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Seasonal fire danger forecasts for the USA

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Abstract. The Scripps Experimental Climate Prediction Center has been making experimental, near-real-time, weekly to seasonal fire danger forecasts for the past 5 years. US fire danger forecasts and validations are based on standard indices from the National Fire Danger Rating System (NFDRS), which include the ignition component (IC), energy release component (ER), burning index (BI), spread component (SC), and the Keetch–Byram drought index (KB). The Fosberg fire weather index, which is a simplified form of the BI, has been previously used not only for the USA but also for other global regions and is thus included for comparison. As will be shown, all of these indices can be predicted well at weekly times scales and there is even skill out to seasonal time scales over many US West locations. The most persistent indices (BI and ER) tend to have the greatest seasonal forecast skill. The NFDRS indices also have a weak relation to observed fire characteristics such as fire counts and acres burned, especially when the validation fire danger indices are used.

Introduction

Predicting the influence of weather on fire ignition and spread is an operational requirement for national and global fire planning by the National Interagency Coordination Center (NICC), which is the USA's support centre for wildland firefighting. NICC is home to seven federal agencies including the Bureau of Land Management, National Park Service, Fish and Wildlife Service and Bureau of Indian Affairs, all in the Department of the Interior; and the Forest Service, in the Department of Agriculture. NICC's Predictive Services produces national wildland fire outlook and assessment products at weekly to seasonal time scales. This is currently done by considering standard National Weather Service (NWS) seasonal forecast products of temperature and precipitation (see Brown *et al*. 2003) along with other indicators, and carefully exercised human judgment.

By contrast, nowcasts of fire danger potential at individual locations have been carried out for decades at individual station locations using the US Forest Service (USFS) National Fire Danger Rating System (NFDRS) (Deeming *et al*. 1977). This process has been automated and implemented nationwide, resulting in web-based displays of the NFDRS indices. The NFDRS explicitly describes the effects of local topography, fuels and weather on fire potential. Fuel moisture models relate moisture content to cumulative precipitation, precipitation extent and variation, temperature and relative humidity. These fire danger nowcasts are updated almost daily, but they allow fire managers to react only to the current weather and climate conditions, rather than plan for the upcoming fire season.

The goal of this paper is to assess whether the NFDRS indices could also be forecast with a state of the art dynamical seasonal prediction model in the hopes that automatic seasonal forecasts could eventually be developed for NICC predictive services. Again, official NWS forecasts are issued only for temperature and precipitation. Forecasts for several more fire-relevant variables, such as relative humidity and wind speed, are still experimental and in many cases the fire community has had to empirically adapt to the official NWS forecasts of temperature and precipitation.

As described previously by Roads *et al*. (2001*a*, 2001*b*), Roads and Brenner (2002) and Chen *et al*. (2001), as part of this effort, the Scripps Experimental Climate Prediction Center (ECPC) has been routinely making experimental, near-real-time, long-range dynamical forecasts since 27 September 1997 of several additional variables relevant to fire danger forecasts. Images from these forecasts are regularly shown on the worldwide web site http://ecpc.ucsd.edu/

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(Roads *et al*. 2003*c*). The global model is a version of the National Centers for Environmental Prediction's (NCEP's) global spectral model (GSM; Kalnay *et al*. 1996; Roads *et al.* 1999) used for the NCEP/NCAR (National Center for Atmospheric Research) reanalysis. With the GSM forecasts as boundary conditions a higher resolution regional spectral model (RSM; Juang *et al*. 1997) is also run for various US and international regions (see e.g. Roads *et al*. 2003*a*, 2003*b*) to provide increased geophysical detail. The initial conditions and sea surface temperature (SST) boundary conditions for these experimental global forecasts come from the NCEP Global Data Assimilation (GDAS) 00 UTC operational analysis, which is available nearly every day in near real time on NCEP rotating disk archives, to interested researchers. Transforming NCEP's higher-resolution operational global analyses to lower (vertical and horizontal) resolution initial conditions for the global model, 7-day global and regional forecasts are made every day and every weekend these global and regional forecasts are extended to 16 weeks.

The Experimental Climate Prediction Center's experimental forecasts are certainly not superior to official forecasts from NCEP, which use not only similar dynamical models (ECPC models are actually older fixed versions of NCEP's constantly improving models), but also take into account other climatic features that are not yet adequately represented in any dynamic model (i.e. various climatic trends, tropical teleconnections, innate human forecast experience, etc.). However, the documented skill of our dynamical system (e.g. Roads *et al*. 2001*a*) does seem to at least be comparable to official forecasts, which indicates that these experimental forecasts may at least be a useful research tool for developing various forecast applications.

We have therefore attempted to develop experimental forecasts of the National Fire Danger Rating System (NFDRS; Deeming *et al*. 1972) in order to augment current USFS nowcasts from station observations and current seasonal forecast output of only temperature and precipitation. Basically, because our dynamical models have demonstrated some skill for forecasting various meteorological variables like temperature, relative humidity and mean wind speed at seasonal time scales, we wish to determine whether the perceived meteorological forecast skill can carry over to forecasts of fire danger and whether the federal fire agencies should develop a more comprehensive seasonal fire danger forecasting capability. Encouragingly, Roads *et al*. (2001*a*) did show that a simplified measure of fire danger, namely the Fosberg (1978) fire weather index (FWI) was capable of being predicted at seasonal time scales, mainly because of the inherent predictability of relative humidity, which is a significant component of the FWI, and as we shall see, other NFDRS indices.

In particular, we examine here US regional spectral model (RSM) weekly to seasonal forecasts of fire danger. The next section describes the methodology (models, validating analysis, error measures) used for this study. Then we compare the geographic temporal and forecast lead variations, and finally present a summary.

Methodology

Global spectral model

The global spectral model (GSM), which was used to provide the boundary conditions for the RSM, has been described previously in many papers (e.g. Roads *et al.* 2003*a*). Again, the GSM is based on the medium range forecast (MRF) model used for the NCEP reanalyses (Kalnay *et al*. 1996; Kanamitsu *et al*. 2002). The GSM has a triangular truncation of T62 (192×94 global Gaussian grid) and 18 irregularly spaced vertical levels. Seven-day GSM forecasts, initialized every day from the 00 UTC NCEP GDAS operational analysis, and 16-week GSM forecasts made every weekend, provide the basic large-scale driving data for the RSM. During the weekly 16-week (and also daily 7-day) forecasts, it is assumed that the initial SST anomaly is constant (persistent). The GDAS initial conditions have been accessed almost every day from 00 UTC 27 September 1997 to present (28LT126 NCEP global analyses were available from 00 UTC 27 September 1997 to 18 UTC 14 March 2000; 42LT170 were available from 00 UTC 15 March 2000 to 18 UTC 14 July 2002; 62LT256 became available 00 UTC 15 July 2002). These higher resolution analyses are transformed to lower resolution initial conditions (18LT62) by linearly interpolating between vertical sigma levels, spectrally truncating the spectral components, and bilinearly interpolating the higher resolution surface grids to our lower resolution grids (and land mask).

Regional spectral model

The RSM was initially developed by Juang and Kanamitsu (1994; see also Juang *et al*. 1997) to provide a regional extension to the GSM, and thus in principle provides an almost seamless transition between the RSM and the GSM or the associated NCEP reanalyses (Kalnay *et al*. 1996; Kanamitsu *et al*. 2002) and the higher resolution region of interest. For this experiment, the grid spacing was chosen to be 60 km at the central point. This horizontal resolution (and 18 vertical levels) is sufficient to resolve many features of interest, although eventually even higher resolution simulations and forecasts need to be attempted for the US West, where the topography exerts a strong control on near-surface features.

Both the GSM and RSM use the same primitive hydrostatic system of virtual temperature, humidity, surface pressure and mass continuity prognostic equations on terrain-following sigma (sigma is defined as the ratio of the ambient pressure to surface pressure) coordinates. Therefore, in the absence of any regional forcing (and intrinsic internal dynamics, any significant physical parameterization differences, and significant spatial resolution), the total RSM solution should be identical to the GSM solution. A minor structural difference is that the GSM utilizes vorticity, divergence equations, whereas the RSM utilizes momentum equations in order to have simpler lateral boundary conditions. The GSM and RSM horizontal basis functions are also different. The GSM uses spherical harmonics with a triangular truncation of 62 (T62) whereas the RSM uses cosine or sine waves to represent regional perturbations about the imposed global scale base fields on the regional grids. The double Fourier spectral representations are carefully chosen so that the normal wind perturbations are anti-symmetric about the lateral boundary. Other model scalar variables (i.e. virtual temperature, specific humidity and surface log pressure) use symmetric perturbations. Finally, except for the scale-dependent horizontal diffusion, the GSM and RSM physically are, in principle, identical. However, there are some minor parameterization differences between the NCEP GSM and this RSM, which has an upgraded physics package comparable to what was used for the NCEP Reanalysis II (see Kanamitsu *et al*. 2002).

The RSM can be initialized directly from the GSM, analysis or reanalysis, or it can use a previous integration to initialize itself. Roads *et al*. (2003*a*) showed that it was best to initialize the RSM every day from the global analysis, as continuous runs affected the regional solution adversely. The first part of an RSM forecast or simulation involves the integration of the GSM, for a nesting period based on the large-scale output. Here, the RSM predicts regional deviations from the large-scale atmosphere base fields, which are linearly interpolated in time between two output periods (6 h). The non-linear advection is first computed at the model grid points by transforming the global and regional spectral components to the regional grid. The global quantities are transformed to the global grid and then bilinearly interpolated to the regional grid; the regional quantities are exactly transformed. These calculations are almost exact (except for the interpolation error for the global quantities) and thus, like the global model, the regional model is free of aliasing and phase error. The linearly interpolated global-scale tendency is then removed so that, in effect, only the portion affecting the regional perturbation is retained. At the horizontal boundaries, the perturbation amplitude approaches zero by a damping function increasing rapidly towards the lateral boundary, which ensures that the boundary tendencies are similar to the original GSM tendencies and features. A semi-implicit time integration scheme is employed to suppress computational modes and also to allow the use of longer time integration steps.

