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WILDLAND FIRE PROBABILITIES ESTIMATED FROM WEATHER MODEL-DEDUCED MONTHLY MEAN FIRE DANGER INDICES

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Abstract

The National Fire Danger Rating System indices deduced from a regional simulation weather model were used to estimate probabilities and numbers of large fire events on monthly and one degree grid scales. The weather model simulations and forecasts are ongoing experimental products from the Experimental Climate Prediction Center at the Scripps Institution of Oceanography. The monthly average Fosberg Fire Weather Index, deduced from the weather simulation, along with the monthly average Keetch-Byram Drought Index and Energy Release Component, were found to be more strongly associated with large fire events on a monthly scale than any of the other stand-alone fire weather or danger indices. These selected indices were used in the spatially explicit probability model to estimate the number of large fire events. Historic probabilities were also estimated using spatially smoothed historic frequencies of large fire events. It was shown that the probability model using four fire danger indices outperformed the historic model, an indication that these indices have some skill. Geographical maps of the estimated monthly wildland fire probabilities, developed using a combination of four indices, were produced for each year and were found to give reasonable matches to actual fire events. This method paves a feasible way to assess the skill of climate forecast outputs, from a dynamical meteorological model, in forecasting the probability of wildland fire severity with known precision.

Introduction

Since the US Forest Service (USFS) National Fire Danger Rating System (NFDRS) was developed (Deeming *et al*. 1977), the indices of the system have been routinely evaluated, updated and standardized at individual stations as a monitoring measure to assess current fire danger at local and national scales. The NFDRS indices reflect average worst case fire potential from the effects of terrain, weather and fuel conditions represented by standard fuel models. Fuel moisture models use weather input such as cumulative precipitation, temperature and relative humidity to determine moisture content of the fuels. Federal, state and local wildland fire management agencies use the NFDRS for quantification of risk, staffing levels, appropriate suppression response, and strategic planning (NWCG Fire Weather Working Team 2005).

Clearly, the reliability and the integrity of the NFDRS depend partially on the quality and quantity of input data obtained from weather stations. Typical difficulties with fire weather station data include insufficient spatial coverage and inconsistent maintenance of weather instruments. An alternative source of fire weather data for the NFDRS is global or regional scale weather analysis in digital formats. A weather model can provide not only dynamically consistent data with ample spatial coverage; it can also provide weather predictions for dynamical forecasts of NFDRS indices with lead times ranging from days to a season or longer.

Recently, Roads et al. (2005) evaluated experimental forecasts of NFDRS indices at weekly to seasonal scales that used long-range weather predictions from a meteorological model. They showed that these indices can be well predicted at weekly time scales when compared with indices computed from weather model-generated one-day forecasts, which they call validation data, because the one-day forecast data are used to “validate” the weekly to seasonal forecasts . Some indices have prediction skill even at seasonal scales, especially over summers in the western US. Similarly, Hoadley et al. (2004, 2006) found that predicted surface weather variables from the fifth-generation Mesoscale Model (MM5) and the daily corresponding NFDRS indices compared reasonably well to the observed weather at selected stations and the corresponding “observed” indices, calculated from the observed weather. Even if predicted fire indices from weather models are skillful at various time scales, there is still a question as to how these model-deduced indices correlate with actual fire statistics, such as number of large fire occurrences and acres burned. Roads et al. (2005) found a rather weak relationship between their monthly-mean validation indices and the observed fire counts or acres burned. Part of their problem might have been the use of simple temporal correlation at each grid point between the validation indices and the actual fire counts. Correlation statistics are typically a poor measure of association when they involve count variables that are small (most fire counts are zero or one). Alternative statistical analyses may better describe associations between modeled fire indices and observed fire counts, including counts of fires of different sizes. Moreover, strategic planning activities in a seasonal time frame typically involve large areas, from regional to national scales, e.g. the US fire season severity assessment. Further analysis is therefore warranted that relates fire activity statistics from large areas to candidate fire weather and index predictors. This paper focuses on the effectiveness of the model simulated NFDRS indices in estimating large fire events.

Others have studied the skill of daily NFDRS indices, produced using weather station data, in estimating probabilities of large fires. Simard et al. (1987) developed an extreme fire potential index, based on NFDRS indices, and employed a threshold value of the index that captured a large number of extreme fire event days with a minimum number of false alarm days. Andrews and Bradshaw (1997) demonstrated how a logistic model may be used to generate probability curves relating daily fire activity in a given forest to NFDRS indices from the closest weather station. Preisler et al. (2004) developed a spatially and temporally explicit logistic model, on a 1-km^2 –day scale, to estimate probabilities of large federal fires in Oregon using NFDRS indices also from weather stations.

In this study a probability model (Brillinger et al., 2003; Brillinger et al. 2006; Preisler et al., 2004; Preisler and Westerling 2007) is used to evaluate the utility of the weather model-simulated monthly fire danger variables, when used one at a time or in combination, in estimating large fire events for the corresponding month. The estimated probabilities are spatially explicit on a one-degree grid-cell level and temporally explicit at a monthly scale. In the following sections we will first briefly introduce the weather model and the NFDRS indices it generates, followed by a description of the observed gridded monthly fire occurrence and acres burned data. The probability models and statistical approaches will then be discussed before the result of the fire probability is evaluated.

Methods

Modeled Fire Weather and Danger Variables

Weather Model

The fire danger variables in this study were adapted from Roads *et al.* (2005), in which the meteorological forecasting system developed at the Experimental Climate Prediction Center (ECPC) (Roads *et al.* 2003) was used. Specifically, the model system uses operational daily 00 UTC analyses from the National Centers for Environmental Prediction (NCEP) Global Data Assimilation (GDAS), which is used for the global extended range weather forecast at NCEP, as initial condition for a regional forecast with up to 16 weeks lead time. The original higher resolution global analysis was first linearly transformed to a triangular truncation of T62 (192 × 94 global Gaussian grid, roughly 150 km grid space resolution at 40°N) and 18 vertical levels so that the subsequent seasonal scale regional forecasts could be done with the available computer resources.

The regional spectral model (RSM) used in this study was originally developed at NCEP (Juang and Kanamitsu 1994; see also Juang *et al.* 1997). The RSM is a regional extension of the global spectral model (GSM; Kalnay et al 1996). In particular, the RSM provides an almost seamless transition from the GSM to the higher resolution region of interest (Chen *et al.* 1999) and thus avoids a common regional model problem when using incompatible physics between the driving global model and the nested regional model (Chen 2001). Except for the scale-dependence built into the horizontal diffusion and some minor adjustment to other physical parameterizations, the GSM and RSM physical parameterizations are, in principle, identical. A modeling system such as the GSM to RSM used here is particularly helpful in isolating the regional downscaling problems caused by potential mismatched model physics between the regional and driving global model (Chen 2001). More discussion of the updated model physics can be found in Hong and Pan (1996). The description of the RSM and the model setup used in this study can be found in Roads et al. (2003).

