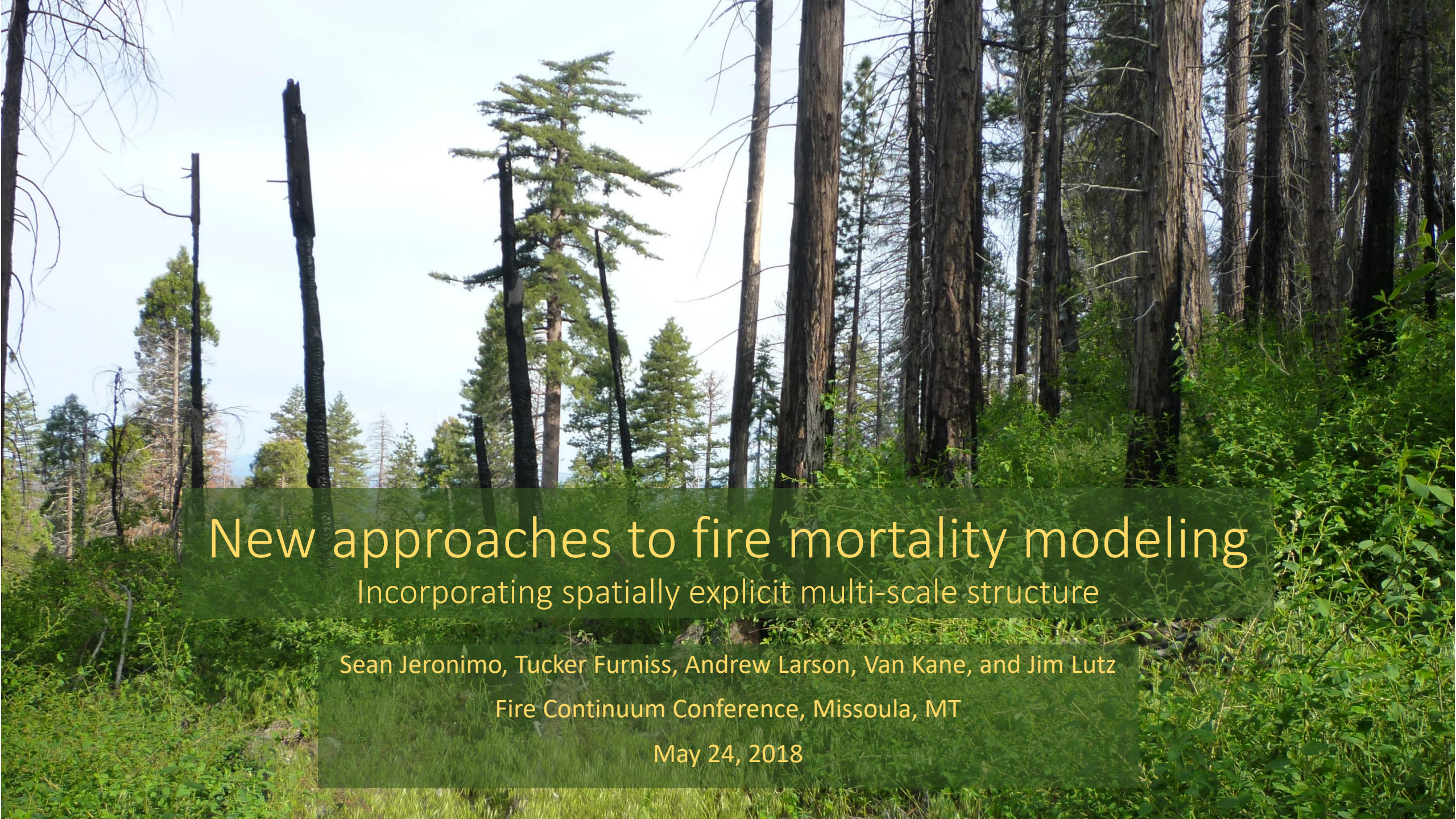


New approaches to fire mortality modeling

Incorporating spatially explicit multi-scale structure

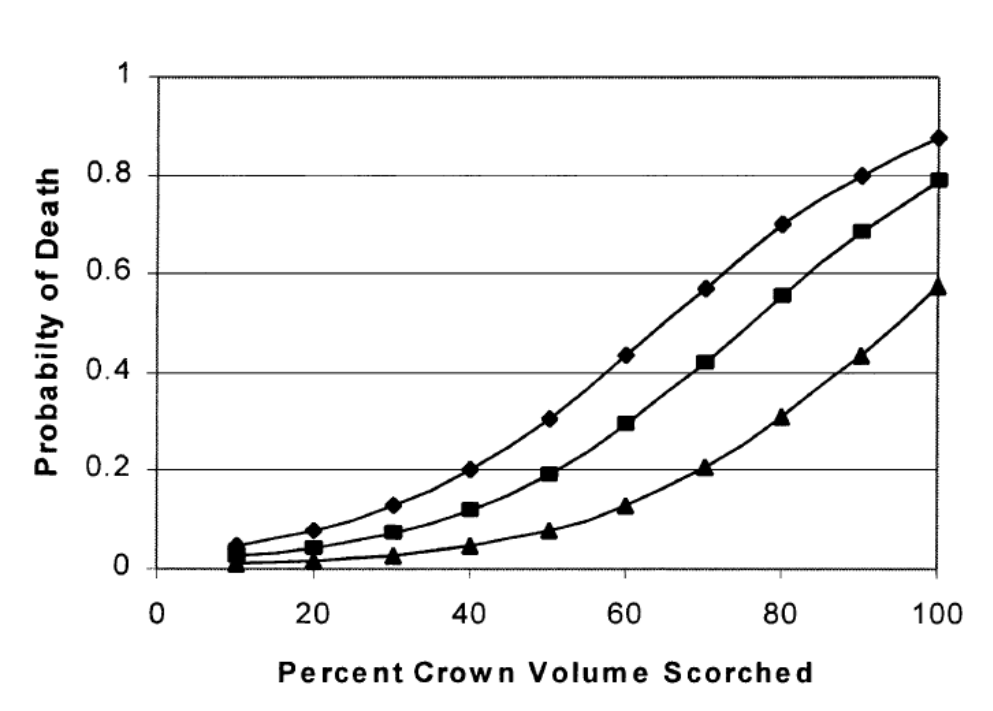
Sean Jeronimo, Tucker Furniss, Andrew Larson, Van Kane, and Jim Lutz

