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Modeling wildfire suppression expenditures in British Columbia: machine learning based approach

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Canada

Outline

- BC wildfire background
- Motivation
- BC individual extended attack wildfire Data
- Main results of previous research
- Causal forests model
- Results
- Conclusion and Discussion

BC wildfire background

- Wildfire suppression in BC is primarily handled by the BC Wildfire Service.
- Most fires are suppressed during initial attack. Fires that escape such initial response become extended attack wildfires.
- Fires in remote regions far from human settlements and deemed low risk may be handled as a modified response fire, resulting in reduced or minimal intervention by authorities.

Motivation

- **Suppression expenditures have been increasing** since 1980s in BC and the rest of Canada; Seven of the last 10 wildfire seasons each costed the province over 250 million dollars in suppression expenditures; over $1 Billion in 2023.
- **Research Gap in Canada:** Drivers of wildfire suppression costs have been well studied in the US; Lack of wildfire suppression cost studies in Canada (Xu and van Kooten 2012; Hope, et al. 2016).

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JOURNAL ARTICLE EDITOR'S CHOICE

Modeling Individual Extended Attack Wildfire Suppression Expenditures in British Columbia FREE

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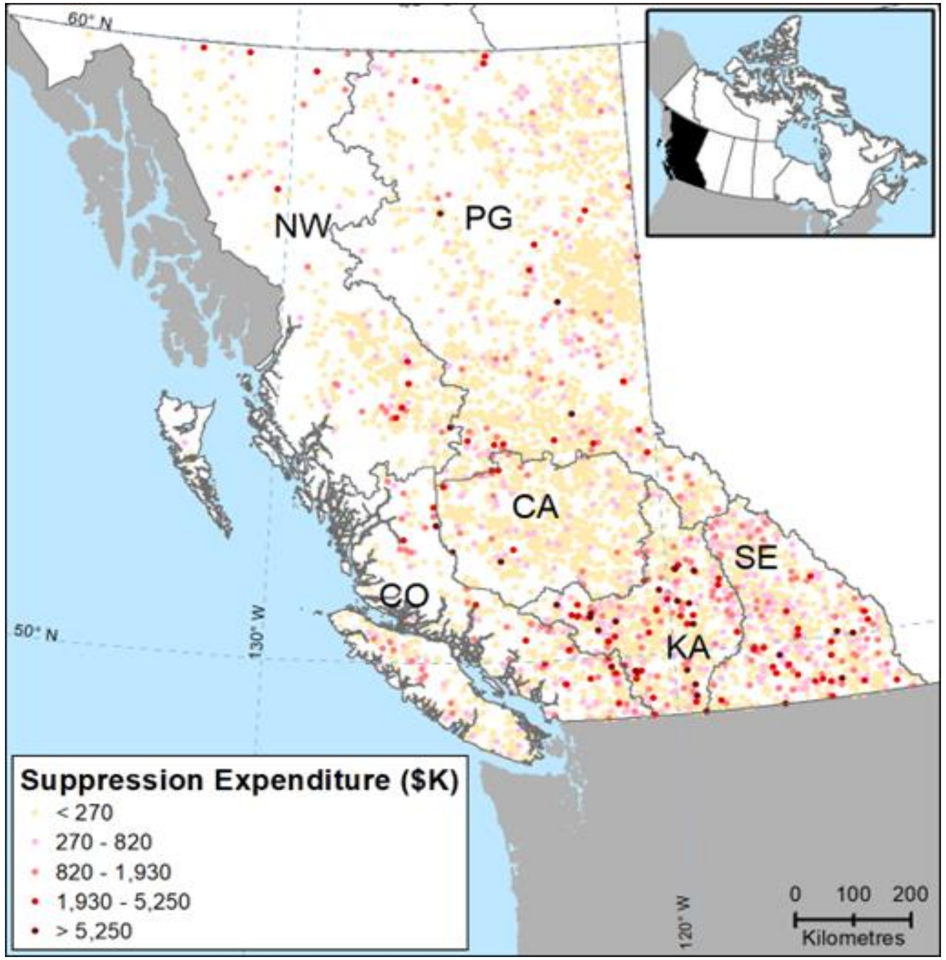
Abstract