Modeled NFDRS Indices

Global analysis from January 1, 1998 through December 31, 2003 was used to initialize the GSM. The 4 times daily output of the one-day forecasts of GSM were then used as initial and lateral boundary conditions of the RSM for one day integration for each initial day. Horizontal grid spacing of 60 km was used in the RSM. The one-day forecasted surface weather variables, including temperature, two-meter relative humidity (R2H) , wind speed from the model, and top 10-cm soil moisture content (SMC1) along with observed precipitation, fuels and slope, were the input for the NFDRS indices computation (Burgan 1988). The major differences of our NFDRS calculation from the standard one is the use of weather model 1-day forecast output, instead of weather station observations. However, in order to avoid the precipitation spin-up problem caused by the imperfect initial condition of the meteorological model for short period integration, the 0.25° X 0.25° observed precipitation (Higgins *et al.* 2000), instead of model precipitation output, was used in computation. Monthly indices used in this study were subsequently derived from the daily indices. Interested readers should refer to Roads *et al.* (2005) and Burgan (1988) for a more detailed description of the NFDRS indices computation. Since not all standard NFDRS indices are useful to fire managers, we chose to examine only spread component (SC), energy release component (ER), burning index (BI), ignition component (IC) and Keetch-Byram (KB) drought component. In addition, Fosberg fire weather index (FFWI, see description below), R2H, and SMC1 from the meteorological model were also included to contrast the skill from NFDRS indices.

FFWI (Fosberg 1978; Fujioka and Tsou 1985), an index derived only from temperature, relative humidity and wind speed, assumes constant grass fuel and equilibrium moisture content as a function of the input weather variables. This index is not part of the NFDRS and requires only instantaneous values from a weather model. Due to its ease of application, FFWI has been used for seasonal fire danger forecasting to provide a first look of global wildfire condition (Roads *et al.* 1995). As will be shown, despite its use of constant fuel information, FFWI offers a significant skill in explaining the fire occurrence at a monthly scale.

All model deduced indices from1-day GSM/RSM forecasts were called 'validating' indices in Roads et al (2005). In the present work these monthly mean indices are used as surrogates for 'observed' values, since one-day forecasts have been found to be very skillful when compared to observations. Interested readers should refer to Roads *et al.* (2005) for detailed descriptions.

Fire Occurrence Data

This work relied on fire history data sets over the western US compiled from federal land management agency fire reports. Westerling et al. (2003) compiled a gridded one-degree latitude/longitude (317 grid cells) data set of monthly fire starts and acres burned from approximately 300,000 fires reported by the USDA Forest Service, the USDI's Bureaus of Land Management and Indian Affairs, and the National Park Service for 1980-2004. However, since we have meteorological model-derived fire danger indices from January 1998 through December 2004, we only used the fire data for the same period. A map of the monthly-mean fire weather index (FFWI) and the locations of large fire events (area burned > 400 ha ≈ 1000 acres) for August 2003 (Figure 1) shows the geographic region and the structure of the spatially and temporally explicit explanatory variables used in this study.

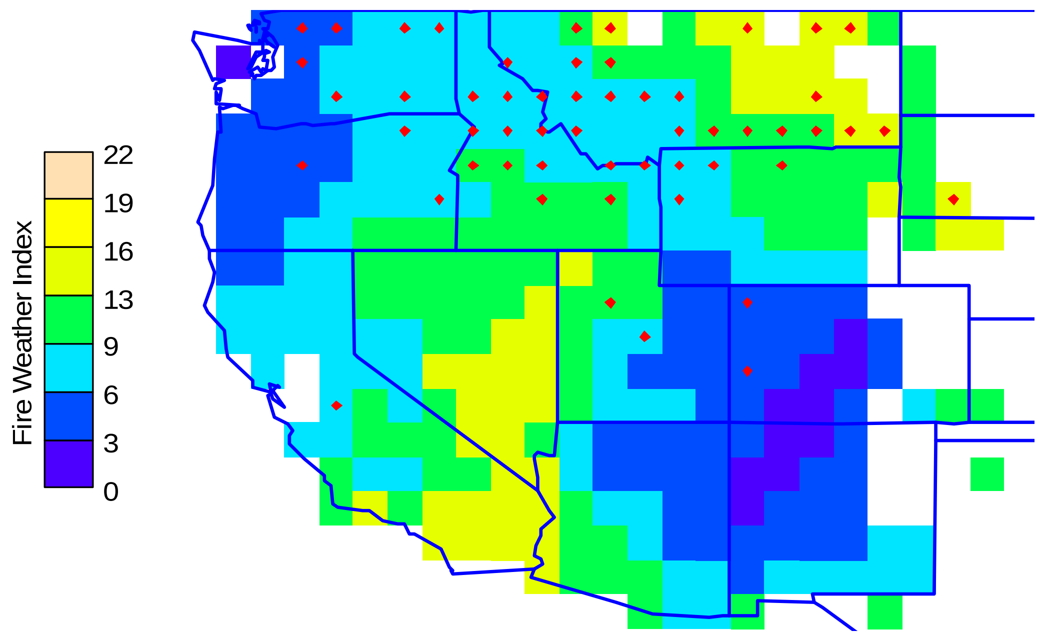

Figure 1: Map of study area (Western US) showing the one-degree grid cells and values of the Fosberg Fire Weather Index for August 2003. Red dots indicate locations of large fire events (area burned > 400 ha ≈ 1000 acres) reported on federal lands for the month of August 2003.

Statistical Methods

Probability models

The statistical approach is based on developing a semi-parametric logistic regression model (Hastie et al. 2001, Preisler and Westerling 2007) using historic monthly fire occurrence data as the dependent variable and weather modeled NFDRS indices as the independent variables.

The regression model estimates two fire danger probabilities: probability of fire occurrence and conditional probability of large fire event. Probability of fire occurrence was defined as the probability of at least one fire of any size occurring in a given one-degree grid cell during a given month of a year. The probability of a large fire event was defined as the probability of the occurrence of a burn area greater than 400 ha (≈ 1000 acres) given at least one fire occurrence in the one-degree cell during a given month of a year. The product of the above two probabilities was used as a measure for fire danger. The 400 ha cut-off for large fires, although arbitrary, aligns with size class F fires. The same methods may be used to estimate probabilities of area burned of any particular size.

