Wildfire Webinar Series: Webinar 4

Modeling & Analytical Tools | Post Fire Analysis

April 29, 2021

Ron Wyden

United States Senator for Oregon

U.S. DEPARTMENT OF ENERGY
OFFICE OF ELECTRICITY

Dynamic Contingency Analysis Tool for Extreme Wildfire Event Planning

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Pacific Northwest National Laboratory

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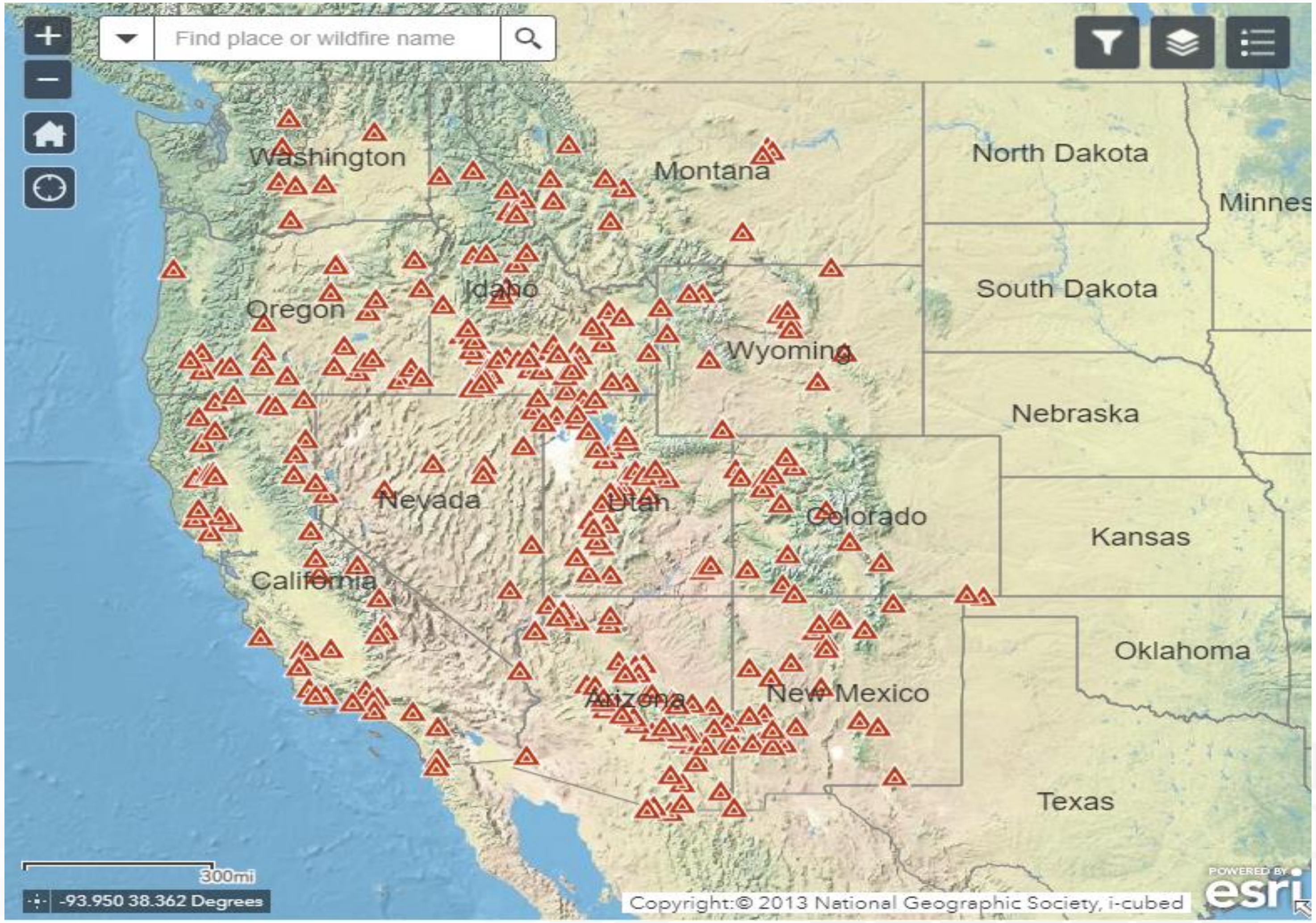
April 29th, 2021

Dynamic Contingency Analysis Tool (DCAT)

- **DCAT significantly improves how we prepare and plan for extreme events**
  - More realistic modeling enables effective decisions
  - Faster computing technology
  - Automatic simulations
- Prepare for extreme events
  - Improved assessment of cascading outage impacts
- Plan for the future
  - Provide information to identify grid enhancements

DCAT simulates finer details of cascading events

DCAT for Extreme Wildfire Event Planning & Mitigation



An illustration of WECC 2019 Wildfire Points [1].

- Historical wildfire events evaluation
- Corrective actions verification
- Preventive mitigation planning

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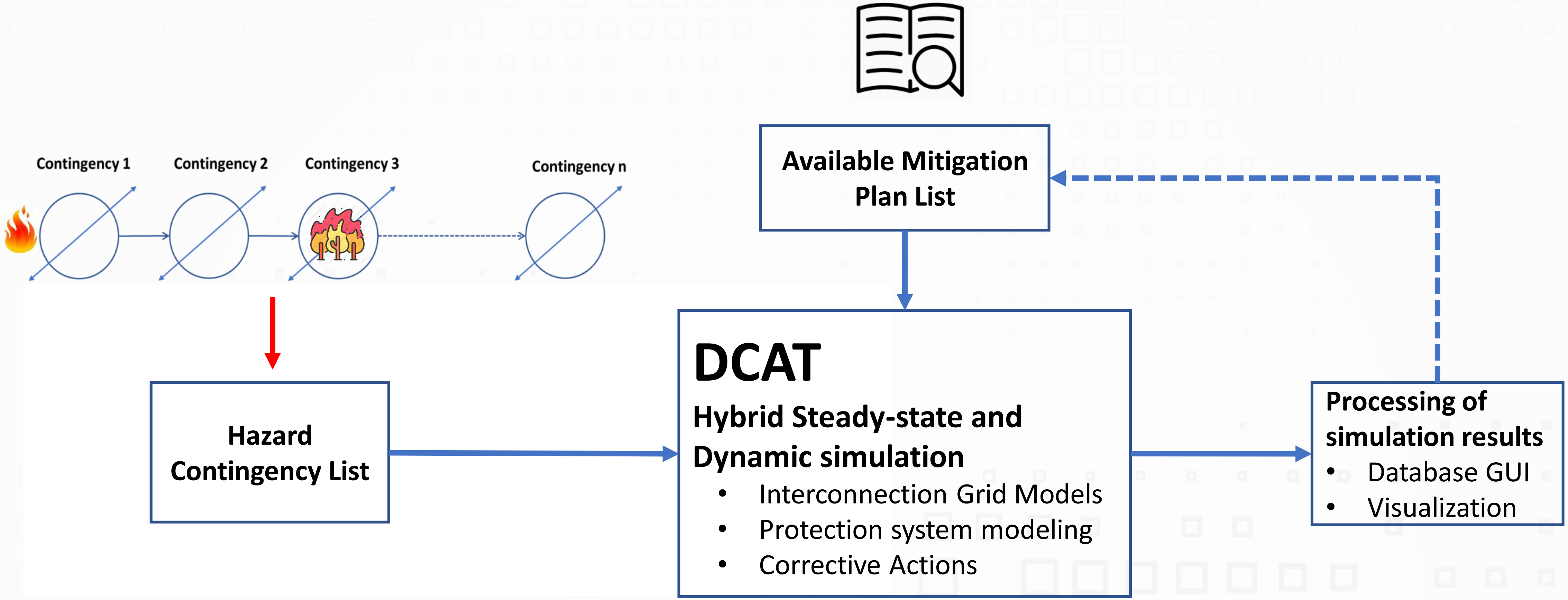
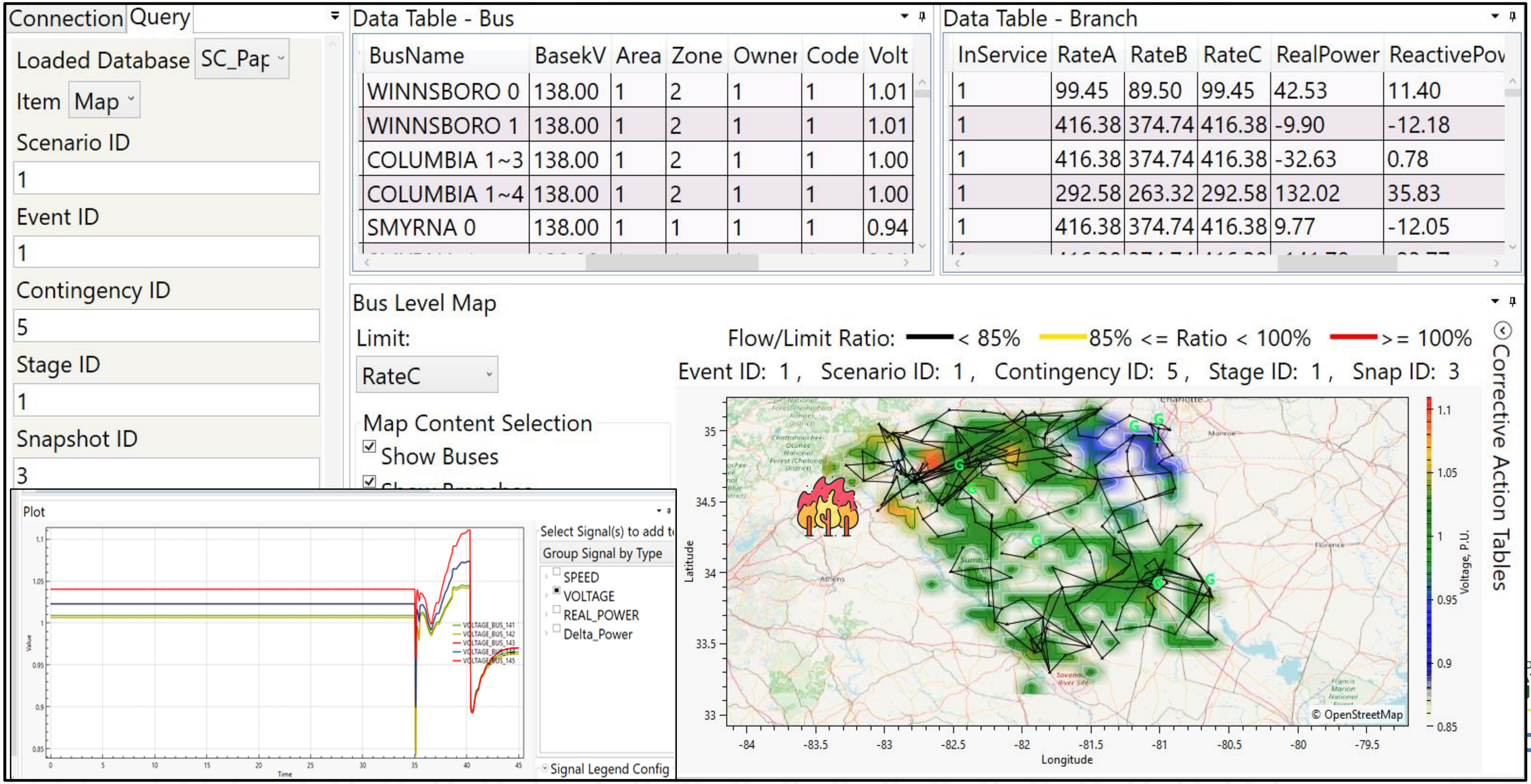
[1] The 2020 State of Interconnection published by Western Electricity Coordinating Council (WECC). Available at: https://www.wecc.org/epubs/StateOfTheInterconnection/Pages/Western-Interconnection.aspx

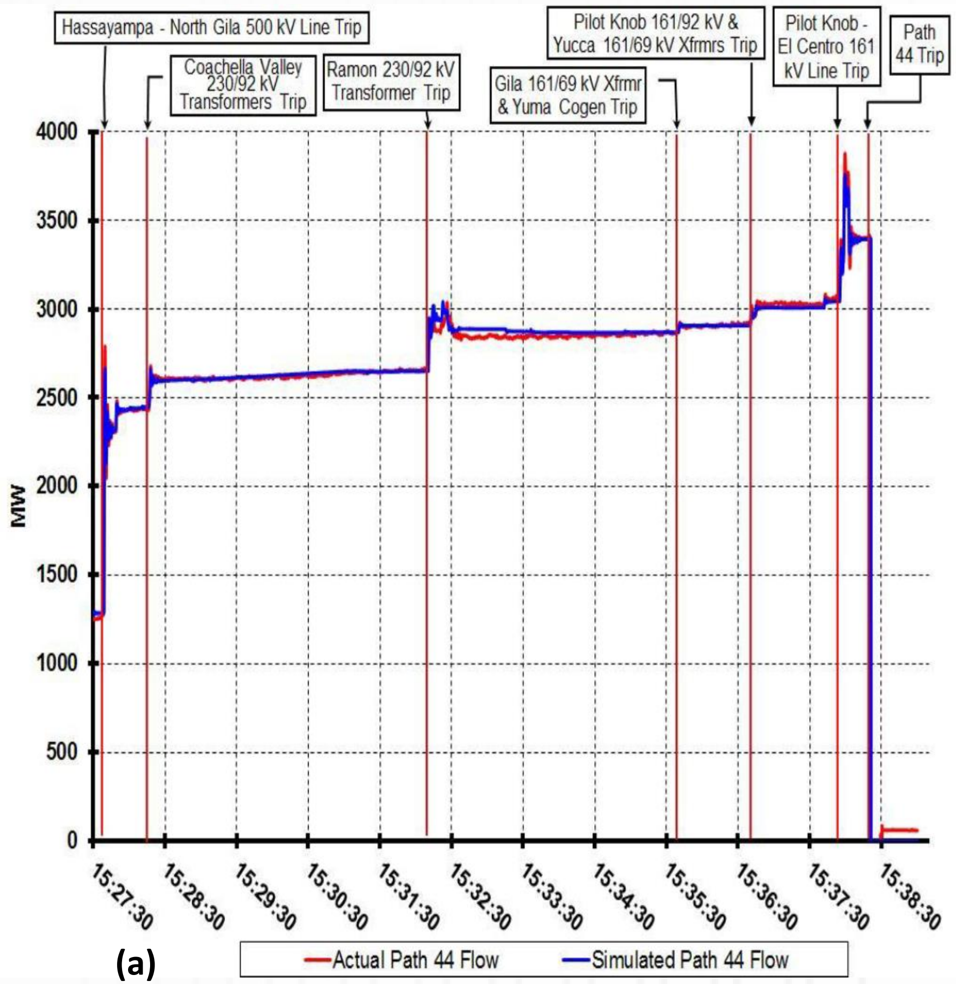
Hazard Contingency Modeling in DCAT



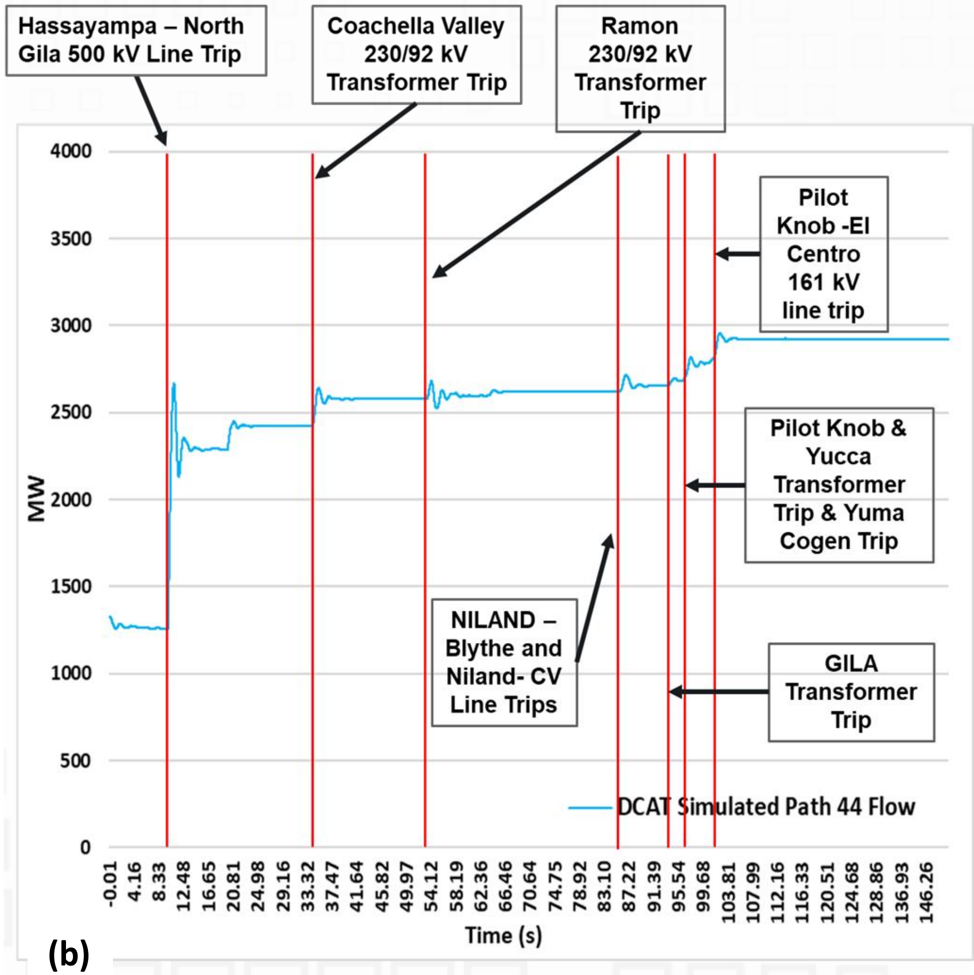
DCAT Analytics – Database and Visualization Modules



DCAT Applied in Western Grid Reliability Analysis



(a)



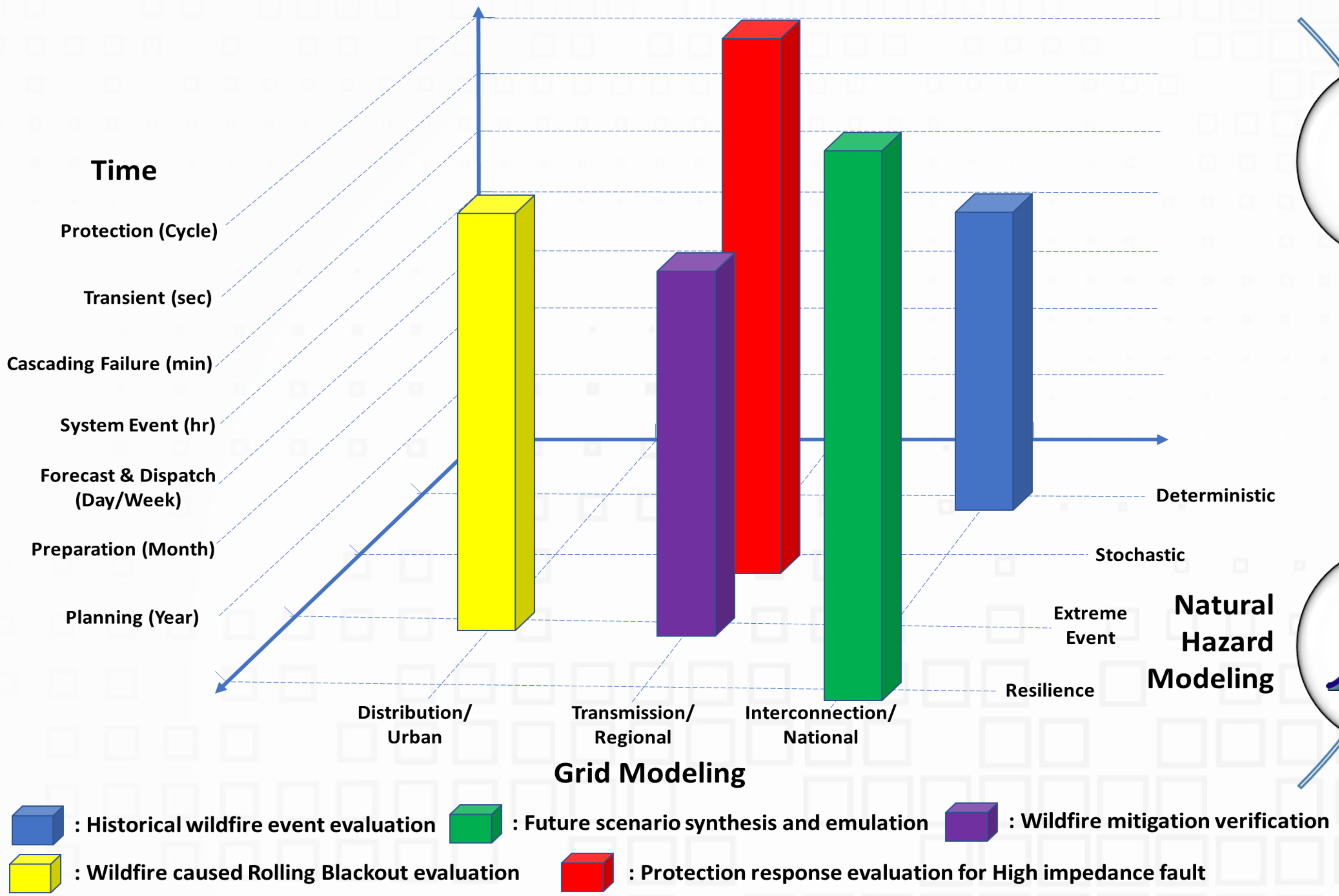
(b)

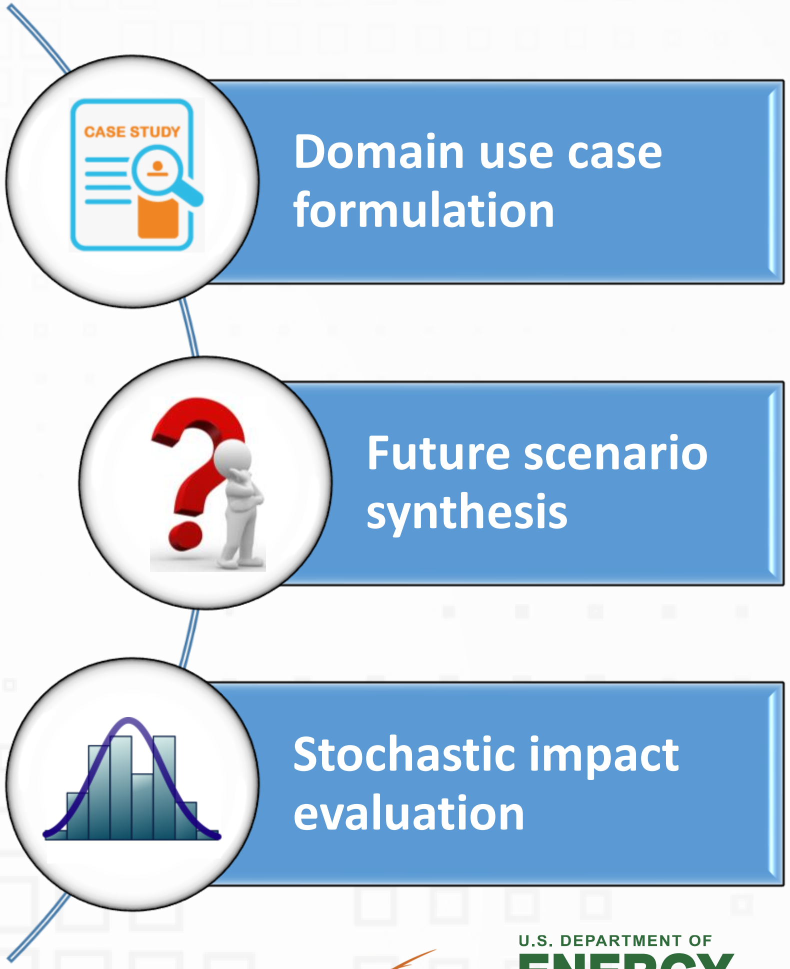
DCAT evaluation of WECC Path 44 for 2011 Pacific Southwest Blackout,

(a) Path flow plot provided in NERC Report [1]
(b) Simulated path flow in PNNL DCAT analysis [2] (full protection actions sequence automation).

[1] “Arizona-Southern California outages on September 8, 2011”, Prepared by the staffs of the FERC and the NERC, April 2012.
[2] X. Fan, et al., "Bulk Electric System Protection Model Demonstration with 2011 Southwest Blackout in DCAT," 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2020, pp. 1-5. doi: 10.1109/PESGM41954.2020.9281441.

DCAT for Extreme Wildfire Event Planning & Mitigation





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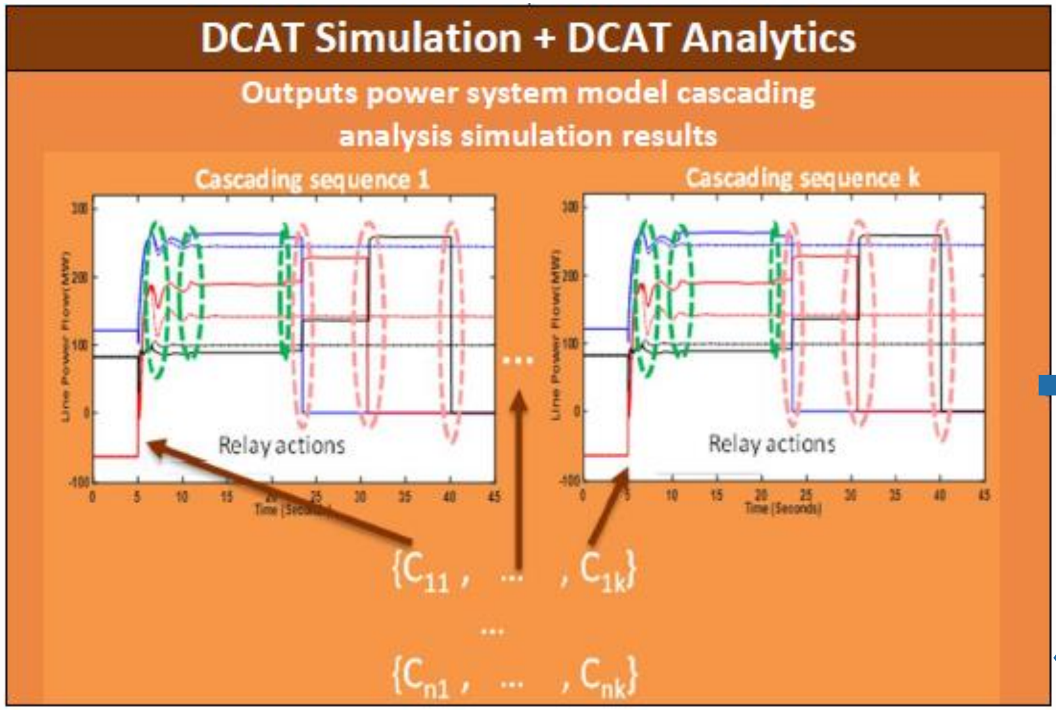
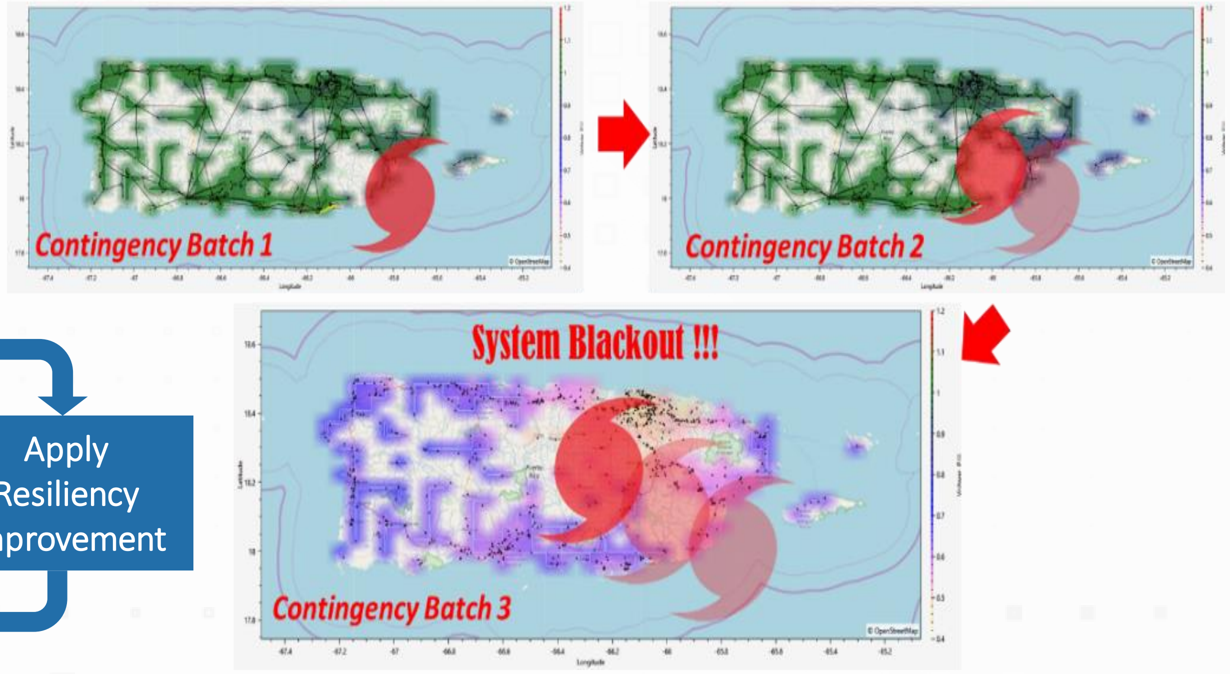
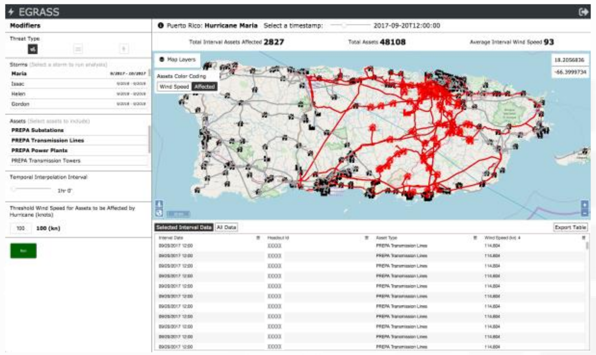
DCAT & EGRASS Can Be Extended for Wildfires



Apply Resiliency Improvement





EGRASS:
Geolocations of threat risk on Infrastructure
- Hurricane
- Wildfire
- Other extreme events

- Thousands of realistic dynamic cascading simulations
- Derive metric-based evaluation
  - Preparation & Planning
  - Mitigation & Corrective Actions
  - Ranking & Recommendation

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Status and Goals

- Goal
  - To develop and provide a DCAT-based framework to evaluate and visualize the impact of wildfires on electricity infrastructure to mitigate service disruption and improve resiliency.
- Status
  - DCAT is protected by a pending U.S. patent and copyright
  - Licenses are available for research, trials, and commercialization
  - Collaborators included ERCOT, Siemens, BPA, GE, and EPRI; additional users, utilities, and vendors are welcome
  - Contact PNNL Senior Commercialization Manager Peter Christensen at peter.christensen@pnnl.gov for more information

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Team Produced Relevant Publications

Technical publications:

- Fan X., U. Agrawal, S.H. Davis, et al. 2020. "Bulk Electric System Protection Model Demonstration with 2011 Southwest Blackout in DCAT." In 2020 IEEE Power & Energy Society General Meeting (PESGM). doi:10.1109/PESGM41954.2020.9281441
- Vyakaranam B., P.V. Etingov, H. Wang, et al. 2020. "Database Management Module Framework for Dynamic Contingency Analysis and Visualization." In IEEE Power & Energy Society General Meeting (PESGM). doi:10.1109/PESGM41954.2020.9281566
- Davis S.H., M.A. Elizondo, X. Fan, et al. 2020. "Data Requirements for Application of Risk-Based Dynamic Contingency Analysis to Evaluate Hurricane Impact to Electrical Infrastructure in Puerto Rico." In CIGRE-US 2020 Next Generation Network Paper Competition.
- Chen Y., K.R. Glaesemann, X. Li, et al. 2020. "A Generic Advanced Computing Framework for Executing Windows-based Dynamic Contingency Analysis Tool in Parallel on Cluster Machines." In IEEE Power & Energy Society General Meeting (PESGM). doi:10.1109/PESGM41954.2020.9281477
- G. Chin, B. McGary, K. Pierce, et al. 2020, "A Dynamic Contingency Analysis Visualization Tool," 2020 IEEE Power & Energy Society General Meeting (PESGM), doi: 10.1109/PESGM41954.2020.9281993.
- K. Sundar, M. Vallem, R. Bent, et al. 2019, "N-*k* Failure Analysis Algorithm for Identification of Extreme Events for Cascading Outage Pre-screening process," 2019 IEEE Power & Energy Society General Meeting (PESGM), doi: 10.1109/PESGM40551.2019.8973425.
- F. Dong, Vyakaranam B., N.A. Samaan, et al., "Restoration of System Security with Optimized Corrective Actions," 2018 IEEE Power & Energy Society General Meeting (PESGM). doi: 10.1109/PESGM.2018.8586309.
- B. Vyakaranam, N.A. Samaan, M. Vallem, *et al.*, "Modeling of Protection Relays using Generic Models in System-Wide Power System Dynamic Simulation Studies," *2018 IEEE Power & Energy Society General Meeting (PESGM)*, doi: 10.1109/PESGM.2018.8586612.
- Q. Huang, B. Vyakaranam, R. Diao, *et al.*, "Modeling zone-3 protection with generic relay models for dynamic contingency analysis," *2017 IEEE Power & Energy Society General Meeting (PESGM)*, , doi: 10.1109/PESGM.2017.8274534.
- N. Samaan, J.E. Dagle, Y.V. Makarov, *et al.*, "Modeling of protection in dynamic simulation using generic relay models and settings," *2016 IEEE Power and Energy Society General Meeting (PESGM)*, doi: 10.1109/PESGM.2016.7741981.

