G-dWOLS Analysis of Different Fire Suppression Methods' Effectiveness on Alberta Wildfires

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What I have done?

In this project, I carried out a data analysis on Alberta wildfires using a novel and powerful statistical method called G-dWOLS. My goal aims at measuring different forest fire suppression methods' effectiveness, or interventions, precisely and causally, so as to develop a strategy of fire suppression that is tailored to an individual fire characteristics. Moreover, G-dWOLS analysis reveals something detailed about how each fire suppression method impacts on an individual fire which inspires us to come up with possible explanations on previous (counter-intuitive) results suggested by others' works.

Confounders and Causal Inference

As we all know, **correlation doesn't mean causation.** In hot summer, ice cream sales and the number of drowning cases increase and they are statistically correlated. However, increment in ice cream sales doesn't cause increased drowning cases. Causation is embedded in correlation usually. To extract the causation from correlation, we need additional tools. **Causal inference is such the process of drawing a conclusion about a causal connection based on the conditions of the occurrence of an effect.** When measuring the effect of a treatment, or intervention, we need a statistical framework and take all confounders, weather temperature in this example, into consideration to avoid heavily biased or even reversed estimated result. It works like a machine which takes the subject's information W and the treatment T, and predicts the subject's outcome Y. Since there are many choices of treatments, we call the differences in the predicted outcomes the causal effect of treatment.

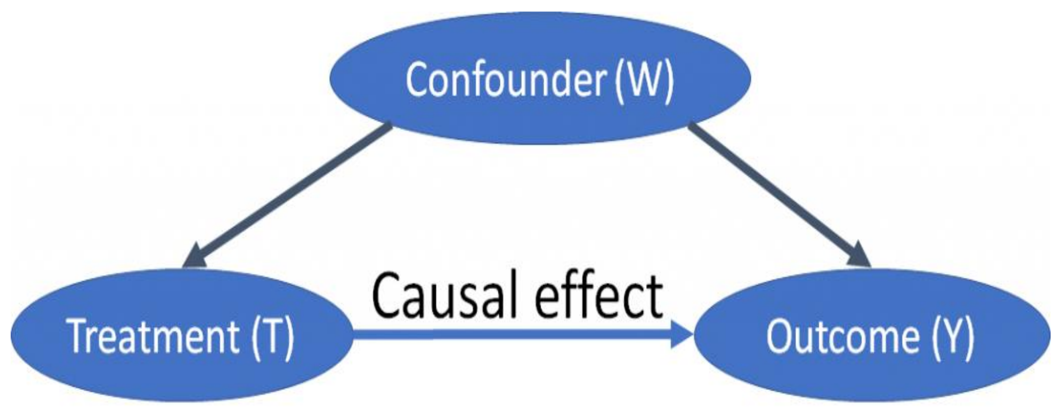
What is G-dWOLS method and why we need this?

There are many approaches to draw the causal effect of treatment. **Generalized dynamic weighted ordinary least squares framework, or G-dWOLS, is one of these candidates in eliminating the bias brought by confounding and extracting the causal effect from an observational dataset.** It is a regression based method which is built upon on the theory of dynamic treatment regimes (DTRs) and it is realized by applying weight which satisfy specified conditions to each estimating equation. The key is, compared to unweighted regression, **G-dWOLS enjoys the property of double-robustness.** In short, for example, there are treatment A and B and the probability of treatment T assigned to a patient depends on his body temperature W. The patient's body temperature after taking the treatment depends on which treatment assigned and his current body temperature. Double-robustness makes sure that if at least one of these two relationships, one between W and T, and one between Y and T, is modeled properly, we will obtain the unbiased result of estimated causal effect of treatment. It is particularly useful since we never know what the true model is and the stability and accuracy of our estimation is significantly augmented. That is why G-dWOLS is powerful in quantifying the effect of treatment.

Data and Background

Forest fire can bring enormous damages in various aspects. Its occurrence and spread are affected by weather, humidity, ground type and so on. The ultimate goal for forest management agency is to deploy resources appropriately and adopt the optimal fire suppression strategy to minimize the loss brought by fires. In this work, the analysis is performed on Alberta's wildfires from years between 2003 and 2014. It is from a publicly available data source issued by Alberta's Agriculture and Forestry ministry. In this context, the treatment, or intervention, is the fire suppression method. There are four kinds of action to suppress the fires. From top to down, they are believed to be decreasing in their potency:

1) Air Tanker,
2) HAC1R (Heli-attack crew with helicopter and rappel capability),
3) HAC1H (Heli-attack crew with helicopter but no rappel capability),
4) HAC1F (Fire-attack crew with or without a helicopter and no rappel capability),
5) Other ground-based action



Identification: Causal effect → Observed effect conditioned on W, $E[Y|T, W]$
Estimation: $E[Y|T, W]$ → Propensity Score Stratification

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.235860	0.260880	-8.570	< 2e-16	***
FWI_D0	0.020474	0.004539	4.511	6.59e-06	***
FWI_D1	0.009133	0.002170	4.209	2.61e-05	***
Year	-0.010078	0.005951	-1.694	0.090392	.
Detection_AgentLKT	0.129601	0.051946	2.495	0.012628	*
Detection_AgentUNP	-0.043431	0.051651	-0.841	0.400471	
Eco_RegionMid-Boreal Uplands	0.228232	0.041791	5.461	4.94e-08	***
Eco_RegionOther	0.152478	0.057780	2.639	0.008341	**
Fuel_TypeM2	-0.181967	0.049865	-3.649	0.000266	***
Fuel_TypeOther	0.082705	0.049053	1.686	0.091847	.
TreatmentHAC1R	2.328445	0.342577	6.797	1.18e-11	***
TreatmentHAC1H	1.693989	0.344039	4.924	8.74e-07	***
TreatmentHAC1F	2.461398	0.343615	7.163	8.94e-13	***
TreatmentGround-based action	1.268188	0.348199	3.642	0.000273	***
PeriodPM	-0.779910	0.130037	-5.998	2.13e-09	***
MonthJuly	-0.097282	0.056563	-1.720	0.085513	.
MonthJune or May	0.111092	0.055970	1.985	0.047212	*
log_Response_Time	0.082103	0.016972	4.838	1.35e-06	***
log_Count_Fire_Overlap	0.667781	0.042104	15.860	< 2e-16	***
log_IA_size	-0.052792	0.019404	-2.721	0.006537	**
FWI_D0:TreatmentHAC1R	-0.026001	0.006285	-4.137	3.57e-05	***
FWI_D0:TreatmentHAC1H	-0.013792	0.006091	-2.264	0.023597	*
FWI_D0:TreatmentHAC1F	-0.019448	0.006298	-3.088	0.002024	**
FWI_D0:TreatmentGround-based action	-0.005049	0.005997	-0.842	0.399948	
TreatmentHAC1R:PeriodPM	0.365259	0.182572	2.001	0.045482	*
TreatmentHAC1H:PeriodPM	0.720043	0.178477	4.034	5.55e-05	***
TreatmentHAC1F:PeriodPM	0.449124	0.181470	2.475	0.013357	*
TreatmentGround-based action:PeriodPM	0.668383	0.187894	3.557	0.000378	***
TreatmentHAC1R:log_Response_Time	-0.104035	0.023277	-4.469	8.01e-06	***
TreatmentHAC1H:log_Response_Time	-0.089251	0.023158	-3.854	0.000118	***
TreatmentHAC1F:log_Response_Time	-0.085090	0.023349	-3.644	0.000271	***
TreatmentGround-based action:log_Response_Time	-0.083382	0.021109	-3.950	7.91e-05	***
TreatmentHAC1R:log_Count_Fire_Overlap	-0.414000	0.058959	-7.022	2.46e-12	***
TreatmentHAC1H:log_Count_Fire_Overlap	-0.441786	0.058572	-7.543	5.38e-14	***
TreatmentHAC1F:log_Count_Fire_Overlap	-0.592688	0.059072	-10.033	< 2e-16	***
TreatmentGround-based action:log_Count_Fire_Overlap	-0.387069	0.057543	-6.727	1.92e-11	***
TreatmentHAC1R:log_IA_size	0.127965	0.027115	4.719	2.43e-06	***
TreatmentHAC1H:log_IA_size	0.098549	0.027423	3.594	0.000329	***
TreatmentHAC1F:log_IA_size	0.082761	0.027776	2.980	0.002899	**
TreatmentGround-based action:log_IA_size	0.048814	0.026901	1.815	0.069651	.

Figure 1: The coefficients of model with interaction terms. The outcome is the logarithm of fire size at the stage being held divided by its size at the initial attack.

