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**Automated prediction of extreme fire weather from synoptic patterns in northern Alberta,
Canada.**

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Abstract

Wildfires burn an average of 2 million hectares per year in Canada, most of which can be attributed to only a few days of severe fire weather. These “spread days” are often associated with large-scale weather systems. We used extreme threshold values of three Canadian Fire Weather Index System (CFWIS) variables – the Fine Fuel Moisture Code (FFMC), Initial Spread Index (ISI), and Fire Weather Index (FWI) – as a proxy for spread days. Then we used self-organizing maps (SOMs) to predict spread days, with sea-level pressure and 500-hPa geopotential height as predictors. SOMs require many input parameters, and we performed an experiment to optimize six key parameters. For each month of the fire season (May – August), we also tested whether SOMs perform better when trained with only one month or with neighbouring months as well. Good performance (AUC of 0.8) was achieved for FFMC and ISI, while nearly good performance was achieved for FWI. To our knowledge, this is the first study to develop a machine-learning model for extreme fire weather that could be deployed in real-time.

1. Introduction

Canada experiences an average of 8000 wildfires per year, burning approximately 2 million hectares (Flannigan *et al.* 2009). Most of this area is burned by relatively few large fires. Stocks *et al.* (2002) found that fires burning ≥ 200 ha are responsible for 97% of the area burned, but only 3% of the total number of fires, in Canada. These fires are usually associated with a prolonged rain-free period followed by high winds, which create ideal conditions for both fire ignition and spread (Shabbar *et al.* 2011; Skinner *et al.* 2002). A large percentage of the area is burned in just a few days with such weather conditions (Rothermel *et al.* 1994; Flannigan and Wotton 2001; Scotto *et al.* 2014). These days are called “spread-event days” (Parisien *et al.* 2005; Podur and Wotton 2011), or “spread days” (Wang *et al.* 2014b), and can be used to estimate potential fire danger (Parisien *et al.* 2013; Wang *et al.* 2015; Wang *et al.* 2016). Thus, predicting the spatial and temporal occurrence of spread days over a large area would be a valuable tool for fire management and prediction.

Skinner *et al.* (1999) show that extreme fire weather is favoured by certain large-scale weather patterns (“synoptic patterns”) in the mid-troposphere (at the 500-hPa pressure level, which is usually 5-6 km above sea level). Specifically, extreme fire weather is common under a strong longwave ridge (high-pressure axis with wavelength of ~ 1000 km), during the breakdown of a longwave ridge, and in the eastern sector of an upper-level shortwave trough (low-pressure axis with wavelength of ~ 200 km). Longwave ridges are often associated with warm, dry weather, which allows the fuels to dry. Meanwhile, shortwave troughs are often associated with

strong wind, which can cause existing fires to spread rapidly. Also, shortwave troughs are sometimes associated with thunderstorms, which can provide an ignition source (lightning). However, these relationships between synoptic weather and wildfire are non-linear and high-dimensional, which means that they cannot be easily modeled by traditional statistical methods (*e.g.*, linear regression). More sophisticated methods are required.

Neural networks (Cheng and Titterton 1994) are well known for their ability to learn non-linear relationships. Self-organizing maps (SOMs), a type of neural network, are also well suited to handle high-dimensional data (*e.g.*, gridded meteorological data). SOMs have been used successfully in many meteorological studies, such as attribution of extreme events to synoptic patterns (Cavazos 2000; Nishiyama *et al.* 2007; Schuenemann *et al.* 2009) and predicting changes in the occurrence of synoptic patterns under climate change (Schuenemann and Cassano 2009, 2010). In most of these cases, the predictors were synoptic pressure fields, because pressure is well forecast by numerical weather prediction (NWP) models (Kanamitsu *et al.* 2002; Colle *et al.* 2003; Krishnamurti *et al.* 2003; Hamill *et al.* 2013). Thus, we hypothesized that by applying a SOM to forecast pressure fields, we could produce good fire-weather forecasts. Specifically, we used sea-level pressure (SLP) and 500-hPa geopotential height (H500) as predictors.

Fire weather in Canada is measured by the empirically based Canadian Fire Weather Index System (CFWIS) (Van Wagner 1987), which is a key component of the Canadian Forest Fire Danger Rating System (CFFDRS) (Stocks *et al.* 1989; Taylor and Alexander 2006). The CFWIS consists of six indices, calculated from observations of four weather variables at 1200 local standard time (LST): 1.5-metre air temperature, 1.5-metre relative humidity, 10-metre wind speed, and precipitation in the last 24 hours. Of the six CFWIS indices, there are three fuel-

moisture codes and three potential-fire-behaviour indices. The fuel-moisture codes – Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), and Drought Code (DC) – are proxies for fuel moisture in three layers of the forest floor. The potential-fire-behaviour indices – Initial Spread Index (ISI), Build-up Index (BUI), and Fire Weather Index (FWI) – are calculated from the fuel-moisture codes. These are proxies for the rate of fire spread, amount of combustible fuel, and overall fire intensity, respectively.

