Revisiting the stratified cost index

A causal analysis

Connor Lennon
Fall 2021

Introduction

Fire Suppression Costs

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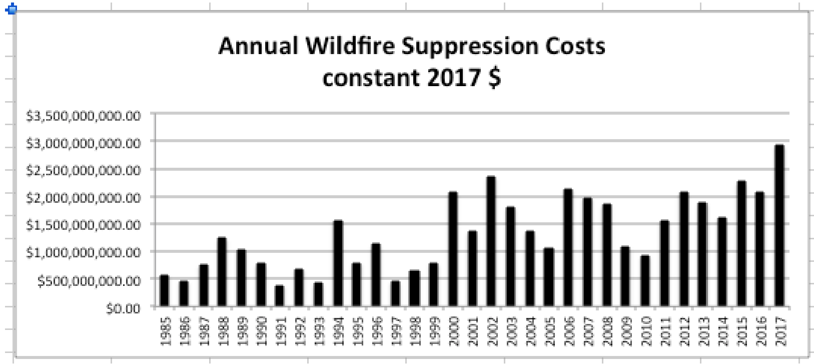

Source: **Wildfire Today**

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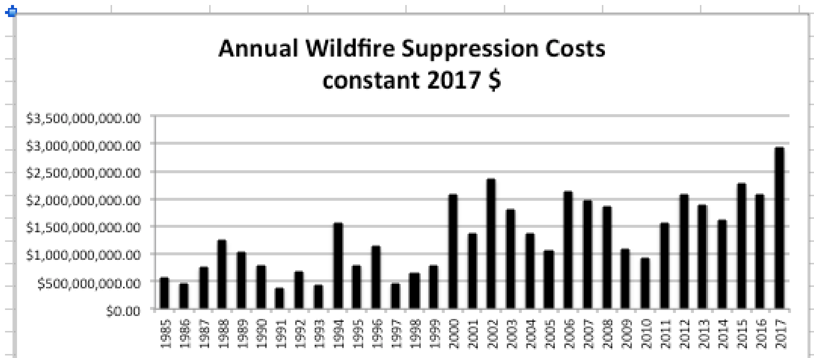

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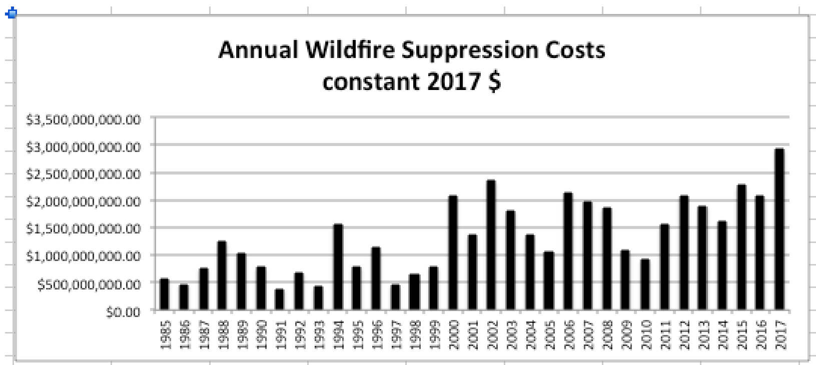

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Why? The forest service, at minimum, has expert data-scientists who have experience with ML (prefer RF and their descendents).

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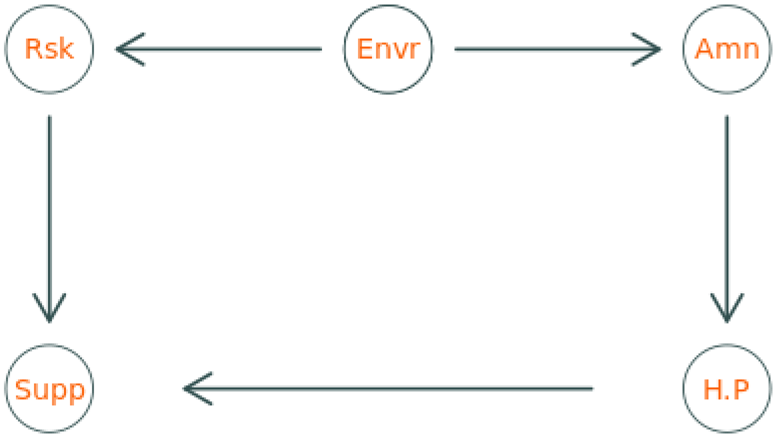
1 A "clarifying" abuse of notation

Basics of D/DML



Illustrate the general idea of what is happening in a simplified version of the causal space:

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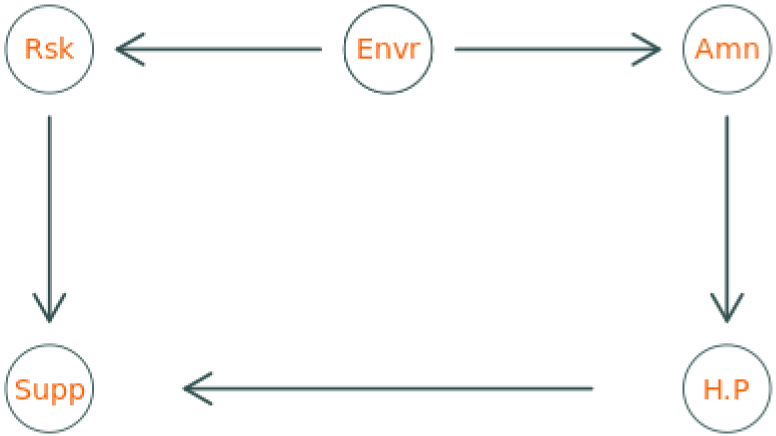

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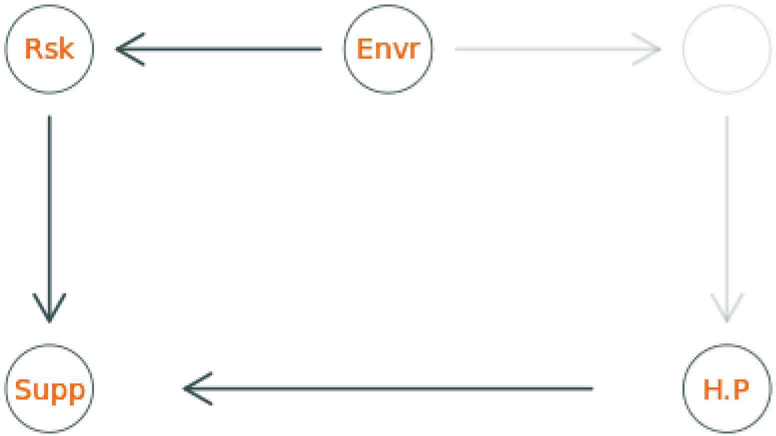

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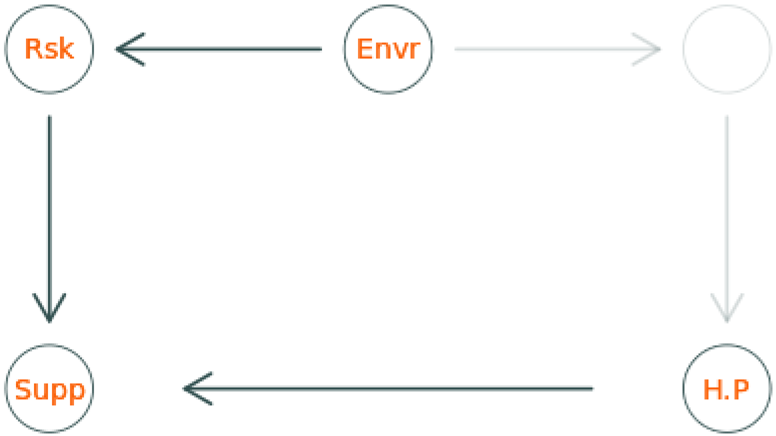

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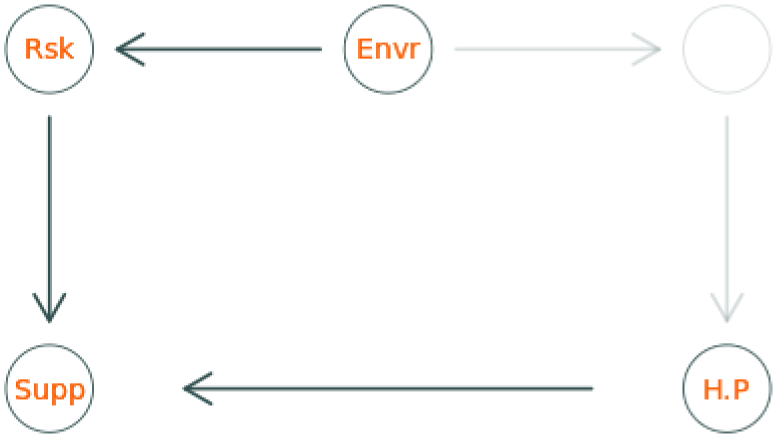

