Third International Symposium on Fire Economics, Planning, and Policy: Common Problems and Approaches. April 29-May 2, Carolina, Puerto Rico.

Seasonal Predictions for Wildland Fire Severity

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Abstract

The National Fire Danger Rating System (NFDRS) indices deduced from the monthly to seasonal predictions of a meteorological climate model at 50-km grid space from January 1998 through December 2003 were used in conjunction with a probability model to predict the expected number of fire occurrences and large fires over the U.S. West. The short-term climate forecasts are ongoing experimental products from the Experimental Climate Prediction Center at the Scripps Institution of Oceanography. The probability model uses non-parametric logistic regression with spline functions for evaluating relationships between covariates and probabilities of fires. The 2-meter relative humidity and the Forsberg fire weather index, along with NFDRS indices of the Keetch-Byram drought index and energy release, were previously found to produce more significant information for the observed big fire events than all the other stand-alone fire weather variables.

Utilizing this previously determined regression relationship between historical fire information and the nowcast fire indices, these predicted indices were skillful in generating fire severity forecasts at monthly and seasonal time-scales. However, certain meteorological model biases, due to a known drying-up defect of the climate model, needed to be removed from the predicted indices before being used as input to the probability model. It was shown that the probability model using the bias-corrected fire danger indices outperformed the one with historic information only. The inter-annual fire frequency variability was predicted particularly well. This dynamical-statistical hybrid climate forecast application demonstrates a potential predictive capability (with specified precision) for the resulting economic impacts with a lead-time varying from a month to a season.

Keywords: fire severity, NFDRS, Seasonal prediction, semi-parametric logistic

Introduction

Wildland fire has been a major worldwide problem affecting million of hectares

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forest shrub lands. In the U.S.A. alone, 2.5 million hectares of wildland has been affected per year between 2000 and 2004 with an annual average suppression cost of $1.2 billion, more than twice that of the previous 5 years (González-Cabán 2005). Part of the cost increase might be due to the increased interface between wildlands and urban areas in today's community (Shafran 2006), but part of it might be the increase of wildland fire frequency and hence the burned area. While the level of affected burned area and associated suppression costs are challenging the national capability to confront the problem, ineffective use of the suppression costs could potentially impede society's willingness to maintain financial support for wildfire management programs.

Therefore, if a management system with the ability to project potential losses due to the impact of wildfires can be developed, it would represent a direct benefit to society and to those agencies with fire suppression responsibility. However, such a management system would require quantified predictions for fire severity and a prediction for the number of fires of different size classes with specific precision, not just fire danger.

Currently there is no operational objective long-range forecast for fire severity. The outlooks for national fire weather and fire danger at weekly to seasonal time scales are provided by the National Interagency Coordination Center (NICC), which is the nation's support center and home to seven federal agencies including the Forest Service, for wildland firefighting. The outlook and assessment are currently done by considering standard National Weather Service seasonal forecast products of temperature and precipitation (see Brown et al. 2003) along with other indicators, and carefully exercised human judgment. Therefore the current decision-making support for wildfire management is rather inadequate. Even the support for long-range fire danger forecast, which requires skillful climate prediction, is at best qualitative.

However, with the constant improvement of knowledge and understanding of climate variations, various numerical climate models have demonstrated their potential capability to offer required fire danger and fire weather predictions to the fire science community. For example, Roads et al. (2005) evaluated experimental forecasts of National Fire Danger Rating System (NFDRS) indices at weekly to seasonal scale using a meteorological model as weather input. They showed that these indices could be well predicted at weekly time scales when appraised against the validation indices deduced from the model 1-day forecasts. Some indices have skill even at seasonal scales, especially over summertime seasons in the western U.S. However, despite the high skill in predicting NFDRS indices, Roads et al. (2005) showed that there was only a weak relationship between their validation indices and the observed fire counts/acres burned.

Preisler et al. (2004, 2007), took a statistical approach to reevaluate the relationship between the model derived NFDRS indices and the observed fire characteristics. They adopted a probability model using non-parametric logistic regression with spline functions to evaluate relationships between fire indices and probabilities of fire occurrence and size. They showed that the probability model outperformed the persistence model based on historic averages alone, and the geographical maps of wildland fire probability were reasonably well matched to the actual fire events. This method paves a feasible way to use climate forecast output from a dynamical meteorological model with a statistical model to forecast the probability of wildland fire severity with specified precisions.

