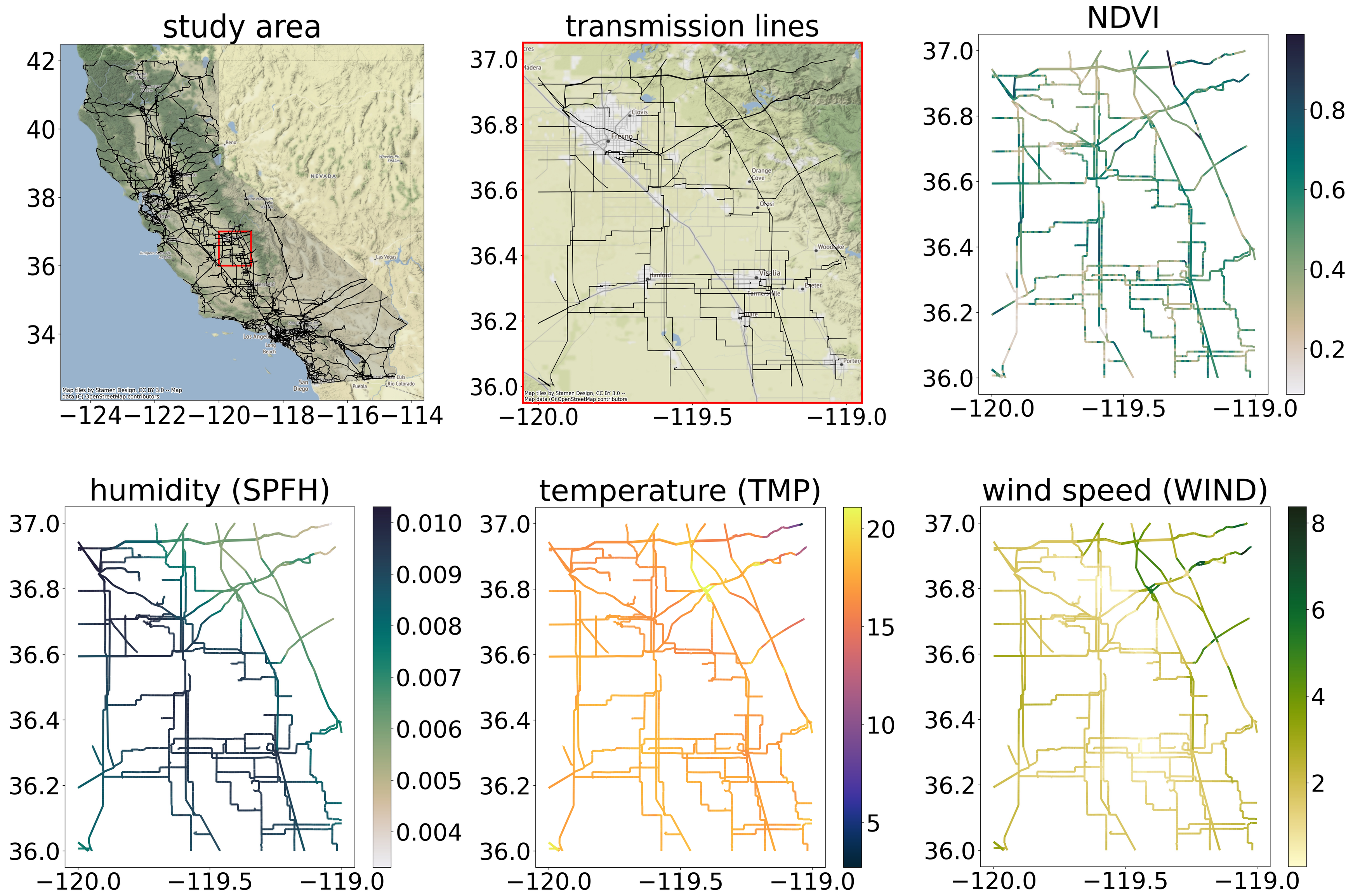


Figure 1: The processed datasets obtained from the U.S. EIA, NASS, and NOAA

Table1: MLEs of the effects of key environmental factors

Parameters	ξ(Scaling)	β_0(Intercept)	β_1(NDVI)	β_2(TMP)	β_3(WIND)	β_4(SPFH)
Estimate	0.7	-2.748	-1.226	0.661	0.887	-0.664

