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Estimation of Forest Fire-fighting Budgets Using Climate Indexes

Zhen Xu and G. Cornelis van Kooten

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Zhen Xu and G.Cornelis van Kooten

ABSTRACT

Given the complexity and relative short length of current predicting system for fire behavior, it is inappropriate to be referred for planning fire-fighting budgets of BC government due to the severe uncertainty of fire behavior across fire seasons. Therefore, a simple weather derived index for predicting fire frequency and burned area is developed in this paper to investigate the potential feasibility to predict fire behavior and fire-fighting expenses for the upcoming fire season using climate indexes. Linear regression models with spatial dummy variables are employed to estimate necessary coefficients that describe relationships across climate events, regional weather conditions, fire behavior and direct fire-fighting expenses in the interior of British Columbia; and Monte Carlo simulation are then used to predict future situations. We conclude that the BC government can use the last-year average solely, or together with January through April climate indexes for planning wildfire budgets for the upcoming fire season.

Keywords: Fire-fighting Expense, Monte Carlo Simulation, Climate Index.

INTRODUCTION

Wildfires are a continual nuisance in British Columbia and may become an even greater problem in the future. During the past decade, an average of about 1,882 wildfires occurred annually, burning more than 110,000 hectares and costing $130 million per year. One obstacle that prevents the British Columbia Forest Service from responding adequately to severe fire incidences relates to the province's fire-fighting budget. In some years, the budget may be insufficient to enable the BC Forest Service to commit resources quickly enough to deal with wildfire; in particular, contracts with fire-fighting service providers call for too little effort when the number and size of fires is outside the 'normal' range. Indeed, the evidence indicates that, following every severe fire season, the provincial government is left with fire-fighting expenses that were greatly higher than expected (Figure 1) – it is as if every severe fire season is a black swan event.

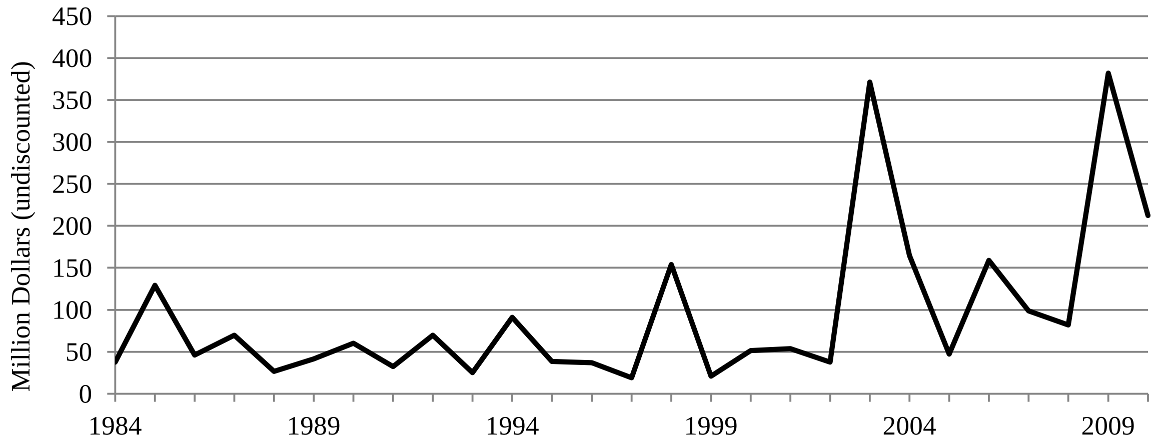

Figure 1: Direct Fire-fighting Expenses by BC Forest Service

Previous studies have shown that wildfires are strongly influenced by climate and associated weather conditions (Flannigan and Wotton, 2001; Hely et al., 2001; Wotton et al., 2003; Flannigan et al., 2005; Stock, 2006; Nitschke and Innes, 2008; Tymstra et al., 2007). Yet, despite the existence of some wildfire indexes for BC, there remains room to improve the statistical modeling of wildfire prediction. The reason relates to the complex nature of the direct and indirect impacts of climate change on wildfire, a complexity that cannot be dealt with using simple correlations and/or simple linear relationships and predictions from climate models.

Several previous studies have employed statistical approaches and forecasts based on historical data. Xu et al. (2011) used Kernel regression models to examine the relationship between wind direction and wildfire frequency in Los Angeles County, California. Collins et al. (2006) examined the relationship between yearly burn area in the western U.S. interior and climate indexes, such as the Atlantic Multidecadal Oscillation (AMO), Pacific Decadal Oscillation (PDO) and Southern Oscillation Index (SOI). They used a linear regression model with lagged values of these climate indexes and argued that a linear combination of indexes should be adequate for predicting future burn area (Balzter et al., 2005). Their results show that the warm-phase AMO and cool-phase PDO have a strong impact on wildfire size, but only in the southern interior of the West and not elsewhere. McKenzie et al. (2004) also estimated the log values of area burned with respect to summer temperatures and precipitation using a bilinear regression model for California and Nevada. Their analyses reveal that the relationship between area burned and climate conditions is highly nonlinear as area burned is dominated by rarely-occurring large fires, and relatively modest changes in mean climate could cause substantial increases in the area burned.

In addition to linear models, measures of statistical dependence between two variables are also employed. Dixon et al. (2008) and Meyn et al. (2009) used the Pearson's correlation coefficient between burn area and climate indexes, while Meyn et al. (2010) conducted a similar study using Spearman's rank correlation coefficient. Westerling and Bryant (2008) considered the small but substantial probability of large wildfires using a logistic regression model. They simulated the relationship for several climate scenarios between large fires and weather conditions, as well as soil conditions, and argued that climate should not be the only driver of current changes in wildfires.

As to spatial autocorrelation, Negreiros (2009) described how to construct a spatial neighborhood model using both inverse distance weights and binary neighborhood matrices. Gómez-Aparicio and Canham (2008), on the other hand, compared linear, logistic and exponential neighborhood models based on Weibull and lognormal neighborhood indexes, but then applied it to the impact of invasive tree species on local ecosystems as opposed to wildfire.

In this study, we develop a simple weather derived index for predicting wildfire for the interior of British Columbia, the most fire prone region in the province. In particular, we develop an index that is based on the estimated impact of temperatures and precipitation on wildfire events. We use historic climate data recorded by weather stations in and around our study area to construct our index, although we also consider scenarios that rely on data from regional climate models. Doing so provides more detailed data features but results in a relatively coarse spatial resolution. We employ much the same data as the current Fire Weather Index (FWI) used by the Wildfire Management Branch (WMB) of the BC Forest Service. These data consist of historical wildfire outbreaks, area burned and Forest Service weather station data. But we extend the work in several directions: (1) In addition to the Forest Service weather data, we employ data from Environment Canada's weather station network. (2) We develop a multiple-equation panel regression model that includes temperatures and precipitation as well as climate factors, such as the Pacific Decadal Oscillation, El Niño and Southern Oscillation. (3) To correct for spatial autocorrelation, we construct a GIS database that facilitates the use of spatial variables (e.g., nearest neighbors). (4) Finally, our ultimate objective is to develop a simple indicator that does not require the input of large amounts of data that may be difficult to collect.

II. STUDY AREA

Our study area constitutes the Northern and Southern Interior Forest Regions of British Columbia, but excludes the Coast region where wildfires are not usually the most destructive natural disturbance (Figure 2). It includes 22 forest districts according to an earlier BC Forest Service classification and encompasses more than 84% of total forestland in British Columbia.[1] The geographic landscape changes dramatically in the interior due to the north-south-oriented Cordilleran mountain system, including the Coast and Rocky mountains. The topography fluctuates greatly in elevation and, as a result, climate conditions also vary critically throughout the region. Temperature is determined primarily by elevation rather than terrain. Precipitation shows a similar spatial pattern in terms of the unique topography but, unlike temperature, it also displays a significant west-east gradient as the Cordilleran Mountains serve as a barrier for both westward flows of cold continental arctic air masses from the rest of Canada and moisture-

[1] The classification was modified by the Ministry of Forests, Lands and Natural Resource Operations in 2011.

laden east-flowing winds from the Pacific Ocean (Meyn et al., 2009).

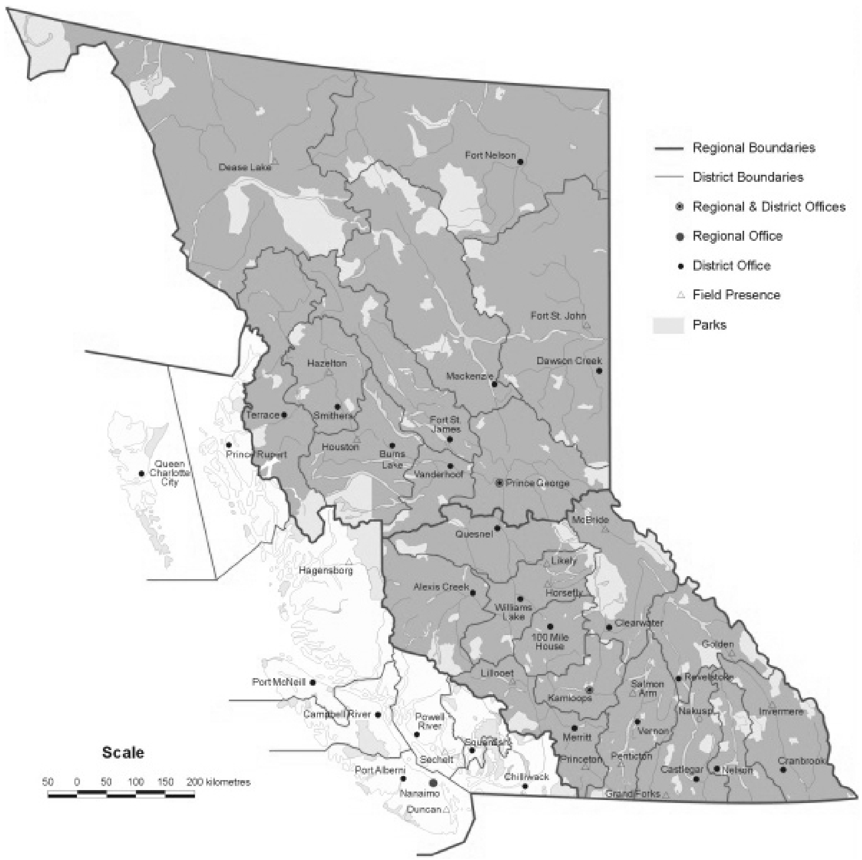

Figure 2: Study Area: Northern and Southern Interior Forest Regions
Source: Ministry of Forests, Lands and Natural Resource Operations http://www.for.gov.bc.ca/mof/maps/regdis/regdismap.pdf

Wildfire activity in the interior can at times be severe and varies greatly according to topography and climate conditions. Figures 3 and 4 give a numerical and spatial illustration of changes in fire density at different fire centres. The Kamloops and Southeast fire centres suffered the highest fire risk during 2000-2009; wildfire incidence and severity are less onerous in the north, especially the northwest. However, for really large fire events, say the largest three percent that contribute to more than 97% of the burned area across Canada (Kurz et al., 2008), spatial distributions are quite different. In Figure 5, we take fire events in July 2009 as an example and group them according to their size. It seems that they do not follow the same pattern as that of wildfires of all sizes. Because fire behavior is uncertain in each season, the distribution of large fires in a single month may not be sufficient to conclude that large fires exhibit a different distribution pattern than all fires; however, if there is a distinct spatial distribution of large fires, it should play a significant role in its impact on fire-fighting costs.

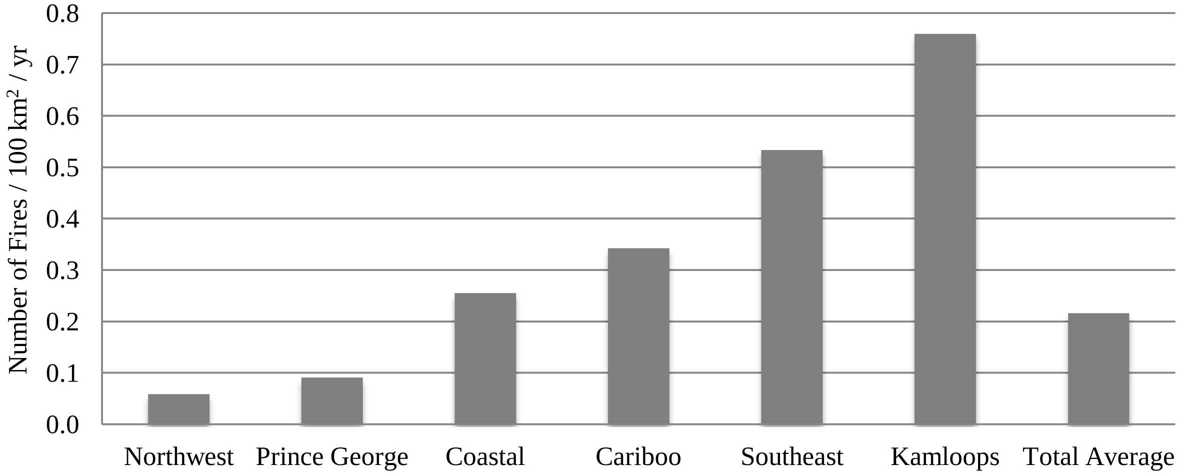

Figure 3: Fire Density across Different Fire Centres, 2000-2009

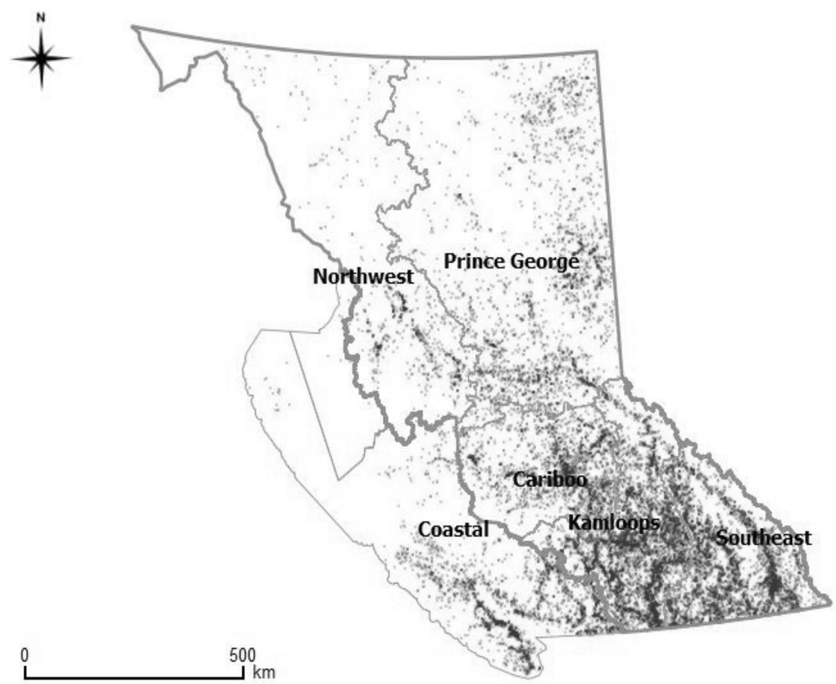

Figure 4: Spatial Distribution of Fire Density in Different Fire Centres, 2000-2009