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In economic analysis, these are assumed to be captured by error terms, directly measured by WTP, part of home price, or estimated through choice

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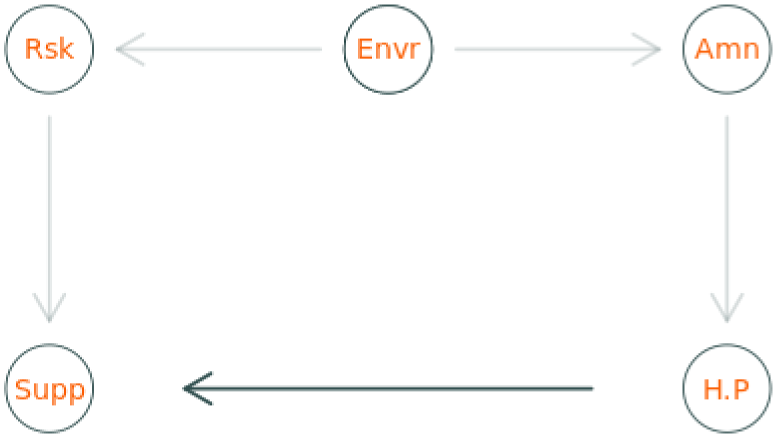

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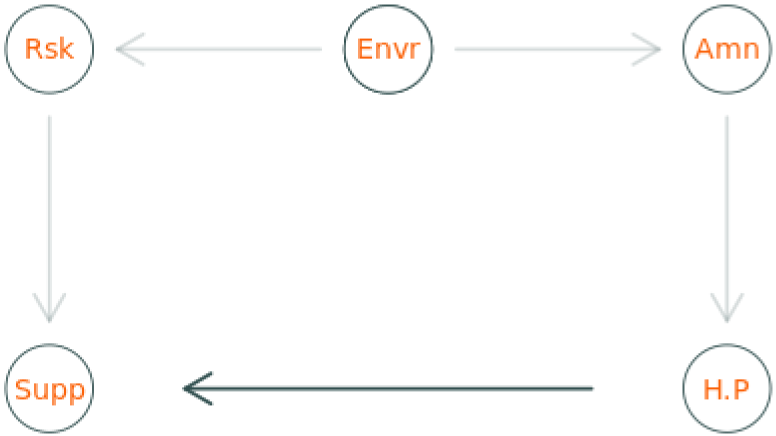

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Rather than use structural assumptions about the functional mapping of features X to $Supp$ or $H.P$, use a functionally appropriate machine learning algorithm to find data-driven version.

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$$\min_{x_1 \ldots x_n} C(\cdot) - NVC_{g,f}(\cdot)$$

Where

- $X \equiv \{x_1 \ldots x_n\}$ is a set of available 'resources'
- $C(\cdot) = \mathbf{w}_g X$ is total suppression costs per acre, where $\mathbf{w}_g$ is a set of non-responsive prices set prior to the current fire season
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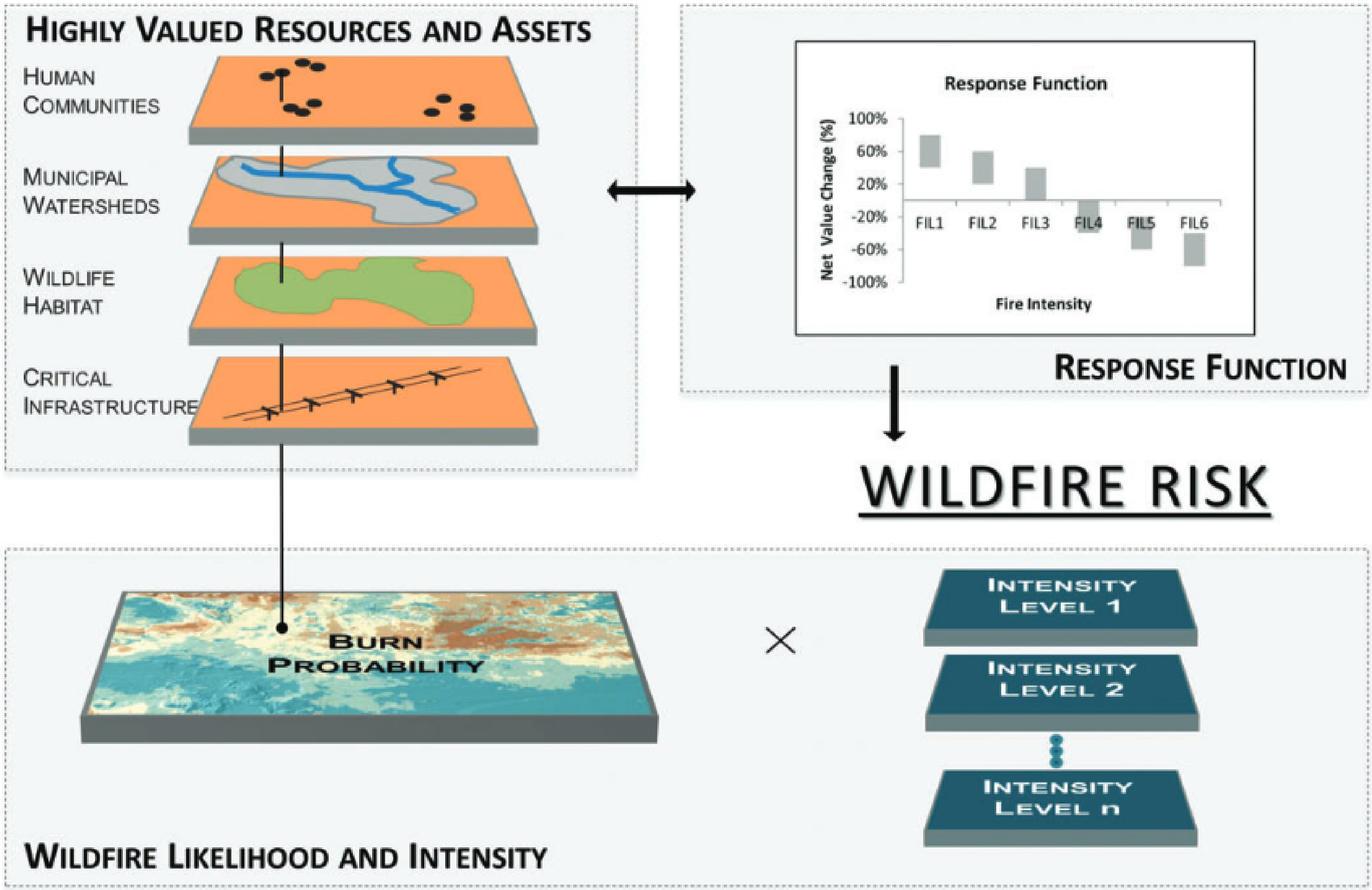

Figure 2—Geospatial context of wildfire risk assessment framework, explicitly recognizing the three components of the "risk triangle" in relation to the locations of HVRAs across the assessment landscape.

Source: Scott et al. 2013 Figure

Inputs to Value

Calculating Expected NVC

Separate from suppression, a fire is internalized as the expectation of a conditional probability distribution over burn intensities **i**

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Important parts -

NVC_i, conditional on burn intensity, is a constant

$P(BP_i|ignition)$ is burn probability for some area of interest. This value is going to now be *path dependent*.

How does fire spread?