We developed models of suppression expenditures for individual extended attack fires in British Columbia using parametric and nonparametric machine-learning (ML) methods. Our models revealed that suppression expenditures were significantly affected by a fire's size, proximity to the wildland–urban interface (WUI) and populated places, a weather based fire severity index, and the amount of coniferous forest cover. We also found that inflation-adjusted individual fire suppression expenditures have increased over the 1981 to 2014 study period. The ML and parametric models had similar predictive performance: the ML models had somewhat lower root mean squared errors but not on mean average errors. Better specification of fire priority as well as resource constraints might improve future model performance.

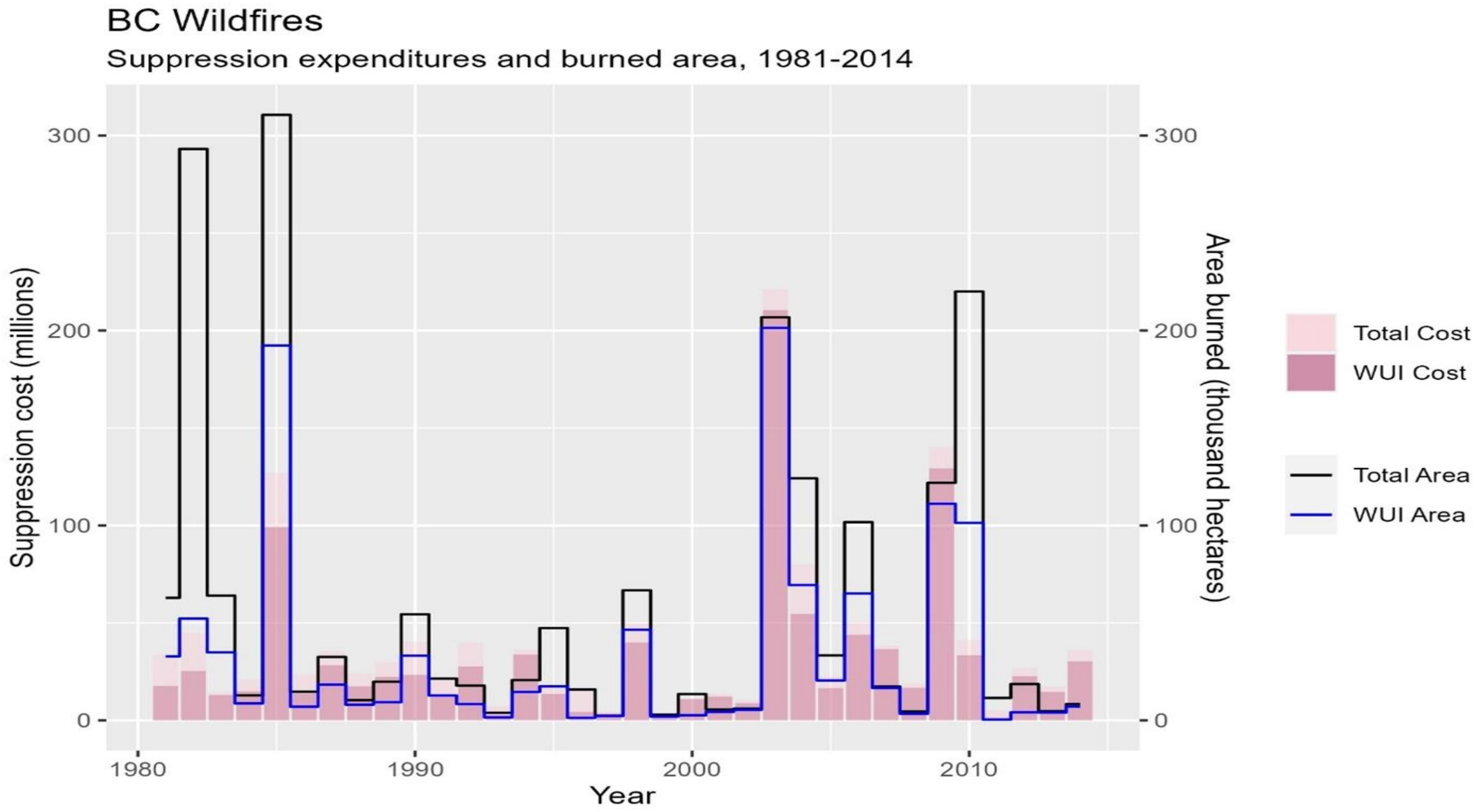
BC Data: 5,459 extended attack wildfires from 1981-2014