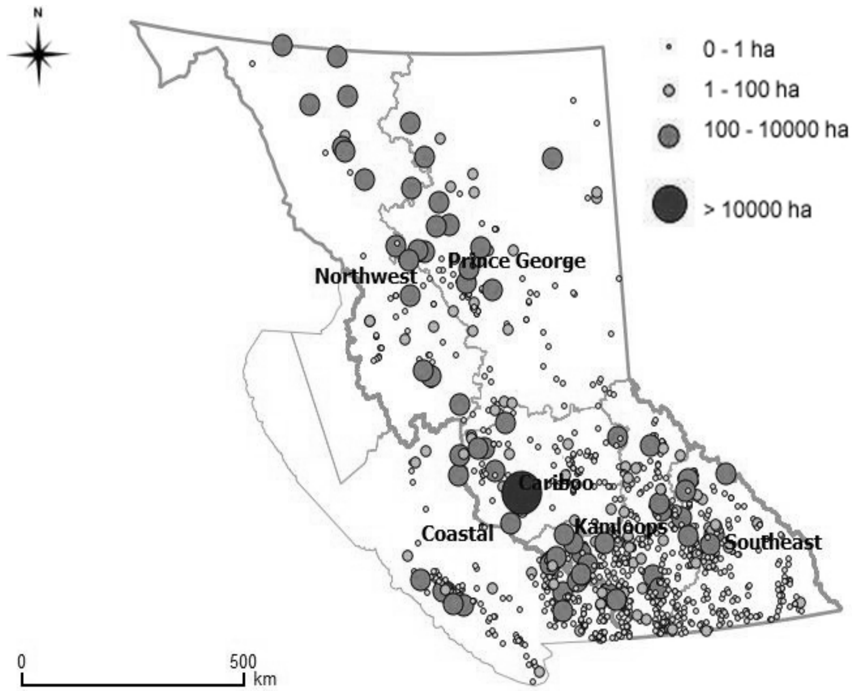

Figure 5: Spatial Distribution of Scaled Fire Events in Fire Centres in July, 2009

III. DATA

To examine the relationship between climate factors and wildfire behavior in the interior of BC, five datasets were constructed: (1) spatial data pertaining to the five forest districts and 22 forest regions; (2) daily regional weather data from available weather stations in the BC interior and their location; (3) monthly data on global climate events; (4) spatial data on historical wildfires; and (5) annual data on government fire-fighting expenses.

Forest district data

We employ the forest region/district classifications in Figure 1, with only one necessary modification that even differs from the province's previous configuration. Because the Skeena Stikine District actually consists of two separate pieces – the Skeena Stikine and Dease Lake areas – we separate this District into these two separate regions for convenience. In total, therefore, we get 22 forest districts in our study area. Data were obtained from the Geo BC service desk provided by the Integrated Land

Management Bureau (http://geobc.gov.bc.ca/). The data pertaining to forest districts include the boundary information, which is used for categorizing fire events and weather conditions, and the elevation of the centroid of each district. Each forest district is identified by a unique ID number and a related name.

Wildfire data

Historical wildfire data from Geo BC are entered into a Geographic Information System (GIS) model, with each fire event represented by a point in space in the GIS layer. It contains all fire events tracked by the WMB since 1950, including actual, suspected and nuisance fires and smoke chases. In this study, we only consider the actual fires with a recorded burned area greater than zero and located inside the spatial layer of the BC forest districts. Thus, our dataset has 122,910 fires since 1950.

Based on the location of each fire event, we calculate the monthly number of wildfires in each forest district, and use GIS to create a variable that indicates the average distance between the location of a fire event and the nearest town in each district. By repeatedly regressing fire-fighting cost with respect to different combinations of distance and fire size, we find that the most significant factors affecting fire-fighting expenses are monthly wildlife frequency, total burn size, and the average distance from nearest town to fires greater than 100 ha. We also created a seasonal dummy variable to identify fire season (May to September) based on historical distributions of fire in each month.

Annual direct fire-fighting costs for the entire province were collected from annual BC Forest Service reports. We assume that only direct fire-fighting expenditures change with fire behavior in a given year; expenditures include fire fighters' wages, equipment costs, aircraft usage fees and so on. Fire detection and monitoring costs, crew training, investment in equipment, and other costs that are independent of the number of fires in a given year are excluded. In addition, even for direct fire-fighting expenses, our data include only the part paid by the provincial government and exclude expenses paid by companies and private landowners. Direct fire-fighting costs were adjusted by the Consumer Price Index to 2002 dollars and constitute the dependent variable in the second-stage regression.

Weather station data

To obtain weather data, we first explored all available weather station data for the province, and then filtered the data according to certain criteria. We created a dataset that includes 1997 weather stations maintained since 1950 by either the Wildfire Management Branch or Environment Canada (EC). Only weather stations in current use and those archived with start and decommission dates were considered. We excluded weather stations located outside the boundary of the GIS layer of our study area, and those used only for recording wind conditions. As a result, we were left with 1229 weather stations whose data were aggregated to represent monthly conditions at each forest district.

Each data record includes ID number, name, location and elevation of a weather station. We ensured that there is sufficient data from at least one weather station in each district in each month to estimate the weather conditions for that district. This turned out to be satisfied when we combined the two datasets from the WMB and EC. In addition, we measured the distance between each weather station and the centroid of the district in which the station is located. The inverse distances will be used as weights to calculate the temperature and precipitation for the centroids.

The weather data are daily and formatted as a big panel that is identified by date and related weather stations. This huge database contains various attributes, including mean temperatures, total precipitation, wind speed, wind direction and relative humidity. However, we only select mean temperatures and total precipitation as regressors in our model, because we assume that wind speed and direction only have instant impacts on fire size (i.e., no lagged effects) rather than on fire occurrence, and that relative humidity is highly related to precipitation. We investigated this hypothesis by running a linear regression model with our existing data, and it turned out that relative humidity is highly related to precipitation, as expected, while the impact of wind speed on fire frequency and burn size appears to be insignificant. For each weather station, the data were first aggregated to a monthly basis; because for some stations temperature and precipitation data are not always available for all days in each month, we only employed the monthly data from those weather stations that have valid data for more than 20 days.

Climate indexes

To take the potential impacts of global climate events into account, we collected data for five climate indexes as listed in Table 1. The determination was made using preliminarily regression analysis relating climate indexes to annual fire frequency throughout the province. Climate index data are also monthly with different time spans. Since climate events exert their impacts over a much larger spatial scale than the regional level, we assume that the impacts of these climate events are identical across districts and only change with time. They serve as the integral circumstance responding to the long-term periodic effects of climate change on wildfires, and are expected to affect the long-term trend of changes in fire behavior.

Table 1: Climatic Indexes in Regression Models

Index	Description	Data Source
EN3	El Niño index, sea surface temperature anomaly (SSTA) at region El Niño 3	Climate Prediction Center, National Oceanic and Atmospheric Administration ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/
PNA	Pacific/North America Pattern index, difference of normalized sea level pressure (SLP) at North Pacific Ocean polar ward of 20°N-90°N	University Corporation for Atmospheric Research http://www.cgd.ucar.edu/cas/catalog/climind/
SOI	Southern Oscillation Index, difference of normalized SLP at Tahiti minus Darwin	University Corporation for Atmospheric Research http://www.cgd.ucar.edu/cas/catalog/climind/darwin.ascii http://www.cgd.ucar.edu/cas/catalog/climind/tahiti.ascii
NAO	North Atlantic Oscillation index, normalized SLP difference between Ponta Delgada, Azores and Stykkisholmur/Reykjavik, Iceland	University Corporation for Atmospheric Research http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#naostatseas
PDO	Pacific Decadal Oscillation index, SSTA at North Pacific Ocean polar ward of 20°N	Joint Institute for the Study of the Atmosphere and Ocean http://jisao.washington.edu/pdo/img/v1v2PDOComp.png

IV. SPATIAL ANALYSIS

Our spatial analysis includes spatial interpolation of weather data for each forest district (combining different spatial attributes from multiple layers) and tests for spatial autocorrelation in terms of fire incidence in each district. We begin by generating the Thiessen polygons for the forest districts in our study area. Considering most of the forest districts have irregular shapes and because some weather stations are much farther from the centroid than others, it is misleading simply to aggregate weather information from all the stations in a district. Rather, to correct such bias, we transform the forest districts to Thiessen polygons based on the locations of their centroids. By transforming to Thiessen polygons, we ensure that the aggregated weather data at the centroid of each forest district give much greater weight to the nearest stations. The transformed Thiessen polygons, which were generated by Quantum GIS (QGIS) for all districts in the study area, are provided in Figure 6. For convenience, we use Thiessen polygons as our new cross section units in the regression model instead of the actual districts.

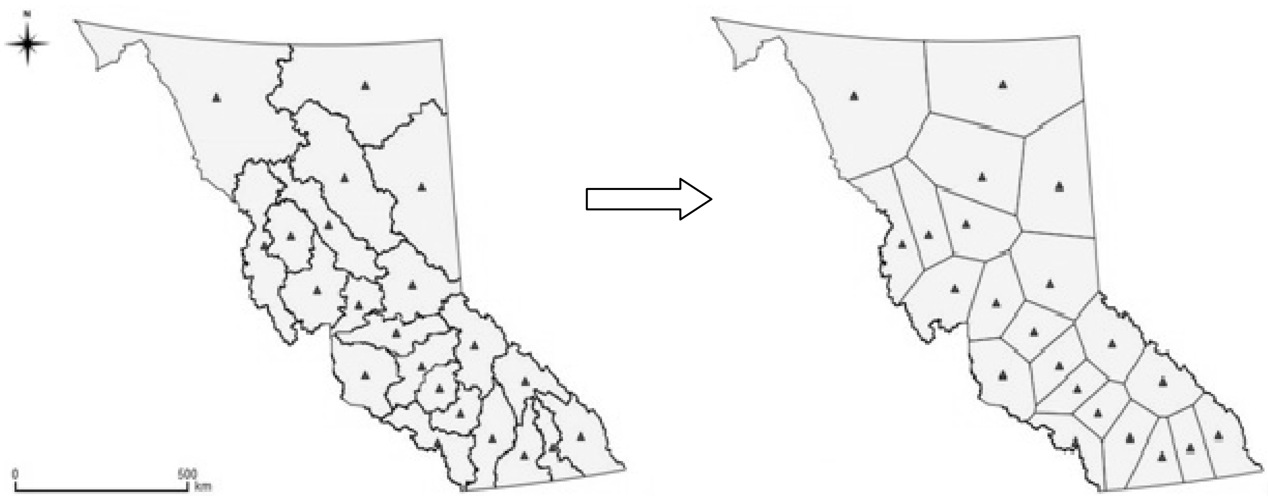

Figure 6: Transforming Forest Districts to Thiessen Polygons based on Centroids

Spatial layer for fire events

To obtain the monthly number of fires in each district, we first filtered the fire layer to exclude those unusable observations and clipped this layer with the forest district layer of the BC interior to get the fire data within it. Then we joined the attributes from two layers together using locations to identify the forest district to which each fire event belongs. By counting the number of fire events and summarizing the burn area in each district by month, we get the total monthly number of fires and total burn sizes. We further separated the monthly data by preset control variables to examine how different locations affect fire-fighting expenses. Examples of the process for fire events that occurred in 2009 are provided in Figures 7 and 8.

To examine whether the number of wildfires of a certain size would affect the fire-fighting expenses more significantly than other fire sizes, we marked all fires according to different burn sizes with black dots by joining the attributes from both the fire layer and the district layer according to the location coordinates attached to each fire event. In Figure 7, we illustrate the fire events that are greater than 100 ha. To examine the potential impact of fires that occurred really close to towns, we added a municipality layer to the current layers and created different buffer zones in terms of distances for each patch to identify the near-town fire events. This is illustrated in Figure 8 for the near-to-town fires located within 5-km buffer zones. Notice that each fire and the nearest town to it are not necessarily located in the same district.