The explanatory variables used in the regression model were the modeled NFDRS indices described above in addition to a purely temporal variable (month-in-year) and a geo-spatial vector variable (latitude and longitude of the one-degree grid cell). The temporal variable (month) was included in the model as a proxy for annual cyclical patterns of fire occurrence and large fire events that may not have been properly captured by the indices. The geo-spatial vector (latitude, longitude) was included in the regression as a surrogate for variables with spatial patterns (e.g. vegetation type, elevation or human activities) that do not change over time. Smooth nonparametric functions of the explanatory variables were used instead of parametric functions, e.g. polynomials, because it is anticipated that relationships between the explanatory variables - in particular between latitude, longitude, month – and large fire occurrence may be complex. Consequently, these relationships will be better characterized by flexible nonparametric functions such as piece-wise polynomials and splines. Further details of the estimation procedure, including the estimation of the smooth functions, can be found in the

Appendix. See also Brillinger et al. (2003), Preisler et al. (2004), and Preisler and Westerling (2007).

Although our estimates were based on a large number of observations (monthly values on 317 grid cells and six years for a total of 22,824 voxels), these observations are likely to be correlated, in particular if there is a strong yearly effect (e.g, overall dry years etc.). Consequently, all standard errors were calculated using the Jackknife procedure (Efron and Tibshirani 1993). Jackknife standard errors were produced by developing six different estimates of the model parameters (each time using data from all years but one), then calculating the Jackknife standard error of the resulting estimates.

Mutual Information Statistics

We used the Mutual Information (*MI*) statistic (Brillinger et al. 2004) to study the strength of the statistical dependencies between explanatory variables (e.g. indices) and the probabilities of fire danger. In particular, we used the *MI* statistic to select the index, or combination of indices, with the most 'information' regarding the probability of fire danger. The MI statistic is similar to the Akaike Information Criteria (AIC), and it is equivalent to the variance explained if both involved variables are Gaussian distributed. Further details regarding the MI statistic are given in the Appendix. The following models were compared using the MI statistic:

1) Historic (climatologic) model (H)

The only explanatory variables used in this model were month-in-year and location (latitude, longitude). With this model each cell has a different probability for each location and month of the year but the probabilities do not change from year to year. The historic model is a spatially and temporally smoothed version of the relative frequencies of observed large fire events for each month of the year and each pixel.

2) Fire danger index model (X)

The explanatory variables in this model include spatial location, month and one fire danger index. Consequently, probabilities in each cell change with location, month in year, and the value of the fire danger index. One model was produced for each index and named after the index.

3) Multiple indices model (C)

The explanatory variables in this model were spatial location, month and a combination of two or more fire danger indices.

The multiple indices model with the 'best' selection of indices was next used to estimate the probabilities of fire occurrence and the conditional probability of a large fire event. Finally the unconditional probability of a large fire event, i.e., the probability that an area of size greater than 400 ha will burn in a one-degree grid cell in a given month and year, was estimated by multiplying the above two estimated probabilities.

Assessing Model Skill

We assessed the goodness-of-fit of the final selected model by producing reliability diagrams (Hosmer and Lemeshow 1989, Wilks 1995). The latter was done by grouping together all cells with similar estimated probabilities (within 3% of each other) and comparing the observed fraction of responses in each group with the corresponding estimated probability of response. A response here was defined as a voxel (one-degree x one-degree x month) with a large fire event. Estimated probabilities for each voxel were produced using cross-validation. Specifically, estimations for a given year were done by using the model parameters from all other years except the year being evaluated.

In an alternative assessment of goodness-of-fit we studied the skill of the model in estimating the distribution of total number of grid cells per month with large fire events by comparing observed numbers of monthly totals for each year with the estimated 50^{th} and 95^{th} percentiles. The estimated percentiles included both natural variation (Poisson) and variation due to the error in the estimated model parameters.

Fire Danger Maps

We produced two types of fire danger maps. The first was based on estimated probabilities of large events using the following rule: Let $\widehat{p}$ be the estimated probability of area burned > 400 ha and SE be an estimate of the standard error of $\widehat{p}$. Then fire danger was defined as

Low	if	$\widehat{p} + 2SE \leq 10\%$.
Moderate	if	$10\% < \widehat{p} + 2SE \leq 30\%$.
High	if	$30\% < \widehat{p} + 2SE \leq 50\%$.
Extreme	if	$\widehat{p} + 2SE > 50\%$.

The size of areas burned (400 ha) and the cutoff probabilities used above are for demonstration purposes only. Managers may decide on other cutoff points for what may be considered a large fire event or acceptable levels of risk. Note that, although conditions are defined as extreme when the probability of a large fire event is > 50% the frequency of times a voxel is designated as extreme is very small. During the six years of our study 'extreme' conditions were observed in only 120 voxels (0.5% of cases), of those cases 63 (52.5%) were actually large fire events.

The second set of danger maps was produced to demonstrate departures from 'normal' conditions, or anomalies. In this study the 'norm' was the estimated probability of a large fire event produced by using the H model. Since our study was based on six years of data (1998-2003) the 'norm' reflected average conditions during these six years. For example, Figure 2 shows the July historical probabilities of large fire events. Highest historic probabilities during the six years of study appear to be in the Washington, southern Idaho and Northern Nevada regions.

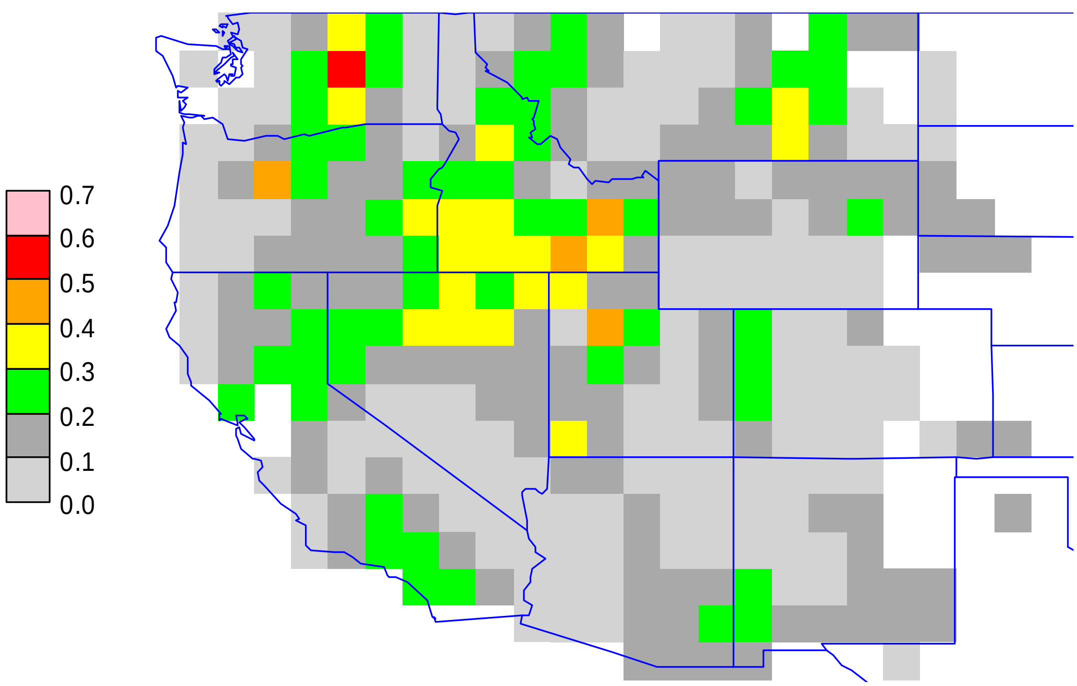

Figure 2: Probabilities of large fire events for the month of July estimated from historic fire occurrence and size data for the period of 1998-2003.