Institutional Reports:

- Vyakaranam B., N.A. Samaan, X. Li, et al. 2019. Dynamic Contingency Analysis Tool 2.0 User Manual with Test System Examples. PNNL-29105. Richland, WA: Pacific Northwest National Laboratory.
- Samaan N.A., J.E. Dagle, Y.V. Makarov, et al. 2017. Dynamic Contingency Analysis Tool (DCAT) User Manual with Test System Examples. PNNL-26197. Richland, WA: Pacific Northwest National Laboratory.
- Samaan N.A., J.E. Dagle, Y.V. Makarov, et al. 2015. Dynamic Contingency Analysis Tool - Phase 1. PNNL-24843. Richland, WA: Pacific Northwest National Laboratory.
- Elizondo M.A., X. Fan, S.H. Davis, et al. 2020. Risk-Based Dynamic Contingency Analysis Applied to Puerto Rico Electric Infrastructure. PNNL-29985. Richland, WA: Pacific Northwest National Laboratory.

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Thank You!

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Sustainable Forest Biomass for Fire Mitigation

Mark Wigmosta – Pacific Northwest National Laboratory
Paul Hessburg – USDA-FS, Pacific Northwest Research Station

April 29, 2021

Restoring fire-prone forests in a changing climate

- Efforts to improve forest health and reduce wildfire fuels are focused on reducing canopy cover in over-stocked forests via mechanical thinning and prescribed burning.
  - More frequent, less intense wildfire
  - Reduced risk to electric transmission/distribution infrastructure
  - Reduced post-fire hydrologic impacts (flash floods, landslides, increased erosion, sedimentation, etc.)
- There is potential to leverage these investments to achieve
  - Concurrent hydrologic benefits
    - Increased snowpack & summer streamflow
    - Increased flow to the hydrosystem
  - Economic and societal benefits through collection of residue for bioenergy
- We examine the interplay among forest restoration, wildfire/smoke emissions, snowpack, streamflow, land sector C stocks, and biomass for energy across treatment scenarios using a decision support application designed for that purpose.

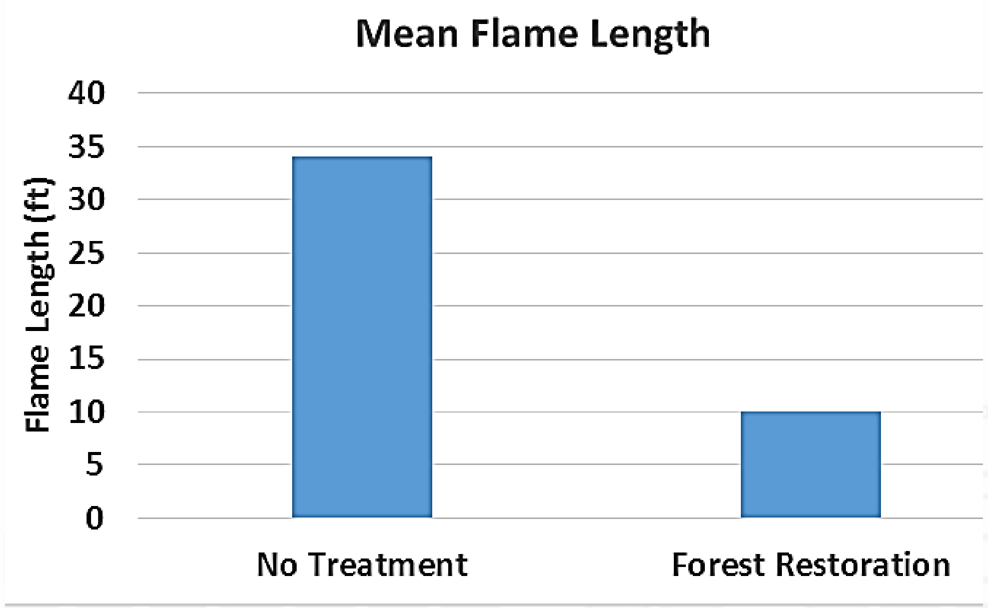
Metrics to quantify the tradeoff analysis

- Fire
  - Burn intensity (flame length, crowning index)
  - Total carbon release
  - Smoke production (PM2.5 and PM10)
- Biomass
  - Merchantable
  - Non-merchantable (residue for energy)
- Hydrology
  - Snowpack characteristics
  - Streamflow (annual, monthly, late season)
- Economics
  - Collection costs
  - Hauling costs

- Forest management is spatially explicit in annual timesteps.
- **Values** for key metrics quantify the reduction in wildfire risk and smoke emissions, available biomass, impacts to streamflow, and associated economics.
- These spatially variable metrics help quantify the synergies and tradeoffs between objectives
- Trade-offs are reflected in the DST

Reduction in wildfire risk through forest restoration

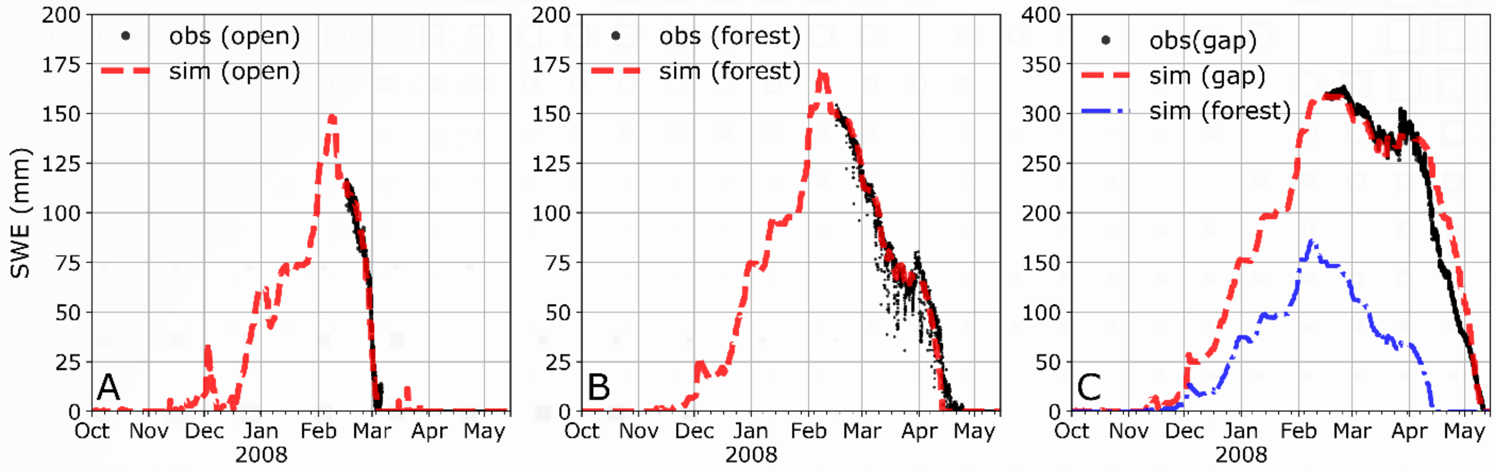
- **Flame length** under all weather conditions, indicates the likelihood that direct fire suppression is an option and whether crownfires will initiate
  - Current evaluation is for restored locations. We can also model change in likelihood of spread between treated and untreated locations, not shown here.



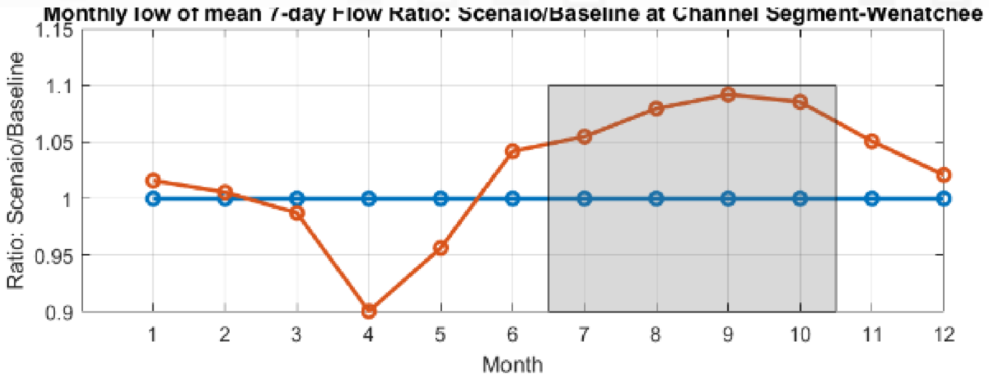
- Significant reduction in flame length on treated pixels

Forest canopy conditions impact the volume and timing of snowmelt and streamflow

Single location at U. of Idaho Experimental Forest



Peak snow water equivalent (SWE) in the canopy gap is twice that of the adjacent forest, and snow cover remains ~three weeks longer



In areas where snowpack supplies late season flows, targeted forest restoration can help increase critical summer low flows

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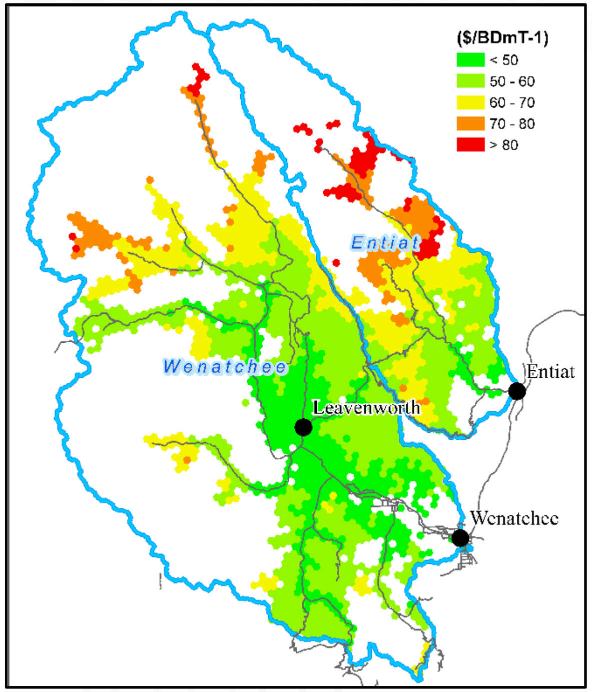
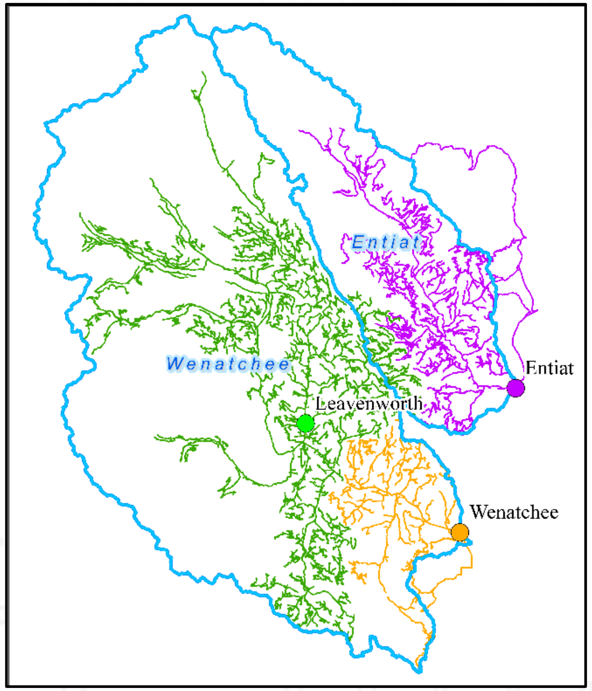
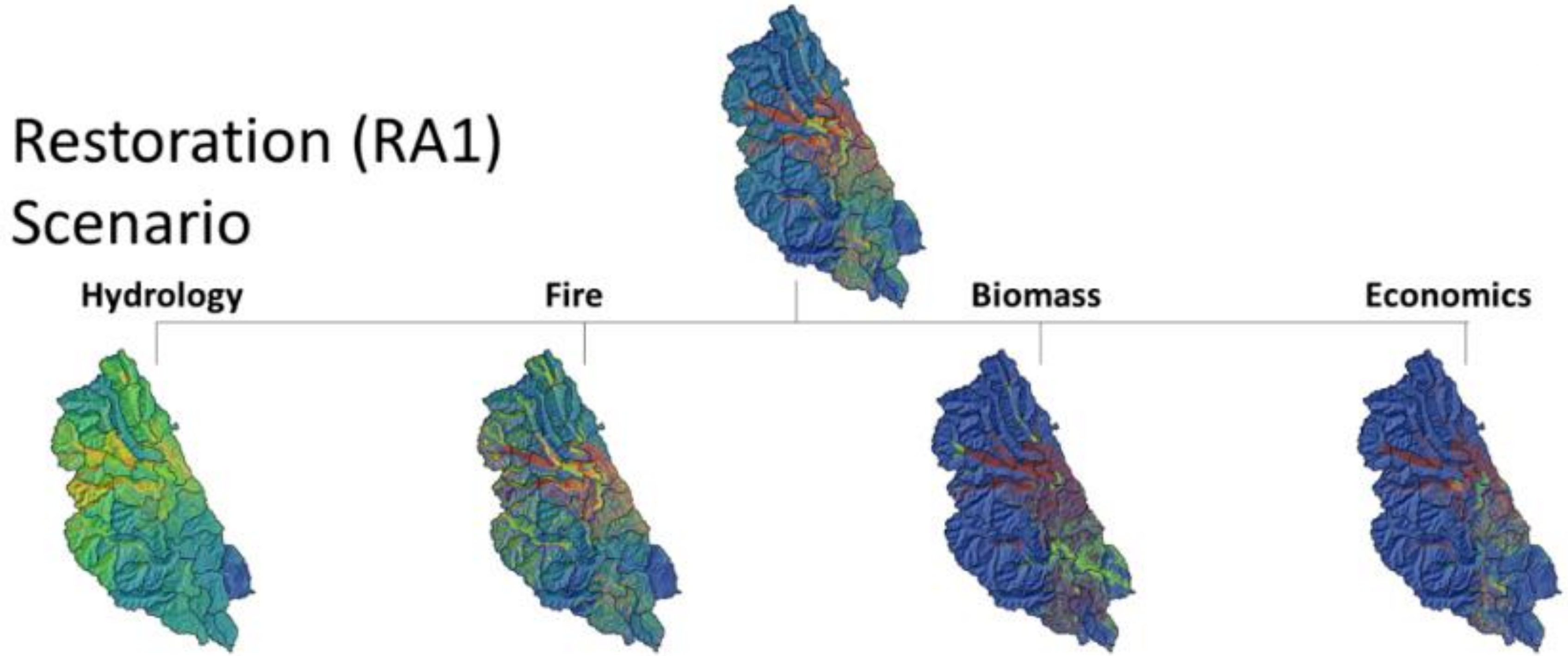
The economics of forest biomass depends on markets, processing, and transport costs





- The road network is a major driver of delivered cost of residue
  - Distance and surface type
- With three potential locations
  - Vast majority of residue could be obtained at the target cost using only the Leavenworth location

Examining the tradeoffs between wildfire, water, bioenergy, and economic sustainability



- **Upper Panel:** Priority locations (warm colors) for forest treatments based on land allocation, derived benefits to hydrology, wildfire risk and smoke emissions reductions, available biomass, and economics
- **Lower Panel:** Priority locations for <u>individual</u> objectives used in tradeoff analysis

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PNNL-USFS Forest Restoration Collaboration

- 2014-2015: ***Development of a Distributed Hydrology Model for use in a Forest Restoration Decision Support Tool to Increase Snowpack in the Upper Columbia***, Washington State Department of Ecology
- 2017-2022: ***Resource Assessment of Sustainable Biomass through Forest Restoration***, US DOE Bioenergy Technologies Office
- 2020-2021: ***Refine and Pilot Test Upper Columbia Distributed Hydrology Soil Vegetation Model and Snow2Flow Decision Support Tool***, Washington State Department of Ecology
- 2021: ***Improving the Timing and Volume of Hydrosystem Inflow through Targeted Forest Management***, US DOE Water Power Technologies Office
- 2021-2022; ***Expanding Forest Management and Promoting Ecosystem Health Services through access to Environmental Markets***, USFS Region 5 National Conservation Investments Fund

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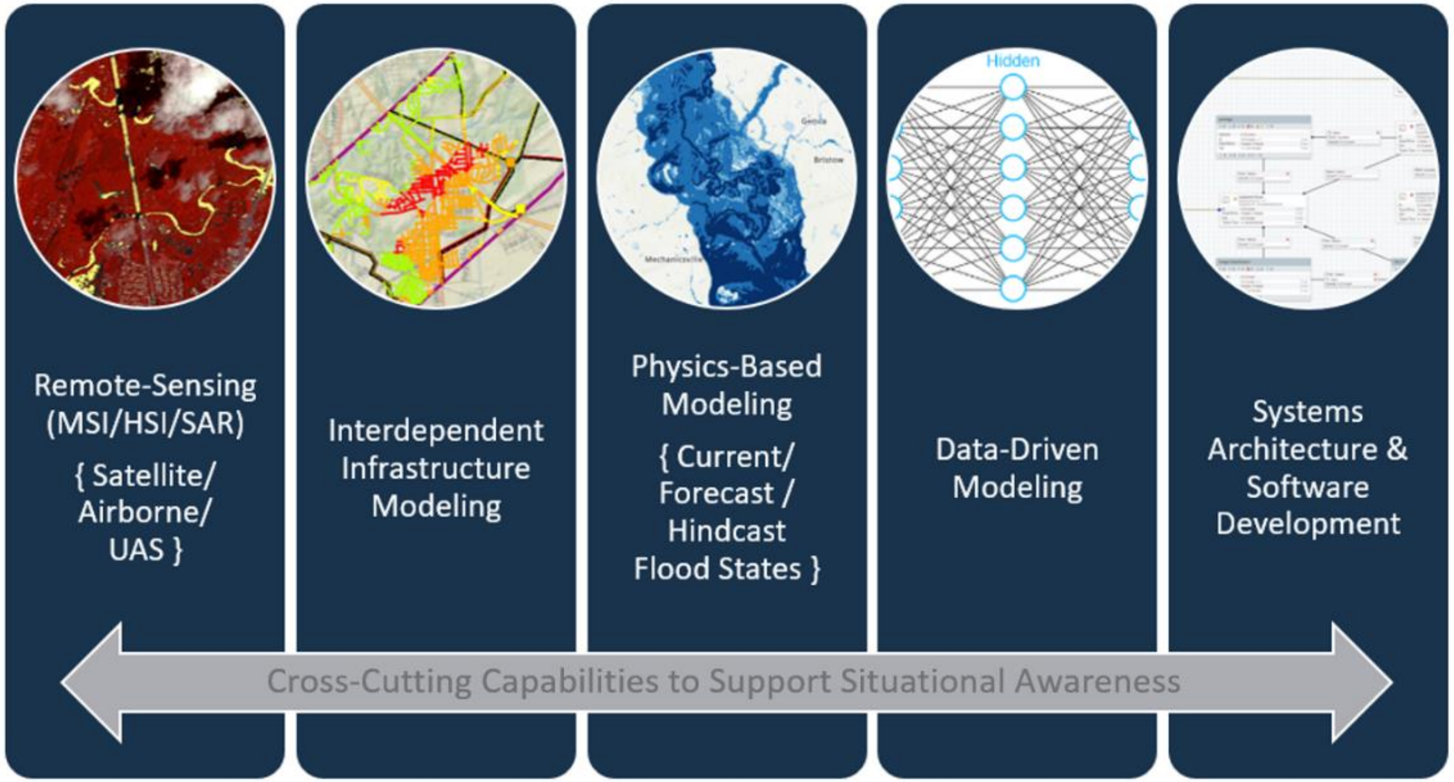
Multi-Sensor Data Fusion for Active Wildfire Monitoring

Andre Coleman – Principal Investigator / Data Scientist
Neal Oman – Project Manager
Todd Hay – Chief Systems Architect
Jerry Tagestad – Remote Sensing Lead / Data Scientist
Jill Brandenberger – Project Advisor

April 29, 2021

Rapid Response Analytics for Situational Awareness

- Driving Questions for Situational Awareness Support
  - What is the spatial extent of the hazard?
  - What is the timing of the hazard?
  - How many people are at risk?
  - What infrastructure are impacted or at risk?
- How Does PNNL Support Events (Pre-, Peri-, Post-Event)?
  - Predictive modeling and simulation
  - Leverage existing simulations (OpenWELL)
  - Assess existing/forecasted risk to infrastructure
  - Imagery-based damage analytics



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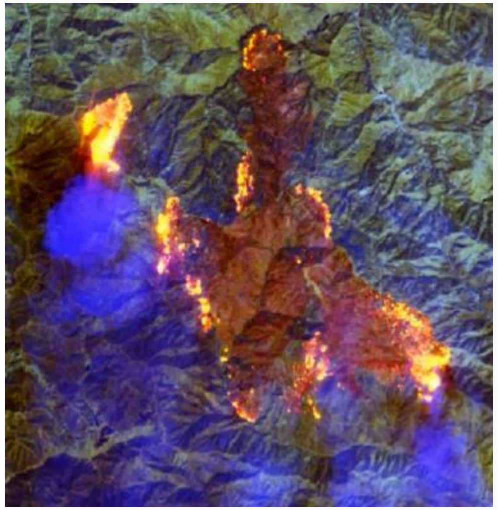
Rapid Response Analytics for Situational Awareness

- 35-year trend analysis indicates positive trend in economic loss[1,2]
  - Hydrologic events - 300% increase
  - Meteorological and climatological events - 200% increase
  - Geophysical events - 50% increase



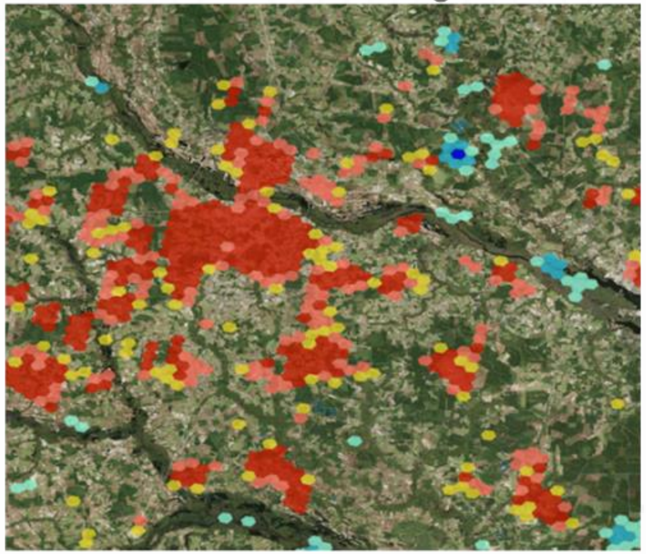
- The frequency, magnitude, and velocity of disaster events requires adaptations in disaster management operations
  - Current operational approaches are not necessarily equipped to handle the influx of diversely available information required for highly dynamic events
- The disaster management community requires accurate, timely, and comprehensive impact assessments frequently throughout the event
  - ≤24-hr recurrence; >24-hrs, usefulness degrades[3]

[1] Hoeppe (2016) [2] Benfield (2018) [3] Hodgson, M.E. et al. (2014)

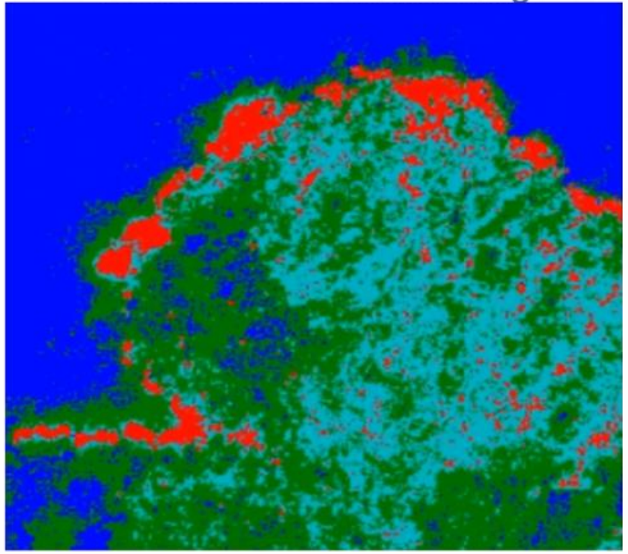
Rapid Analytics for Disaster Response (RADR)

Optical/SAR Flood Detection

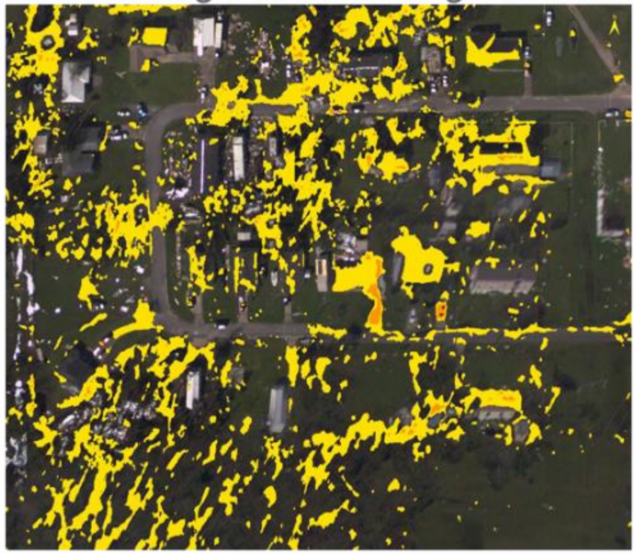
Structural Damage



Active Wildfire Monitoring

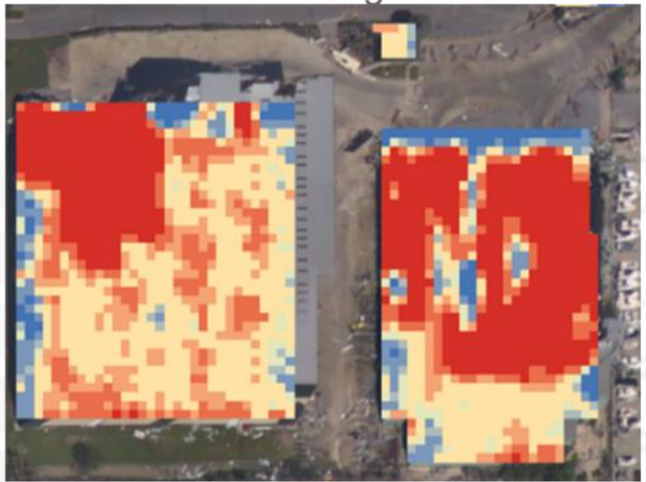


Vegetation Damage

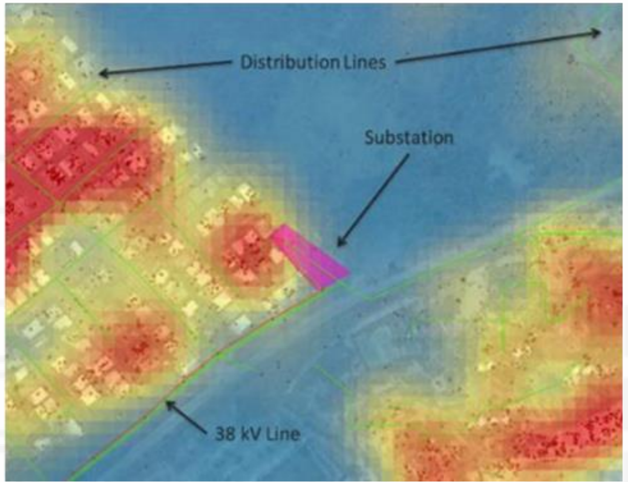


Infrastructure Damage

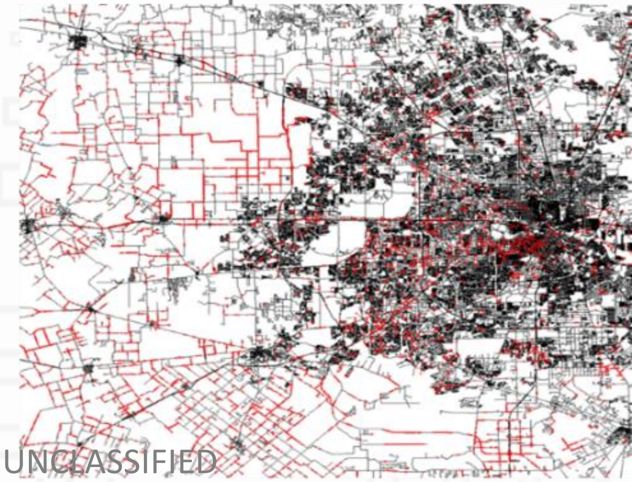
Structure Damage Detection



Rubble/Debris Detection



Transportation Barriers



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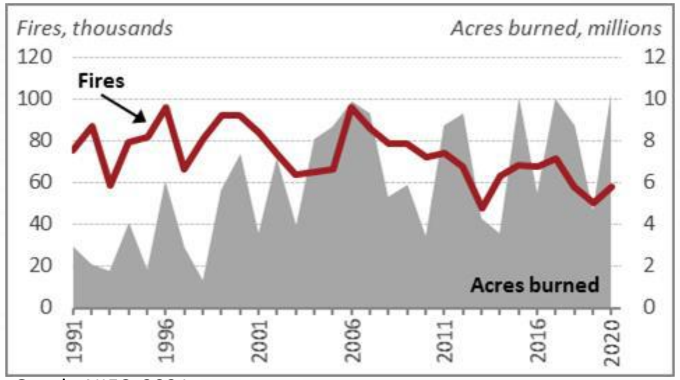
2020 Wildfire Season in Review