- Fires in the north of BC are larger size but less expensive to suppress
- Fires in the south of BC are smaller in size but more expensive to suppress

Fire Centre)	# Fires	Mean Fire Size	Mean Cost/Hectare	Mean Cost
BC	3,156	721	$4,149	$347,653
North-West	283	**1,889**	$2,239	$225,152
PG	**1089**	814	$2,368	$155,009
Cariboo	420	918	$3,311	$282,614
Coastal	276	173	**$8,926**	$387,807
Kamloops	591	459	$5,997	**$682,440**
South-East	497	404	$4,932	$474,072

BC Data: Fire near the WUI

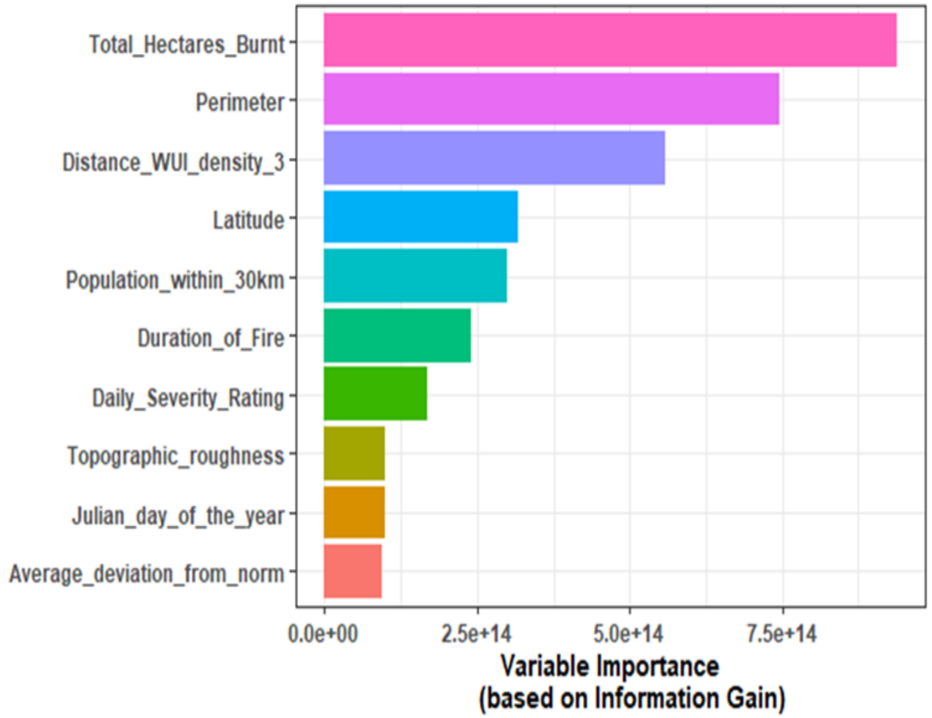


Main results of previous research (MacMillan et al. 2022)

Models: A negative binomial model was created as well as two non−parametric models using the random forests and gradient boosting machine learning algorithms.

Independent variables:

- fire characteristics (Size, Duration, Perimeter, cause);
- fire environment (Slope, Elevation, Aspect, Topographical Roughness, Fuel Type, % of Coniferous, Region, and Land Tenure);
- value at risk (Distance to the nearest WUI, Population within 30km);
- fire response variables (Discovery size, Delay, Fire load anomaly).