Maps of estimated departure from the norm were produced using the odds ratio statistic. Specifically, maps were produced of the odds of a large event relative to the historic odds as estimated by the given six years of observed fire data. The rules used to produce the maps were as follows: define $\hat{\pi}_C$ and $\hat{\pi}_H$ as the probabilities of an area greater than 400 ha burning in a given voxel estimated using the C and the H models, respectively. Let $\hat{\theta} = \log(\hat{\gamma})$ be the logarithm of the estimated odds ratio, $\hat{\gamma} = \hat{\pi}_C / (1 - \hat{\pi}_C) \div \hat{\pi}_{\mathrm{H}} / (1 - \hat{\pi}_{\mathrm{H}})$, i.e. the logarithm of the odds relative to historic values. Fire danger maps were produced using the rules:

$$\begin{array}{lll} \text{Lower than historic} & \text{if} & \hat{\theta} + \hat{\sigma} < 0 \\ \text{Normal} & \text{if} & -\hat{\sigma} \le \hat{\theta} \le \hat{\sigma} \\ \text{Higher than historic} & \text{if} & \hat{\theta} - \hat{\sigma} > 0 \end{array} \qquad [1]$$

With the above rule a voxel is designated as normal if the log-odds of a large fire event for a given month are within one standard deviation ($\hat{\sigma}$) from the historic odds for that month (i.e., odds ratio equal one, or equivalently logarithm of odds equal zero). A voxel is designated as higher than historic if the log-odds for a large fire event are greater than one standard deviation from the historic odds.

Results

Plots of standardized mutual information statistics for various models (Figure 3) demonstrate the relative importance of each fire danger or fire weather index on the probability of fire occurrence and conditional probability of large fire event. All MI values in the plot are relative to the H model. The standardized MI for the H model was set to zero. The two indices, FFWI and R2H indicated the highest relative increase in strength of dependence with fire occurrence (Figure 3a) when added individually to the H model. The linear correlation between R2H and FFWI is high (r = - 0.92). The latter is expected because R2H is one of the input variables for computing FFWI. Indices with highest relative increase in strength of dependence with the conditional probability of a large fire event were KBDI, FFWI, IC and R2H (Figure 3b).

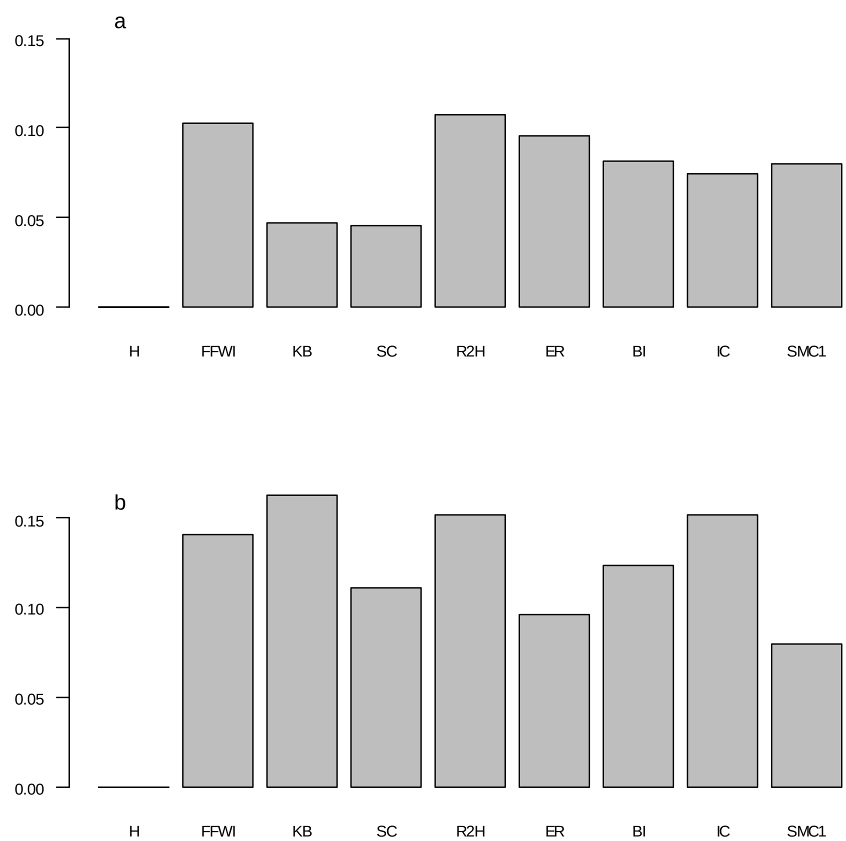

Figure 3: Standardized mutual information statistic describing the dependence of (a) probability of fire occurrence and (b) conditional probability of a large fire event on each fire danger/weather index when added to the historic model. All values are relative to the historic (H) model value which was set to zero. The height of each bar is the fraction increase in MI when an index (e.g. ER) is added to the historic model, i.e. $(MI_{ER} – MI_H)/MI_H$.

Models with multiple indices were developed by adding indices one at a time to the historic model starting with FFWI. Values of the MI statistic estimated for each of the models are presented in Figure 4. We chose to start with FFWI because it was the index that showed dependence with both probabilities of fire occurrence and conditional probability of large area burn. The order in which the indices were added to the probability model was such that those with the smallest correlation with FFWI were added first. For example, the column labeled +KB is the standardized MI produced for a model with the combination of the indices FFWI, ER and KB in addition to the variables, location and month, that are in the historic model.

