Isolating the Primary Drivers of Fire Risk to Structures in California

Michael Gollner, Associate Professor

Maryam Zamanialaei, Dwi Marhaendro Jati Purnomo, Maria Theodori
Department of Mechanical Engineering, University of California, Berkeley

Daniel San Martin
Departamento de Informática, Universidad Técnica Federico Santa María, Valparaíso

Ali Tohidi, Yiren Qin, Arnaud Trouvé
Department of Fire Protection Engineering, University of Maryland, College Park.

Chris Lautenberger
CloudFire, Inc.

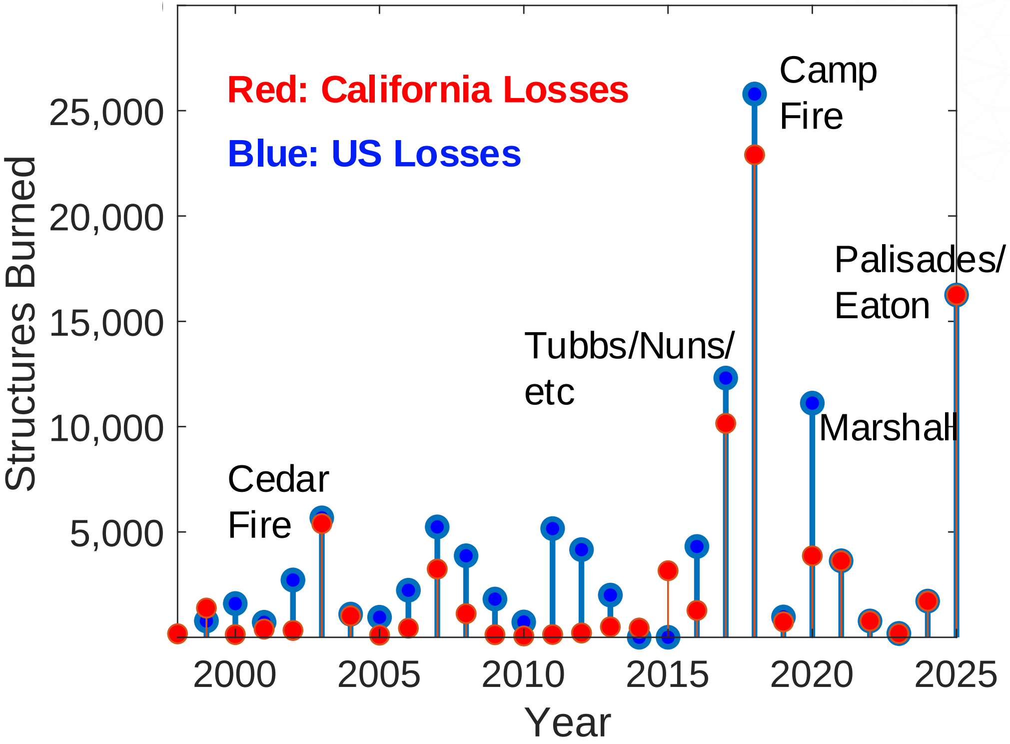
Primary Project Support from Forest Health Grant 8GG21815

Berkeley Fire Research Lab

Photo Credit: Melia Robbinson

Wildland-Urban Interface (WUI) Fires

Tubbs Fire / Melia Robbinson



Data: CA (CAL FIRE), US (NIFC)


Palisades Fire/Robert Gauthier/Los Angeles Times


Eaton Fire/Jeff Gritchen, Orange County Register/SCNG

Palisades Fire/Ethan Swope / AP


Camp Fire/Hector Amezcua/Sac Bee


Modeling WUI Fires:
A Huge Challenge
Coffey Park
Santa Rosa, CA
Tubbs Fire

Pathways to Fire Spread

Radiation

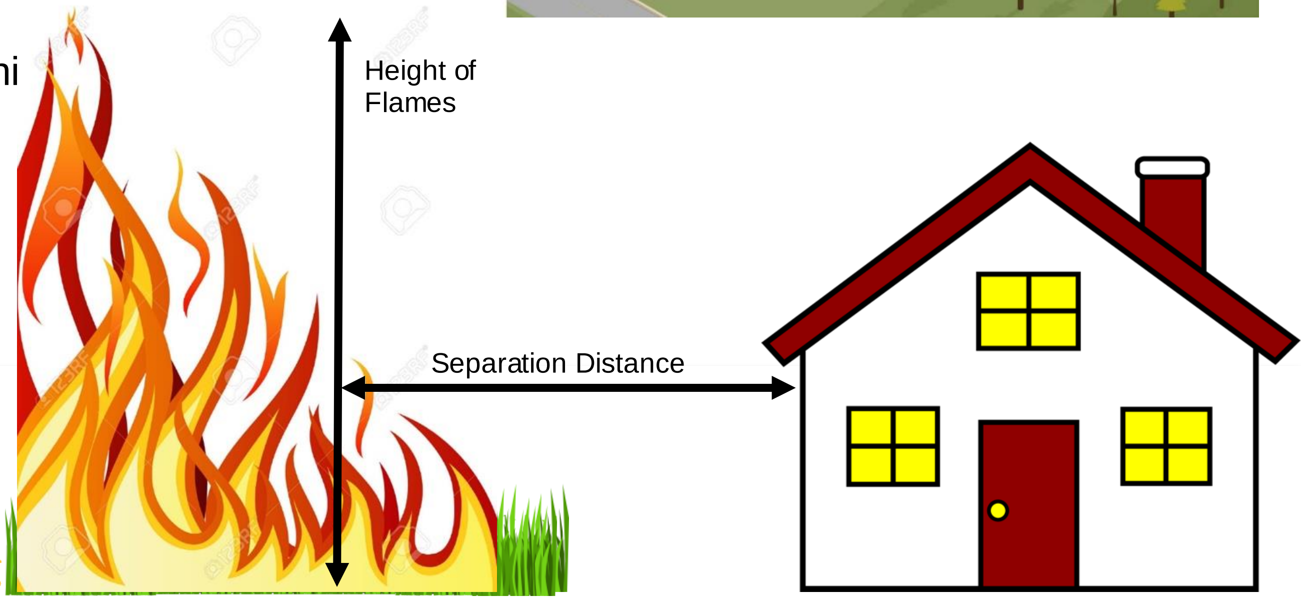
Originally thought to be responsible for most/all ignitions

Direct Flame Contact

Smaller flames from nearby sources

Embers or Firebrands

Small burning particles whi



Pathways to Fire Spread

Radiation

Originally thought to be responsible for most/all ignitions

Direct Flame Contact

Smaller flames from nearby sources

Embers or Firebrands

Small burning particles which cause spot ignitions

Pathways to Fire Spread

Radiation

Originally thought to be responsible for most/all ignitions

Direct Flame Contact

Smaller flames from nearby sources

Embers or Firebrands

Small burning particles which cause spot ignitions

Pathways to Fire Spread

Radiation

Originally thought to be responsible for most/all ignitions

Direct Flame Contact

Smaller flames from nearby sources

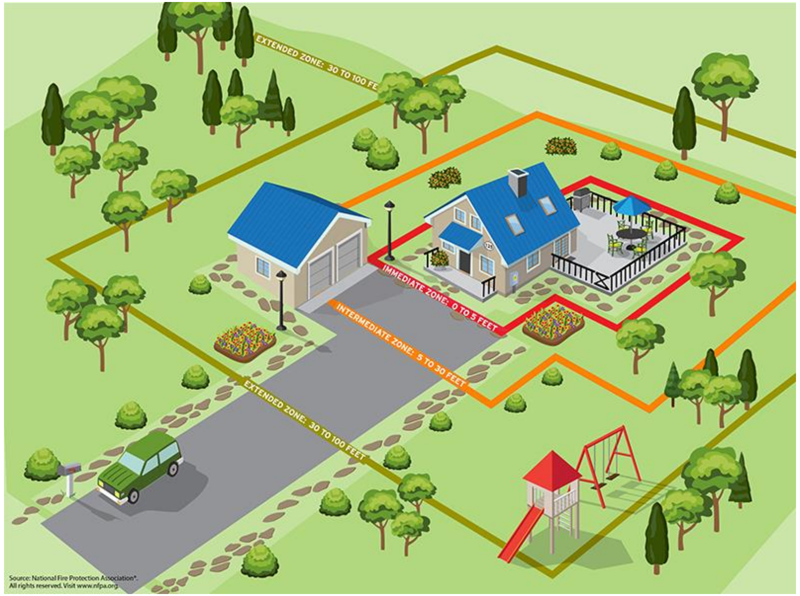
Embers or Firebrands

Small burning particles which cause spot ignitions

Nathan Trauernicht, UC Davis Fire @ Tamarack Fire

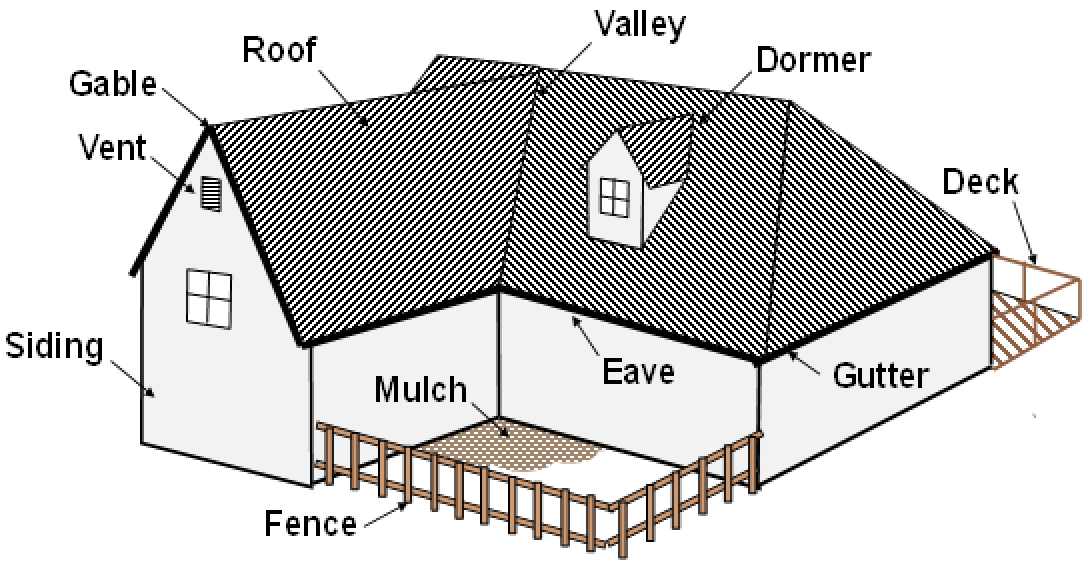
Mitigation: Defensible Space and Hardening

Defensible Space



Clear nearby fuels

Home Hardening



Prevent ignition from small flames/embers

Hakes, Raquel SP, et al.." *Fire technology* 53 (2017): 475-515.