Here we use SOMs to predict extreme fire weather in northern Alberta, where wildfires are common and weather conditions have been monitored for decades. SOMs were trained on SLP and H500 fields to produce “map types,” or typical composite SLP-H500 fields; then a fire-weather climatology was created for each map type. This conditional climatology involves statistics of the three dependent variables: FFMC, ISI, and FWI. Our main objectives were to (a) develop a general framework for using SOMs to predict fire weather and (b) create a set of calibrated SOMs for predicting extreme fire weather in northern Alberta.

2. Data and methods

2.1. Study area

Our main study area was northern Alberta (Figure 1(a)). Throughout Alberta between 1961 and 2014, wildfires burned an average of 147 800 ha per year, with a minimum of 1750 ha in 1962 and maximum of 1 357 190 ha in 1981 (Blouin *et al.* 2016). Most of these fires occurred in the northern part of the province, which is heavily forested (Stocks *et al.* 2002).

To eliminate edge effects, we buffered northern Alberta with parts of western Saskatchewan, eastern British Columbia, and the southern Northwest Territories. Thus, the full study area reaches 53-63 °N and 108-122 °W (Figure 1(a)). This area consists mainly of two

ecozones (Ecological Stratification Working Group 1996), the Taiga Plains in the northwest and Boreal Plains elsewhere (Figure 1(b)).

2.2. Data sources

2.2.1. Dependent variables

We used three CFWIS indices as dependent variables: FFMC, ISI, and FWI. These are proxies for the probability of fire ignition, potential fire intensity, and potential growth rate respectively (Van Wagner 1987). Thresholds of 91 for FFMC, 8.7 for ISI, and 19 for FWI were used to define extreme fire weather (Table 1). FFMC of 91 (corresponding to a moisture content of 10%) is a reasonable threshold for vigorous fire spread (Wotton 2009). The thresholds for ISI (8.7) and FWI (19) are also linked to active spread days in Canada (Podur and Wotton 2011). CFWIS indices were calculated from weather variables observed at 1200 LST, provided by Environment Canada (EC) (2015a) and Alberta Agriculture and Forestry (AAF) (2015). The EC (AAF) dataset contains 560 (318) stations in our study area, covering 1953 – 2007 (1975 – 2009). See Figure 1(a) for station locations.

For the EC dataset, CFWIS indices were calculated using the R function `fwi` (Wang *et al.* 2017). For the AAF dataset, CFWIS indices were already calculated. Inputs for the CFWIS indices should include accumulated precipitation from 1200-1200 LST, but precipitation in the EC dataset is measured from 0600 – 0600 UTC (2300 – 2300 LST in northern Alberta). Thus, the offset between the two measurement periods was 11 hours. However, our model focuses on *extreme* fire weather, which usually occurs only after a prolonged dry period. Thus, the 11-hour offset was an issue only when precipitation occurred at the end of a prolonged dry period.

2.2.2. *Predictor variables*

In datasets with many grid cells (as in Figure 1(b)), the dimensionality increases quickly with the number of variables. For example, if there are 500 grid cells, adding one variable increases the dimensionality by 500. High dimensionality leads to longer processing time, more memory usage, and often overfitting. These symptoms are part of the “curse of dimensionality”. In similar studies (where SOMs were trained with many grid cells), only 1 – 3 variables were used (e.g., Hewitson and Crane 2002; Reusch *et al.* 2005; Nishiyama *et al.* 2007; Schuenemann *et al.* 2009; Schuenemann and Cassano 2009, 2010). In this study we used two predictor variables, the aforementioned SLP and H500.

SLP and H500 drive the surface and upper-level winds, respectively, which allows them to significantly impact surface weather conditions. Low pressure generally leads to cool and wet (poor burning) conditions, while high pressure generally leads to warm and dry (good burning) conditions. For example, as mentioned in Section 1, longwave pressure ridges often lead to warm and dry conditions, which promote the drying of fuels.

SLP and H500 fields were downloaded from the North American Regional Reanalysis (NARR) (Mesinger *et al.* 2006). The NARR is an atmospheric and hydrological dataset, created using output from the National Centers for Environmental Prediction (NCEP) – Department of Energy (DOE) Global Reanalysis, the NCEP Eta model, the Noah land-surface model, and observed precipitation. NARR data are provided on a 32-km grid with 3-hour time steps. We used every fourth grid cell (every second grid cell in both *x*- and *y*-directions), which increased the grid spacing to 64 km. This helped to mitigate high-dimensionality problems.