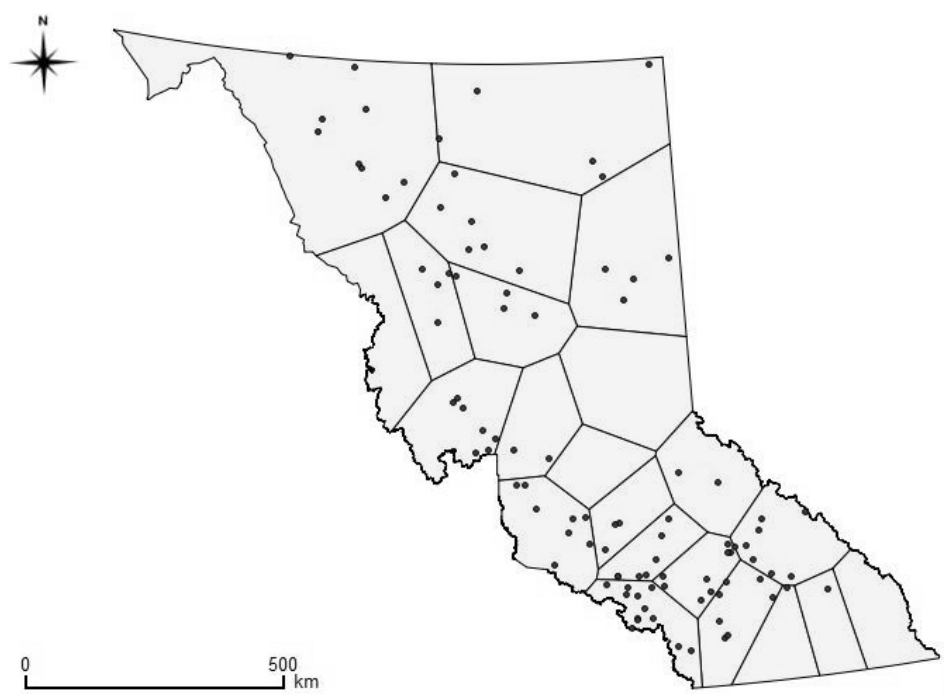

Figure 7: Fires Greater than 100 ha

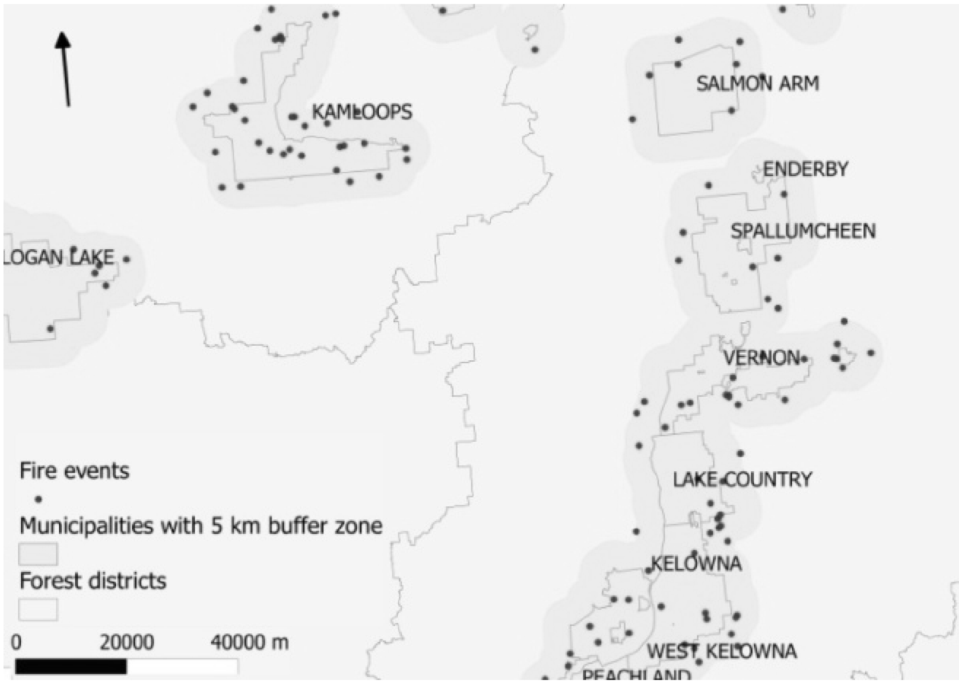

Figure 8: Fires within a 5-km Buffer Zone

Spatial autocorrelation of fire behavior

Using the combined spatial layer for fire events and district boundaries, we tested the spatial autocorrelation of fire behavior throughout the entire study area on the basis of districts. We constructed the tests in three different ways. We first used the nearest neighbor analysis provided by QGIS to examine the evenness of the spatial distribution of fire events in each year based on their locations and the distances between every event and their nearest neighbor. Second, we used Geary's C index and, third, Moran's I index to test potential autocorrelations of number of fires and burn size by district with their neighbors.

The nearest neighbor analysis uses the Nearest Neighborhood Index (NNI) to evaluate how observations of interest are distributed across a certain area. Basically, the value of NNI ranges from 0 to 2.15. The closer NNI is to zero, the more clustered is the distribution; in contrast, values close to 2.15 are indicative of a uniform distribution, while NNI=1 represents a random distribution. There are two different formulae for calculating NNI. We employed a method specified by Corral-Rivas et al. (2010):

$$(1) \qquad NNI = \frac{\sum_{i=1}^{n} d_{i,j}}{n} \Big/ \frac{1}{2}\sqrt{S/n} \; , \quad 0 < i, j \leq n; \;\; n, S > 0 \; ,$$

where the numerator refers to the average distance of all *n* fires to their nearest neighbors, with d_i denoting the distance of fire *i* from its nearest neighbor *j*, and *S* the area of the minimum square that embraces all fire events. For every year, we calculated the NNIs for all fires greater than 100 ha and the total average.

As indicated in Figure 9, the NNI changes dramatically from a clustering tendency to a more uniform one over time. The overall average NNI of 0.785 shows a primarily random distribution with a mild clustering tendency in all 60 years, which means that the spreading pattern for large fires is generally spatially random in most years but with several notable exceptions where a significant uniform distribution is apparent. As we only examine the NNI for large fires, the distribution of all fires could be different given that the characteristics of large fires might differ from those of small ones. Large wildfires likely consume more fuel per hectare and consume it more rapidly that smaller fires; if fuel characteristics (e.g., fuel load, species composition) vary across the province, one might expect clustering behavior. Further, large fires may require greater management effort per hectare, particularly to prevent their spread.

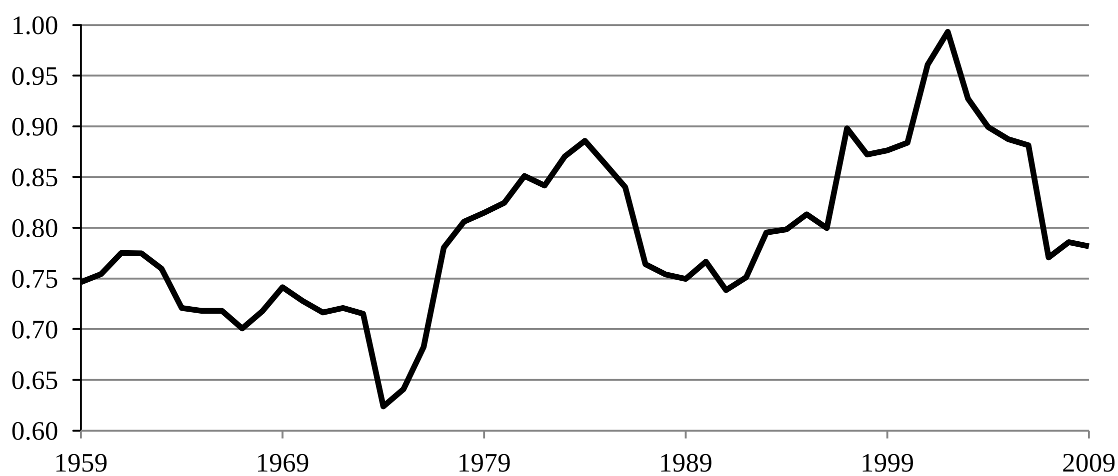

Figure 9: Ten-Year Moving Average of NNI, 1959 - 2009

For potential spatial autocorrelation of fire frequency among districts, we calculated the values of Geary's C (Geary, 1954) and Moran's I (Moran, 1950) indexes. According to the results presented in Figure 10, we believe that fire frequency in each district is at least somewhat affected by its neighbors. Thus, we need to include certain variables in our model to account for such spatial autocorrelation. We discuss this in more detail in the following section.

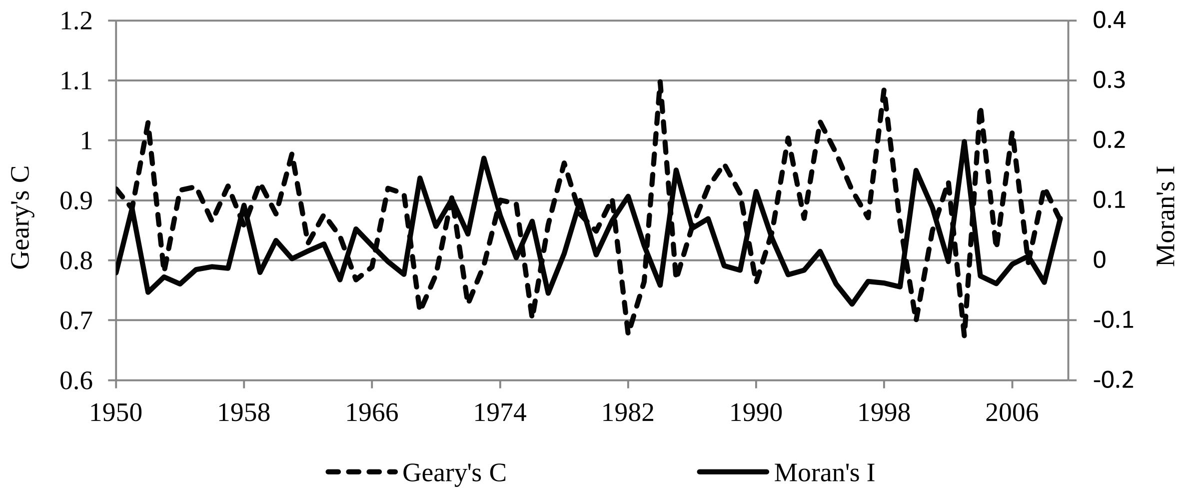

Figure 10: Spatial Autocorrelations of Fire Frequency among Districts

Weather data aggregation

Weather station data were adjusted for distance and elevation during the aggregation, but only weather stations in the same polygon were used. Because the number and the spatial distribution of available weather stations for each district vary across months due to the different decommission dates, we first grouped the weather stations by Thiessen polygons and months as a panel, and then measured distances between the available stations and the centroids for each district in each month. As an example, consider the Quesnel Forest District in Figure 11. We first found the centroid for this district and obtained the distances between the five stations in the district and the centroid, respectively. We then weighted the weather data from each of the stations using inverse distances to obtain representative weather conditions for the entire district. Since not all stations are available for all the years, the number of weather stations used in each year varies, so we used start and decommission dates for archived stations to determine when to include them in the aggregation.

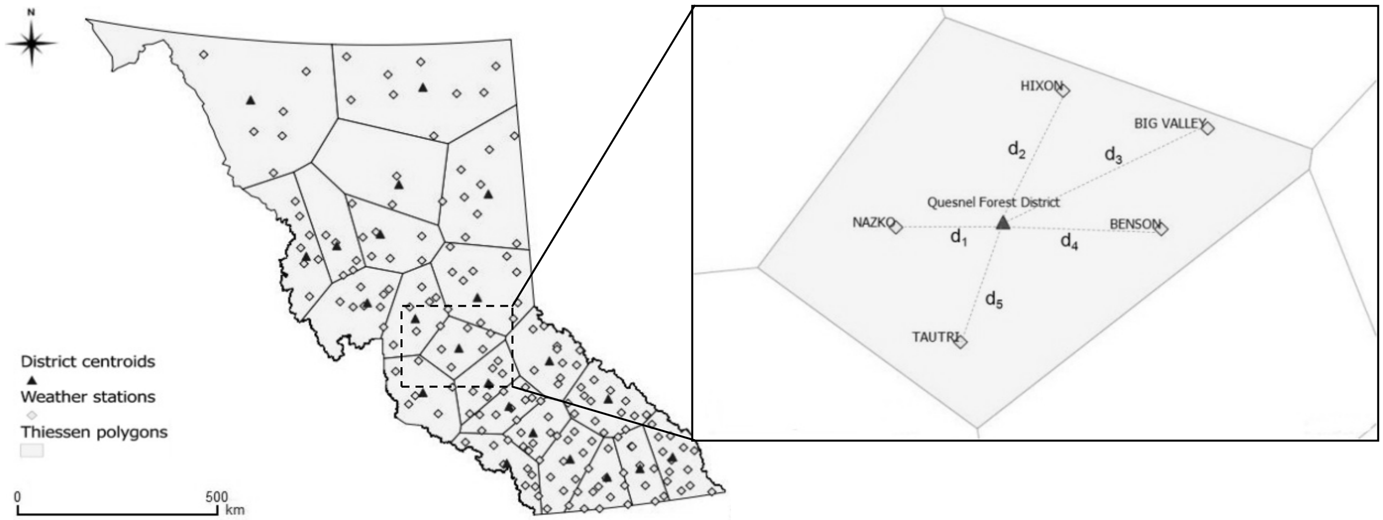

Figure 11: Weather Data Aggregation for the Quesnel Forest District in July, 2009

In addition to the distance adjustment, we also considered the gradient changes in temperature resulting from elevation differences; we assumed that precipitation has no such elevation related problem, or at least it was not a significant influencing factor in this study. Adjustment for elevation in some previous studies had been done using specific lapse rates, such as 6.5℃ /km, or by calculating monthly lapse rates in terms of different seasons and meteorological conditions (Stahl et al., 2006). In the current study, we simply used the global standard lapse rate of 6.5℃ /km. We first adjusted the temperature data from all weather stations in each district so it corresponded to the elevation at the district centroid, and then adjusted the data using the weighted moving average discussed above.