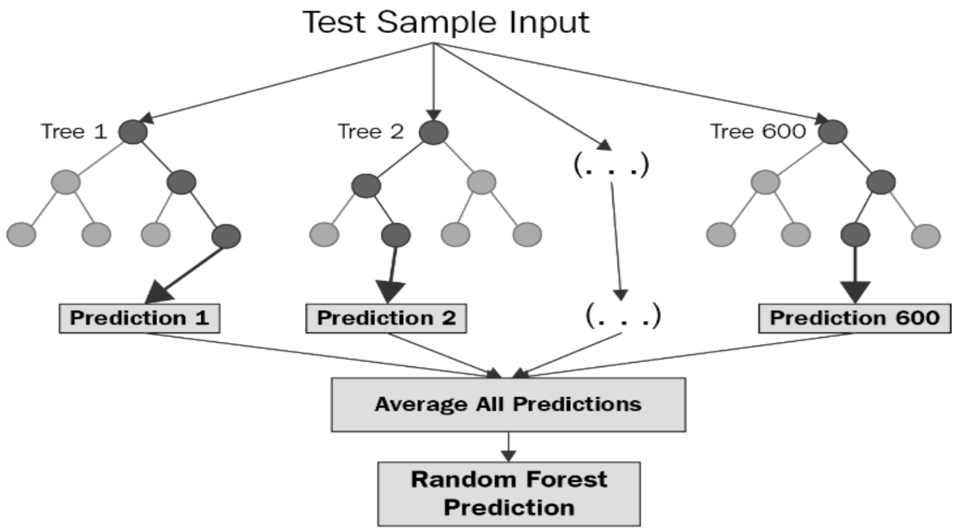


Main results:

- Suppression expenditures were significantly affected by fire size, distance to the WUI and populated places, a weather-based fire severity index, and the amount of coniferous forest cover.
- We find the machine learning models perform better on the measure of root mean squared error and comparably on the other performance metrics.

Causal forests

Random forests (Breiman, 2001): use random subsamples of training data to grow regression trees with random feature splits, bagging similar data into different leaves, and the average prediction of all of these uncorrelated trees is used as the predicted value of outcome.



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Causal forests (Athey and Wager 2018) extend random forests further to allow for statistical inference. The causal forest algorithm estimates two separate regression forests: one for the outcome (Y) and one for the treatment assignment (W). These are then combined to estimate the individualized conditional average treatment effects (CATE):

$$\tau(X)=E[Y(W=1)-Y(W=0)|X]$$

Obtains the expected change in outcome Y for unit change in treatment W, conditioned on X.