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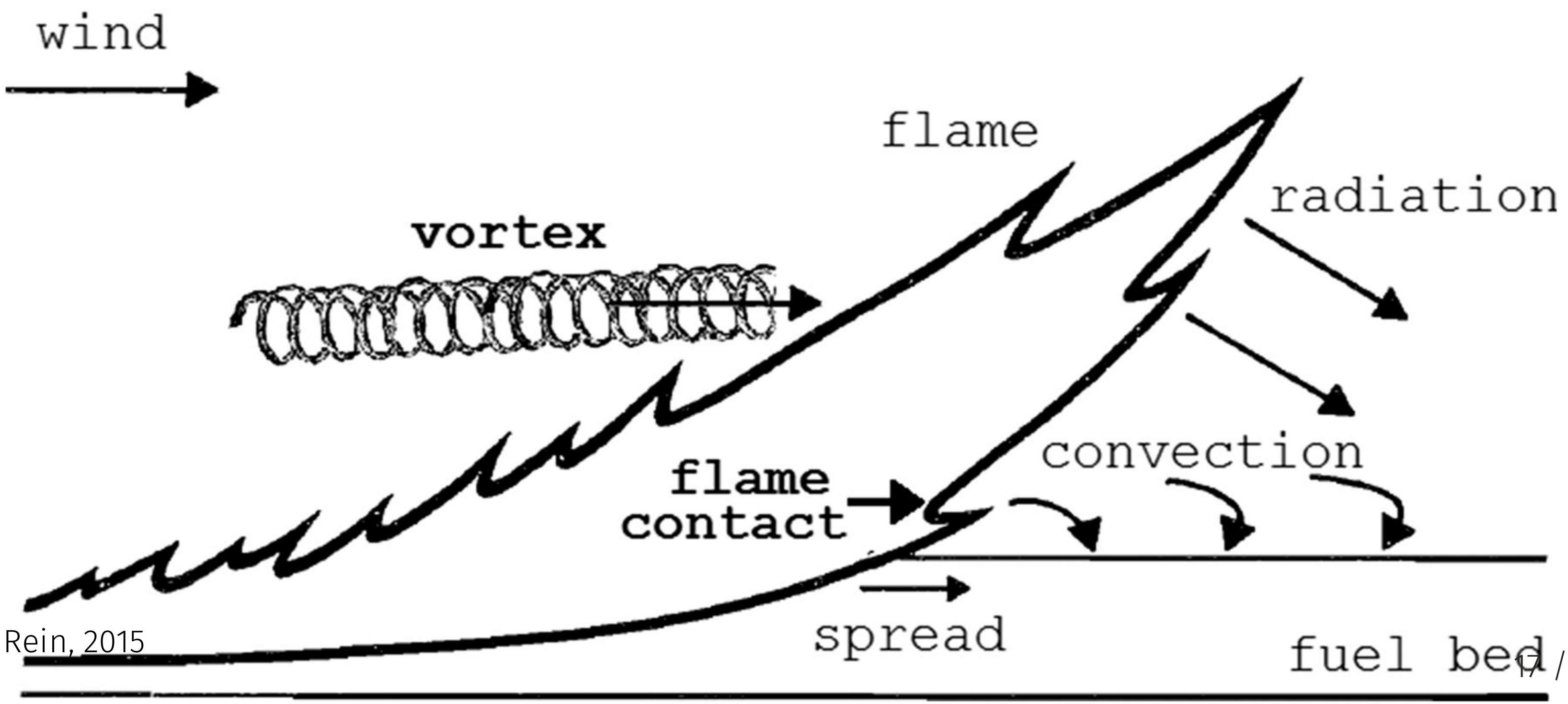

Rein, 2015

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Crown fires are fires that occur in the canopy of trees. Increase spotting* which lead to damage much further away from the fire

* **Spotting**: When burning debris like leaves, grasses are blown much further away by the wind. image source: nwcg.gov

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This has actually already been done in an existing work - *Unraveling the Complexity of Wildland Urban Interface Fires (Mahmoud & Chulahwat)*

A cell's probability of burning at a given intensity level **i**, is a function of the threat vector graph $G = (V, \mathcal{E})$ where $V = \{v_1, \ldots, v_n\}$ are nodes (cells) and $E \subset NxN$ are edges.

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for cell in position $X = x$ and $Y = y$

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Where n_c and n_r are neighborhoods goverened by the Rothermel burn model, and $s \in \{-x, -y\}$ are all cells in a risk consideration set except (x,y)

- Radiance and Convection have adjacency determined by cell-adjacency and wind direction
- Spotting adjacency is a function of **topology**, distance, **fuel type** and wind speed/direction and expected weather turbulence as well as (expected) vertical wind gradient.

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- Period 1. Fire Managers observe initial conditions and make a bulk order to optimize $E[C(\cdot) - NVC_{g,f}(\cdot)]$, where resources can be used to produce actions on a grid.

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- Period 1. Fire Managers observe initial conditions and make a bulk order to optimize $E[C(\cdot) - NVC_{g,f}(\cdot)]$, where resources can be used to produce actions on a grid.

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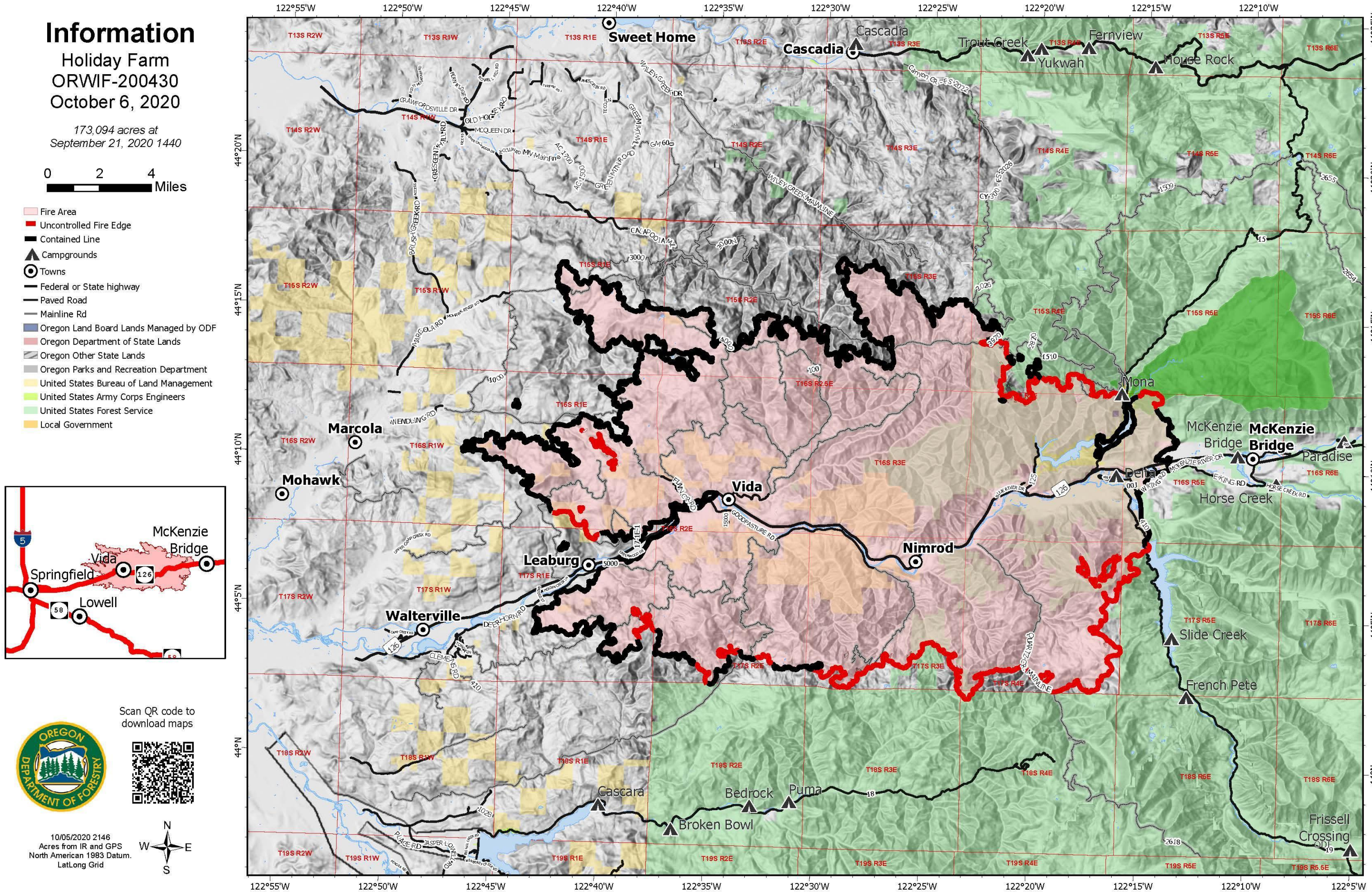
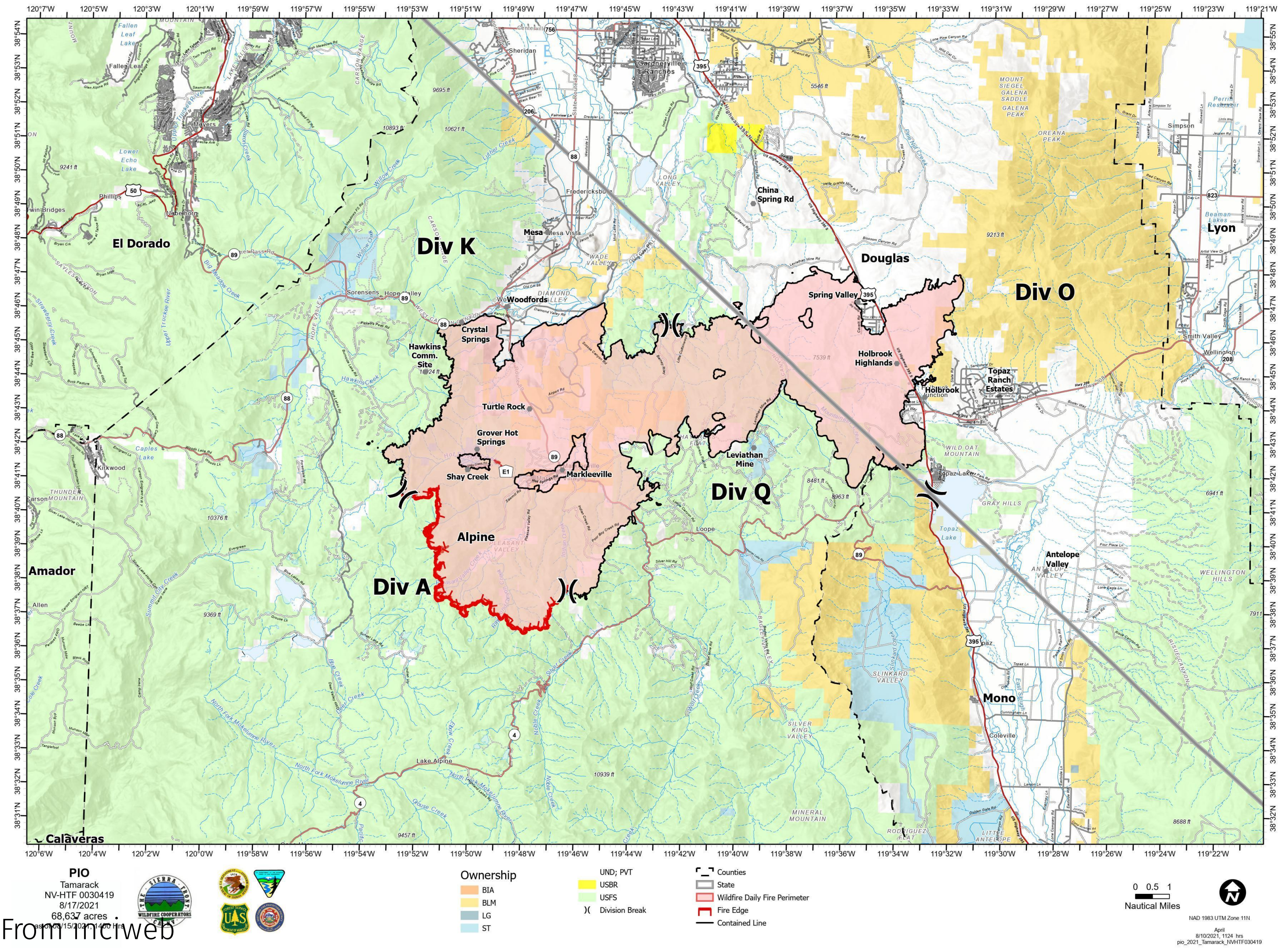
For the data I have, this seems to line up with what I've observed more closely than a **GACC** that centrally optimizes resource dispatches (should