Fire danger indices

The NFDRS indices describe characteristics of fire danger, given the conditions of fuel, topography and weather (Fig. 1*a*,*b*). Note that the basic inputs to the NFDRS include precipitation, temperature, relative humidity and wind speed as well as fuels and slope. The standard weather input to the

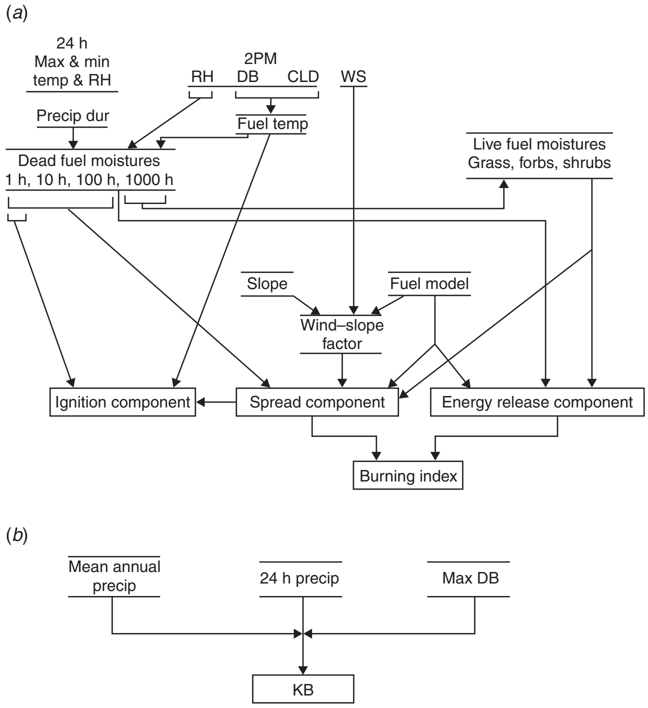

Fig. 1. (*a*) National Fire Danger Rating System indices and necessary inputs. (*b*) The Keetch–Byram drought index. DB, dry bulb temperature; CLD, cloudiness; KB, Keetch–Byram drought index; RH, relative humidity; WS, wind speed.

NFDRS comes from weather station data, which is assumed to apply to a large but undefined area surrounding each weather station; vegetation (fuel) types and slope are also defined for each weather station and are assumed to apply to the same surrounding area. The major difference from standard NFDRS calculations is that here gridded fuels, weather forecasts and topography data are used. The fuels and orography (slope) data were defined initially at 1 km spatial resolution and then the nearest 1 km grid point was used for a coarser-scale 100 km grid. The observed precipitation (25 km) and forecast model output (60 km) was similarly interpolated to the 100 km grid. Ultimately, the NFDRS indices calculated on the 100 km grid were interpolated back to the standard RSM 60 km grid.

For later comparison to the gridded fire danger indices, Fig. 2 shows the gridded fuels (see also Table 1) and slopes used for these calculations. Slopes (Fig. 2*b*) are used to reflect the fact that fire burns faster upslope than on flat ground. The type of vegetation or available fuel (Fig. 2*a*) is also important for describing the fire danger. Sixteen (Table 1) of the 20 NFDRS fuel models were used to represent the vegetation types across the USA (Burgan 1988), defining fuel characteristics such as depth, load by live and dead classes, heat content, fuel particle size, etc. Because the variability of fuel bed characteristics is almost infinite, each fuel model in the fire danger rating system must necessarily represent a rather

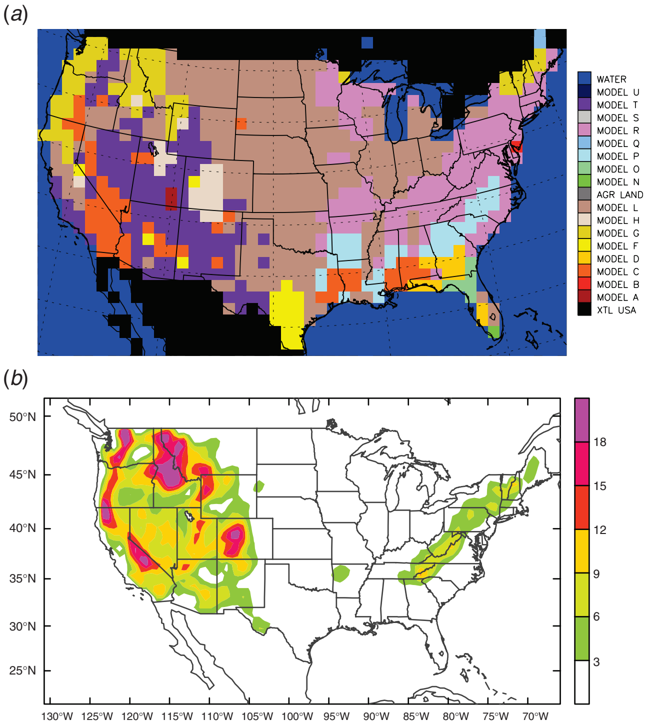

Fig. 2. (*a*) Fuel models used for these National Fire Danger Rating System (NFDRS) calculations (see Table 1). Fuel pixels are plotted on the 100 km fire danger model grid. (*b*) Slope used for these NFDRS calculations. Slopes interpolated to the RSM 60 km grid.

Table 1. Fuel models used for the coterminous USA
The slash models (I, J, K) and the leaf-off hardwood model (E) were not mapped

Vegetation type/ fuel model	Description
Grass	
A	Western annual grasslands
C	Open pine stands where grasses and forbs are primary ground fuel
L	Western perennial grasslands
N	Sawgrass prairies of south Florida
Shrub	
B	Mature California mixed chaparral, 6+ feet tall.
D	Palmetto-gallberry understory–pine overstory of SE coastal plains
F	Mature closed chamise and oakbrush, young chaparral, pinyon-juniper
O	Dense brush fields of SE United States, typically 6+ feet tall
S	Alpine tundra with low shrubs, moss, lichens
T	Sagebrush-grass types of the Great Basin and Intermountain West
Conifer	
G	Dense conifer with heavy accumulation of litter and downed woody material
H	Healthy stands of short needle conifers
P	Closed, thrifty stands of long-needled southern pines
Q	Upland Alaska black spruce or jack pine stands in the Lake states
U	Closed stands of western long-needled pines
Hardwood	
R	Hardwood areas after the canopies leaf out

broad range of vegetation types. Basic data source was the 1 km resolution land cover map released in 1991 by the EROS Data Center (Loveland *et al*. 1991). The LC map was converted to an NFDR fuel model map through a combination of 2546 ground sample plots scattered across the USA, and consultation with fire managers from across the country. Again these fuel models and slopes were defined at 1 km resolution but the fire danger calculations were done on a 100 km grid and then interpolated to the RSM 60 km grid for these comparisons.

It should be noted that we do not include all of the standard NFDRS indices and components. Human- and lightning-caused fire occurrence indices, and the fire load index in the NFDRS (Deeming *et al*. 1972, 1977; Burgan 1988) were not used because they have not been particularly useful to most fire managers. The outputs of the NFDRS used here were the spread component (SC), energy release component (ER), burning index (BI), ignition component (IC), Keetch–Byram (KB; Keetch and Byram 1968) drought component and Fosberg fire weather index (FWI), which are further defined below. Basic equations for SC, ER, BI and IC are described by Cohen (1985), and additional NFDRS technical documentation is provided by Bradshaw *et al.* (1983).

1. Spread component is an index of the forward rate of spread at the head of a fire. A spread component of 30 means that the fire should be progressing about 30 feet per minute at the head. The SC is quite sensitive to wind speed, and moderately sensitive to slope, especially if the fuel is dry. The SC is expressed on an open-ended scale; it has no upper limit.
2. Energy release component is a number related to the available energy per unit area within the flaming front at the head of a fire. That is, if you think of a fire burning through an area of vegetation, the ER is a measure of the amount of heat released from the time the head of the flaming front first enters an area, until the tail of the flaming front leaves it. The ER is a cumulative or 'build-up' type of index. As live fuels cure and dead fuels dry, the ER values get higher, thus providing a reflection of drought conditions. The scale is open-ended and, as with the other components, is relative. Daily variations in the ER are due to changes in moisture content of the live and dead fuels. ER is not affected by wind speed, thus it is reasonably stable from day to day.
3. Burning index is a number related to the contribution of fire behaviour to the effort of containing a fire. The BI is derived from a combination of the SC and the ER, so it is strongly affected by wind speed, and varies considerably from day to day. It has an open-ended scale.

Table 2. Seasonal correlations among the various USFS fire danger indices (IC, BI, ER, KB, SC), FWI, fire statistics (CN and AC), and a few meteorological variables (P, WSP, T, RH)

	FWI	P	WSP	T	RH	CN	AC	IC	BI	ER	KB	SC
FWI	1.00											
P	−0.32	1.00										
WSP	0.38	0.28	1.00									
T	0.60	−0.13	−0.05	1.00								
RH	−0.89	0.40	−0.06	−0.75	1.00							
CN	0.15	−0.10	−0.02	0.22	−0.19	1.00						
AC	0.36	−0.25	0.07	0.31	−0.40	0.35	1.00					
IC	0.59	−0.26	0.17	0.34	−0.55	0.22	0.29	1.00				
BI	0.65	−0.32	0.13	0.46	−0.67	0.26	0.38	0.90	1.00			
ER	0.43	−0.25	0.01	0.43	−0.53	0.29	0.31	0.54	0.71	1.00		
KB	0.18	−0.17	−0.07	0.22	−0.26	0.11	0.21	0.12	0.33	0.37	1.00	
SC	0.54	−0.23	0.18	0.23	−0.45	0.12	0.25	0.81	0.77	0.24	0.15	1.00

AC, acres burned; BI, burning index; CN, fire counts; ER, energy release component; FWI, fire weather index; IC, ignition component; KB, Keetch–Byram drought index; P, precipitation; RH, relative humidity; T, temperature; SC, spread component; WSP, windspeed.

It is important to remember that computed BI values represent the near upper limit to be expected if a fire occurs in the worst fuel, weather and topography conditions for this fuel type.

4. Ignition component is a rating of the probability that a firebrand will cause a fire requiring suppression action. Because it is expressed as a probability, it is scaled from 0 to 100. An IC of 100 means that every firebrand will cause an 'actionable' fire if it contacts a receptive fuel. Likewise, an IC of 0 would mean that no firebrand would cause an actionable fire under those conditions. The IC is more than the probability that a fire will start (given a firebrand); it has to also have the potential to spread. Therefore the SC values are part of the calculation of the IC. Because the IC is a function of both the moisture content of small dead fuel and wind speed, it has significant daily fluctuations.
5. The Keetch–Byram drought index was not part of the original NFDRS (Deeming *et al*. 1972, 1977), but was added in a 1988 revision (Burgan 1988). It is a stand-alone index that can be used to measure the affects of seasonal drought on fire potential. The KB's relationship to fire danger is that, as the index value increases, the vegetation is subjected to increased stress due to moisture deficiency. At higher values desiccation occurs and live plant material is assumed to die, thus adding to the dead fuel loading on the site. Also, an increasing portion of the duff/litter layer becomes available fuel at higher index values.
6. Fire weather index was derived by Fosberg (1978) who assumed constant fuel (vegetation = grass) characteristics (see also Fujioka and Tsou 1985; Roads *et al*. 1991, 1997), based on equilibrium moisture content (a function of temperature and relative humidity) and wind speed. This index is not explicitly a part of the NFDRS and requires only instantaneous values of temperature, relative humidity and wind speed. Hence the FWI is most easily applied in practice and was included here because it had been used previously to assess the potential for seasonal fire danger forecasting. It also provides a first look at global fire danger conditions.