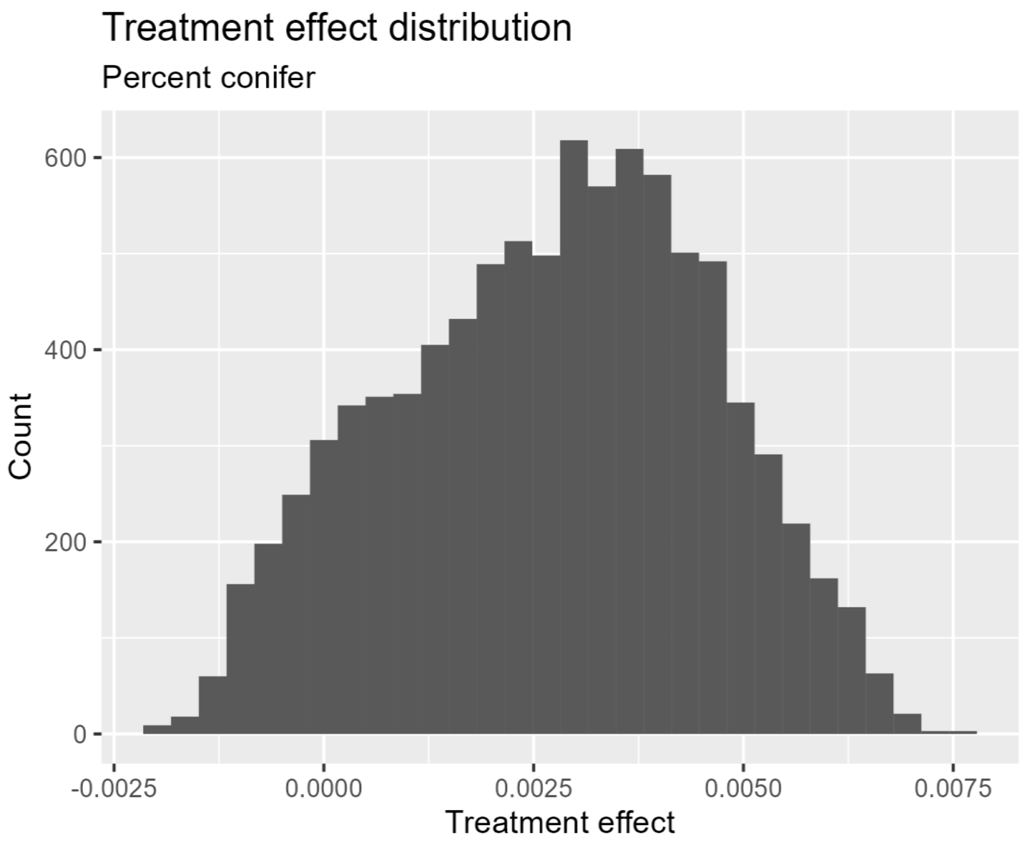
Results

	MacMillan et al. (2022)	Causal Forest		
		4-40 ha	40-200 ha	>200ha
Ln fire size	0.380***	0.219**	0.413***	0.329***
Ln perimeter	0.177***	0.434***	0.213**	0.573***
Duration	0.055***	0.014	0.021**	0.024***
Julian day	0.072***	0.022***	0.022***	0.040***
Julian day squared	0.000***	-0.000***	-0.000***	-0.000***
Fire year	0.018***	0.015***	0.016**	0.012
Natural Cause		0.180*	0.297*	0.101
Ln DSR	0.251***	0.220***	0.348***	0.481***
Ln slope	0.070***	0.085***	0.093**	0.100
Ln roughness	0.030**	0.043**	-0.070*	-0.008
Timber fuel	0.438***	0.157**	0.307**	0.187
Percent conifer	0.002**	0.003***	0.007***	0.005***
Ln population_Within_30km	-0.006	-0.002	0.058***	0.042**
Ln distance to WUI	-0.049**	0.005	-0.072	-0.222***
Ln delay	-0.071*	-0.228***	-0.134	-0.254***
Ln discovery size	-0.104***	-0.176***	-0.166***	-0.182***
Ln fire load anomaly		0.110***	0.108**	0.055

Average treatment effect: the mean of all individual treatment effects in the entire population

- The average treatment effect are broadly consistent with MacMillan et al. (2022).
- The percentage of conifers was found to be significant. For example, a 1% change in conifer cover near the location of ignition for a fire is expected to change the suppression expenditure for the fire by about 0.3-0.7%.
  - Fuel treatment reducing provincial conifer cover by 1% could reduce provincial suppression expenditure by $0.3-$2.8 million dollars per year.

Results



- **Heterogeneous treatment effect :** unlike in a regression model, where varying an input variable is expected to change the outcome at the rate determined by the corresponding regression coefficient, a causal forest can predict this rate of change for a specific set of input covariates.
- How the causal effects vary with observable characteristics? Systematically identify sub-population by quantile plotting: optimal policy design to optimize resource allocation; targeted policy only when set of conditions are met.

Conclusion and Discussion

- Causal forests allowing for flexible modeling of complex interactions in high dimensions can be used to predict change in wildfire suppression expenditure for given change in some predictor or any set of input variables.
- Heterogeneous treatment effect of certain variables can be explored to have targeted policy and optimize resource allocation.
- Predicted treatment effects may benefit from further investigation, including by use of fire simulations and non-BC data.

Thank you!