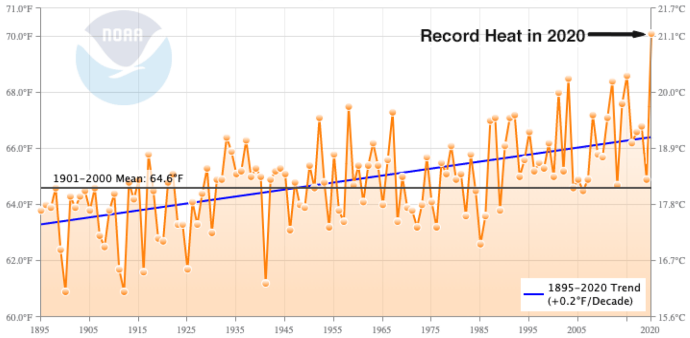
- For 2020 in the U.S.
  - 10.3 million acres burned
    - 1.4x higher than the 2010-2020 10-yr average; 3x higher than the 1990-2000 10-yr average
    - Long-term trends suggest flat trend on the number of fires
    - Strong positive trend in the total acreage burned
  - CA: 5 of the top 20 largest fires
  - CO: 3 of the state's largest fires

  - ~18k structures lost
  - $3.6B in fire suppression costs
  - $16.6B in direct costs
    - i.e., insurance claims plus estimates for uninsured
  - Estimated $130-150B in indirect costs
    - i.e., environmental cleanup, lost business, tax revenue, property and infrastructure repairs

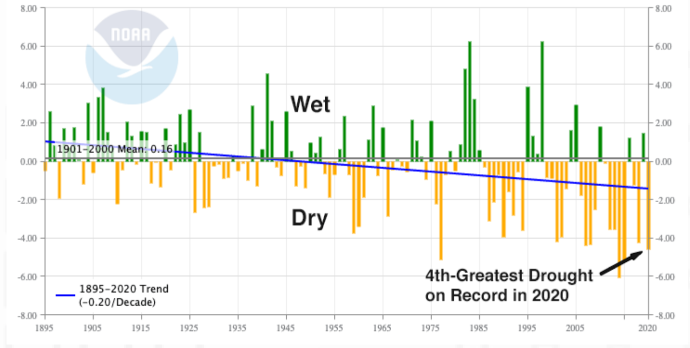


Graph: NIFC, 2021

Western U.S. Average Temperature, Aug-Oct



Western U.S. Palmer Drought Severity Index (PDSI), October



Technology Needs in Wildfire Response

- Use of high-resolution satellite imagery to help meet demand
  - Imaging aircraft are in high-demand – generally prioritized for high complexity fires
- Persistent monitoring (10-15-minute intervals)
- Automated algorithms to process imagery and generate analytics
  - Move away from human analyst image interpretation
  - Produce standardized map products in common geospatial data formats/delivery protocols
- Imaging at 10m GSD (commonly used sensors at 375m and 1km GSD)
- Automated early fire detection
- Semi-continuous fire behavior forecasting with up-to-date high-fidelity inputs

RADR FIRE

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TECH WHEN IT COUNTS FOR THOSE WE COUNT ON
FIRST FIVE

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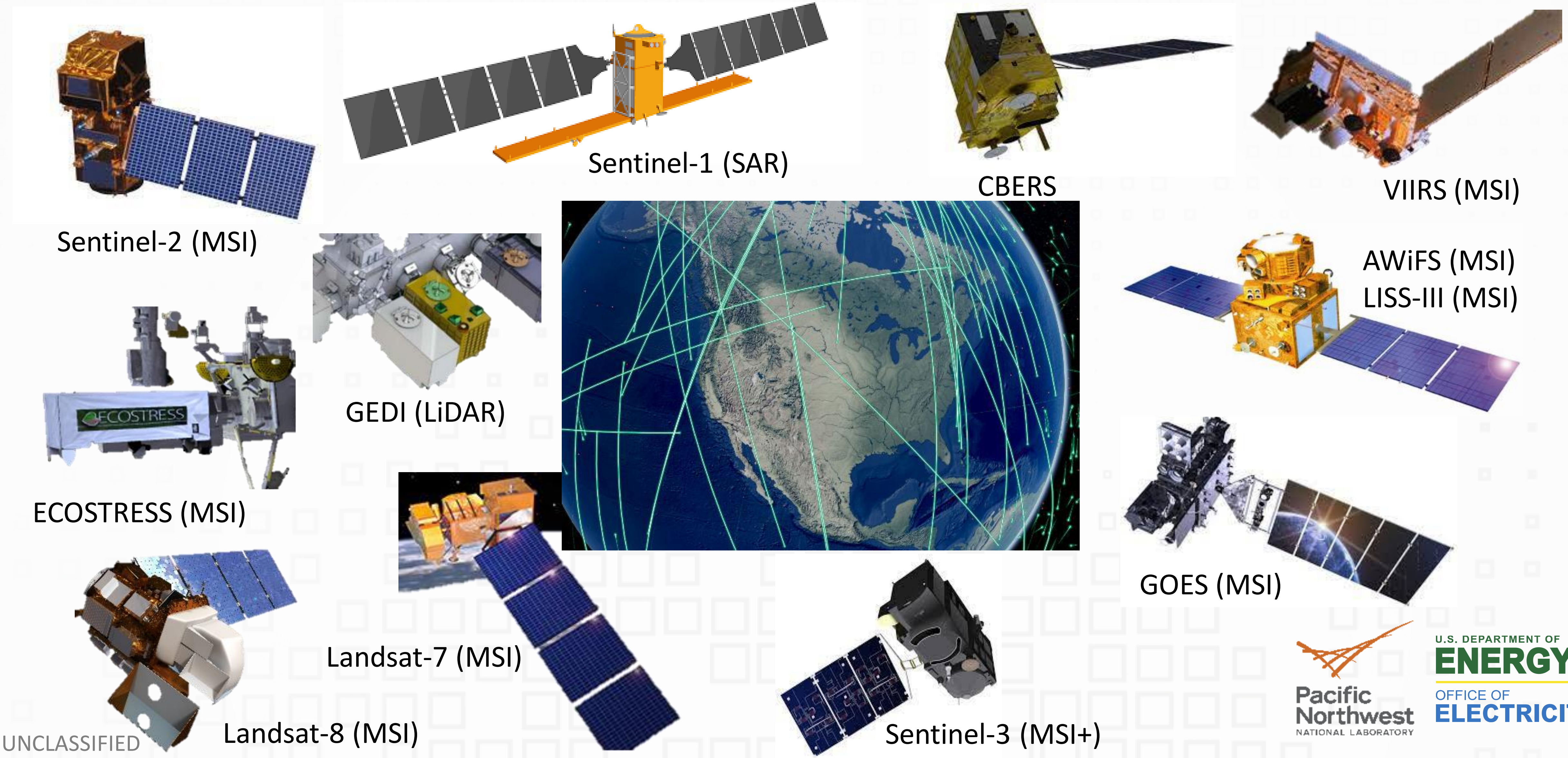
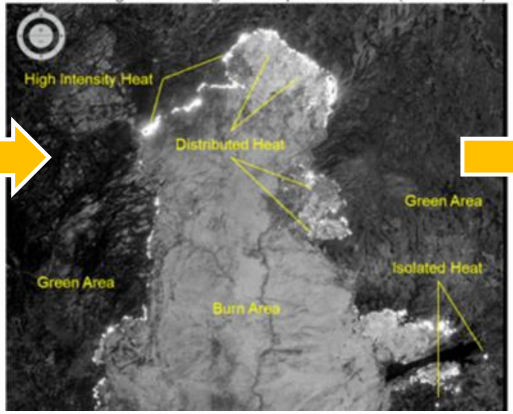
Remote Sensing of Wildfire

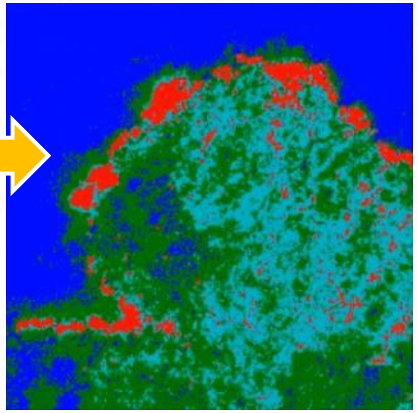


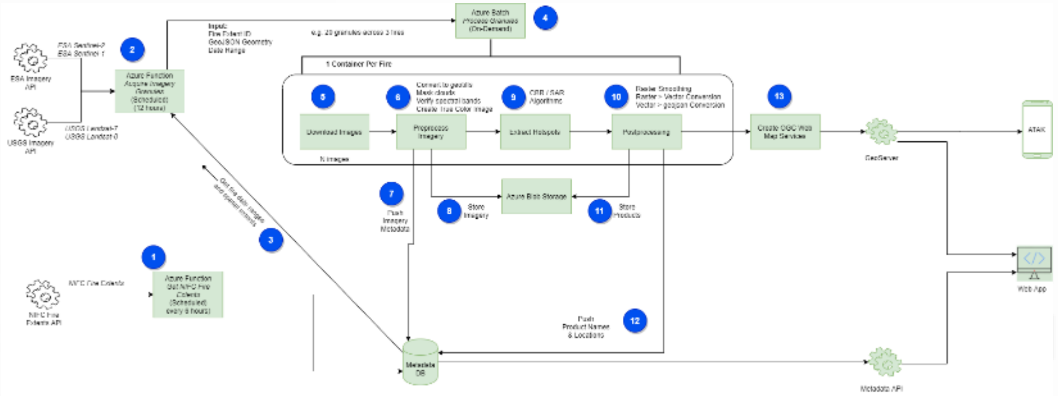
Rapid Analytics for Disaster Response (RADR) - Wildfire

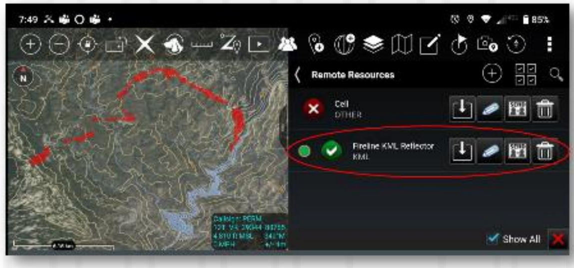
Visible Imagery (Sentinel-2)

RADR xBR Algorithm using SWIR spectral bands (20m GSD)





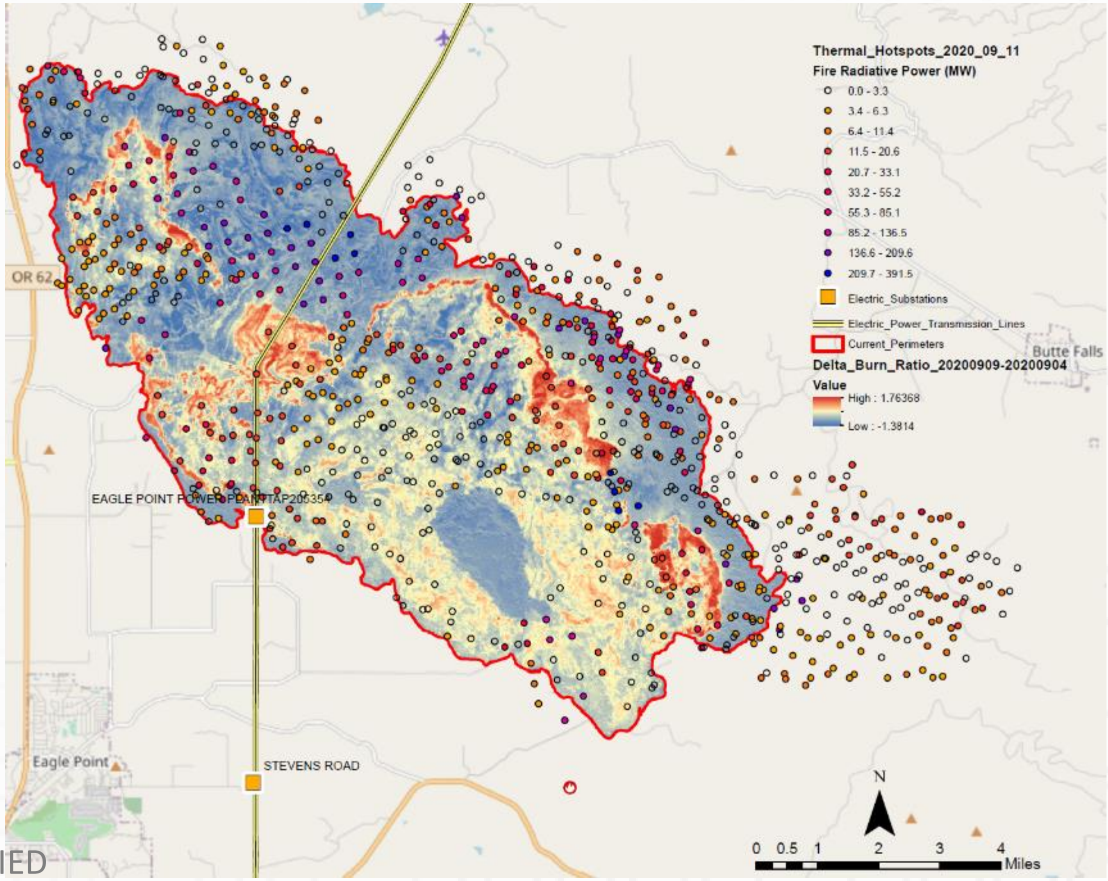


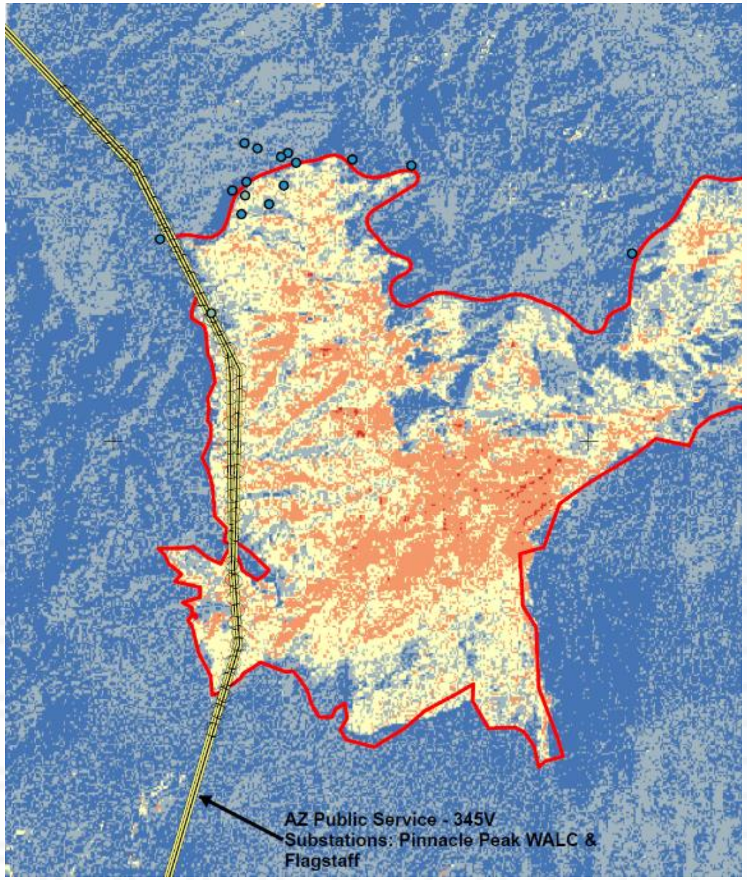


- Automated, end-to-end, cloud-based, open-data solution that retrieves and utilizes specialized imagery from numerous high-resolution (<30 m) earth observation satellites
- Provide situational awareness on the active fire front, spot fires, scattered heat, post-burn intensity, and unburned areas
- Time-series results disseminated via website, mobile app, and web services

Rapid Analytics for Disaster Response (RADR) - Wildfire

- Risk analytics for critical energy infrastructure
- Where the fire is, how intensely it has burned, where it is going?
- Critical for post-fire assessments / post-fire flood and debris flow risk





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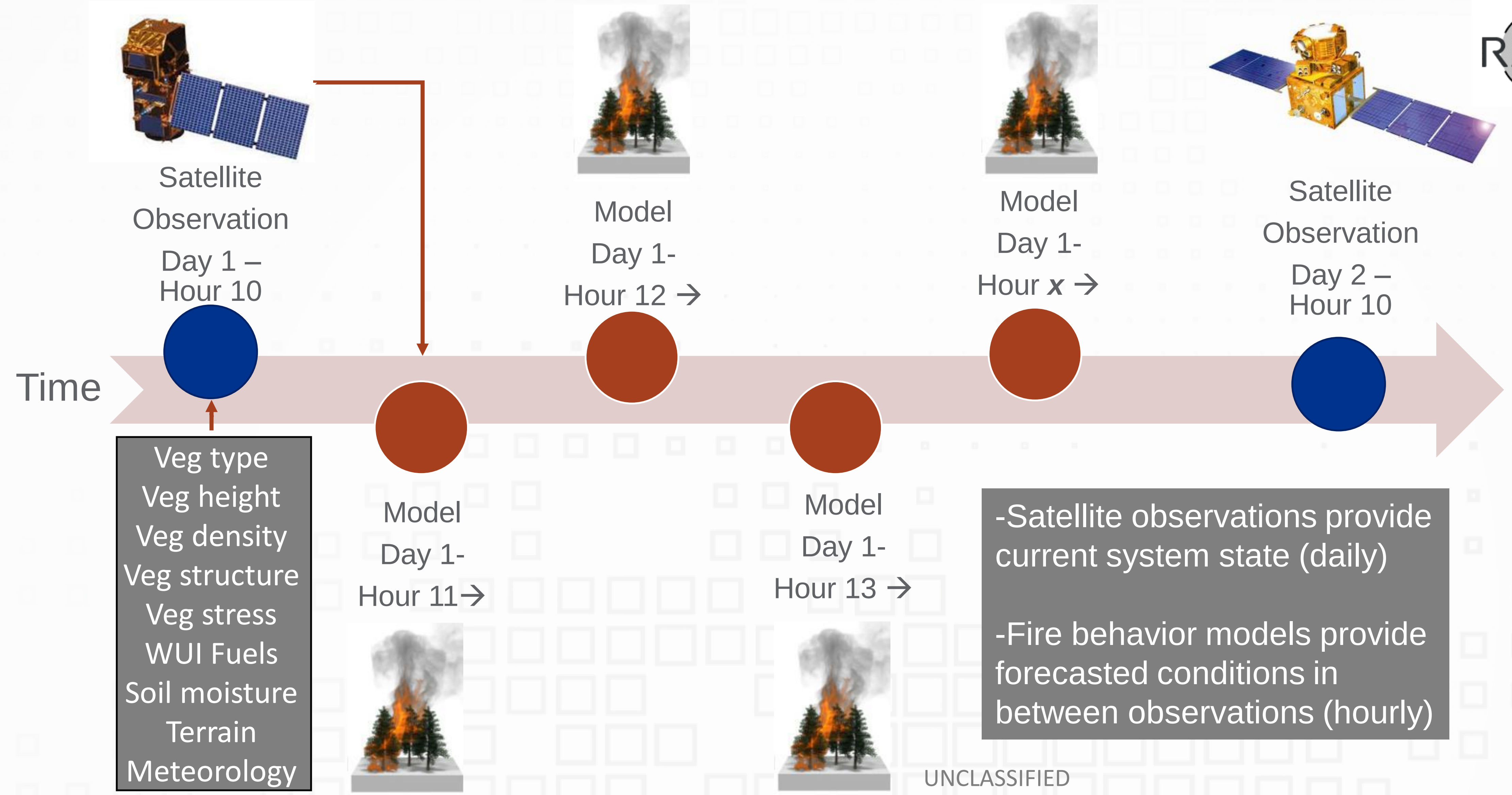
Wildfire Behavior Modeling



-Satellite observations provide current system state (daily)

-Fire behavior models provide forecasted conditions in between observations (hourly)

RADRFIRE

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Tech When It Counts · For Those We Count On · First Five

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U.S. Department of Energy Office of Electricity

RADR-Fire Team

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- Todd Hay – Chief Systems Architect (Todd.Hay@pnnl.gov)
- Jerry Tagestad – Remote Sensing Lead (Jerry.Tagestad@pnnl.gov)
- Jill Brandenberger – Project Advisor (Jill.Brandenberger@pnnl.gov)

Russ Burtner – UI/UX Design
Daniel Corbiani – Cloud System Architect
Kyle Larson – Remote Sensing Developer
Lee Miller – Geospatial Developer
Corey Oldenberg – Cloud Developer
Bill Perkins – Fire Behavior Modeling

Daniel Farber – Fire Behavior Modeling
Marena Richardson – Software Engineer
Danielle Rubin - Software Engineer
Tim Seiple – Geospatial Cloud Developer
Yi Shaw – UI/UX Design

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Thank You!

Andre.Coleman@pnnl.gov

XAI Models of Wildfire Risk and Risk Management

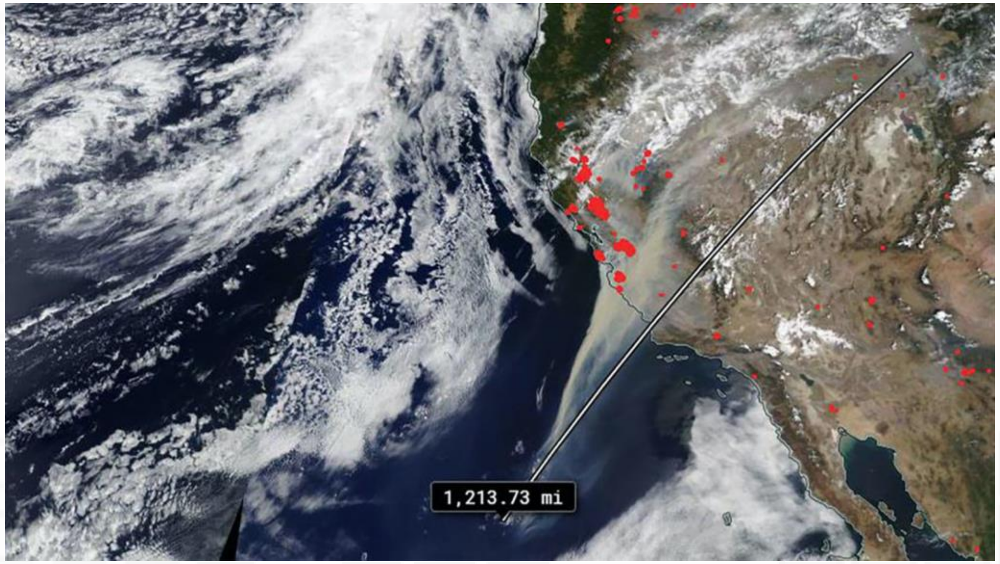
Qing Zhu (qzhu@lbl.gov)

Lawrence Berkeley National Lab

04/29/2021

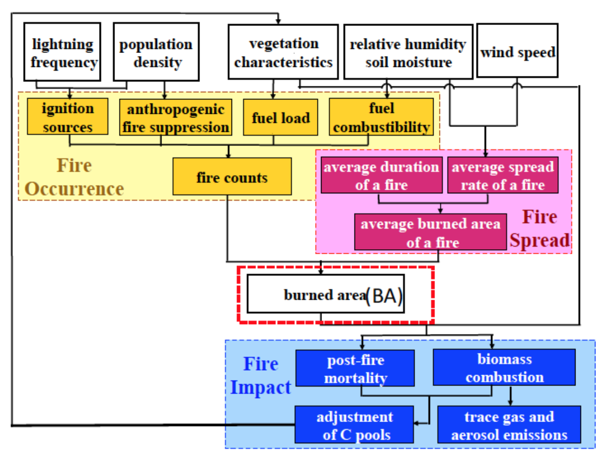
Overarching goals

1. **Map wildfire risk with variable temporal scales**
    - e.g., day, week, month, seasonal scales
2. **Evaluate effects of potential management on reducing wildfire risk**
    - e.g., prescribed fire, forest thinning, reduce litter/CWD fuel availability



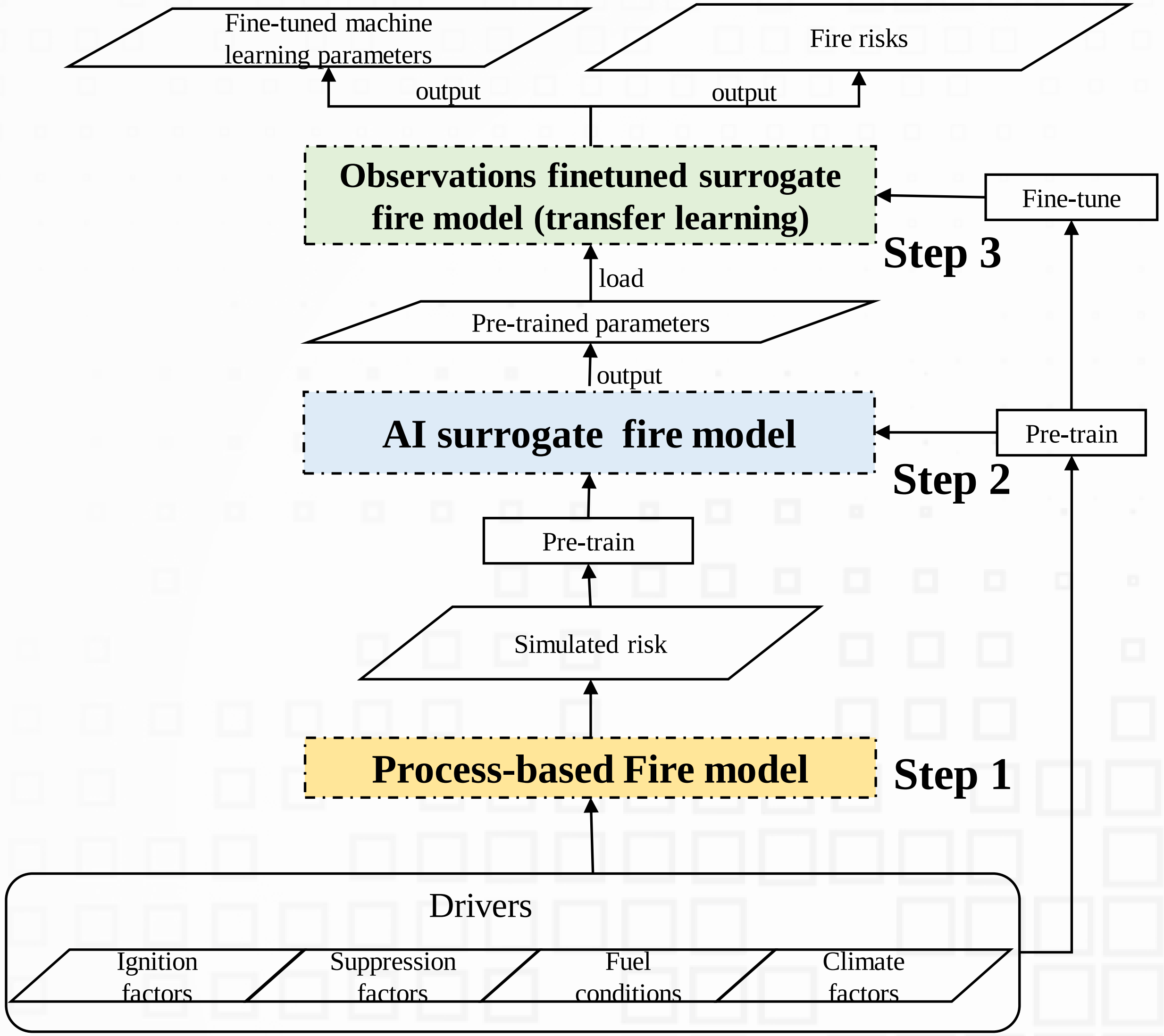
Objectives

- Test hybrid modeling framework with mechanistic/AI (XAI) fire models for risk assessment
- Model wildfire risk probability, dynamically across space and time
- Model multiple management practices and their potential impacts
- Continuously improve the risk model with transfer learning and using observational data



+

Technical Approach



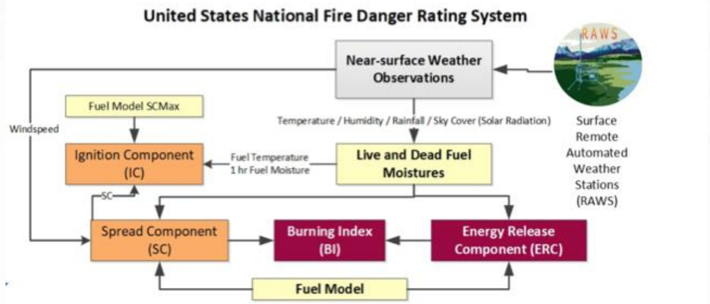
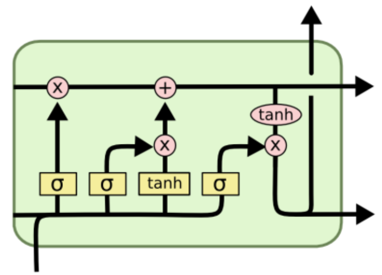


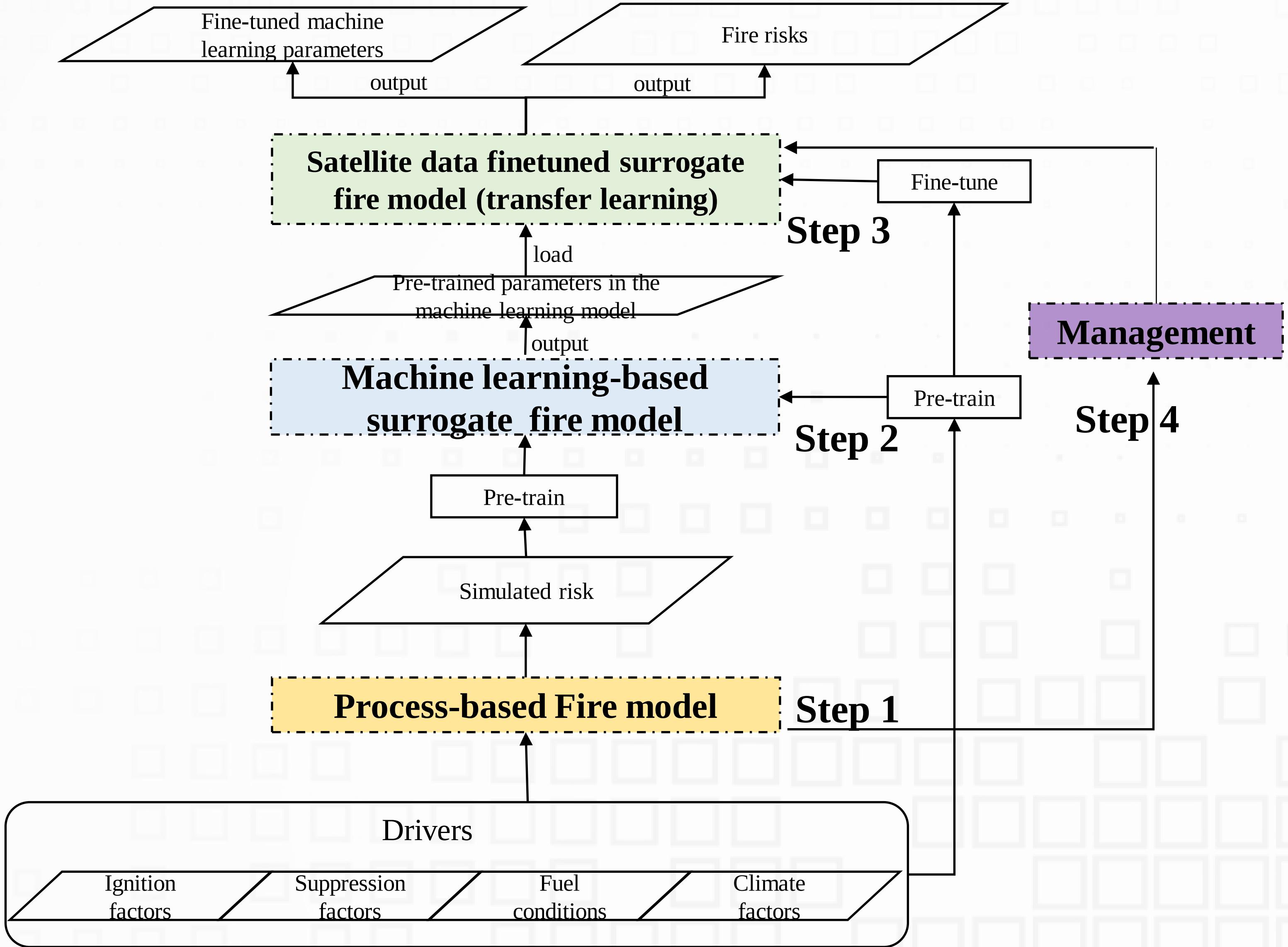
Figure 1. Basic flow diagram of the US National Fire Danger Rating System.