Using the validation data described below, the anomaly correlations (monthly means removed) of these parameters with each other and a few meteorological parameters over the US West (land region west of 105°W) are shown in Table 2. The standard fire danger indices (IC, BI, ER, KB, SC) all are fairly well correlated, with the IC, BI and ER having the highest correlations. By contrast the ER and SC have little correlation and the KB has little correlation with any of the other indices. The FWI is also well correlated with all indices, except for the KB. All indices (except for the KB) indicate strong correlation (negative) with RH and, except for the KB and SC, significant positive correlations with temperature. Precipitation is weakly correlated with all indices but does show a strong positive correlation with RH, which again is more strongly related to the various indices (except for KB). In short, the ER, KB, SC and perhaps the FWI appear to be somewhat independent measures, whereas the other indices are strongly related to the ER, KB or SC. It should be noted that these correlations change little for weekly and seasonal means and for that matter, even when the entire US is taken into account. The correlations are also similar when forecasts rather than validation data are used. It should be noted that the data appear to follow a normal distribution for seasonal means but less so for weekly means and so it was somewhat surprising that the correlations among weekly means were comparable to correlations among monthly and seasonal means.

Validating analyses

For our main validation effort, we now use 1-day GSM/RSM forecasts, made every day from 00 UTC analysis initial conditions, as the basic meteorological variables for calculating validating fire danger indices. There are only three missing 00 UTC initial states in more than a 2-year period and for these periods we used a previous 2-day forecast to generate the associated daily flux files. These 1-day forecasts are not exactly the same as the operational analysis, which is based on 4 × daily 6-h forecasts from the latest high-resolution global model, or the reanalysis, which is based on 4 × daily 6-h forecasts with the model we use for our forecasts, but they do form a useful approximation that can at least be used to estimate forecast skill upper bounds. As discussed by Roads *et al*. (2001*a*), global forecasts validated against the 1-day GSM/RSM forecasts are only slightly more skillful than forecasts validated against NCEP's operational analysis.

Although the 1-day forecast/analysis validation is certainly useful in the absence of other validating datasets, at least there are better approximations to the US precipitation from observations. For example, the National Climatic Data Center and first-order station network along with the precipitation network of the River Forecast Centers were utilized by Higgins *et al*. (2000) to develop gridded daily precipitation (25 km resolution), which we also use here for evaluation of the model GSM and RSM forecasts. In the comparisons below, we mostly use the 1-day RSM forecasts (observed precipitation is used in place of the 1-day RSM precipitation) to validate the RSM weekly to seasonal forecasts.

To summarize, the validation for these fire danger forecasts come from using forecast/observation analysis as input to the fire danger code. Fire danger indices are then initialized from this validation set but subsequently use forecasts after the initial day, including forecast precipitation, to drive the fire danger forecasts. As will be shown, these fire danger forecasts have substantial but regular biases from the validating fire danger analysis. It should be noted that one potential advantage for the NFDRS indices over the FWI indices is that they depend more on previously accumulated features. This means that we can use observed variables (like precipitation) up to the beginning of the forecast and then let the forecast model start from these somewhat realistic initial states. It would be even more useful to eventually include more observations into the validating and initializing fire danger dataset in much the same way current land data assimilation efforts are using available observations to define the surface hydrologic state. It should also be noted that a separate validation effort using actual station observations was carried out by Reinbold *et al*. (2005) and, although the skill was lower, there were many similarities, suggesting that our approximate validation procedure using 1-day forecasts is reasonable.

Fire statistics

While the forecasts need to first be validated with the initial state, which presumably is a better approximation to actual fire danger, we also need to compare the validation and forecast fire danger indices with characteristics of observed fires. Recently Westerling *et al*. (2001, 2002, 2003*a*, 2003*b*) developed an extensive database of gridded (1-degree grid) monthly fire counts and acres burned from fire reports to several federal agencies for most of the western states (the spatial extent of the available fire statistics can be seen in Fig. 3*g*,*h*; see also Figs 4, 6). The statistics include only those fires that were reported and managed and hence are not likely to represent all fire counts. The statistics also include anthropogenic as well as natural fires. Despite their limitations, these fire statistics do at least provide a starting point for assessing a fire danger forecast analysis system. For convenience these fire statistics were interpolated to the model grid with the requirement that each model grid point have at least three surrounding grid points with information. The fire data were further interpolated to weekly means although, as shown later, this transformation did not then indicate that weekly forecasts had any additional skill. Following Westerling *et al.* (2002), the log of the acres burned was used, as this provided a more normal distribution. There is some indication that fire counts should also be similarly transformed but, because fire counts are not normally used to assess fire activity, we decided to defer this transformation for this paper. Because of our concern with the interpolation of these statistics to a higher resolution grid, ultimately when correlations were computed, all variables were averaged back to a 1-degree grid. This made the correlations only slightly larger, however.

Skill measures

As discussed by Roads *et al*. (2001*a*), skill can be measured in several different ways. We first of all compared the means of the forecasts with the validating analyses in order to make sure that the forecast model produced reasonable results. The forecasts tend to have small biases that are related to a tendency for the forecast model to drift away from the initial state towards the model climatology. Still, these biases are substantially larger than model anomalies, especially at seasonal time scale and we need to remove these systematic biases before assessing the skill of the model. The variability of the forecasts (standard deviation) is then compared in order to understand whether the forecast variability is similar to the validating analysis variability. Finally, correlations of the forecasts with the validating analyses as well as with the fire occurrence and size statistics provide us with our standard measure of skill. There are several other measures that can be used to describe skill but correlations do provide a basis for determining whether the skill is at least significant. Further work will be required to determine if this significant forecast skill is actually useful to a fire manager. Details about all of the skill measures used here can be found in Roads *et al*. (2001*a*).

Forecasts

Geographical variations

As shown in Fig. 3, summertime (ensemble mean of seasonal forecasts initialized in May, June, July) fire danger is certainly

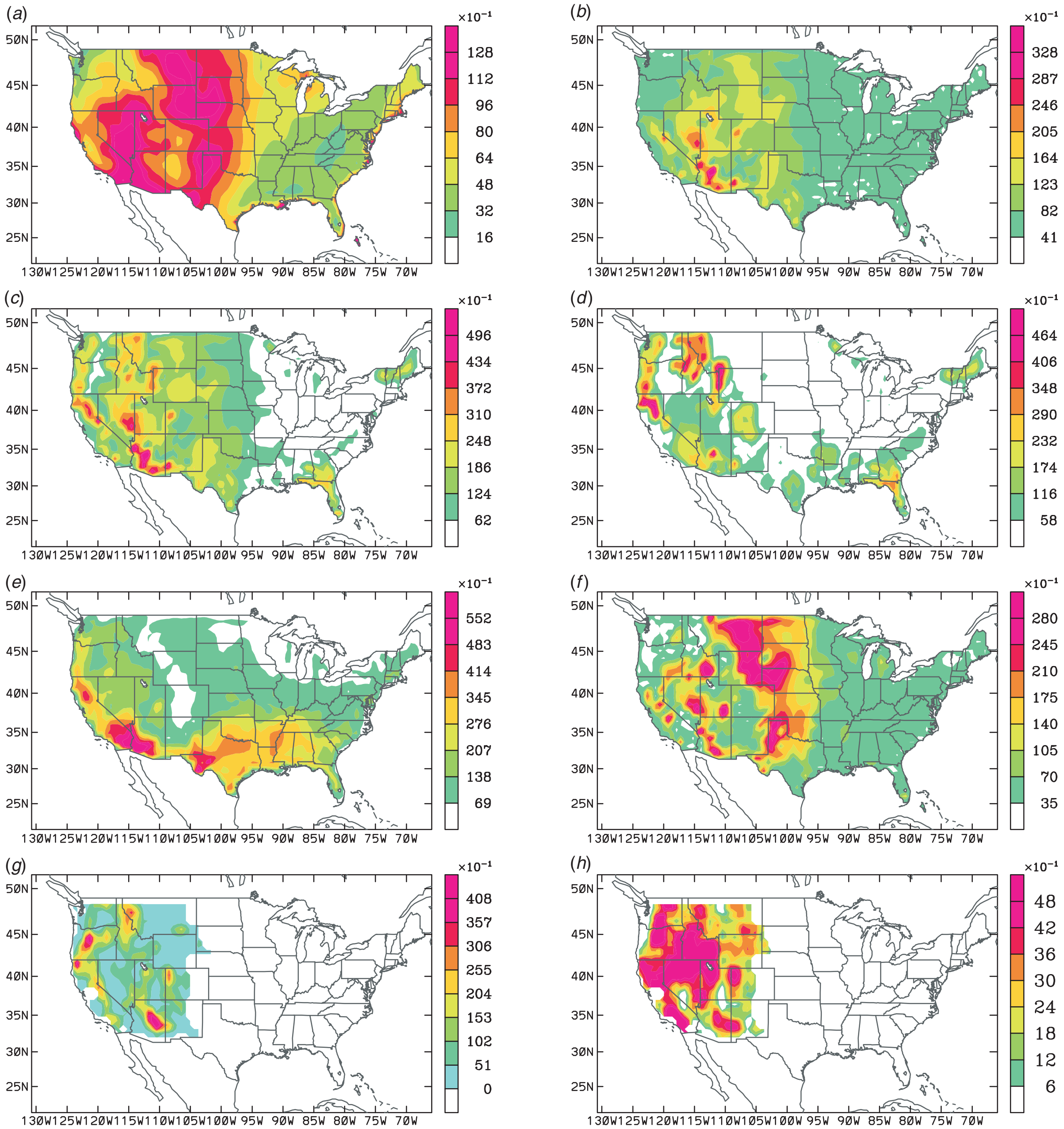

Fig. 3. Summer seasonal mean validation means: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

greatest in the US West, with the ER emphasizing the Northwest forests, the IC and BI emphasizing the dry Southwest, and the SC emphasizing the Rocky Mountain Front Ranges. The FWI is similar to the SC, in part because of the wind speed influence, which is strong east of the Rocky Mountains, and in part because the FWI assumes grass as the fuel model everywhere, which may result in greater fire spread. There is also some influence on the FWI by the relative dryness of the Southwest. Again this dryness is also present in the IC, BI and KB although, as shown previously in Table 1, variations in the KB and FWI are not well correlated. Presumably the higher resolution features of the standard NFDRS indices (IC, BI, ER, SC) are related to the higher-resolution fuel characteristics embedded in these indices. In fact, the FWI can have remarkably high variations over the adjacent ocean (not shown), due to the higher wind speeds, which is another