Holiday Farm Fire



From inciweb

Tamarack Fire



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Home Values

The model for housing prices fairly baseline. For individual i buying a home in cell positioned at (x, y)

$$Value_{x,y,i} = g(v_{x,y,i}, b_{x,y,i}, \gamma_i) + \varepsilon_i$$

Where g is a function of...

viewshed amenities $v_{x,y,i}$ which is produced through a spatial kernel weighting of surrounding cells, based on their content and intervening topology

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ε_i is an additively separate error term that factors in non-environmental amenities (such as school quality) and γ_i is a term that captures individual preferences for different viewsheds and backyard amenities.

Home Values

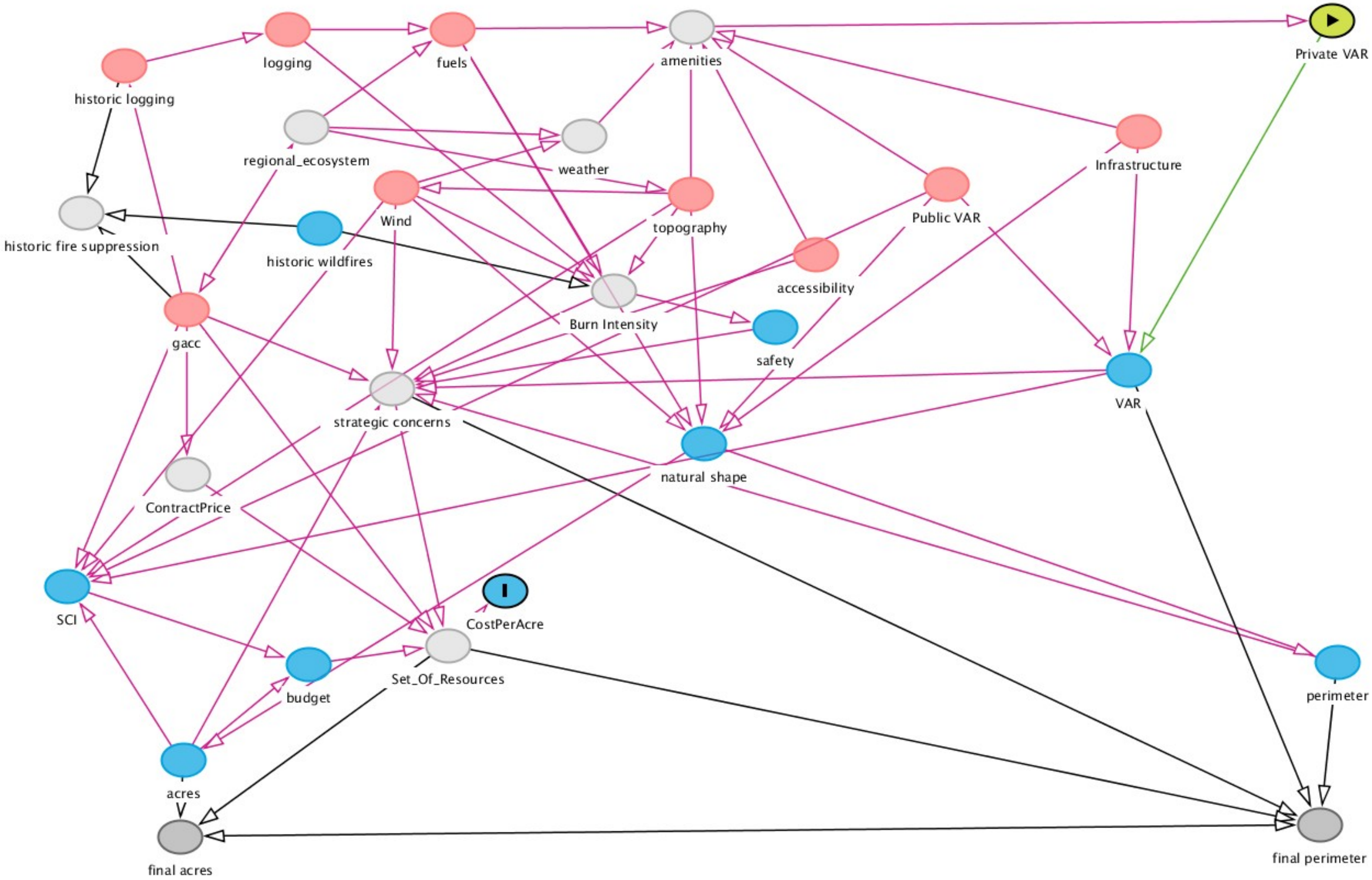
Then, expected value, conditional on tract membership is

$$E[Value_{x,y,i}|Block = t] = E[g(v_{x,y,i}, b_{x,y,i}, \gamma_i)|Block = t] + c_t$$

The error term decomposes into its block-level mean because it is additively separable and not dependent on spatial location.

So long as $\exists\, c_t\ s.t.\ c_t \neq 0$, estimating through D/DML should produce meaningful results.