Fire Continuum Conference, Missoula, MT

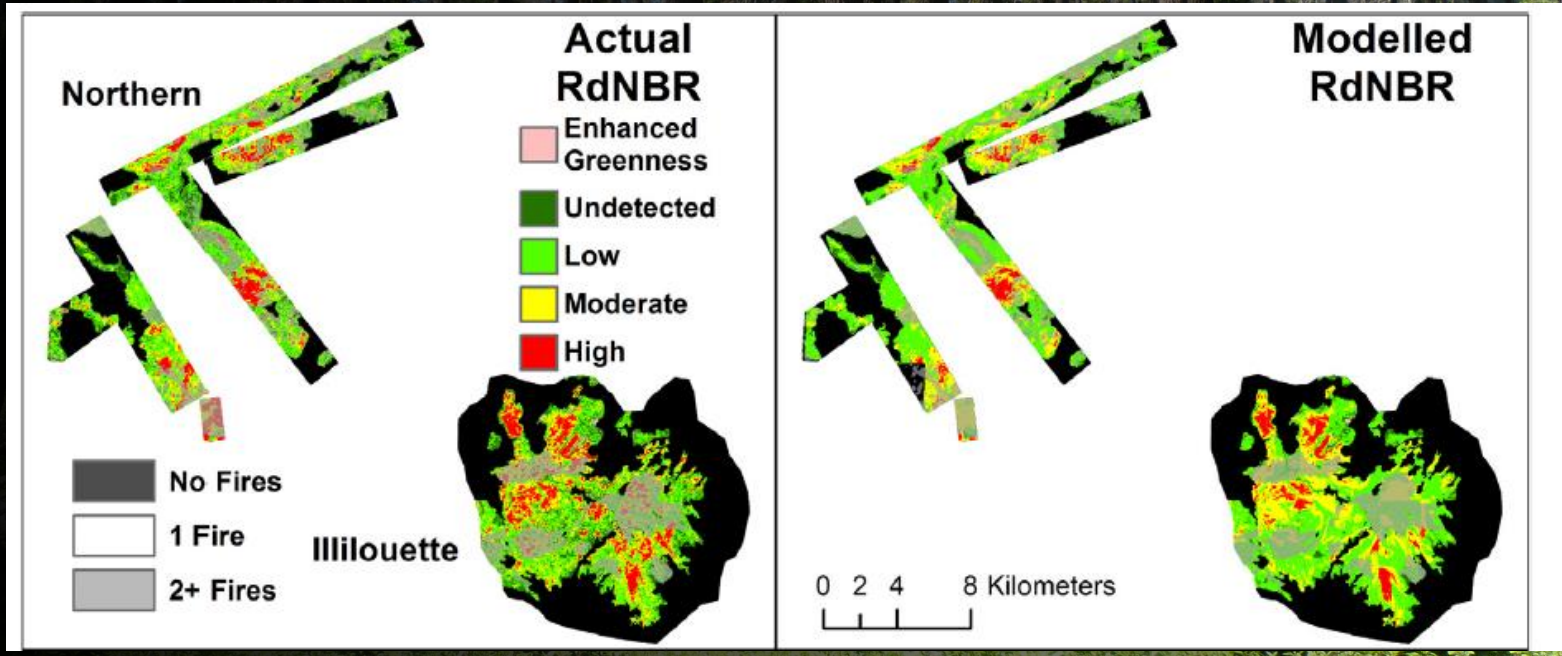
May 24, 2018

Improving mortality models

- Multi-scale framework
- Spatial pattern

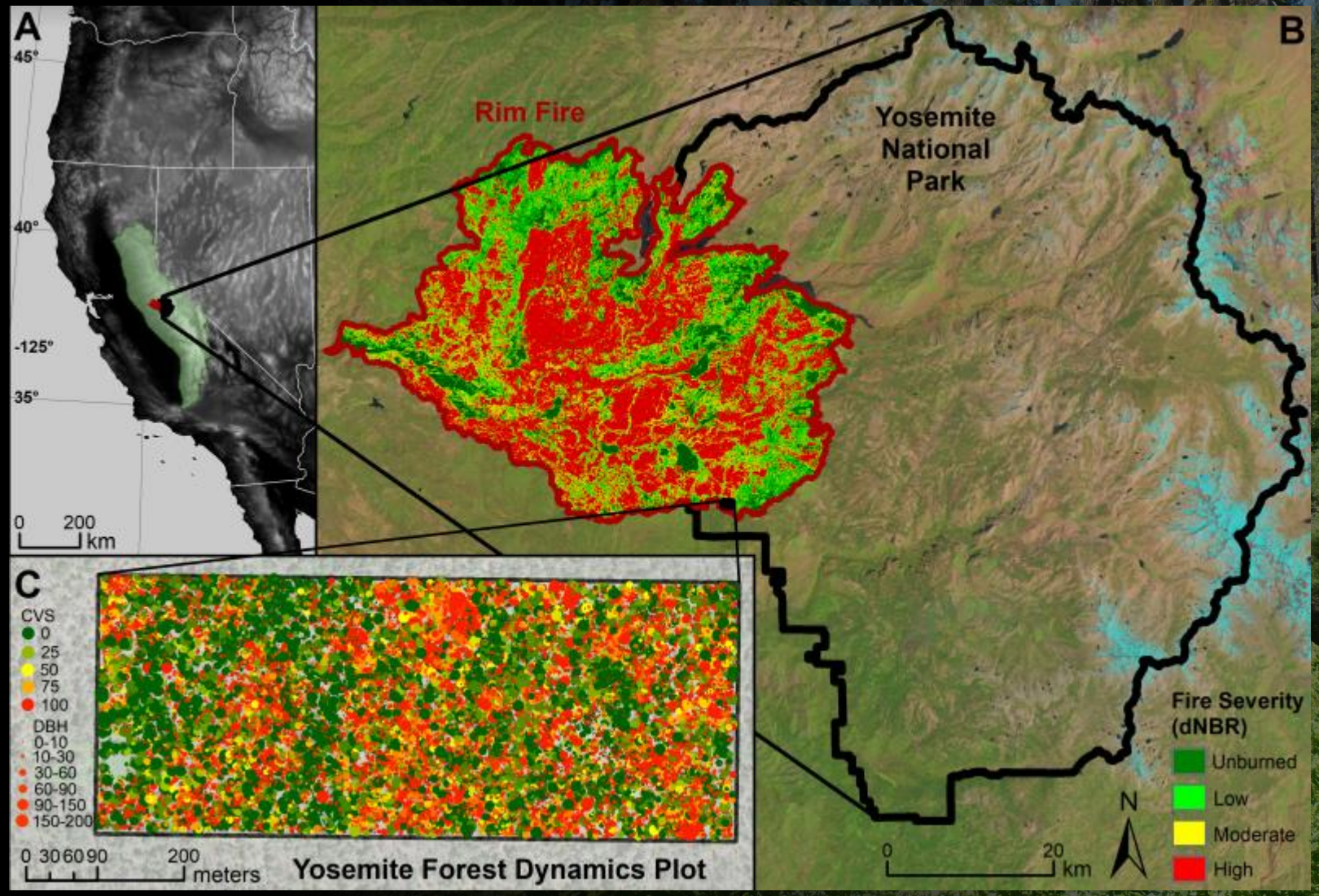


Stephens & Finney 2002



Kane et al. 2015

Study area: 2013 Rim Fire in Yosemite NP



Study 1: improving post-fire logistic regression models

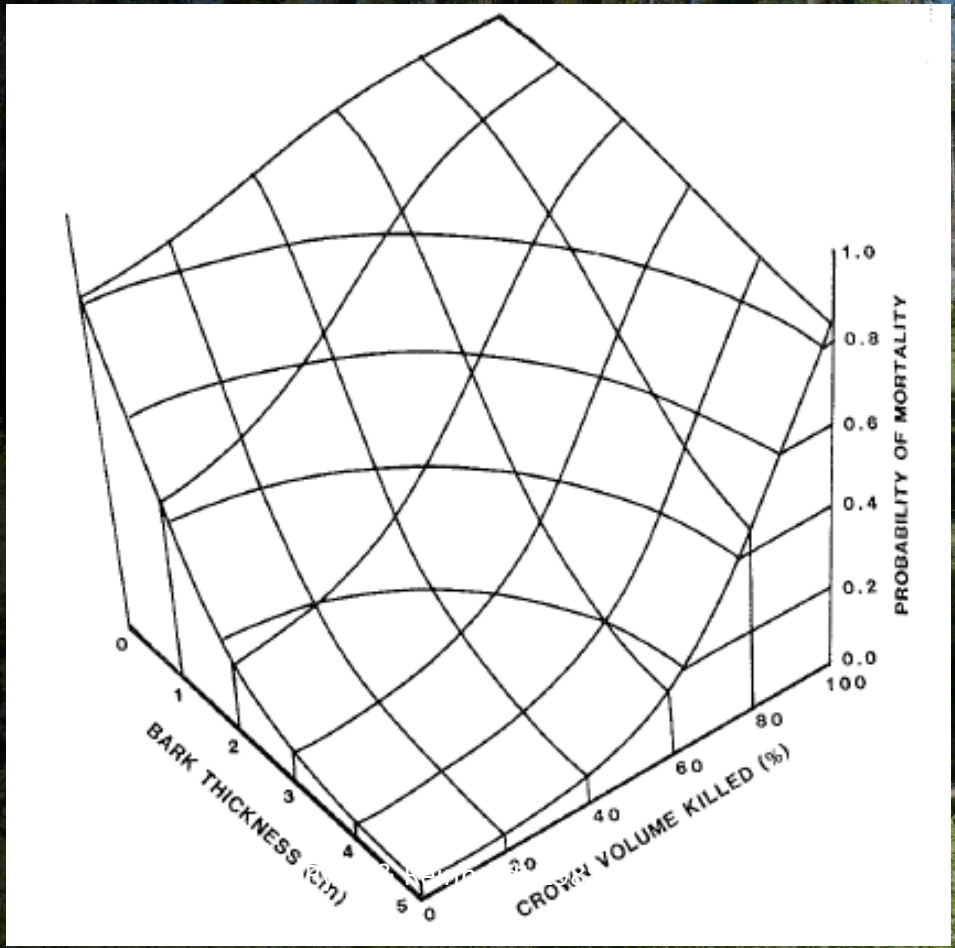
Models

FOFEM / FFE-FVS / BehavePlus

- Ryan & Reinhardt (1988) –derived

Localized FOFEM-like

DBH only

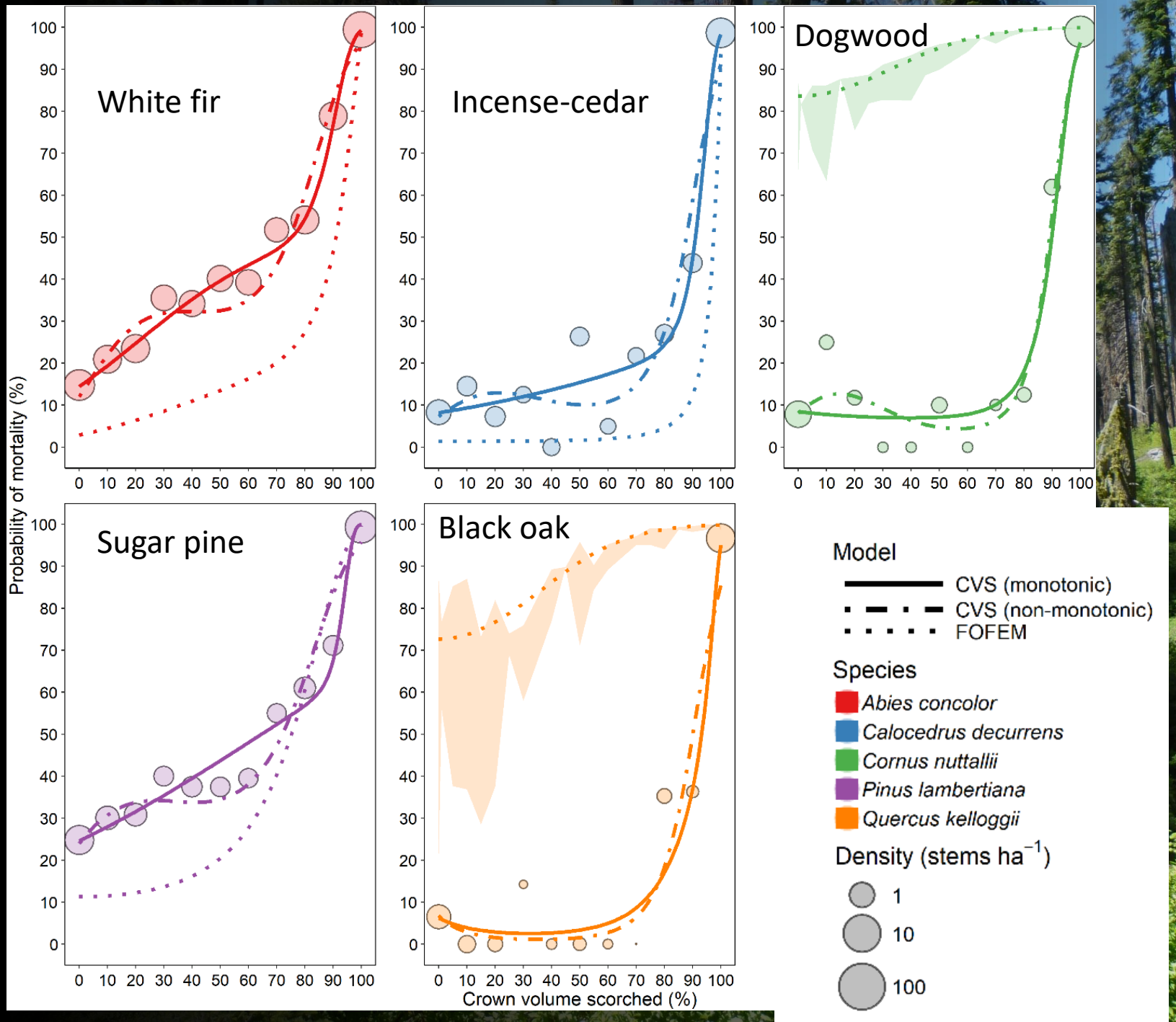


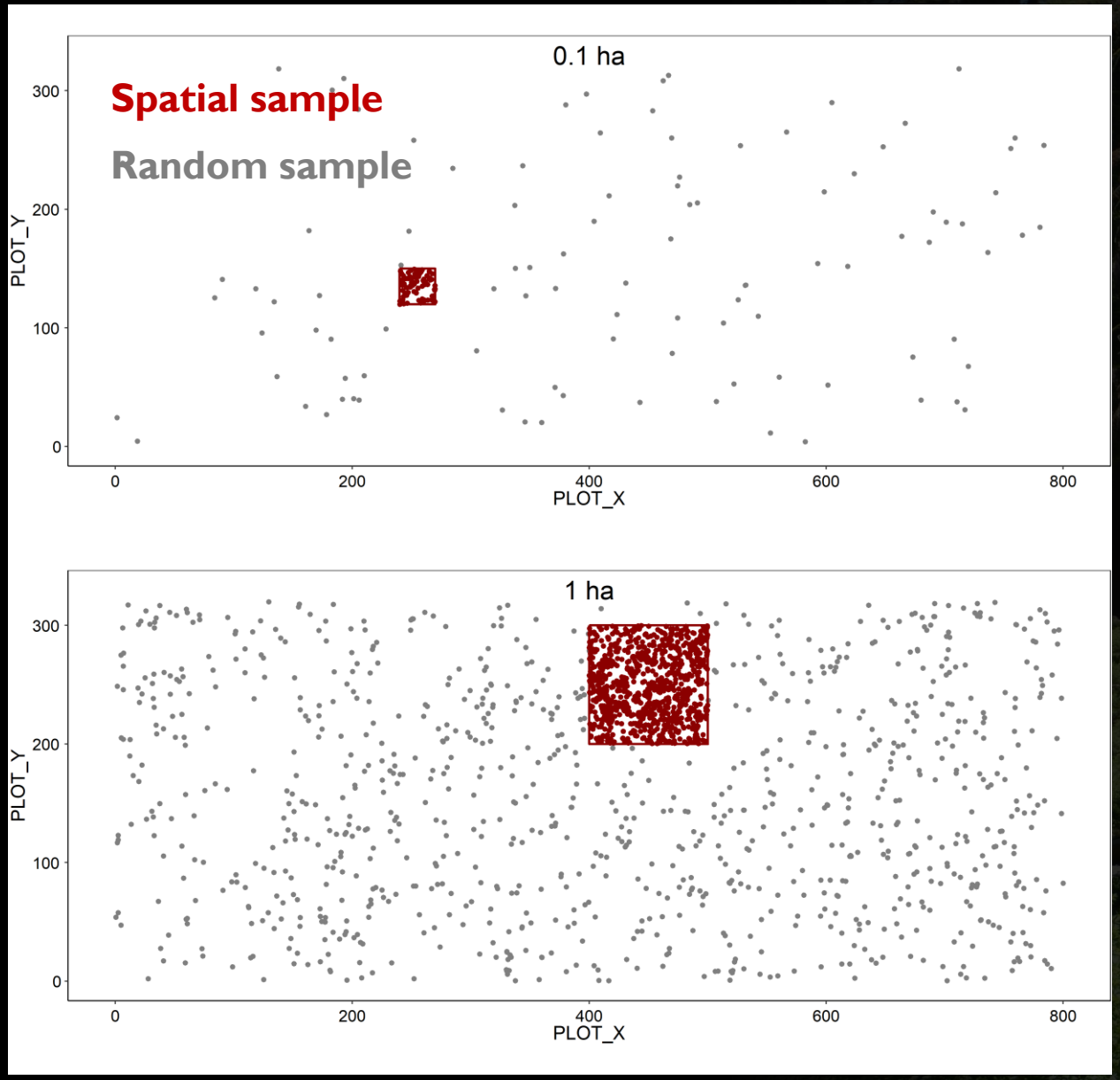
Tree-scale results

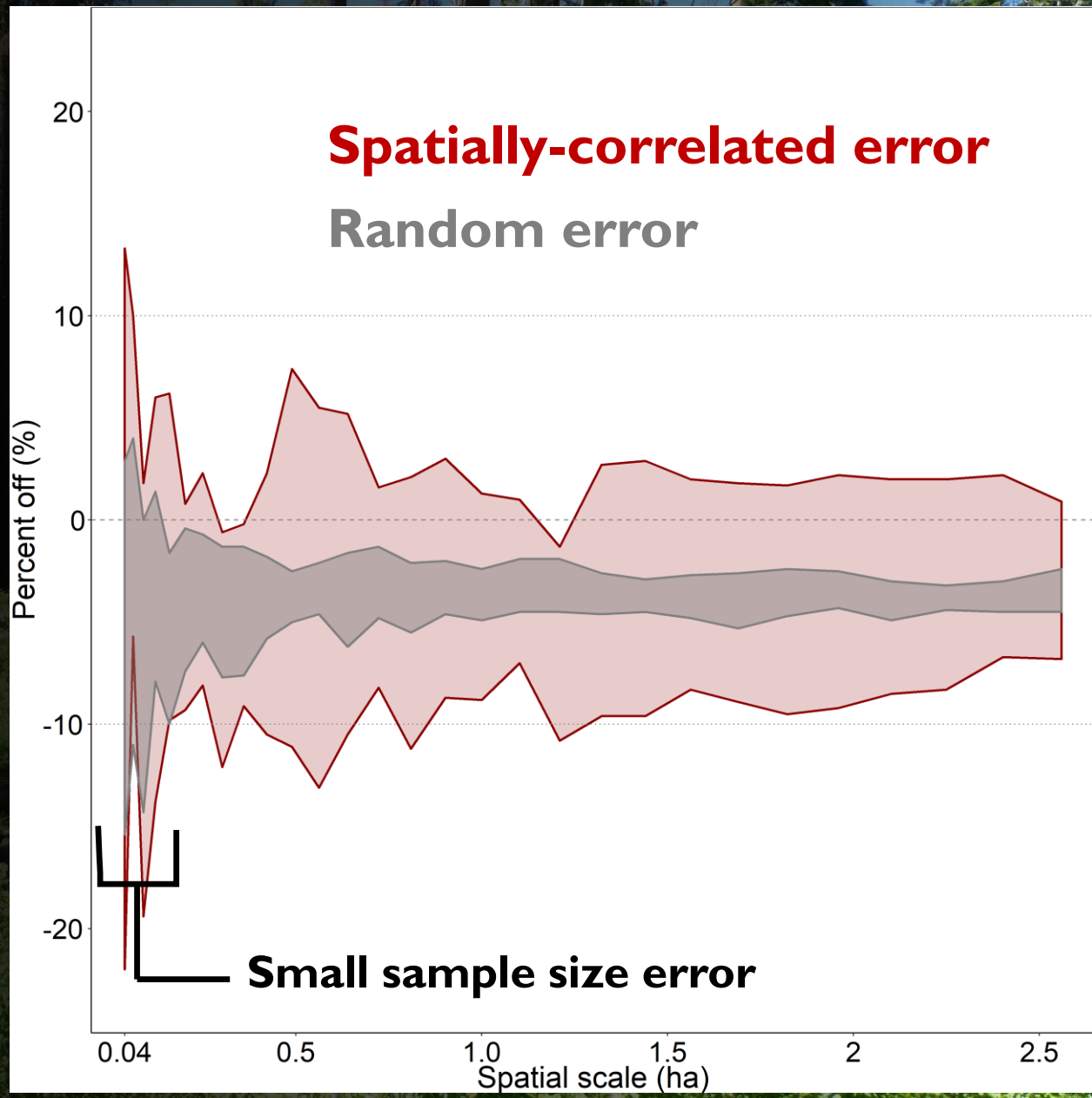
All >90% accuracy, except:

- DBH-only, ~80%
- FOEM for hardwoods, ~80%

Population-scale results →




0.1 ha
Spatial sample
Random sample
PLOT_Y
PLOT_X
1 ha
PLOT_Y
PLOT_X

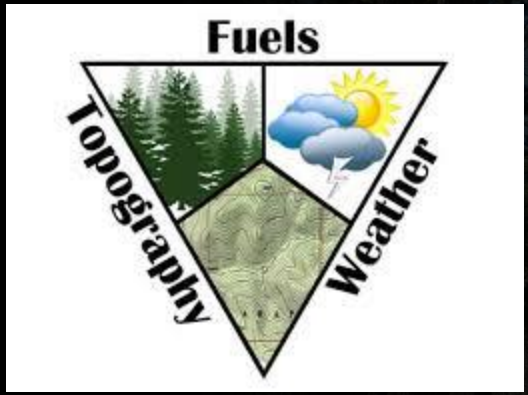

Spatially-correlated error
Random error
Percent off (%)
Small sample size error
Spatial scale (ha)

Conclusions