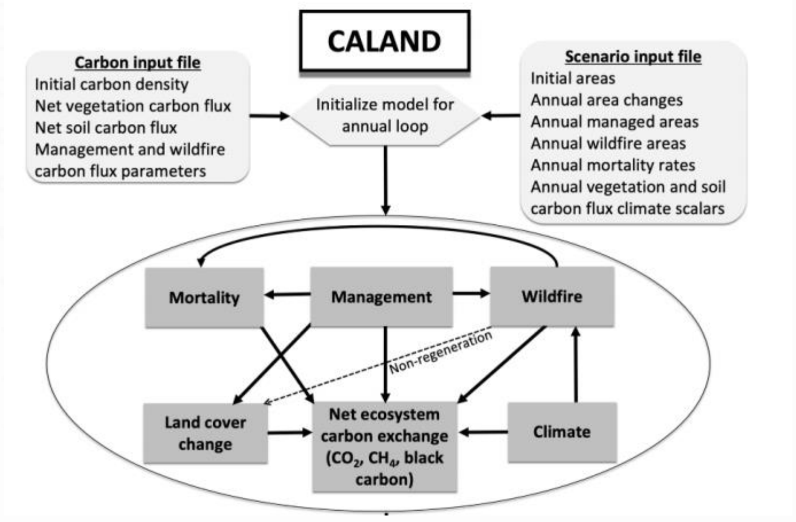
Process-based risk index: Interpretable, less accurate



AI-based risk estimate: accurate, but less interpretable and no physical constraints

Technical Approach



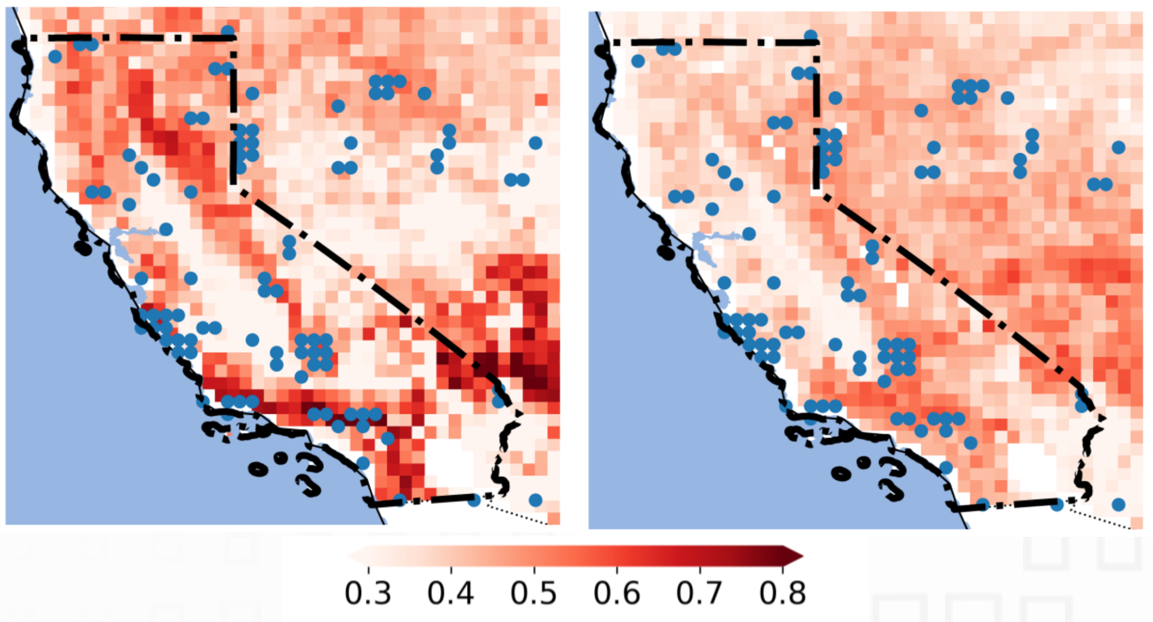


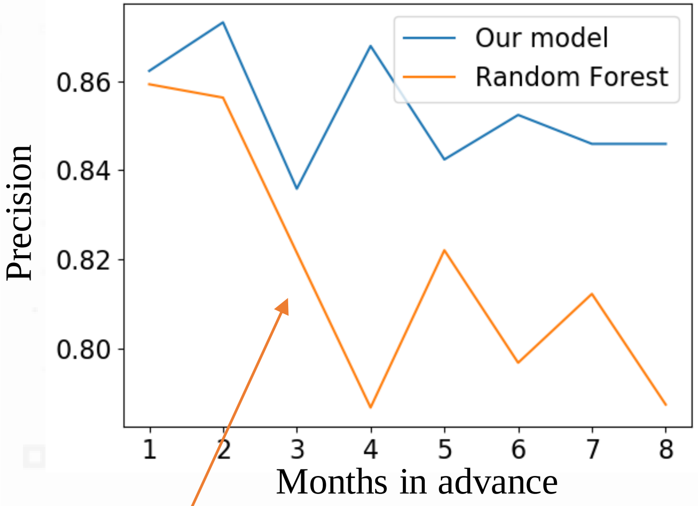
Simmonds et al., 2021

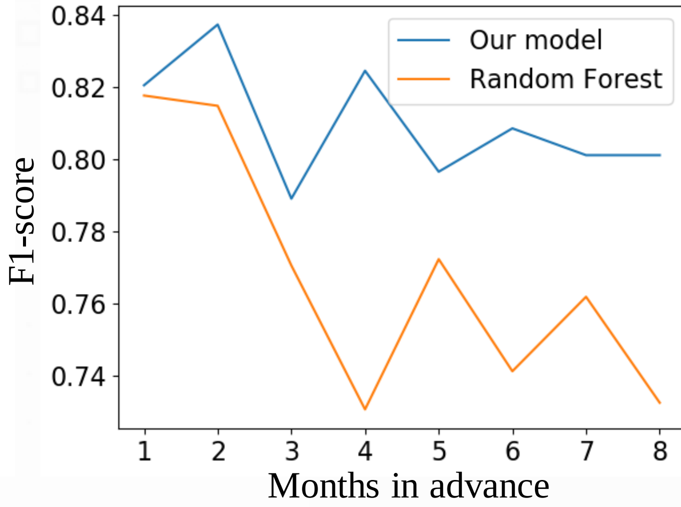
Applications over CA

Our XAI model

Random forest model (Jing Li 2020)







Jing Li 2020

2012-2016: 368 large fires (Burned area > 4 Km^2), 216 small fires

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Capability Summary

In 3 month **Wildfire Early warning system**

Fire risk map with multiple time leads

- Fire risk map with daily leading time
- Fire risk map with weekly leading time
- Fire risk map with monthly leading time
- Fire risk map with seasonal leading time

+

In 6 month **Wildfire mitigation tool**

Fire risk map with/without management

- Daily-weekly leading time: e.g., monitoring, resource allocation, powerline shutdown
- Monthly-seasonal leading time: e.g., prescribed fire, forest thinning

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Thank You!

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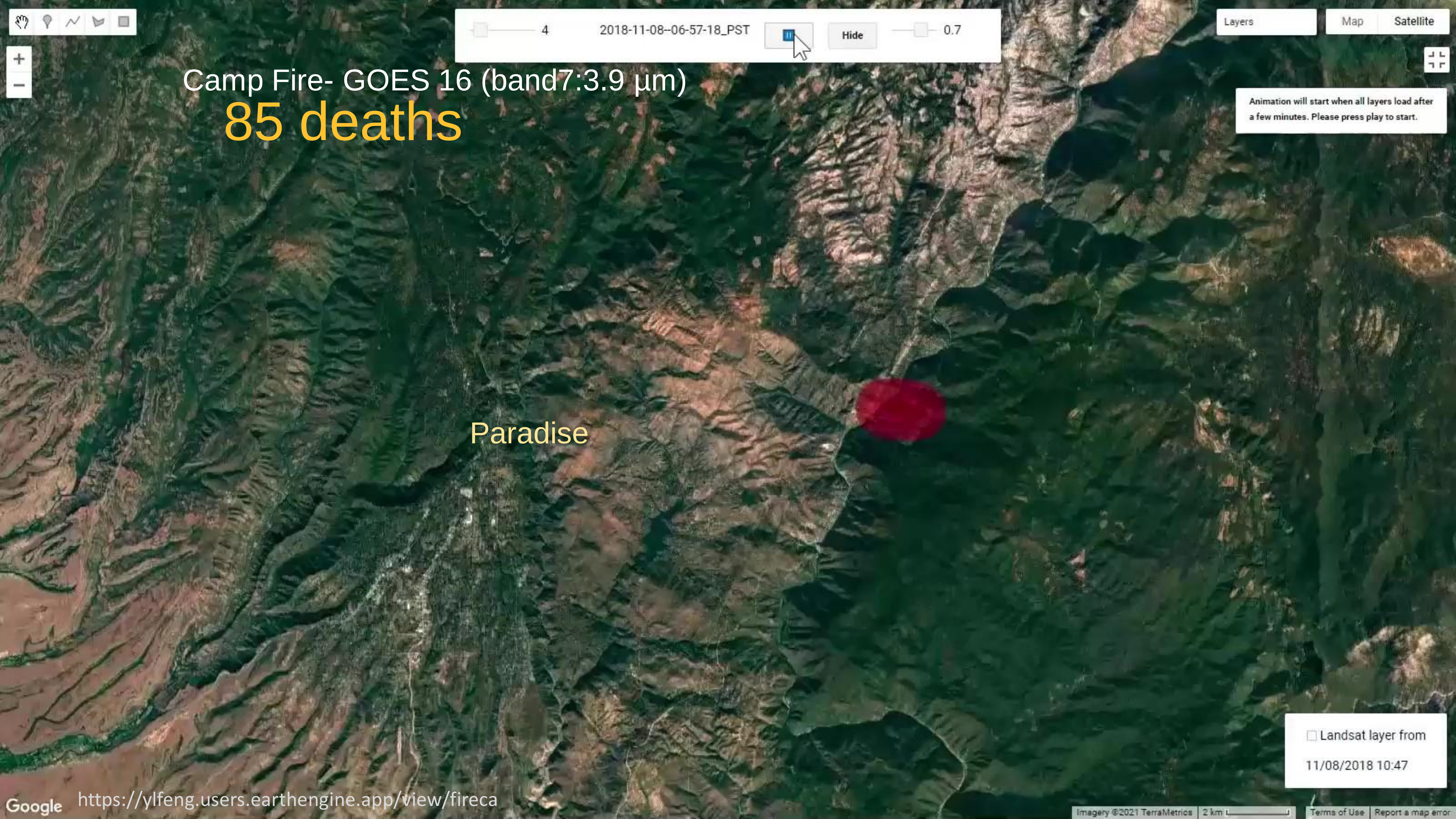
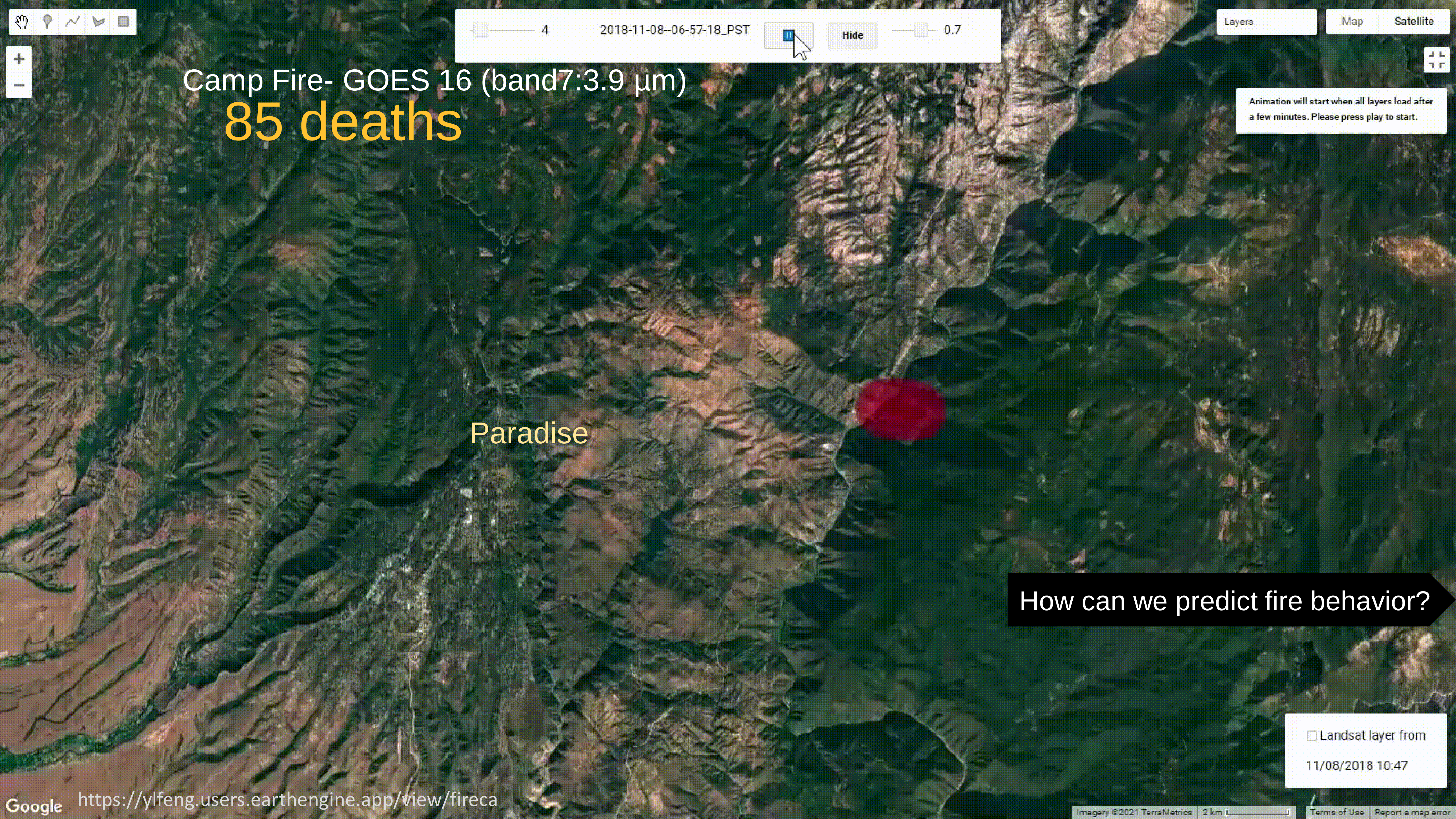
Predictability of Fire Behavior and Effects in the Wildland Urban Interface in California

Robinson Negrón-Juárez
robinson.inj@lbl.gov

EARTH & ENVIRONMENTAL SCIENCES

April 29, 2021


4
2018-11-08--06-57-18_PST
Hide
0.7
Layers
Map
Satellite
Camp Fire- GOES 16 (band7:3.9 µm)
85 deaths
Animation will start when all layers load after a few minutes. Please press play to start.
Paradise
Landsat layer from
11/08/2018 10:47
Google
https://ylfeng.users.earthengine.app/view/fireca
Imagery ©2021 TerraMetrics
2 km
Terms of Use
Report a map error



4
2018-11-08--06-57-18_PST
Hide
0.7
Layers
Map
Satellite
Camp Fire- GOES 16 (band7:3.9 µm)
85 deaths
Animation will start when all layers load after a few minutes. Please press play to start.
Paradise
How can we predict fire behavior?
Landsat layer from
11/08/2018 10:47
Google
https://ylfeng.users.earthengine.app/view/fireca
Imagery ©2021 TerraMetrics
2 km
Terms of Use
Report a map error

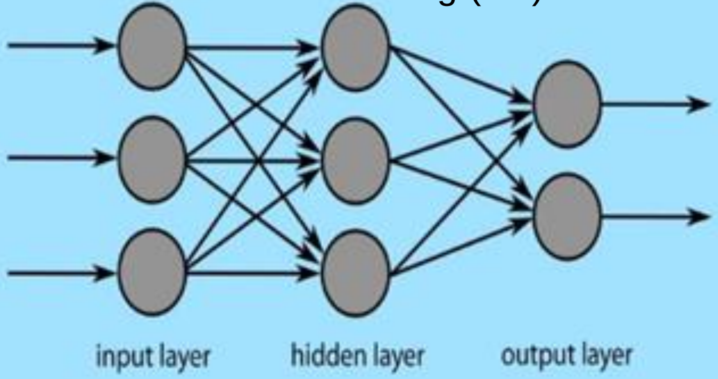
ML Fire Behavior Model: Interactively Calibrated with Satellite Data

Our Strategy

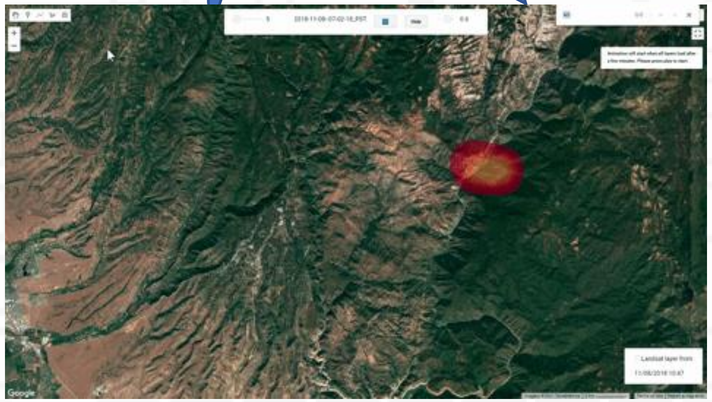
What are the critical mechanisms driving the predictability of fire behavior?

Biogeophysical Variables
Vegetation type, structure, conditions
Soil type
Soil moisture
Topographic characteristics (slope, aspect elevation)
Weather/Climate
Wildfire history (spread, burn rate and intensity, etc.)

Machine Learning (ML)



Wildfire Behavior Predictions



How does vegetation regrow after fires?

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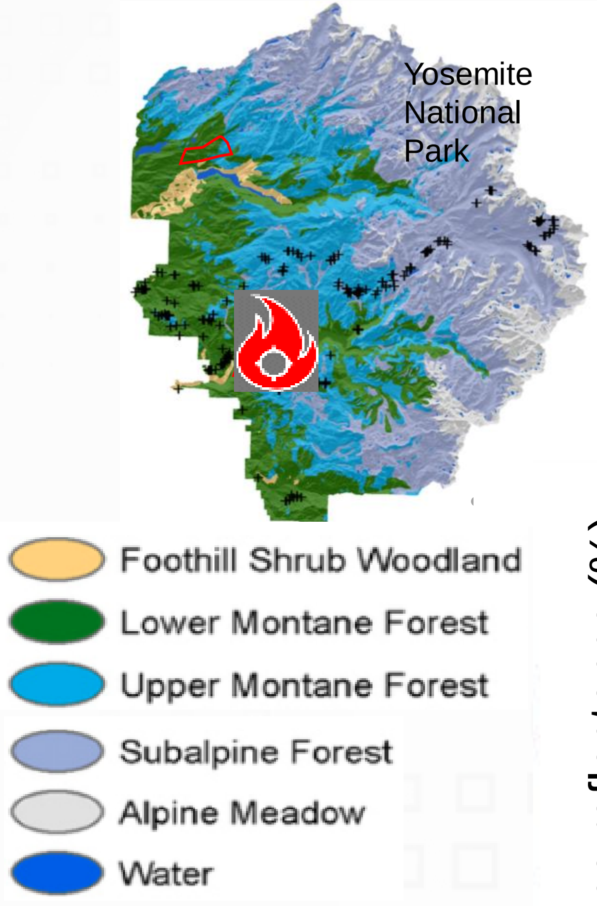
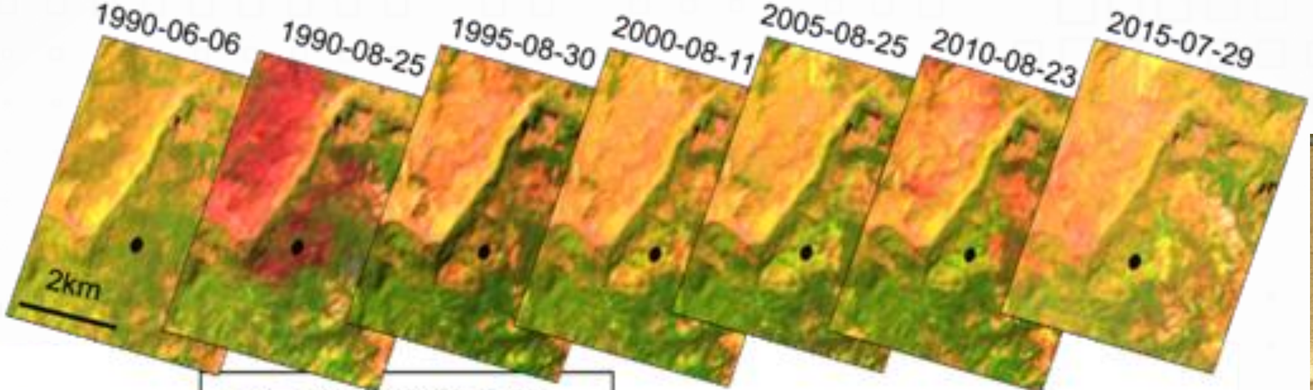
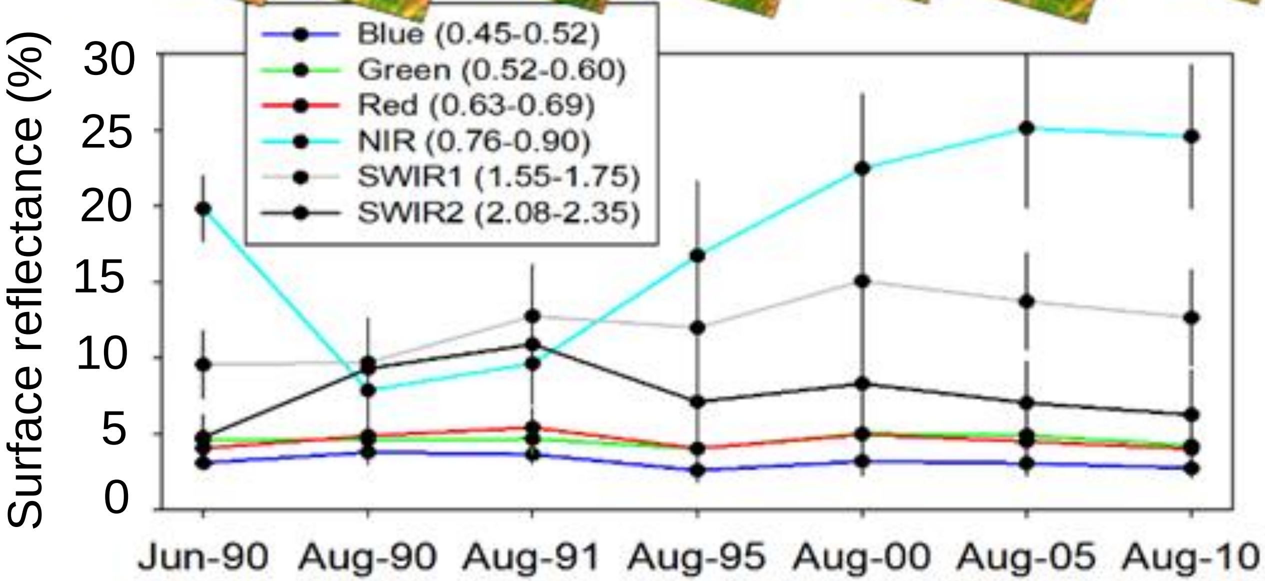
Forest Recovery/Regrowth



Steamboat Fire 1990-08-07, 24.7 km^2 (6,106 ac)





Validate/improve models

Source: R. Negron-Juarez (unpublished)

FATES simulates and predicts growth, death, and regeneration of plants

Windthrows

Clear-cutting

Burning

FATES (The Functionally Assembled Terrestrial Ecosystem Simulator) reproduced the trajectory and recovery time for windthrows and clear-cutting events

NGEE–TROPICS
NEXT-GENERATION ECOSYSTEM EXPERIMENTS

Negron-Juarez et al. 2020, *Biogeosciences*
https://doi.org/10.5194/bg-17-6185-2020

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Summary

- We can implement a Machine Learning model for accurate short-term prediction of wildfire behavior and effects
- We have created a framework that integrates remote sensing, field data and modeling for regrowth following fires
- We can produce reliable short/long term predictions of fire behavior and effects

Los Angeles Times

CALIFORNIA

El Dorado fire sparked by pyrotechnic device used during gender-reveal party at Yucaipa park

Sep 7, 2020

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Robinson Negron-Juarez

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Earth and Environmental Sciences Area

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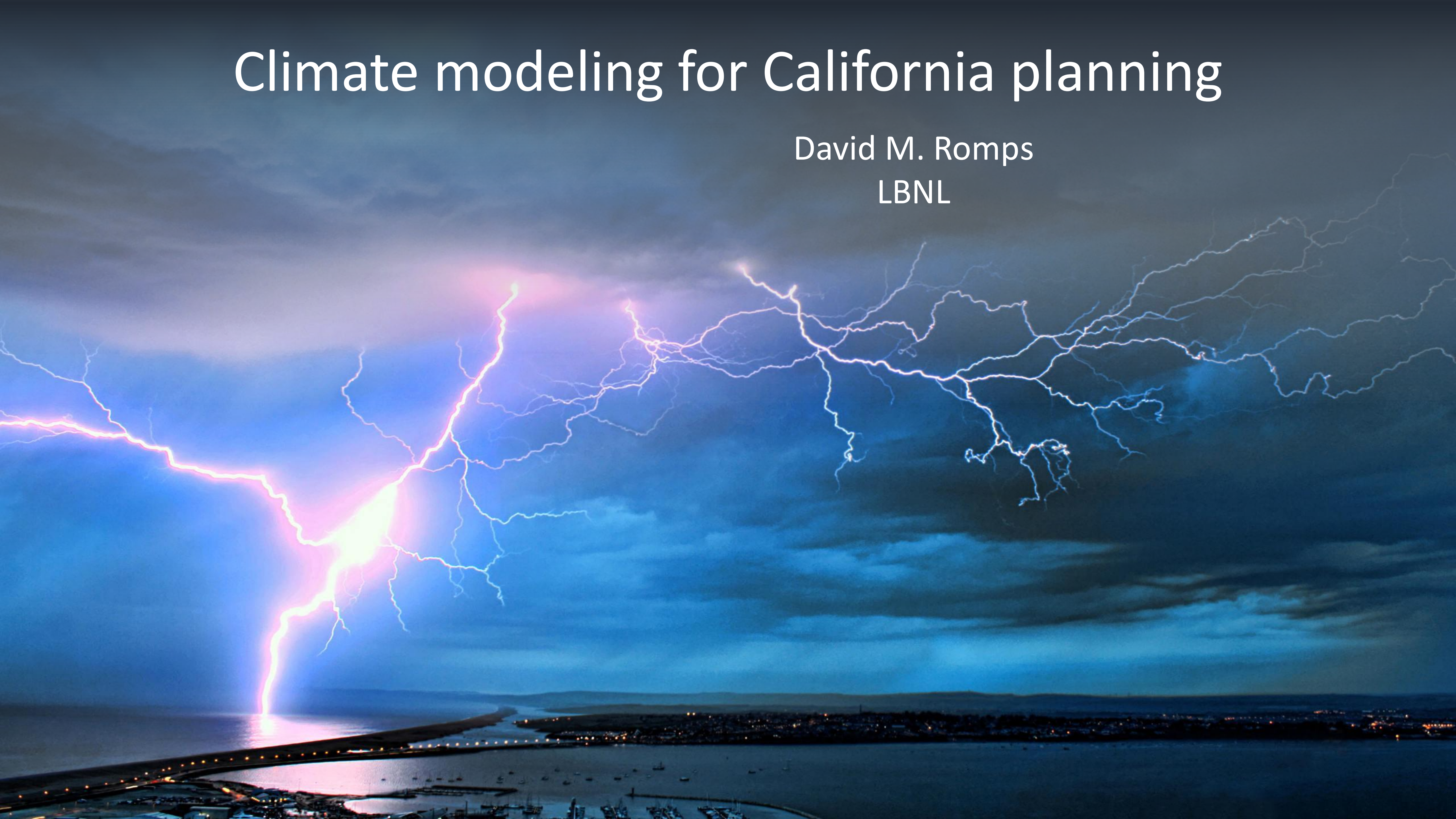
Climate modeling for California planning