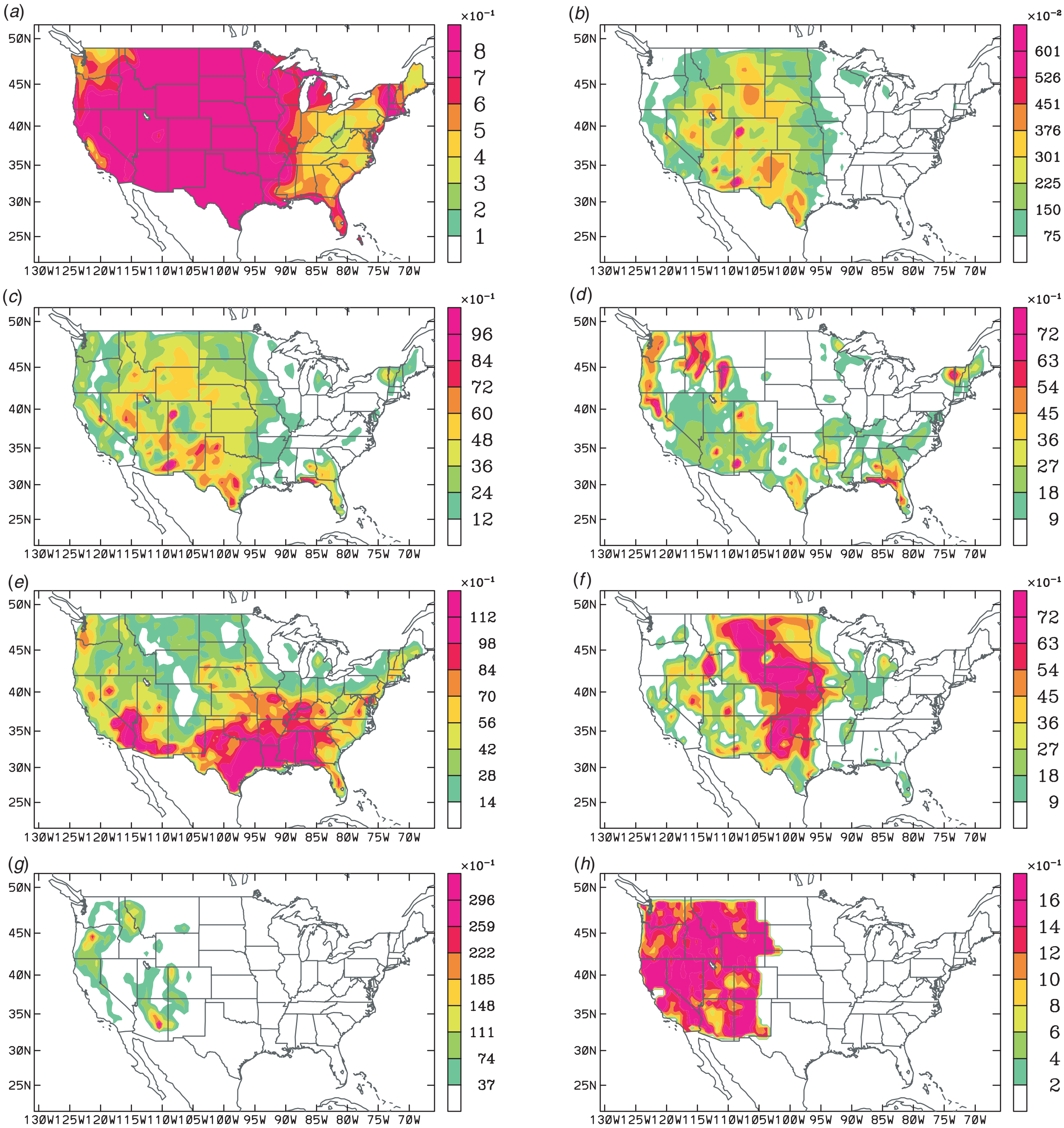

Fig. 4. Summer seasonal mean validation standard deviations: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

limitation associated with its use (a basic assumption of the FWI is an implicit grassland fuel model everywhere). Finally, as shown in Fig. 3*g*,*h*, the NFDRS indices do have an overall relationship with fire counts (CN) and acres burned (AC) although it is clearly not a one-to-one relationship. Fire counts tend to be especially large over Oregon, northern Idaho and Arizona, which are also related to the acres (log) burned.

The seasonal forecast has several seasonal biases (not shown). The SC forecasts tend to be too extreme in the region of Great Plains high wind speed, and this is also reflected in the FWI, which also has biases along the West coast. All indices have bias over Texas, which is presumably related to a bias in the forecast relative humidity (RH). For the most part the biases are positive but some negative biases do show up in

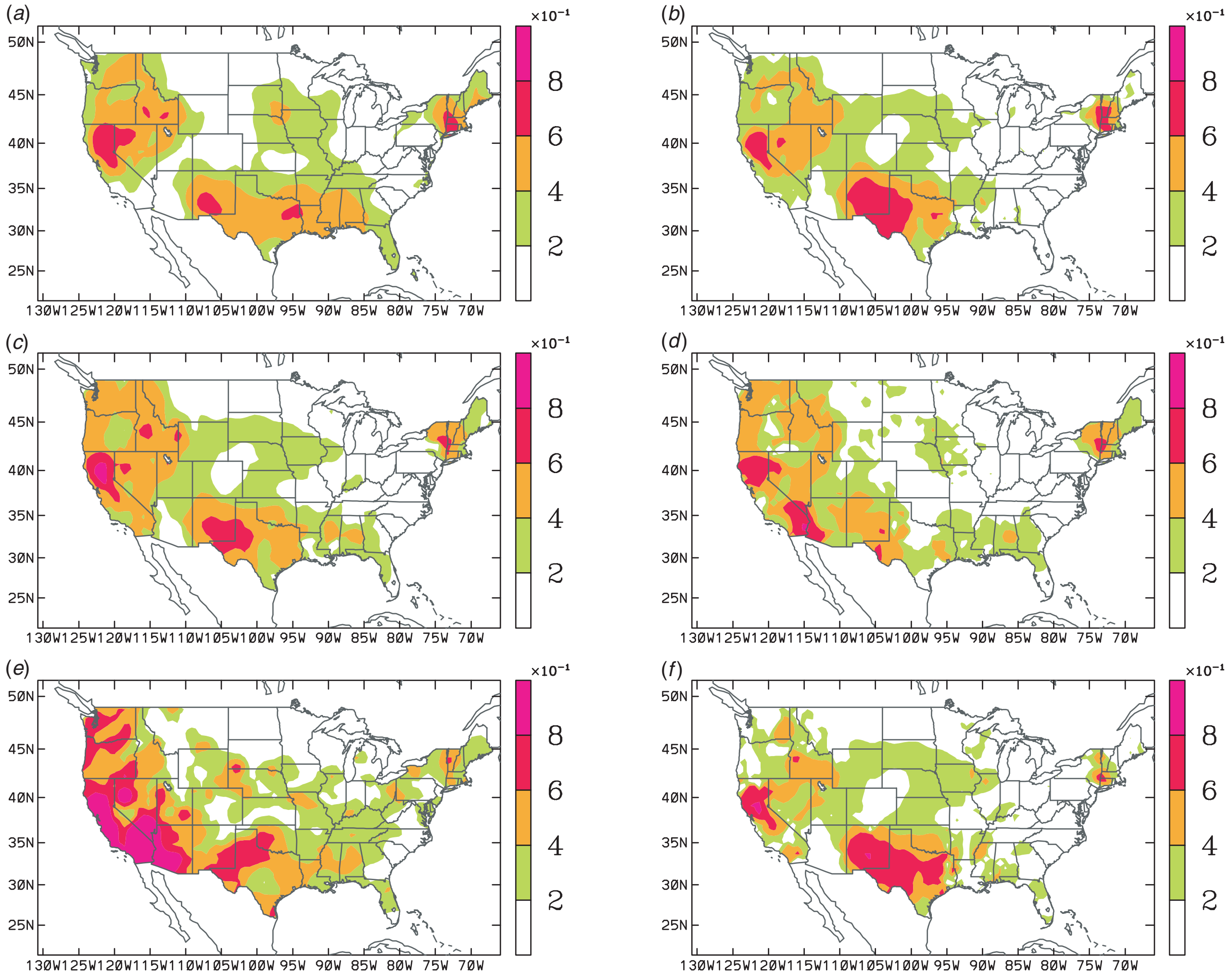

Fig. 5. Summer seasonal mean correlations between forecast and validation: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; and (*f*) spread component.

the KB over the US West and East. The SC and FWI also have low biases over Montana and Wyoming. However, the biases are somewhat smaller than the climatological values and thus seasonal forecast climatologies have a high resemblance to the validating seasonal climatologies.

The variability as measured by the seasonal standard deviations (Fig. 4) reflects, in part, the summertime climatic means. For example, the SC and FWI s.d. values are strongest over the Central US; the ER s.d. is largest over the Northwest; the KB s.d. is strongest in the south; the BI and IC s.d. values are strongest in Arizona, New Mexico and Texas; the CN variability is strong in specific regions of Oregon, northern Idaho and Arizona. Interestingly, the regions of largest seasonal forecast discrepancies (not shown) occur in regions where weak s.d. occurs. For example, the forecast IC, ER, SC, BI and to some extent the FWI is much stronger over the US East. The forecast KB s.d. is especially strong over the North Central. Only in a few places is the forecast s.d. weaker than the validating s.d.

This erroneous s.d. over the US East may help to explain why, at seasonal time scales, the US West is relatively better predicted (Fig. 5). Unfortunately, because the seasonal biases are greater than the standard deviations of seasonal averages, it is mandatory that some bias correction be made for the forecasts. Here, this bias correction was implicit as the correlations use only the anomalies from the forecasts or validations. Again, a separate climatology was developed for each forecast lag. Interestingly, the forecast correlations are not greatest where the means or s.d. values are greatest and may be more related to where the skill in making the forecasts of basic meteorological variables, like relative humidity, is greatest.