Part 1: Data- Driven WUI Risk to Structures

- Mitigation must be applied to reduce the risk of structure losses in the future
- Need methods to relate features/exposure to losses
- Previous analyses have several drawbacks:
    - No quantitative data ranking one mitigation measure vs. another
    - Analysis of losses using only linear correlations or statistics (no interrelationships)
    - No exposure data (fire and embers) from wildland to structures

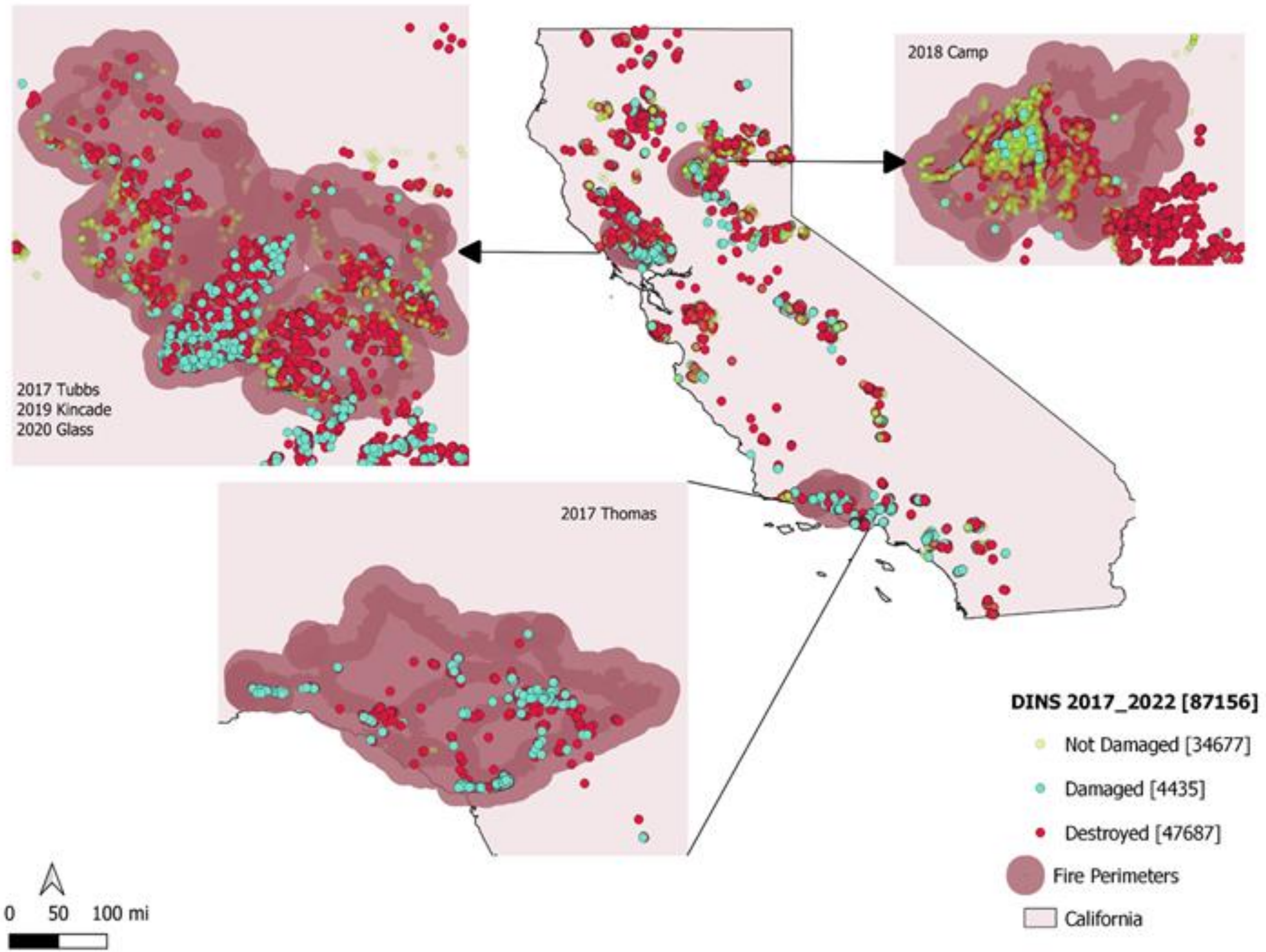
Part 1: Data- Driven WUI Risk to Structures

- Create a WUI Dataset for Analysis and Model Validation:
  - Using DINS (Ground Truth), remotely sensed data and ***modeled*** exposure
- Quantify Significance of WUI Features on Structure Destruction:
  - Use SHAP Values and feature contributions
- Focus on 5 past fires in California:

WUI Fire	Acres Burned	Destroyed Structures
2017 Tubbs	36,807	5,636
2017 Thomas	281,893	1,063
2018 Camp	153,336	18,804
2019 Kincade	77,758	374
2020 Glass	67,484	1,528

CAL FIRE DINS - Damage INSpection data

WUI data: values= 47,000 Unique data point= 45,947



Combining and processing datasets

Collected Data	DINS	• **Structure Features:** Roof, siding, windows, vent, eaves, etc. • **Year Built**
Missing Data	Defensible Space	• Airborne LiDAR data for Sonoma County ○ 1 m. resolution raster for veg intensity • Aerial and Street View Imagery
	Structure Separation	• Calculated with MS Structure Footprints
	Flame and Embers	• **Generated by reconstructing past fires** • Models run with vegetation and *limited* urban spread - extract fire intensity and ember cast
	Undamaged structures	• Adding undamaged structures for past fires (MS Footprints, OSM, Imagery)
Validation Data	Ground Truth & RS	• DINS • MODIS , VIIRS, GOES

Defensible Space Assessment

No defensible space

Zone 0 and 1 clear

Zone 0: First five feet

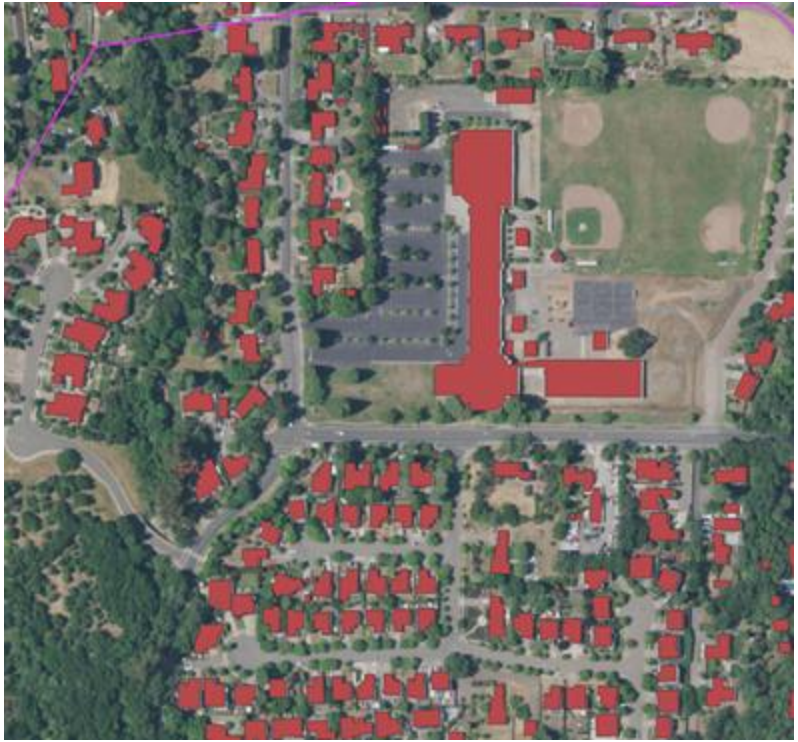
Zone 1:Within 30 feet

Zone 2: Within 100 feet

Defensible space is the buffer between a structure and the surrounding area.