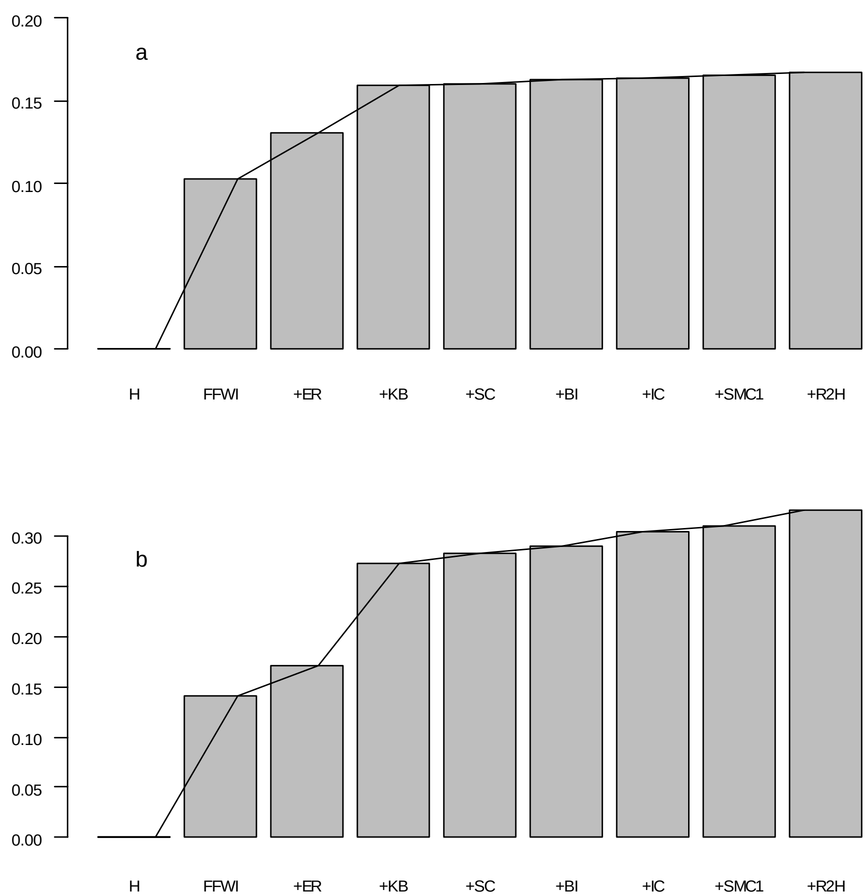

Figure 4: Standardized mutual information statistic for models with multiple indices. All values are relative to the historic (H) value which is set to zero. The models were developed by adding indices consecutively in the order seen in the figures (left to right).

Standardized values of MI increased with each addition of a new index to the H model (Figure 4). However, increases after the first few indices were relatively small. The final model (C) for the probability of fire occurrence used in the rest of the paper included the indices FFWI, ER and KBDI. The final model for the conditional probability of large fire included FFWI, ER, KBDI and R2H. The multiple indices model may be thought of as a probability model based on a 'new' index which consists of a combination of the four indices, FFWI, ER, KBDI and R2H.

Interpreting effects of explanatory variables is not easy particularly when the variables are correlated. For example, R2H is inversely proportional to FFWI ($r = -0.92$, Figure 5). However this relationship appears to be less well defined during dry (low R2H) and high FFWI weather. The variability around the mean increases with increasing FFWI and decreasing R2M, and the correlation decreases (when R2M < 50 and FFWI > 10, $r = -0.37$). Consequently, it is not surprising that both R2M and FFWI contribute significant information to the model. Wind may be playing a critical role under the circumstances.

Since the purpose of our statistical model is to estimate probability of fire danger, the ultimate test of a given model with a selected set of indices is its skill in describing observed events. To demonstrate the skill of estimating the occurrence of large fire events, we plotted the observed fraction of large fire events *vs.* the estimated probabilities from the H and the C models (Figure 6). The observed fraction is the number of cases with observed large fire events as a percentage of the number of cases at each estimated probability level. The scatter points of observed fractions of large fire events

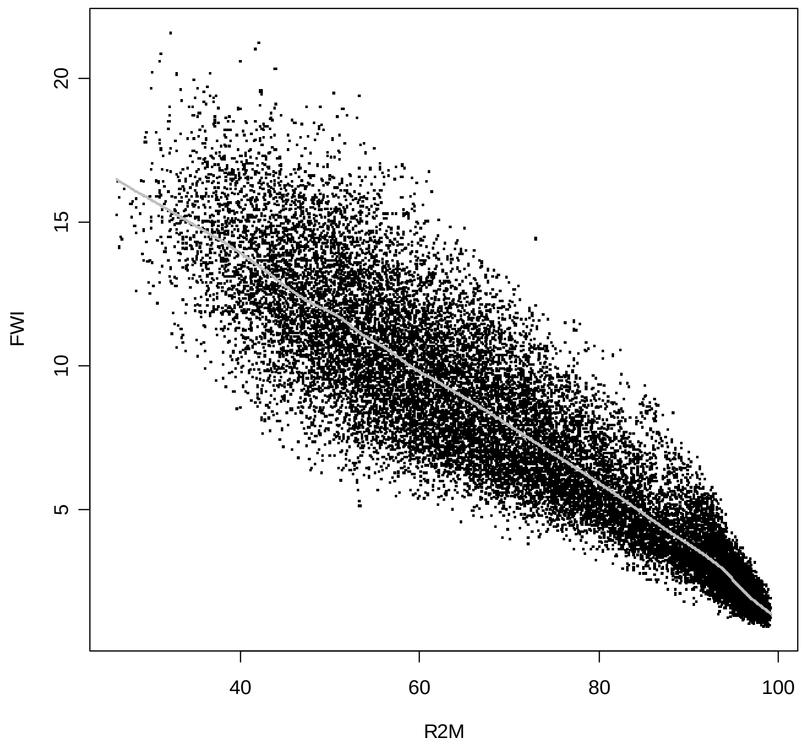

Figure 5: Scatter plot of FFWI values against R2M. The variability around the mean level is seen to increase under dry conditions - higher values of FFWI and lower values of R2M.

were mostly within the expected point-wise 95% confidence bounds, which are represented by the two dashed lines, for both models. The larger confidence bounds for larger probabilities are likely due to the small number of cases at the higher probability groupings. The overall Chi-square goodness of fit statistic improved from 36.8 (P-value = 0.0008) for model H to 19.2 (P-value = 0.51) for model C. Moreover, estimated probabilities using model C spanned a wider range of values (0 to 0.72) than those of the historic model H estimates (0 to 0.56). A model with no skill will have the same estimate (no range in the values) for all locations and times.