2.3. *Data-processing*

Synoptic-scale wind is driven by horizontal pressure gradients, rather than single point values. Thus, we trained the SOMs with horizontal pressure gradients. These were calculated by the finite-difference equations below.

$$\frac{\partial Q_{i,j}}{\partial x} = \frac{Q_{i+1,j} - Q_{i-1,j}}{2\Delta x} \quad (\text{Equation 1(a)})$$

$$\frac{\partial Q_{i,j}}{\partial y} = \frac{Q_{i,j+1} - Q_{i,j-1}}{2\Delta y} \quad (\text{Equation 1(b)})$$

Q is the relevant variable (SLP or H500); $Q_{k,m}$ is the value at grid cell (k, m) ; and Δx and Δy are the zonal and meridional grid spacings, respectively (both 64 km for our data). The result is four gradient components at each grid cell. Thus, taking the gradient doubles the number of variables.

Because the predictor and dependent variables have different time resolutions (3 and 24 hours, respectively), we averaged the predictors for each day over 24 hours (eight time steps). This averaging was complicated by two factors: (a) CFWIS indices are time-referenced in LST, while predictors are time-referenced in UTC; (b) although CFWIS indices are based on weather conditions observed at 1200 LST, they are calculated to represent late-afternoon burning conditions (Van Wagner 1987). Late afternoon is 1500 – 1800 LST, or 2200 – 0100 UTC in northern Alberta, so CFWIS indices in northern Alberta are valid for approximately 0000 UTC. Thus, for each day D , we averaged predictors from the last eight time steps before 0000 UTC (0000 UTC, 0300 UTC, ..., 2100 UTC of day $D - 1$). This allowed predictors and CFWIS indices to be linked in time. Averaging was done independently for each gradient component at each grid cell.

Thus, predictor variables were transformed in two ways: gradient calculation and time-averaging. In general, the order of operations would matter. However, since a linear finite-difference operator (Equation 1) was used, the average gradient is the gradient of the average.

The three datasets (EC, AAF, and NARR) cover different time periods. We used the common years, 1979 – 2007, for training and testing.

2.4. *Using SOMs to predict extreme fire weather: basic ideas*

At the simplest level, a SOM is a two-dimensional array of neurons. Each neuron has two properties: its position in the array, and a “codebook vector” or “map type,” which is a pattern found in the training data. Each training example is a predictor field, consisting of the four gradient components at each grid cell in Figure 1(b). The dimensions of the neuron layer and predictor fields are independent. However, the dimensions of a map type equal the dimensions of a predictor field (252 grid cells by 4 variables). As the SOM is trained, each map type becomes more similar to a subset of the training data; in other words, map types are “adjusted to” the training data. However, if the SOM is trained for too long, it will overfit and generalize poorly to new data.

After training the SOM, map types are correlated with fire weather. In other words, a conditional climatology is created for each dependent variable, given each map type. Assuming that (a) conditional climatologies hold for new data and (b) good forecasts of SLP and H500 are available, map types can be used to make good fire-weather forecasts on new data.

The fire season in northern Alberta is roughly May through August (Skinner *et al.* 2002). Thus, we trained SOMs for one month at a time, which allowed them to implicitly account for seasonality (*e.g.*, the same synoptic pressure pattern might cause different fire-weather

conditions in May than in August). Lastly, to control for overfitting, the data for each SOM were split into a test set (1980, 1985, 1990, 1995, 2000, 2005) and training set (the other 22 years). For more details on using SOMs to predict fire weather, see supplementary material.

2.5. Forecast evaluation

SOMs were evaluated with receiver operating characteristic (ROC) curves (Metz 1978). For each SOM and each dependent variable V , the ROC curve is created as follows.

1. Generate forecasts of extreme-value probability ($\hat{p}_{extreme}$ in Equation 4(a) of supplementary material) for the test set (over all grid cells G and dates D).
2. Find unique values of $\hat{p}_{extreme}$ (“thresholds”). For each threshold p^* , call any $\hat{p}_{extreme} \geq p^*$ a “yes” forecast and any $\hat{p}_{extreme} < p^*$ a “no” forecast. Then calculate the true-positive rate (TPR) and false-positive rate (FPR).
3. Plot TPR-FPR pairs on a graph (as in Figure 2).

$$TPR = \frac{\# \text{ of true positives}}{\# \text{ of actual positives}} \quad (\text{Equation 2(a)})$$

$$FPR = \frac{\# \text{ of false positives}}{\# \text{ of actual negatives}} \quad (\text{Equation 2(b)})$$

For each ROC curve, area under the curve (AUC) was used to measure performance. AUC varies from 0.0 to 1.0, and higher values are considered better. Commonly used thresholds for a “fair” and “good” predictor are 0.7 and 0.8, respectively (Luna-Herrera *et al.* 2003; Muller *et al.* 2005; Mehdi *et al.* 2011).

2.6. Tuning (calibration of input parameters)

Using the framework developed in supplementary material, we trained SOMs with various input parameters, with the goal of optimizing parameters for each dependent variable and

month. However, it was impossible to experiment with all parameters, so some were fixed using *a priori* reasoning. These “controlled parameters” are listed in Table 2, while “experimental parameters” are listed in Table 3.