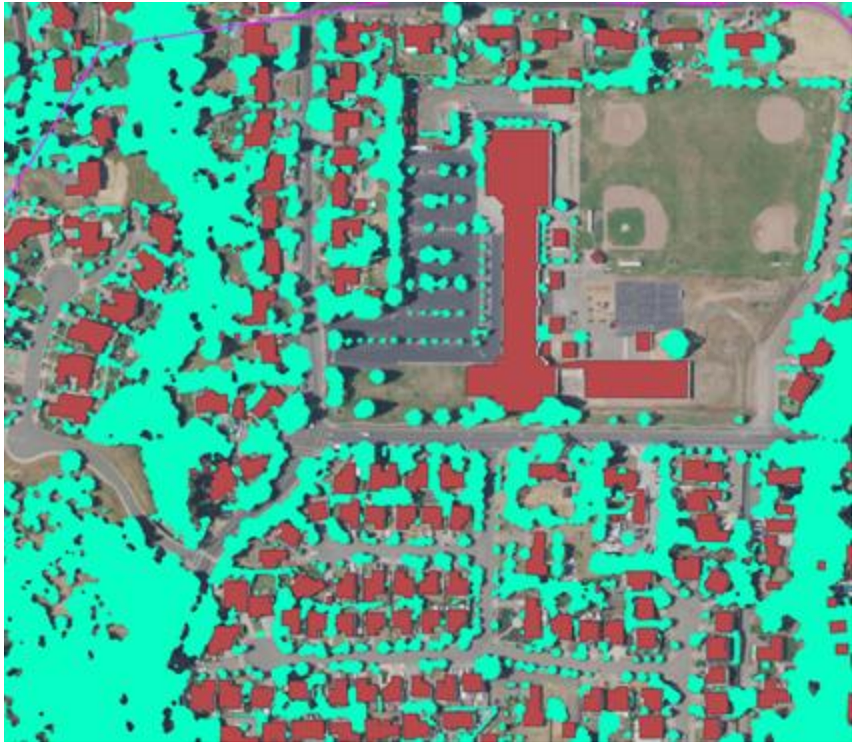
Separation Distance

Structure Separation Distance + Unburned structures



MS Building Footprints - script analysis

Vegetation Separation Distance



LIDAR (Sonoma County)

Exposure from Fire Modeling

Current Limitations

No inclusion of exposure from neighboring structures

Underlying physics

Validation data

Input data resolution

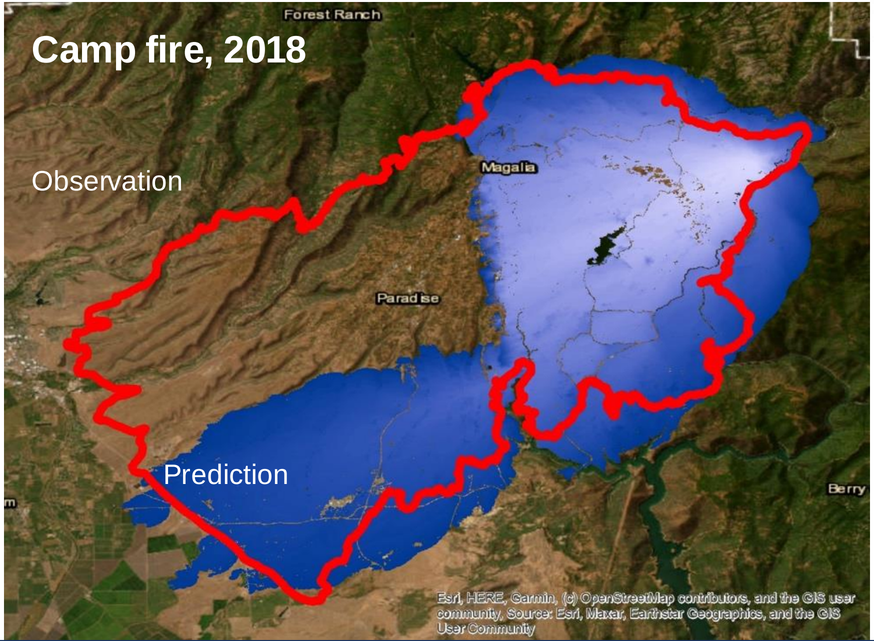
Structure-to-structure spread

Inputs
- Vegetation
- Weather
- Topography

Models
- Surface fire
- Crown fire
- Ember

Wildfire model: **ELMFIRE**

Outputs
- Spread rate
- Ember cast
- Flame length



Raquel S. P. Hakes, Sara E. Caton, Michael J. Gollner, Daniel J. Gorham, "A Review of Pathways for Building Fire Spread in the Wildland Urban Interface Part II: Response of Components and Systems and Mitigation Strategies in the United States," *Fire Technology, 53, 475–515, 2017*. doi: 10.1007/s10694-016-0601-7

WUI fire spread model: HAMADA + ELMFIRE

K_d: downwind reach of fire [m]

K_s: sidewind reach of fire [m]

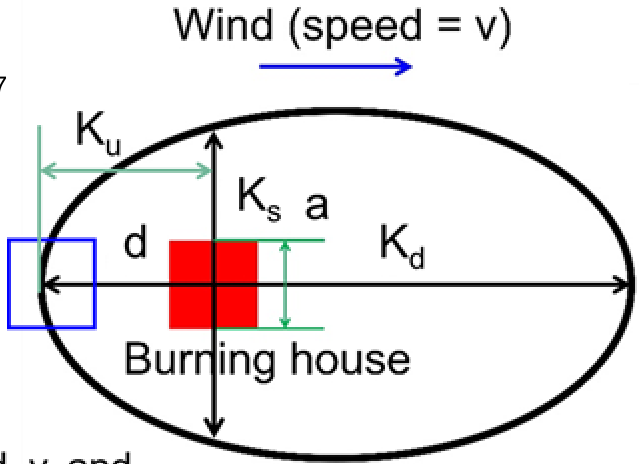
K_u: upwind reach of fire [m]

v: wind speed [m/s]

a: house size [m]

d: separation distance [m]

T_d, T_s, and T_u: are functions of a, d, v, and fire resistant buildings



$$K_d = \left[\frac{(a+d)}{T_d}\right](t)$$

$$K_s = \left(\frac{a}{2} + d\right) + \left\{\left[\frac{(a+d)}{T_s}\right](t - T_s)\right\}$$

$$K_u = \left(\frac{a}{2} + d\right) + \left\{\left[\frac{(a+d)}{T_u}\right](t - T_u)\right\}$$

T_d: downwind propagation time [min]

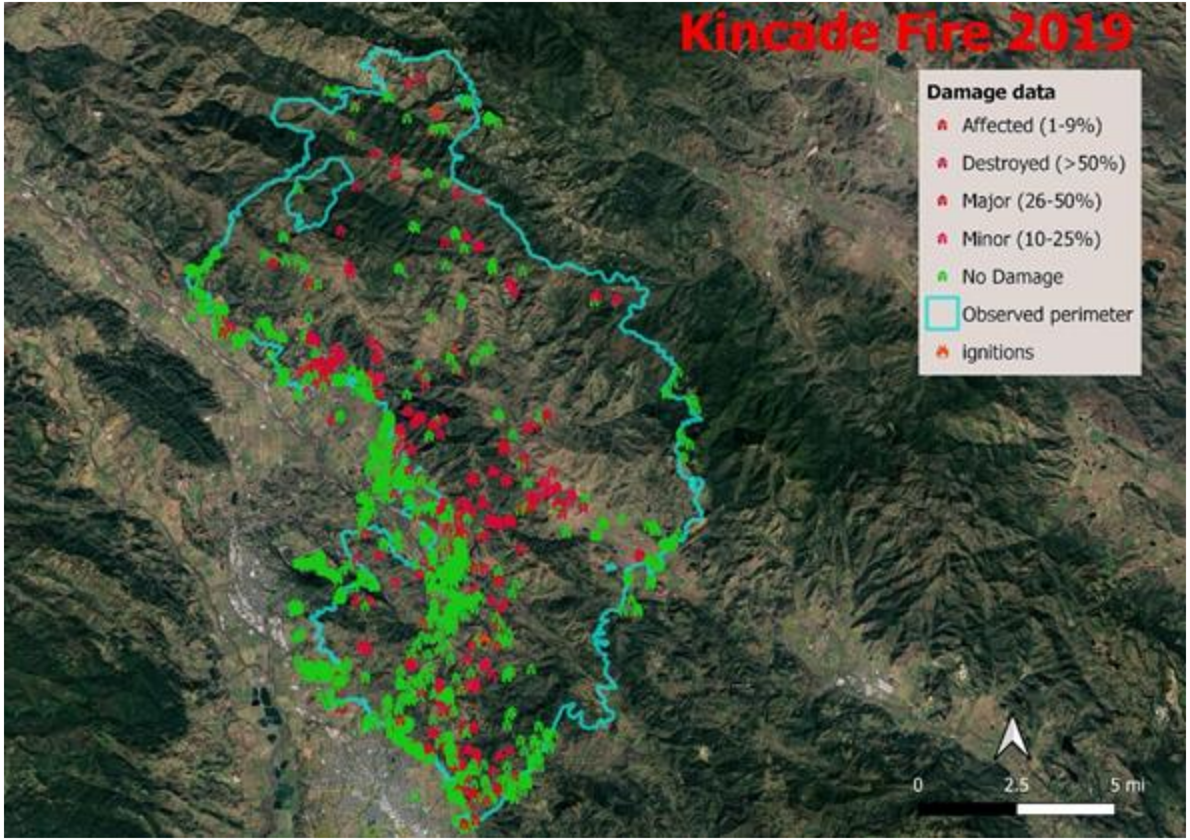
T_s: sidewind propagation time [min]

T_u: upwind propagation time [min]

t: characteristic time [min] e.g., 120 min

Hamada, M. (1951). On the Rate of Fire Spread. Study of Disasters, 1.
Purnomo DM et al. (2024) Integrating an urban fire model into an operational wildland fire model to simulate one dimensional wildland–urban interface fires: a parametric study. International Journal of Wildland Fire 33, WF24102.doi:10.1071/WF24102