	Air Tanker	HAC1R	HAC1H	HAC1F	Ground-based action
n	624	1985	1128	1503	199
FWI_Dm1 (mean (SD))	11.18 (8.41)	12.94 (8.67)	13.52 (9.04)	10.20 (7.79)	29.42 (9.74)
FWI_Dm2 (mean (SD))	10.29 (8.41)	11.89 (9.21)	11.66 (9.62)	10.49 (8.60)	24.79 (9.83)
FWI_D0 (mean (SD))	9.28 (8.21)	14.54 (9.20)	10.08 (7.22)	11.43 (8.23)	28.40 (8.97)
FWI_D1 (mean (SD))	7.57 (8.03)	9.18 (9.42)	8.46 (8.13)	8.43 (8.43)	20.27 (13.14)
FWI_D2 (mean (SD))	7.75 (8.18)	8.83 (9.62)	8.37 (8.22)	7.53 (8.10)	15.89 (14.15)
Year (mean (SD))	8.29 (3.80)	5.61 (3.11)	5.82 (3.13)	5.59 (3.01)	5.76 (3.38)
Detection_Agent (%)					
AIR	94 (15.1)	347 (17.5)	183 (16.2)	536 (35.7)	40 (20.1)
LKT	288 (46.2)	1067 (53.8)	698 (61.9)	543 (36.1)	103 (51.8)
UNP	242 (38.8)	571 (28.8)	247 (21.9)	424 (28.2)	56 (28.1)
Eco_Region (%)					
Clear Hills Upland	135 (21.6)	448 (22.6)	1 (0.1)	817 (54.4)	51 (25.6)
Mid-Boreal Uplands	387 (62.0)	1486 (74.9)	1002 (88.8)	353 (23.5)	9 (4.5)
Other	102 (16.3)	51 (2.6)	125 (11.1)	333 (22.2)	139 (69.8)
Fuel_Type (%)					
C2	383 (61.4)	1370 (69.0)	896 (79.4)	1013 (67.4)	119 (59.8)
M2	145 (23.2)	368 (18.5)	97 (8.6)	249 (16.6)	33 (16.6)
Other	96 (15.4)	247 (12.4)	135 (12.0)	241 (16.0)	47 (23.6)
Period = PM (%)	49 (7.9)	1974 (99.4)	1122 (99.5)	1471 (97.9)	187 (94.0)
Month (%)					
August to October	183 (29.3)	310 (15.6)	126 (11.2)	254 (16.9)	49 (24.6)
July	223 (35.7)	927 (46.7)	557 (49.4)	709 (47.2)	82 (41.2)
June or May	218 (34.9)	748 (37.7)	445 (39.5)	540 (35.9)	68 (34.2)
log_Duration_BH (mean (SD))	2.50 (1.61)	1.72 (1.58)	2.12 (1.50)	1.86 (1.72)	2.70 (1.81)
log_Response_Time (mean (SD))	7.49 (1.71)	7.64 (1.51)	6.89 (1.64)	4.44 (3.22)	6.97 (2.06)
log_Count_Fire_Overlap (mean (SD))	3.38 (1.00)	3.68 (0.97)	3.92 (0.99)	3.84 (0.98)	4.11 (1.23)
log_IA_size (mean (SD))	-2.74 (2.00)	-3.72 (1.39)	-0.58 (1.87)	-2.86 (1.96)	-1.45 (2.64)

← Table 1: Summary of fire's characteristics conditional on the observed treatment.

Table 2: → Characteristics under each predicted best treatment following the model with logarithm of fire size at the stage being-held divided by its size at the initial attack as response.