Structural Causal Model



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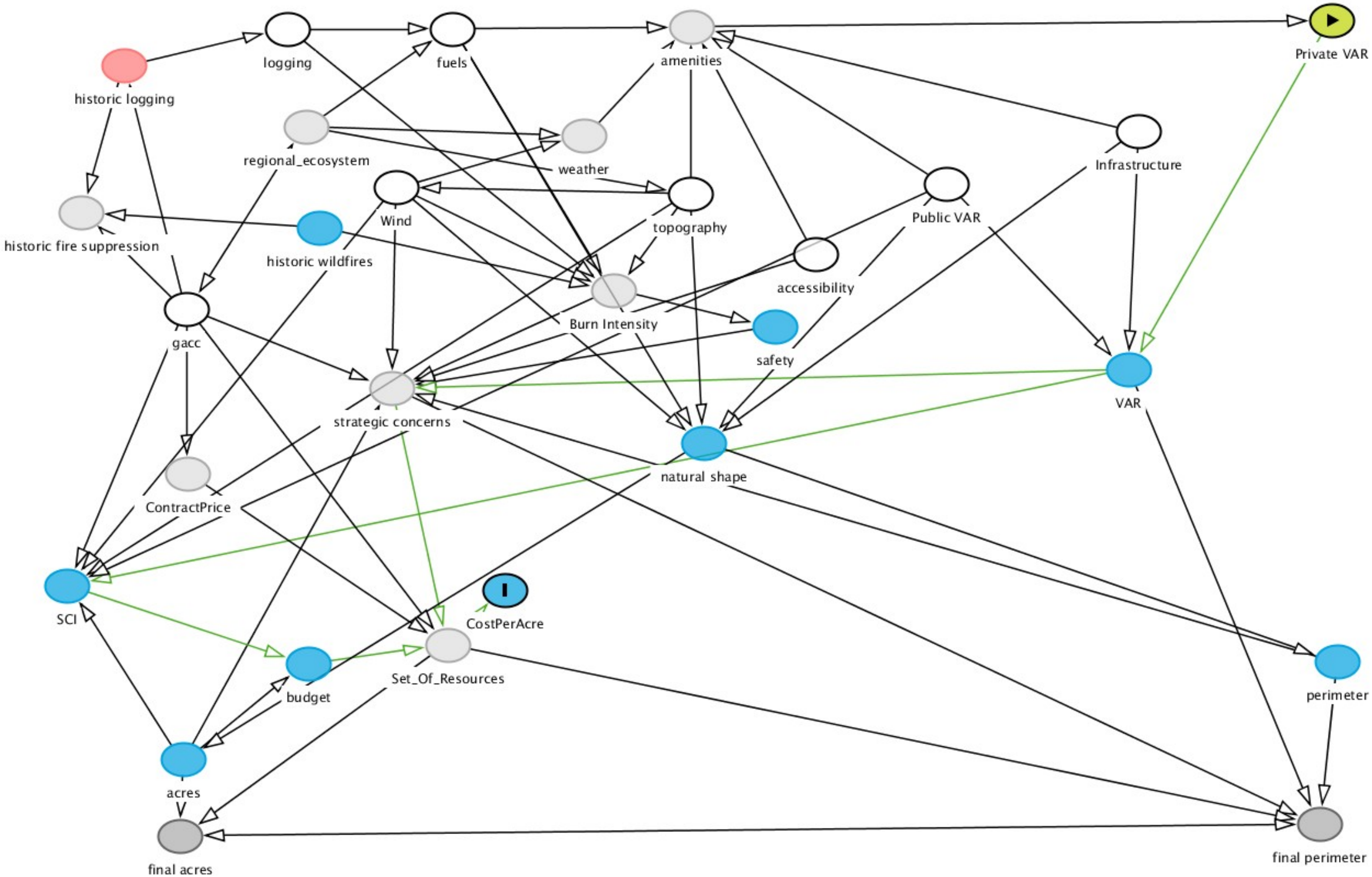

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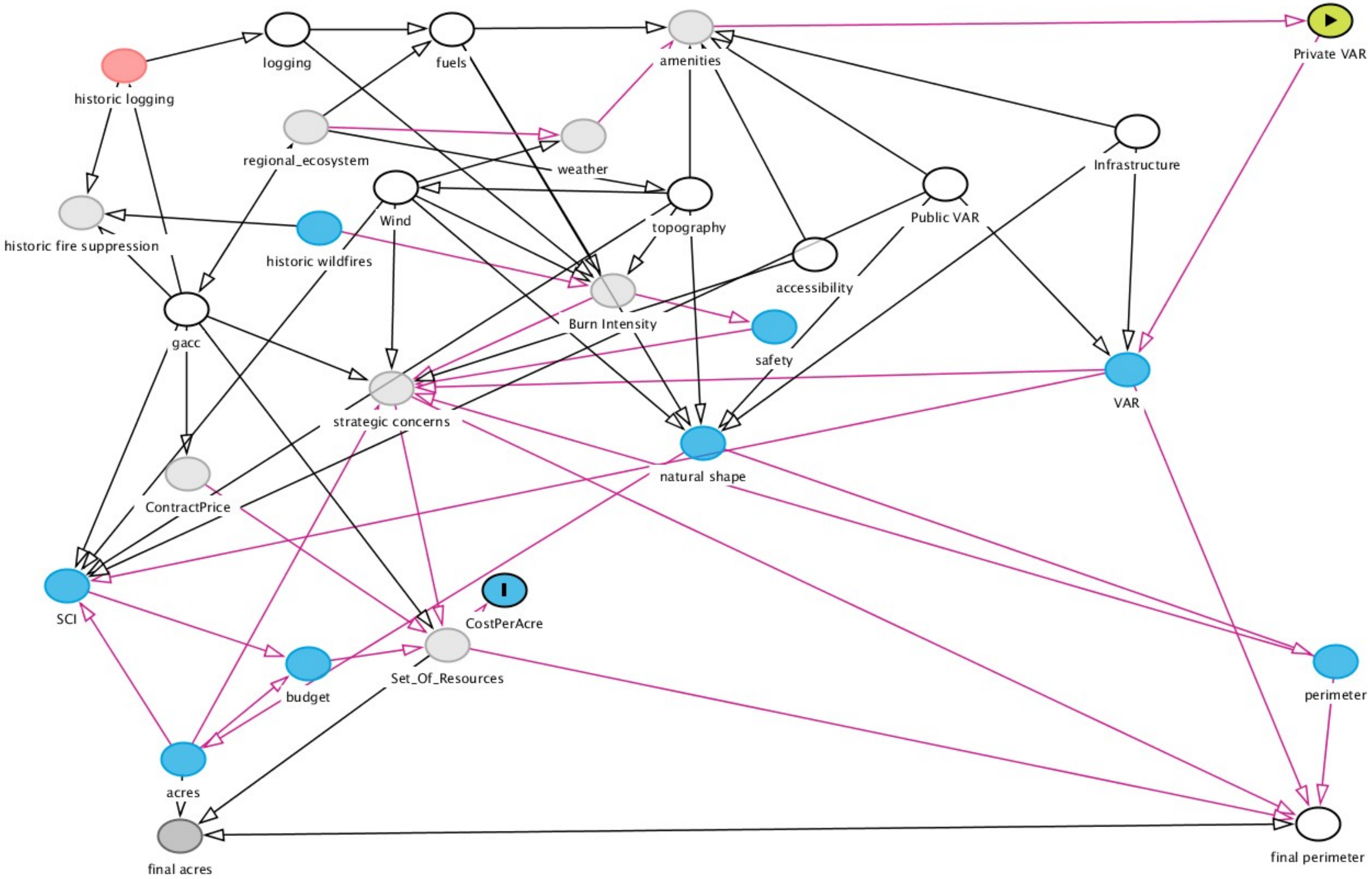

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1.) encode *possible* adjacencies that are both *data driven* and *spatially driven* at the same time,