Fire Reconstruction: Kincade Fire 2019



Kincade Fire, 2019

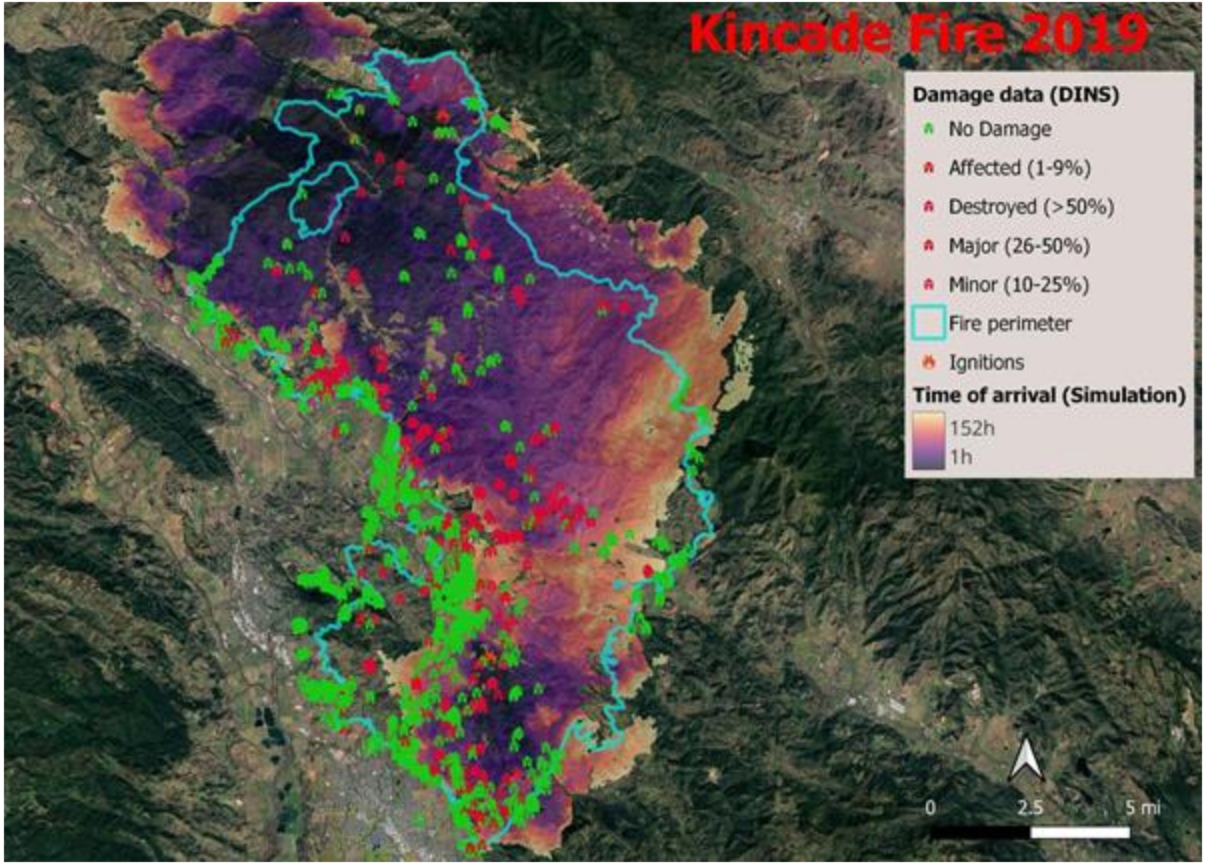
DINS Losses +
Observed fire perimeter:
GeoMac-NIFC

Fire Reconstruction: Kincade Fire 2019

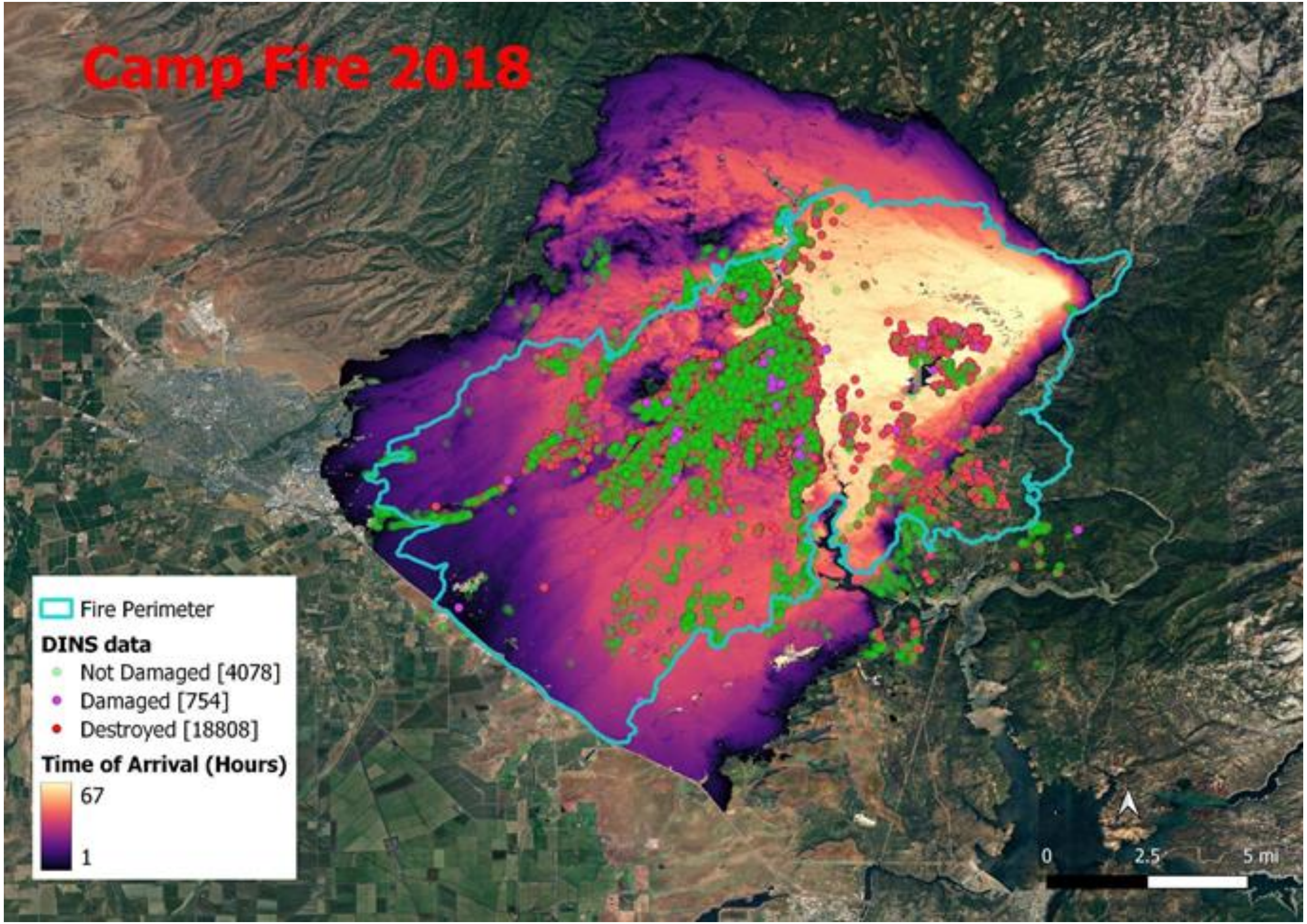
DINS Losses +
Observed fire perimeter:
GeoMac-NIFC

+
SIMULATION:
ELMFIRE + HAMADA

=
Flame Length
Ember



Fire Reconstruction: Camp Fire 2018



Extracting Significance of WUI Features

- Features are inter-related so linear or statistical methods can't capture their influence

- We attempt to fit the data to a machine learning (ML) model using ***regression and classification methods*** and extract the importance of individual features.

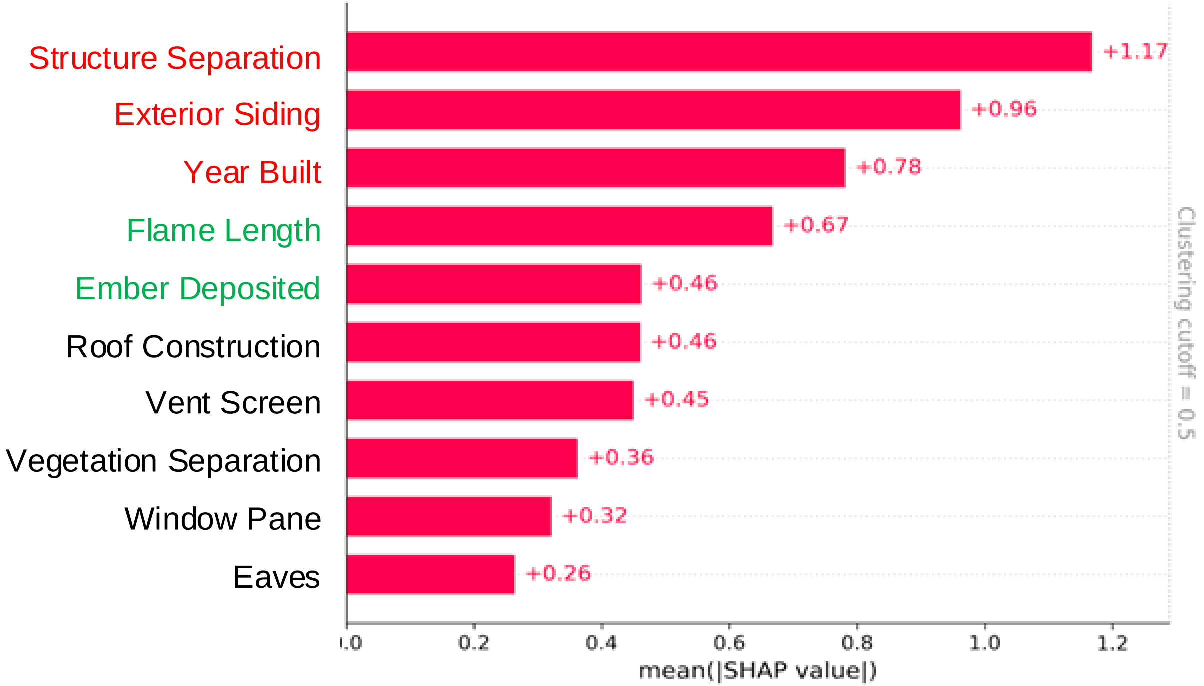
- It is important to first "clean/preprocess" the data and avoid biases, ensuring compatibility and enhancing the overall performance of the models:
  - ***Imputation*** was explored due to the presence of numerous NaN values in the dataset.
  - ***Standardized*** the numerical variables and ***Encoded*** categorical variables

