Wildfire Webinar Series: Webinar 4

Modeling & Analytical Tools | Post Fire Analysis

April 29, 2021
Ron Wyden
United States Senator for Oregon
Dynamic Contingency Analysis Tool for Extreme Wildfire Event Planning

Xiaoyuan Fan, Ph.D., Energy and Environment Directorate
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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].

[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
Hybrid Steady-state and Dynamic simulation
- Interconnection Grid Models
- Protection system modeling
- Corrective Actions

Available Mitigation Plan List

Processing of simulation results
- Database GUI
- Visualization

Hazard Contingency List

Contingency 1 → Contingency 2 → Contingency 3 → Contingency n
DCAT Analytics – Database and Visualization Modules
DCAT Applied in Western Grid Reliability Analysis

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]

DCAT for Extreme Wildfire Event Planning & Mitigation

Domain use case formulation

Future scenario synthesis

Stochastic impact evaluation

Grid Modeling

- Historical wildfire event evaluation
- Future scenario synthesis and emulation
- Wildfire mitigation verification
- Wildfire caused Rolling Blackout evaluation
- Protection response evaluation for High impedance fault
DCAT & EGRASS Can Be Extended for Wildfires

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

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

Apply Resiliency Improvement
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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Technical publications:


Institutional Reports:


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
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.
Flame length under all weather conditions, indicates the likelihood that direct fire suppression is an option and whether crownfires will initiate.

- Significant reduction in flame length on treated pixels

Current evaluation is for restored locations. We can also model change in likelihood of spread between treated and untreated locations, not shown here.
Forest canopy conditions impact the volume and timing of snowmelt and streamflow

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
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 individual objectives used in tradeoff analysis
PNNL-USFS Forest Restoration Collaboration


• 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

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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
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
  - \(\leq 24\)-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
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
Remote Sensing of Wildfire
Rapid Analytics for Disaster Response (RADR) - Wildfire

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
Wildfire Behavior Modeling

- Satellite observations provide current system state (daily)
- Fire behavior models provide forecasted conditions in between observations (hourly)
RADR-Fire Team

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Daniel Farber – Fire Behavior Modeling
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Yi Shaw – UI/UX Design
Thank You!

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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

Process-based risk index: Interpretable, less accurate

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

**Drivers**
- Ignition factors
- Suppression factors
- Fuel conditions
- Climate factors

**Step 1**
- Process-based Fire model
- Simulated risk
- Pre-train

**Step 2**
- AI surrogate fire model
- Pre-trained parameters
- Output
- Pre-train

**Step 3**
- Observations finetuned surrogate fire model (transfer learning)
- Fine-tune
- Fire risks
- Output
- Fine-tuned machine learning parameters
- Output

United States National Fire Danger Rating System

Pre-trained parameters output

Fine-tuned machine learning parameters output

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

**Process-based Fire model**
- Drivers
  - Ignition factors
  - Suppression factors
  - Fuel conditions
  - Climate factors

**Step 1**
- Simulated risk
- Pre-train

**Step 2**
- Pre-trained parameters in the machine learning model
- Machine learning-based surrogate fire model

**Step 3**
- Satellite data finetuned surrogate fire model (transfer learning)
- Fine-tune

**Step 4**
- Management
- Fire risks
- Output

Simmonds et al., 2021
Applications over CA

Our XAI model

Random forest model (Jing Li 2020)

2012-2016: 368 large fires (Burned area > 4 $Km^2$), 216 small fires
## 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
Thank You!

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

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Camp Fire - GOES 16 (band7:3.9 µm)

85 deaths

Paradise

https://ylfeng.users.earthengine.app/view/fireca
Camp Fire - GOES 16 (band 7: 3.9 µm)

85 deaths

Paradise

How can we predict fire behavior?

https://ylfeng.users.earthengine.app/view/fireca
ML Fire Behavior Model: Interactively Calibrated with Satellite Data

Our Strategy

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.)

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

Wildfire Behavior Predictions

How does vegetation regrow after fires?
Forest Recovery/Regrowth

Steamboat Fire 1990-08-07, 24.7 km² (6,106 ac)

Yosemite National Park

Source: R. Negron-Juarez (unpublished)
FATES simulates and predicts growth, death, and regeneration of plants

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

Negron-Juarez et al. 2020, Biogeosciences
https://doi.org/10.5194/bg-17-6185-2020
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
El Dorado fire sparked by pyrotechnic device used during gender-reveal party at Yucaipa park
Robinson Negron-Juarez
Lawrence Berkeley National Lab
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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
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
Lightning is made by storms
We find variables that correlate with lightning today...
The balance of evidence $\rightarrow$ global warming increases US lightning

We find variables that correlate with lightning today...

...and plug those into global climate models.

They predict a $\sim 50\%$ increase by 2100.

Change in lightning by 2100

CAPE $\times$ P  PW10  IFluxT  I $\times$ G

Four different “variables”
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
Abatzoglou and Williams (2016)

An extra **100% already** from direct effect of warming on vegetation

Changes to ecosystems

Changes to rain

Changes to wind

An extra $\sim 50\%$ by 2100 from increased lightning?
Thank You!

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Attention-Based Long-Short-Term-Memory Model

Wildfire prediction with flexible lead time

W.J. Riley
Lawrence Berkeley National Laboratory
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
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

An ignition related variable or hidden state vector
A suppression related variable or hidden state vector
A fuel related variable or hidden state vector
A climate related variable or hidden state vector
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
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
Thank You!

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

Bin Wang, Research Scientist,
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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]

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.
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

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<th>Definition</th>
<th>Score</th>
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<td>Recall</td>
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<tr>
<td>True negative rate</td>
<td>0.78</td>
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Confusion matrix (threshold = 0.5)

Blue curves: historical wire-down events
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

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.
• Assume the powerline with high wildfire risk shut-downs, perform the proposed strategy.
Optimal Decision Making Preliminary Results

• Assume the powerline with high wildfire risk shuts down, perform the proposed strategy
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)
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
Preliminary Results

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

LBNL

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Mengqi (Molly) Yao, Ph.D.

Larry Dale, Ph.D.

UC Berkeley
Thank you!

Bin Wang, wangbin@lbl.gov
Graph representation of WECC models with 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

\[
\min \sum \Delta D + \sum \Delta P_g
\]

- 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
**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!

Oroville Spillway Failure, 2017

Hurricane Harvey Flood Simulation Timeline
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
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
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

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<th>Data Types and Sources</th>
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<td>Data</td>
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<tr>
<td>Rainfall</td>
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<td>Soils</td>
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<td>River Gage</td>
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<tr>
<td>Levee\Dam</td>
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<td>Infrastructure</td>
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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

Days to Dry
- <1
- 1-5
- 5-10
- 10-15
- >15

Flood Dry Time

Maximum Flood Depth

Flood Wave Arrival Time
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)
• 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)
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
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

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

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