In this study, we will adopt this hybrid-model concept to examine the predictability of fire severity using climate model predicted fire danger indices in Roads et al. (2007) as the input to the statistical probability model proposed in Preisler et al. (2007). The climate model predicted fire danger variables as well as the fire occurrence data will be given in the next section, followed by the description of the statistical probability model, the evaluation result, and discussions.

Data

Predicted fire danger variables

The fire danger variables in this study were adapted from Roads *et al.* (2005), in which a global to regional meteorological forecasting system developed at the Experimental Climate Prediction Center (ECPC) (Roads *et al.* 2003) was used. The modeling system consists of a global spectral model (GSM) and a regional spectral model (RSM). The RSM, originally developed at National Centers for Environmental Prediction (NCEP) (Juang and Kanamitsu 1994; see also Juang *et al.* 1997), is a regional extension of the 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). The GSM is a frozen version of the operational NCEP global model. Descriptions of the GSM and RSM and the model setup used in this study can be found in Roads et al. (2003).

The model system used operational 00 UTC analyses from the NCEP Global Data Assimilation as initial conditions. The forecast evaluation period was from January 1, 1998 through December 31, 2003 with a 16-week forecast launched on each Saturday initialized by 00UTC analysis. The initial sea-surface-temperature and sea ice anomalies were persisted throughout each integration. The 4 times daily output of the GSM was subsequently used as initial and lateral boundary conditions for the RSM. Horizontal grid spacing of RSM was 60 km. The forecasted surface weather variables, including temperature, two-meter relative humidity (R2M), wind speed from the model, and top 10-cm soil moisture content along with the precipitation, fuels and slope, were the input for the NFDRS indices computation (Burgan 1988) and Fosberg fire weather index (FFWI; Fosberg 1978; Fujioka and Tsou 1985). The major difference of our NFDRS calculation from the standard one is the use of the meteorological model forecast output, instead of weather station observations. Not all fire danger indices are useful to us in this study. Preisler et al. (2007) concluded that only FFWI, R2M, and two indices from NFDRS, i.e. energy release component (ER) and Keetch-Byram (KB) drought component, were important for the statistical model to be described later. Adding other indices increased only negligible skill. Therefore throughout this study, we use these four variables as input fire danger variables for the statistical model.

To initially evaluate the skill of the meteorological model in producing these fire danger indices, a set of model deduced indices from 1-day GSM/RSM forecasts was produced, and is called 'validating' indices. Similar to Roads et al (2005), these monthly mean indices are used as surrogates for 'observed' values, since 1-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 and a comparison of these indices.

All 16-week forecasts were arranged into monthly mean according to their respective calendar month. For example, outputs of the 16-week forecast starting from June 27, 1998 were grouped and averaged into monthly forecasts of lag 0 of July 1998, lag 5 of August 1998, and lag 9 of September 1998. Therefore for each target month, there are independent monthly forecasts with lead-times from 0 to 11 weeks. These monthly forecasts were further averaged into seasonal forecasts with 3 possible lags, i.e. 0, 1, and 2 weeks. These long-range forecasted indices do possess prediction skills as seen in the temporal correlation maps (f*ig.* 1) for the 1-week lag seasonal forecast against those "observed". As described in Roads (2005), these "observed" indices were actually calculated from a series of 1-day forecasts of the modeling system. Since 1-day forecasts have been found to be very skillful when compared to observations, these validating indices were used as surrogates for the "observations." This evaluation was done over the entire fire season from May through October of each year. Therefore a total of 36 independent forecasts were used. It can be seen that all 3 indices and R2M are highly skillful at seasonal scale over the U.S. West region with the highest correlation of FFWI over the Great Basin and California area. However, the forecast skills of these variables are somewhat deteriorated over the northern boundary of the U.S Northwest and the eastern portion of the U.S. Southwest. Since precipitation has been recognized as the most difficult meteorological variable to predict (e.g. Chen et al. 1993), it is not surprising to see that the model fire danger prediction is skillful over the climatologically dry regions.