As shown in Fig. 6, the correlation of the validation NFDRS indices with AC is somewhat spotty but certainly

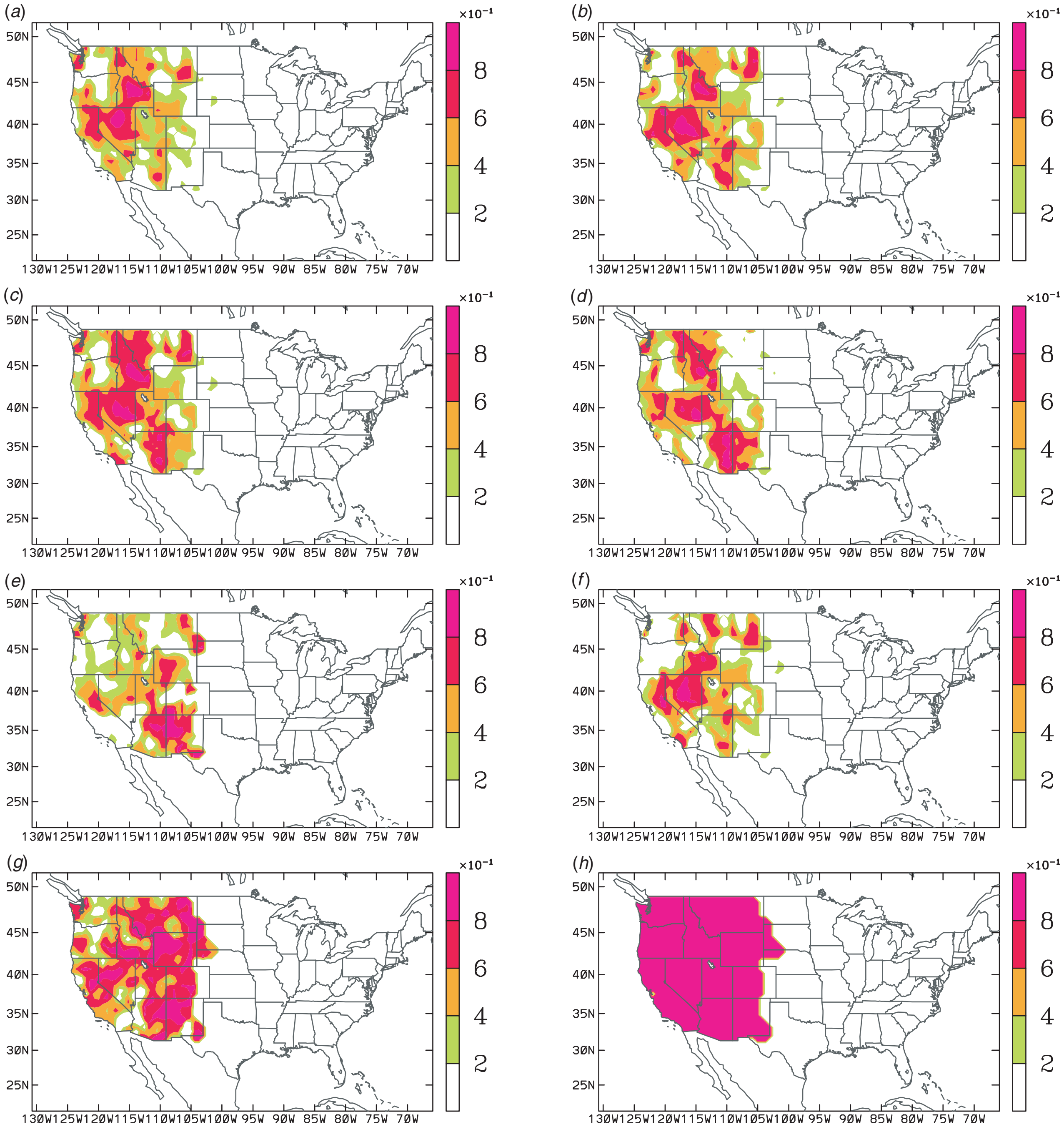

Fig. 6. Summer seasonal mean correlations between validation National Fire Danger Rating System indices, fire counts and acres burned with: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

significant in specific regions. For example, the FWI tends to be most useful over Nevada and Idaho, whereas the KB is more useful over the four corners area. These correlations are substantially reduced for the forecast correlations (Fig. 7), which have a tongue of high correlation over northern California, Nevada, Oregon and Idaho.

Temporal variations

Figure 8 shows the US West (US land region west of 105°W where fire statistics are available) average time series for the various NFDRS indices. Note that all forecast indices tend to be somewhat larger than the validating indices, especially

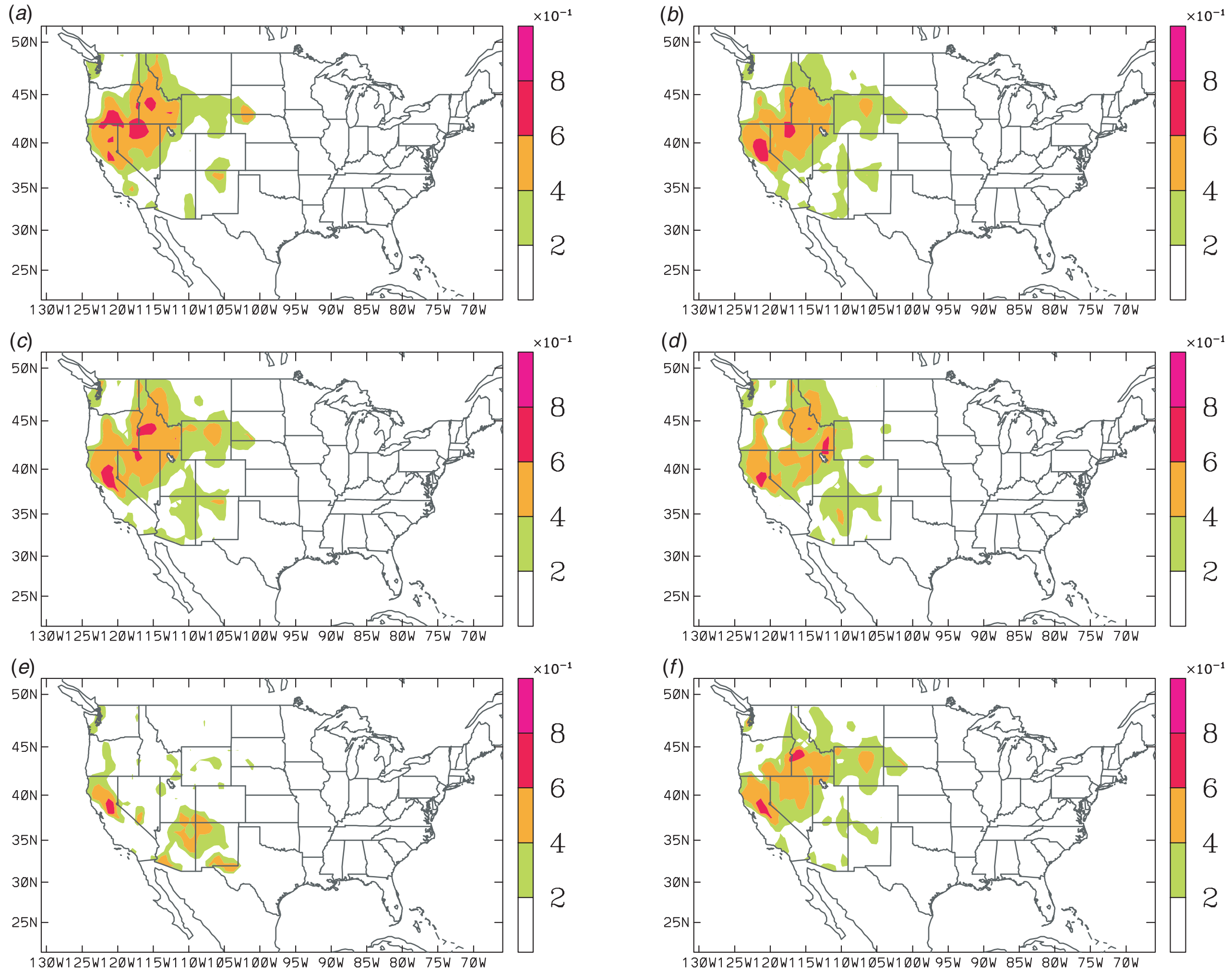

Fig. 7. Summer seasonal correlations with acres burned and forecast National Fire Danger Rating System indices: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; and (*f*) spread component.

during the springtime. However, despite the bias, it is clear that both the seasonal forecasts and validating 1-day forecasts/observations have similar time series. The summer and early fall have the greatest potential for fire danger, with most indices peaking in late summer (August); the KB peaks even later in fall and early winter. There appears to be a particularly anomalous KB during the fall and winter (2001/2002), which does not show up in weekly or even monthly time series. It is not clear why this KB anomaly shows up in these forecasts, given that the precipitation forecasts do not appear overly anomalous (Roads 2004*a*) and the other forecasts (Roads 2004*b*) do not appear similarly anomalous. However, it should be noted that there does appear to be an increased bias in all components beginning in July 2001, which may be related to when NCEP changed its global analysis system, including an increase in resolution. All of the indices do have the same seasonal variation as the fire statistics (CN and AC), with the largest values occurring during the summer. The validation NFDRS indices also have the same overall variability with the largest values occurring during the summer of 2000. Unfortunately, the forecast variability does not really capture this as forecast fire danger remained high during the summer of 2001.

As shown in Fig. 9, both the seasonal forecasts and validations have similar time series of variability (s.d.). The summer and early fall have the greatest potential for fire danger, with most indices peaking in late summer (August); the KB peaks even later in fall and early winter. It should be noted, however, that the FWI does not have a clear seasonal variation, presumably because of the counteracting effects of decreased summertime winds and decreased relative humidity and increased wintertime winds and relative humidity.

The correlations of the forecast indices with the validating indices (Fig. 10) show the large differences between

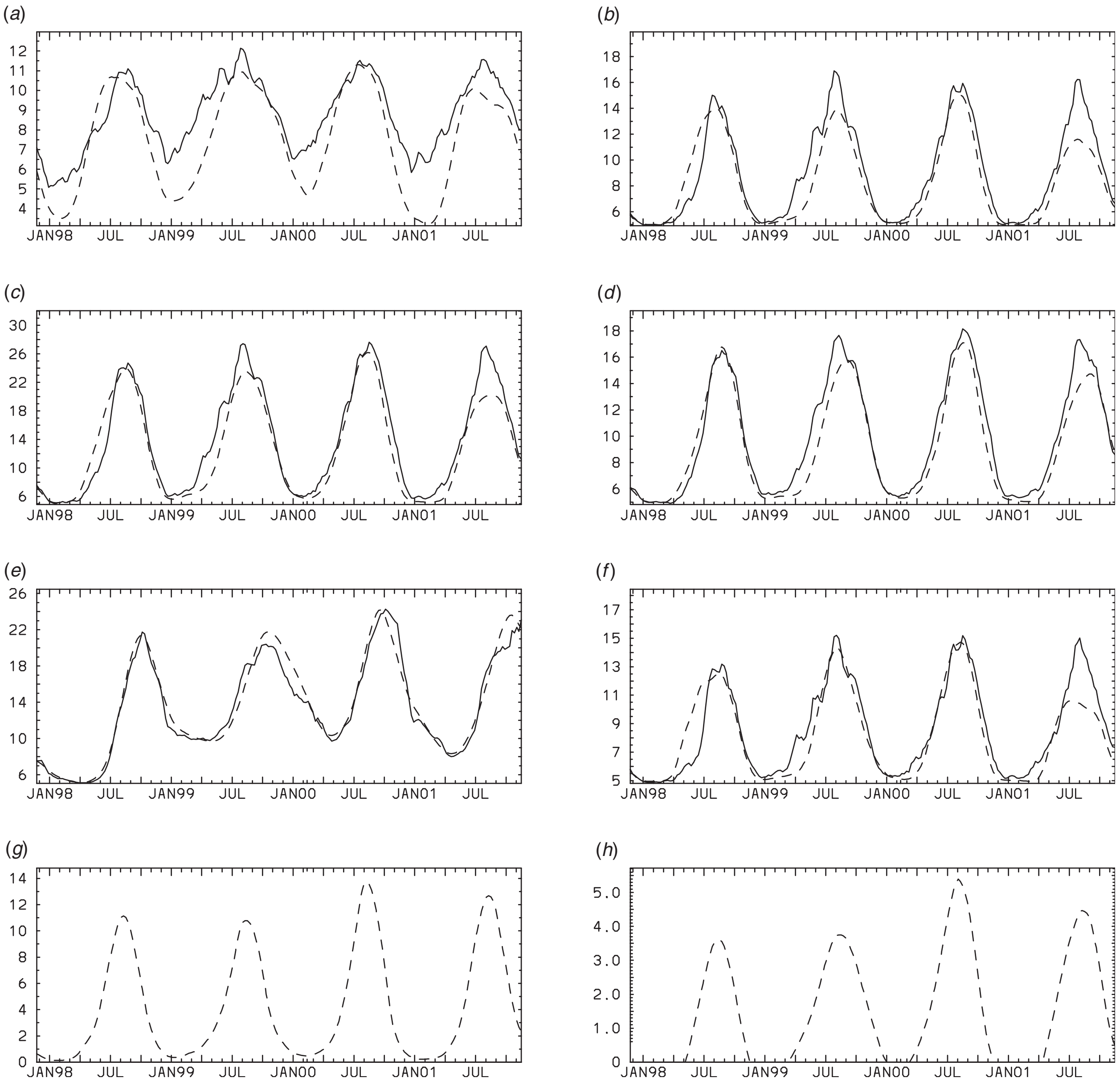

Fig. 8. Seasonal forecast (solid lines) and validation (dashed lines) US West means: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

