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Geographic and temporal factors that seem to explain human-caused fire occurrence in Whitecourt Forest, Alberta

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Abstract

Accurate daily human-caused fire occurrence predictions are a very important component in fire danger rating and as an aid in the daily deployment of expensive suppression resources.

We chose a subset of 28 variables to study how differently weather, vegetation, topography, human development, and time of the year relate to wildfire occurrence in Whitecourt Forest, Alberta, and to test their usefulness for daily human-caused fire occurrence prediction modeling. Geographic data was analyzed using a geographic information system.

The results of this study indicate that fire occurrences do relate to some topographic, vegetation, and development variables, such as distance to a road, at a level comparable to some temporal and weather variables (relativy humidity, for instance), more widely accepted in previous fire occurrence prediction models.

Introduction

The ability to accurately predict daily human-caused fire occurrence is a very important component in developing a fire danger rating system for an area. This information also assists in the daily deployment of expensive suppression resources.

Timing and location of human-caused wildfires in a forest are dependent on the site-related variables that determine the number, distribution and risk of the human sources of ignition, the ease of ignition and spread (topographic and weather-related variables,) the effect of prevention efforts, and the detection capabilities in the forest. These parameters vary in time and also geographically within a forest, placing a different risk of wildfire in every site, at every point in time.

Daily fire occurrence models developed before have primarily focused in historic fire and weather data relations (Lynham 1991). Chou *et al.* (1990)

explored some geographic and spatial factors in human-caused fire occurrence using geographic information system (GIS) technology.

Also making use of the powerful capabilities of a GIS, we have chosen another subset of variables to study how differently weather, vegetation, topography, development, and time in the year relate to wildfire occurrence and to test their usefulness for a future daily human-caused fire occurrence prediction model to be developed shortly in Whitecourt Provincial Forest, Alberta (figure 1).

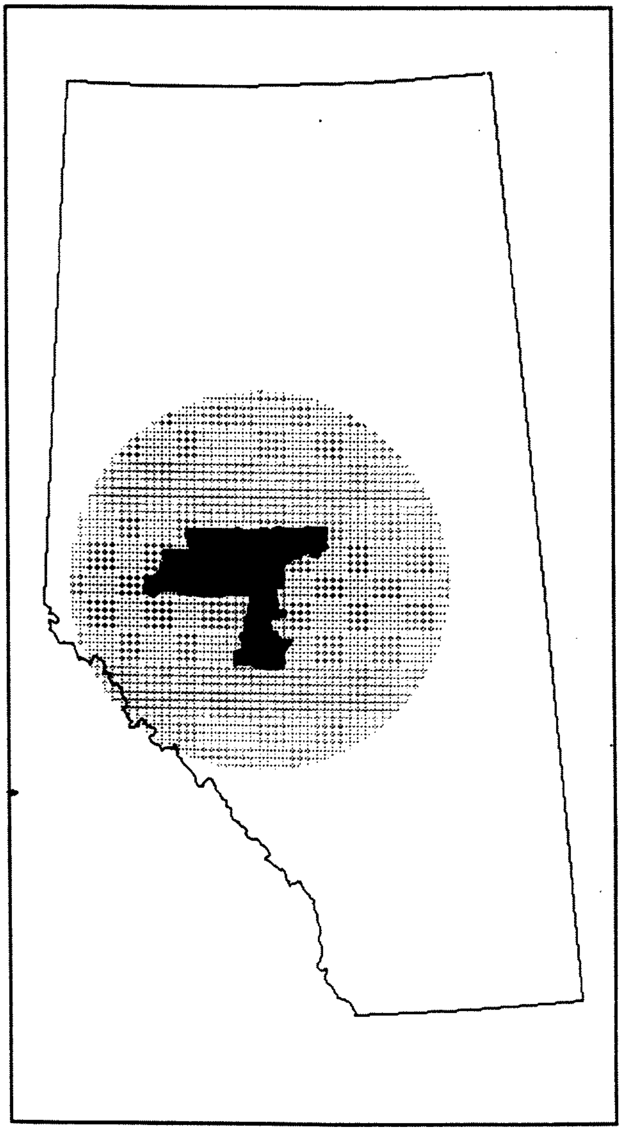

Figure 1: *Whitecourt Provincal Forest in Alberta.*

Methods

Geographic variables

The sites for the analysis, and their attributes, were determined through the processing of the geographic data needed (available in digital form from different sources), within an ARC/INFO system (ESRI 1991). Fire occurrence data was available from the records in the Alberta Forest Service, Forest Protection Branch, Edmonton, many years back, but only data from 1986 to 1990 was used to keep agreement with the dating of the geographic information.