For two of the six experimental parameters, values were set by a coefficient rather than directly, following suggestions in SOM_PAK. The first is number of epochs, which was set using Equations 3.

$$N_e^{rough} = \frac{d N_{neurons}}{4 N_{training}} \tag{Equation 3(a)}$$

$$N_e^{fine} = d \frac{N_{neurons}}{N_{training}} \tag{Equation 3(b)}$$

N_e^{rough} (N_e^{fine}) is the number of epochs for rough- (fine-) tuning; d is a coefficient; $N_{neurons}$ is the number of neurons; and $N_{training}$ is the number of training examples. The second is initial neighbourhood radius, which was set using Equations 4.

$$\sigma_0^{rough} = c_1 \max(N_{rows}, N_{cols}) \tag{Equation 4(a)}$$

$$\sigma_0^{fine} = c_2 \sigma_0^{rough} \tag{Equation 4(b)}$$

σ_0^{rough} (σ_0^{fine}) is the initial radius for rough- (fine-)tuning; c_1 and c_2 are coefficients; N_{rows} is the number of rows, and N_{cols} is the number of columns, in the neuron array.

2.6.1. Tuning, Phase One

For each dependent variable, we trained SOMs with all 5760 combinations of the six experimental parameters. In this phase SOMs were trained for July only, without the use of neighbouring months. This decreased processing time and allowed all 5760 combinations to be tested. By tuning parameters for July only, we assumed that optimal parameters (a) are similar for a SOM trained with or without neighbouring months and (b) are similar for all months in the

fire season.

2.6.2. *Tuning, Phase Two*

For each dependent variable, the top 25 SOMs (those with the best AUCs) from Phase 1 were used in Phase 2. Each of the 25 SOMs was trained for all months of the fire season, both with and without neighbouring months. The procedure is as follows, for each dependent variable V .

1. Find the top 25 SOMs from Phase 1. Call these S^* .
2. For each S^* and each month (May – August), retrain the SOM twice: once with neighbouring months, once without. Keep all other parameters as they were in Phase 1.
3. For each month (May – August), find the best SOM from step 2.

The result of this experiment is one chosen SOM for each dependent variable and month.

3. Results

3.1. *Phase One*

Figure 2(a) shows the best ROC curve for each dependent variable. The AUCs were approximately 0.782 for FFMC, 0.765 for ISI, and 0.717 for FWI. Thus, SOMs trained with July only achieved nearly good performance for FFMC and ISI, but only fair performance for FWI.

For each dependent variable, Figure 3 shows the distribution of experimental parameter for the best 25 SOMs. In general, the best d -coefficients were 25 and 100, leading to the fewest and most epochs respectively. The best neighbourhood functions were bubble and Epanechnikov (the two non-Gaussian functions), for FFMC, the two Gaussian functions for ISI,

and Epanechnikov for FWI. For neighbourhood radius, there was no clear winner for FFMC and ISI; the best combination for FWI was $c_1 = c_2 = 1/4$, which leads to the smallest neighbourhood radii. For the gradient-distance exponent, there was also no clear winner for FFMC and ISI; higher values were strongly preferred for FWI. *K*-means was clearly the best clustering method for all dependent variables. Lastly, fewer map types were preferred for FFMC and ISI; there was no clear winner for FWI.

3.2. Phase Two

For the chosen SOMs, Figures 2(b-e) show ROC curves and Table 4 shows the distribution of experimental parameters. The top AUC was 0.837 for FFMC (August), 0.802 for ISI (August), and 0.782 for FWI (May). Thus, good (nearly good) performance was achieved for FFMC and ISI (FWI). In general, performance was worse in the middle of the fire season (June and July, as opposed to May and August).

Figure 4 is to Phase 2 as Figure 3 is to Phase 1. However, SOMs in Figure 4 were selected in a slightly different way. For each dependent variable and month, we selected the top five SOMs trained with neighbouring months and the top five without. Otherwise, many of the SOMs selected would have been trained on the same time period, which would decrease the generality of the results.

Differences between Figures 3 and 4 are summarized below. The best *d*-coefficients in Phase 2 were 50 for FFMC, 25 for ISI and FWI – which suggests that better performance occurs with fewer epochs. In contrast, the best values in Phase 1 were 25 and 100, which suggested optima at both ends of the spectrum. For neighbourhood function and radius, Phase 2 results were inconclusive for all dependent variables. For the gradient-distance exponent, higher values

were preferred for all dependent variables in Phase 2. This is consistent with, but stronger than, Phase 1 results. Lastly, the best number of map types in Phase 2 was ≤ 20 for FFMC (consistent with Phase 1), ≥ 60 for ISI (opposite of Phase 1), and ≤ 20 for FWI (inconclusive in Phase 1).