We developed a weighted matrix W in which all distances $d_{i,j,t}$ in time t $(t = 1, \ldots, T)$ between the centroid of forest district i ($i = 1, \ldots, I$) and weather station j ($j = 1, \ldots, J_i$, where J_i is the number of weather stations in district i) are measured as a weighted index $W_{i,j}$.

(2) $$W = \begin{bmatrix} W_{1,1} & \cdots & W_{1,T} \\ \vdots & \ddots & \vdots \\ W_{I,1} & \cdots & W_{I,T} \end{bmatrix}$$

For any given district *i* and month *t*,

(3) $W_{i,t} = [W_1 \quad W_2 \quad \cdots \quad W_{J_i}]$,

where

(4) $W_{j_i} = w_{j_i} / \sum_{j_i=1}^{J_i} w_{j_i}$

(5) $w_{j_i} = \frac{1}{d_{i,j,t}^{\beta}}, \beta \geq 1$

In Equations (4) and (5), W_{ji} is the weight of weather station *j* in district *i*; w_{ji} is the inverse of the distance ($d_{i,j,t}$) between weather station *j* and the centroid of district *i* at time *t*; and β is a smoothing parameter that weakens the impact of weather data that are from relatively farther weather stations. With such a weighted matrix, weather data $X_{i,t}$ from all available weather stations in any given district *i* and month *t* can then be weighted as:

(6) $$X_{i,t} = [x_1 \quad x_2 \quad \cdots \quad x_{J_i}] \times \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_{J_i} \end{bmatrix} = \begin{bmatrix} x_1 w_1 / \sum_{j_i=1}^{J_i} w_{j_i} & & \\ & \ddots & \\ & & x_{J_i} w_{J_i} / \sum_{j_i=1}^{J_i} w_{j_i} \end{bmatrix}$$

V. REGRESSION MODELS

A two-stage regression model is employed. In the first stage, we estimate monthly wildfire behavior and projected weather conditions based on climate indexes. In the second stage, the results from the first stage regressions are aggregated to create an annual time-series that is then used to estimate the annual fire-fighting expenses for all forest districts.

Fire behavior estimation

For the estimation of wildfire behavior, we employ a linear regression model in which fire frequency and burned area are functions of weighted temperatures and precipitation, inverse distance to the nearest town, and district dummy variables:

(7) $$N100_{i,t} = a_0 + a_1 \times TEMP_{i,t} + a_2 \times PREC_{i,t} + \sum_{k=1}^{21} a_{k+2} \times D100I_{i,t} \times D_k + u_i^a + \varepsilon_{i,t}^a$$

(8) $$S100_{i,t} = b_0 + b_1 \times N100_{i,t} + b_2 \times D100_{i,t} + b_3 \times TEMP_{i,t} \times PREC_{i,t} \times SDUM_t + \sum_{k=1}^{21} b_{k+3} \times D100_{i,t} \times D_k + u_i^b + \varepsilon_{i,t}^b$$

where $N100_{i,t}$ and $S100_{i,t}$ are, respectively, the number of fires greater than 100 ha and related burn size at time t in district i. $TEMP_{i,t}$ *and* $PREC_{i,t}$ are the respective monthly mean temperature and monthly total precipitation at time t in district i. $D100$ and $D100I_{i,t}$ are the average distance of all fires in district i to the nearest town in month t and its inverse value, respectively. $SDUM_t$ is a dummy variable indicating whether it is fire season or not, D_k serve as dummy variables that capture the district-dependent effects of distances, while u_i is addressed to represent the fixed effects specific to district i, and $\varepsilon_{i,t}$ refers to for the error term in each equation. For convenience, all the dummy variables used in the model are listed in Table 2.

We examine several possible independent variables for Equations (8) and (9), and find that similar regressors behave quite differently. Temperature and precipitation have a statistically significant affect on number of fires, but are insignificant in explaining burn size – only a significant interaction or combined impact of temperature and precipitation on burn size is found to occur during the fire season. One possible reason is that, once ignition spots appear and except for temperatures and precipitation that determine soil moisture and dryness of fuel load above ground, the primary factors impacting the speed at which fires spread include some instantaneous conditions such as transient wind speed and relative humidity. Not surprisingly, the number of fires in a period strongly affects burn sizes in that same period.

Table 2: Dummy Variables in the Regression Model

Variable Name	Description	Value and Condition
1st stage regression		
D1 … D21	District dummy variables that control spatial impacts of certain independent variables in terms of particular district	Only D1 = 1, if forest district 1 … Only D22 = 1, if forest district 22
SDUM	Seasonal dummy that indicates whether a certain impact occurs during the fire season or not	SDUM = 0, if January to April or October to December SDUM = 1, if May to September
2nd stage regression		
YDUM	Structural shift dummy that indicates whether the current year is before or after the structural break (which is detected for 1983 in the regressions of fire-fighting expense and wildfire behavior)	YDUM = 0, if in or before 1983 YDUM = 1, if after 1983

In addition to weather conditions, the average inverse distance to the nearest town has a similar impact, although the spatial autocorrelation of average distance on burn size is weaker. We employ district dummy variables to capture the district effects, with quite good statistical results. If fire prone areas are far from towns where fire-fighting facilities are located, there are more fires than in areas closer to town. However, when it comes to burn size, things appear to be different. We assume that fire-fighting activity is more readily initiated when fires get beyond a certain size and/or threaten nearby communities, but that, until some threshold is reached, wildfires are treated as a natural process that reduces fuel load and benefits forest ecosystems. In that case, the relation between distance to the nearest town and fire size is likely an inverse one. In addition to distance, some fire scenes may be quite difficult to reach with ground fire-fighting equipment due to the geographical conditions even though they are not far from town, and this gives a fire more time to increase in size. These factors indicate that fire size is an important determinant explaining fire-fighting expenses in our second-stage regression, even though fire size is difficult to explain using long-term climate variables.

Modeling temperature and precipitation

To predict what will happen in the upcoming fire season, we need to use projected temperatures and precipitation rather than historical data. To examine the validity and robustness of our model as a predictive tool, we estimate temperatures and precipitation based on climate indexes, global temperature anomalies, monthly mean atmospheric CO_2 concentration, and related lagged and dummy variables. We use normalized temperatures as the dependent variable in the regressions to get rid of the seasonal trend, but employ unadjusted precipitation because it does not exhibit a strong seasonal trend in our study area.

Monthly mean temperatures and precipitation are regressed on the one-month lagged values of the mean forest-district specific temperatures and precipitation, average concentration of atmospheric CO_2, and global temperature anomalies. Also included as regressors are climate indexes lagged by one month, climate indexes averaged over the immediate months before the upcoming fire season (January to April), and the annual mean value of the indexes for the previous year. The lags on regional weather conditions are meant to take into account possible spatial autocorrelation, while average global temperature anomalies and atmospheric concentration of CO_2 are used to capture the long-term global climate trend. Since climate indexes usually exert their influence 'behind the scenes,' three variables with different time spans address this potential impact.

A regression with one-month lags can only estimate temperatures and precipitation and thus predict wildfire for the next month. Such a regression provides a warning of fire risk for the next month and thereby an ability to reallocate some fire-fighting resources, but it cannot affect decisions regarding fire-fighting budgets, which are usually set at the beginning of a fiscal year (which begins April 1). To predict wildfire behavior in advance, say at the beginning of a year, we need to estimate temperatures and precipitation with longer period lags. Therefore, we consider another estimation model with regressors with yearly lags only.

An alternative way to estimate temperatures and precipitation with climate indexes and other climate conditions is to use projected data from regional climate models. In that case, independent variables from the same period as the dependent variables could be employed in the regression to capture the relatively short-term effects. We first examine the effects of various annual, seasonal and monthly lags on temperatures and precipitation; then the effects of yearly lags only; and, finally, the effects of yearly lags, seasonal lags, monthly lags and variables from the same period. The results are given in Appendix Tables A-2 to A-5.

With different explanatory variables, the results indicate that the regression including both lagged explanatory variables and explanatory variables from the same period performs somewhat better than the other models based on R^2 statistics. The regression that includes only annual lags as explanatory variables has the lowest fit statistic. This implies that serial autocorrelation coming from lagged explanatory variables declines as the length of the lagged period increases; in that case, if we only use variables from last year (explanatory variables lagged one year), the model fit would decline. Upon comparing estimates of temperatures and precipitation in each regression, we find current temperature to be affected by what happened last month and the preceding year, while precipitation is impacted to a lesser extent by what happened in the previous year. Notice that we multiply the lagged explanatory variables with spatial dummy variables, which means that those lagged explanatory variables have significant spatial effects in terms of district locations. This implies that changes in monthly mean temperature show a unique geographical pattern with respect to average elevation, latitude and longitude. In contrast, precipitation seems to be less related to long-term changes both temporally and spatially.

Estimating fire-fighting expenses

Unlike weather data, fire-fighting expenses have never been systemically scaled down to the forest district level but are only reported for the whole province. To estimate fire-fighting expenses, a second-stage regression uses annual non-expense data aggregated across districts. We generate the annual fire frequency and burn size by first taking the average for all districts in a single month and then for all months in each year. Notice that these aggregated data only represent fire conditions in the interior of BC, not those of the entire province. However, fire conditions in the interior of BC have historically accounted for an overwhelming proportion of fire-fighting expenses; hence, we believe that fire frequency and the burn size in the BC interior are the appropriate regressors to use in the second-stage regression.

As to the generation of annual average distances to the nearest town, we employ a slightly different approach whereby the annual average values are calculated on the basis of non-zero data only; otherwise, the values would be quite small and close to each other due to the large number of zeros inside the matrix. We run the regression with a time-series model for the 60-year period from 1950 to 2009. A plot of the data suggests that there may be a structural shift in the data in early 1980s, across which our regressors vary significantly. A Chow test for possible structural breaks in the fire-fighting expense data finds that the most statistically significant break occurs in 1983 (Table 3). We address this by running two different regressions and compare them. One includes a dummy variable to capture the break in 1983 and the other simply shortens the time series from 1984 to 2009; the results of both regressions are provided in Table 4.

Table 3: Chow Test for Possible Structural Shifts[a]

Possible breakpoints	1982	1983	1984	1985
F-statistic	30.7997	54.12933	51.1700	47.7993
Probability F(4,49)	0.0000	0.0000	0.0000	0.0000
Log likelihood ratio	75.4098	101.3916	98.6552	95.3784
Probability $\chi^2(4)$	0.0000	0.0000	0.0000	0.0000
Wald Statistic	123.1989	216.5173	204.6799	191.1973
Probability $\chi^2(4)$	0.0000	0.0000	0.0000	0.0000

[a] Null Hypothesis: No structural shift in the data series in each year.

Not surprisingly, we find that, for 1950 to 2009, more than 70% of the fluctuation in fire-fighting expenses can be explained by annual fire frequency and burn size, and the interaction between these variables and distance to the nearest town. Although we also included a trend variable (YDUM) in the regression to account for a temporal increase in fire-fighting expenditures that might be due to higher costs of equipment, say, we find this variable to be statistically insignificant. In contrast, if we consider only the period 1984 through 2009, we find that more than 93% of the fire-suppression expenses are determined solely by the annual fire frequency and monthly burn size. In this case, neither the distance nor the trend variable was statistically significant.

Table 4: Estimated Coefficients for Fire-fighting Expenses

Time series of 1950-2009 with structural shift in 1983		Time series of 1984-2009 without structural shifts	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
TREND	1.5933*** (0.5948)	S100A	0.0025*** (0.0003)
S100A × D100A	0.0001*** (0.0000)	N100A	0.5698** (0.2540)
N100A	2.9198** (1.1649)		
S100A	-0.0069*** (0.0019)		
N100A × D100A	-0.0297* (0.0163)		
YDUM	31.8512 (20.1542)		
R^2	0.720		0.935
SE of the estimate	70.428		87.722

VI. SIMULATION

We employ Monte Carlo simulation and historic weather data to predict fire behavior and its potential impact on fire-fighting expenses for the upcoming fire season. For the simulations, we use the estimated coefficients and their standard errors, plus the standard error of the estimate, from the previous section. We first simulate the weather index for weather data estimation, and then use the results to simulate the fire frequency and burn size, and, lastly, we simulate the fire-fighting expenses. Different scenarios are developed to correspond with different combinations of the lagged variables in the first-stage regression and the structural shift problem in the second one. For comparison, we consider a separate scenario in which projected weather data from climate models are used directly rather than the estimated weather data from our regression models. A description of what is included in the various scenarios is given in Table 5.