Thorough model evaluation

- How do predictions scale up?
- How does accuracy vary by species, demographic class?
  - E.g., large trees are uniquely important, but small trees dominate evaluation
- Where is the error coming from?
  - E.g., spatially non-random mortality agents, edaphic stressors

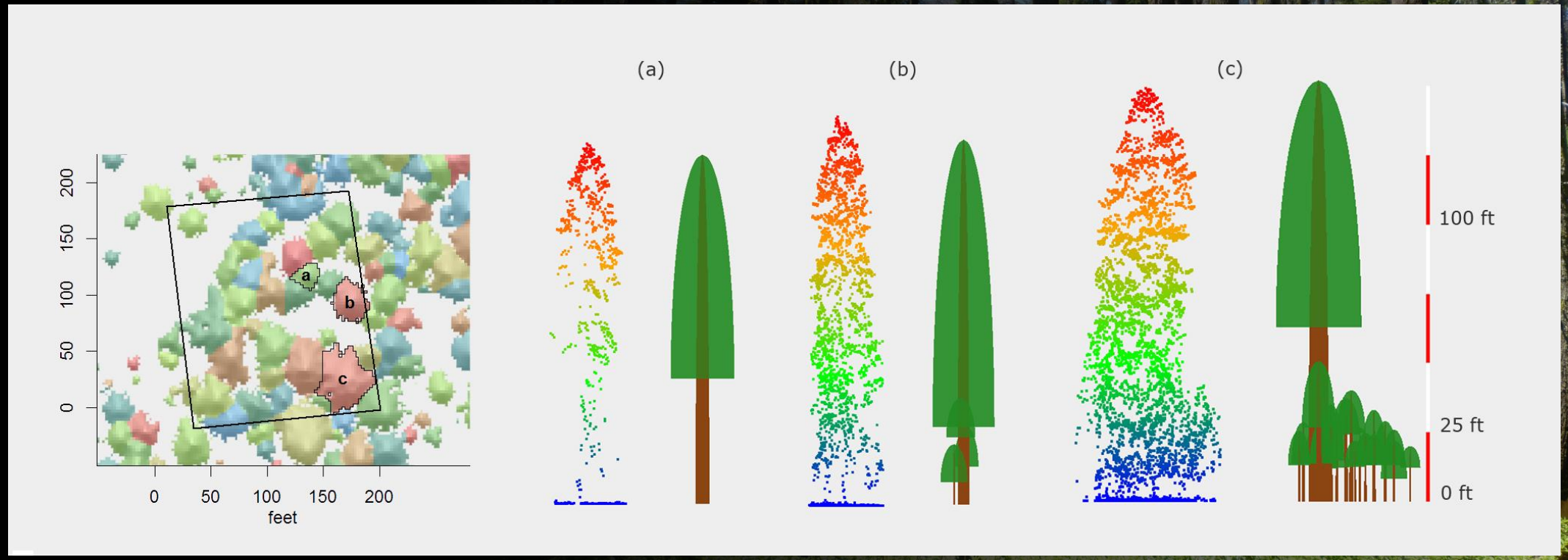
Study 2: Predicting immediate and delayed mortality at multiple scales using pre-fire lidar data



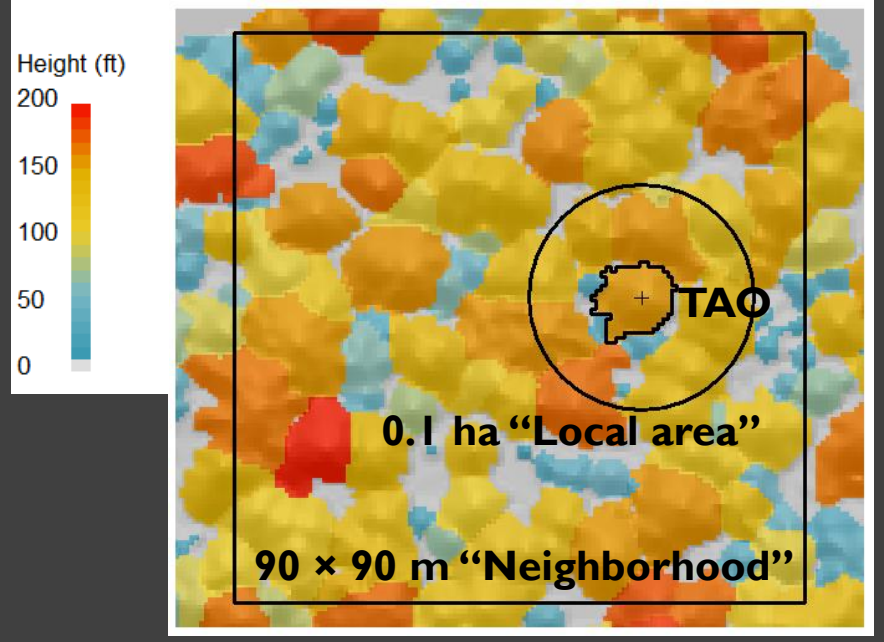
Integrating top-down and bottom-up effects

1. What elements of forest structure explain or predict tree mortality rates at various scales?
2. What are the mechanisms of mortality associated with the important predictors?

Lidar tree detection – “Tree-approximate objects”

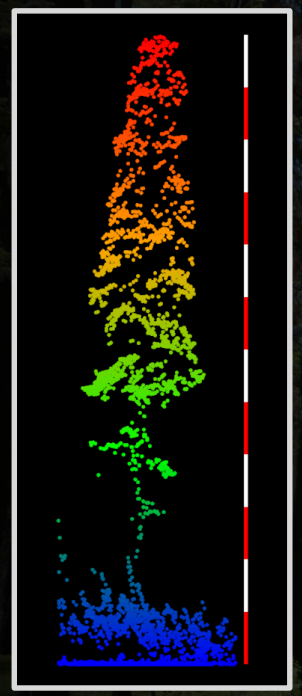


Lidar structural measurements



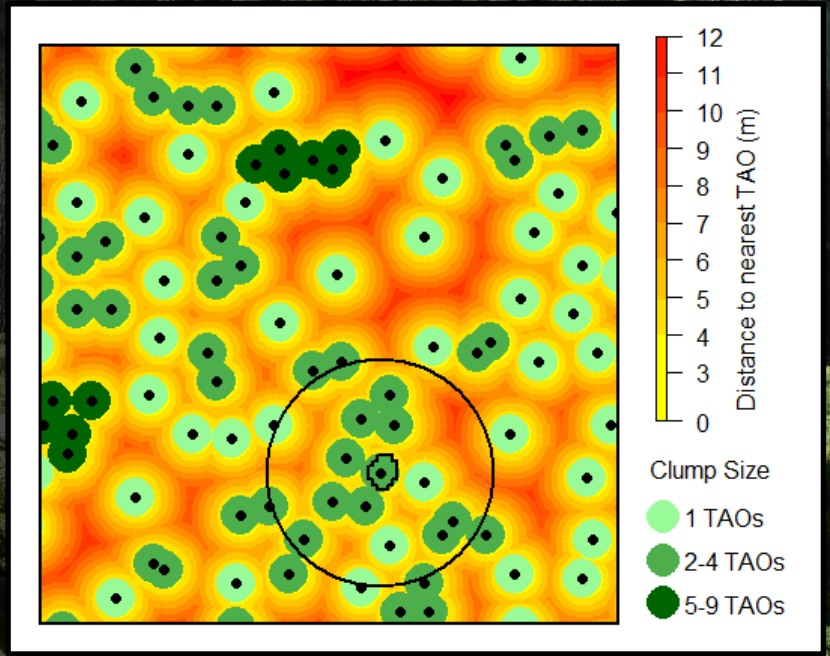
Scales

TAO



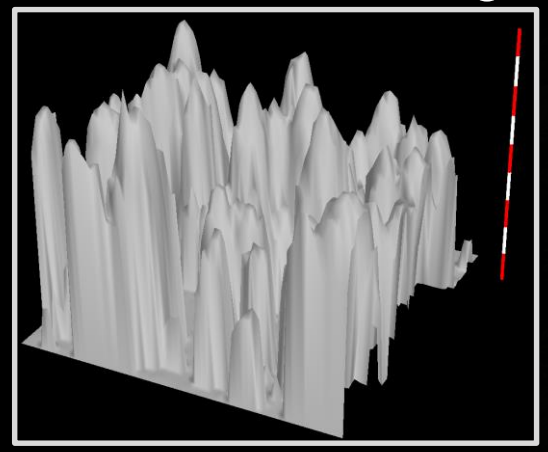
height
crown profile
bulk density
fuel weight
leaf area
…