the weekly forecasts and the seasonal forecasts. Correlations change from around 0.7 for the weekly forecasts to 0.2 for the seasonal forecasts. The time of minimum skill appears to be in early summer. Late summer and fall are relatively better predicted, except for the KB, which is predicted best during the winter and spring. There is also a weak indication of a forecast skill decline in the fall of 2001, when an especially anomalous KB was noted previously.

The correlations of the seasonal validating and forecast NFDRS indices with AC (Fig. 11) is fairly low although there is at least a tendency for the validating NFDRS indices to have somewhat higher skill than the forecast NFDRS indices, as indicated previously in Figs 6 and 7. There is also a tendency for the wintertime forecast skill to be somewhat greater, presumably because of the increased difficulty in describing and forecasting summertime precipitation as well as other relevant meteorological variables. The interannual variability is especially large though. Note for example the increased skill in the winter and spring of 1998, followed by a slow decline until the summer of 2000 when increased skill again occurred. This may indicate that it is easier to forecast extreme events.

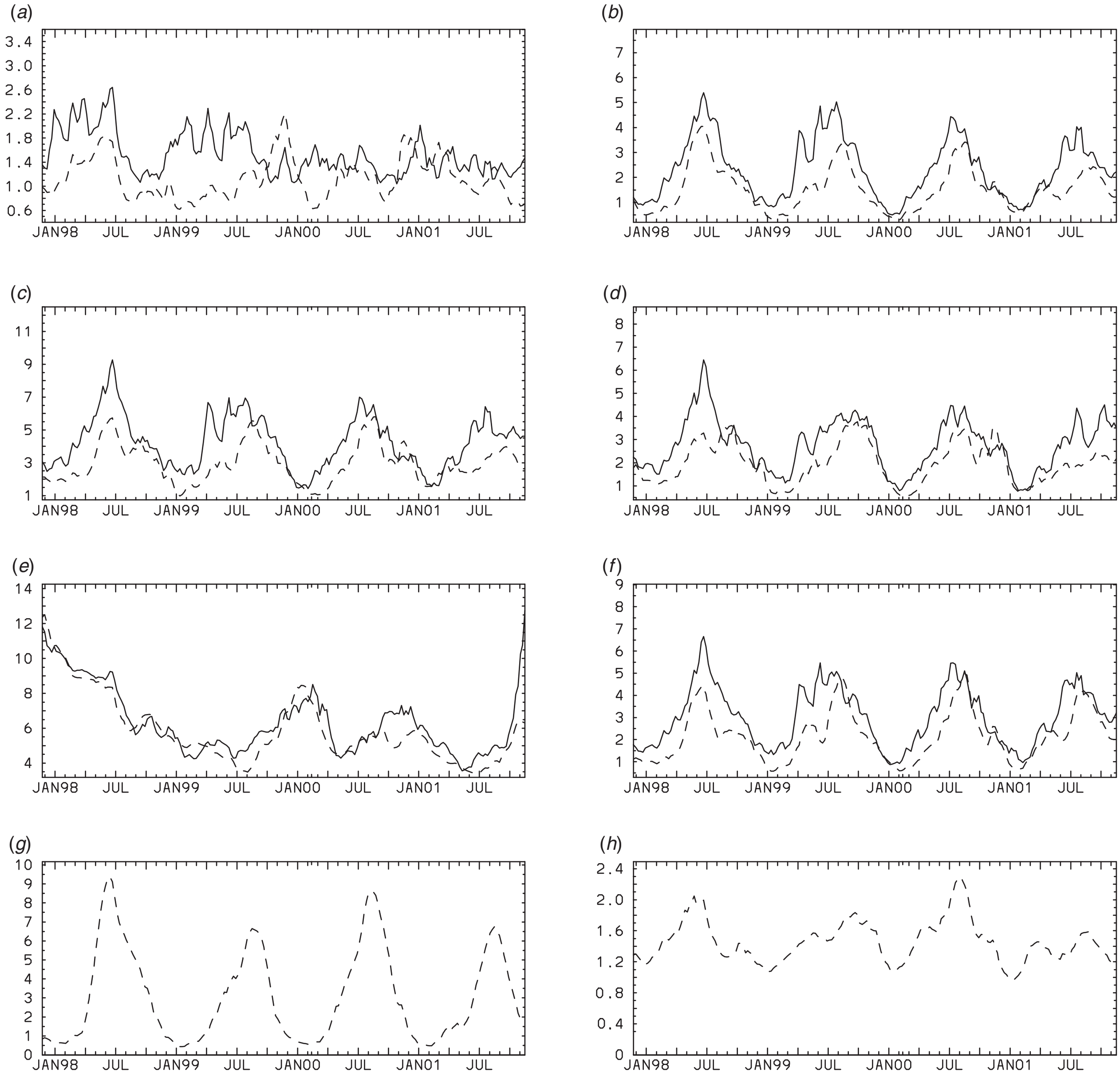

Fig. 9. Seasonal forecast (solid lines) and validation (dashed lines) monthly US West standard deviations: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

Forecast lead relations

Figure 12 shows the forecast lead relationships for the climate means. Basically, the bias in the indices is a linear function of forecast time, which means that the monthly and seasonal biases can be approximated by the bias at the midpoint of the month (2 weeks for the first month, 6 weeks for the first season). The forecast standard deviations (not shown) are also a function of forecast lag and averaging period, with the smallest variations occurring for seasonal means.

The correlations of the forecast with validations (Fig. 13) show the strong forecast skill at 1 week, followed by a sharp decline towards zero. However, note that the seasonal and monthly correlations tend to be somewhat larger than the weekly correlations and these correlations may be significant. The greatest skill occurs in predicting the KB, followed by the BI and ER and then the IC and SC. The FWI skill is comparable to the SC, in part because of the stronger dependence of these indices on wind speed. Persistence forecasts are also shown and, while these forecasts are somewhat inferior to the dynamical forecasts, they do indicate that indices with longer persistence are better predicted at seasonal time scales.

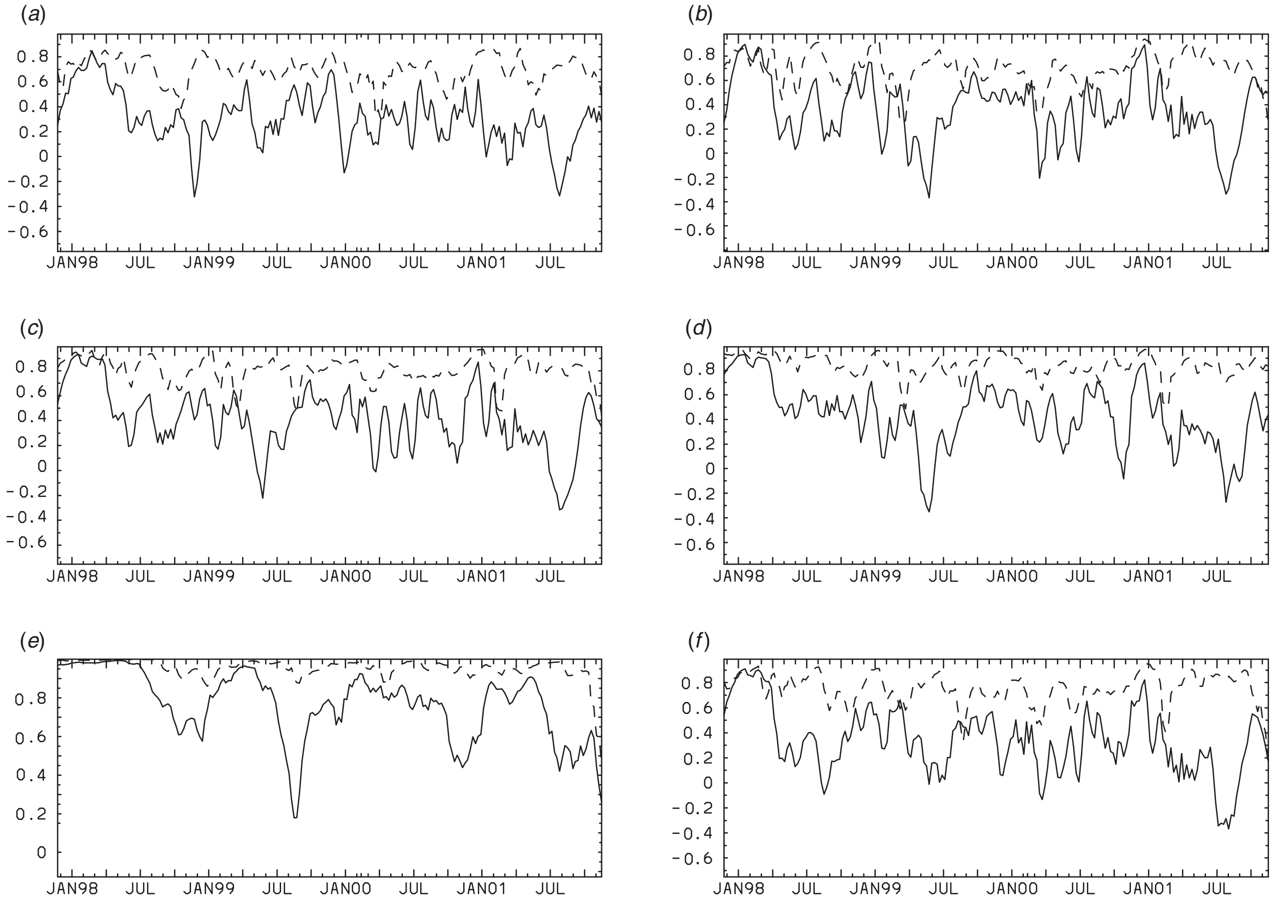

Fig. 10. Seasonal forecast (solid lines) and weekly forecast (dashed lines) US West correlations: (*a*) fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; and (*f*) spread component.