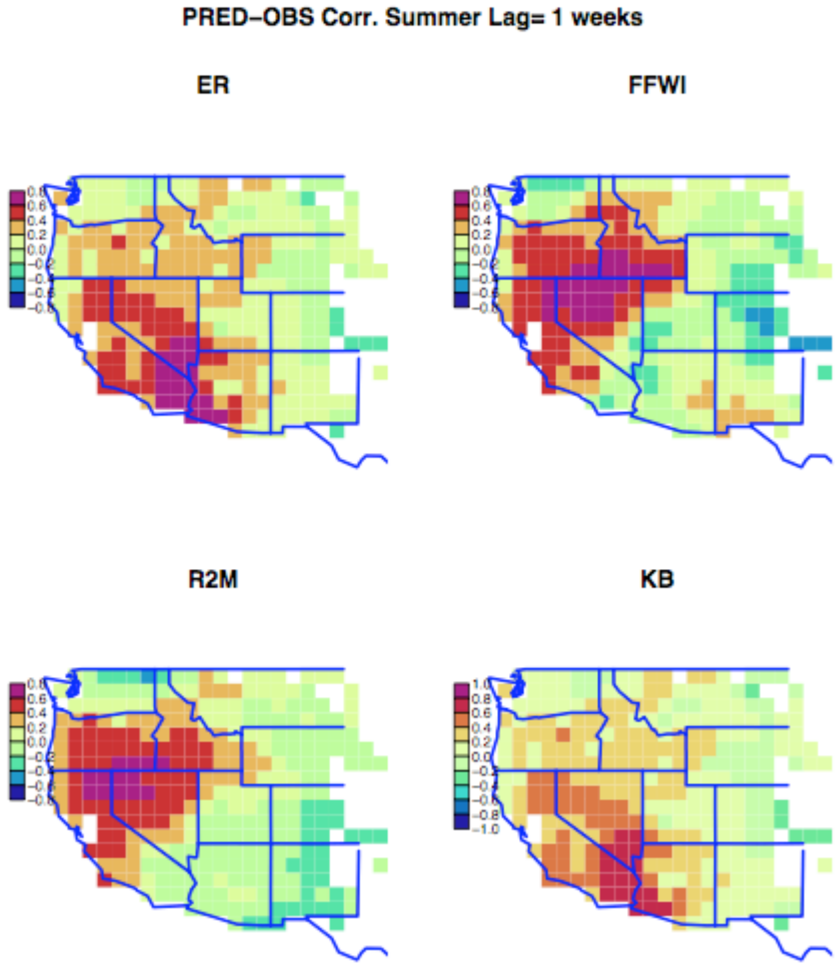

Figure 1. —Seasonal correlations for the input fire indices (ER, FFWI and KB) and 2-meter relative humidity (R2M). "Observed" and 1-week lag forecasts for May through October from 1998 to 2003 are used. Grid points with correlation coefficients larger than 0.32 passed 95% confidence level student t-test.

Fire Occurrence Data

This work relied on fire history datasets over the western U.S. Westerling et al. (2003) compiled a gridded one-degree latitude/longitude (317 grid cells) dataset 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 1980-2003. However, we only used the data from January 1998 through December 2003 to match the period of the meteorological model-derived fire danger indices. As in Preisler et al. (2007), the fire starts and acres burned have been merged into a set of data with large fire events (area burned > 400 ha ≈ 1000 acres). Throughout this study, all model derived fire danger variables (*fig.* 1) were interpolated to the same one-degree latitude/longitude grids as the fire data.

Statistical Methods

Adopting a semi-parametric logistic regression approach (Hastie et al. 2001, Preisler and Westerling 2007), a probability model of fire has been developed using historic monthly fire occurrence data as the dependent variable and meteorological model output derived fire danger indices as the explanatory (or 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 of danger for a big fire event. The 400 ha cut-off for large fires, although arbitrary, aligns with size class F fires. The same methods might be used to estimate probability spectrum of area burned, if the historic dependent as well as explanatory variables were sufficient.

The explanatory variables used in the regression model were the modeled fire danger 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. Interested readers should refer to, e.g., Brillinger et al. (2003), Preisler et al. (2004), and Preisler et al. (2007) for details.

Two probability models from Preisler et al. (2007) were used in this study. The first one is the historic (climatologic) model (or H-model). There are no fire danger variables used in this model, except month-in-year and location (latitude, longitude). With this model each grid has a different probability for each month of the year, but the probabilities do not change from year to year. The H-model is in fact a spatially and temporally smoothed function of the observed large fire frequency at each grid cell. The second probability model is the combined indices model (or C-model). The explanatory variables in this model were spatial location, month and a combination of four fire danger variables, i.e. FFWI, ER, KB and R2M. Therefore, by feeding the C-model with a set of predicted monthly fire danger variables, a map of predicted probability of large fire events over the U.S. West will be created.