	Air Tanker	HAC1R	HAC1H	HAC1F	Ground-based action
n	920	495	3017	540	467
FWI_Dm1 (mean (SD))	13.18 (8.77)	13.33 (9.46)	12.31 (9.24)	13.68 (9.28)	12.57 (9.54)
FWI_Dm2 (mean (SD))	11.52 (8.87)	12.67 (11.87)	11.50 (8.99)	12.30 (8.89)	12.15 (10.88)
FWI_D0 (mean (SD))	14.15 (8.89)	13.09 (9.06)	12.10 (9.11)	13.01 (8.90)	12.43 (10.40)
FWI_D1 (mean (SD))	9.76 (9.23)	9.62 (9.05)	8.70 (9.06)	9.34 (9.57)	8.88 (9.52)
FWI_D2 (mean (SD))	9.00 (8.99)	8.98 (9.24)	8.17 (8.99)	9.36 (9.78)	8.21 (9.25)
Year (mean (SD))	5.64 (3.34)	5.36 (3.09)	6.26 (3.32)	5.51 (3.23)	5.84 (3.05)
Detection_Agent (%)					
AIR	146 (15.9)	103 (20.8)	738 (24.5)	136 (25.2)	77 (16.5)
LKT	553 (60.1)	228 (46.1)	1482 (49.1)	248 (45.9)	188 (40.3)
UNP	221 (24.0)	164 (33.1)	797 (26.4)	156 (28.9)	202 (43.3)
Eco_Region (%)					
Clear Hills Upland	169 (18.4)	174 (35.2)	831 (27.5)	107 (19.8)	171 (36.6)
Mid-Boreal Uplands	680 (73.9)	251 (50.7)	1764 (58.5)	348 (64.4)	194 (41.5)
Other	71 (7.7)	70 (14.1)	422 (14.0)	85 (15.7)	102 (21.8)
Fuel_Type (%)					
C2	729 (79.2)	334 (67.5)	2077 (68.8)	378 (70.0)	263 (56.3)
M2	84 (9.1)	77 (15.6)	543 (18.0)	82 (15.2)	106 (22.7)
Other	107 (11.6)	84 (17.0)	397 (13.2)	80 (14.8)	98 (21.0)
Period = PM (%)	834 (90.7)	439 (88.7)	2646 (87.7)	486 (90.0)	398 (85.2)
Month (%)					
August to October	93 (10.1)	64 (12.9)	583 (19.3)	77 (14.3)	105 (22.5)
July	427 (46.4)	243 (49.1)	1373 (45.5)	254 (47.0)	201 (43.0)
June or May	400 (43.5)	188 (38.0)	1061 (35.2)	209 (38.7)	161 (34.5)
log_Duration_BH (mean (SD))	2.09 (1.49)	1.77 (1.55)	1.89 (1.68)	1.94 (1.63)	2.45 (1.70)
log_Response_Time (mean (SD))	6.53 (2.37)	6.58 (2.46)	6.51 (2.56)	6.35 (2.67)	7.14 (2.77)
log_Count_Fire_Overlap (mean (SD))	3.93 (1.03)	3.72 (1.00)	3.67 (0.98)	3.89 (0.96)	3.86 (1.09)
log_IA_size (mean (SD))	-1.72 (2.32)	-3.22 (1.90)	-2.84 (1.96)	-2.75 (1.97)	-2.36 (2.65)

Analysis and Result

To begin with, the original dataset is filtered and preprocessed. The final sample size is 5439. Variables that seems not to be so relevant or are obviously correlated with others are excluded. Some factor variables have categories merged to avoid small cell counts. Additionally, for stability's sake, log transformation is done on the variables that are heavily right skewed. The expert's choice among these fire suppression methods depends on many environmental factors assessed and known at that time, and not all fire suppression methods would be practical in some fires. Thus, we create Table 1 and observe the characteristics of fires classified by their fire suppression methods applied. Weights on estimating equations are calculated following the details in the methodology of G-dWOLS. Weighted regression is exercised on the outcome model and the regression result is shown in Figure 1. A new Table 2 is created to summarize the characteristics of fires categorized by their best treatment estimated, to give a sense of which fire characteristics are associated with each particular recommended suppression method.

Conclusion

G-dWOLS provides a similar result as exhibited by the previous work. The air tanker, which is thought to be the most aggressive method, is the least effective one according analyses. Instead, helicopter and ground-based action are shown to be the more powerful intervention. Neverthesless, we don't stop at overall effects, but dig further to look for tailored suppression strategies. Thanks to the resistance to incorrect model specification brought by double-robustness property and the regression based DTR framework, we obtain more insights. In previous work in this dataset, only a single value, the population level averaged effect of each fire suppression method, is given using the confounding adjustment method like OW, IPW, TMLE and so on. G-dWOLS analysis provides us the quantified effect of each interaction terms, which ARE given in Figure 1 and indeed tell us more about this story. These terms show that the power of a specific fire suppression method is largely affected by the fire's characteristics at the individual level, such as fuel type, ecological region, logarithm of fire size at initial attack and so on. Disadvantageous conditions for air tanker, as the baseline, could be represented by the variable the number of additional fires burning and the response time so that the coefficient for interaction between treatment and these two are negative.

Additionally, Alberta's wildfire review also agrees, to some extent, with our new findings. Resources for helicopter based method and ground-based action is much more sufficient than ones for air tanker and it may explains why it comes to big fires, air tanker pales in comparison to other methods less desirable as a "blanket" (un-tailored) strategy. To sum up, although it is challenging to evaluate the effect of fire suppression methods using observational data, G-dWOLS, as a regression based method, help demystify what really happens as well as enlighten us to search for clues from other perspectives.

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