Extracting Significance of WUI Features

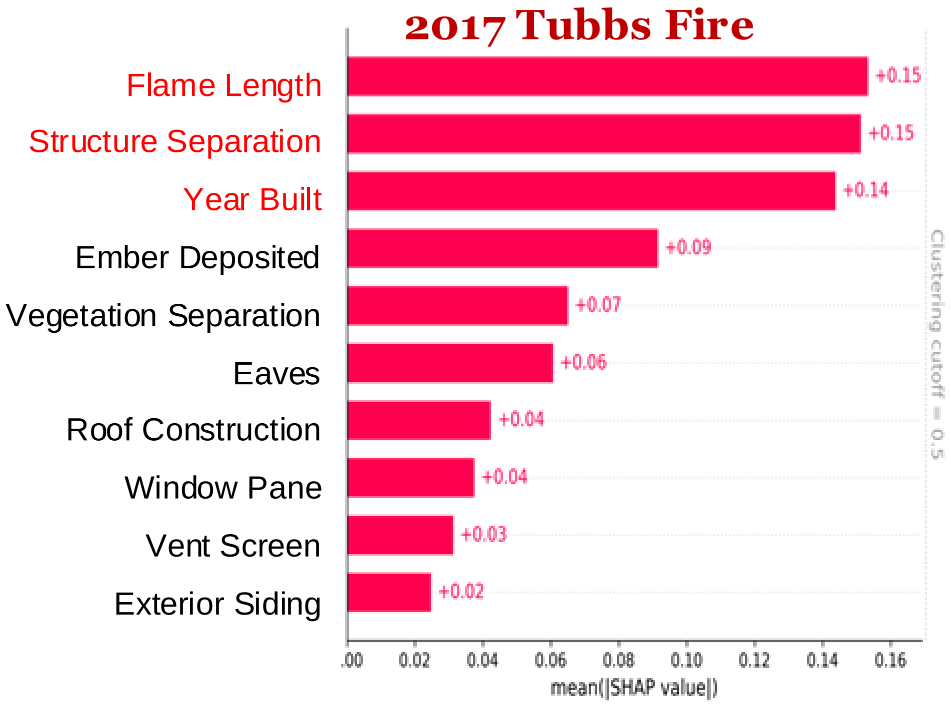
- We explore 4 models and use the "best fit"
  - *Linear/Logistic regression*
  - *Random Forest*
  - *Gradient Boosting/ XGBoost*
  - *CatBoost*
  - **XGBoost showed better results in overall accuracy .**
- We extract feature contributions through SHAP (SHapley Additive exPlanations)
  - Interpreting machine learning models
  - Ensuring consistency and local accuracy

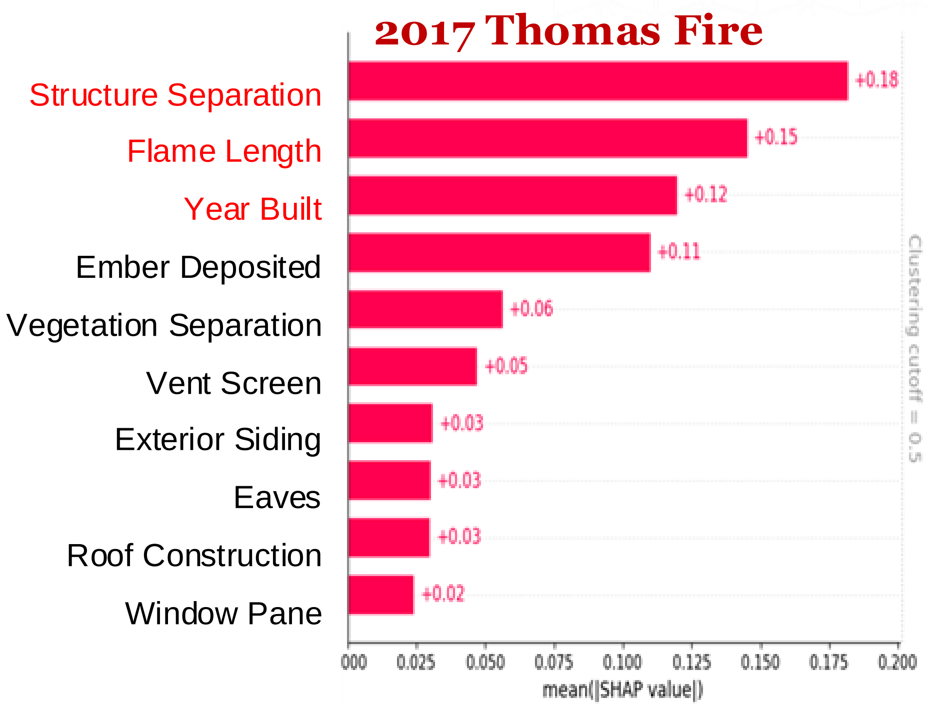
Feature Contributions Using XGBoost and SHAP Values

Stacked WUI data: 5 Past fires (2017-2022)



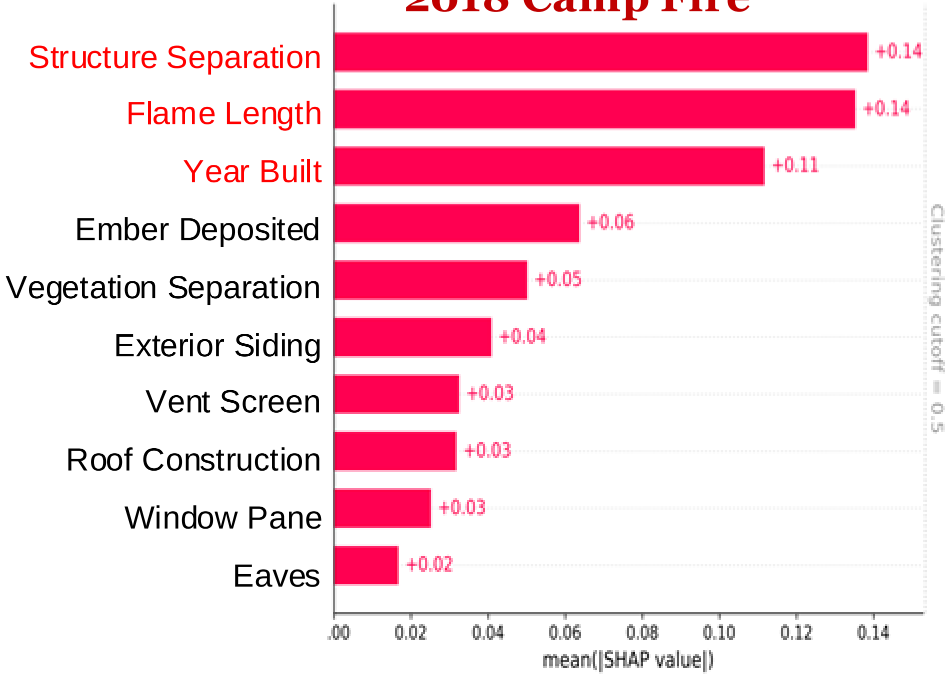
Feature Contributions Using XGBoost and SHAP Values