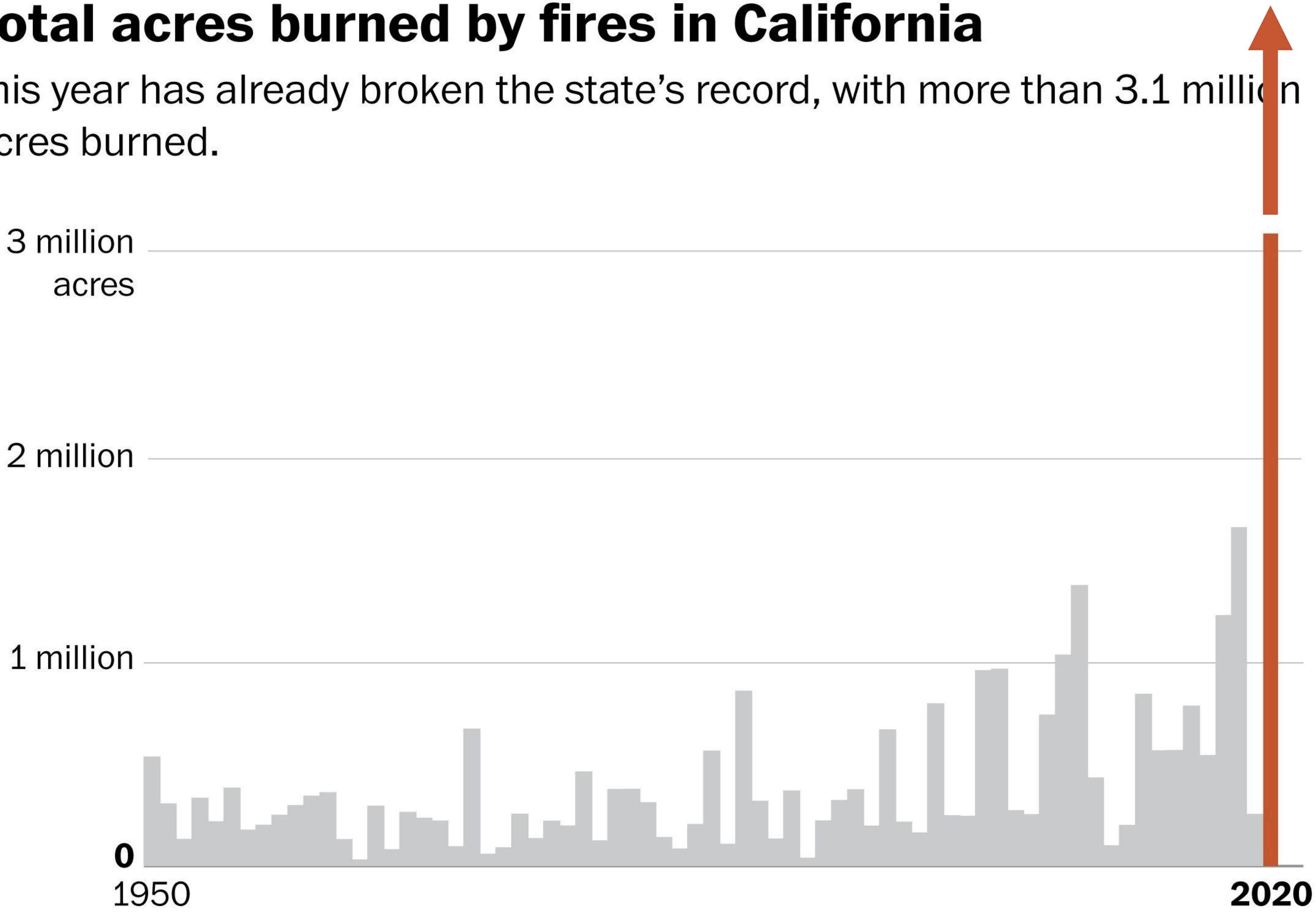
David M. Romps
LBNL




HISTORIC HEAT IN DEATH VALLEY
FURNACE CREEK VISITOR CENTER, DEATH VALLEY, CA
AUGUST 16, 2020
130°
HIGHEST RECORDED GLOBAL
TEMPERATURE SINCE 1931
*PRELIMINARY DATA
AccuWeather

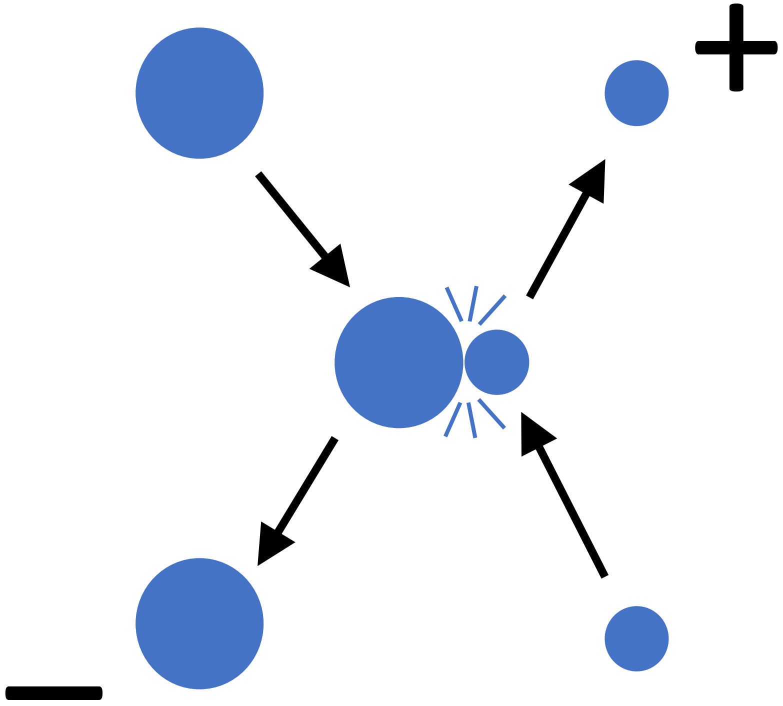
Total acres burned by fires in California

This year has already broken the state's record, with more than 3.1 million acres burned.



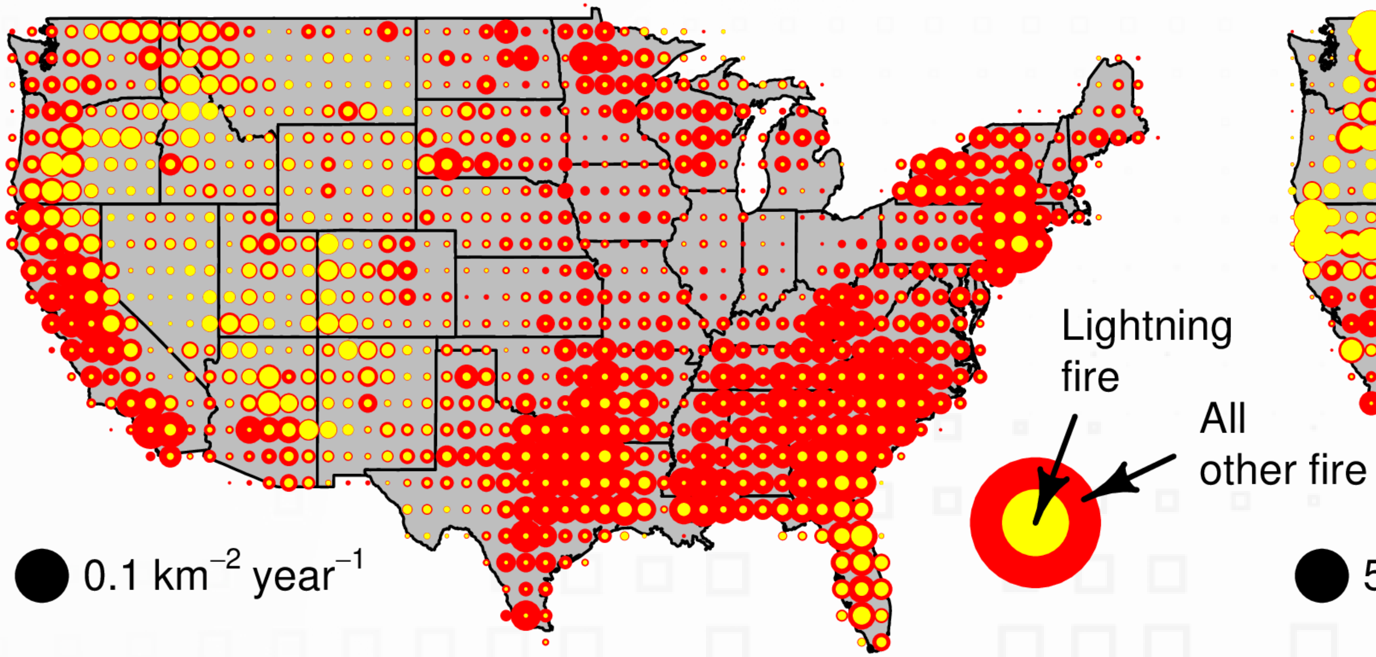
Data as of Sept. 10
Source: CalFire

LAUREN TIERNEY/THE WASHINGTON POST

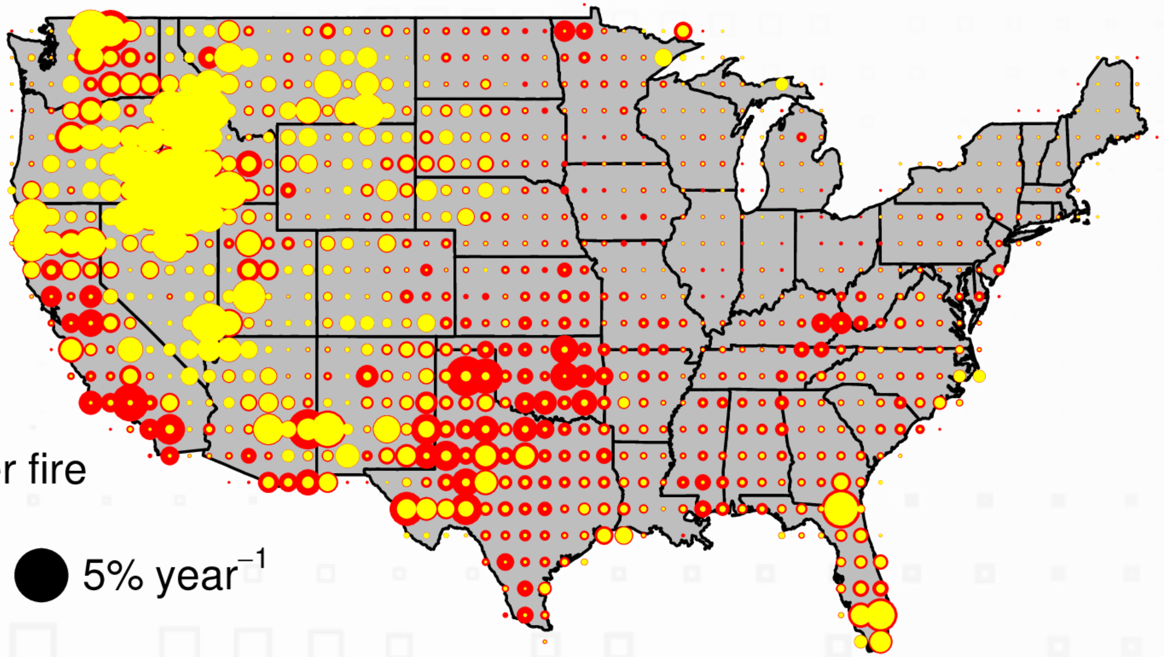


Lightning is made by storms

Current rate of fires



Current rate of burned area



Romps and Seeley, in prep

The balance of evidence → global warming increases US lightning

We find variables that correlate with lightning today…

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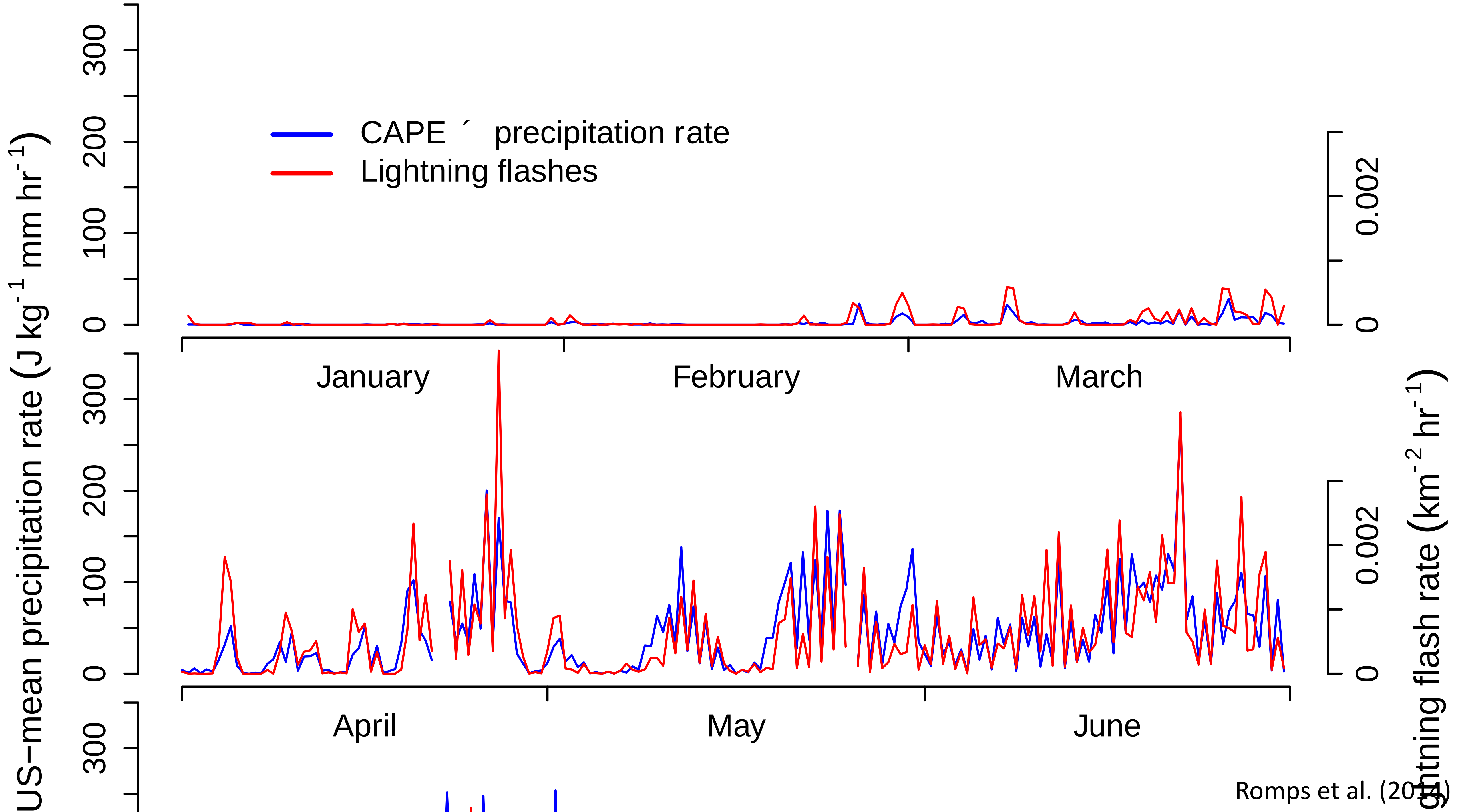


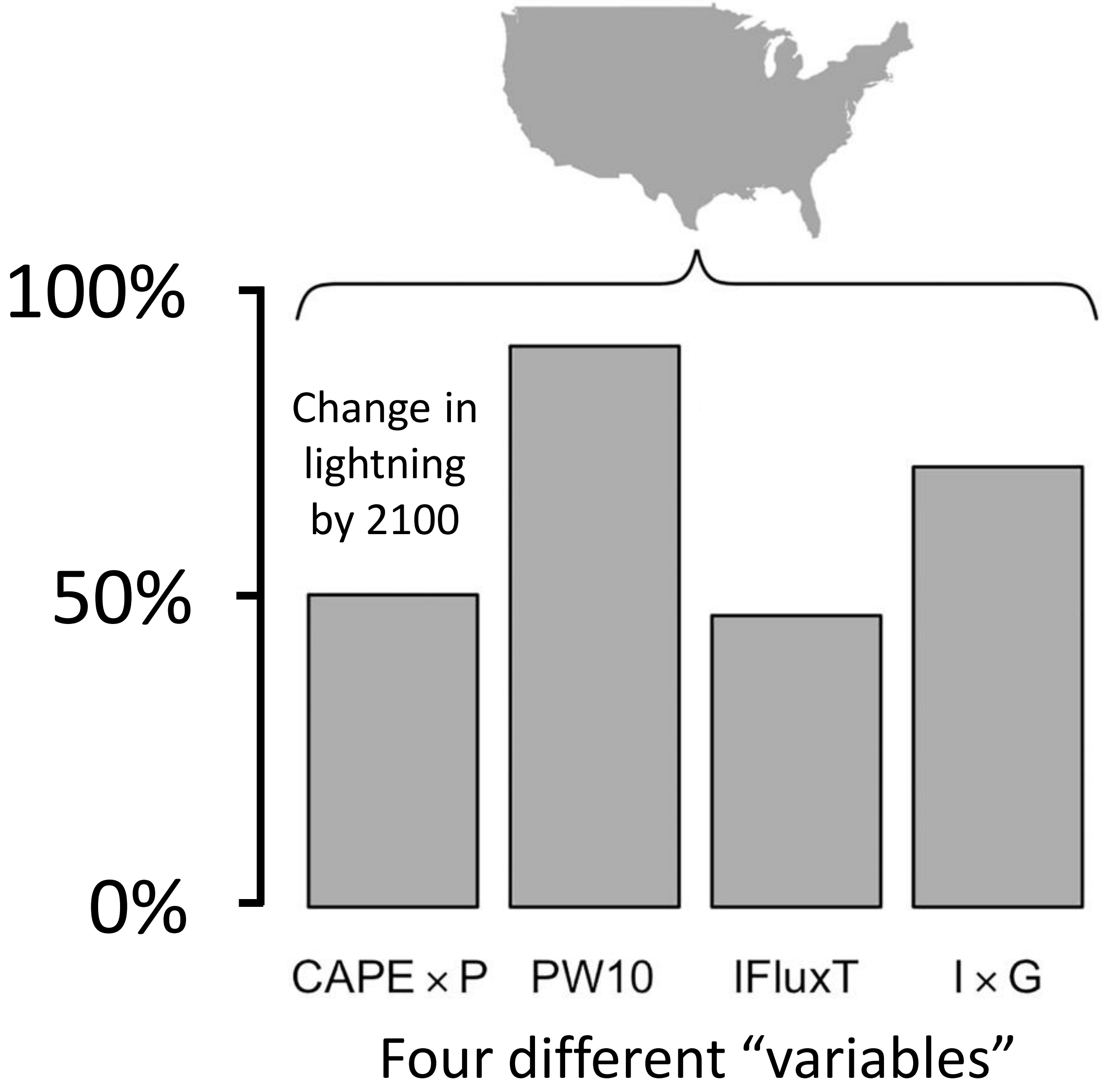
CAPE ´ precipitation rate
Lightning flashes
US−mean precipitation rate (J kg-1 mm hr-1)
Lightning flash rate (km-2 hr-1)
0
100
200
300
0
0.002
January
February
March
April
May
June
Romps et al. (2014)

The balance of evidence → global warming increases US lightning

We find variables that correlate with lightning today…

…and plug those into global climate models.

They predict a ~50% increase by 2100.



Romps (2019)

We can speculate that more lightning
→ more wildfire

But a 50% increase in lightning by 2100 is **not** the big story

The big story is the direct effect of warming on the flammability

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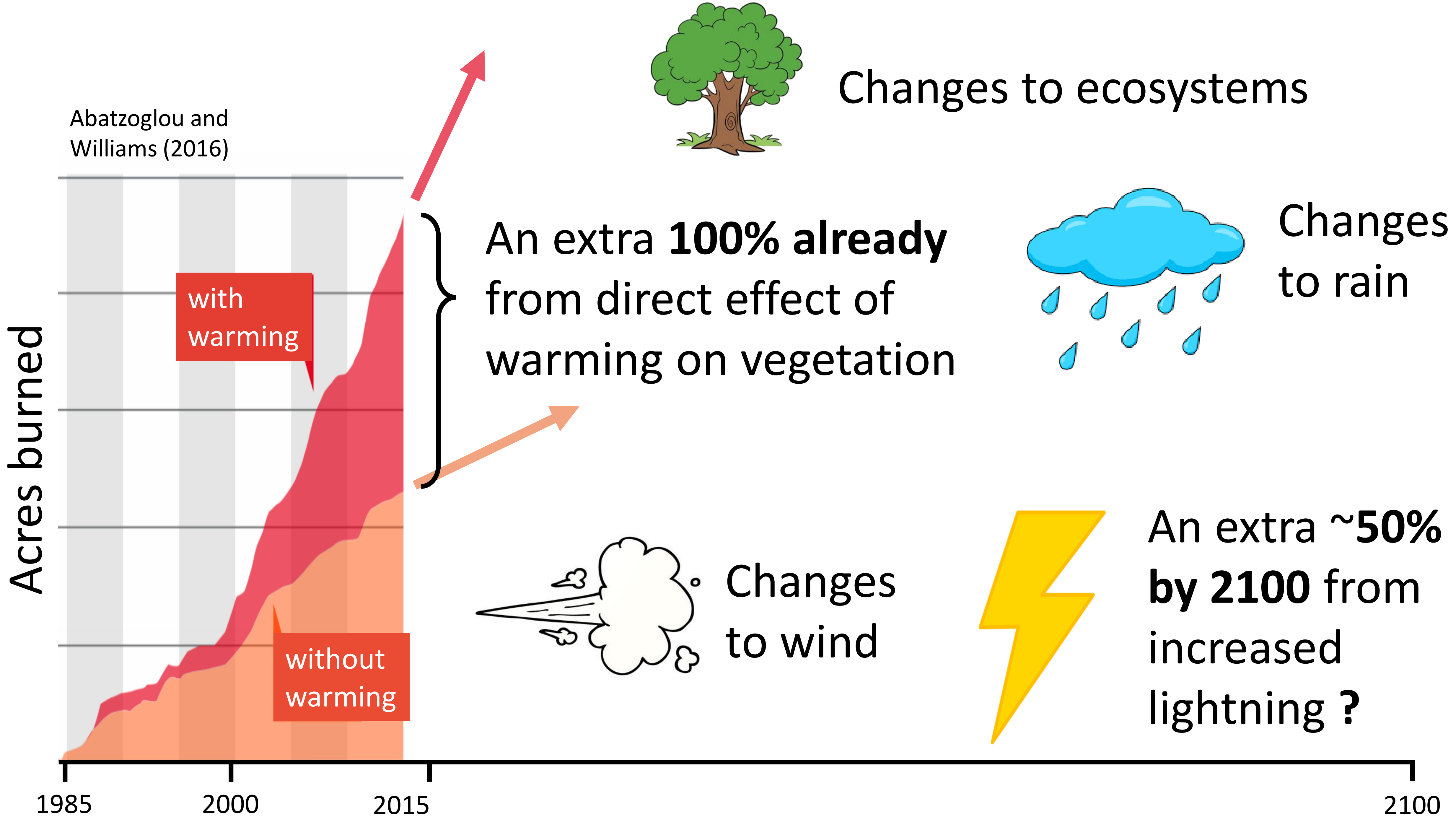

Abatzoglou and Williams (2016)
Acres burned
with warming
without warming
An extra **100% already** from direct effect of warming on vegetation
Changes to ecosystems
Changes to rain
Changes to wind
An extra ~**50% by 2100** from increased lightning **?**
1985
2000
2015
2100

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Thank You!

dromps@lbl.gov

Attention-Based Long-Short-Term-Memory Model

Wildfire prediction with flexible lead time

W.J. Riley
Lawrence Berkeley National Laboratory

04/28/2021

Overarching goals

- Burned areas predictions with high accuracy and flexible lead time:
  - Up to 8-months ahead of fire season
  - Interpretable
- Example strategy described here covers 14 GFED global wildfire regions, including the U.S.
  - Currently at 0.5° resolution
  - Southern Hemisphere South America, Northern Hemisphere Africa, Southern Hemisphere Africa
- Approach is only limited by resolution of input information

BONA	Boreal North America
TENA	Temperate North America
CEAM	Central America
NHSA	Northern Hemisphere South America
SHSA	Southern Hemisphere South America
EURO	Europe
MIDE	Middle East
NHAF	Northern Hemisphere Africa
SHAF	Southern Hemisphere Africa
BOAS	Boreal Asia
CEAS	Central Asia
SEAS	Southeast Asia
EQAS	Equatorial Asia
AUST	Australia and New Zealand

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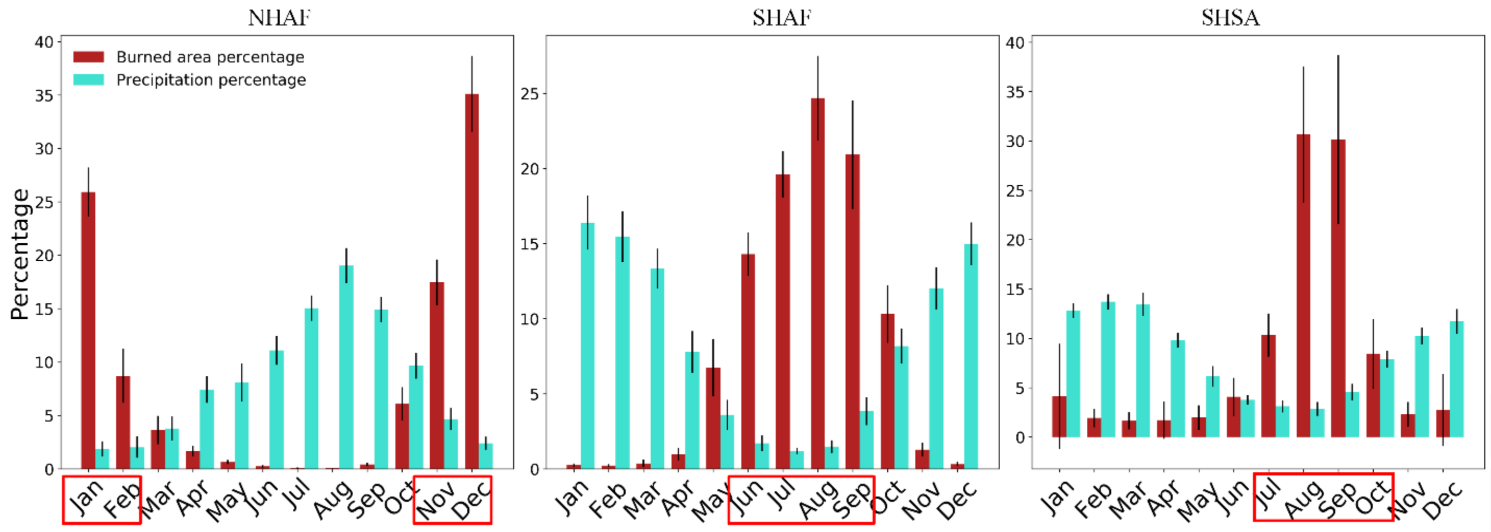
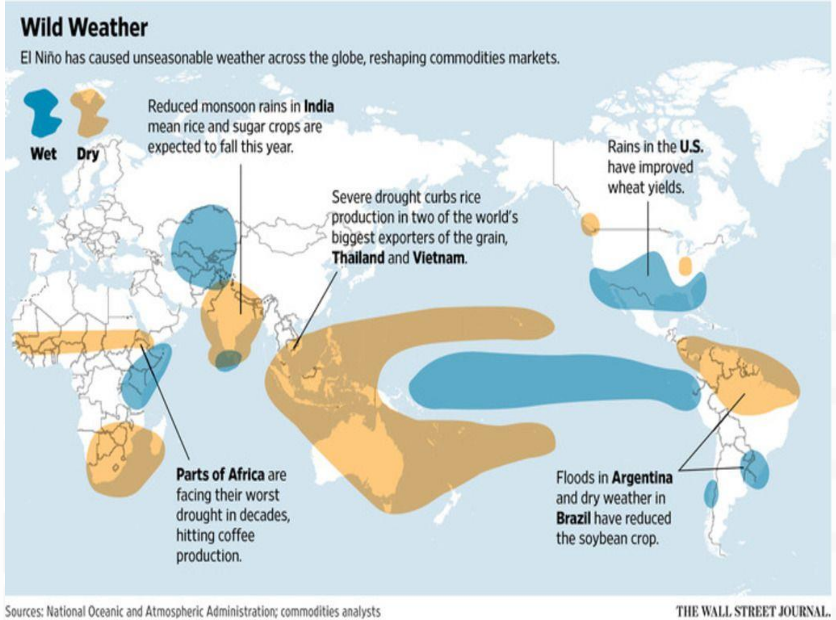
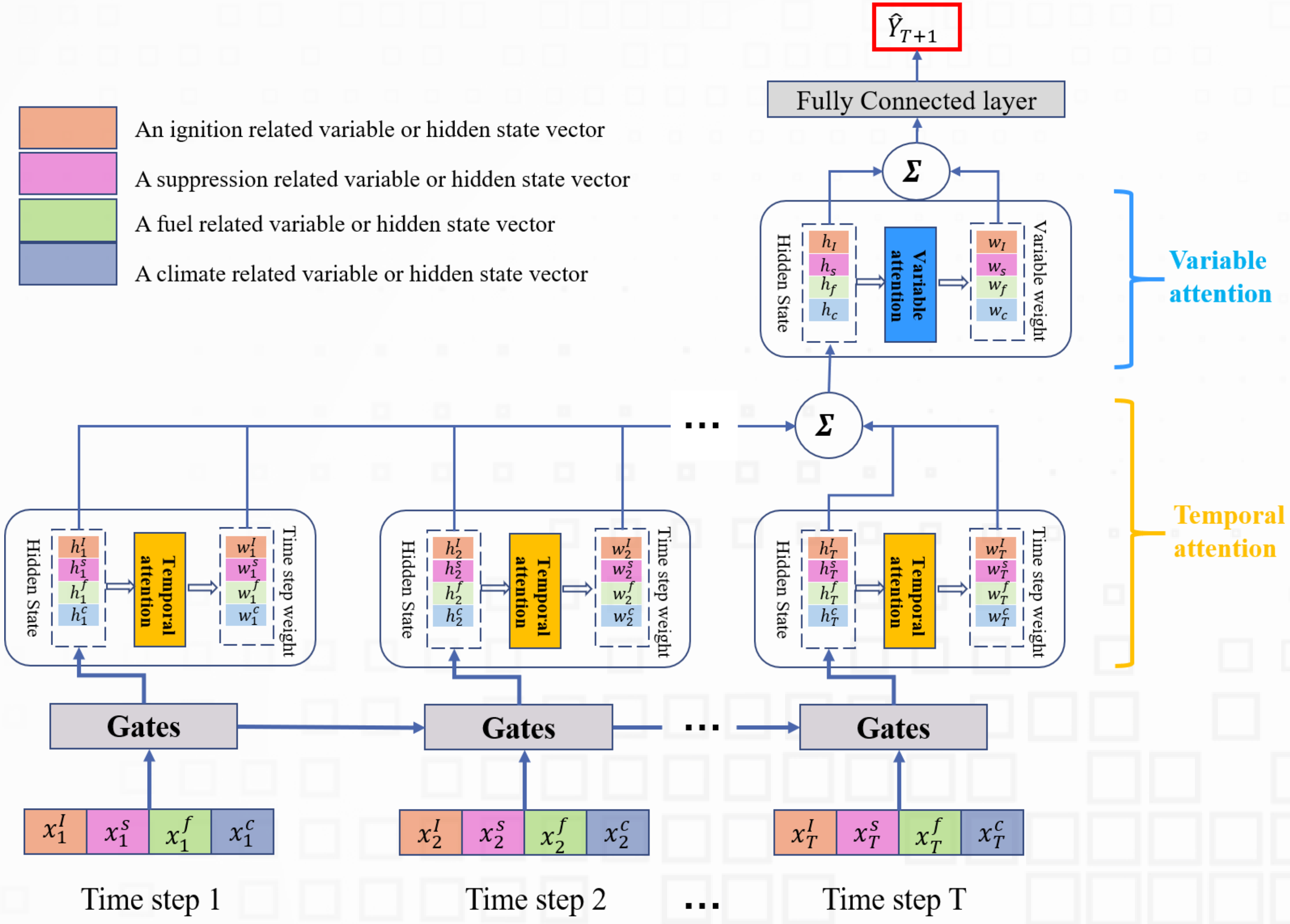
Objectives