The study area (» 20,000 km^2) was divided in cells of 800 m of side through a griding process in ARC/INFO. We assigned the following attributes to each cell:

aspect classified as flat, north, south, east, and west,

elevation in meters,

slope in percentage,

distance to closest *lake* in meters,

distance to closest *lookout tower* in meters,

distance to closest *river* in meters,

distance to closest *road* in meters, as shown in *figure 2,*

distance to closest *town* in meters,

fuel category as in the Fire Behaviour Prediction System (Forestry Canada 1992),

property, classified in forest management area, forest quota area, patented land, and other,

forest age in years,

forest height in meters,

forest commerciality classified as lumber, roundwood, low uncommercial, high uncommercial,

forest density classified as 0-25%, 26-50%, 51-75%, 76-100%,

visibility from n lookout towers, with n varying from 0 to over 3,

district, a dummy variable to account for general differences among forest districts other than area, and,

number of *fire occurrences* in the cell in the period 1986-1990, from 0 to 3.

The total number of 800 m cells in which the Whitecourt Forest could be divided, with their geographic characteristics and past fire history, formed the population for analysis.

If no topographic, development, or vegetation variable were related to fire occurrence, then we would expect the cells with occurrence equal or greater than one (fire cells) to have the characteristics of a random sample taken from the population. Thus, the frequency distribution of a variable x_i among the fire cells (the sample) would be equal to the frequency distribution of x_i in the population encompassing all cells in the forest.

Figure 2: *Partial ARC/INFO grid of euclidean distance to roads.*

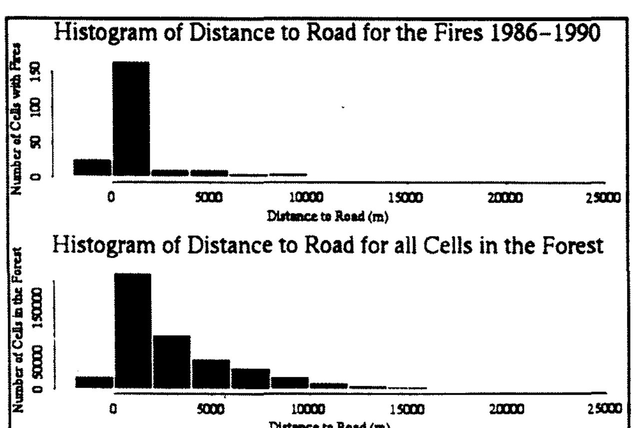

Figure 3: *Histograms for comparison between frequency distributions: variable distance to road.*

To test our hypothesis, we calculated the frequency distributions of the geographic variables for the fire cells (233) and for all cells in the forest (about 30,500 depending on the missing values of the variable). The values obtained from ARC/INFO grids were grouped in classes in the SAS system (SAS Institute Inc. 1985) to remove noise in the data caused by partition in cells, prior to calculating the frequency distributions (histograms for the variable distance to road are shown in figure 3). Then, we applied the Chi-square goodness-of-fit test (Dickinson Gibbons 1976) to every pair of sampled and hypothesised distributions.

The overall lack of fit is calculated in the Chi-square goodness-of-fit test through the following statistic:

$$Q=\sum_{i=1}^{i=r} \frac{(O_i-E_i)^2}{E_i}$$

where E_i = expected frequency in the class i
O_i = observed/sampled frequency in the class i
r = number of classes

The sampling distribution of is approximately the Chi-square distribution with r-1 degrees of freedom, when the sample is sufficiently large (n>30).

Small ***Q*** values support the agreement between distributions, while large ***Q*** values favour rejection of the null hypothesis H0 of equal frequency distributions in fire cells and all cells in the forest. The decision rule chosen was to reject H_0 if $Q > C^2_{.01,r-1}$ (we selected a =.01 significance level).

Temporal variables

The units for the temporal analysis were the days in the Fire Seasons 1986-1990 and their weather and temporal variables were extracted from historic records available at NoFC, Forestry Canada, in Edmonton.

We considered for this part the following variables:

Codes and Indices in the Canadian Forest Fire Weather Index (CFS 1987): *Fine Fuels Moisture Code*(FFMC), *Duff Moisture Code*(DMC), *Drought Code*(DC), *Initial Spread Index*,(ISI) *Buildup Index*(BUI), and *Fire Weather Index*(FWI).

Temperature in centigrades,

Relative humidity in percentage,

Wind speed in km/h,

Visibility in meters,

Weekday, Monday to Sunday, and,

Month, April to October.