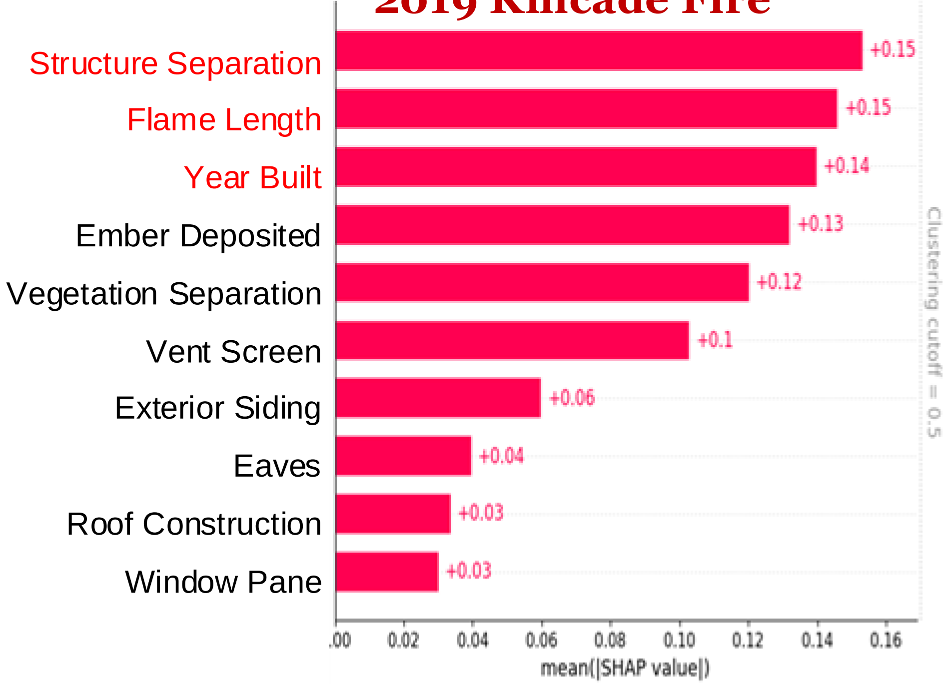


Feature Contributions Using XGBoost and SHAP Values

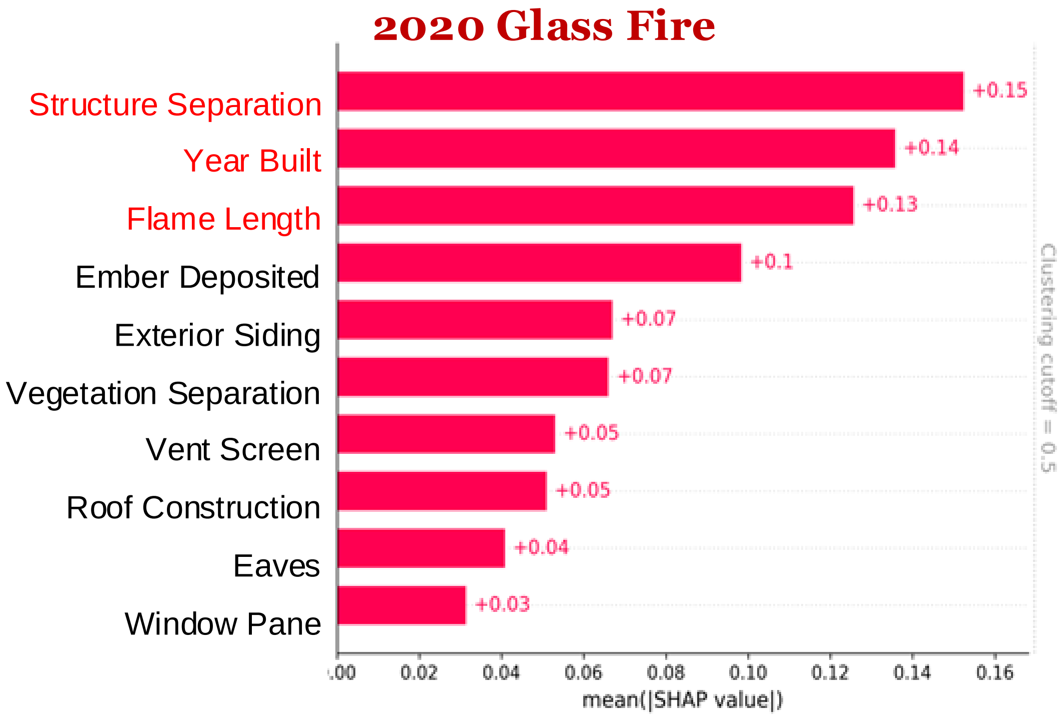
2018 Camp Fire



2019 Kincade Fire

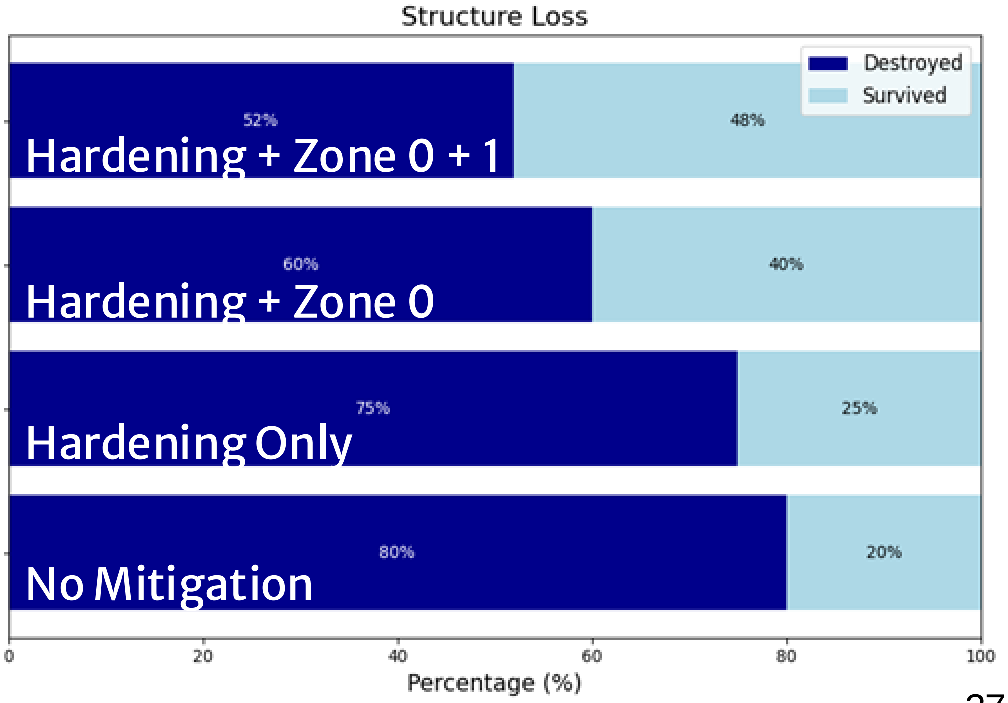


Feature Contributions Using XGBoost and SHAP Values



Influence of Mitigation Factors

- ML model can be used as a predictive tool (~82% accuracy)
- Potential influence of different mitigation strategies tested
- Probability of surviving increases with hardening + defensible space
- Even without moving (spacing) structures, can drastically cut down on losses
- Does not incorporate dynamic (spread) or suppression effects



PART II: New WU-E Model

Novel coupled WU-E[1] modeling framework

Wildland-**U**rban **E**xtension fire model

Geospatial inputs

- Fuels (wildland)
- Weather
- Topography

- Fuels (built)

Submodels

- Surface fire
- Crown fire
- Spotting (firebrands)

- Direct flame contact
- Radiation
- Spotting (firebrands)

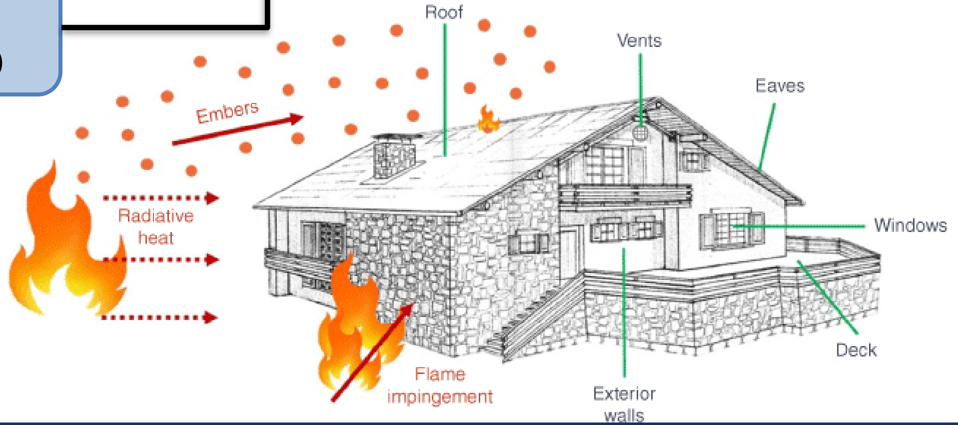
Modeling tool

Key outputs

- Rate of spread
- Heat flux
- Ember cast

Model Benefits:

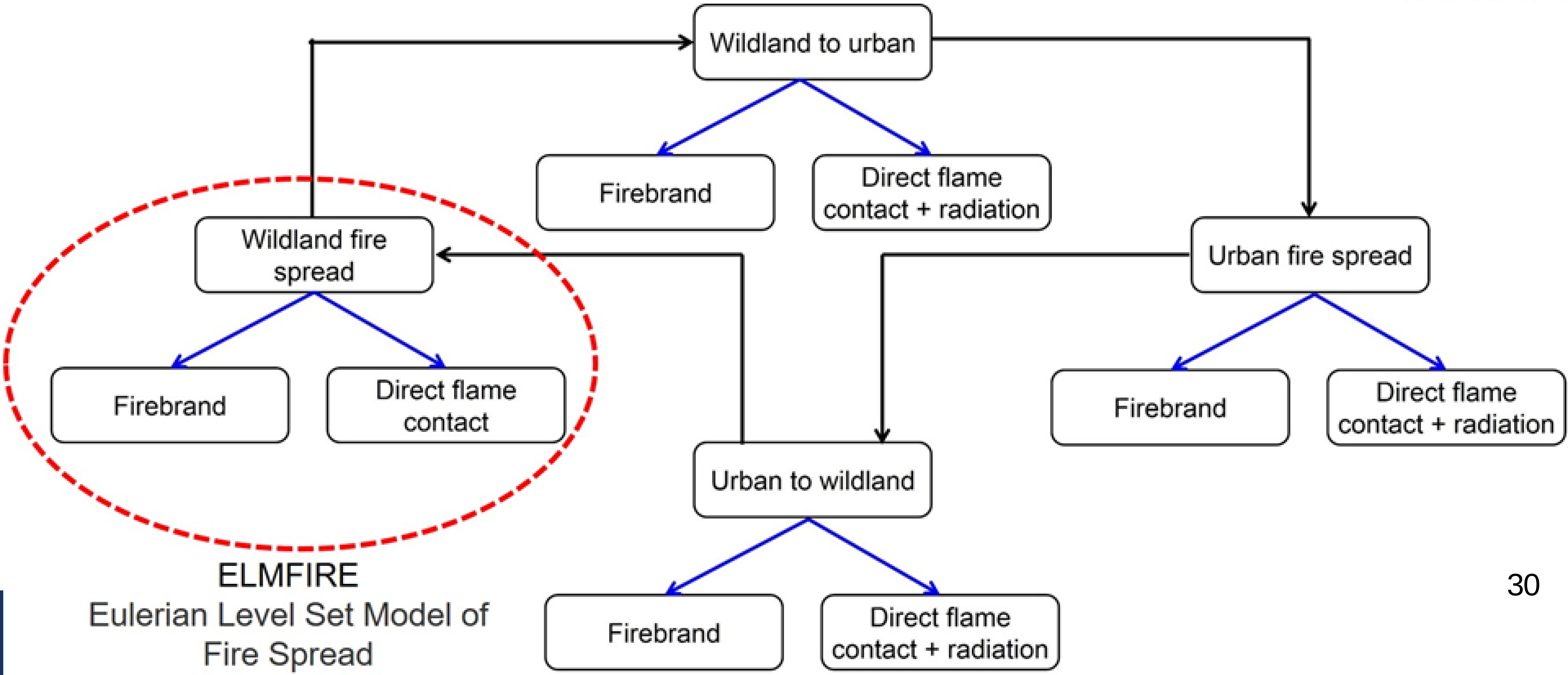
- Spreads through structures
- Incorporates effects of mitigation
- Links wildland-> structures -> wildland
- Integrates with existing management & risk frameworks