- Explore multiple Machine Learning (ML) methods for wildfire prediction
- Enhance interpretability of ML model with attention mechanism
- Diagnosis of mechanistic relationships underlying wildfire prediction
- Integrate impacts of historical local condition memory on wildfire burned area
- Integrate impacts of oceanic forcing (e.g., NINO, AMO, TNA, TSA indices) on wildfire burned area





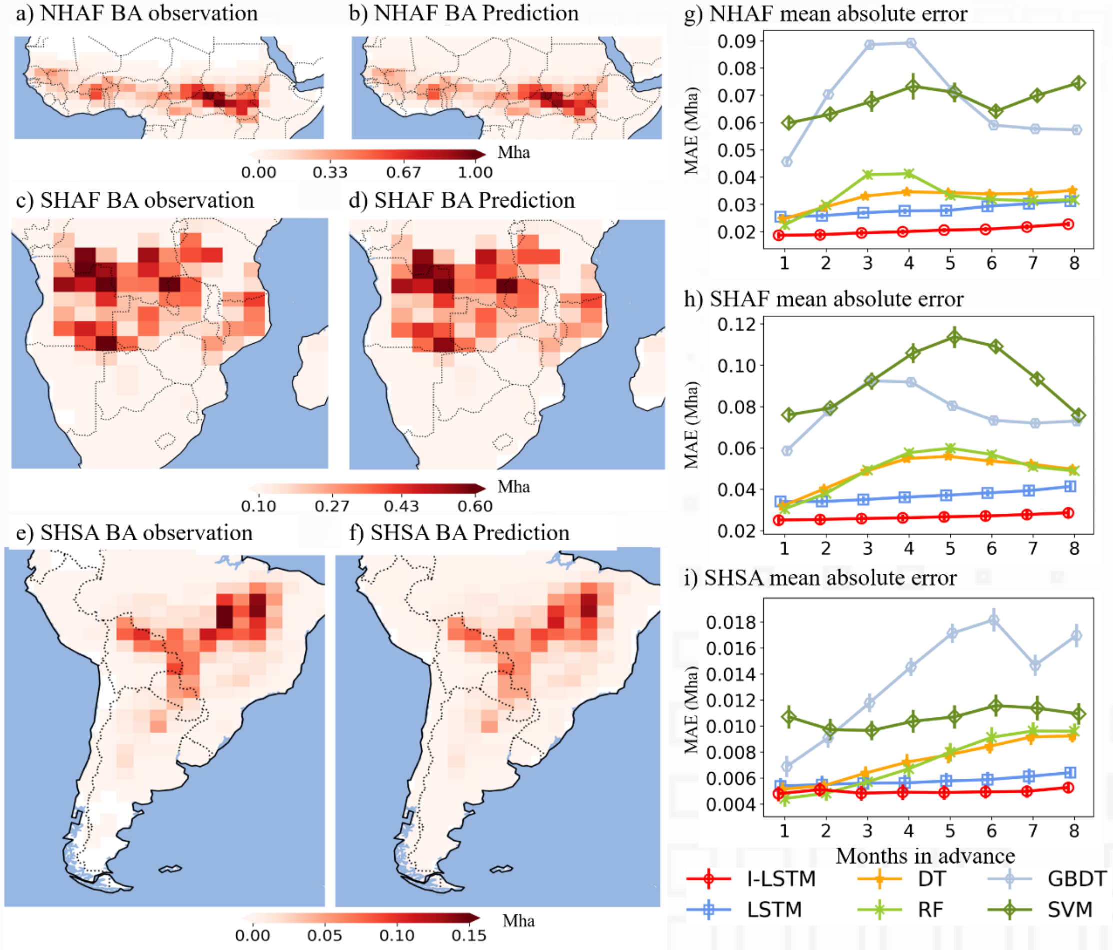
Technical Approach



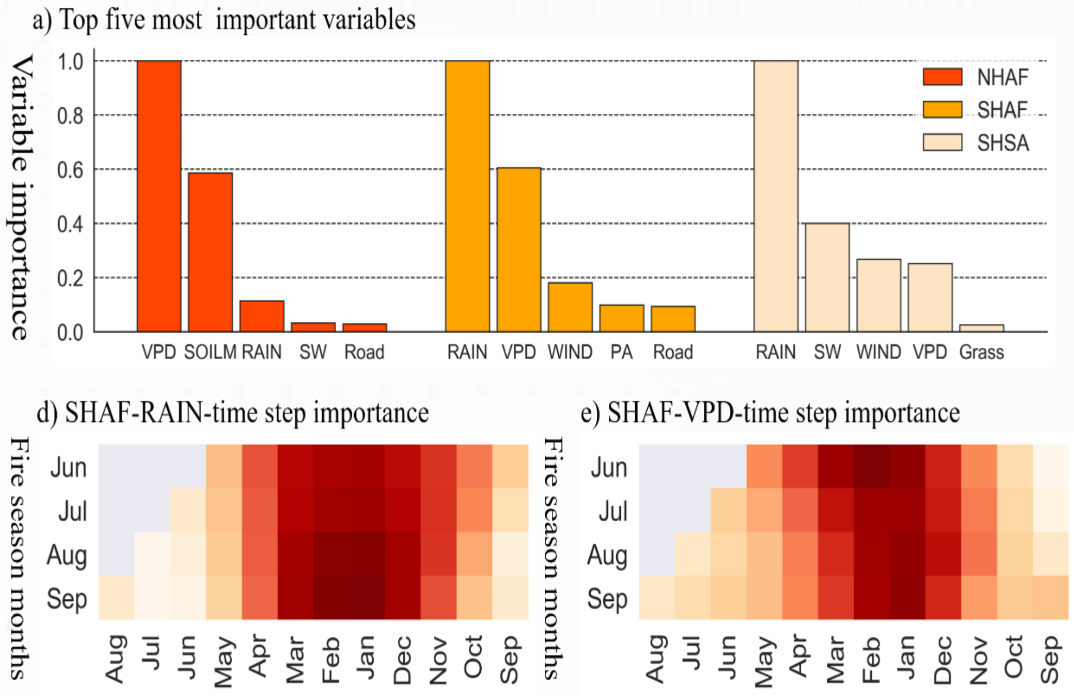
Ensemble of ML models:

- Random forest
- Decision Tree
- Gradient Boosting Decision Tree
- Support Vector Regression
- Long-Short-Term-Memory
- Interpretable Long-Short-Term-Memory

Applications



Examples for major tropical wildfire regions.

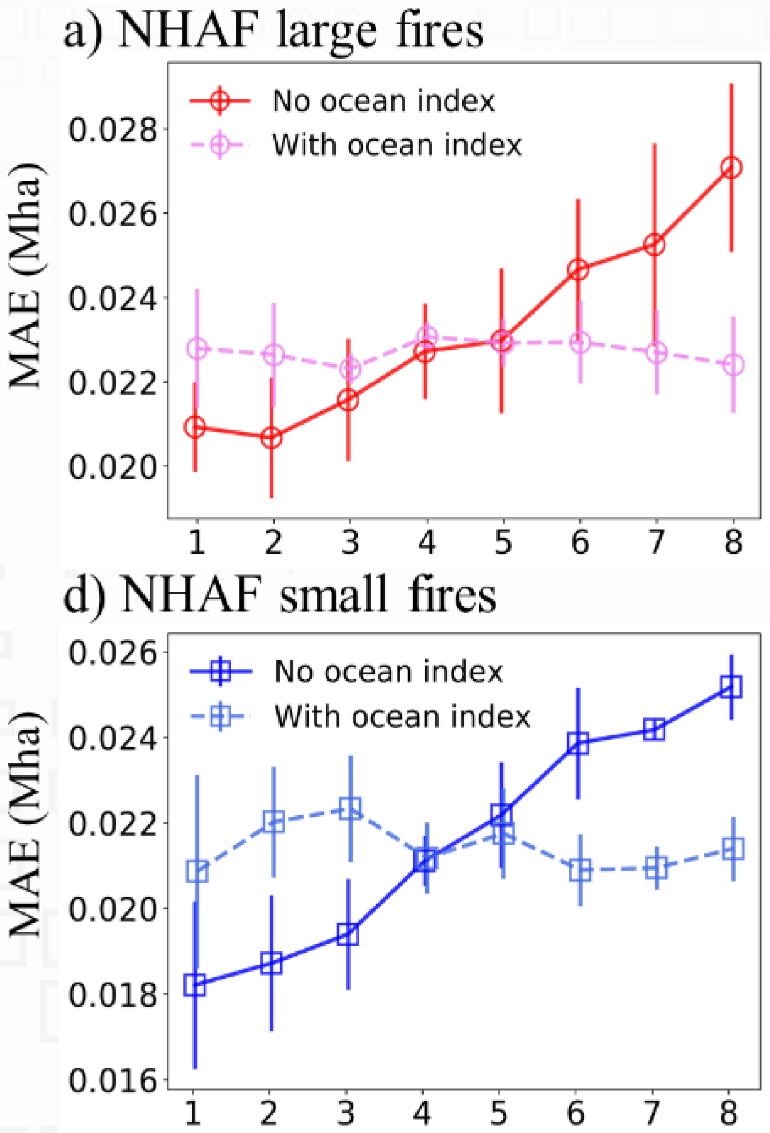


Long dependency of burned area on historical memory of local wetness

Yuan et al. (in prep.)

Longer-Term Prediction

- Integrating ocean indices improves 6-8 month lead time predictions



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Capability Summary

- High accuracy prediction across space and time
  - ➢Short lead time (1-4 month) prediction use local conditions
  - ➢Longer lead time (5-8 month) prediction rely on oceanic precursors
- Interpretable ML model reveals process interactions
  - ➢Non-linearity of environmental controls
  - ➢Spatial heterogeneity of dominating controller
- Readily applicable for U.S. or CA-specific wildfire prediction

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Thank You!

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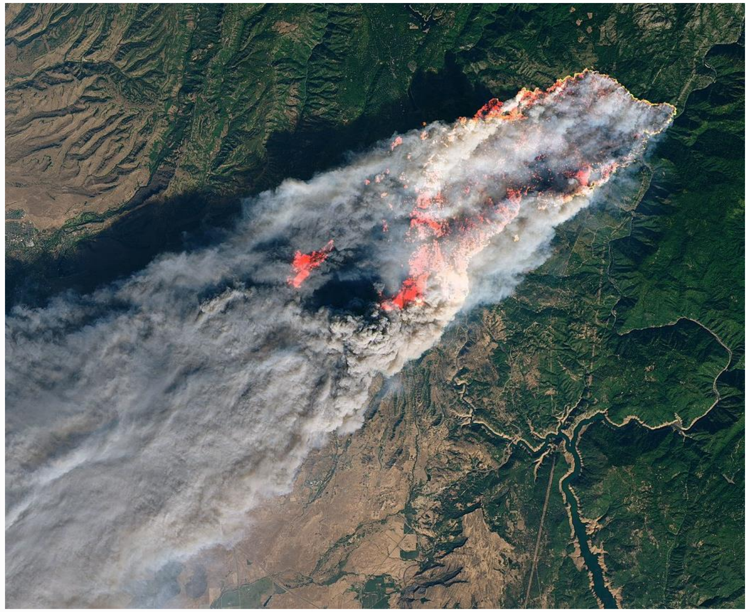
Data-Driven Wildfire Risk Model and Grid De-Energization Strategies

Bin Wang, Research Scientist,
wangbin@lbl.gov

4/29/2021

Wildfire has cause significant damages in past decades

- Largest wildfire season in CA 2020: 9,639 fires had burned 4,397,809 acres [1]
- PG&E file of bankruptcy due to Campfire 2018: powerline ignition caused wildfire killed 84 people and 9.3 billion in housing damage [2]
- To prevent wildfire event, PSPS(public safety power shutoff) in 2019 turned off millions of customer accounts, causing huge economic and society impacts [3]



Campfire 2018

[1] 2020 National Large Incident Year-to-Date Report (PDF). Geographic Area Coordination Center(Report). National Interagency Fire Center. December 21, 2020. Archived from the original (PDF) on December 29, 2020. Retrieved January 13, 2021.
[2] https://www.nytimes.com/2020/06/16/business/energy-environment/pge-camp-fire-california-wildfires.html
[3] P. Gas and E. Company, "Pacific gas and electric companyamended 2019 wildfire safety plan," tech. rep., 2019.

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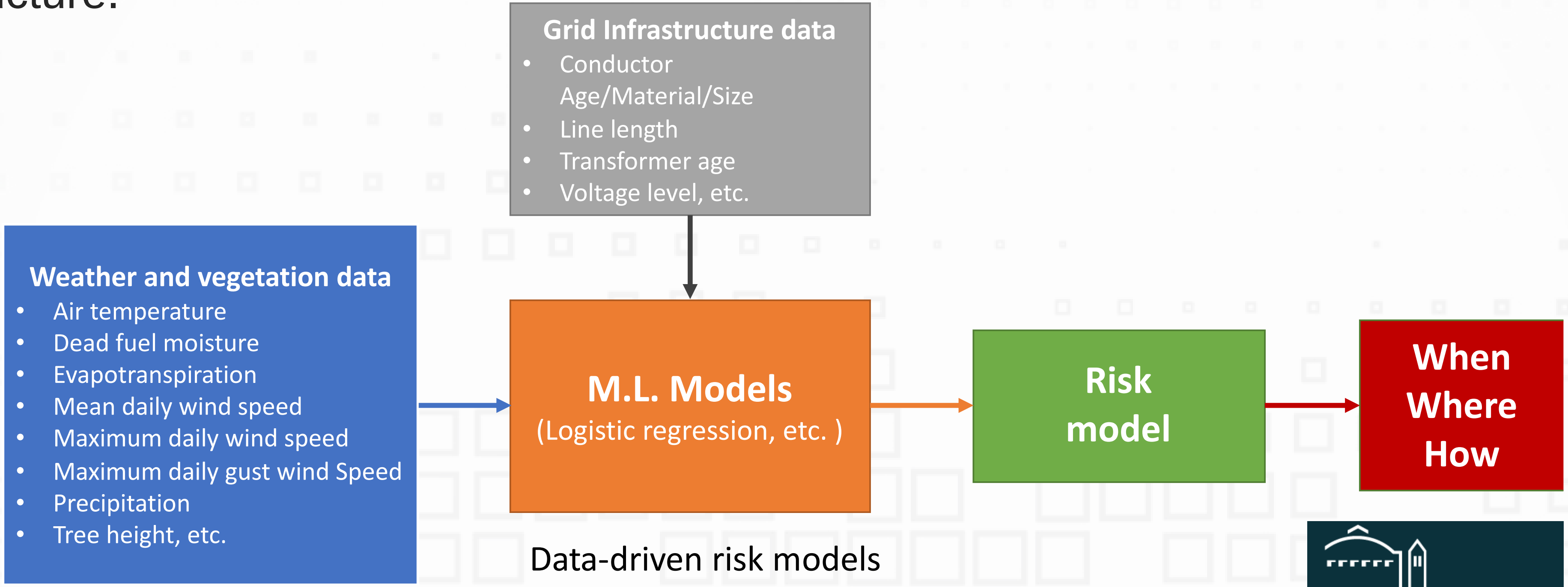
Data-driven Wildfire Risk Model

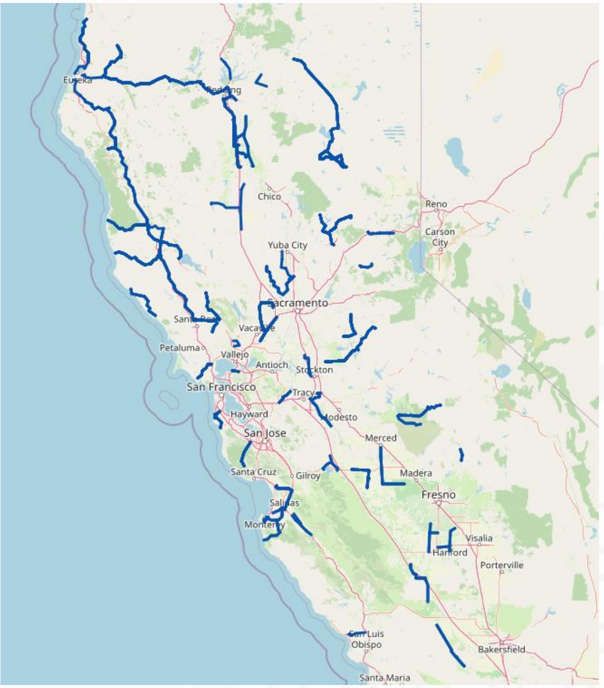
- Goal: Predict power-grid-induced wildfire probability and future fire exposure risks in transmission and distribution systems to inform better de-energization strategies. The data-driven methods will map the wildfire ignition risks to powerlines.
- Methodology: Machine learning techniques that leverage enormous data sets on weather and infrastructure.



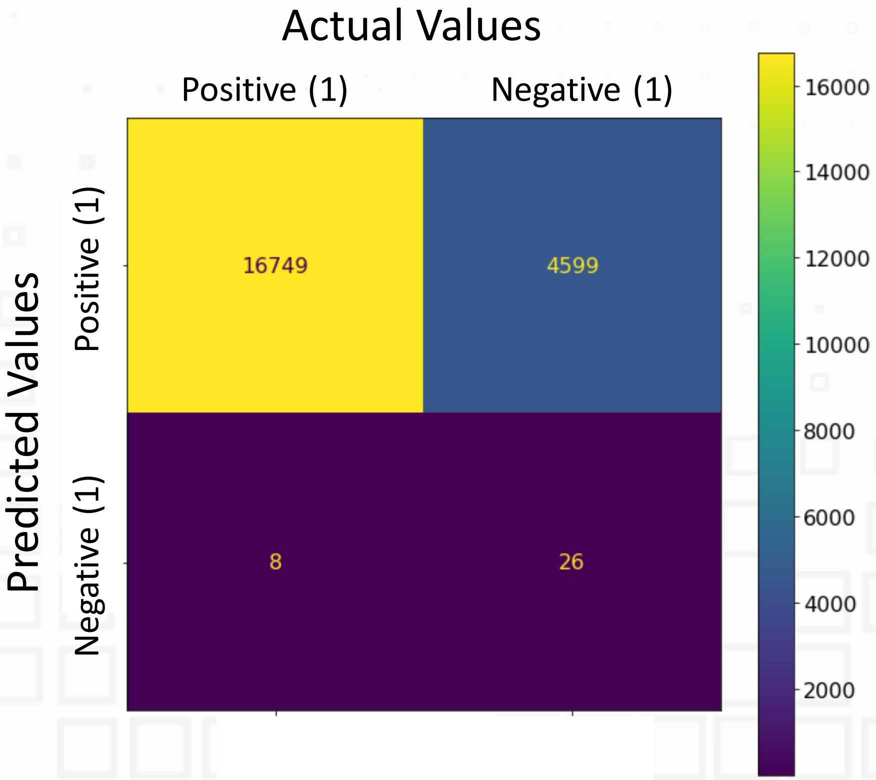
Data-driven risk models

Transmission System Risk Model

- Logistic regression model to predict the wire-down events in the transmission system
  - Training data: year 2015-2018 weather, vegetation, and infrastructure data with total 83,180 non-wire-down records and 71 wire-down records.
  - Test data: year 2019 with 21,348 non-wire-down records and 34 wire-down records



Blue curves: historical wire-down events



Confusion matrix (threshold = 0.5)

	Definition	Score
Recall	$\frac{TP}{TP+FN}$	0.76
True negative rate	$\frac{TN}{TN+FP}$	0.78

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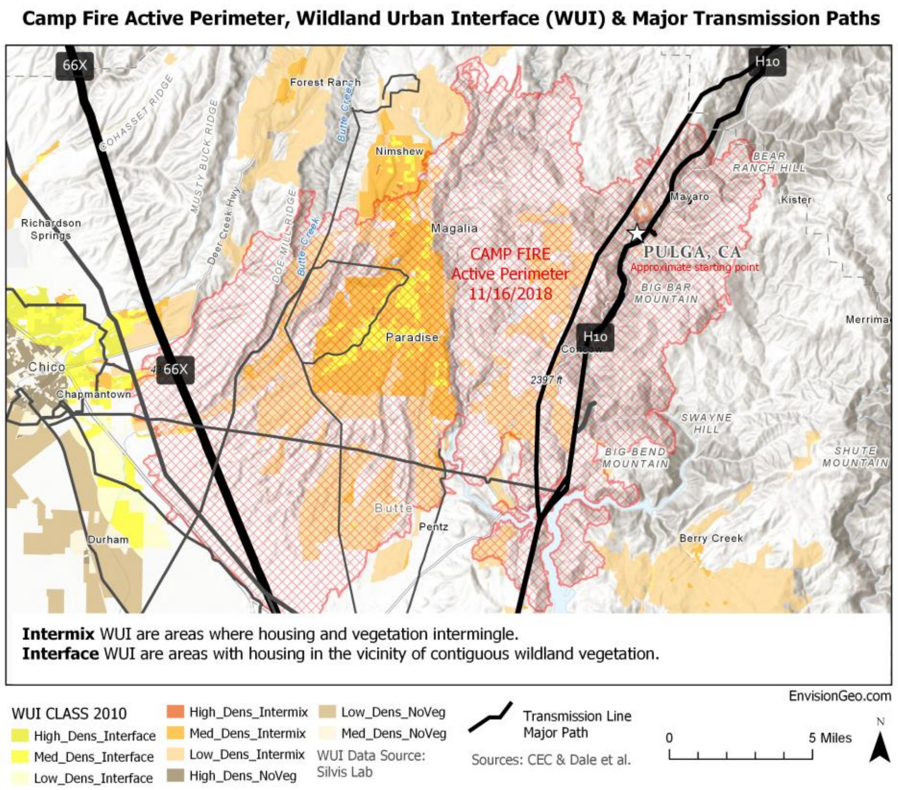
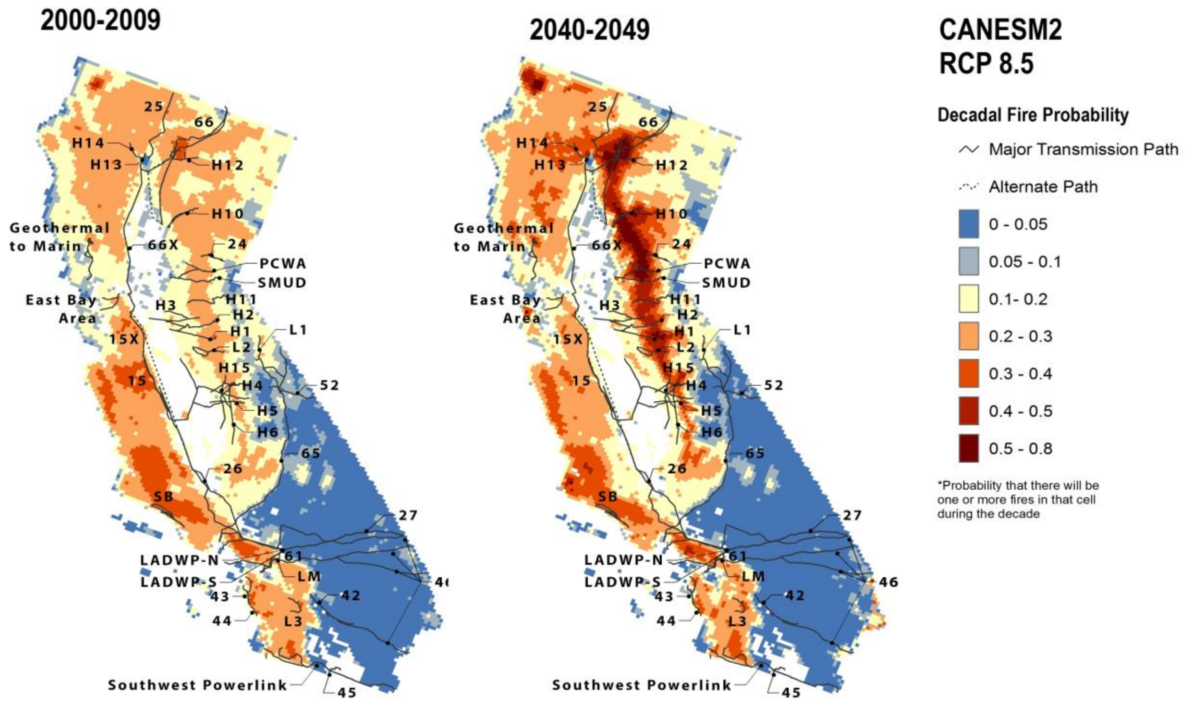
Wildfire Exposure Risk Model

- Applied UC Merced model to project wildfire exposure risk of transmission lines based on historical records
- Accounted for multiple wildfire ignition sources:
  - Environmental ignitions (natural causes: lightning, etc.; human causes, e.g. campfire, etc.)
  - Powerline ignition risk





https://www.energy.ca.gov/sites/default/files/2019-12/Forests_CCCA4-CEC-2018-002_ada.pdf

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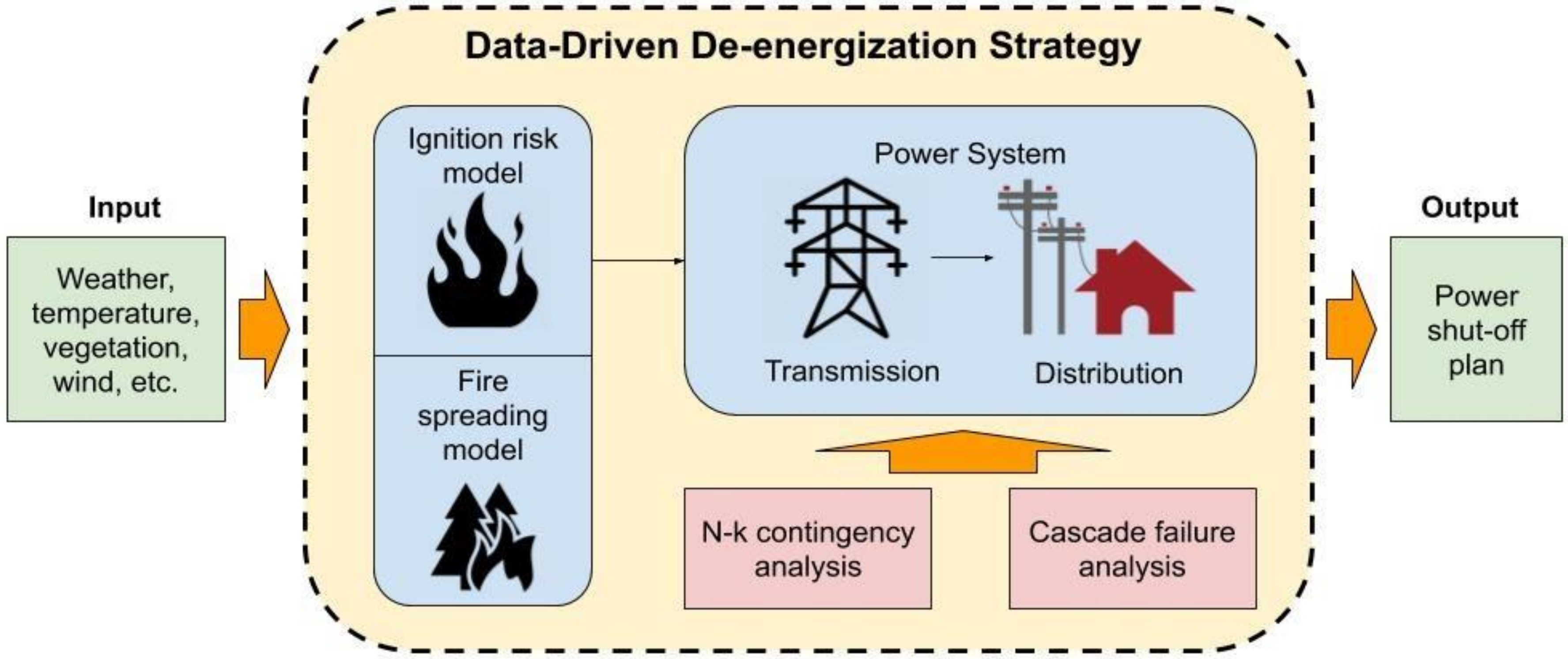
Data-driven decision-making framework

- Goals:
  - Develop data-driven optimal decision-making (de-energization and power shut-off) strategies given the wildfire risks as inputs and evaluate the reliability and economics implications of various fire-related planning and operation policies



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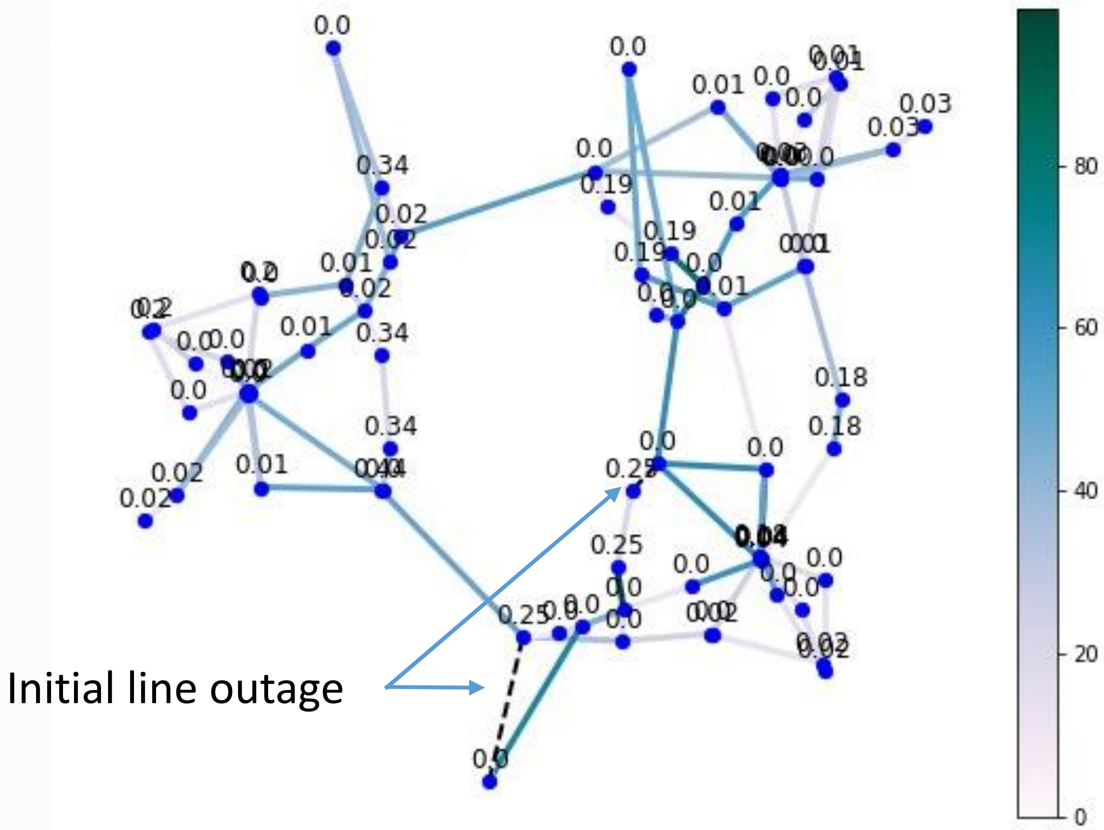
Optimal Decision Making Preliminary Results