For all dependent variables in June and FWI in August, the best SOMs were those trained with neighbouring months. Also, for these four variable-month pairs, nearly all SOMs trained with neighbouring months were better than all SOMs trained without. For the other eight variable-month pairs, the opposite was true.

Based on these results, recommended values of experimental parameters are given in Table 5.

4. Discussion and conclusions

The chosen SOMs were consistently good or nearly good predictors of FFMC and ISI, but only fair predictors of FWI. As discussed in Van Wagner (1987), FFMC and ISI respond more quickly to changes in weather conditions than does FWI. This is because the FWI formula involves BUI (a proxy for combustible fuel), which has a much longer response time. To account for this, we made the *e*-folding time and maximum lags longer (1 and 8 days, respectively) for FWI. However, FWI predictions still had the worst performance of all three variables. Perhaps this is because FWI's response to weather conditions does not follow the exponential decay assumed in Equations 4 of the supplement, or perhaps the values chosen for *e*-folding time and maximum lag were inappropriate.

Inferior SOM performance in June and July was probably due to increased thunderstorm activity in these months. Thunderstorms often produce heavy rain and strong winds, both of which significantly impact fire weather. However, thunderstorms are subsynoptic-scale phenomena, which makes them harder to predict with synoptic weather patterns (*e.g.*, pressure

fields at 64-km resolution). This shortcoming could potentially be improved by (a) downloading predictor fields from a higher-resolution model or (b) using additional variables with a stronger relation to thunderstorm activity, such as convective available potential energy (CAPE). However, these approaches would increase the number of (a) grid cells or (b) variables, which would increase the risks associated with high dimensionality (Section 2.2.2).

The best SOMs for June were those trained with neighbouring months, which suggests that the relationship between predictors (SLP and H500) and fire weather is fairly constant from May through July. This also suggests that other predictors of fire weather (those not included in the SOMs) are fairly constant over the three months. For May, July, and August, the best SOMs were those trained without neighbouring months, which suggests that non-included predictors (*e.g.*, temperature and humidity) changed significantly over the neighbouring months. This result was unexpected, since temperature and humidity in northern Alberta change more from May – July (the neighbours of June) than, for example, from June – August (the neighbours of July). For example, see climate normal for Athabasca, Fort McMurray, Grande Prairie, and High Level (Environment Canada 2015*b*). Perhaps July results worsened with neighbouring months simply because July has more thunderstorm activity, so fire weather in July is less dependent on synoptic patterns than in neighbouring months.

Previous machine-learning studies in fire weather have attempted to predict only human-caused fire ignition (Cunningham and Martell 1973; Martell *et al.* 1987, 1989; Garcia *et al.* 1995; Wotton *et al.* 2003), only lightning-caused fire ignition (Krawchuk *et al.* 2009), large-fire ignition (both lightning- and human-caused) (Preisler *et al.* 2004; Preisler and Westerling 2007; Bradstock *et al.* 2009), or area burned and number of fires (Carvalho *et al.* 2008). Also, a few studies have related fire activity to synoptic weather patterns, but without explicitly developing a

predictive model. Skinner *et al.* (1999) used *K*-means clustering to find H500 patterns associated with large fires in Canada, and Crimmins (2006) used SOMs to find 700-hPa height patterns associated with extreme fire weather in the southeastern U.S. Pereira *et al.* (2005) used linear regression on May – August precipitation and H500 to predict June – September burned area in Portugal. Although they developed a predictive model, it requires data for the first four months of the fire season, which precludes it from real-time use.

To the best of our knowledge, this is the first study to develop a fire-weather-prediction model that could be deployed in real-time. We chose to predict fire *weather*, rather than *activity*, due to human stochasticity involved in the latter (*e.g.*, human-caused ignition and suppression efforts). Weather is arguably the best predictor of fire activity over time periods of a month or longer (Cary *et al.* 2006; Abatzoglou and Kolden 2013). Also, NWP-forecast pressure fields and daily CFWIS indices are already ubiquitous in Canadian fire management. Thus, our product could be a useful and easily applied tool for fire-management agencies throughout Canada. However, our models apply only to northern Alberta, so separate SOMs would need to be trained for other regions.

Our current SOM approach may have benefits over traditional approaches of predicting extreme fire weather. The standard way of predicting extreme fire weather is to take the forecast values of surface temperature, relative humidity, wind speed and 24-h precipitation and then calculate the FWI System indices. Predicted values of these surface meteorological variables used in the conventional approach are not nearly as accurate as predicted values of SLP and H500. This suggests that SOMs may provide a better and more robust method to flag potential extreme fire-weather events. This could contribute to the development of an early warning system so that fire management agencies could ensure resources are available and in position.

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Tables

Table 1: Parameters used for correlation and forecast evaluation.