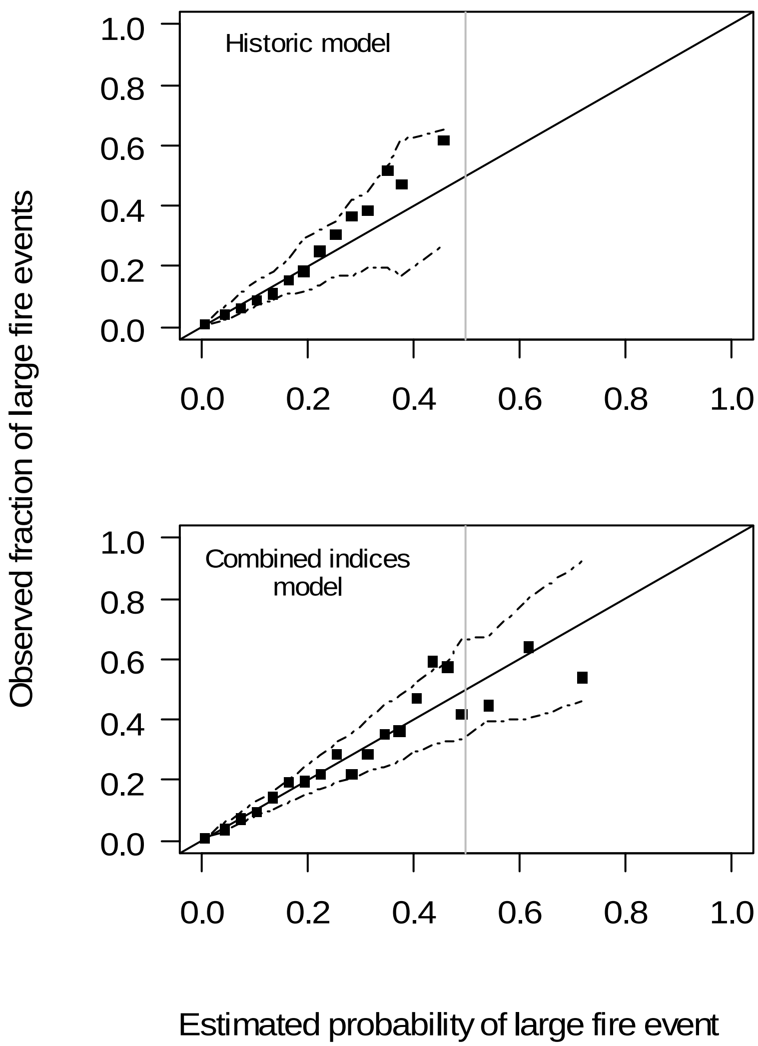

Figure 6: Reliability diagrams showing the observed fraction of large events plotted against estimated probability for: (top) the historic model and (bottom) multiple indices model. Dashed lines are the approximate point-wise 95% confidence bounds.

Fire danger maps, based on the final multiple indices model, were produced for each July from 1998 through 2003 (Figure 7) along with the location of events that actually occurred. In these maps a cell was designated as low danger if the estimated probability of an event was significantly less than 10%; moderate if the estimated probability was between 10%-30%; high if the estimated probability was between 30%-

50%; and extreme if the estimated probability was significantly greater than 50%. The skill of the model for estimating large fire events at a given grid cell seems reasonable when observed response (presence/absence of a large fire event) at a given grid and month was compared with estimated fire danger. The maps presented here (Figure 7) and similar maps for other months (not shown) may be used by fire managers to assess the spatial and temporal fire danger. However, with intense fire potential during every fire season over the West, these maps do not highlight anomalies.

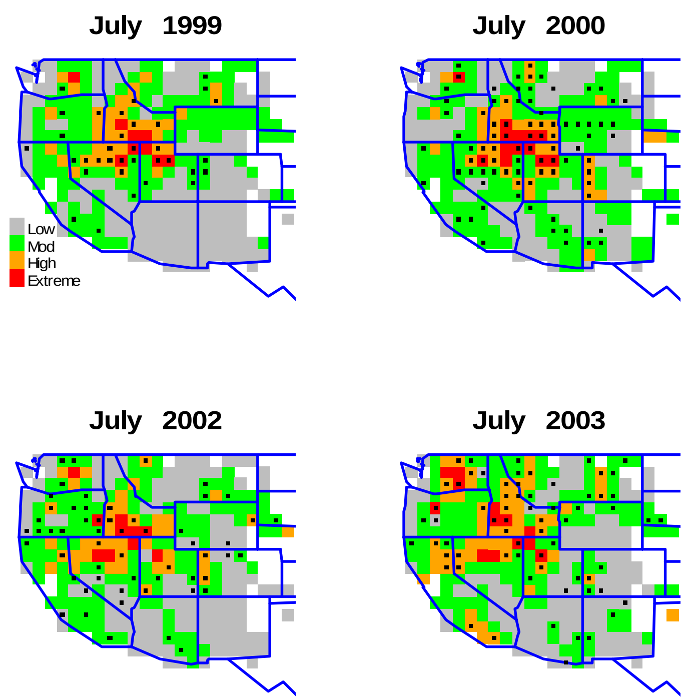

Figure 7: Observed cells with large fire events (dots) and maps of fire danger based on estimated probabilities of large fire events.

An alternative set of maps showing anomalies are those based on departure from normal conditions, as given by estimated odds ratios relative to historic estimates (see Eq. 1). Maps of odds ratios are particularly useful when accompanied by maps of estimated probabilities of large fire events. For example, the estimated odds of a large fire event appeared to be higher than the norm in the southwestern states during May 2002 and in the northwestern states in August 2003 (Figure 8 left panels). The estimated probabilities for May 2002 in the Southwest (Figure 8 top right panel), although higher than normal, were nevertheless quite low (<20%). The small number of observed events is consistent with the low probabilities. On the other hand, in August 2003 the estimated odds for the northwestern states were higher than the norm and the probabilities were also high (mostly > 50%). Many large fire events were observed during this period.