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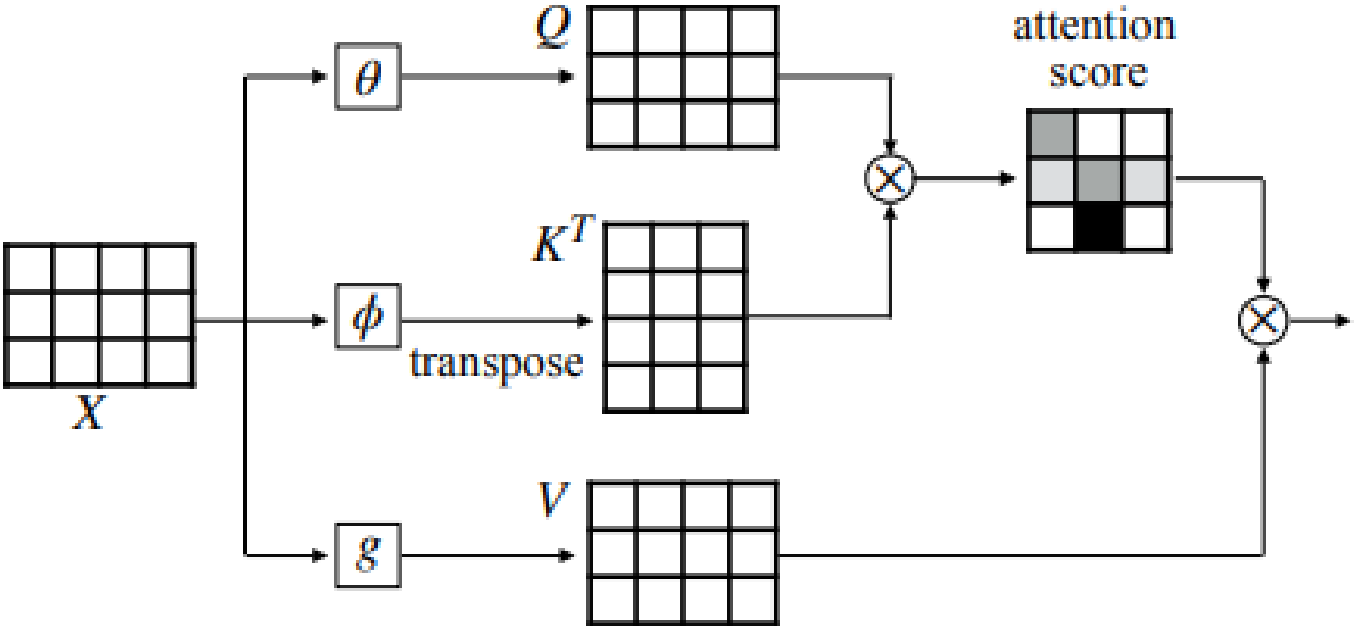

Inputs are multiplied by learnable weights into three matrices **Queries** **Keys** and **Values**.

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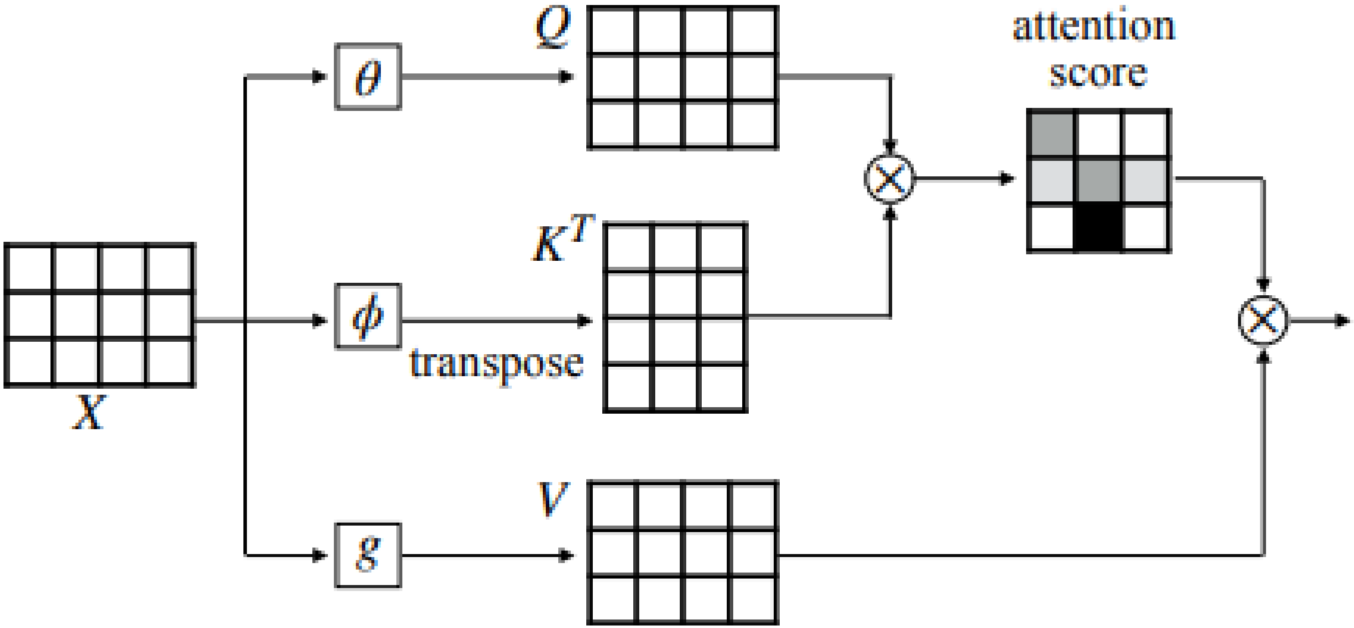

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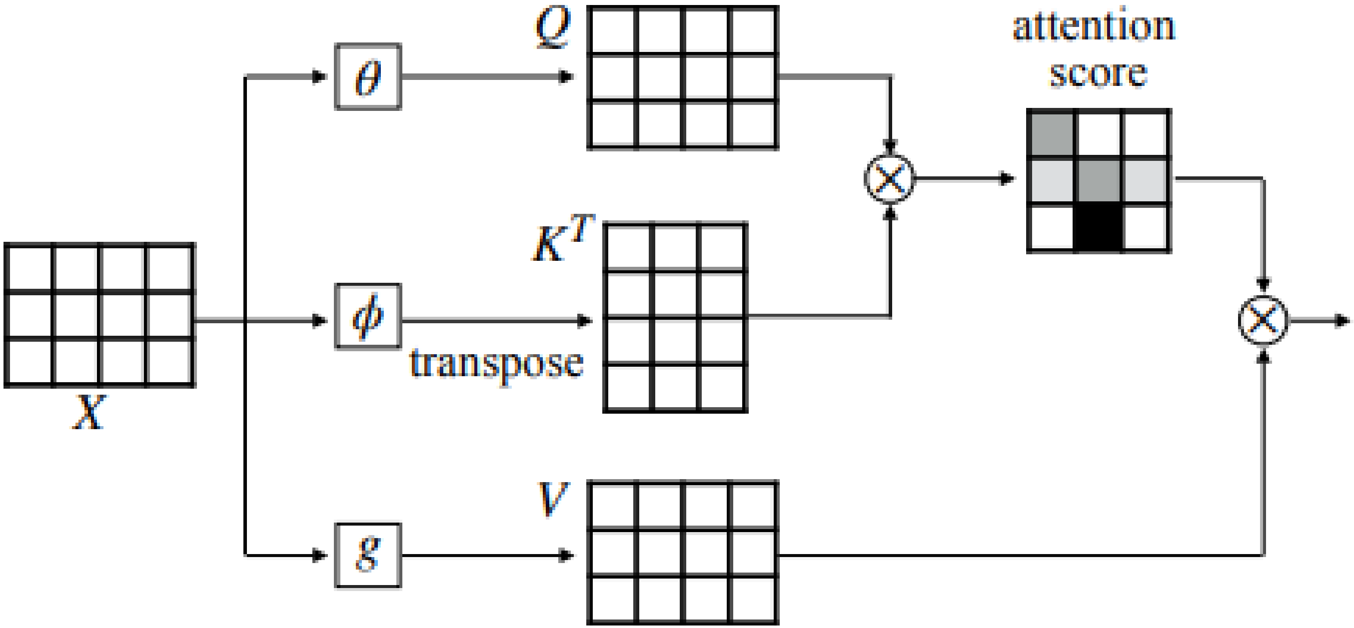