Table 5: Comparison of Different Simulation Scenarios

Model Specification	Scenarios			
	1	2	3	4
1st stage regression				
Including yearly lag variables	Y	Y	Y	N
Including seasonal lag variables	Y	Y	Y	N
Including monthly lag variables	Y	N	N	N
Including variables from the same period	N	N	Y	N
2nd stage regression [a]				
Using 1950-2009 baseline with a structural break in 1983	Y / N	Y / N	Y / N	Y / N
Using 1984-2009 baseline without structural breaks	N / Y	N / Y	N / Y	N / Y

[a] We simulate all four scenarios for both regressions in the second stage.

Using the regression results in the previous section, we generate the values for all coefficients in the simulation by randomly drawing from the normal distributions characterized by the previous regression results and run the Monte Carlo simulations using MATLAB. The simulations are done with three steps: First, we simply use the historic fire frequency and related burn size for each district in each month to simulate the overall fire-fighting expenses by taking an average over 10,000 iterations. In this step, we hind-cast costs for the period 1950-2009 on the basis of the 1984-2009 baseline estimates. This enables us to examine the explanatory power of the model. Since there is no simulation for the weather conditions and fire behavior, simulation in this step contains only a single scenario. The results are provided in Figure 12.[2]

The simulation in Figure 12 exhibits a similar trend to the historic situation in the long run, but underestimates extreme values. However, as shown in the figure, a 95% confidence interval nearly embraces all historic expenses except the very extreme ones, which indicates that our model performs well in simulating historic fire-suppression costs. Notice that the simulation in this case has nothing to do with our estimates of weather or fire behavior because we simply use historic values of these variables to

[2] In Figure 12 and Appendix figures, costs are displayed in 2002 dollar and ±std indicates a 95% confidence interval.

estimate the fire behavior and thus fire-fighting costs directly.

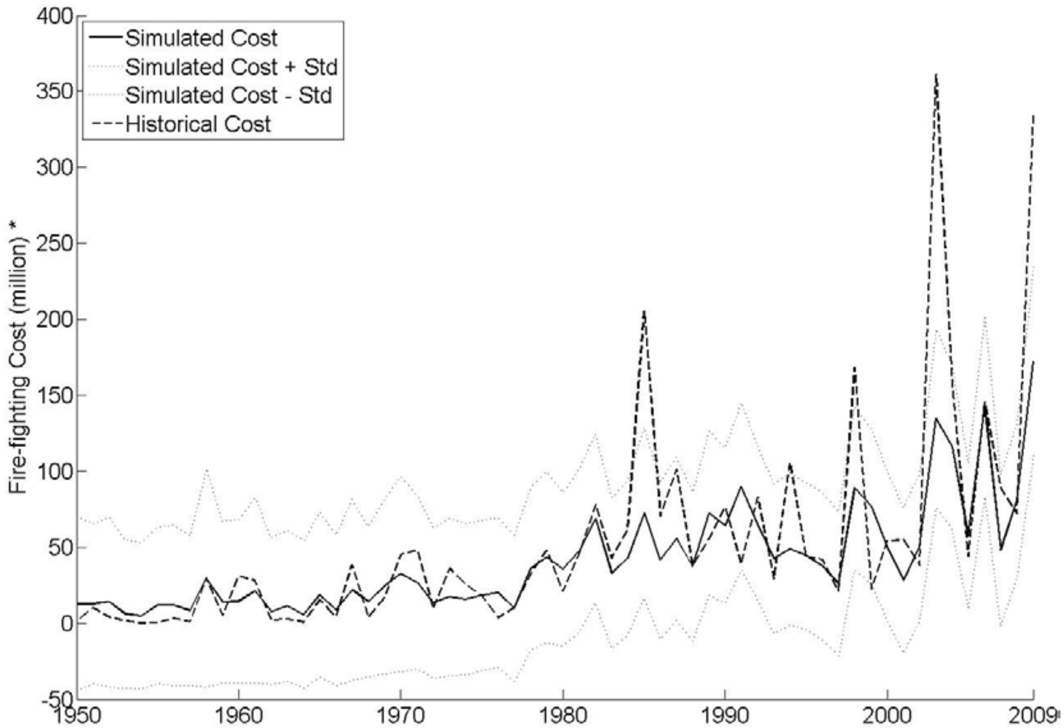

Figure 12: Simulation based on Historic Weather Condition and Fire-fighting Costs

In the second step, we use simulated weather and fire behavior data to examine how well our model tracks historic fire-fighting expenses – to test the predictive ability of the model. In this case, we start by generating the weather data using our model described in the last section (i.e., that based on the regression results found in Tables A-2 to A-5) and then inputting the simulated weather data into the estimated regression equations (7) and (8) (Table A-1) to determine fire behavior. We first simulate the monthly mean temperature and precipitation in terms of different scenarios for 1960-2009, using information on climate indexes, global temperature anomalies and monthly mean atmospheric CO_2 (and lagged and dummy variables). The scenarios begin in 1960 because CO_2 data are available only from 1958, with the presence of lagged variables in the regression model preventing us from starting earlier.

Besides the weather data, we also need average distances from fires to the nearest town for each district, but there is no way to get such values as we cannot simulate the exact locations of individual fire events in our model (which is also not our intent). To address this problem, we begin by assigning the value of zero to all districts without a simulated fire event in a given month, but generate average distances and corresponding inverse values for those districts and months with fire events using an assumed Gamma distribution (Figure 13). The parameters of this distribution are estimated from historic average distances. The specified Gamma distribution determines the value of average distances given that there will be one or more simulated fire events in a certain district for each month. Given that, for the historic period 1960-2009, we know where and when fire events occur, this is not a problem for hind-casting. The problem occurs for our third test, namely, projecting future fire-suppression expenses for 2010. For the future period, we do not know whether and where fires will occur. Therefore, the simulation for 1960-2009 is still not a true prediction compared to the simulation for 2010 (presented below).

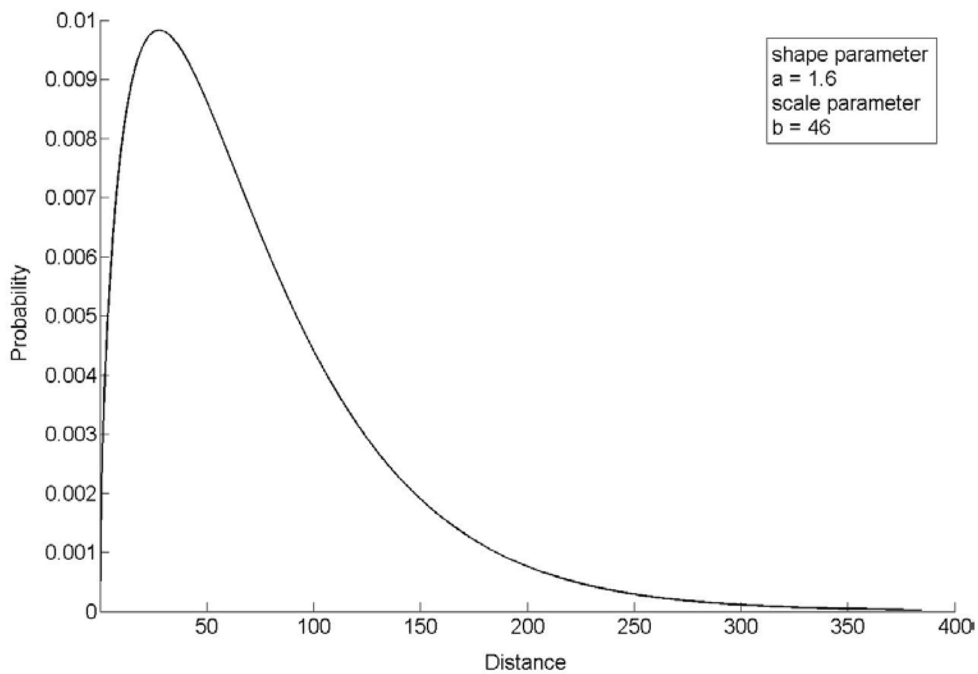

Figure 13: Gamma Distribution for Determination of the Average Distances

For the hind-cast where we simulate weather data, we employ our model to provide estimated weather data for the first three scenarios in Table 5, but for the fourth scenario we employ projected weather data from the ClimateWNA regional climate model developed by Wang et al. (2012). ClimateWNA involves multiple sources of climate data, including the PRISM (Daly et al. 2002) monthly data used for the reference period (1961-1990) and, indeed, a much longer period (1901-2009), and future climate datasets for the 2020s, 2050s and 2080s generated by various global circulation models (Mitchell and Jones 2005; Mbogga et al. 2009). We calculate the monthly weather data for each district based on the latitude, longitude and elevation of its centroid as predicted by the latest ClimateWNA 4.62 version.

The results are provided in the Appendix. In Figure A-1, we compare the respective simulation results of all scenarios with the historic pattern, using input data for 1984-2009 as a baseline; in Figure A-2, we provide the same comparison but using the 1950-2009 baseline with a structural break in 1983. Comparing the simulated means across the two figures, we find that simulations using the 1950-2009 baseline model generate a much wider confidence interval (CI) than the 1984-2009 model, as expected from the R^2 goodness-of-fit statistics (Table 3), but the means exhibit a similar trend. However, the use of randomly generated distances using a Gamma distribution also results in a large increase in the CIs.

The simulations in Figure A-2 are better able to predict fire-fighting expenses before the 1980s than those in Figure A-1, with those in Figure A-1generally higher than those in A-2. This is partly due to the existence of the 1983 break in the series that captures an apparent change in the government's policy towards fire suppression. As expected, simulations based on 1984-2009 perform better in estimating fire-fighting costs after 1983, and they better capture the large fluctuations in expenses that the model upon which simulations in Figure A-2 are based appear to miss. However, it is difficult to determine which of the different scenarios in each figure is somehow relatively better. We discuss this along with the predicted results for 2010 in the following.

As to predicting 2010 fire-fighting costs, we lack a historic reference for both the monthly average number of fires (ignitions) and, once fires have started, the average distances of fires to the nearest town. Because of the large variances associated with the 1950 to 2009 baseline model, we consider only the regression model for 1984-2009 and limit our scenarios to 2 and 4 only. Scenario 1 contains one-month lagged variables, which, in practice, are too close to act as an appropriate predictor for an annual fire-fighting budget. For Scenario 3, on the other hand, we need to use projected climate indexes to estimate the monthly mean temperature and precipitation to simulate fire behavior in the same month. In that case, it is more reasonable to generate monthly mean temperature and precipitation data from regional climate models directly, which is what we do in scenario 4.

The simulation process for 2010 is nearly the same as that for 1960-2009, except for the way we obtain the distance measures. Since we cannot use historic fire occurrence to decide a priori whether wildfire events occur in 2010, we first use a draw from a Binomial distribution function (in lieu of the historic 0/1 value as to whether there are wildfires in a given month) to determine whether fires occur in a particular month. Then, we choose a random value from a Gamma distribution the distance from the nearest town. The two probabilities are then multiplied together. For each district, therefore, we first estimate the probability that fires would occur in a certain month on the basis of historic wildfire occurrence in that month based on data for 1960 to 2009, and then multiply this from a draw from a Gamma distribution with parameters based on historical data (Figure 13). This is then used in conjunction with the regression results in Table 4 to simulate fire-fighting expenses. As a comparison, we also conduct a simulation that simply employs the average monthly, randomly-determined distance for the years 1960 through 2009 but then extended to 2010. Then, we end with a simulation that employs random average distances but doubles the burn size to adjust for potential extreme situations. The results of these three simulations for scenarios 2 and 4 are provided in Figure A-3.[3]

As expected, the top two panels (based on simulations but without random distances) appears to best

[3] Random determination of average distances refers to whether a fire has occurred or not (value equals zero); the same Gamma distribution is used in all situations to generate specified distances if a fire occurs. The average distances in 2010 in the first two panels of Figure A-3 are also randomly determined.

track the actual situation; perhaps surprisingly, the variances for scenarios 2 and 4 are similar. However, the top two panels greatly underestimate the most extreme actual fire-fighting expenses. This situation is even more severe in the middle two panels where distances are based on sampling from the Binomial-Gamma distributions; simulated fire-fighting expenses are flatter than they are in the top two panels. The results in the bottom two panels (based on random sampling to obtain distance and a doubling of burn size) exhibit a significant upward shift in projected fire-fighting expenses compared to the middle panels, thereby providing an improved tracking of extreme values but at the expense of overestimating most of the relatively normal expenses. Comparisons of the actual fire-suppression expenses and the simulated ones for 2010 are provided in Table 6.

Table 6: Comparison of Simulated Fire-fighting Costs for 2010 ($2002 millions)

Source	Scenario 2	Scenario 4
Actual 2010 expenditure	182.2	182.2
Simulated values without random average distance	85.5	103.3
Simulated values with random average distance	87.7	137.0
Simulated values with random average distance and doubled burn size	168.3	213.0

Notice that the top two panels in Figure A-3 are only applicable for predicting the fire expenses for 2010, rather than for continuous predictions across the entire horizon. However, since our intent is not to look farther into the future, it is still useful for our purpose. In contrast, the simulations in the bottom four panels in Figure A-3, every single year in the entire range from 1960 to 2010 acts as the upcoming future in terms of the previous year given that no historic data from the same period are used. The implication of such simulations lies with our ability to investigate the robustness of our model in performing continuous prediction. Therefore, in Table 7, we illustrate a correlation test between the simulation results in Figure A-3 and historic series.