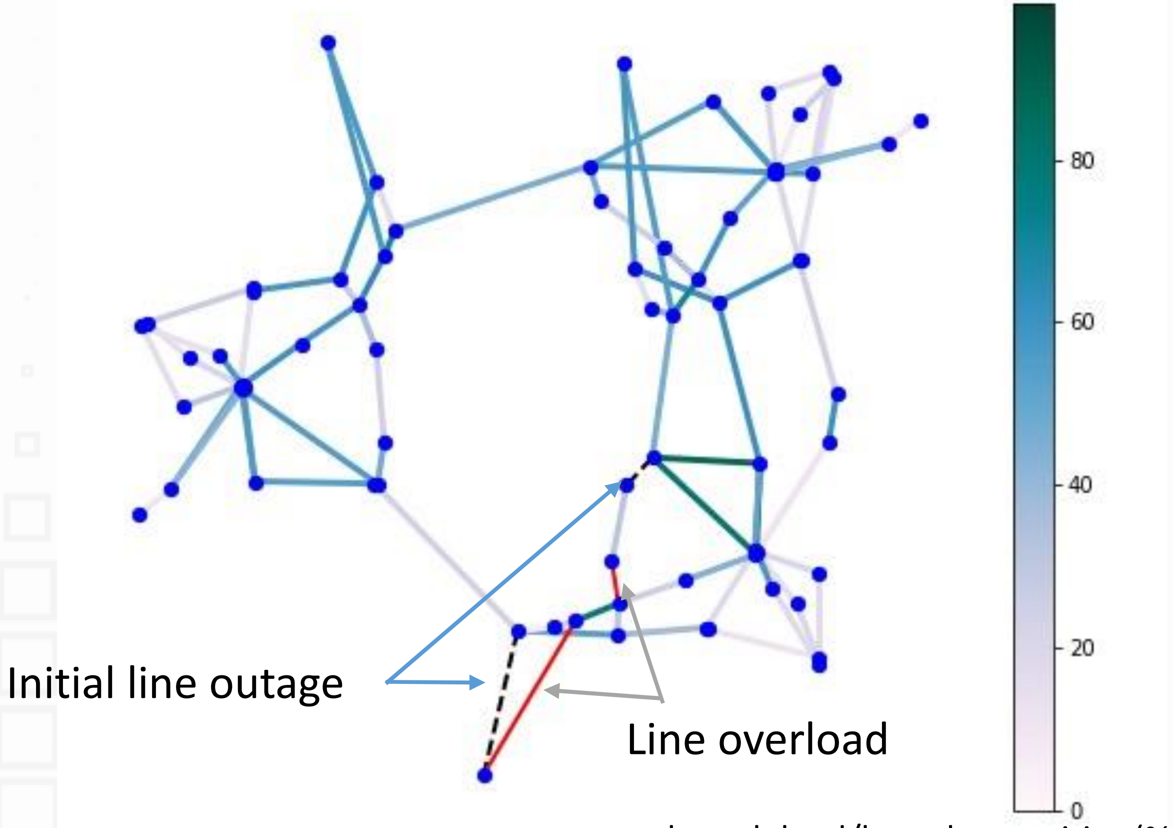
- Assume the powerline with high wildfire risk shut-downs, perform the proposed strategy

Optimal load shedding



branch load/branch capacities (%)

Line overload at cascade stage 1 without optimal load shedding

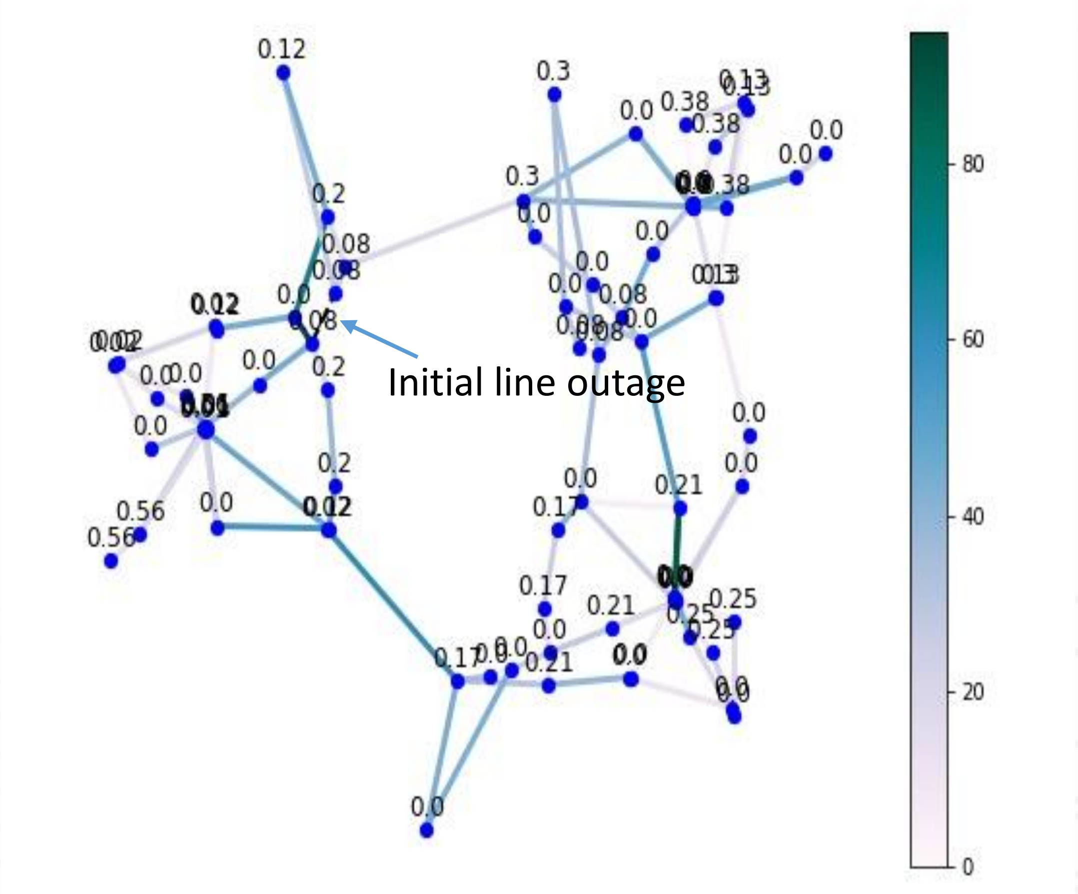


branch load/branch capacities (%)

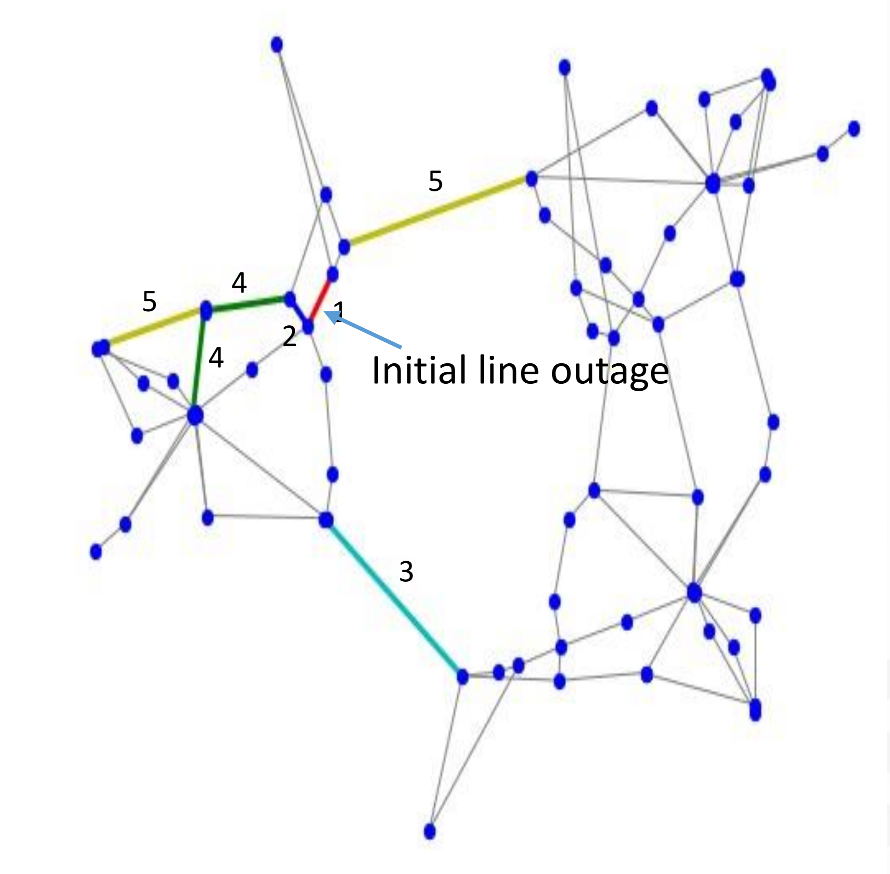
Optimal Decision Making Preliminary Results

- Assume the powerline with high wildfire risk shuts down, perform the proposed strategy

Optimal load shedding



Cascading failure without optimal load shedding



Data-driven Optimal Decision Making Framework

- To reduce calculation complexity, a data-driven model is developed based on the OPF problem
  - Map the OPF problem to a multi-label classification problem

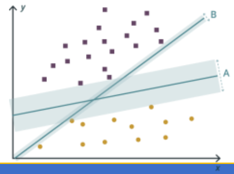
Data-driven problem modeling

Features

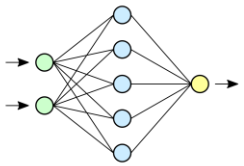
- Generator status (P_g)
- Load profile (P_d, Q_d)
- Powerline ignition risk topology (N)

Classification models

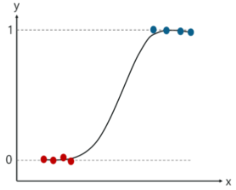
Support vector machine (SVM)



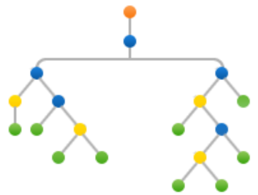
Neural network



Logistic regression



Decision Tree



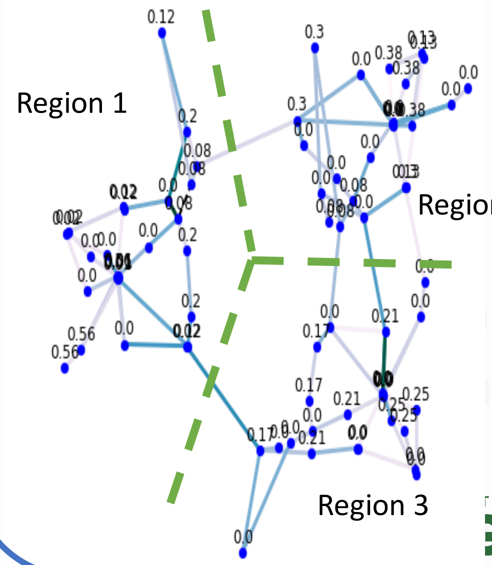
Regional multi-label outputs

- Generator scale up (0/1)
- Generator scale down (0/1)
- Load shedding (0/1)

Cascade failure prevention

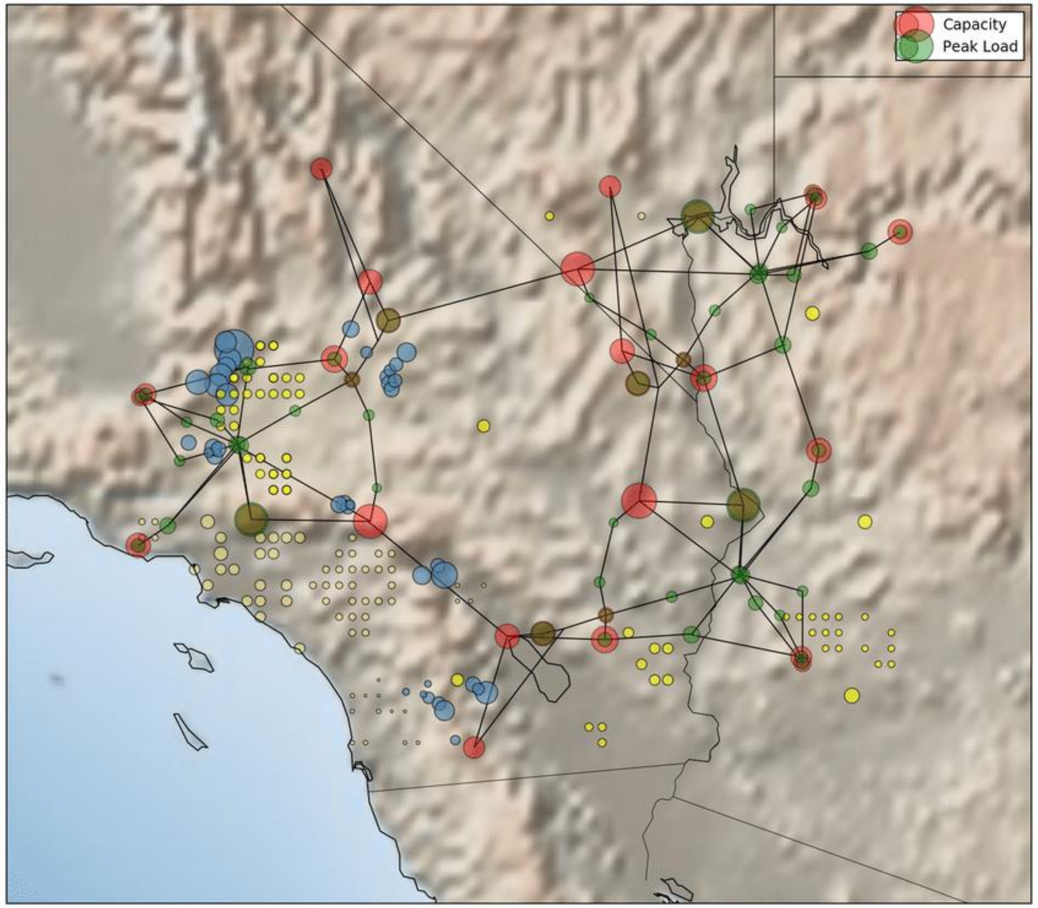
- Cascade failure (0,1)

OPF results



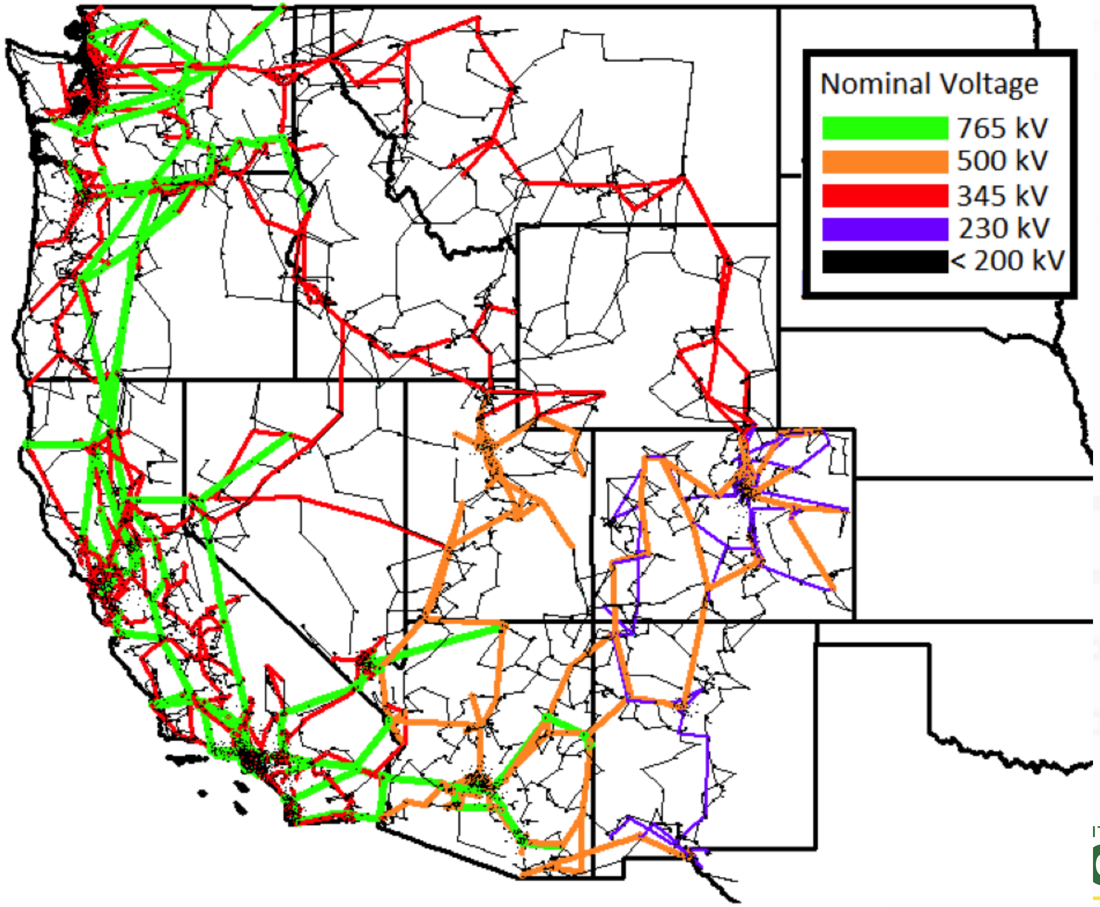
Transmission Network Datasets

RTS-GMLC Test Case



Map of the Reliability Test System-Grid Modernization Lab Consortium (RTS-GMLC) system overlaid on the southern California, Nevada, and Arizona region. Blue and yellow dots represent wind and solar resources, respectively.

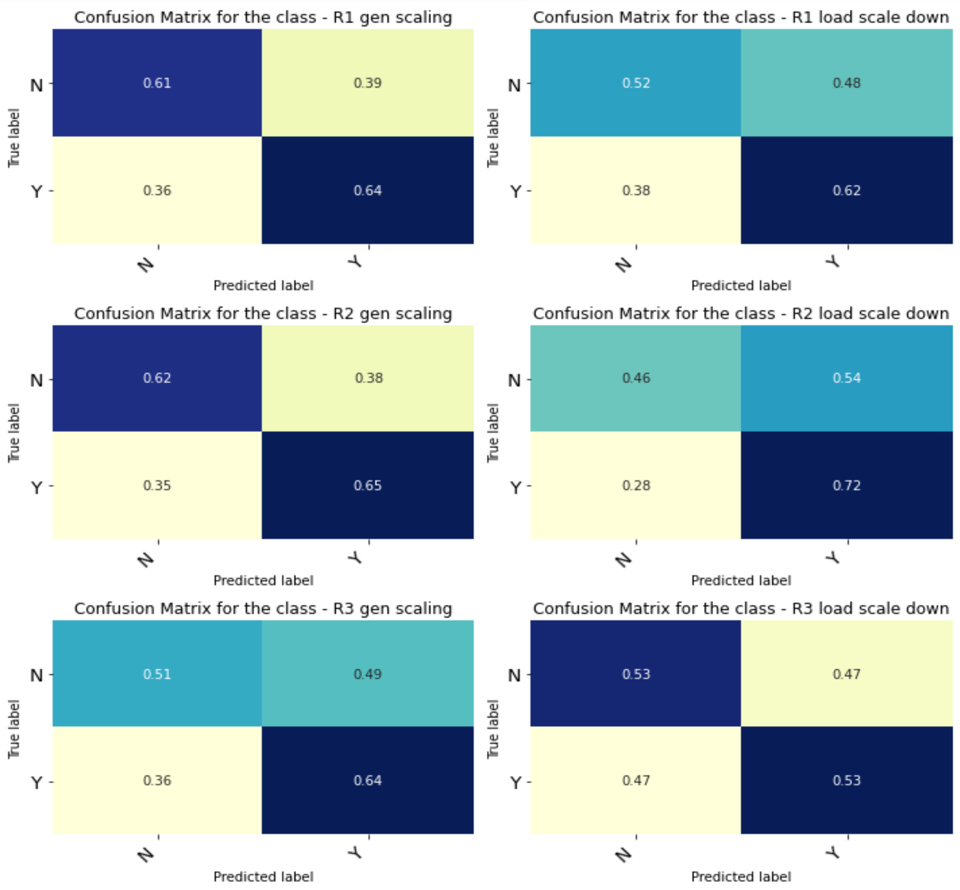
ACTIVSg10k: 10000-bus synthetic grid on footprint of western United State

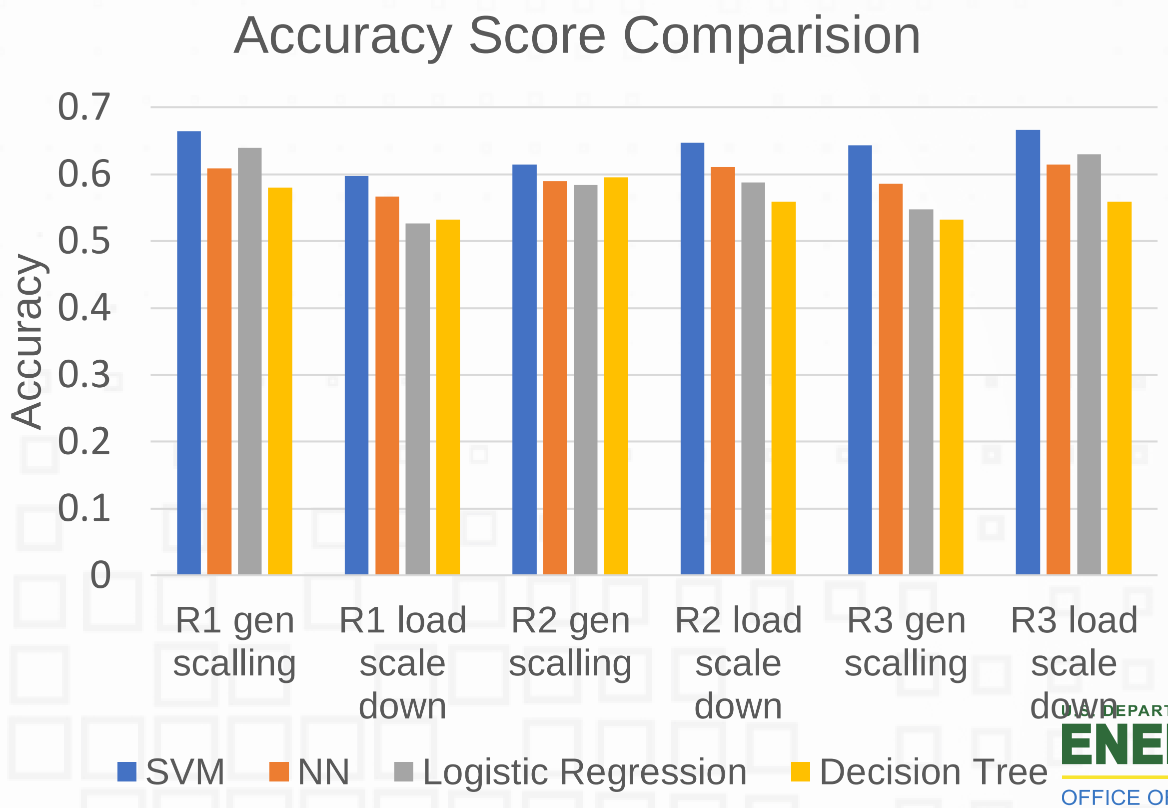


https://electricgrids.engr.tamu.edu/electric-grid-test-cases/activsg10k/
https://github.com/GridMod/RTS-GMLC

Preliminary Results

- Accuracy of 50% – 70% classification (line overload) prediction is achieved using support vector machine and multi-layer NN
  - Multi-label optimal decision classification with SVM





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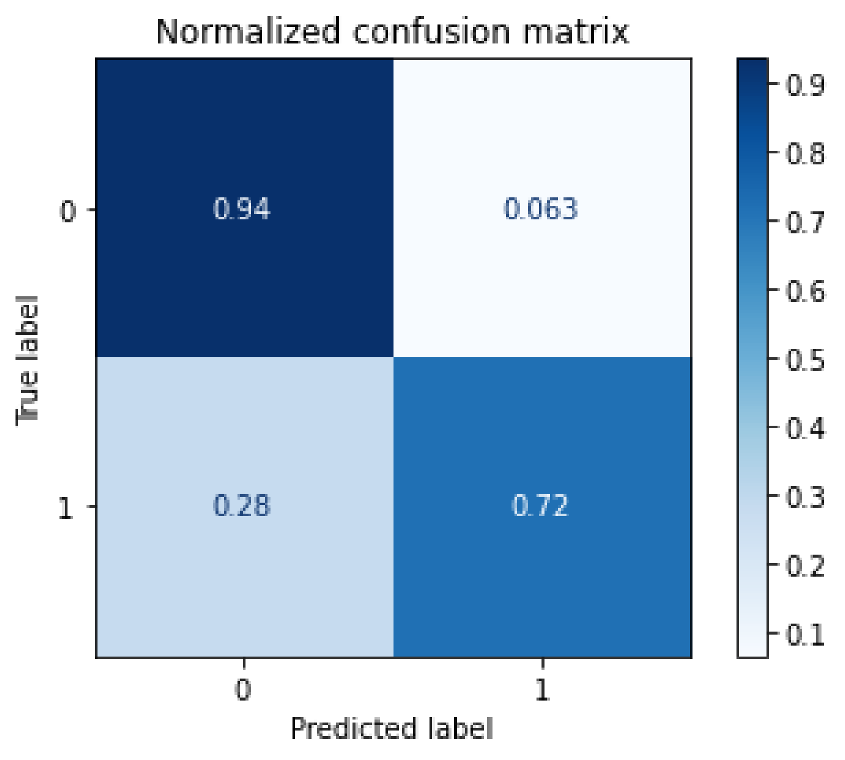
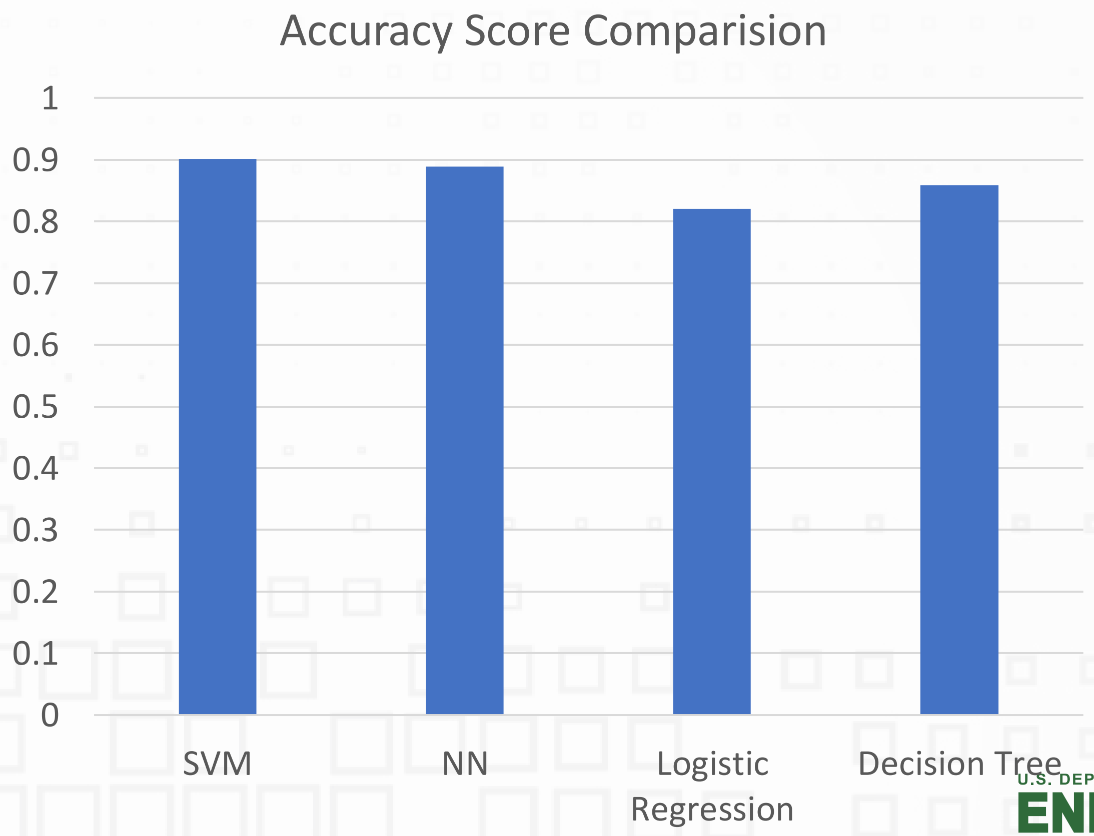
Preliminary Results

- Achieved a 70% - 95% accuracy in cascade failure warning
  - Multi-label optimal decision classification with SVM

Cascade failure warning classification with SVM





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Ongoing activities and future work

- Limitations and challenges
  - Test cases are relatively small
  - Scarcity of wildfire and grid asset datasets
  - Network connectivity/topology is difficult to encode in ML algorithms
- Partner w/ utilities
  - Reached out to PG&E, SCE
  - Scheduling regular meeting w/ PG&E wildfire (meteorology and operation) teams
- Next steps:
  - Investigate multiple machine learning techniques and compare their performances.
  - Capture wildfire ignition risks and the complexities of infrastructure investment/hardening.
  - Balance the desire to maximize grid reliability and to minimize network upgrade costs, e.g. investment on distributed energy resources to enhance grid resilience.
  - Extend the current approach to larger networks, i.e. Western Electricity Coordinating Council (WECC) models
  - Explore deep graph-based machine learning techniques that encode the temporal and spatial network complexities

Team

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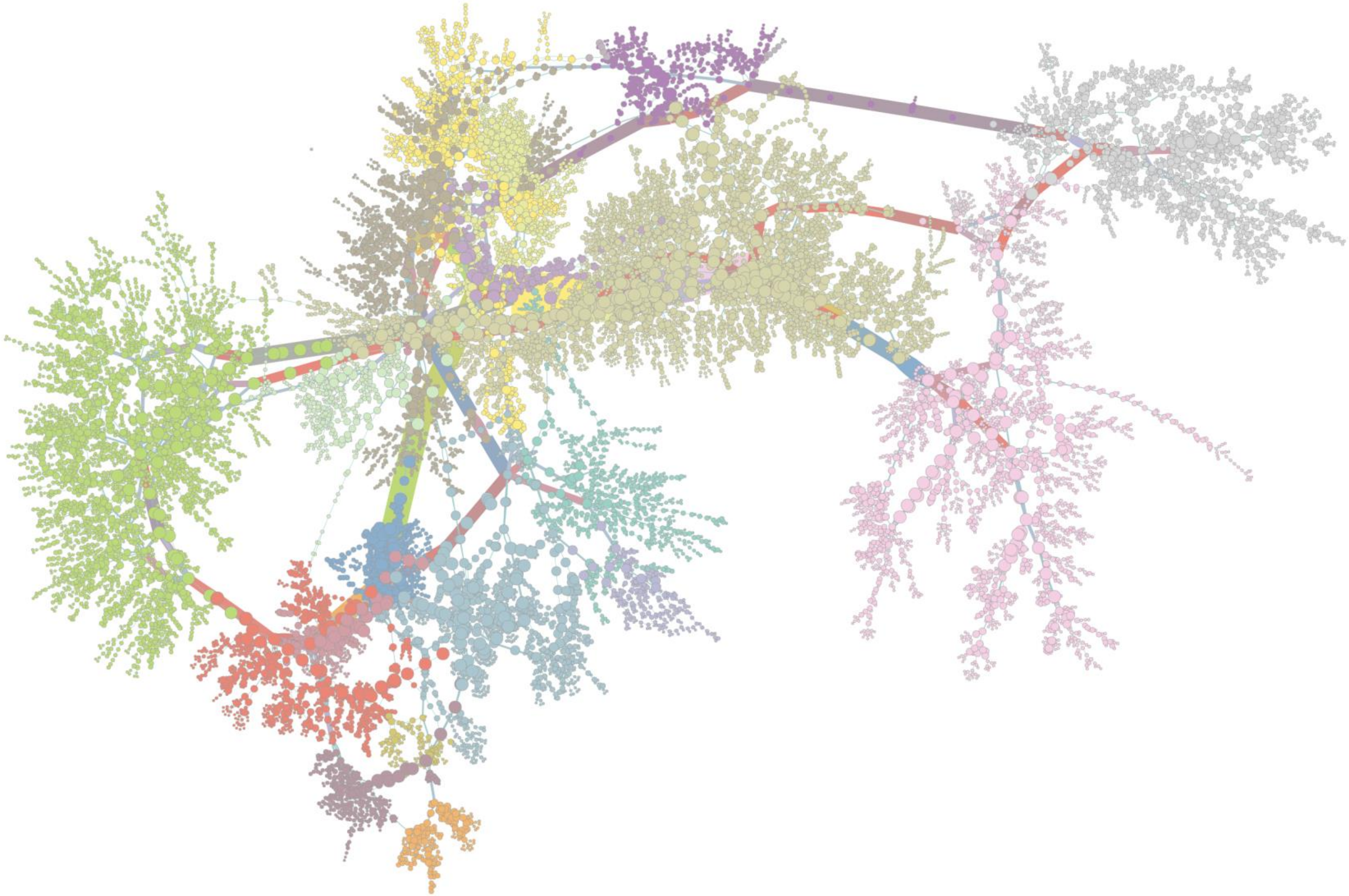
Thank you!