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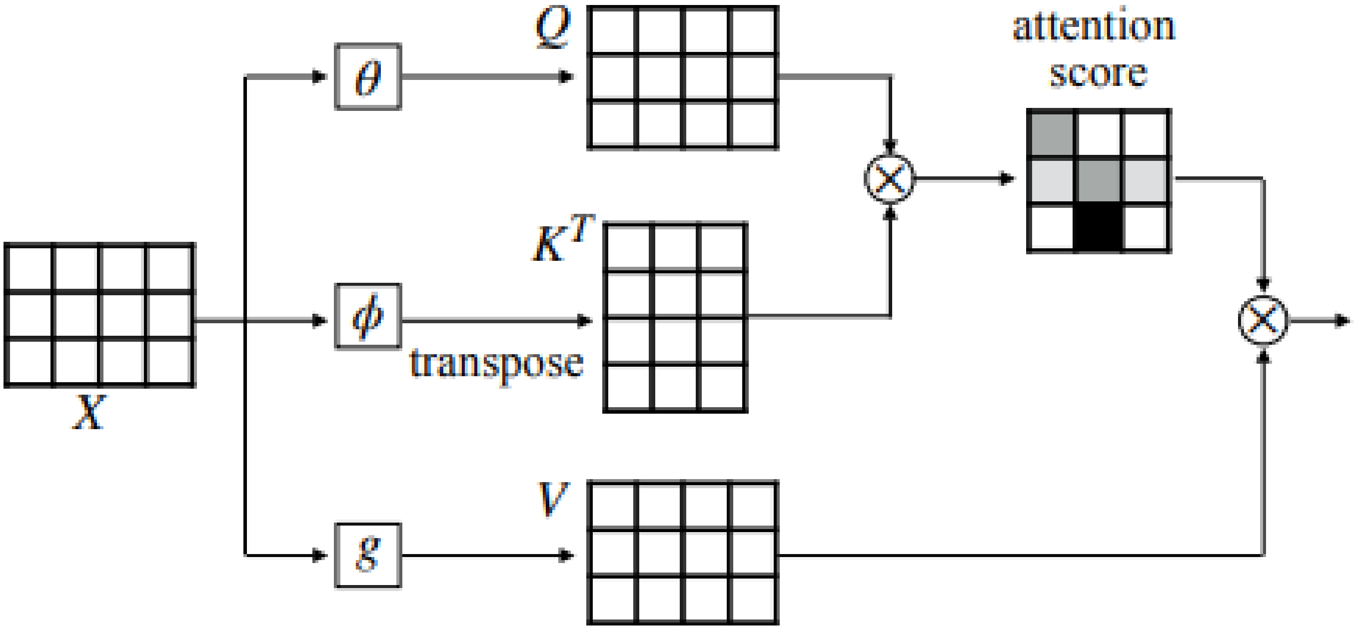

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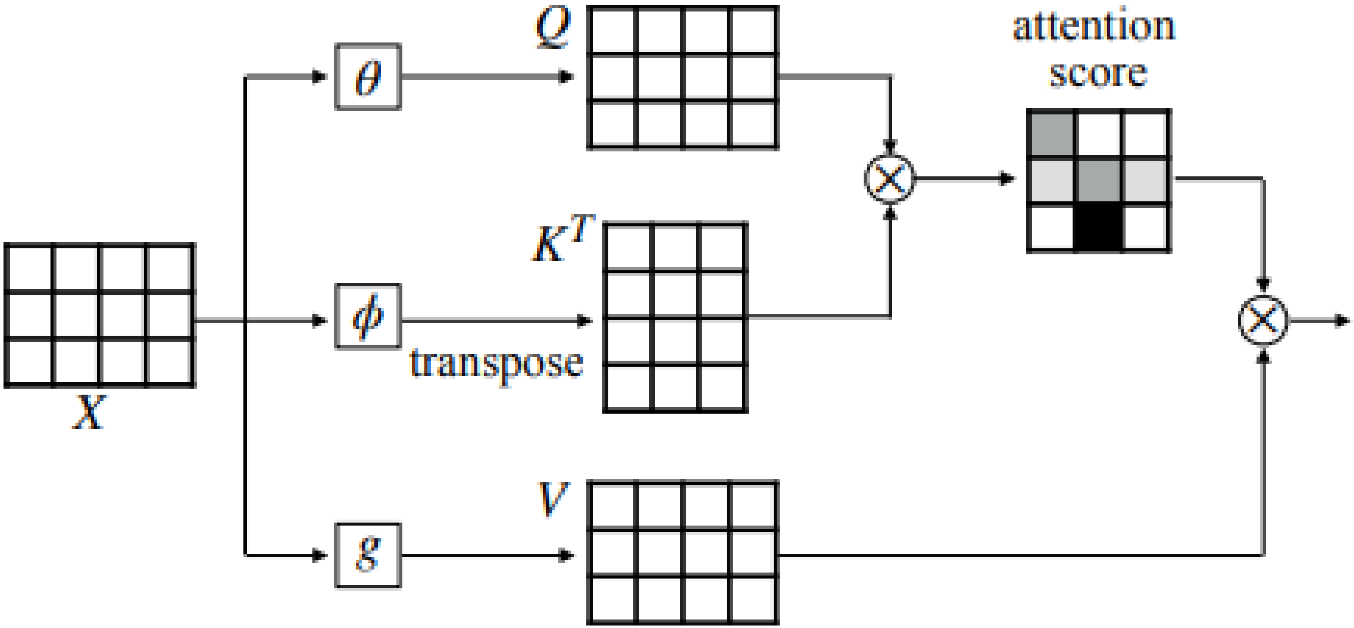

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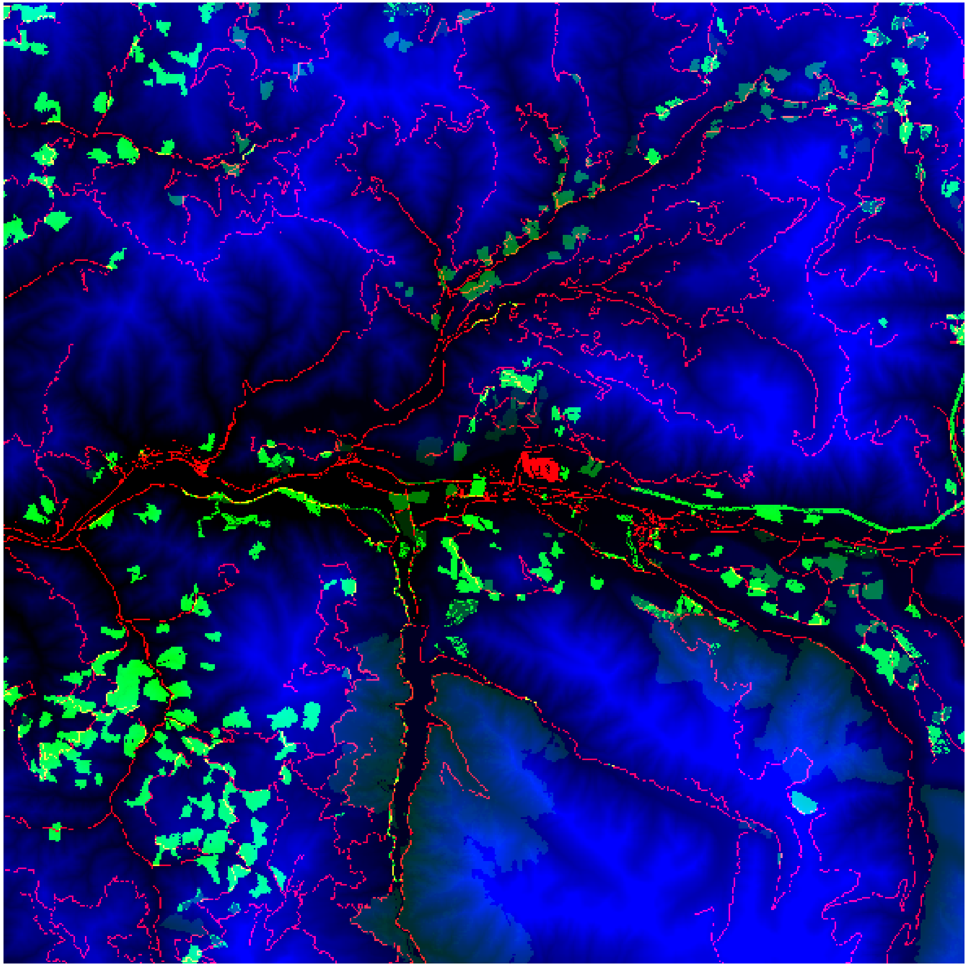
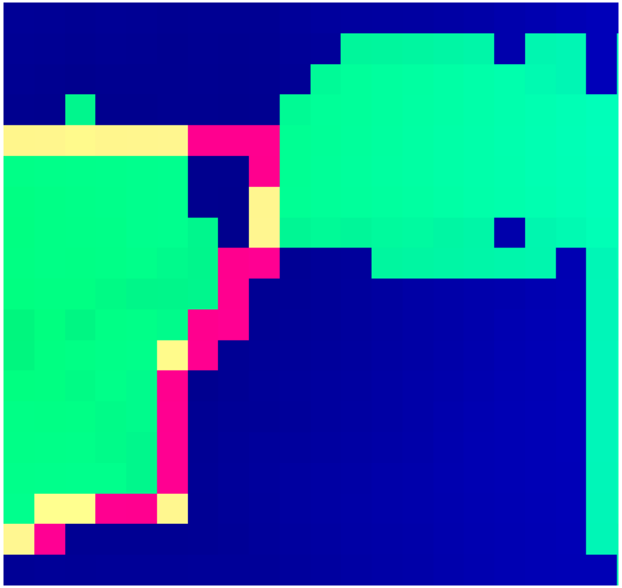
Let's look at the data

Holiday Farm Fire



One 'input'



- *Hint* The upper right hand corner of prior slide
- Patches have a context of 20x20 (26 if you count the convolution) cells, or .6x.6 km. This input would be processed through a convolutional layer, with a stride of 1 and a 12x12 kernel first.