Results

Since we trained the C-model using 'validating' meteorological 1-day forecasted fire danger variables (Preisler et al. 2007), some care had to be taken when the monthly forecasts described above were to be used as input to the C-model. Numerical meteorological models are never perfect, and are prone to having defects, such as a tendency to drift to a biased state when they are integrated for a long period of time. The meteorological model we used in this study is no exception. It had a dry bias such that the model soil moisture was depleted somewhat and the precipitation reduced as the integration continued (Roads and Chen 2000; Chen and Roads 2005). To partially counter this bias and perhaps other not-so-obvious defects, we first constructed the monthly mean of each forecasted fire danger variable at each corresponding lag. The differences of these monthly mean climatologies of the 12 lag forecasts and the corresponding monthly mean 1-day "validating" fire danger variables were subsequently removed from the original forecasted fire danger variables before feeding them to the C-model.

Although the forecast evaluation period covered only 6 years, meaning there were only 6 monthly maps to compute a respective monthly climatology, this correction appeared to be quite effective in removing the known dry bias of the weather input as suggested by the goodness-of-fit of the reliability diagrams (*fig. 2*). These were done by grouping together all cells from the monthly forecasts with similar predicted probabilities within a certain bin for each lag forecast, and the fraction of how many of these cells were observed with fires were computed over the entire space and time. If a forecast was perfect, the observed fraction of cells with fire to the total cell number would be identical to the predicted probability of fires, and thus a point would be on the diagonal line. The ranges of 95 percentiles from the binomial distribution with respective probability and size of sample were represented with two dashed curves. The wider ranges at high probability resulted from fewer cell numbers. As can be seen, the scattered points for the un-corrected C-model are mostly under the diagonal line, indicating over-predicted fire danger, presumably a response to fire danger indices from a dry environment. This over-predicted fire danger is not only true for cases at extreme probability; the over-prediction becomes severe even at lower probability at larger forecast lags. The bias-corrected C-model, on the other hand, effectively removed most of the over-prediction, especially at lower fire probability.

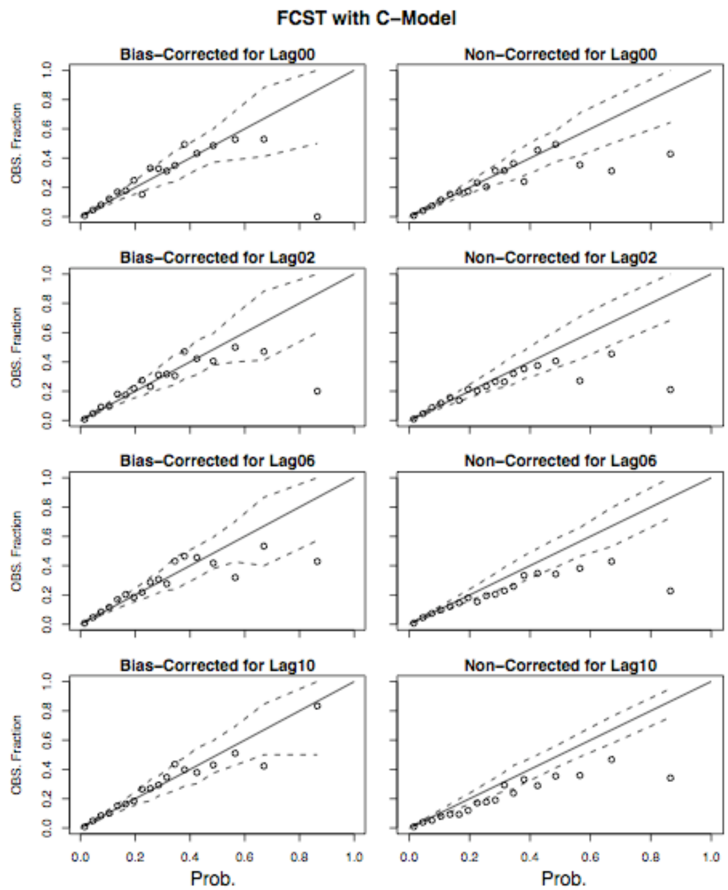

Figure 2. —Reliability diagrams for the forecasted probability C-model with the respective forecast lags. Left side panels are those from bias-corrected indices, and right side panels are those using uncorrected outputs. Reliability diagram shows the observed fraction of large fire events plotted against predicted probability from the C-model. The two dashed curves mark the 95 percentiles for binomial distribution with respective size (number of cells) and probability.