Thresholds for FFMFC, ISI, and FWI are based on Taylor and Alexander (2006), Wang *et al.* (2014*b*), and Podur and Wotton (2011), respectively. *e*-folding times for FFMFC and FWI are based on San-Miguel-Ayanz et al. (2003) and personal correspondence with Mike Wotton, respectively. The *e*-folding time for ISI equals that for FFMFC, since ISI is based only on FFMFC and the current day’s wind speed. For each dependent variable, maximum time lag is the greatest lag *k* such that w_k (the weight in Equation 4 of supplementary material) is non-negligible (order of 10^{-3} or greater).

Dependent Variable	Extreme-value Threshold	Maximum Time Lag (days)	<i>e</i> -Folding Time (hours)
FFMC	91	6	16
ISI	8.7	6	16
FWI	19	9	24

Table 2: Controlled parameters (used for training and clustering).

Training Parameters	Possible Values	Chosen Value	Reason for Chosen Value
Dimensions of neuron layer	M, N (both positive integers)	Automatic	SOM_PAK determines the best M and N , from number of neurons and ratio between top two eigenvalues of training data (Kohonen <i>et al.</i> 1996).
Initialization method	Random, principal components	Principal components	Map types were initialized along the first two principal components of the training data. This leads to a better fit, reducing epochs needed for rough- and fine-tuning.
Number of neurons	Positive integer	5000	SOM performance increases with $N_{neurons}$ (Ultsch and Mörchén 2005). 5000 is a compromise between performance and computing resources.
Shape of neuron array	Sheet, cylindrical, toroidal	Rectangular	Easier to understand and visualize.
Topology of neuron array	Hexagonal, rectangular	Hexagonal	Easier to understand (each neuron has 6 equidistant neighbours, rather than 4 edge neighbours and 4 corner neighbours).
Training mode	Batch, sequential	Batch	Decreases runtime.

Clustering Parameters			
Training mode (<i>K</i> -means only)	Batch, sequential	Batch	Decreases runtime.
Number of epochs (<i>K</i> -means only)	Positive integer	500	To ensure convergence. If <i>K</i> -means converges before 500 epochs, algorithm stops.
Number of iterations (<i>K</i> -means only)	Positive integer	20	<i>K</i> -means is non-deterministic, so we use the best iteration. Results usually do not improve after 20 iterations.
Linkage method (AHC only)	Average, centroid, complete, median, single, Ward, weighted	Ward	Ward's is the only method that we had time to generalize from Euclidean to gradient distance.

Table 3: Experimental parameters (used for training and clustering).

Parameter	Values Tested	Explanation (if necessary)
Number of epochs	$d = 25, 50, 75, 100$	d is a coefficient, used in Equations 3 to determine the number of epochs.
Neighbourhood function	Bubble, Gaussian, bubble-Gaussian, Epanechnikov	See Equation 2 in supplementary material.
Neighbourhood radius	$c_1 = \frac{1}{2}$ $c_2 = \frac{1}{2}$ $c_1 = \frac{1}{2}$ $c_2 = \frac{1}{4}$ $c_1 = \frac{1}{4}$ $c_2 = \frac{1}{2}$ $c_1 = \frac{1}{4}$ $c_2 = \frac{1}{4}$	c_1 and c_2 are coefficients, used in Equations 4 to determine the initial neighbourhood radii for both rough- and fine-tuning.
Exponent in gradient distance (L)	1.0, 1.5, 2.0	See Equation 3 in supplementary material.
Clustering method	<i>K</i> -means, AHC	Main difference is that AHC (<i>K</i> -means) is (non-)deterministic.
Number of clusters (final map types)	20, 40, 60, 80, 100	

Table 4: Best SOM for each dependent variable and month.

AUC values are a 95% confidence interval over 100 bootstrap replicates. d , c_1 , c_2 , and L have the same meaning as in Table 4.

Variable	Month	AUC	Neigh Months	d	L	Neigh Func'n	c_1	c_2	Clust Method	Map Types
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			Used?							
FFMC	May	[0.779, 0.787]	no	75	1.5	bubble	$\frac{1}{4}$	$\frac{1}{2}$	<i>K</i> -means	20
	Jun	[0.735, 0.743]	yes	50	2.0	bubble	$\frac{1}{2}$	$\frac{1}{2}$	<i>K</i> -means	20
	Jul	[0.773, 0.790]	no	50	1.5	bubble	$\frac{1}{2}$	$\frac{1}{2}$	<i>K</i> -means	20
	Aug	[0.829, 0.845]	no	25	1.0	Gauss	$\frac{1}{4}$	$\frac{1}{4}$	AHC	60
ISI	May	[0.763, 0.774]	no	25	1.5	Gauss	$\frac{1}{4}$	$\frac{1}{2}$	<i>K</i> -means	40
	Jun	[0.730, 0.737]	yes	25	1.5	bubble	$\frac{1}{2}$	$\frac{1}{4}$	<i>K</i> -means	60
	Jul	[0.758, 0.771]	no	25	1.0	Gauss	$\frac{1}{4}$	$\frac{1}{4}$	AHC	60
	Aug	[0.794, 0.810]	no	25	1.5	Gauss	$\frac{1}{4}$	$\frac{1}{2}$	<i>K</i> -means	40
FWI	May	[0.777, 0.787]	no	100	1.5	Gauss	$\frac{1}{2}$	$\frac{1}{2}$	AHC	40
	Jun	[0.710, 0.717]	yes	25	2.0	bubble	$\frac{1}{4}$	$\frac{1}{4}$	<i>K</i> -means	60
	Jul	[0.712, 0.722]	no	25	1.0	Gauss	$\frac{1}{4}$	$\frac{1}{4}$	AHC	60
	Aug	[0.718, 0.725]	yes	25	2.0	bubble	$\frac{1}{4}$	$\frac{1}{2}$	<i>K</i> -means	60