Despite the significant skill in forecasting the actual fire danger indices (which is summarized in Fig. 14), there is only a weak lead relationship with the forecast and validating NFDRS indices and AC. The strongest relationships occur for seasonal averages. This may be related in part to the use of monthly fire statistics. In fact, as is also shown in Fig. 14, there is little difference between using the validating analysis and the seasonal forecast for these NFDRS correlations with fire extent (AC). Despite this low skill there is an indication that the indices are at least somewhat related to fire occurrence and surprisingly that the simplified FWI is the overall best (but really indistinguishable from the other indices). Finally, we should mention that we believe there is much work that is still needed to develop better indices and better measures of fire extent and occurrence, as well as better analysis and forecast models.

Summary

The goal of this paper was to determine the skill of a dynamical model in forecasting seasonal fire danger ratings. During the past decade, seasonal forecasts have certainly become more commonplace, although making an explicit connection to the fire danger community has been typically lax. Instead it is commonly assumed that forecasts of standard monthly mean temperature and precipitation should be made and that applications communities would somehow adapt to using these monthly means. Here we have shown that it is quite possible to make the forecasts compatible with what the fire applications community needs: daily time series of a few critical variables (e.g. temperature, relative humidity, wind speed, precipitation) in order to drive fire danger models.

As was shown, there was probably significant seasonal forecast skill for all of the standard fire danger ratings (IC, BI, ER, KB, SC) as well as the FWI, which had previously been used to assess fire danger forecast skill. Persistence forecasts were also shown and, while these forecasts are somewhat inferior to the dynamical forecasts, they did indicate that indices with longer persistence were better predicted at seasonal time scales. These seasonal fire danger forecasts had significant skill even for 1-month forecast leads (12 week averages of weeks 5–16). It would be of interest to determine the forecast skill for one season lead (e.g. out to 7 months),

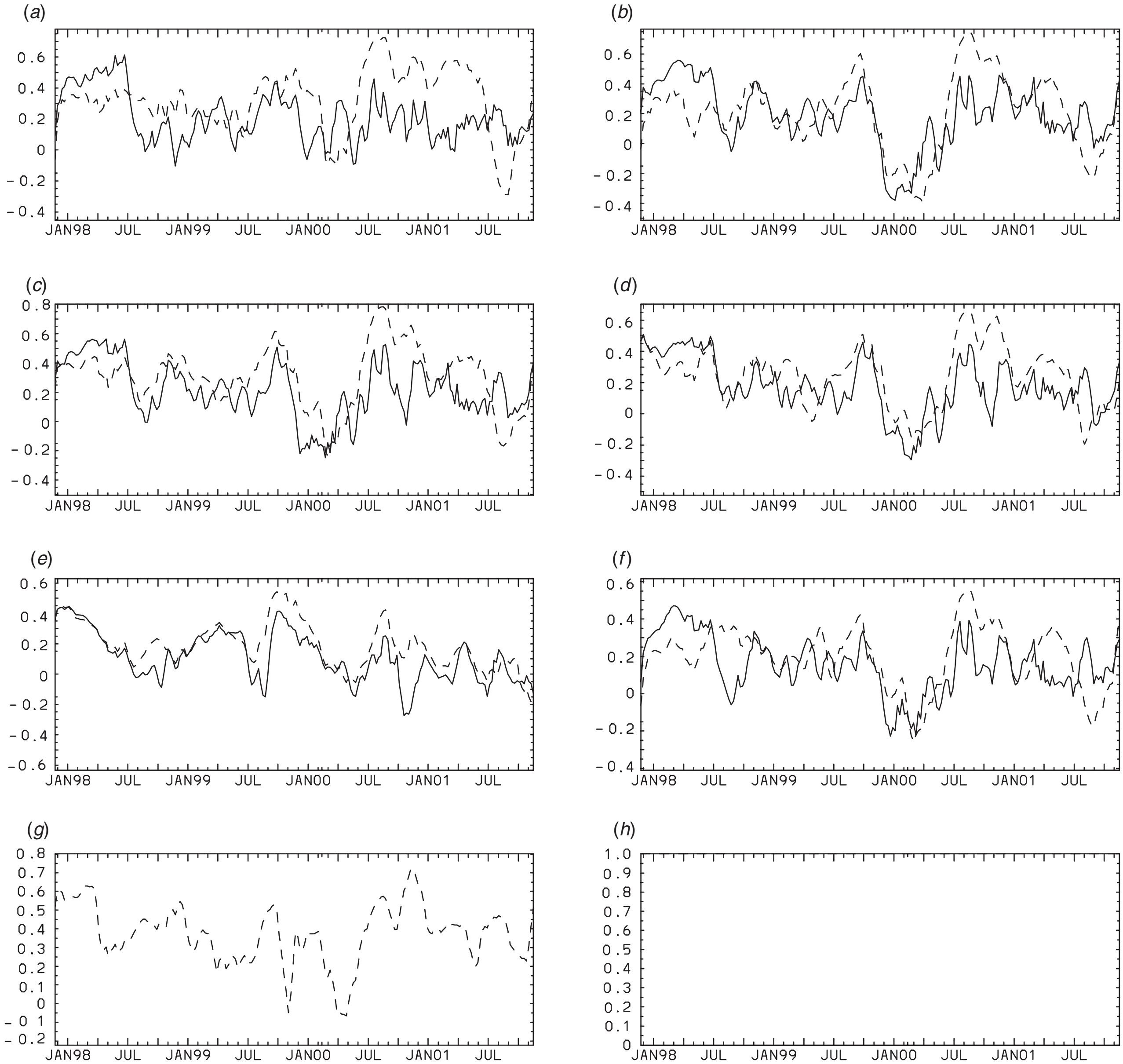

Fig. 11. Summer seasonal mean correlations between forecast (solid lines) and validation (dashed lines) National Fire Danger Rating System indices and acres burned. (*a*) Fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

although this would mean a substantial increase in computer time and storage (almost double) in order to produce these ultra long-range forecasts.

It was further shown that the fire danger indices are related to fire statistics such as fire counts and acres burned, especially when the validating was used rather than forecast output. Still, the relationships are weak and further improvements should be possible. In fact, fire danger indices are now evolving towards making use of more remotely sensed vegetation characteristics instead of trying to parameterize these relationships from complex averaging of meteorological input. In this regard the experimental fire potential index (FPI), first investigated in 1996 at the USFS Intermountain Fire Sciences Laboratory and then refined in collaboration with the US Geological Survey EROS Data Center (EDC), is a major augmentation to standard USFS fire danger indices (Burgan *et al*. 1998). The FPI model combines Relative Greenness derived from the normalized difference vegetation index (NDVI) data derived from NOAA AVHRR data to generate 1-km resolution fire potential maps on a daily basis.

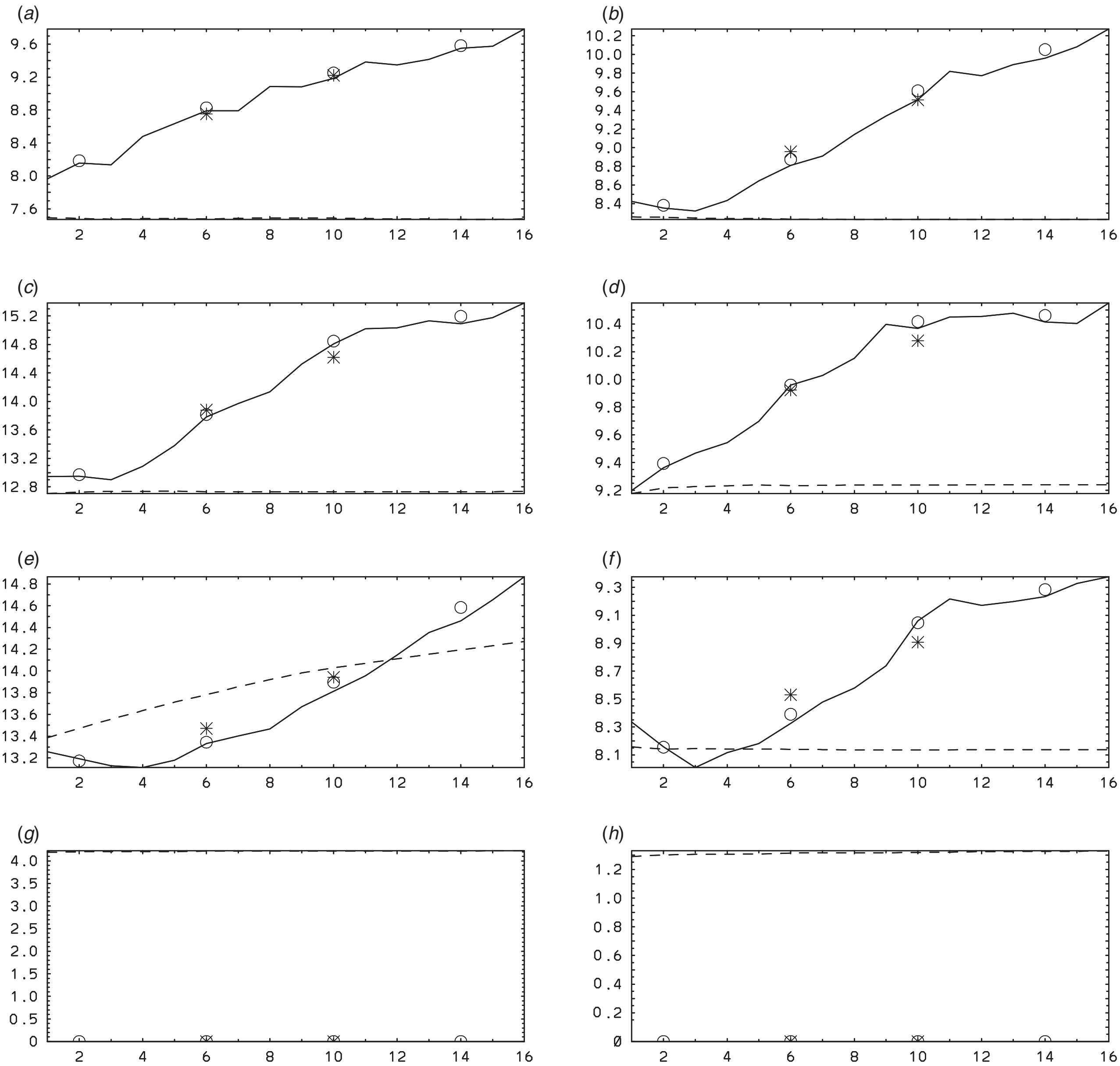

Fig. 12. Forecast weekly means (solid lines), validation weekly means (dashed lines), forecast monthly means (○) and seasonal means (∗) as a function of forecast lead-time. Monthly and seasonal forecast values are plotted at the centre points (i.e. week 2 for month 1 and week 6 for first season). (*a*) Fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; (*f*) spread component; (*g*) fire counts; and (*h*) acres burned.