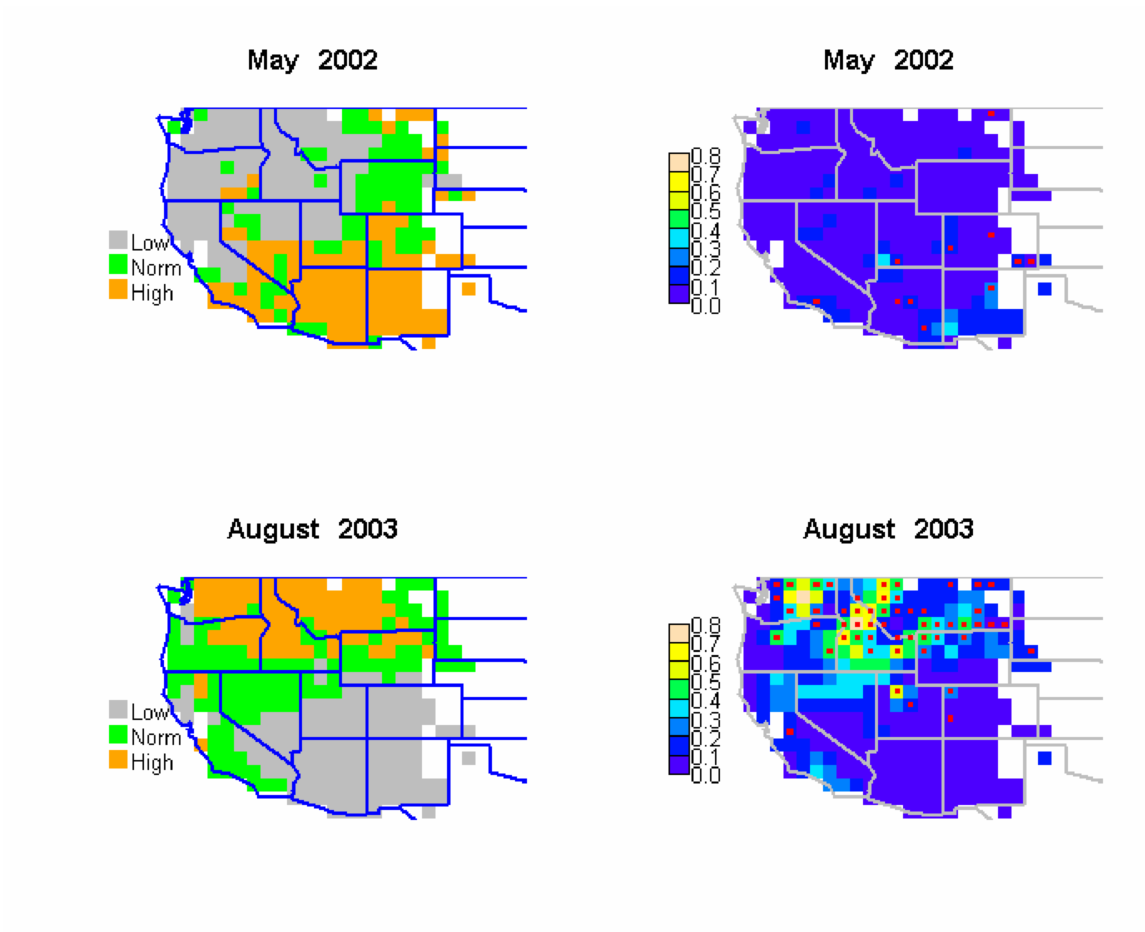

Figure 8: Maps of odds relative to historic (left panels) and estimated probabilities (right panels) of large fire events for two time periods. Red dots indicate locations of observed events during that period.

Another useful output of the probability model is the estimated total number of large fire events. Totals were obtained by adding the estimated probabilities over all cells in a region. For example in Figure 9 we show the monthly estimated, as well as the observed, large fire events for the northwestern and southwestern states separated at 40°N latitude. The plots give the estimated 50th and 95th percentiles (solid curves) and the observed numbers of cells with large fire events (dots). The 50th percentiles estimates from the historic model are also given in grey lines. Historically, the Southwest appeared to lag the Northwest by one month in reaching the peak of large fire occurrence during the fire season. Over the northwestern region, higher than normal numbers of big fire events were observed, and well estimated, for years 2000 and 2003. In summer 2001 the observed number of cells with large fire events was greater than the upper 95th percentile. Using estimated 95th percentiles one expects observations to exceed this level approximately 5 percent of the time. In the southwestern region, the inter-annual variations of fire events were not as apparent during the 6 years of our study. However, summer of 2002 shows an observed early peak in June, compared to the historical model. The latter was well captured in the estimates produced by the multiple indices model. The higher and lower odds relative to historic estimates over the northwestern and southwestern states for May 2002 and August 2003 respectively (Figure 8), can also be found in the figures of monthly totals (Figure 9). Overall, the observed numbers were distributed around the 50 percentile estimates with 4.1% (6/144) of the cases above the 95th percentile curve. In our example we used arbitrary north and south regions. Similar estimates may also be produced for smaller areas such as individual Geographic Area Coordination Centers (GACCs) for fire management use. Even though our results were

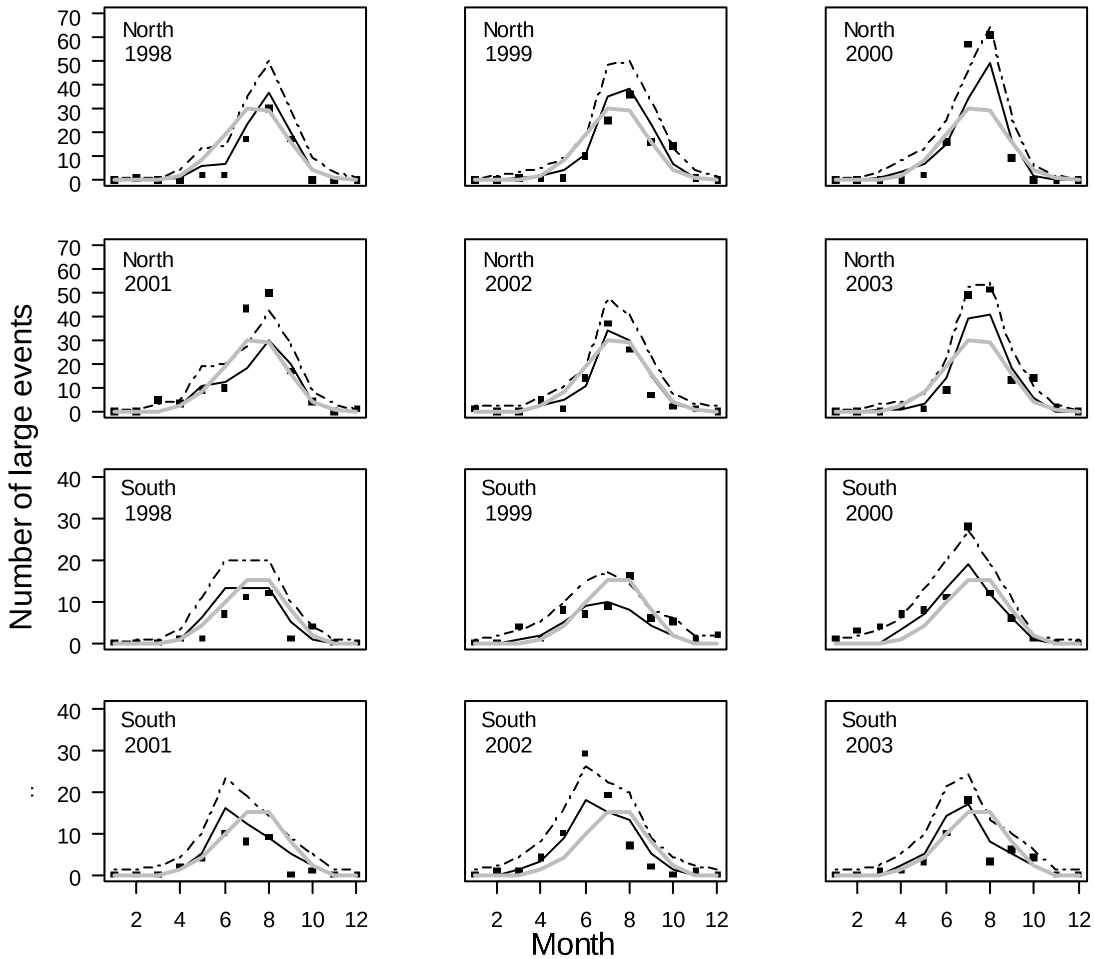

Figure 9: Observed (dots) and estimated (curves) number of one-degree cells with large fire events. Solid curves are the estimated 50th percentile of the fitted distribution. Dashed curves are the estimated 95th percentile of the distribution. Grey curves are estimated 50th percentiles of historic model.