Table 7: Correlations between Historic and Simulated Fire-fighting Costs

Results	Correlation with actual costs
Scenario 2 without random average distance	0.8133
Scenario 4 without random average distance	0.8032
Scenario 2 with random average distance	0.4426
Scenario 4 with random average distance	0.4332
Scenario 2 with random average distance and doubled burned size	0.5986
Scenario 4 with random average distance and doubled burned size	0.5429

Table 8: Equality Tests between Historic and Simulated Fire-fighting Costs [a]

Results	p-values for means	p-values for medians	p-values for variances
Scenario 2 without random average distance	0.0431	0.1657	0.0393
Scenario 4 without random average distance	0.0446	0.0294	0.0461
Scenario 2 with random average distance	0.0504	0.3221	0.0728
Scenario 4 with random average distance	0.0619	0.3221	0.0945
Scenario 2 with random average distance & doubled burn size	0.8705	0.8430	0.6807
Scenario 4 with random average distance & doubled burn size	0.5821	0.5525	0.5541

[a] The p-values for means, medians and variances are calculated by ANOVA F-test, Brown-Forsythe test and Med. Chi-square test, respectively. The null hypothesis is that all series have the same mean, median or variance. We assume that the null hypothesis should be rejected if the p-value is smaller than 0.1.

As expected, the 2010 projected fire-fighting expenses for each scenario are strongly correlated with actual 2010 expenditures. The scenarios with historic-dependence average distances exhibit the highest correlations followed by the doubled burn size scenarios, while the scenarios with randomly generated average distances show the least connection with historic values (Table 7). By comparing each pair of the two scenarios in Table 7, test results indicate that scenario 2 has a relatively stronger correlation with historic values than scenario 4 (which is based on weather information from a regional climate model). In contrast, for the tests for equality of means and variances, only the results for the doubled burn size scenarios indicate not to reject of the null hypothesis that the mean and variance of simulated and historic values are identical. The null hypothesis is rejected in the case of the other two simulations. The tests of medians, however, show significant equality to the historic values across all situations even at the 95% confidence level, except for scenario 4 without random distance generation. According to Tables 7 and 8, we believe that, by increasing the burn size, we can improve the overall equality of our simulation results to the historic situation, but simultaneously decrease the correlation between them, while a random determination of the average distances to the nearest town results in a significant drop in the correlation but with less impact on their equality.

In general, our model is quite robust as a predictor of next year's expected fire-fighting expenses. Our approach, therefore, constitutes a 'convincing, easy-to-use and flexible precursor' for predicting fire behavior and potential fire-suppression costs in the near future. Indeed, using our model, the provincial government will have sufficient time during January and March to project its fire-fighting expenses for the next fiscal year. By doing so, the recent past values of certain historic climate indexes (see Table 1) can be employed for prediction of direct fire-fighting expenditure for the upcoming fire season.

VII. CONCLUSION

In this study, we investigated various statistical relationships between climate and wildfire behavior, and their direct impact on British Columbia's fire-fighting costs, using spatial analysis and statistical regression models for the BC interior. Based on the regression results, we projected fire-fighting costs for upcoming fire seasons using Monte Carlo simulation. Considering that fire behavior may differ greatly across a landscape and with regional weather conditions, forest district dummy variables and climate indexes were used to estimate regional weather conditions. We also limited fire events to ones greater than 100 hectares in size because fire-fighting expenses are more sensitive to large fires, as suggested by preliminary analyses.

Fire-fighting expenses largely depend on the number of large fires per month and related burn sizes. Large fires in one district might, in some years, influence outbreaks of large (>100 ha) wildfires in another district, so forest district dummy variables were used to capture the spatial autocorrelation of wildfire incidence. Spatial differences do not arise solely because forest conditions, such as tree species and fuel load, differ across districts, but also because weather conditions, mainly temperatures and precipitation, can vary significantly from one district to another for reasons related primarily to terrain.

Most studies that predict wildfire behavior under changing climate conditions (including this one) attempt to determine how climate factors, and eventually climate change, affects the risk of ignition and how wildfires spread after combustion is under way. In that regard, it is important to model the myriad of factors that are involved, including different landscapes, tree species, fuel loads, prevailing wind direction, and so on. Many climate-biophysical models are able to provide insights into the risk of fire and how one might reduce fuel load to minimize the risk of fire (Graetz et al. 2007). Others have developed indexes that serve as an indicator of risk of wildfire (Meyn et al. 2010) or predict the direction and spread of fire (Xu et al. 2011). In contrast, we sought to predict an economic variable, fire-fighting expenditure, which would facilitate budget planning by provincial decision makers. This meant that the model needed to be based, in the final analysis, on one or more variables that were readily observable and policy makers could easily understand. Our model is a statistical model, but the state variables needed to predict fire-fighting expenses constitute several simple series that are readily available from the internet, namely, the Pacific Decadal Oscillation, El Niño and Southern Oscillation climate indexes, the amount of CO_2 in the atmosphere, and the global temperature anomaly.[4]

Together with lagged weather conditions specific to each district, we successfully estimated monthly average temperatures and precipitation on the basis of five different climate indexes and their seasonal and annual averages. However, climate events are not usually expected to have distinct impacts at relatively small spatial scales; rather, we found that they tend to have an impact on long-term trends in temperatures and average seasonal changes. Indeed, we discovered that we could use historically observed climate

[4] The data sources for climate indexes used in this paper are listed in Table 1, and we obtain the global CO_2 and temperature anomaly data from ftp://ftp.cmdl.noaa.gov/ccg/co2/trends/co2_mm_mlo.txt and http://www.metoffice.gov.uk/hadobs/hadcrut3/diagnostics/global/nh+sh/monthly, respectively.

indexes instead of projected temperatures and precipitation to estimate fire behavior and fire-fighting expenses at least four months ahead of the start of fire season. The model developed in this study is quite robust in simulating fire-suppression costs for the past 60 years, and gives a realistic prediction of next fiscal year's expected outlays, at least based on two different scenarios for 2010. We believe that the model is sufficiently robust to use as a simple but handy indicator for planning fire-fighting budgets in advance. This could, of course, have implications for other policies related to forest management and fire suppression.

Further research is required to draw a better link between the simple climate indexes identified in this study and the prediction of fire risk and/or fire budgets. It is necessary to identify the relationship between the climate indexes we use and the predictions of highly local temperature and precipitation from regional climate models. Clearly, out results suggest that there is a relationship: information from the regional climate models provides a better predictor of the actual 2010 fire-fighting expense than does our model based on climate indexes, but the latter performs better over a longer period (Tables 7). We also need to investigate the relationship between forest fires, fire size and distance to the nearest town (as a proxy for responding to wildfire incidences); such distances can be particularly large in some of the bigger forest districts, such as the Skeena Stikine Forest District in the northwest. Dummy variables representing the preponderance of particular tree species at a fire site may also be needed to address the susceptibility of some tree species to ignition, as might the age of trees on a site. Finally, there are other spatial regression models that need to be considered to address various statistical methods for estimating spatial issues (e.g., Cotteleer et al. 2011; LeSage and Pace 2009; Lesage and Parent 2007).

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APPENDIX

Table A-1: Estimated Coefficients for Number of Fires (>100 ha) and Burned Sizes [a]

Number of Fires		Burned Size	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
TEMP	0.0251***	N100	110.1152***
	(0.0033)		(13.7126)
PREC	-0.0015***	D100	11.4408***
	(0.0002)		(3.7053)
D100I × D1	487.0158***	TEMP × PREC × SDUM	-0.1495**
	(27.7944)		(0.0630)
D100I × D2	41.1828***	D100 × D1	-5.3407
	(6.5359)		(3.7337)
D100I × D3	223.9951***	D100 × D2	-12.9308**
	(8.7862)		(6.0467)
D100I × D4	89.1033***	D100 × D3	18.2193***
	(2.6188)		(3.8012)
D100I × D5	209.0115***	D100 × D4	13.0877***
	(16.7824)		(4.0812)
D100I × D6	38.1885***	D100 × D5	-3.0734
	(8.6786)		(3.7792)
D100I × D7	14.9264***	D100 × D6	-13.5354***
	(3.7108)		(4.5955)
D100I × D8	9.3288***	D100 × D7	-10.9990
	(2.3510)		(8.3854)
D100I × D9	4.3145***	D100 × D8	-2.6744
	(0.9898)		(5.2574)
D100I × D10	11.1920***	D100 × D9	-2.3544
	(2.1944)		(4.9053)
D100I × D11	12.3513***	D100 × D10	-1.0432
	(1.6822)		(4.4834)
D100I × D12	25.9160***	D100 × D11	-12.8486***
	(3.7928)		(4.8813)
D100I × D13	93.2872***	D100 × D12	-11.1086**
	(4.8609)		(5.1212)
D100I × D14	20.6825***	D100 × D13	-12.8752***
	(2.9786)		(4.5743)
D100I × D15	222.0294***	D100 × D14	2.9302
	(12.2745)		(6.3934)
D100I × D16	1.8864***	D100 × D15	-5.0281
	(0.3914)		(3.8428)
D100I × D17	7.9600***	D100 × D16	0.3835
	(1.6071)		(8.4539)
D100I × D18	20.0090***	D100 × D17	7.9238
	(1.8557)		(8.3805)
D100I × D19	7.9745***	D100 × D18	-0.4395
	(1.2527)		(6.1136)
D100I × D20	32.9534***	D100 × D19	-3.2474
	(2.9441)		(9.0062)
D100I × D21	9.0481***	D100 × D20	-15.2107**
	(0.9869)		(6.9977)
		D100 × D21	6.2598
			(7.2947)
R^2:	*0.3847*		*0.2019*
S.D. dependent var:	*0.9560*		*1344.6570*

[a] For all tables, *, **, *** denote significance at 0.1, 0.05, 0.01 levels, respectively. (-1) indicates a one-period lag.

Table A-2: Weather Data Estimation including Yearly, Seasonal and Monthly Lags [a]

Temperature		Precipitation	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
CO2(-1)	0.0169*** (0.0007)	CO2(-1)	-0.1339*** (0.0144)
GTEMP(-1)	0.2610*** (0.0581)	PRECN(-1)	-7.8527*** (0.4165)
PRECN(-1)	-0.0292*** (0.0071)	TEMP(-1)	0.5970*** (0.0397)
EN3(-1) × SDUM	0.1399*** (0.0198)	EN3(-1) × SDUM	1.0854 (0.7578)
EN3S × SDUM	0.1074*** (0.0345)	EN3S × SDUM	-2.8072** (1.3360)
EN3A	0.0399* (0.0208)	EN3A	0.4921 (0.7795)
NAO(-1) × SDUM	-0.0208*** (0.0069)	NAO(-1) × SDUM	-1.0229*** (0.2662)
NAOS × SDUM	0.0742*** (0.0121)	NAOS × SDUM	0.3945 (0.4665)
NAOA	-0.0926*** (0.0151)	NAOA	-0.2269 (0.5804)
PDO(-1) × SDUM	-0.1248*** (0.0152)	PDO(-1) × SDUM	1.8846*** (0.5863)
PDOS × SDUM	0.0466** (0.0212)	PDOS × SDUM	1.8882** (0.8181)
PDOA	0.0173 (0.0149)	PDOA	2.2093*** (0.5747)
PNA(-1) × SDUM	0.0026 (0.0040)	PNA(-1) × SDUM	-0.7009*** (0.1569)
PNAS × SDUM	-0.0043 (0.0063)	PNAS × SDUM	0.7303*** (0.2414)
PNAA	0.0525*** (0.0100)	PNAA	1.1175*** (0.3843)
SOI(-1) × SDUM	-0.0173* (0.0093)	SOI(-1) × SDUM	0.0989 (0.3623)
SOIS × SDUM	0.0508*** (0.0152)	SOIS × SDUM	-0.7963 (0.5883)
SOIA	-0.0177 (0.0122)	SOIA	1.2931*** (0.4717)
TEMPN(-1) × D1	0.2536*** (0.0321)	PREC(-1) × D1	0.4890*** (0.0270)
TEMPN(-1) × D2	0.2565*** (0.0331)	PREC(-1) × D2	0.4421*** (0.0257)
TEMPN(-1) × D3	0.2153*** (0.0330)	PREC(-1) × D3	0.4105*** (0.0272)
TEMPN(-1) × D4	0.1527*** (0.0326)	PREC(-1) × D4	0.3545*** (0.0282)
TEMPN(-1) × D5	0.4724*** (0.0318)	PREC(-1) × D5	0.3099*** (0.0324)
TEMPN(-1) × D6	0.2685*** (0.0328)	PREC(-1) × D6	0.4080*** (0.0265)
TEMPN(-1) × D7	0.2098*** (0.0334)	PREC(-1) × D7	0.6569*** (0.0106)
TEMPN(-1) × D8	0.2231*** (0.0331)	PREC(-1) × D8	0.4507*** (0.0249)
TEMPN(-1) × D9	0.2443*** (0.0327)	PREC(-1) × D9	0.5204*** (0.0205)
TEMPN(-1) × D10	0.2764*** (0.0330)	PREC(-1) × D10	0.3198*** (0.0303)

Table A-2: Weather Data Estimation including Yearly, Seasonal and Monthly Lags (Cont.)