To better compare the goodness-of-fit, we computed χ^2 for the bias-corrected and un-corrected C-models alongside that of the H-model (*fig.* 3). Smaller χ^2 indicates better fit to the diagonal line in the reliability diagram; larger χ^2 demonstrates either worse prediction or cases when the temporal and spatial distributions of cells with fire were off from observed, again presumably caused by the dry biased weather prediction. For forecasts at short lags, there are small differences between corrected and un-corrected C-models. Both models predicted fires with statistical distribution no different from that observed and were better than the H-model (the constant thin solid line) at 95% confidence level. But at longer lags, with increasing χ^2, the uncorrected C-model apparently diverged statistically from the corrected one, or most importantly from the observation.

Although we can pretty much draw a preliminary conclusion that we should use the corrected C-model based on the reliability diagram and its χ^2, the analysis so far

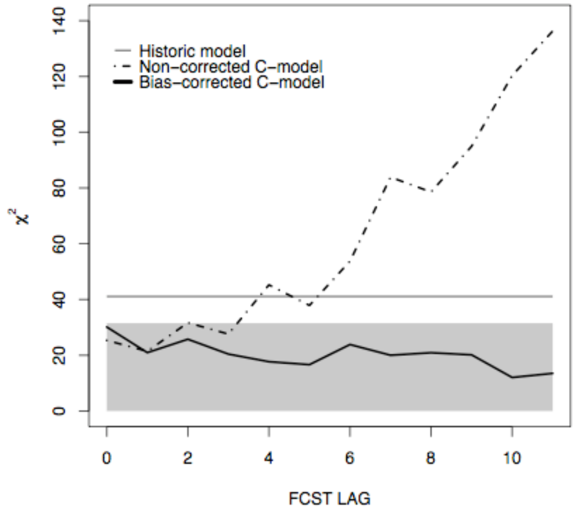

Figure 3. —χ^2 of the observed and predicted fire cells as a function of forecast lags. Solid thin line is the Historic model, dot-dashed line and solid heavy lines are for uncorrected and corrected C-models. 95% and higher confidence levels are shaded.

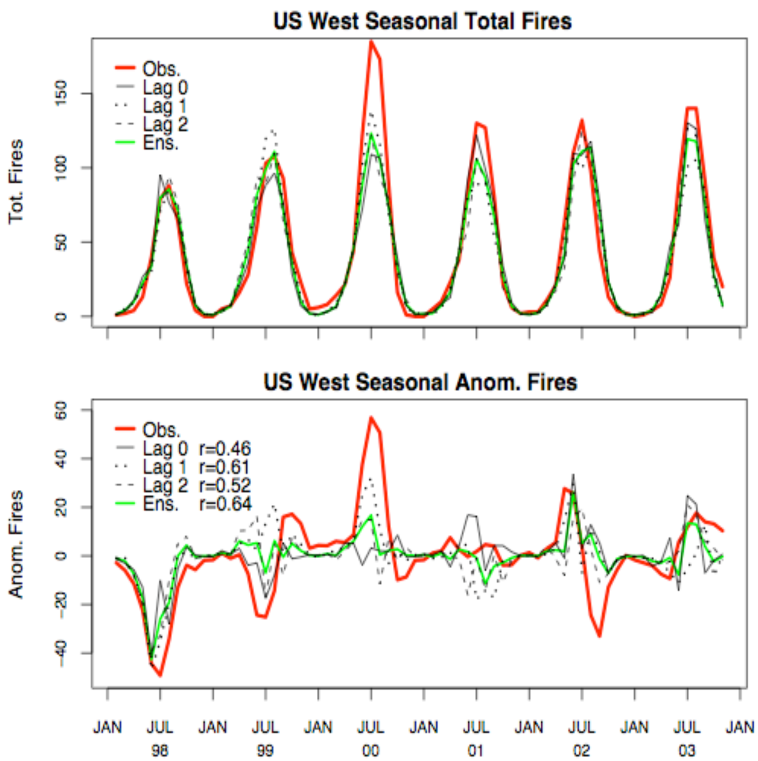

Figure 4. —3-month (seasonal) sum of the total (top) and anomalous (bottom) time series. The observed 3-month running sums are in heavy red lines, while the predicted fire numbers are in thin solid, dotted, and dashed lines for forecasts with 0, 1, and 2-week lags with respective temporal correlations (d.o.f 70) of 0.46, 0.61, and 0.52. The ensemble mean forecasts are in green lines with a correlation of 0.64.