Local area and Neighborhood

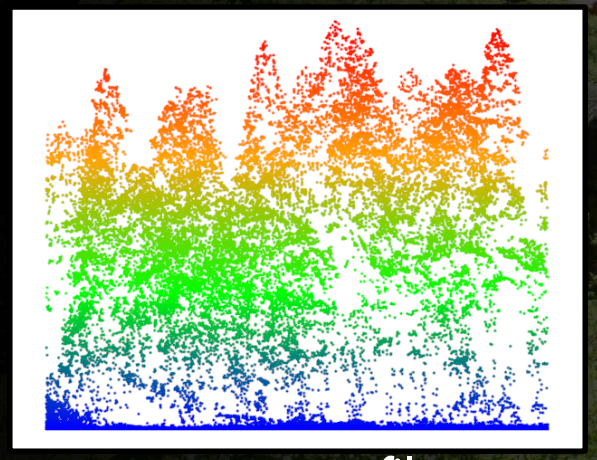


density
spatial patterns:
- clump sizes
- canopy openings

Neighborhood

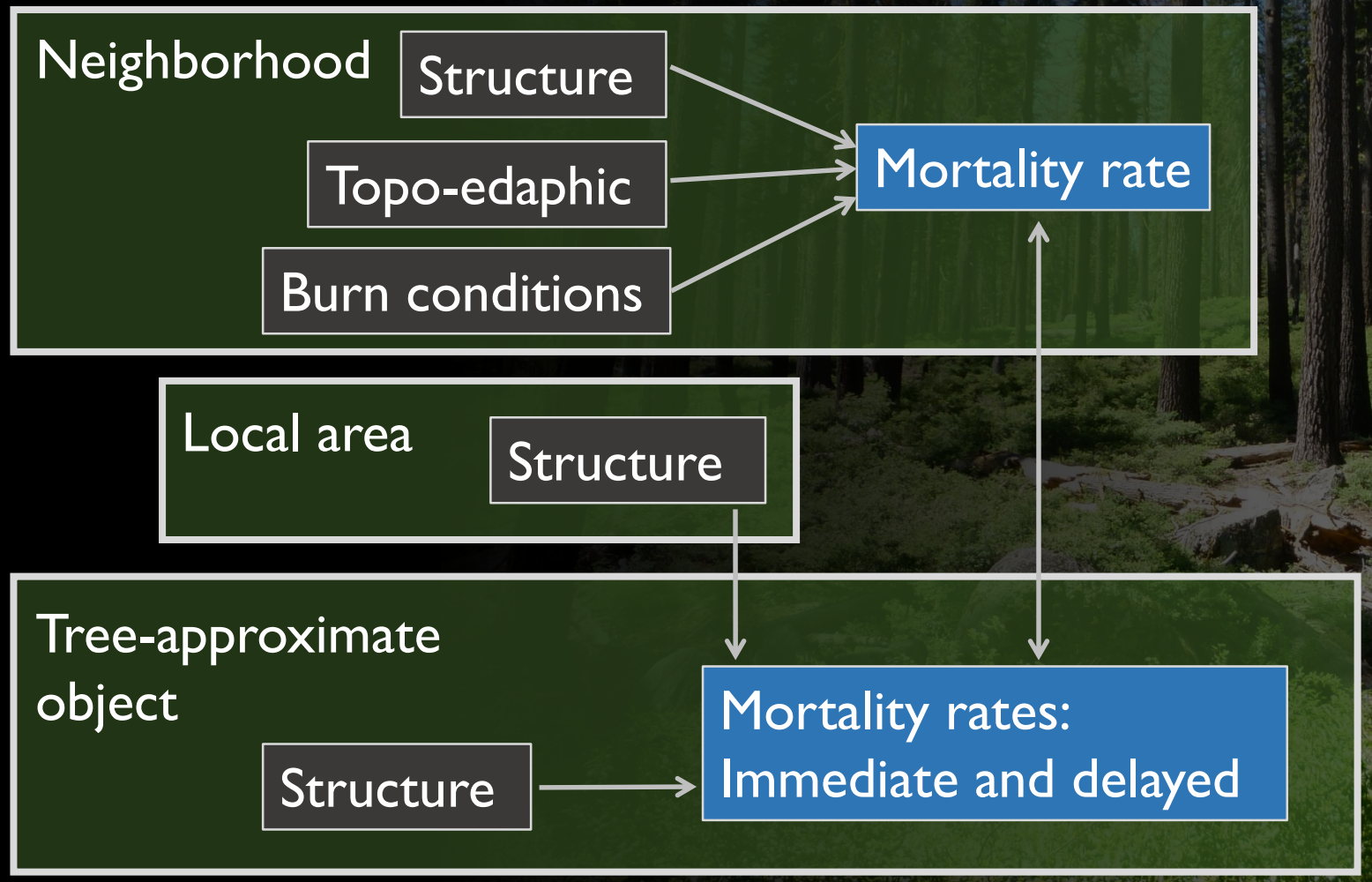


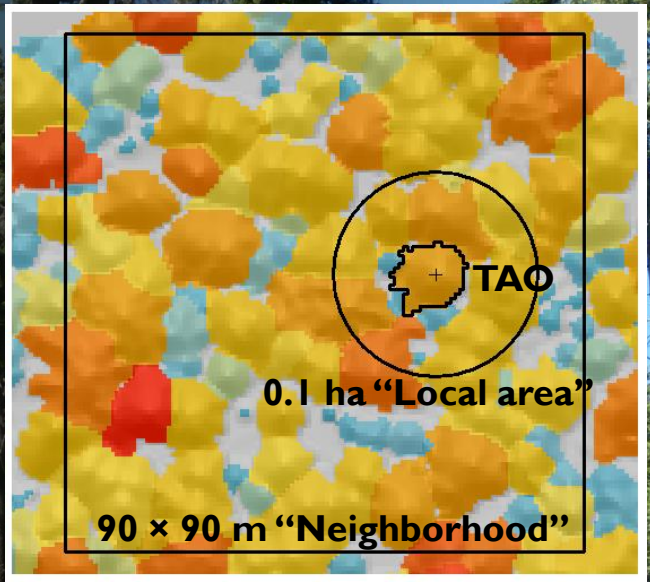
canopy complexity



canopy profile

Multi-scale modeling framework



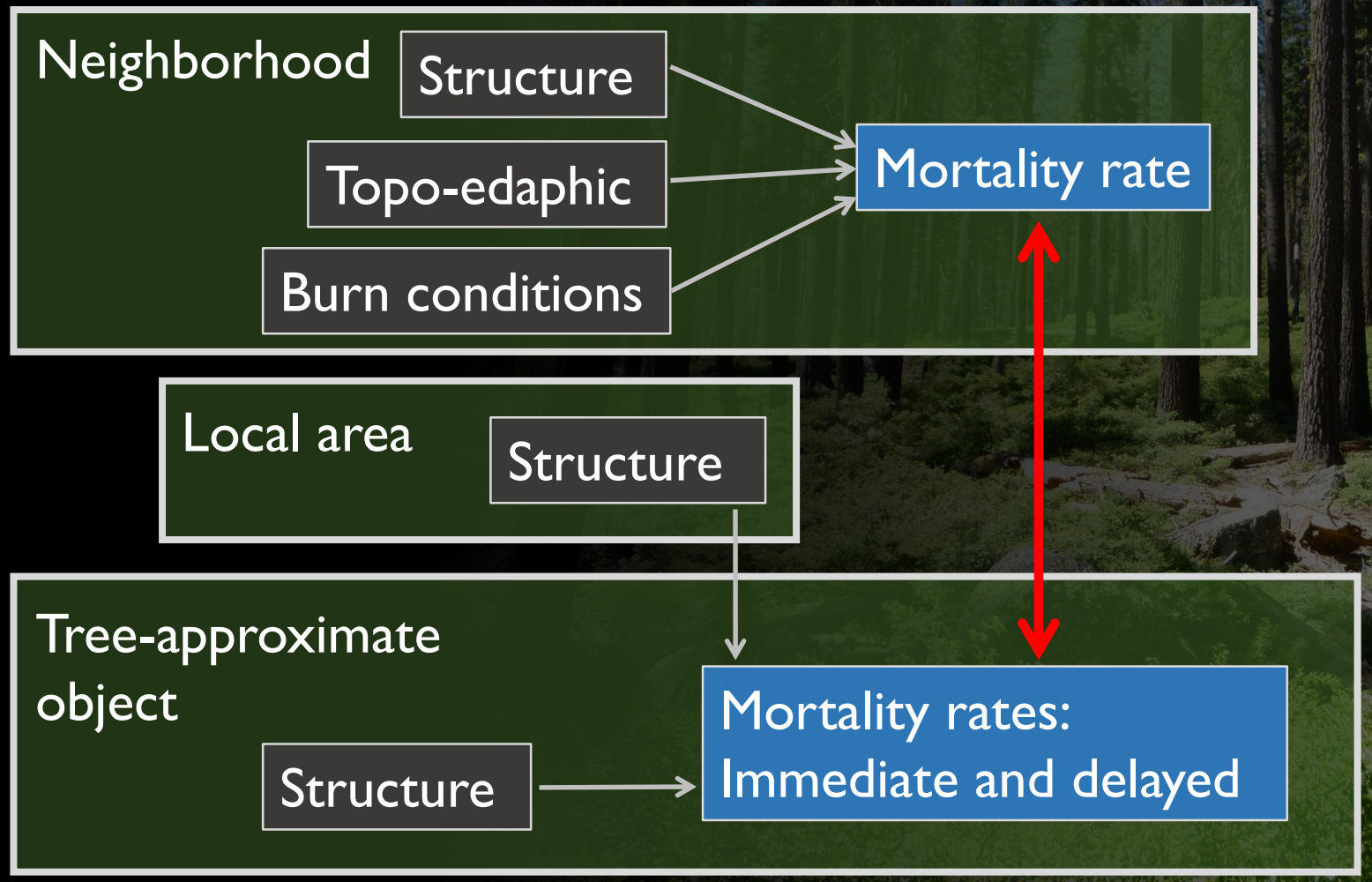


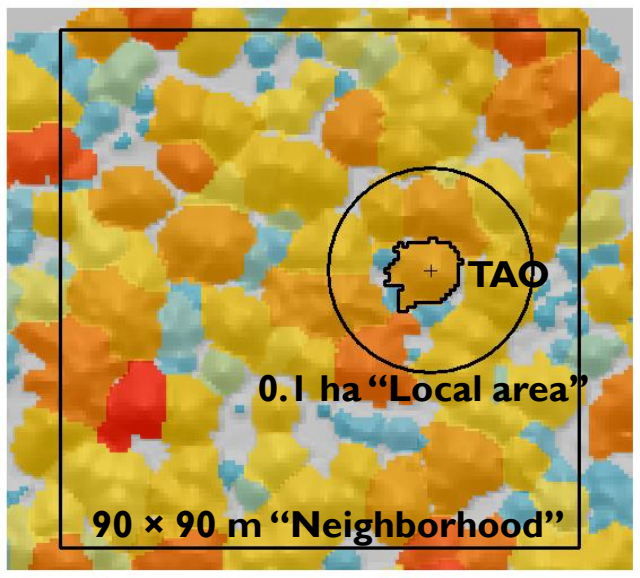
Scales

Predictors

Responses

Multi-scale modeling framework





Scales

Predictors

Responses

Neighborhood-scale results

Important predictors:

- Actual evapotranspiration
- Canopy cover

} Fuel amount

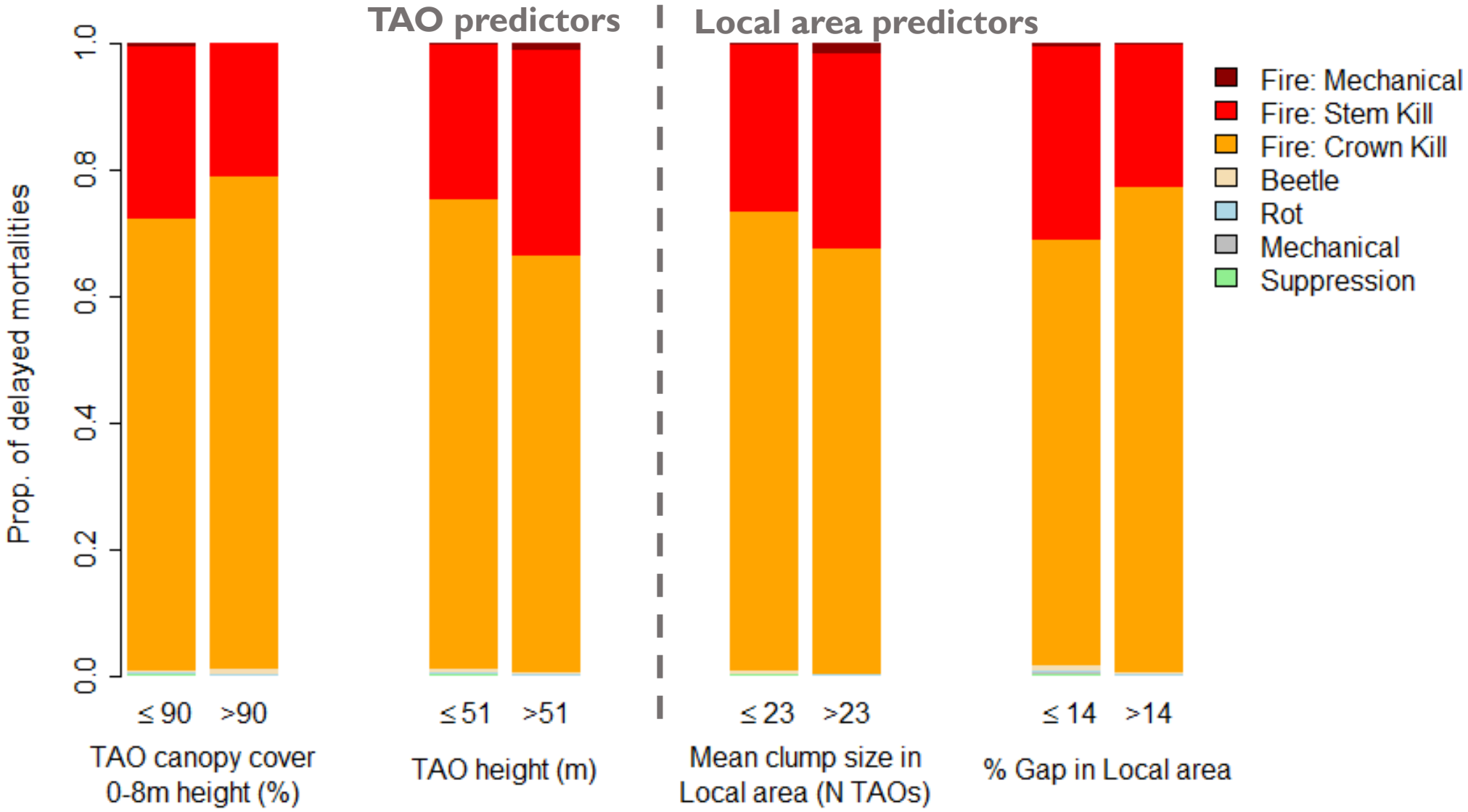
- Area in gaps
- Canopy complexity (rumple)

} Fuel configuration

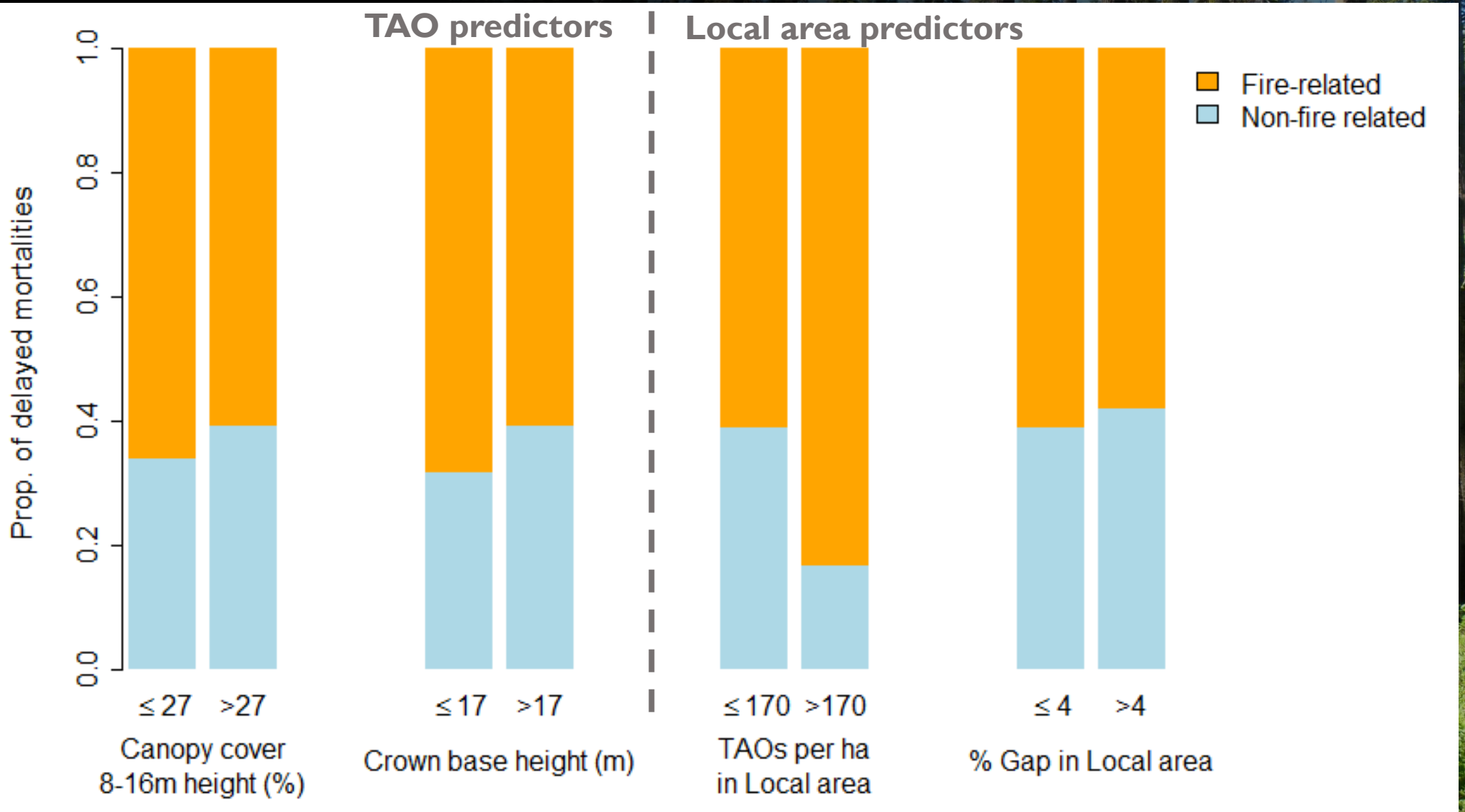
- Max temp. on burn day
- Energy release component

} Burn weather

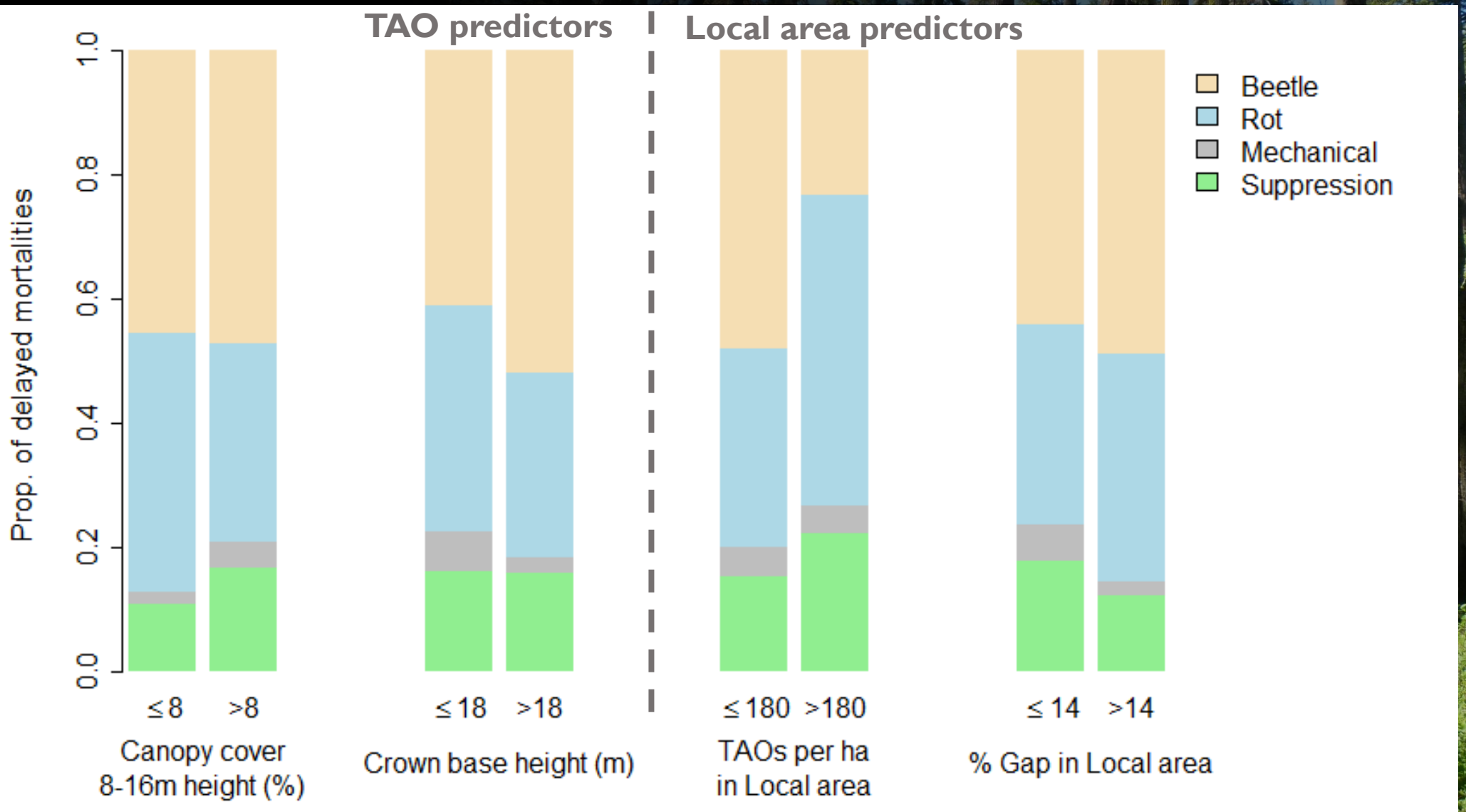
TAO-scale results – immediate mortality



TAO-scale results – delayed mortality



TAO-scale results – delayed mortality



Conclusions

- Inter-scale linkages important
- Important predictors at multiple scales for all models
- Spatial pattern predictors important for all models
  - Especially local density and open space
- Density-dependent effects for delayed mortality
  - Both fire-related and non-fire-related mortality