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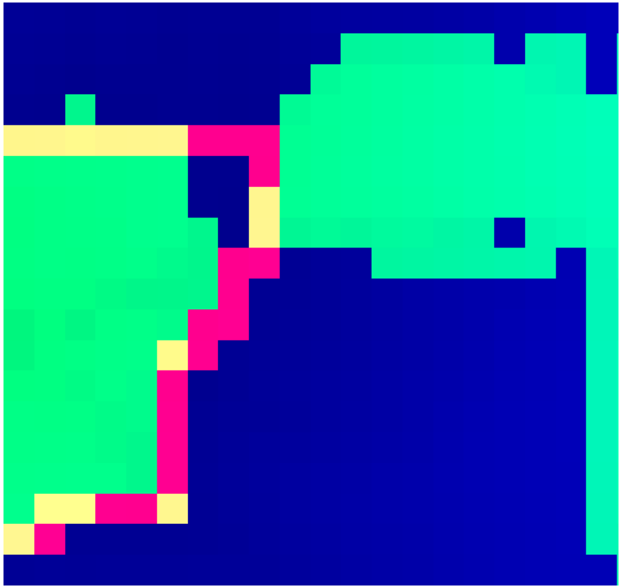

Visible inputs at the moment are Imperviousness (**red**), elevation, (**blue**), and Vegetation disturbance (**green**)

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Luckily, almost all of the extrema of the inputs are known, so no need to worry about excluding test set for normalization 🥳

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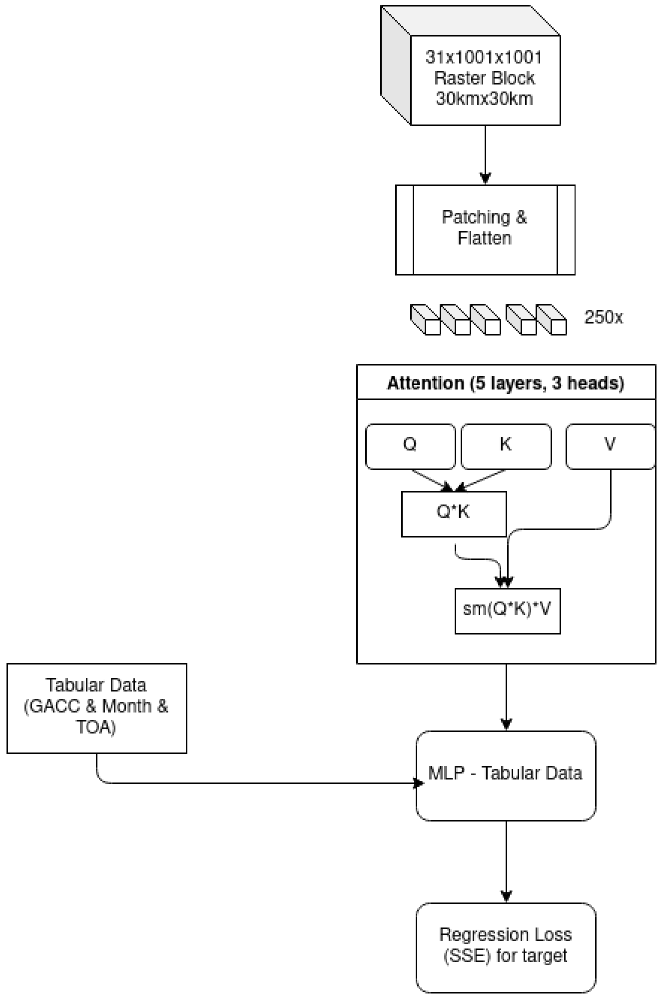
In addition, used coarse dropout, dropout, L2 regularization, random rotations (up to 15 degrees), and 5-cell masking or padding around the

Model Diagram



MLP: Multi-layer perceptron - ie, classic neural network

Back to Metrics

Now that we've covered that theory - let's incorporate it into our PLR format from above.

Assume: $\frac{pw}{acres} = f(X, Property\,Values, \varepsilon, grid = gr)$ so that...

$$log(\frac{cost}{acre}) = f_l(X_{f,gr}) + \theta log(Property\,Value\;20km) + log(\varepsilon_f)$$

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From this, can use MoM with one of two neyman orthoganal moment conditions

1.) $E[[Y - (Price - g(x)) * \theta - f_l(X)][Price - g(x)]] = 0$

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Original - Coef Log(Housing Value within 20km) only on large fires

- **.1131**, SE - not reported, but p-value = 0.00
- OOS **Rsquared of .18** in the west, .11 in the east

Results

Table 3. OLS regression models, western and eastern United States.

Variable	National Forest System Regions 1–6		National Forest System Regions 8–9	
	Coefficient	P value	Coefficient	P value
ln(Total acres burned)	−0.3238	0.000	−0.1941	0.006
Fire enviroment				
Aspect (cosine)	−0.1675	0.005	0.1009	0.263
Aspect (sine)	−0.1066	0.149	−0.4388	0.000
Slope	0.0057	0.003	0.0065	0.059
Elevation	Not in model		Not in model	
Grass	−0.5703	0.000	−0.5339	0.015
Brush	−0.3613	0.075	2.0391	0.026
Slash	0.2817	0.175	0.3503	0.261
Timber	0.5032	0.001	0.4981	0.038
FIL 2	0.8442	0.000	0.2206	0.265
FIL 3	1.3224	0.000	0.8458	0.000
FIL 4	1.6930	0.000	1.0424	0.000
FIL 5	1.8715	0.000	0.8160	0.010
FIL 6	1.7865	0.000	1.6956	0.000
ERC	0.0113	0.000	0.0047	0.112
Values at risk				
ln(Distance to nearest town)	Not in model		0.3029	0.014
ln(Total housing value 5)	0.0059	0.686	0.0329	0.188
ln(Total housing value 20)	0.1131	0.000	0.1703	0.098
Wilderness area	−0.2123	0.151	0.6703	0.017
IRA	0.1453	0.311	0.5806	0.213
Other SDA	0.1788	0.363	−0.6272	0.208
Wild × ln(distance to boundary)	−0.4309	0.000	0.7580	0.002
IRA × ln(distance to boundary)	0.0861	0.272	−0.1413	0.622
SDA × ln(distance to boundary)	−0.0905	0.313	−0.2781	0.187
Detection time				
Ln(Detection delay)	0.0353	0.171	−0.1859	0.000
Square of ln(detection delay)	−0.0184	0.037	0.0581	0.001
Suppression strategy				
Initial suppression strategy: confine	Not in model		0.6958	0.000
Initial suppression strategy: contain	Not in model		1.0056	0.002
Resource availability				
ln(Average deviation)	−0.0970	0.093	Not in model	
Region				
Region 2	−0.5398	0.016		
Region 3	−0.0792	0.643		
Region 4	0.1283	0.446		
Region 5	0.9631	0.000		
Region 6	0.9697	0.000		
Region 8			0.8122	0.000
Constant	4.587	0.000	0.3919	0.699

(Dependent variable = ln(wildland fire suppression expenditures/acre), R^2 (West) = 0.44, R^2 (east) = 0.49, n (West) = 1141, n (East) = 409), RMSE (West) = 1.5086 RMSE (East) = 1.1308. IRA, inventoried roadless areas; OLS, ordinary least squares; SDA, special designated areas.

Results II

DML - Coef Partialed out MoM estimator. Alone

- **.03817**, 95% - CI = **[-.02577, .1021]**
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DML - Coef Pseudo-instrument MoM estimator

- .0138, estimate, jacobian explodes (no CI) - don't like that.

Results III

Results from 2020-2021 data (including small fires) appear to have even stronger effects from the 20km bound around the ignition point

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Left to do:

Lots

- re-estimate the original model separating eastern and western models to get updated regression estimates
- estimate the remaining 9 folds for DML to get better (and tighter) estimates. Relying on 1 fold may be misleading.