Bin Wang, wangbin@lbl.gov

Back-up Slides



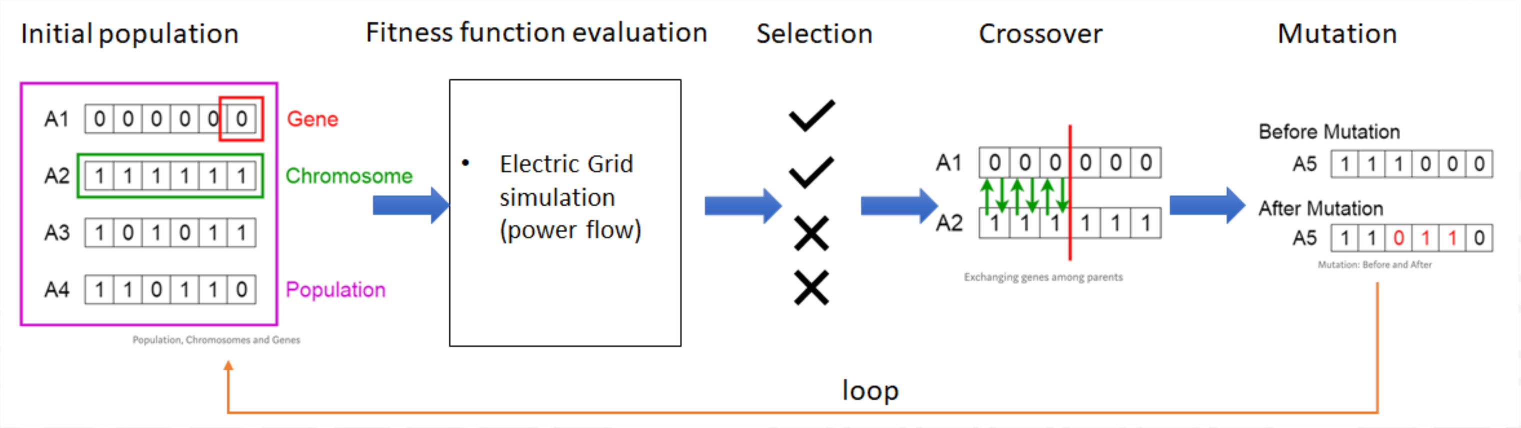
Graph representation of WECC models w/ multiple areas. More complex graph-based machine learning is being investigated over this large-scale network.

Optimal Decision Making Strategy

- Design optimal power flow problem to reduce load shedding and generator power variation with the presence of wildfire ignition risks
- Objective: Minimize load shedding, reduce generator power variation, and prevent cascade failure

$$\min \sum_{G} \underbrace{\Delta D}_{\text{load shedding}} + \sum_{G} \underbrace{\Delta P_g}_{\text{generator power variation}}$$

- Constraints: power flow constraints with transmission limit constraints
- Algorithm: genetic algorithm (GA) that is parallelized



https://towardsdatascience.com/introduction-to-genetic-algorithms-including-example-code-e396e98d8bf3#:~:text=A%20genetic%20algorithm%20is%20a,offspring%20of%20the%20next%20generation.

Rapid Infrastructure Flood Tool (RIFT)

David R. Judi, PhD

April 29, 2021

Background: Tool Development for Infrastructure Response to Extreme Events

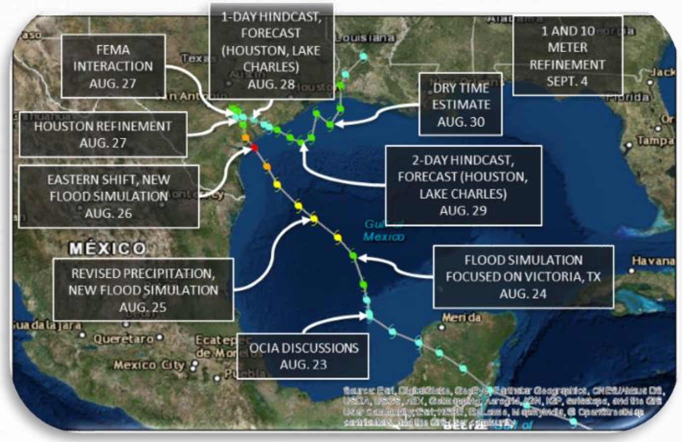
Objective: Develop and apply state of the art infrastructure analytics needed to support infrastructure stakeholder requirements. These analytics are used to characterize:

- Infrastructure system fragility, stability, and resilience
- Infrastructure dependencies on natural systems
- Infrastructure interdependencies
- Economic and community interoperability with infrastructure

WEATHER EXTREMES ARE THE MOST FREQUENT AND SIGNIFICANT CAUSES OF WIDESPREAD INFRASTRUCTURE DISRUPTION

Enhancing Situational Awareness in Extreme Events: Flood Example

- Capability Development is Guided by the EOC/Infrastructure Mission and Relevant Questions:
  - *What is the spatial extent of flooding?*
  - *When will the flood arrive?*
  - *How long will the flood remain?*
  - *How many people are at risk?*
  - *Which infrastructure assets are at risk?*
- How Do We Support Flood Events?
  - **Predictive modeling and simulation (real-time, near real-time)**
  - Imagery-based damage analytics
  - Access and leverage previously simulated events- Go to the WELL!



Hurricane Harvey Flood Simulation Timeline

Oroville Spillway Failure, 2017

What is RIFT?

- Rapid Infrastructure Flood Tool (RIFT)
- Hydrodynamics
  - Physics-based, state-of-the-art numerical techniques and computing resources
- Data
  - Readily available geospatial datasets
- Decision Support
  - Planning, response, recovery, and mitigation
- Targeted Audiences
  - Infrastructure owner/operators, federal, state, and local emergency operation centers

RIFT is used to characterize local-scale impacts from large-scale, regional flood events

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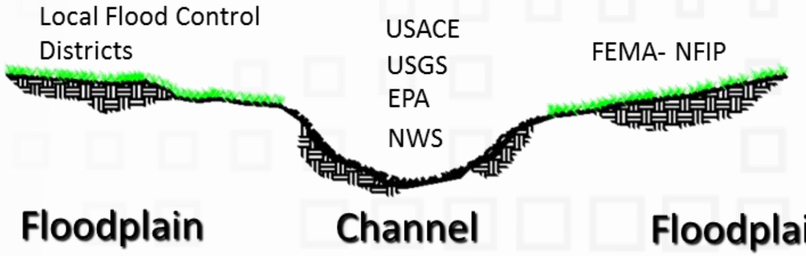
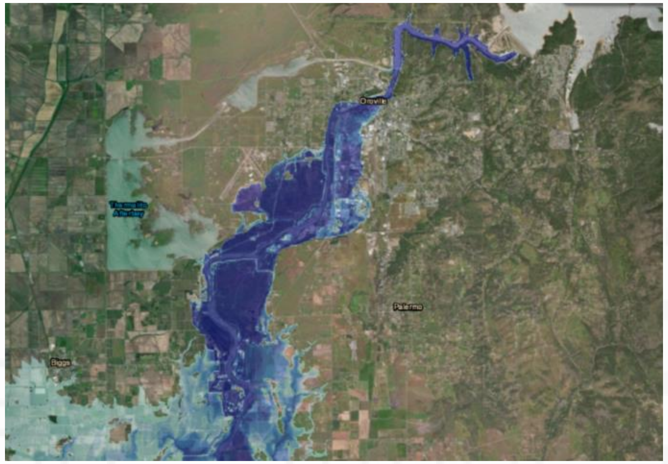
Intended RIFT Applications

RIFT was developed for a diversity of events with potential to **disrupt infrastructure assets that lie outside of the floodway**



- Extreme precipitation (e.g., rainfall-runoff)
- Dam failure
- Levee failure
- Spring snowmelt
- Coastal flooding
- Tsunami
- **Post-fire runoff**

Oroville Dam, 2017



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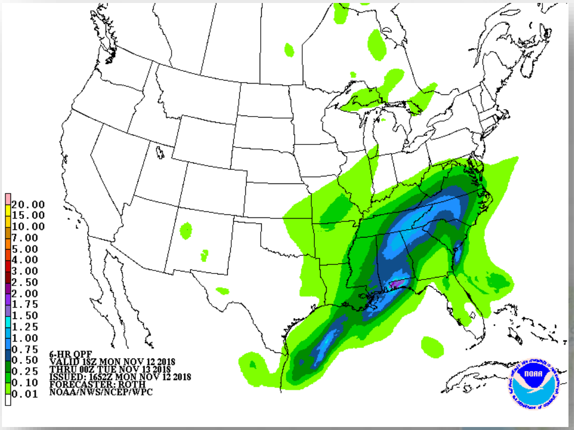
RIFT Data Requirements

- RIFT was intentionally designed to ingest readily-available data to minimize requirements (source, topography)
- CONUS data is a first resource, but supplemented with local data as needed



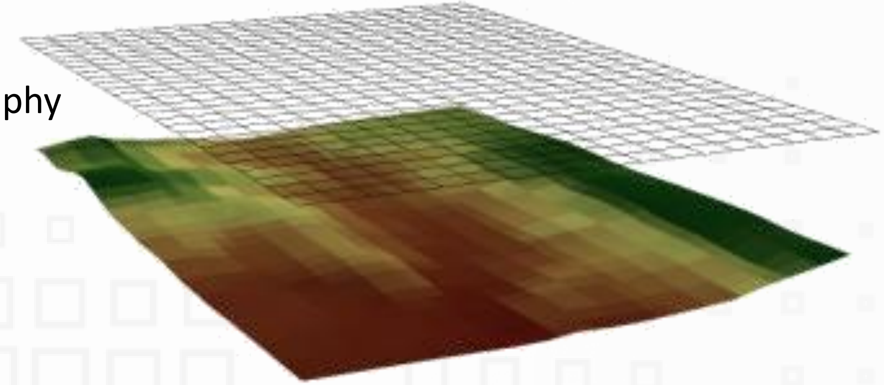
Quantitative Precipitation Forecast

Quantitative Precipitation Estimate

Data Types and Sources

Data	Sources	Type
Rainfall	NOAA	Spatial, Temporal
Topography	USGS, State, Local	Spatial
Land Use\Land Cover	NLCD (USGS)	Spatial
Soils	NRCS, Local	Spatial
River Gage	USGS, NOAA, Local	Spatial, Temporal
Levee\Dam	USACE	Spatial
Infrastructure	HSIP, State, Local	Spatial

Topography



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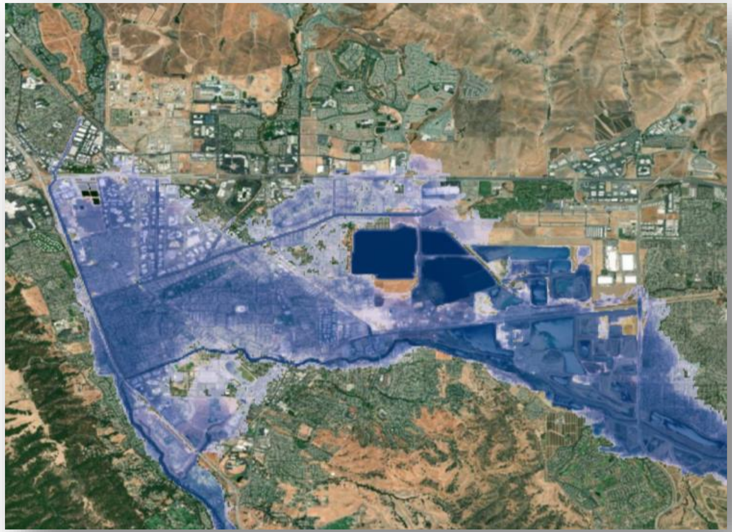
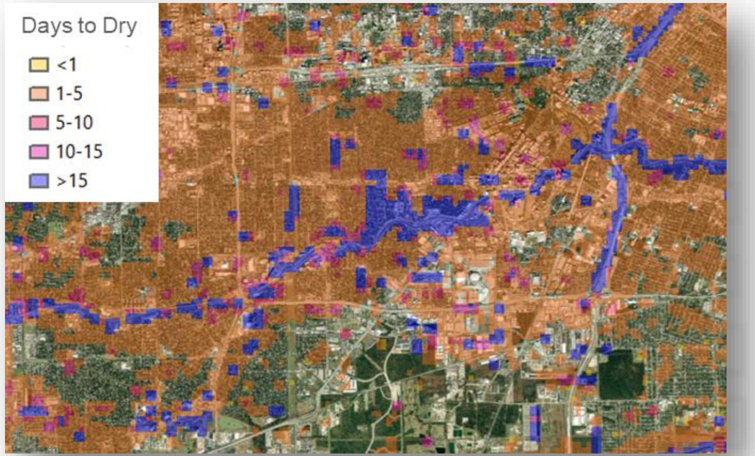
RIFT Data Products

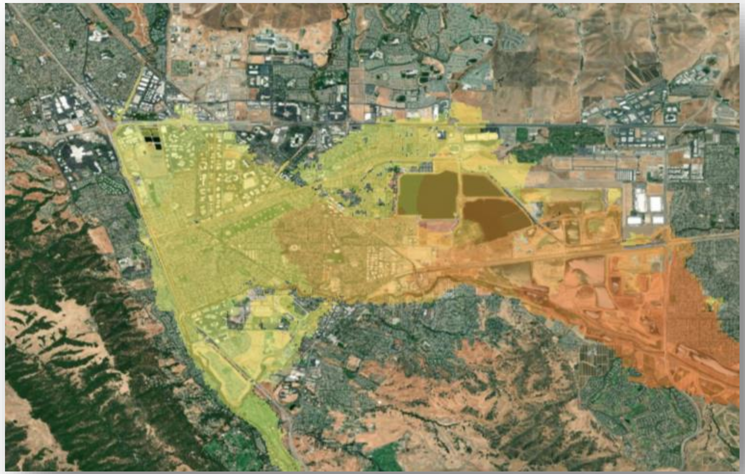
- All data products are based on fine spatial-temporal evaluation of flood depth and velocity
- Multiple derivative data products available to help support situational awareness needs
- All data products readily ingestible in geospatial platforms
    - Multiple formats available



Maximum Flood Depth



Flood Dry Time



Flood Wave Arrival Time

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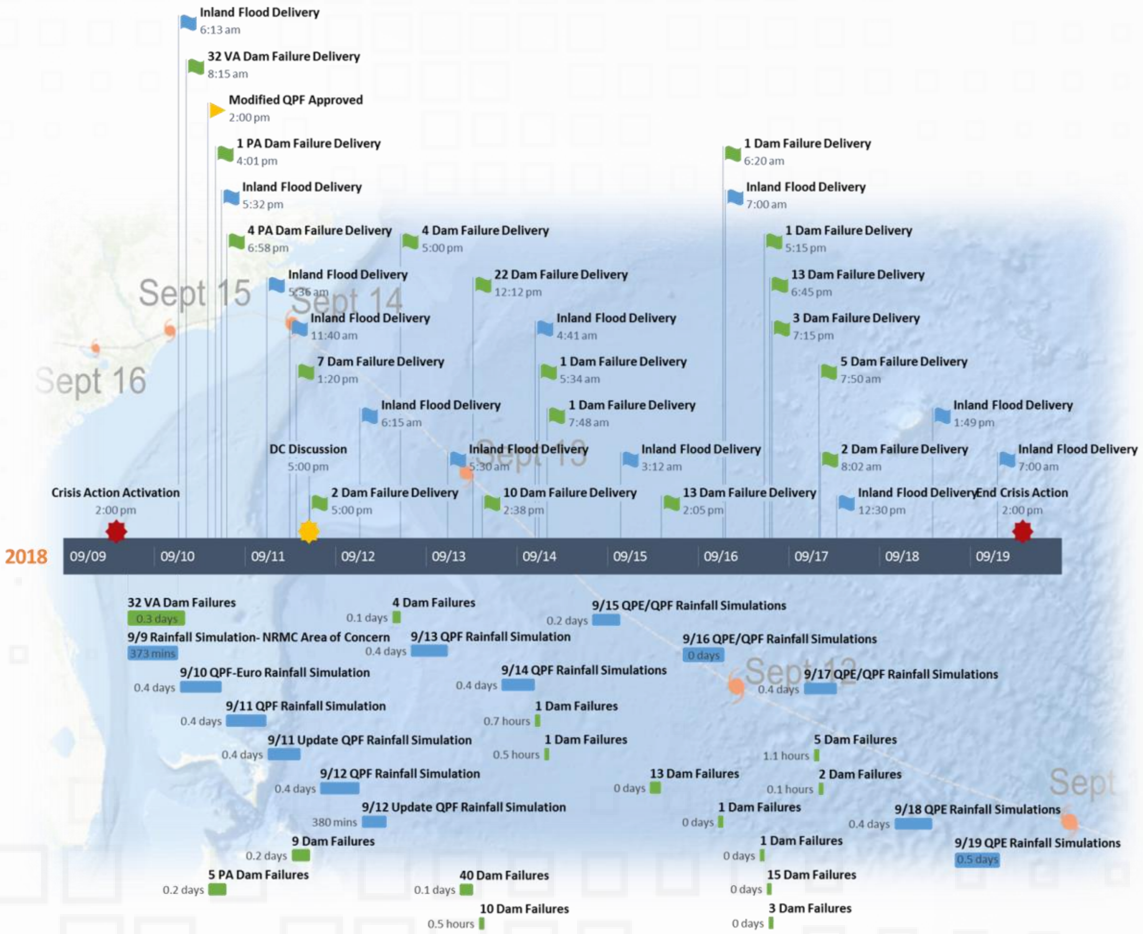
RIFT for Rapid Situational Awareness During Extreme Events

RIFT has been utilized to enhance situational awareness in the emergency response community for 15 years

- Combination of archived simulations (WELL) and near real-time simulations
- Create spatial awareness of flood hazards within minutes to hours
- Growing number of stakeholders (federal, state, local)



Hurricane Florence Simulation Timeline and National Impact

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RIFT for Characterization of Post-Fire Flood Impacts

- Fires have drastic **impact on vegetative cover and soil structure** and have significant impact on the hydrology
  - **Increase in volume of runoff**
  - **Increase in velocity of runoff**
- RIFT can reflect fire changes through infiltration and surface roughness parameterizations based on **ground-based and satellite-based burn severity and vegetation surveys**
- RIFT provides a **simulation testbed to identify locations of high-impact consequences** for Pre and Post-Event
  - Areas of previously undefined flood risk
  - Areas of high potential for erosion
  - Identify mitigating actions to optimize protection and restoration at the wildland-urban interface

Devastating floods in downstream communities occurred following the Las Conchas Fire in New Mexico (2011)

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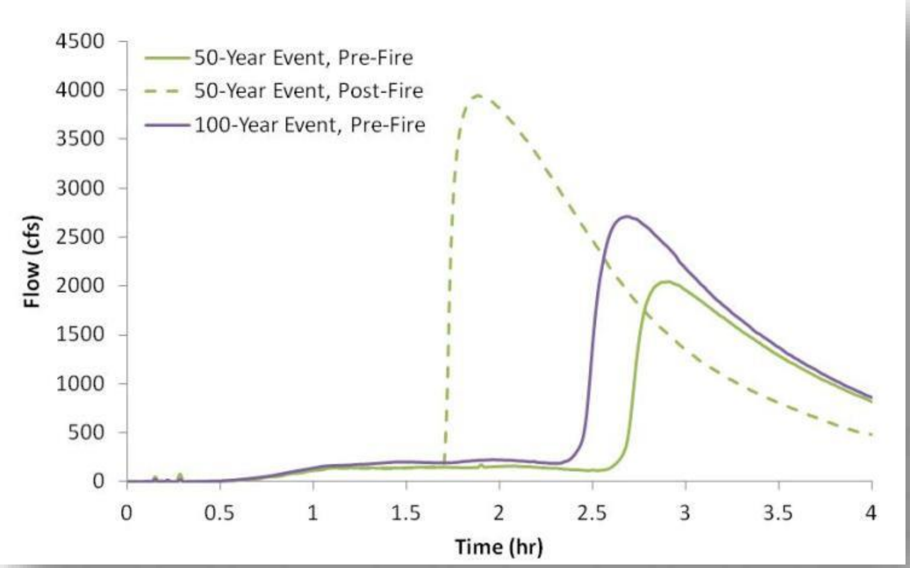
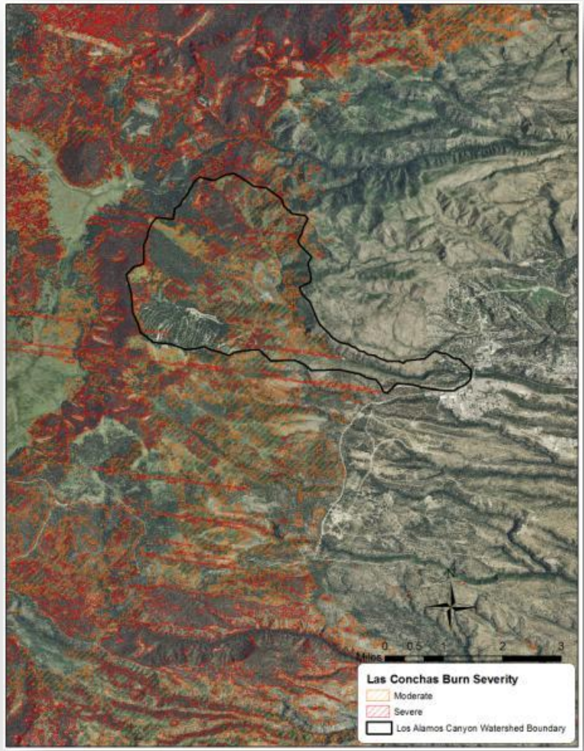
Las Conchas Fire, New Mexico (2011)

- June 2011 fire in Northern New Mexico burned 150,000 acres that threatened Los Alamos National Laboratory
- Comparison of pre and post fire runoff characteristics (magnitude, timing)



Pre and Post-Fire Runoff from Design Storm Events



Burn Severity Map

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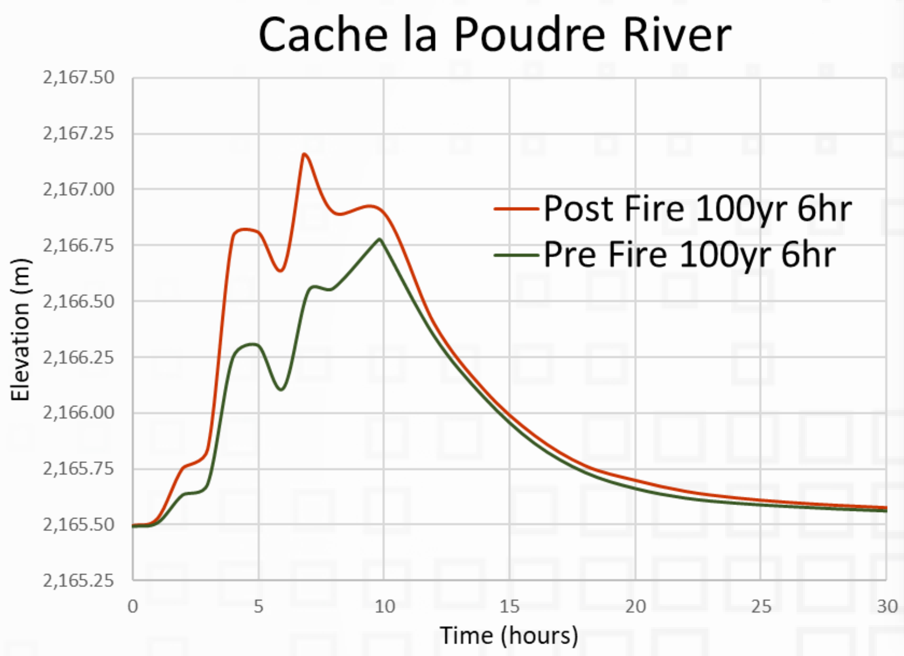
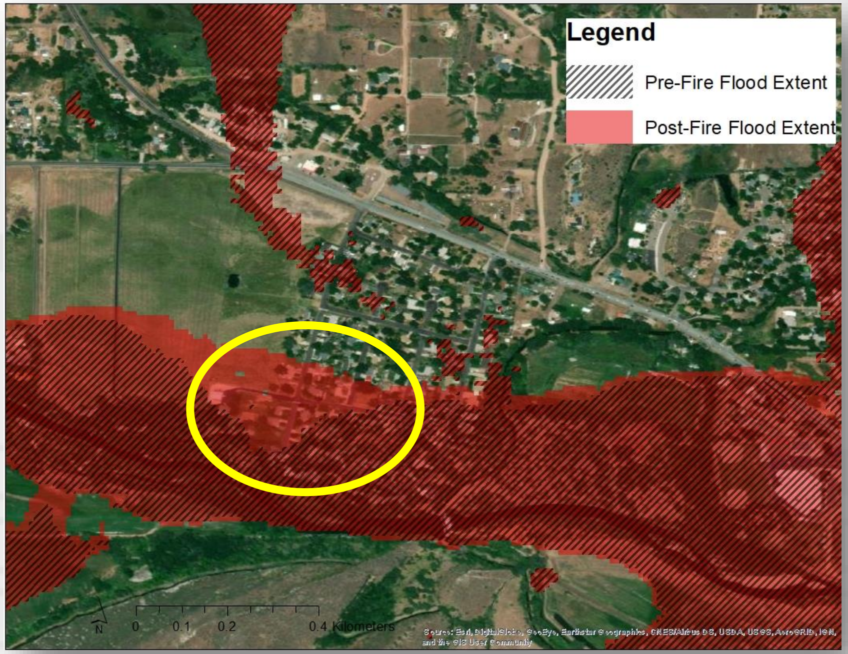
Cameron Peak Fire, Colorado (2020)

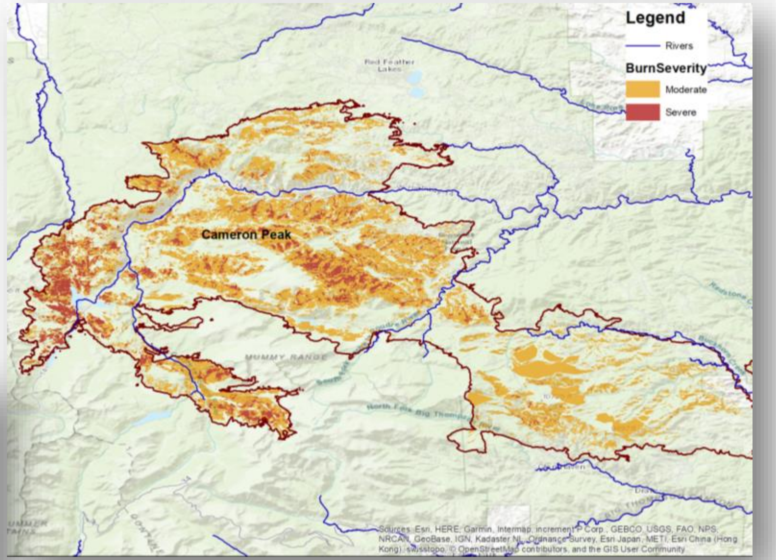
- August 2020 fire that burned 208,000+ acres burned in Colorado's Larimer and Jackson County
- Quantify changes in burned-area runoff in the headwaters of the Cache la Poudre River and local areas of increased flood risk



Change in Runoff



Change in Local Flood Risk



Cameron Peak Fire Burn Severity

*Most significant historical rainfall occurs in the foothills, outside burned area

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Summary

- RIFT has been used to facilitate situational awareness for a variety of extreme events, including dam failures, spring melt, hurricanes, and other extreme rainfall events
- RIFT has been applied to post-fire conditions to characterize downstream flood impacts
- Current RIFT efforts include cloud-based automation to facilitate response and interaction with emergency response community

Team RIFT

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Thank You!

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