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Table 5: Recommended values for experimental parameters.

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For number of epochs, also experiment with other values as time allows.

Parameter	Dependent Variable		
	FFMC	ISI	FWI
Number of epochs	$d \leq 25$	$d \leq 50$	$d \leq 25$
Neigh function	Try all functions.		
Neigh radius	Try all combinations of c_1 and c_2 .		
Exponent in distance metric (L)	Try 1.5 and 2.0.		
Clustering method	<i>K</i> -means		
Number of clusters (final map types)	≤ 20	≥ 60	≤ 20

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FIG. 1. [a] Location of study area and weather stations used for CFWIS indices. [b] Ecozones in study area and grid points used for predictor fields. AB, BC, and SK are the Canadian provinces of Alberta, British Columbia, and Saskatchewan respectively. NWT is the Canadian Northwest Territories.

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FIG. 2. Best ROC curves for different months and phases of tuning experiment. In each case the solid line (shading) shows the mean (95% confidence interval) over 100 bootstrap replicates. The 95% confidence interval for AUC is marked next to each ROC curve. [a] Phase 1. [b] Phase 2, May. [c] Phase 2, June. [d] Phase 2, July. [e] Phase 2, August.

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FIG. 3. For each dependent variable, bar graphs show the distribution of experimental parameters from the top 25 SOMs in Phase 1.

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FIG. 4. Same as Fig. 4, except for Phase 2.

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Automated prediction of extreme fire weather from synoptic patterns in northern Alberta, Canada. – Supplement

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1. Using SOMs to predict extreme fire weather: framework

1.1. Training the SOM

SOMs were trained with the SOM_PAK toolbox for MATLAB (Kohonen *et al.* 1996). Training was done in two stages, rough-tuning and fine-tuning. Each stage consists of multiple epochs. During an epoch, each training example (predictor field) is presented to the SOM once. For each epoch t and training example i , all neurons j are updated by the following equation.

$$\overrightarrow{MT_j} \leftarrow \overrightarrow{MT_j} + f_{\text{neigh}}(\sigma, \|\overrightarrow{r_{n^*}} - \overrightarrow{r_j}\|)(\overrightarrow{x_i} - \overrightarrow{MT_j}) \quad (1)$$

$\overrightarrow{MT_j}$ is the map type for the j^{th} neuron; $f_{\text{neigh}}(\sigma, \|\overrightarrow{r_{n^*}} - \overrightarrow{r_j}\|)$ is the neighbourhood function; σ is the neighbourhood radius; n^* is the winner neuron (that whose map type is most similar to $\overrightarrow{x_i}$); $\|\overrightarrow{r_{n^*}} - \overrightarrow{r_j}\|$ is the distance in map space between the winner neuron and j^{th} neuron; and $\overrightarrow{x_i}$ is the i^{th} training example.

The neighbourhood function determines the update weight for each neuron j , based on its distance from the winner neuron n^* in map space (*i.e.*, the Euclidean distance between the positions of neurons j and n^*). Neurons closer to n^* are given a higher update weight, so their map types are adjusted more strongly towards the training example. Meanwhile, the neighbourhood radius is the distance from n^* at which the neighbourhood function drops to zero (or a very small value, if the neighbourhood function is Gaussian). Throughout both rough- and fine-tuning, the neighbourhood radius decreases to 1, so that only n^* and its immediate neighbours are updated.

As a concrete example, the Gaussian neighbourhood function is as follows. The meaning of each variable is the same as in Equation 1.

$$f_{neigh}(\sigma, \|\vec{r}_{n^*} - \vec{r}_j\|) = \exp\left(-\frac{\|\vec{r}_{n^*} - \vec{r}_j\|^2}{2\sigma^2(t)}\right) \quad (2)$$

During rough-tuning, the neighbourhood radius is larger; thus, the SOM is more sensitive and requires fewer epochs to learn patterns in the training data. During fine-tuning, the neighbourhood radius is smaller, so the SOM is less sensitive and needs more epochs. The two-stage training method reduces the risk of overfitting, as fine-tuning only may fit the SOM to noise in the training data.