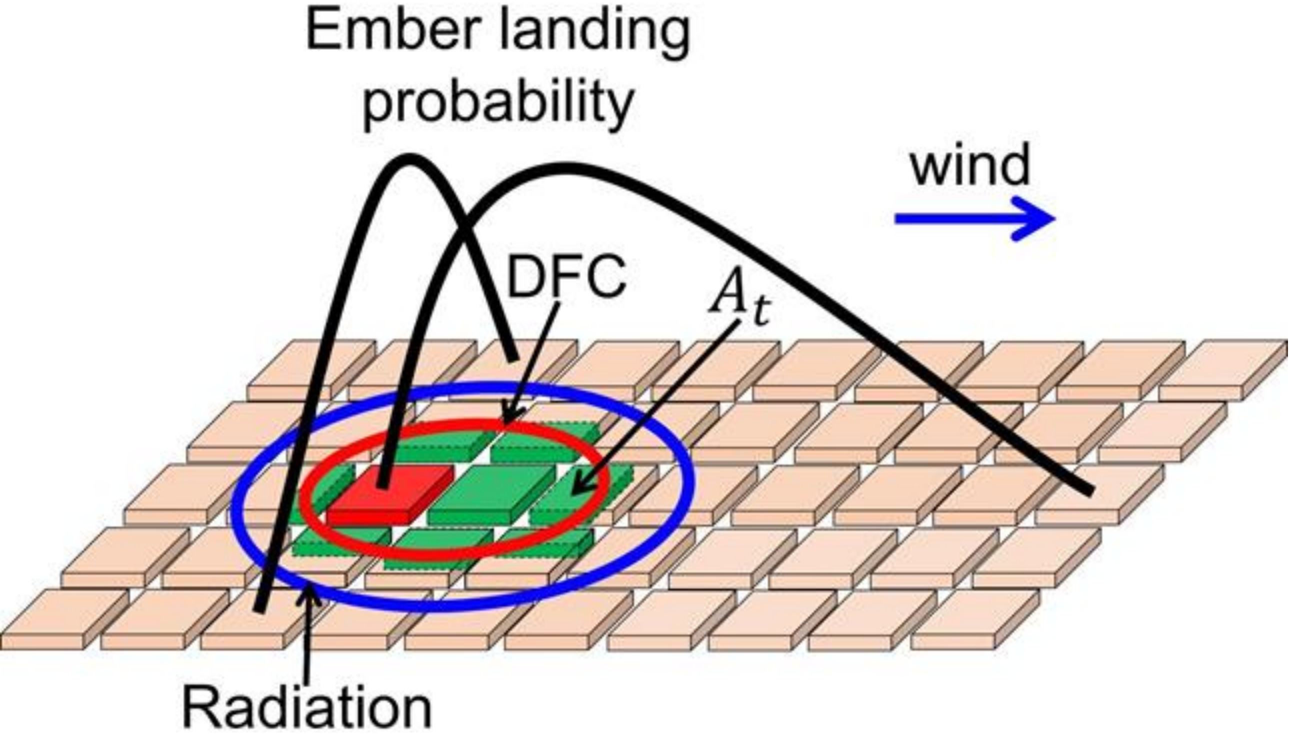
[1] Purnomo, D., et al. Reconstructing modes of destruction in wildland-urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute.*

Purnomo DM et al. (2024) Integrating an urban fire model into an operational wildland fire model to simulate one dimensional wildland–urban interface fires: a parametric study. International Journal of Wildland Fire 33, WF24102.doi:10.1071/WF24102

WU-E



WU-E (cont'd)



Q_t: heat received by target [kW]

$\dot{q}_c$: DFC at target cell [kW]

$\dot{q}_r''$: radiation from source [kW/m^2]

HRR: heat release rate [kW]

α_c : DFC coefficient

α_r : radiation coefficient

A_t: contact area with flame [m^2]

Δx: cell size [m]

μ: mean

σ: std. deviation

Purnomo, D. M. J., et. al. (2024). Reconstructing modes of destruction in wildland–urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute, 40*(1–4), 105755. https://doi.org/10.1016/j.proci.2024.105755

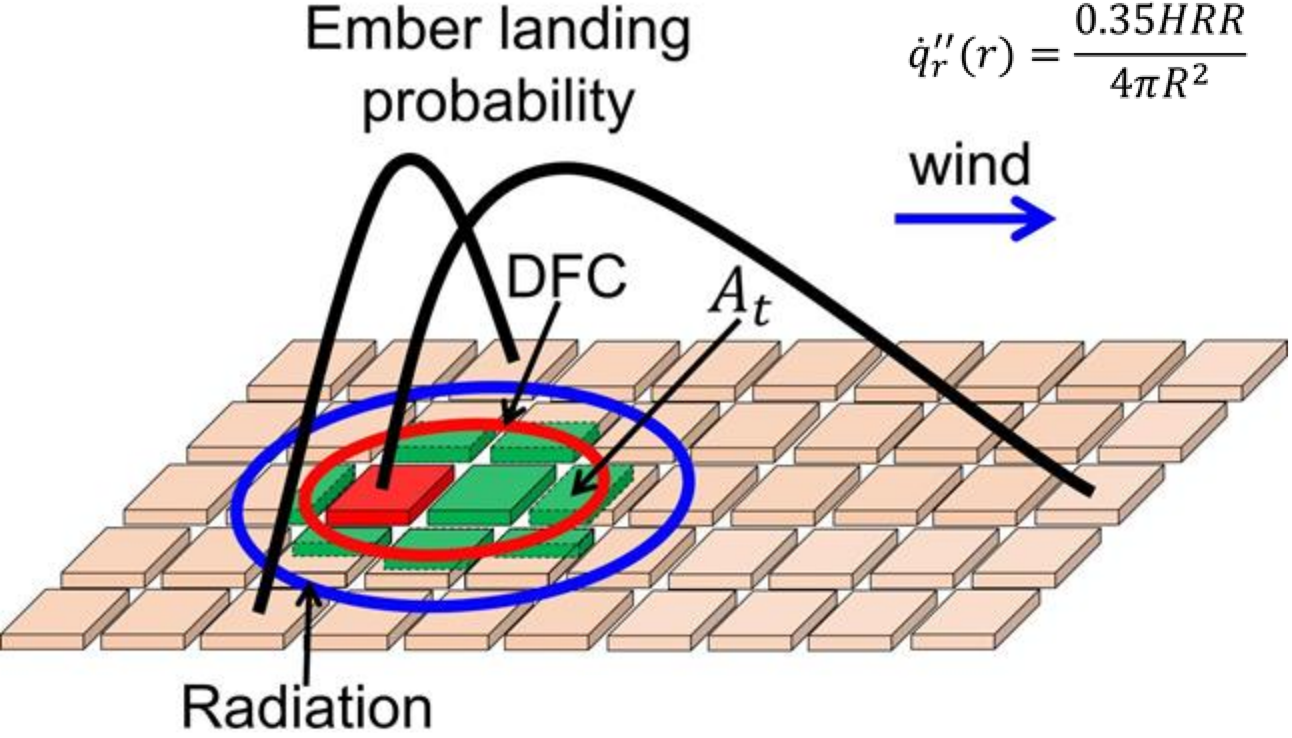
WU-E (cont'd)

DFC radiation

$$Q_t = \alpha_c \dot{q}_c + \alpha_r \dot{q}_r'' A_t$$

$$\dot{q}_c(x, y) = \frac{HRR \cdot A_t}{\Delta x^2}$$

$$\dot{q}_r''(r) = \frac{0.35 HRR}{4\pi R^2}$$



Q_t: heat received by target [kW]

$\dot{q}_c$: DFC at target cell [kW]

$\dot{q}_r''$: radiation from source [kW/m^2]

HRR: heat release rate [kW]

α_c : DFC coefficient

α_r : radiation coefficient

A_t: contact area with flame [m^2]

Δx: cell size [m]

μ: mean

σ: std. deviation

Purnomo, D. M. J., et. al. (2024). Reconstructing modes of destruction in wildland–urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute, 40*(1–4), 105755. https://doi.org/10.1016/j.proci.2024.105755