Temperature		Precipitation	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
TEMPN(-1) × D11	0.2318***	PREC(-1) × D11	0.5383***
	(0.0329)		(0.0193)
TEMPN(-1) × D12	0.1826***	PREC(-1) × D12	0.2798***
	(0.0338)		(0.0320)
TEMPN(-1) × D13	0.2227***	PREC(-1) × D13	0.6573***
	(0.0328)		(0.0134)
TEMPN(-1) × D14	0.2450***	PREC(-1) × D14	0.3890***
	(0.0343)		(0.0288)
TEMPN(-1) × D15	0.2927***	PREC(-1) × D15	0.1507***
	(0.0332)		(0.0399)
TEMPN(-1) × D16	0.2219***	PREC(-1) × D16	0.2706***
	(0.0328)		(0.0338)
TEMPN(-1) × D17	0.1991***	PREC(-1) × D17	0.2100***
	(0.0329)		(0.0383)
TEMPN(-1) × D18	0.1886***	PREC(-1) × D18	0.3207***
	(0.0327)		(0.0308)
TEMPN(-1) × D19	0.2597***	PREC(-1) × D19	0.4578***
	(0.0325)		(0.0235)
TEMPN(-1) × D20	0.2267***	PREC(-1) × D20	0.5455***
	(0.0326)		(0.0185)
TEMPN(-1) × D21	0.2145***	PREC(-1) × D21	0.2374***
	(0.0330)		(0.0358)
R^2:	*0.3733*		*0.3544*
S.D. dependent var:	*0.9685*		*36.9780*

[a] CO2 is the monthly mean CO2 density in atmosphere; GTEMP is the global temperature anomaly; TEMPN and PRECN are the normalized monthly mean of temperature and precipitation; EN3S and EN3A are the mean of EN3 from Jan. to Apr. and from the previous year, respectively (same denotation pattern for other climate indexes); TEMPLS, TEMPLW, PRECLS and PRECLW are means of temperature and precipitation in the previous summer and winter before the current fire season, respectively.

Table A-3: Weather Data Estimation including Yearly Lags only

Temperature		Precipitation	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
CO2LY	0.0168*** (0.0005)	CO2LY	-0.0626*** (0.0149)
GTEMPLY × SDUM	0.9489*** (0.0562)	EN3A	0.4133 (0.7725)
PRECLW × SDUM	-0.0012*** (0.0002)	NAOA	0.1665 (0.6091)
EN3A	-0.0224 (0.0203)	PDOA	3.5606*** (0.5708)
NAOA	-0.1046*** (0.0150)	PNAA	1.3663*** (0.3900)
PDOA	0.0496*** (0.0145)	SOIA	1.3410*** (0.4890)
PNAA	0.1024*** (0.0099)	PRECLS × D1	-0.2639*** (0.0829)
SOIA	-0.0347*** (0.0125)	PRECLS × D2	0.0765 (0.0640)
TEMPLS × D1	0.0530*** (0.0113)	PRECLS × D3	0.0037 (0.0489)
TEMPLS × D2	0.0384*** (0.0079)	PRECLS × D4	-0.0053 (0.0538)
TEMPLS × D3	0.0407*** (0.0078)	PRECLS × D5	-0.0702 (0.0706)
TEMPLS × D4	0.0188*** (0.0058)	PRECLS × D6	0.0365 (0.0752)
TEMPLS × D5	0.0398*** (0.0055)	PRECLS × D7	0.4032*** (0.0518)
TEMPLS × D6	0.0375*** (0.0058)	PRECLS × D8	-0.0992 (0.0912)
TEMPLS × D7	0.0239*** (0.0078)	PRECLS × D9	0.0353 (0.0501)
TEMPLS × D8	0.0207*** (0.0056)	PRECLS × D10	-0.0815 (0.0868)
TEMPLS × D9	0.0307*** (0.0057)	PRECLS × D11	0.0866 (0.0686)
TEMPLS × D10	0.0270*** (0.0047)	PRECLS × D12	-0.0974 (0.0684)
TEMPLS × D11	0.0531*** (0.0083)	PRECLS × D13	0.2228*** (0.0588)
TEMPLS × D12	0.0164*** (0.0043)	PRECLS × D14	-0.1954*** (0.0509)
TEMPLS × D13	0.0556*** (0.0089)	PRECLS × D15	-0.2910*** (0.0838)
TEMPLS × D14	0.0277*** (0.0048)	PRECLS × D16	-0.1322 (0.0806)
TEMPLS × D15	0.0477*** (0.0070)	PRECLS × D17	-0.1344 (0.0890)
TEMPLS × D16	0.0201*** (0.0049)	PRECLS × D18	-0.0871 (0.0744)
TEMPLS × D17	0.0150*** (0.0043)	PRECLS × D19	0.0924 (0.0742)
TEMPLS × D18	0.0368*** (0.0070)	PRECLS × D20	0.1855*** (0.0633)
TEMPLS × D19	0.0307*** (0.0044)	PRECLS × D21	-0.2099* (0.1102)
TEMPLS × D20	0.0510*** (0.0077)	PRECLW × D1	0.2702*** (0.0582)

Table A-3: Weather Data Estimation including Yearly Lags only (Cont.) [a]

Temperature		Precipitation	
Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
TEMPLS × D21	0.0227*** (0.0052)	PRECLW × D2	0.0495 (0.0602)
TEMPLW × D1	0.0397*** (0.0089)	PRECLW × D3	-0.0647 (0.1149)
TEMPLW × D2	0.0523*** (0.0117)	PRECLW × D4	-0.0572 (0.1114)
TEMPLW × D3	0.0394*** (0.0083)	PRECLW × D5	-0.0400 (0.0738)
TEMPLW × D4	0.0371*** (0.0107)	PRECLW × D6	0.0592 (0.0700)
TEMPLW × D5	0.0756*** (0.0062)	PRECLW × D7	0.2152*** (0.0205)
TEMPLW × D6	0.0538*** (0.0091)	PRECLW × D8	0.1830*** (0.0573)
TEMPLW × D7	0.0333* (0.0181)	PRECLW × D9	0.2393*** (0.0444)
TEMPLW × D8	0.0455*** (0.0144)	PRECLW × D10	0.0600 (0.0866)
TEMPLW × D9	0.0601*** (0.0120)	PRECLW × D11	0.2254*** (0.0541)
TEMPLW × D10	0.0603*** (0.0102)	PRECLW × D12	0.0106 (0.0803)
TEMPLW × D11	0.0638*** (0.0112)	PRECLW × D13	0.2769*** (0.0329)
TEMPLW × D12	0.0572*** (0.0148)	PRECLW × D14	0.2167*** (0.0493)
TEMPLW × D13	0.0712*** (0.0134)	PRECLW × D15	-0.0933 (0.0657)
TEMPLW × D14	0.0662*** (0.0131)	PRECLW × D16	0.0241 (0.0746)
TEMPLW × D15	0.0709*** (0.0111)	PRECLW × D17	-0.0965 (0.0933)
TEMPLW × D16	0.0965*** (0.0203)	PRECLW × D18	0.0482 (0.0778)
TEMPLW × D17	0.0790*** (0.0176)	PRECLW × D19	0.1202** (0.0575)
TEMPLW × D18	0.0746*** (0.0152)	PRECLW × D20	0.1671*** (0.0373)
TEMPLW × D19	0.1534*** (0.0190)	PRECLW × D21	-0.0813 (0.0597)
TEMPLW × D20	0.1077*** (0.0179)		
TEMPLW × D21	0.0733*** (0.0163)		
R^2:	*0.3488*		*0.2778*
S.D. dependent var:	*0.9685*		*36.9780*

[a] CO2LY and GTEMPLY are the annual mean of CO2 and GTEMP in the previous year, respectively.

Table A-4: Temperature Estimation including Yearly, Seasonal, Monthly Lags and Variables from the Same Period

Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
CO2	0.0081*** (0.0006)	TEMPN(-1) × D14	0.2621*** (0.0328)
GTEMP	1.1178*** (0.0539)	TEMPN(-1) × D15	0.2971*** (0.0318)
EN3 × SDUM	0.0760*** (0.0179)	TEMPN(-1) × D16	0.2455*** (0.0314)
EN3S × SDUM	0.0462 (0.0325)	TEMPN(-1) × D17	0.2367*** (0.0315)
EN3A	-0.0021 (0.0197)	TEMPN(-1) × D18	0.2003*** (0.0312)
NAO × SDUM	-0.0163** (0.0065)	TEMPN(-1) × D19	0.2821*** (0.0312)
NAOS × SDUM	0.0635*** (0.0115)	TEMPN(-1) × D20	0.2447*** (0.0312)
NAOA	-0.0699*** (0.0144)	TEMPN(-1) × D21	0.2314*** (0.0315)
PDO × SDUM	0.0011 (0.0130)	PRECN × D1	-0.0436 (0.0302)
PDOS × SDUM	0.1106*** (0.0187)	PRECN × D2	-0.0541* (0.0305)
PDOA	-0.0003 (0.0142)	PRECN × D3	-0.2150*** (0.0305)
PNA × SDUM	-0.0505*** (0.0037)	PRECN × D4	-0.3378*** (0.0308)
PNAS × SDUM	0.0763*** (0.0057)	PRECN × D5	-0.0242 (0.0312)
PNAA	0.0426*** (0.0096)	PRECN × D6	-0.0886*** (0.0312)
SOI × SDUM	0.0108 (0.0087)	PRECN × D7	-0.1009*** (0.0313)
SOIS × SDUM	0.0071 (0.0145)	PRECN × D8	-0.0875*** (0.0309)
SOIA	-0.0220* (0.0117)	PRECN × D9	-0.1564*** (0.0314)
TEMPN(-1) × D1	0.2506*** (0.0307)	PRECN × D10	-0.1742*** (0.0313)
TEMPN(-1) × D2	0.2518*** (0.0318)	PRECN × D11	-0.1330*** (0.0303)
TEMPN(-1) × D3	0.2279*** (0.0315)	PRECN × D12	-0.2318*** (0.0313)
TEMPN(-1) × D4	0.1710*** (0.0311)	PRECN × D13	-0.2039*** (0.0305)
TEMPN(-1) × D5	0.4664*** (0.0305)	PRECN × D14	-0.1578*** (0.0296)
TEMPN(-1) × D6	0.2780*** (0.0314)	PRECN × D15	-0.0626** (0.0316)
TEMPN(-1) × D7	0.2036*** (0.0319)	PRECN × D16	-0.2026*** (0.0304)
TEMPN(-1) × D8	0.2254*** (0.0316)	PRECN × D17	-0.2714*** (0.0301)
TEMPN(-1) × D9	0.2314*** (0.0313)	PRECN × D18	-0.2002*** (0.0313)
TEMPN(-1) × D10	0.2860*** (0.0315)	PRECN × D19	-0.1622*** (0.0307)
TEMPN(-1) × D11	0.2422*** (0.0314)	PRECN × D20	-0.1504*** (0.0305)
TEMPN(-1) × D12	0.1990*** (0.0322)	PRECN × D21	-0.1494*** (0.0311)
TEMPN(-1) × D13	0.2186*** (0.0313)	*R^2:* *S.D. dependent var:*	*0.4273* *0.9685*

Table A-5: Precipitation Estimation including Yearly, Seasonal, Monthly Lags and Variables from the Same Period

Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
CO2	-0.0545*** (0.0139)	PREC(-1) × D15	-0.3152*** (0.0352)
EN3 × SDUM	0.6956 (0.6813)	PREC(-1) × D16	-0.0402 (0.0308)
EN3S × SDUM	-0.9269 (1.2566)	PREC(-1) × D17	-0.1537*** (0.0355)
EN3A	0.9919 (0.7453)	PREC(-1) × D18	-0.0050 (0.0275)
NAO × SDUM	-0.6617*** (0.2509)	PREC(-1) × D19	0.2628*** (0.0213)
NAOS × SDUM	0.3830 (0.4443)	PREC(-1) × D20	0.3414*** (0.0163)
NAOA	-0.6215 (0.5543)	PREC(-1) × D21	-0.1024*** (0.0314)
PDO × SDUM	3.2250*** (0.5008)	TEMP(-1) × D1	1.2785*** (0.1958)
PDOS × SDUM	-1.2085* (0.7238)	TEMP(-1) × D2	1.7470*** (0.2330)
PDOA	2.3319*** (0.5494)	TEMP(-1) × D3	0.5884*** (0.1584)
PNA × SDUM	1.4354*** (0.1483)	TEMP(-1) × D4	0.7401*** (0.1764)
PNAS × SDUM	-0.8514*** (0.2199)	TEMP(-1) × D5	0.8625*** (0.1914)
PNAA	1.2551*** (0.3677)	TEMP(-1) × D6	1.2160*** (0.1972)
SOI × SDUM	-0.7123** (0.3362)	TEMP(-1) × D7	5.2252*** (0.2604)
SOIS × SDUM	0.7482 (0.5619)	TEMP(-1) × D8	1.9394*** (0.2388)
SOIA	1.2353*** (0.4503)	TEMP(-1) × D9	1.5375*** (0.2147)
PREC(-1) × D1	0.1029*** (0.0255)	TEMP(-1) × D10	1.3395*** (0.2139)
PREC(-1) × D2	0.1209*** (0.0227)	TEMP(-1) × D11	1.6177*** (0.2242)
PREC(-1) × D3	0.0322 (0.0252)	TEMP(-1) × D12	1.1004*** (0.2267)
PREC(-1) × D4	-0.0241 (0.0266)	TEMP(-1) × D13	2.6447*** (0.2380)
PREC(-1) × D5	-0.0837*** (0.0286)	TEMP(-1) × D14	1.1085*** (0.2327)
PREC(-1) × D6	0.0938*** (0.0234)	TEMP(-1) × D15	1.2797*** (0.2316)
PREC(-1) × D7	0.5238*** (0.0097)	TEMP(-1) × D16	0.8927*** (0.2467)
PREC(-1) × D8	0.1781*** (0.0220)	TEMP(-1) × D17	0.8832*** (0.2352)
PREC(-1) × D9	0.2883*** (0.0182)	TEMP(-1) × D18	0.3830* (0.2215)
PREC(-1) × D10	-0.0166 (0.0271)	TEMP(-1) × D19	0.8840*** (0.2465)
PREC(-1) × D11	0.2938*** (0.0170)	TEMP(-1) × D20	1.7808*** (0.2568)
PREC(-1) × D12	-0.0609** (0.0303)	TEMP(-1) × D21	0.9799*** (0.2337)
PREC(-1) × D13	0.4754*** (0.0121)	TEMP × D1	-1.7324*** (0.2062)
PREC(-1) × D14	0.0918*** (0.0260)	TEMP × D2	-1.7017*** (0.2344)

Table A-5: Precipitation Estimation including Yearly, Seasonal, Monthly Lags and Variables from the Same Period (Cont.)