As per Equation 1, the winner neuron (that with the most similar map type) must be found for each training example. Usually this is the map type with the minimum Euclidean distance from the training example. However, we defined a new distance function, called the “gradient distance,” which accounts for the fact that vector fields are being compared rather than scalar fields. In experiments (not shown), SOMs performed much better when trained with the gradient distance. The following equation compares gradient vectors for one variable at one grid cell.

$$d(\vec{\nabla}x_1, \vec{\nabla}x_2) = [1 - \sin(\theta_1)\sin(\theta_2) - \cos(\theta_1)\cos(\theta_2)][\|\vec{\nabla}x_1\|^L + \|\vec{\nabla}x_2\|^L] \quad (3)$$

x is the relevant variable (SLP or H500); θ is the orientation of the gradient vector; $\sin(\theta_1)\sin(\theta_2) + \cos(\theta_1)\cos(\theta_2)$ is the dot product between gradient vectors [thus, $1 - \sin(\theta_1)\sin(\theta_2) - \cos(\theta_1)\cos(\theta_2)$ is the difference between gradient directions]; $\|\vec{\nabla}x\|$ is the gradient magnitude; and L is an arbitrary exponent. If $L > 1$ ($L < 1$), differences between the gradient magnitudes (directions) are more heavily emphasized. The “gradient distance” between two predictor fields (*e.g.*, a map type and training example) is the sum of Equation 3 over all variables and grid cells.

1.2. Clustering the SOM

Following Ultsch and Mörchén (2005), we used a very large number of map types, then grouped similar map types into clusters. We used one of two clustering algorithms: either K -means (MacQueen 1967) or agglomerative hierarchical clustering (AHC) (Ward 1963). We used the gradient distance (Equation 3) to compare map types. After clustering, the mean of each cluster was computed; these means became the new map types. The number of original (clustered) map types was 5000 (20-100).

1.3. Correlating the SOM

Correlation and forecast evaluation (Section 1.4) require three input parameters for each dependent variable (FFMC, FWI, and ISI): the extreme-value threshold, e -folding time, and maximum time lag. Table 1 shows the values used.

SOM correlation involves creating a conditional climatology of the dependent variables for each map type. The procedure is described below for each map type M , dependent variable

V , and grid cell G . Let k_{max} be the maximum time lag for V .

1. Find all training examples for which M is the most similar map type.
2. For all such training examples and each time lag k from $1 \dots k_{max}$ days, link all values of V within 100 km of grid cell G to map type M .
3. For each time lag k from $1 \dots k_{max}$ days, calculate the frequency of extreme V within 100 km of G .

Since the distribution of weather stations does not match the 64-km grid used for map types, a buffer distance was required to link map types and dependent variables spatially. As shown above, we chose a buffer distance of 100 km. In experiments (not shown), SOM performance was similar for buffer distances of 50 and 200 km. We chose 100 km subjectively, as this produced the easiest maps for us to interpret. The buffer distance could easily be changed, depending on users' needs.

1.4. Forecast evaluation

Evaluation consists of two steps: (a) predict dependent variables for test cases and (b) compare predictions with true values.

The following procedure was used to predict test cases for each dependent variable V , on date D at grid cell G . Again, let k_{max} be the maximum time lag for V .

1. For each time lag k from $1 \dots k_{max}$ days, find the most similar map type (M_k) on date $D - k$.
2. For each time lag k from $1 \dots k_{max}$ days, find the frequency of extreme V , within 100 km of grid cell G , under map type M_k . Let this frequency (calculated in Section 1.3) be f_k .
3. Combine all frequencies f_k into a single value. This is done with an exponential

weighting scheme:

$$\hat{p}_{extreme} = \frac{\sum_{k=1}^{k_{max}} w_k f_k}{\sum_{k=1}^{k_{max}} w_k} \quad (4a)$$

$$w_k = \exp\left(-\frac{k-1}{\tau}\right) \quad (4b)$$

k is the time lag (days); k_{max} is the maximum time lag for variable V (days); w_k is the weight for the k^{th} time lag; f_k is the frequency of extreme V at time lag k ; τ is the e -folding time for variable V (days); and $\hat{p}_{extreme}$ is the resulting forecast. More specifically, this is the forecast probability of extreme V on day D , within 100 km of grid cell G .

Once the above procedure has been repeated for each grid cell, a spatial map of the forecast probabilities can be produced. Figure S1 shows the forecast probabilities of extreme ISI at 0000 UTC 1 Jun 1995 (a test case, since 1995 was not used in training). This was during the historic Mariana Lake fire (around 56 °N and 112 °W). The resulting forecast (panel g) is close to the observed ISI field (panel m).

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