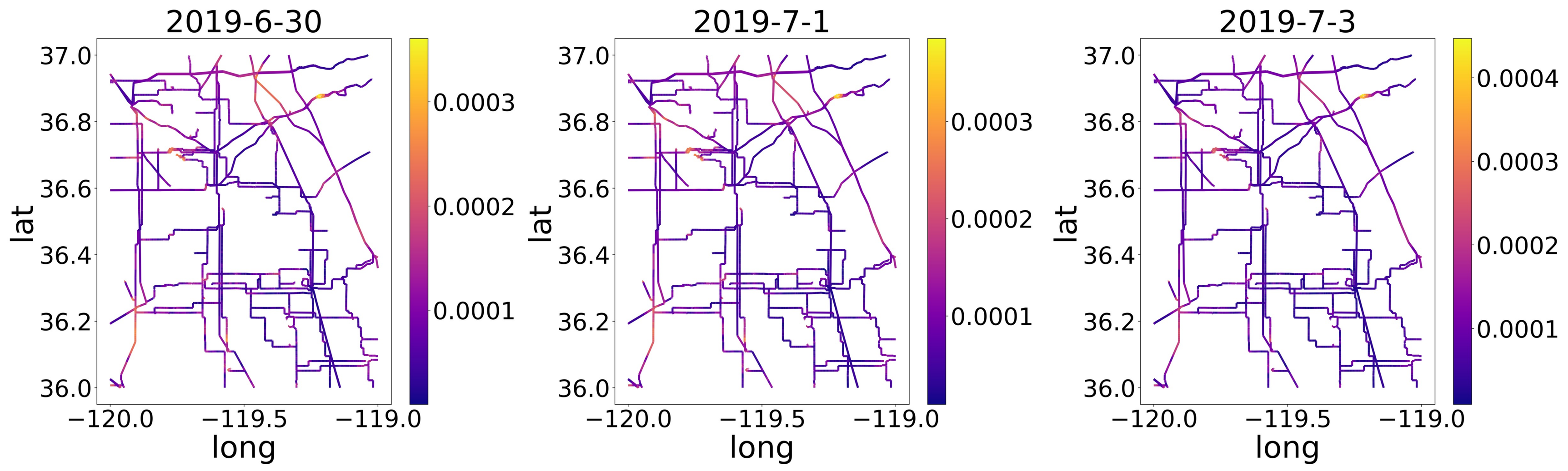


Figure 2: Estimated (the first one) and predicted (the last two) wildfire risks

- Different power line segments are associated with different wildfire risks due to the spatially- and temporally-varying covariate information.
- It is also seen that the predicted wildfire risks change smoothly over time.