In similar fashion with the geographic study, we considered the total number of days in the five fire seasons the population for analysis, and the days with one or more fires (fire days) a sample to be investigated in its randomness with respect to the population.

The null hypothesis in this case stated that the frequency distribution of a variable x_i among the fire days (the new sample) would be equal to the frequency distribution of x_i in the population encompassing all days in the forest.

We calculated the frequency distributions of the temporal variables for the fire days (199) and for all days in the population (4,082), with SAS, and applied the Chi-square goodness-of-fit test to every pair of sampled and hypothesised distributions. The same decision rule was used in both geographic and temporal variable testing.

Results and discussion

The values obtained for ***Q*** and $C^2_{.01,r-1}$ are shown in Table 1 for all geographic variables considered, with the number of classes r, the result of the test and its P-value:

Table 1: *A list of geographic variables and their Chi-square test values.*

r	variable	Q	$\chi^2_{.01,r-1}$	reject H_0	P-value
10	road distance	177.38	21.7	yes	< .001
4	property	84.07	11.3	yes	< .001
10	town distance	61.70	21.7	yes	< .001
11	elevation	49.06	23.2	yes	< .001
4	district	36.68	11.3	yes	< .001
5	fuels	33.50	13.3	yes	< .001
5	f.commerciality	19.13	13.3	yes	< .001
8	forest age	19.34	18.5	yes	.005< P <.010
6	forest height	17.98	15.1	yes	.001< P <.005
8	lake distance	16.99	18.5	no	.010< P <.025
5	forest density	9.11	13.3	no	.050< P <.100
4	visibility	8.83	11.3	no	.025< P <.050
7	lookout distance	6.68	16.8	no	>.100
7	slope	3.92	16.8	no	>.100
7	river distance	3.35	16.8	no	>.100
5	aspect	2.51	13.3	no	>.100

Table 2: *A list of temporal variables and their Chi-square test values.*

r	variable	Q	$\chi^2_{.01,r-1}$	reject H_0	P-value
6	ISI	242.14	15.1	yes	< .001
10	FWI	237.70	21.7	yes	< .001
9	FFMC	200.43	20.1	yes	< .001
8	rel. humidity	161.74	18.5	yes	< .001
7	month	103.27	16.8	yes	< .001
9	DMC	98.13	20.1	yes	< .001
7	BUI	76.34	16.8	yes	< .001
11	wind speed	29.02	23.2	yes	.001< P <.005
7	DC	16.61	16.8	no	.010< P <.025
8	visibility	14.19	18.5	no	.025< P <.050
5	temperature	10.16	13.3	no	.025< P <.050
7	weekday	4.46	16.8	no	>.100

The same information is provided for the temporal variables in Table 2.

Even when this is an approximate test and P-values are asymptotic approximates, the approximation to ***Q*** provided by the Chi-square distribution can be considered reliable in this case, because the sample size is sufficiently large and the test is robust. Also, recommendations have been followed with respect to the expected frequencies E_i (not smaller than 5)(Dickinson Gibbons 1976).

The test clearly indicates that fire occurrences are not randomly distributed throughout the Whitecourt Forest with respect to topographic, vegetation, and development variables; distance to road, land ownership, distance to town, topographic elevation, district, fuels and some forest characteristics all affect location of wildfires. Also, fire occurrences do not distribute randomly over time with respect to all temporal and weather variables; ISI, FWI, FFMC, relative humidity, month, DMC, BUI, and wind speed appear to be related to timing of fire occurrences, and in that order of importance.

Curiously enough, variables traditionally regarded as relevant to the human fire problem, such as slope and weekday, did not show that importance in this test. In the case of slope, this might be due to lack of variability in data values caused by the general flatness of the study area. In all other cases, there was enough variability in data values in the populations to assume that any trend in fire occurrence would be picked up by the test.

Conclusions

Human-caused wildfire occurrences are rare events that exhibit complex relationships with geographic and temporal variables, which in turn make prediction of occurrence difficult.

There is a great degree of randomness associated with the fire occurrence prediction process, and we will never be able to account for particularities in human behaviour, for instance. But until now we have not yet taken full advantage of some geographic and temporal relationships that appear to be quite well defined as a result of this study, and may improve current predictions.

GIS technology makes possible the investigation of geographic patterns in human-caused wildfires for their incorporation in fire occurrence prediction model building. After this process of variable selection, we consider essential that variables such as distance to road and property are included in new models, and considered at the same level of importance than the usual weather variables.

Acknowledgments

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