Incorporating spatial structure into mortality models is essential

Fire is, inescapably, a spatially structured process

Typical individual-level and landscape-level models miss the big (or small) picture

Bring models in line with ecological understanding of fire and mortality

- Include spatial context in model form and evaluation
- Include predictors and perform evaluation at multiple scales

Acknowledgements

Field personnel:
Etta Crowley
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100s of YFDP volunteers
(yfdp.org)

School of Environmental and Forest Sciences
UNIVERSITY of WASHINGTON
College of the Environment

Model definition

Neighborhood TPH live pre-fire

$Nn_i \sim \text{Poisson}(\lambda_n^{N_i})$

Neighborhood TPH dead post-fire

$Nm_i \sim \text{Binomial}(\pi_i, \lambda_n^{N_i})$

TAO number of trees, live pre-fire

$Tn_j \sim \text{Poisson}(\lambda_n^{T_j})$

TAO number of trees in classes *immediate mortality*, *delayed mortality*, and *surviving*, post-fire

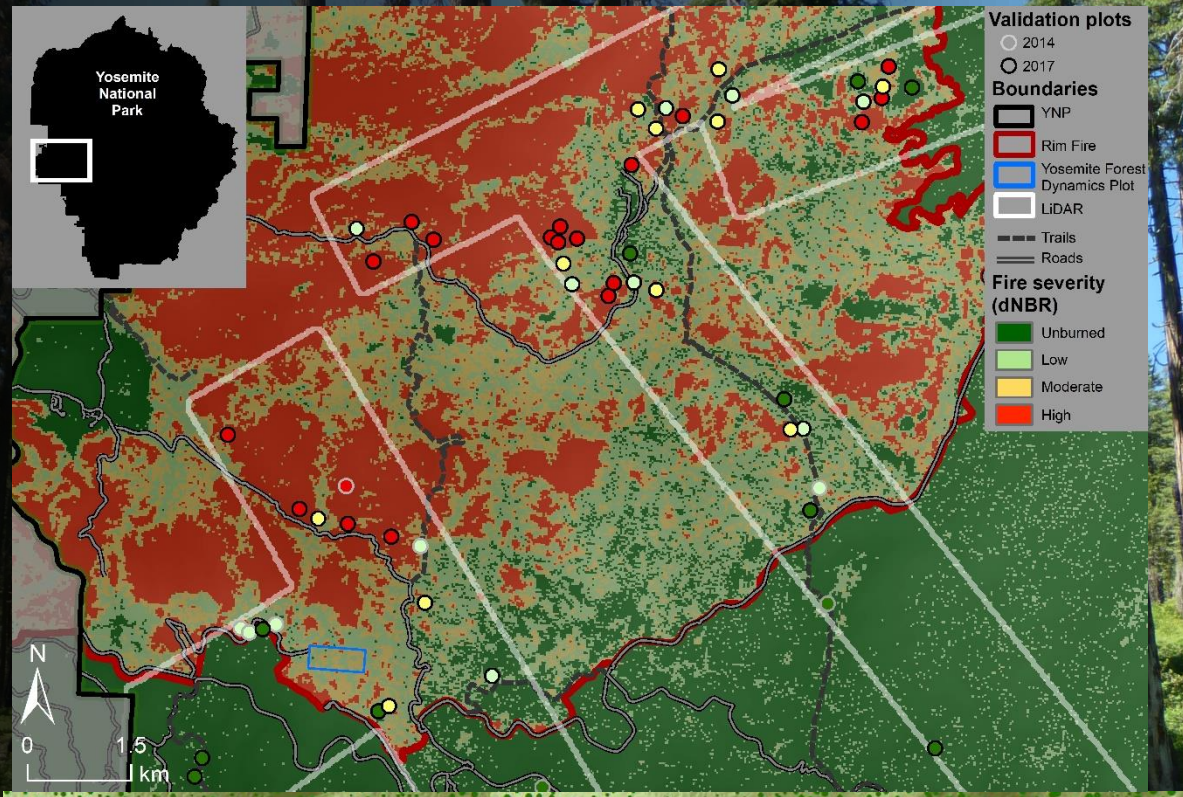
$Tm_j \sim \text{Multinomial}(\pi_{j,c}, \lambda_n^{T_j})$ for c in $\{1, 2, 3\}$; $\sum_c \pi_{j,c} = 1$

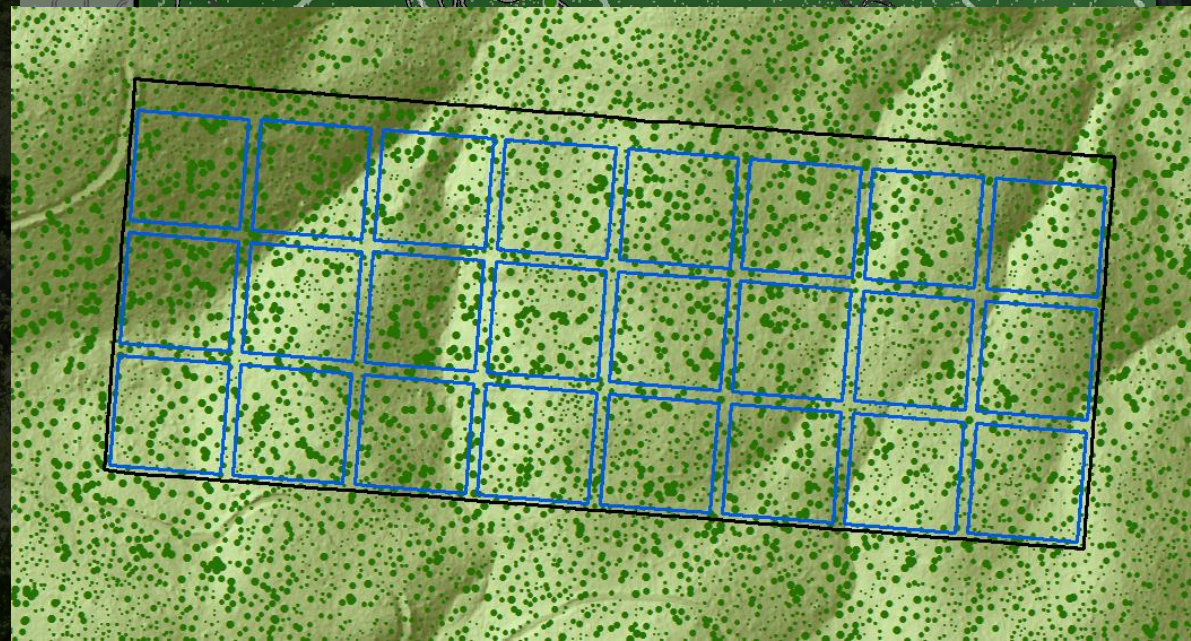
All λ and π modeled as glm's with inter-scale interaction terms

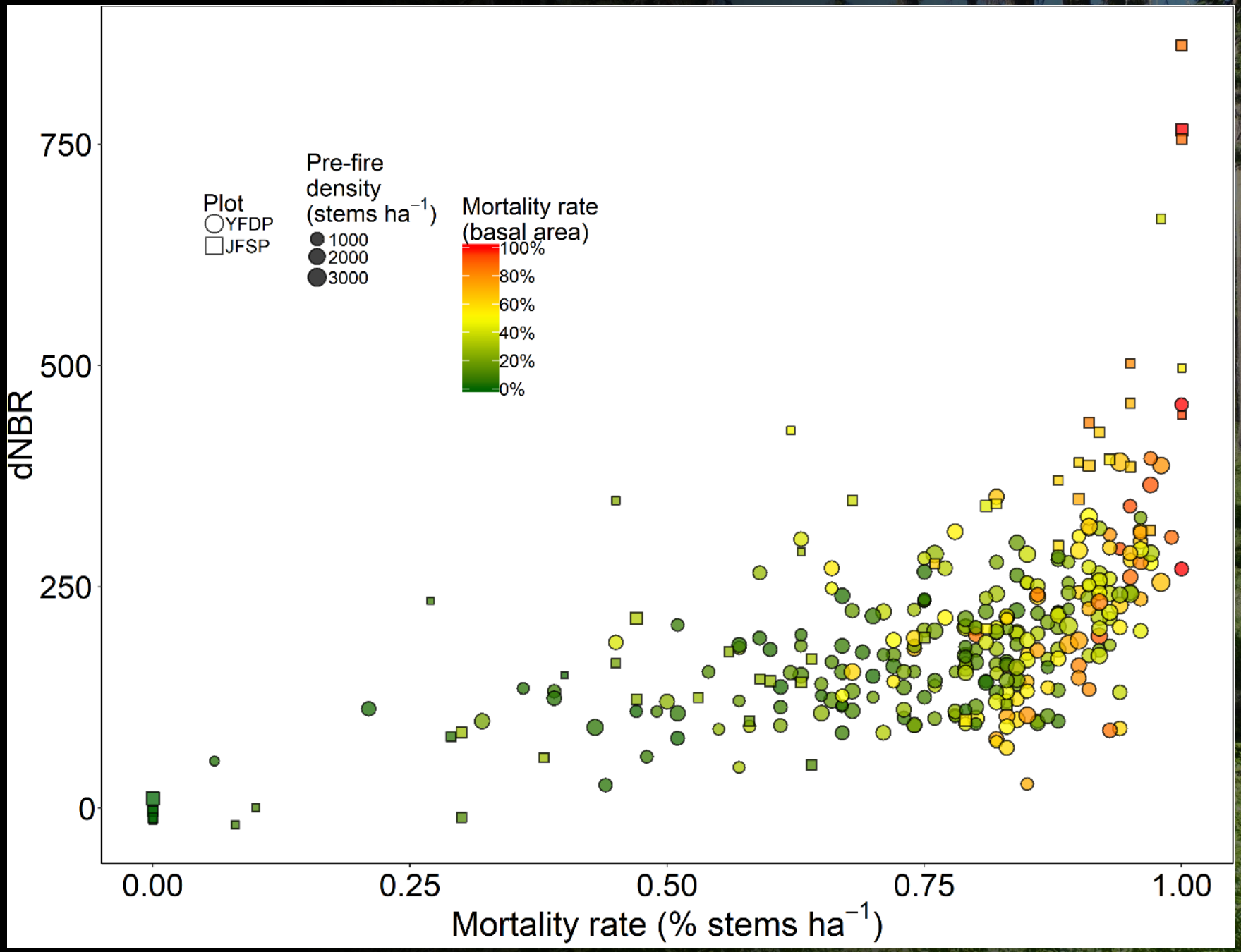
Holdout set

Neighborhood-level predictions made from all data to cover wide range of biophysical variation

TAO-level predictions made only on YFDP, 54 validation plots used as independent testing data