Independent Variables	Coef. (Std. Error)	Independent Variables	Coef. (Std. Error)
TEMP × D3	0.3857**	TEMP × D13	-4.2708***
	(0.1581)		(0.2425)
TEMP × D4	0.0051	TEMP × D14	-1.5641***
	(0.1778)		(0.2351)
TEMP × D5	-0.8631***	TEMP × D15	-1.8229***
	(0.1926)		(0.2342)
TEMP × D6	-1.3783***	TEMP × D16	-1.6917***
	(0.1991)		(0.2494)
TEMP × D7	-5.8798***	TEMP × D17	-1.4810***
	(0.2676)		(0.2366)
TEMP × D8	-2.7663***	TEMP × D18	-1.0266***
	(0.2413)		(0.2256)
TEMP × D9	-1.7445***	TEMP × D19	-2.0099***
	(0.2159)		(0.2519)
TEMP × D10	-1.5888***	TEMP × D20	-3.3951***
	(0.2146)		(0.2610)
TEMP × D11	-2.2172***	TEMP × D21	-2.6597***
	(0.2287)		(0.2371)
TEMP × D12	-1.2147***	*R^2:*	*0.4120*
	(0.2264)	*S.D. dependent var:*	*36.9780*

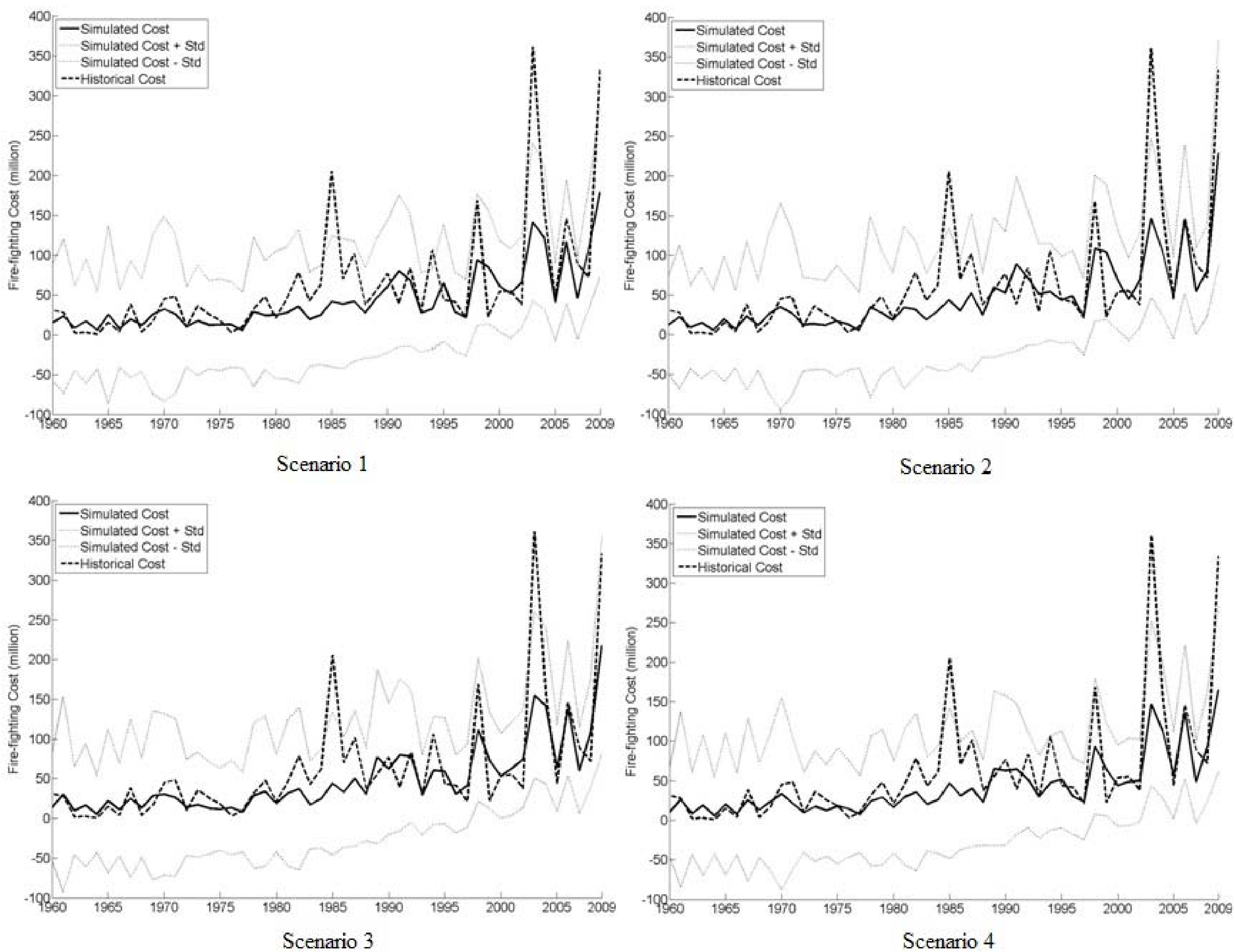

Figure A-1: Historic and Simulated Fire-fighting Costs with a 95% CI, 1984-2009 Baseline

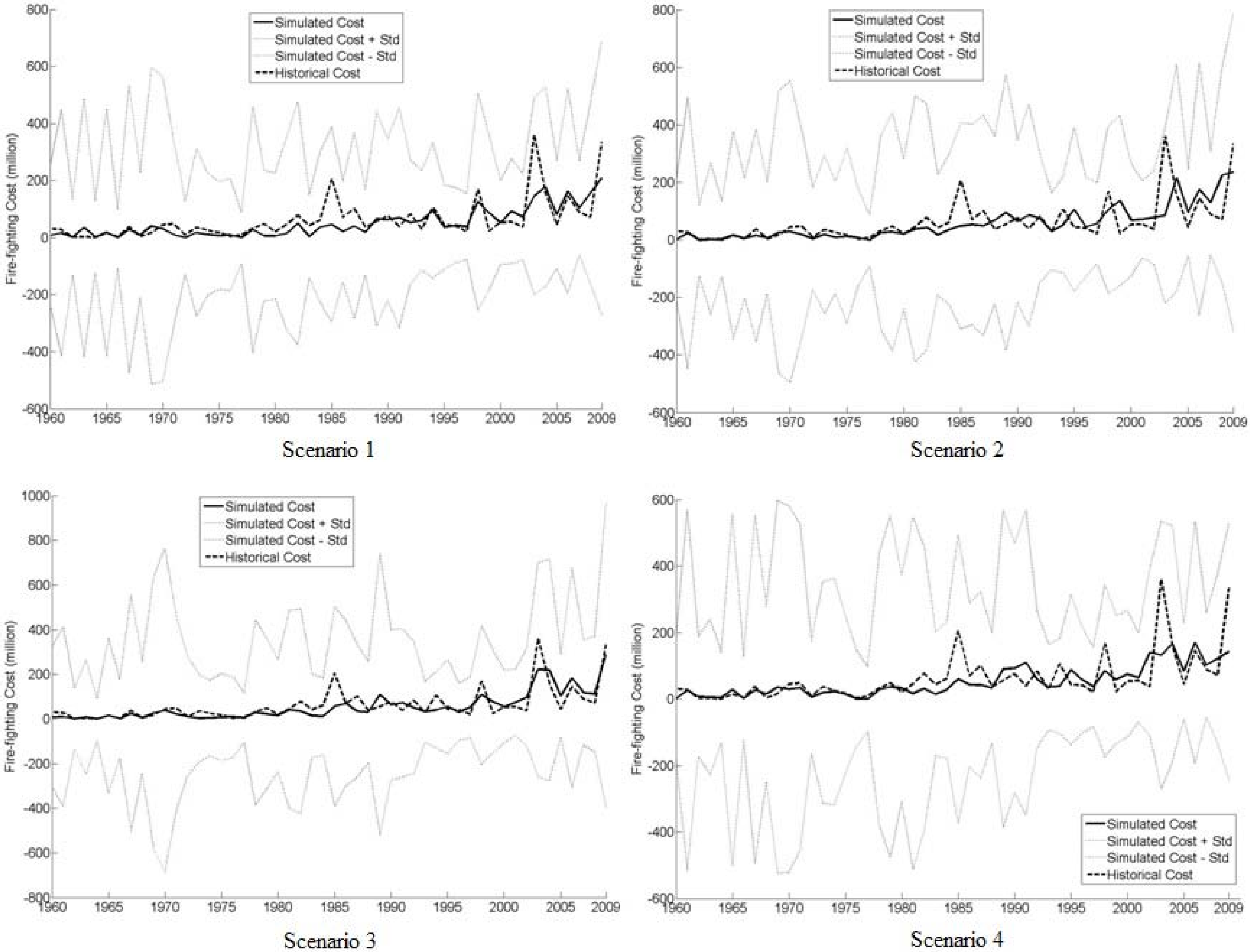

Figure A-2: Historic and Simulated Fire-fighting Costs with a 95% CI, 1950-2009 Baseline

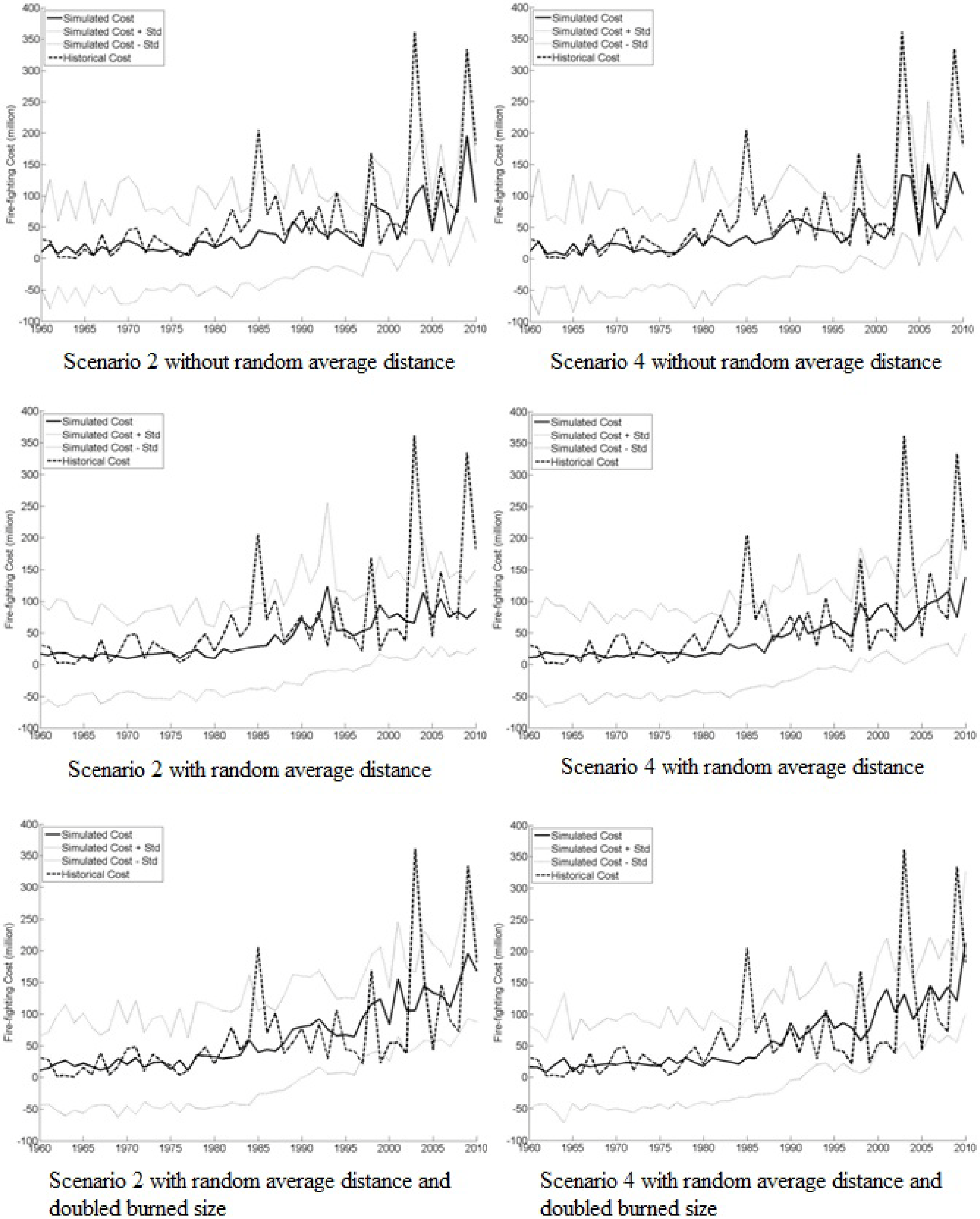

Figure A-3: Simulated Fire-fighting Costs Adjusted for Average Distances and Burn Sizes