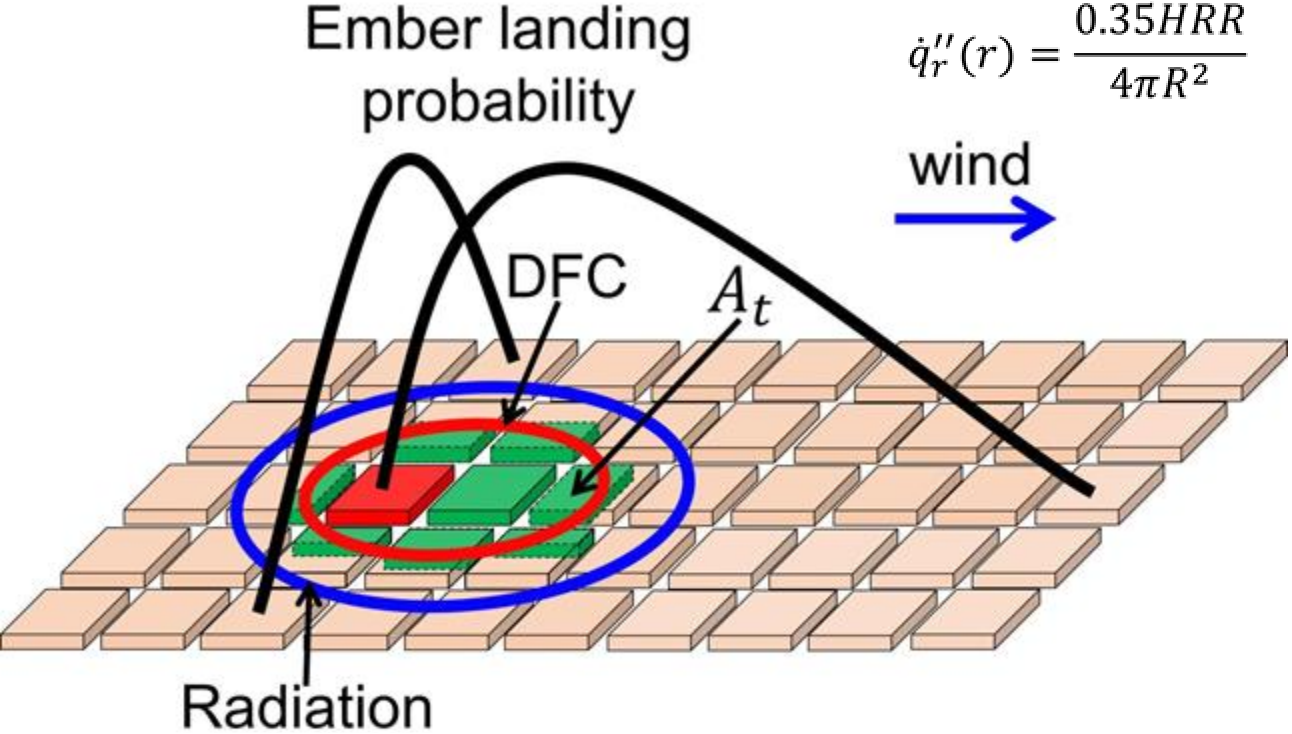
WU-E (cont'd)

DFC **radiation**

$$Q_t = \alpha_c \dot{q}_c + \alpha_r \dot{q}_r'' A_t$$

$$\dot{q}_c(x,y) = \frac{HRR \cdot A_t}{\Delta x^2}$$

$$\dot{q}_r''(r) = \frac{0.35 HRR}{4\pi R^2}$$



Ember

lognormal

$$P(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right).$$

normal

$$P(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}$$

Q_t: heat received by target [kW]

$\dot{q}_c$: DFC at target cell [kW]

$\dot{q}_r''$: radiation from source [kW/m^2]

HRR: heat release rate [kW]

α_c : DFC coefficient

α_r : radiation coefficient

A_t: contact area with flame [m^2]

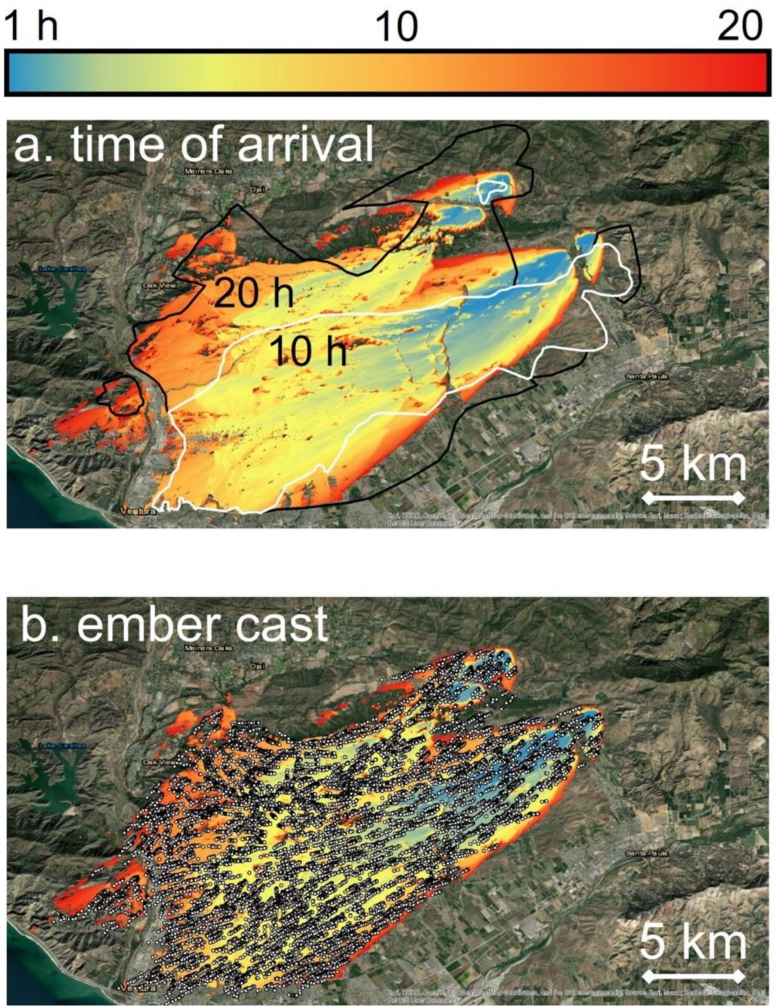
Δx: cell size [m]

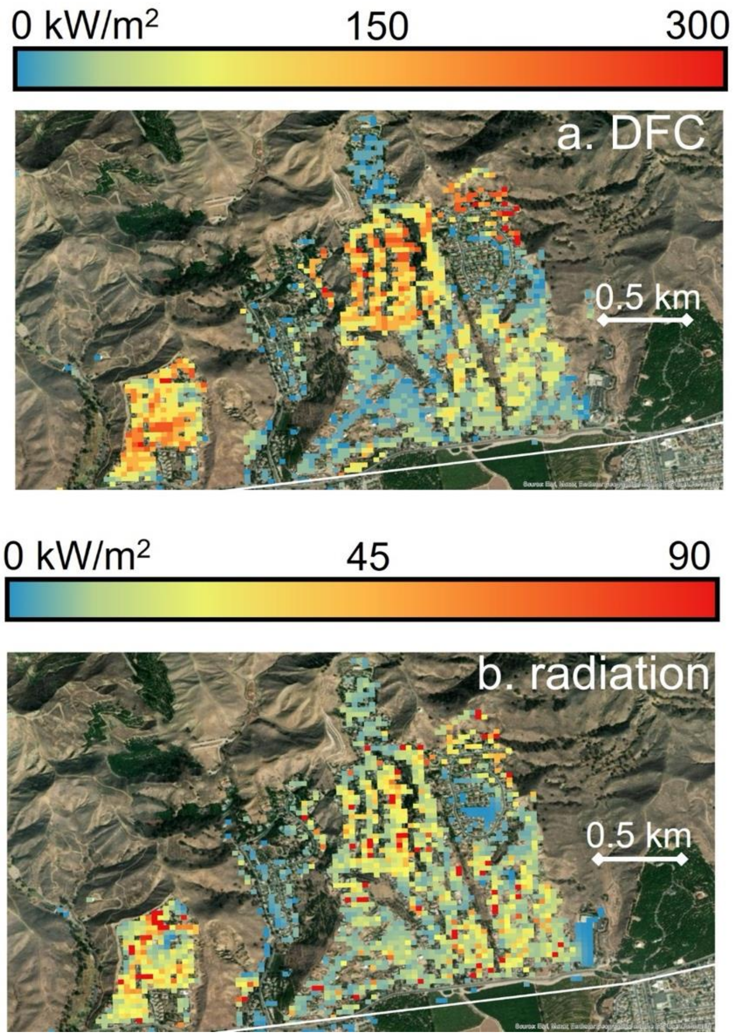
μ: mean

σ: std. deviation

Purnomo, D. M. J., et. al. (2024). Reconstructing modes of destruction in wildland–urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute, 40*(1–4), 105755. https://doi.org/10.1016/j.proci.2024.105755

Thomas Fire (2017)
With WUI Spread





Comparison of WUI models capabilities

HAMADA

- Provide **time of arrival** outputs
- Provide **ember cast** outputs
- Provide **fireline intensity** outputs.
- **Limited** structural **property variations**

WU-E

- Provide **time of arrival** outputs
- Provide **ember cast** outputs
- Provide **fireline intensity** outputs.
- **Flexible** structural **property variations**
- Provide **fire incident intensity** outputs
- **Physical framework for improvement**

Conclusions

- Significant factors leading to building destruction in the WUI:
  - Structure Separation Distance
    - Fire spread in the WUI often depends on building arrangement
  - Exposure : Fire intensity and firebrands/embers
    - Flame Length critical role in determining the intensity and spread of the fire across different landscapes
    - Ember exposure key because a wide area is impacted by embers
  - Building features (vents, siding, fences, decks, etc.) - ***Home Hardening***
    - Importance varies depending on the fire and specific building construction
  - ***Defensible Space*** (Vegetation Separation Distance), particularly in Zone 0, plays a crucial role in mitigation.
  - Year built: Year that primary structure in parcel was constructed (confounding parameter)
  - Data-driven ML model useful for some predictions (e.g., response function) and impacts of mitigation
- New model, **WU-E**, improved previously-used model (HAMADA), by providing fire incident intensity outputs, flexible structural properties variations, and an adaptable physical framework for spread.

Preprint paper: *https://doi.org/10.21203/rs.3.rs-5776626/v1*; *ELMFIRE Code:* *https://elmfire.io/*

2025 AI in Fire Engineering Summit

May 28-30, 2025

Berkeley, California, USA

SFPE FOUNDATION

Grand Challenges Initiative

SFPE Foundation | NFPA | RESEARCH FOUNDATION RESEARCH FOR THE NFPA MISSION | Berkeley Engineering | PEER

https://www.sfpe.org/2025aisummit/

Thank you!

Work supported by Forest Health Grant 8GG21815