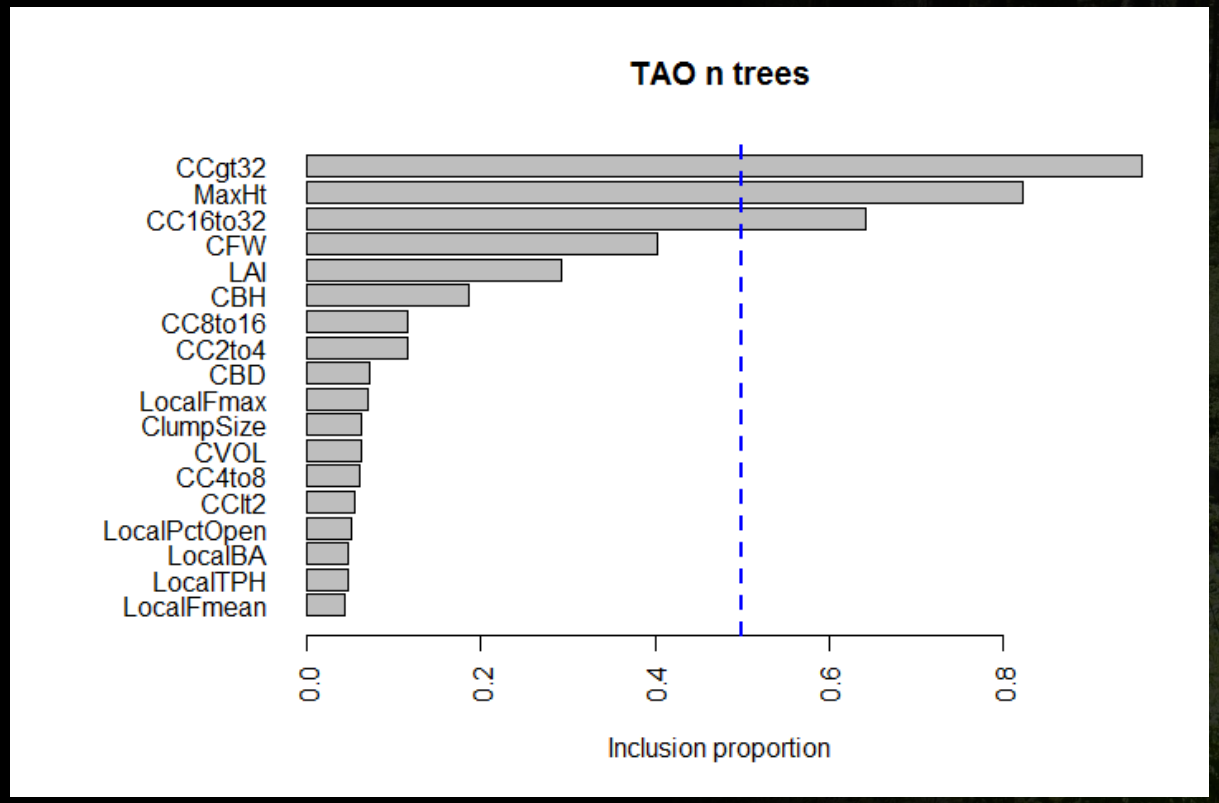



Plot
YFDP
JFSP
Pre-fire density (stems ha^{-1})
1000
2000
3000
Mortality rate (basal area)
100%
80%
60%
40%
20%
0%
dNBR
750
500
250
0
0.00
0.25
0.50
0.75
1.00
Mortality rate (% stems ha^{-1})

Model fitting and selection

Fit models in a Bayesian framework using Markov chain Monte Carlo

Used indicator variable selection with spike-and-slab priors

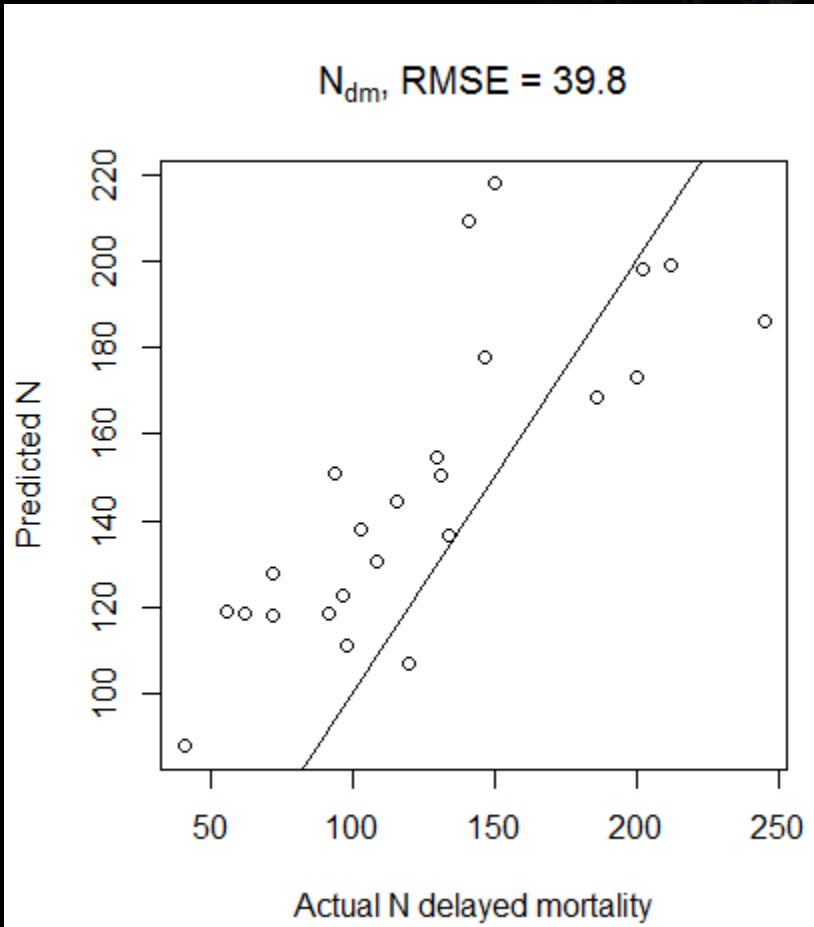


Combinations of predictors that are more likely given the observed data are included more often

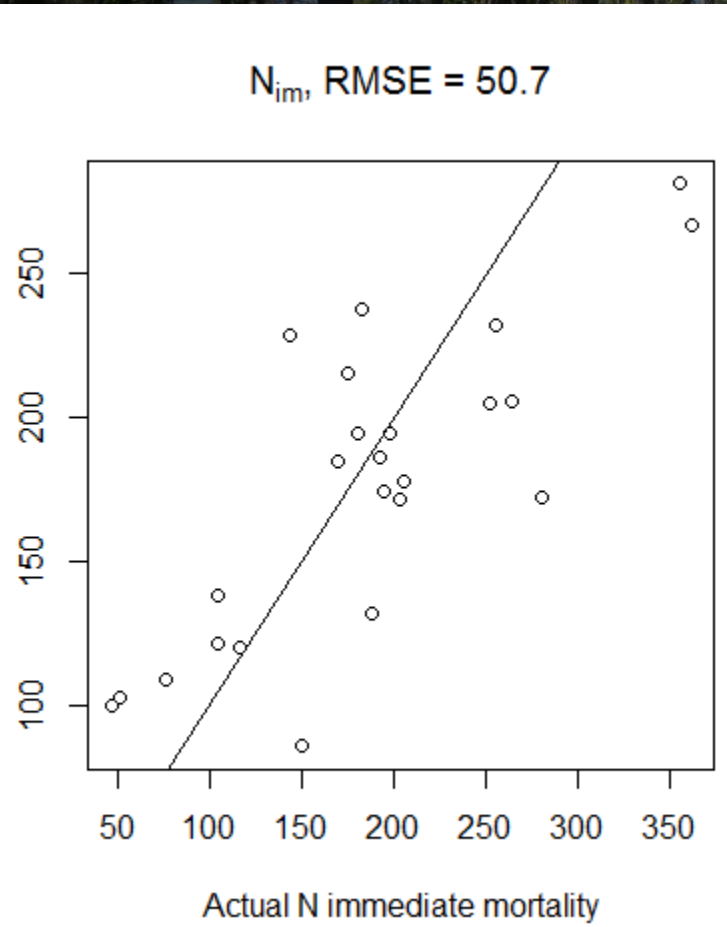
Iteratively removed predictors that appeared less than 50% of the time until a stable set was reached

Model assessment: in-sample

N deaths, delayed

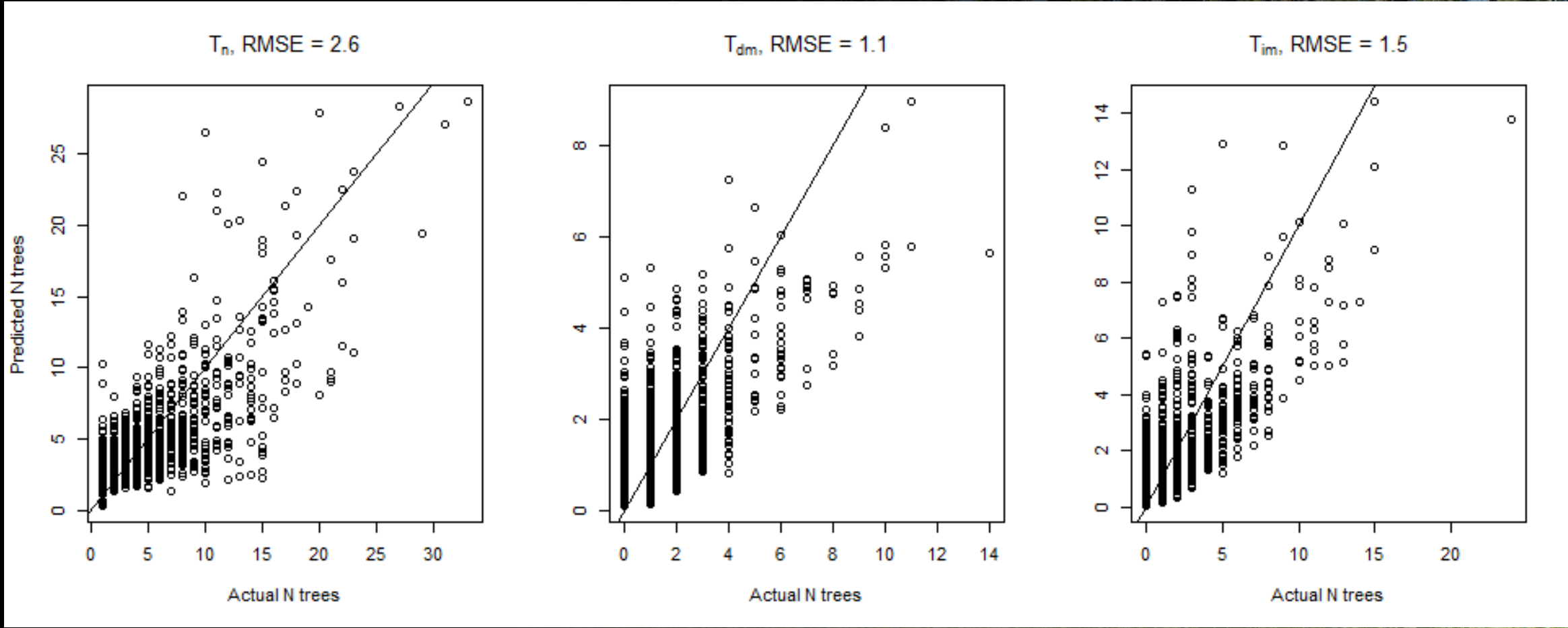


N deaths, immediate



Model assessment: in-sample

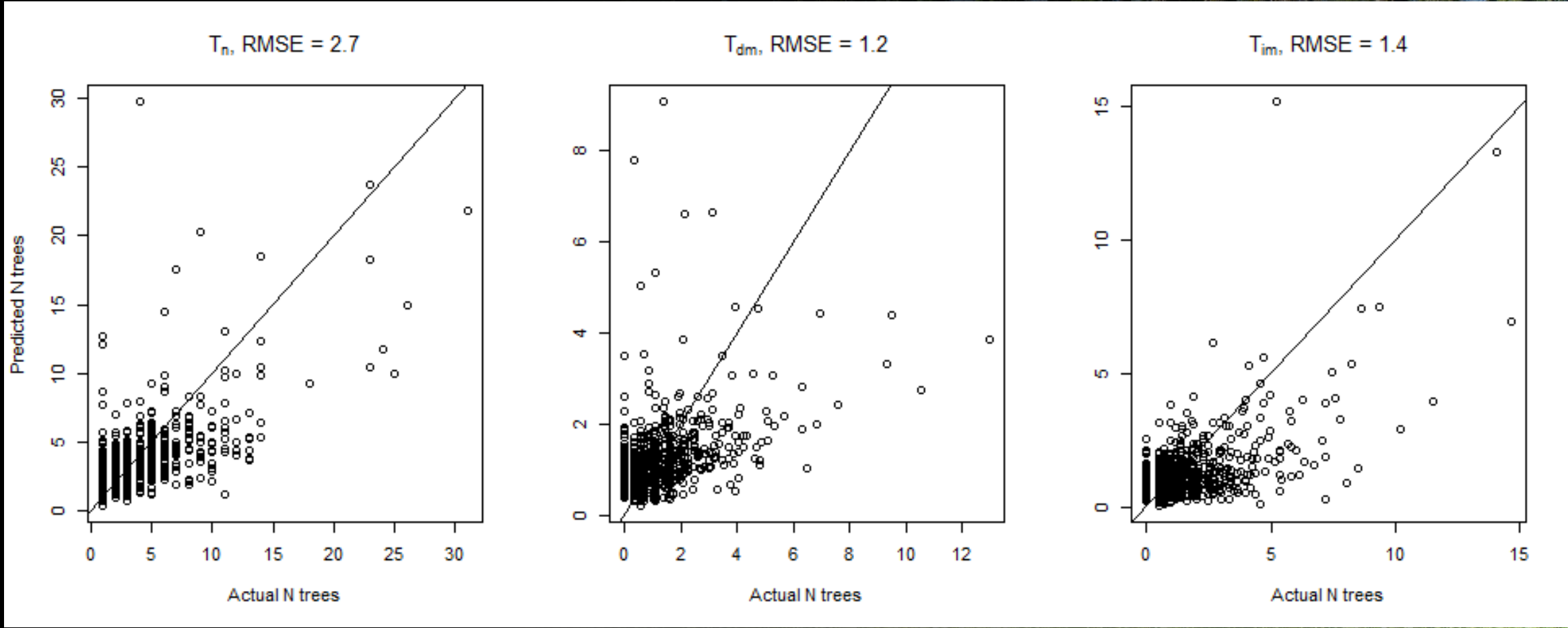
N trees | Delayed mort | Immediate mort



TAO-level accuracy is messier than neighborhood-level, but explains 50-55% of variance