based on a large number of observations, the time span of the study was only six years. It remains to be seen if the same selected variables will give similar skill when tested on other years with more, or less, severe fire seasons.

Summary and Discussion

A statistical method of estimating probabilities of large wildland fire events has been applied to the monthly mean fire danger indices produced by the numerical weather prediction products from the ECPC. The derived indices with the most information for estimating monthly probabilities of large fire events were FFWI, KBDI, ER, and R2H. No additional information appeared to be gained by adding further indices to those listed above. These variables were subsequently chosen to construct a combined index that was used to estimate monthly probabilities of large fire events on a one-degree grid cell over the western United States. The estimated probabilities were then compared with observed frequencies of large events in order to assess the skill of the model.

Probability models, such as the one described here, are not only practical for selecting variables and producing maps of fire danger, they are also useful in assessing the skill of the fire danger indices in estimating (and eventually forecasting) frequencies of wildland fire events. NFDRS was probably originally designed to support fire fighting tactics on a daily basis. Some of the indices, such as SC, BI and IC, are sensitive to short term variation of weather components, especially wind speed. These indices, therefore, might lose their high frequency characteristics when a long term (e.g. monthly) average is taken, as was the case in this study. Thus it is not surprising to see that some of these model-derived indices did not contribute additional information to those slow varying indices, such as KB and ER, in describing observed large fire events. What is surprising is that FFWI, an index determined by weather variables alone, appeared to have a significant contribution to the probability of large fires. Further analysis, possibly at the daily time-scale, is required.

It is promising that a combination of fire danger indices appeared to have some skill in estimating the probability of large fire events at a monthly scale. Adding a select set of indices to the historic model appeared to improve the skill of the model in estimating expected numbers of large events. Furthermore, estimated probabilities at each cell may be developed into monthly anomaly maps for fire danger. The probability maps showed reasonable agreement with the observed fire events.

While probability maps are useful in identifying high fire danger areas to fire managers, a more useful application may be the ability to compare the total number of large fire events against historic estimates over a region in a probabilistic manner. Roads et al. (2005) showed that although the meteorological model predicted fire danger indices reasonably well even at seasonal time scale, the associations (as measured by the correlation coefficient) between the observed fire occurrence/acreage-burned and their "observed" (validating) fire danger indices were poor. Part of the reason could be that point-to-point temporal correlation is not adequate when describing nonlinear relationships between variables that are not Guassian. Additionally, correlation studies to evaluate FDRS indices are not suitable for estimating or forecasting frequencies of fires. Here we have proposed an alternative procedure for evaluating the association between derived fire danger indices and fire characteristics that may also be used to estimate, and eventually forecast, frequencies of large fires with known precision. The results indicated that the estimated distribution of the number of large fire events agrees reasonably well with those observed.

Similar analyses need to be done with forecasted fire weather/danger indices to assess the skill of the forecasted variables on predicting large fire events in order for this method to be truly useful for fire managers. Future work will address the skill of predicting large fires at different lead times and at smaller temporal and spatial scales. With fire occurrence data at the individual fire scale and forecasted fire weather/danger indices at the daily and 1 km scale we should be able to develop forecasts over small regions within administrative units so that the prediction can be used for fire management operation.

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Appendix

The logistic regression lines used to estimate the probabilities of fire occurrence and large fire events is specified in the following equation

$$\text{logit}(p_v) = \beta_o + g_1(lon_v, lat_v) + g_2(month_v) + \sum_{m=1} h_m(X_{mv}) \qquad \text{[A1]}$$

where the subscript, v, indicates the one-degree by one-month voxel; p is set to either the probability of ignition or conditional probability of large fire given ignition; (lon, lat) are the longitude and latitude of the midpoint of the grid cell; X_m are explanatory fire weather and fire danger variables. The function h is a nonparametric smoothing function (Hastie et al. 2001); g_2 is a periodic spline function (for estimating month-in-year effect); and g_1 is a thin plate spline function (for estimating the spatial surface as a function of lon and lat). Estimation was done with the R statistical package (R Development Core Team, 2004). The procedure within the R package consists of first running the bs (basis spline) function on each of the explanatory variables, then using the outputs from the bs runs as the new explanatory variables in a simple logistic regression routine. A periodic spline function (bs.per) is used for the month variable to allow for a smooth transition between the months of December and January. For the two-dimensional spline function of *(lon, lat)* the thin plate spline function (ts) is used to produced the necessary variables.

The *MI* statistic was defined as follows: let Y indicate the occurrence of a fire (or alternatively, a large fire event) and X indicate the logit line (linear predictor) as described in Eq. A1, then the *MI* statistic is given by

$$MI_{X,Y} = E\left\{\log \frac{p_{X,Y}(X,Y)}{p_X(X)p_Y(Y)}\right\} \qquad \text{[A2]}$$

where $p_{X,Y}(X, Y)$, $p_X(X)$ and $p_Y(Y)$ are the joint and marginal distributions of X, Y respectively. For the bivariate normal case $1\text{-}e^{-2MI_{x,y}}$ is the coefficient of determination. In general, $MI_{X,Y} = 0$ when X and Y are independent and $MI_{X,Y} \leq MI_{Z,Y}$ if Y is independent of X given Z (Brillinger 2004). A similar and more commonly used statistic for choosing between models is the Akaike information criterion (*AIC*) given by $AIC_{X,Y} = -2E\left\{\log \frac{p_{X,Y}(X,Y)}{p_X(X)}\right\}$. Although *AIC* and *MI* often give similar results, as was the case in the present study, *AIC* does not have the same interpretation as the MI statistic as a measure of the strength of statistical dependence.

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SUMMARY

Fire danger indices evaluated from a regional simulation weather model were used to estimate probabilities of large fire events on monthly and one degree grid scales. This paves a way to assess the skill of climate forecast outputs in predicting wildland fire severity with known precision.