only demonstrated that the predicted fire severity possessed similar statistical properties to those of observed fire events. They revealed little information regarding how skillful the predictions were. To examine the prediction skill, we constructed some time series of the predicted number of fires and displayed them with the observations (*fig.* 4). The predicted number of fires was done by taking the area sum of the probability of each predicted map produced from the C-model. The observed number of fires was simply the sum of cells with fire. The top panel shows the total fire number over the entire evaluation domain from January 1998 through December 2003, the bottom panel is the anomalous time series for the same period with their respective climatology removed. Each seasonal sum was made by taking the sum of 3 consecutive monthly predictions from the same forecast, and was plotted at the center of the 3 months. Three possible forecast time series could be made with forecast lags of 0, 1 and 2 weeks. Since these three sets of forecasts were cast with initial conditions 1 or 2 weeks apart, they practically formed a "poor-man" 3-member ensemble forecast and the ensemble mean was given in green curve. As shown in the top panel, the observation shows intense annual cycles for the total number of fires, with a peak around July. There was also a slight increasing trend for the summertime peaks. All 3 sets of forecasts, including the ensemble mean, in general, followed the observed annual cycle quite well. They even reproduced the slight upward trend as observed. However, the true forecast skill of this hybrid model can only be tested with the anomalous plot in the bottom panel. Except for the high positive anomaly in the summer of 2000, all three forecasts and the ensemble mean fairly predicted the peaks and valleys in summertime with temporal correlations exceeding the 95% confidence student-t test (70 d.o.f.). There was even one forecast that somewhat caught the extreme positive anomaly at summer of 2000. These are skillful forecasts, and are obviously much better than forecasts made with climatology (H-model), which would have been a constant zero in the bottom panel.

Summary and Discussion

A statistical method of estimating probabilities of large wildland fire events has been applied to the monthly to seasonal fire danger indices forecasts produced by the numerical climate prediction model from the ECPC. Specifically, following Preisler et al. (2007), the predicted monthly mean fire danger indices, FFWI, KBDI, ER, and R2M, were used as input variables for the statistical probability model to estimate monthly probabilities of large fire events over the western United States. The predicted probabilities were then compared with observed frequencies of large events in order to assess the skill of this dynamical-statistical hybrid modeling system. The evaluation period was from January 1998 through December 2003. Despite the use of persistent sea-surface-temperature and sea ice anomalies for the climate model, it is encouraging to see that the prediction of the fire danger indices from the climate model was quite useful in generating the projected wildland fire severity.

From this preliminary study, we found that special attention to the prediction data was needed to counter the drift or bias of the climate prediction model. This was simply done by removing the differences between the forecast and validating (1-day forecast) climatologies from the predicted fire danger indices before feeding them to the probability model. The procedure was straightforward but the apparent dry bias and hence the over-estimated fire severity prediction was effectively corrected. This is particularly true when compared to the observed fire events. The resulting statistical characteristics of fire probability prediction were not only improved over the bias un-corrected set, they were also superior to using the fire climatology only. Thus the inter-annual variability of the predicted fire frequency was predicted fairly well. Furthermore, the prediction seemed to be particularly useful if ensemble forecast mean was taken.

While the fire severity prediction over the U.S. West might be useful in quantifying fire danger to fire managers, a more useful application might be the ability to forecast monthly or seasonal fire frequency over a region in a probabilistic manner. For example, a fire severity forecast over the juridical area of a regional operation center of the Geographic Area Coordination Center (GACC; http://gacc.nifc.gov/). However, to evaluate the skill of the forecast over such a small area is not an easy task using the prediction data presently available to us. In this study, since we have only 6 years of prediction and validating analysis, we had to compensate the shortage of temporal points with the abundant spatial points for the statistics to be meaningful. Future study should address the use of longer periods of climate forecast data (e.g. Roads et al. 2007) and fire data (e.g. Westerling et al. 2003) to examine the predictability of fire severity. Using such datasets, not only could we focus our analysis on a smaller GACC region, we would also not be limited to only two classes of fire, i.e. no fire or large fire, as in the analysis of this study. Instead, a probability spectrum (sizes of fires) could be readily produced.

Probability models, such as the one described here, are not only practical in producing maps of fire danger, they are also useful in assessing the skill of each fire danger in estimating and/or forecasting frequencies of wildland fire events. However, the indices in NFDRS were probably originally designed to support firefighting tactics on a daily basis. Some of the indices, such as SC, BI and IC, are sensitive to short-term variations 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 a future extensive re-evaluation of those indices excluded from Preisler et al. (2007) and this study is needed. In particular, we will focus on how to best accumulate the daily information given in these wind-sensitive indices into monthly or even seasonal variables.

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