Validation and Comparison

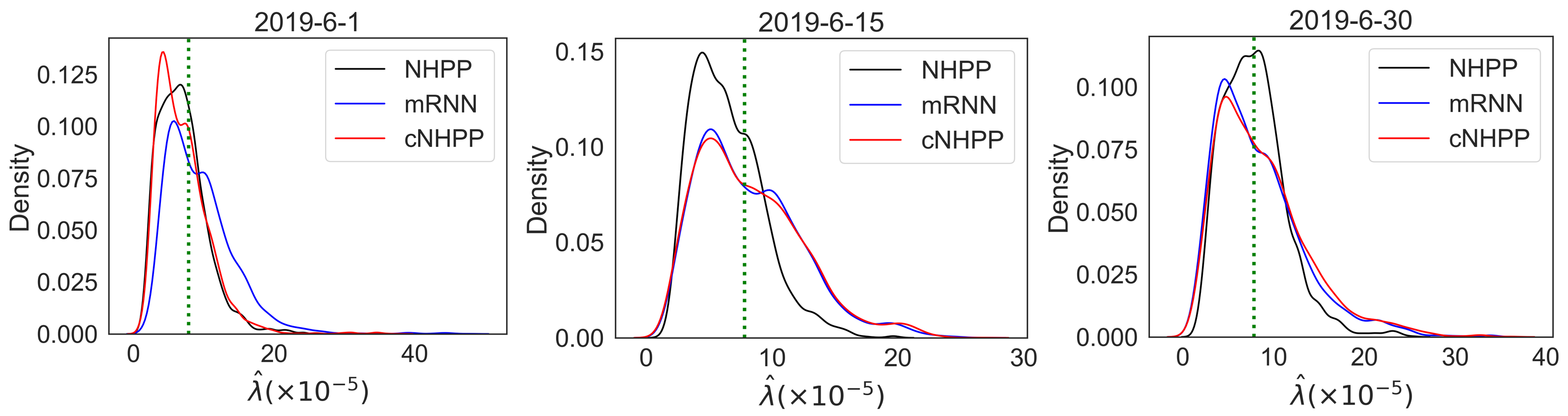
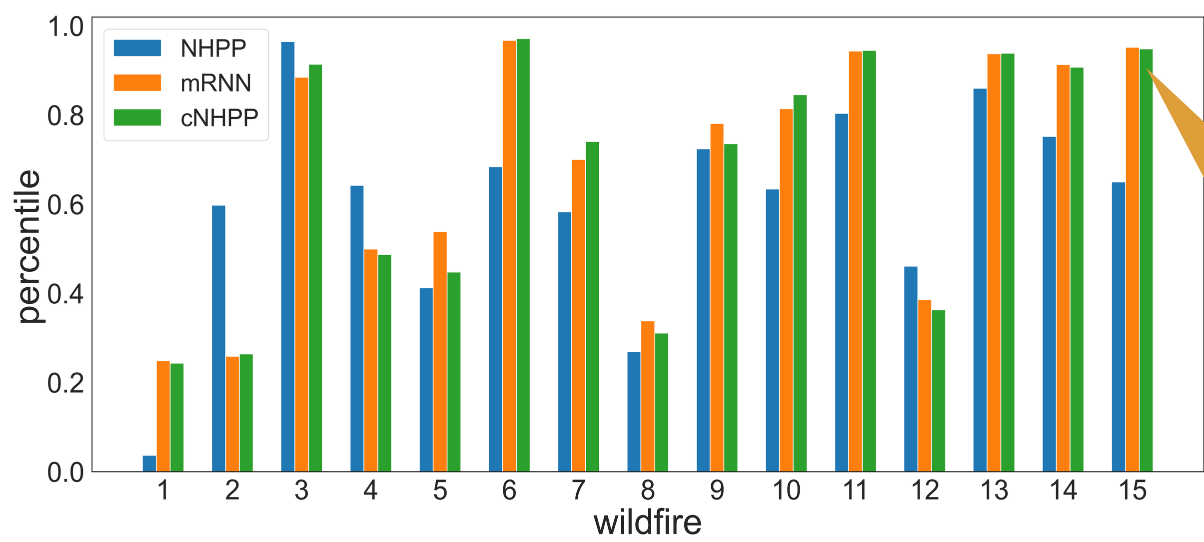


Figure 3: Distribution of estimated wildfire intensities on power transmission lines.



The effectiveness of the proposed approach that accounts for historical cumulative effects and spatial dependency when modeling wildfire risks.

Figure 4: The ranking of the estimated risk for the lines (with fires) among all lines.

Conclusions

- We proposed a new spatio-temporal point process model known as the Convolutional NHPP on a linear network. The proposed approach has been applied to model and predict wildfire risks on major transmission lines in California, utilizing the real datasets.
- The summary of this research can refer: Wei, G., Qiu, F., & Liu, X. (2022). Convolutional non-homogeneous Poisson process with application to wildfire risk quantification for power delivery networks. *arXiv preprint arXiv:2301.00067*.