Model assessment: out-of-sample

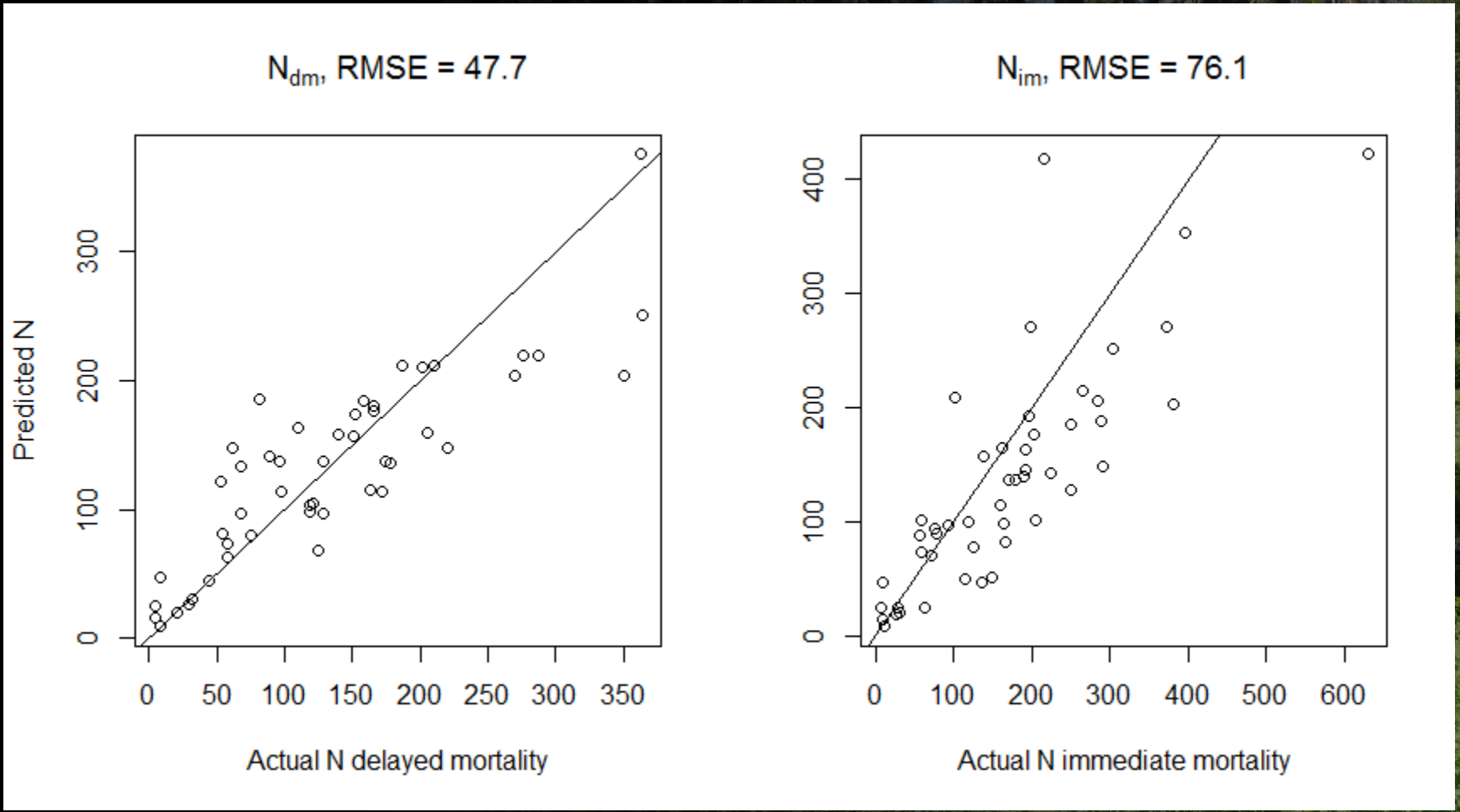
N trees | Delayed mort | Immediate mort



Out-of-sample accuracy is essentially equal to in-sample accuracy

Model assessment: out-of-sample

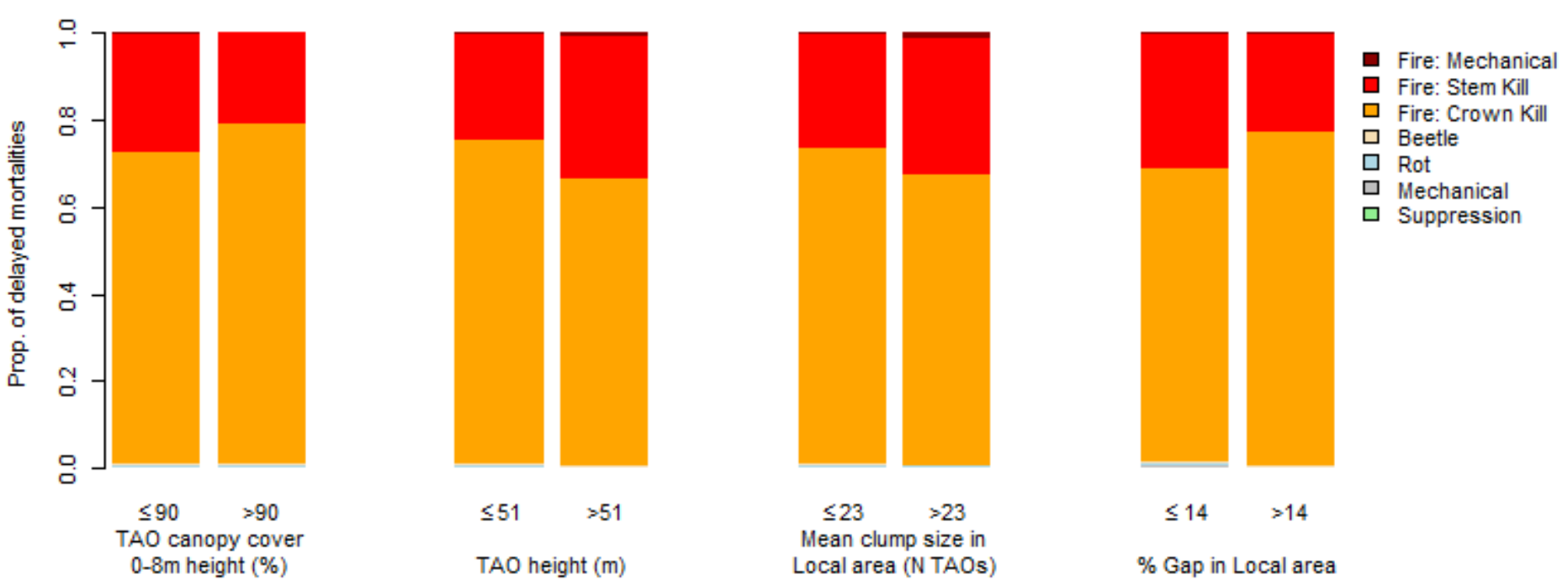
N deaths, delayed



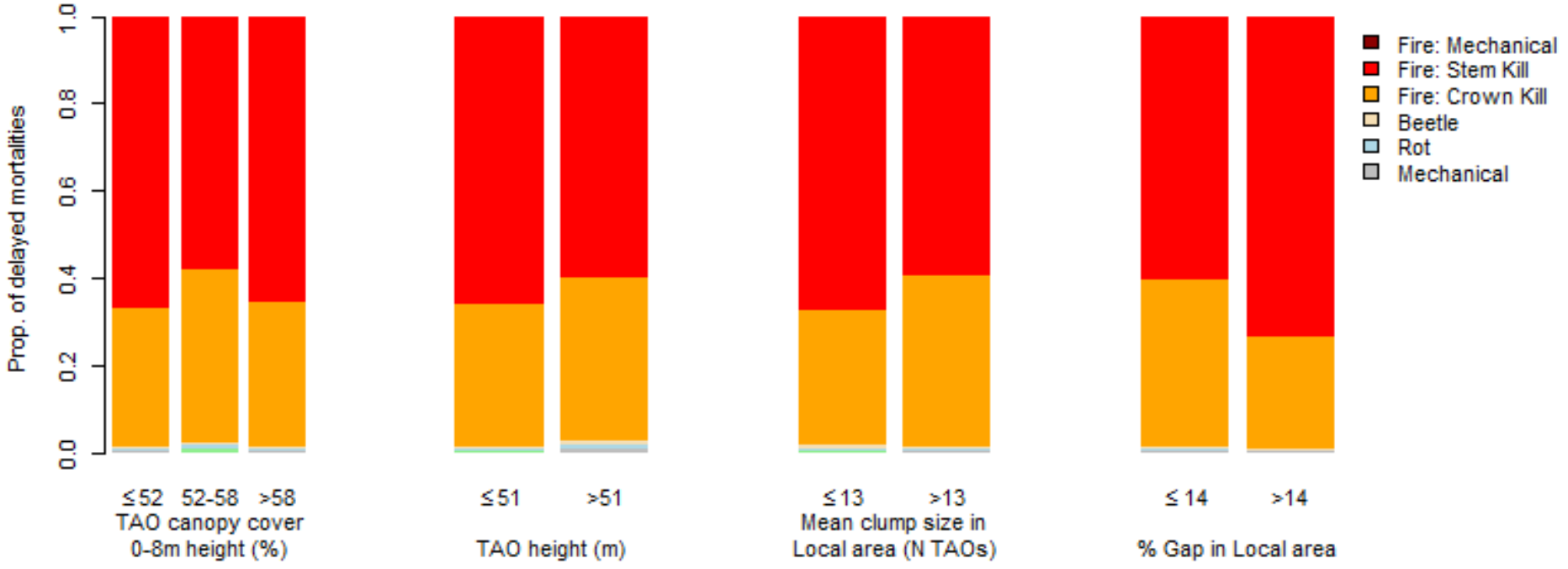
N deaths, immediate

Out-of-sample accuracy is better than in-sample accuracy

FAD1


Prop. of delayed mortalities
0.0
0.2
0.4
0.6
0.8
1.0
≤90
>90
TAO canopy cover
0-8m height (%)
≤51
>51
TAO height (m)
≤23
>23
Mean clump size in
Local area (N TAOs)
≤ 14
>14
% Gap in Local area
Fire: Mechanical
Fire: Stem Kill
Fire: Crown Kill
Beetle
Rot
Mechanical
Suppression

FAD2


Prop. of delayed mortalities
0.0
0.2
0.4
0.6
0.8
1.0
≤52
52-58
>58
TAO canopy cover
0-8m height (%)
≤51
>51
TAO height (m)
≤13
>13
Mean clump size in
Local area (N TAOs)
≤ 14
>14
% Gap in Local area
Fire: Mechanical
Fire: Stem Kill
Fire: Crown Kill
Beetle
Rot
Mechanical