One potential advantage for this index is that fire danger could potentially be assessed for other regions, where good fuel models do not currently exist.

Finally, although NFDRS indices are widely used by the USFS and other agencies (NIFC) to guide decisions involving fire danger, it should be emphasized that the fire danger rating of an area is only one, imperfect, tool to assess 'fire business' decisions. The emphasis is on imperfect because fire danger rating information is not a final answer by itself; it must be considered along with the manager's local knowledge of the area and consequences of a decision when arriving at the best solution for a particular problem. Given the current low forecast skill, seasoned experienced judgement remains a critical aspect of fire danger forecasts.

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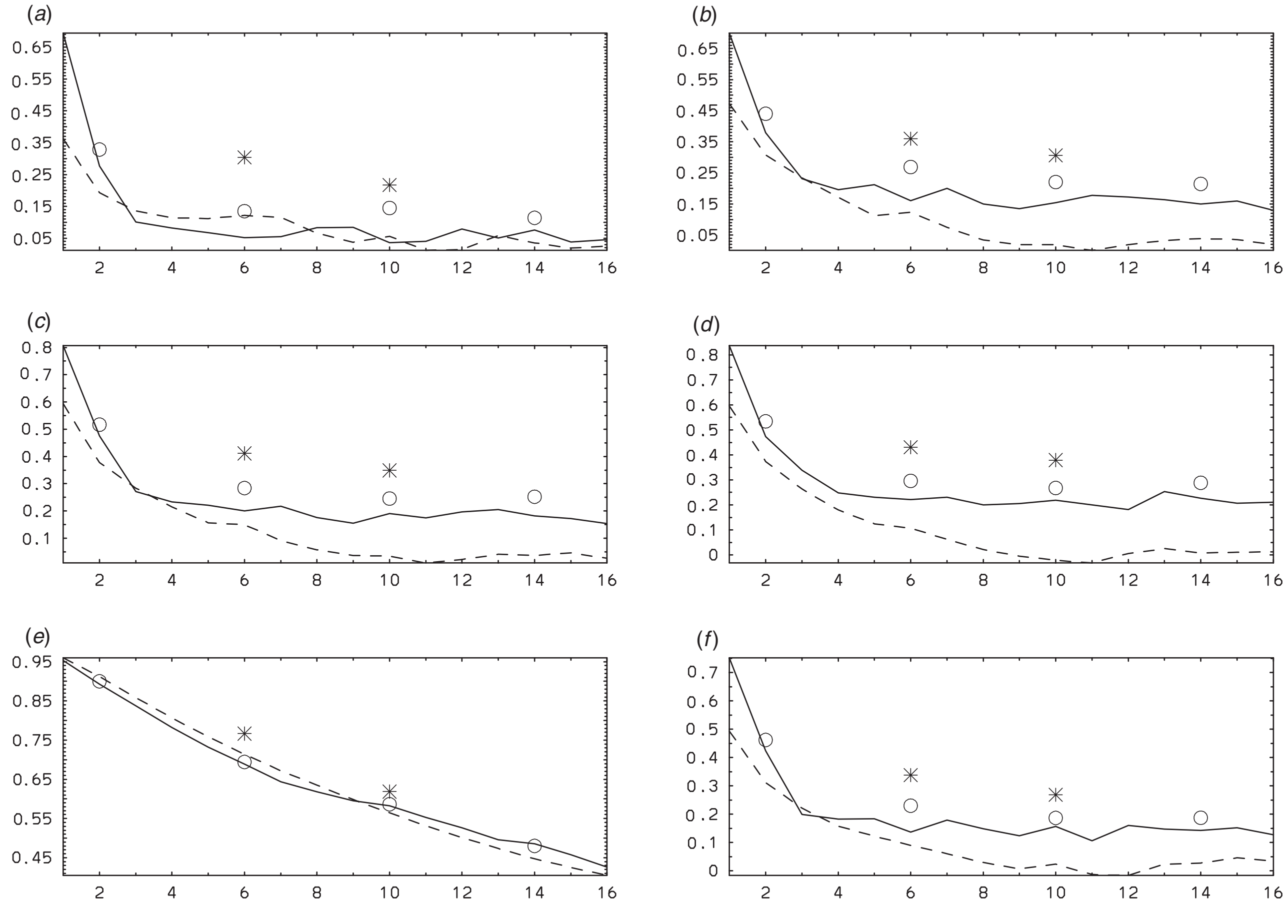

Fig. 13. Forecast weekly (solid lines), persistence weekly (dashed lines), forecast monthly (○) and seasonal (∗) correlations as a function of forecast lead-time. Monthly and seasonal values are plotted at the centre points (i.e. week 2 for month 1 and week 6 for first season). (*a*) Fire weather index; (*b*) ignition component; (*c*) burning index; (*d*) energy release component; (*e*) Keetch–Byram drought index; and (*f*) spread component.

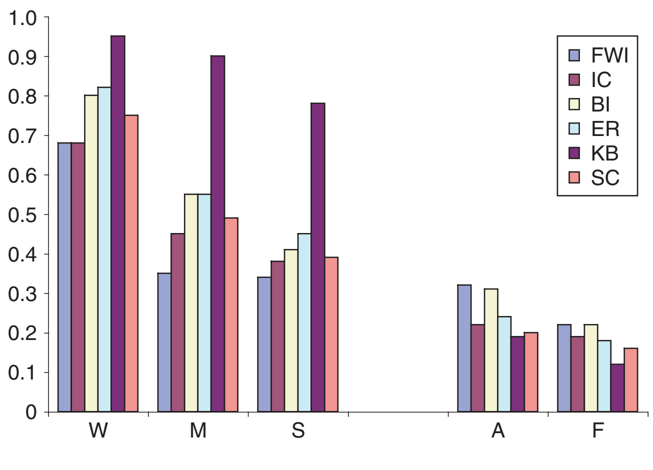

Fig. 14. Summary forecast skill for weekly (W), monthly (M), seasonal (S) forecasts of fire weather index (FWI), ignition component (IC), burning index (BI), energy release component (ER), Keetch–Byram drought index (KB) and spread component (SC) in comparison to the validating analysis. Also shown are the correlations of seasonal means of the validating analysis (A) and seasonal forecasts (F) for these same indices with the seasonal mean acres burned.

are those of the authors and do not necessarily reflect the views of NOAA or USFS. We are grateful to A. Westerling for providing us with his fire statistics.

References

Bradshaw LS, Deeming JE, Burgan RE, Cohen JD (1983) 'The 1978 National Fire-Danger Rating System: technical documentation.' USDA Forest Service, General Technical Report INT-169.

Brown TJ, Barnston A, Roads JO, Martin R, Wolter KE (2003) 2003 seasonal consensus climate forecasts for wildland fire management. *Experimental Long-Lead Forecasts Bulletin* **12**. Available at http://grads.iges.org/ellfb/Mar03/brown/brown.htm [Verified 19 January 2005].

Burgan RE (1988) '1988 revisions to the 1978 National Fire-Danger Rating System.' USDA Forest Service, Southeastern Forest Experiment Station Research Paper SE-273. (Asheville, NC)

Burgan RE, Klaver RW, Klaver JM (1998) Fuel models and fire potential from satellite and surface observations. *International Journal of Wildland Fire* **8**, 159–170.

Chen S-C, Roads JO, Wu M (2001) Seasonal forecasts for Asia: global model experiments. *Journal of Terrestrial-Atmospheric-Oceanic Sciences* **12**, 377–400.

Cohen JD (1985) 'The National Fire-Danger Rating System: basic equations.' USDA Forest Service, General Technical Report PSW-82.

Deeming JE, Lancaster JW, Fosberg MA, Furman RW, Schroeder MJ (1972) 'National Fire-Danger Rating System.' USDA Forest Service, Rocky Mountain Forest and Range Experiment Station Research Paper RM-84. (Fort Collins, CO)

Deeming JE, Burgan RE, Cohen JD (1977) 'The National Fire-Danger Rating System—1978.' USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-39. (Ogden, UT)

Fosberg MA (1978) Weather in wildland fire management: the fire weather index. In 'Proceedings of the Conference on Sierra Nevada Meteorology', South Lake Tahoe, NV. pp. 1–4.

Fujioka FM, Tsou T-H (1985) Probability modeling of a weather index. In 'Preprints of the eighth conference on fire and forest meteorology', Detroit, MI. pp. 239–243. (Society of American Foresters)

Higgins R, Shi W, Yarosh E, Joyce R (2000) 'A gridded precipitation database for the United States (1963–1999).' NCEP Climate Prediction Center Atlas no. 7. (Climate Prediction Center, NCEP: Camp Springs, MD)

Juang H, Kanamitsu M (1994) The NMC nested regional spectral model. *Monthly Weather Review* **122**, 3–26. doi:10.1175/1520-0493(1994)122<0003:TNNRSM>2.0.CO;2

Juang H, Hong S, Kanamitsu M (1997) The NMC regional spectral model. An update. *Bulletin of the American Meteorological Society* **78**, 2125–2143. doi:10.1175/1520-0477(1997)078<2125:TNRSMA>2.0.CO;2

Kalnay E, Kanamitsu M, Kistler R, Collins W, Deaven D, *et al.* (1996) The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society* **77**, 437–471. doi:10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2

Kanamitsu M, Ebisuzaki W, Woolen J, Potter J, Fiorino M (2002) NCEP/DOE AMIP-II reanalysis (R-2). *Bulletin of the American Meteorological Society* **83**, 1631–1643. doi:10.1175/BAMS-83-11-1631(2002)083<1631:NAR>2.3.CO;2

Keetch JJ, Byram GM (1968) 'A drought index for forest fire control.' USDA Forest Service, Southeastern Forest Experiment Station Research Paper SE-38. (Asheville, NC)

Loveland TR, Merchant JW, Ohlen DO, Brown JF (1991) Development of a land-cover characteristics database for the conterminous U.S. *Photogrammetric Engineering and Remote Sensing* **57**, 1453–1463.

Reinbold HJ, Roads JO, Brown TJ (2005) Evaluation of ECPC's fire danger forecasts with RAWS observations. *International Journal of Wildland Fire* **14**, 19–36.

Roads JO (2004*a*) Experimental weekly to seasonal, global to regional US precipitation forecasts. *Journal of Hydrology* **288**, 153–169. doi:10.1016/J.JHYDROL.2003.11.033

Roads JO (2004*b*) Experimental weekly to seasonal US forecasts with the regional spectral model. *Bulletin of the American Meteorological Society* **85**, 1887–1902. doi:10.1175/BAMS-85-12-1887

Roads J, Brenner S (2002) Global model seasonal forecasts for the Mediterranean region. *Israel Journal of Earth Sciences* **51**, 1–16.

Roads J, Ueyoshi K, Chen S-C, Alpert J, Fujioka F (1991) Medium-range fire weather forecasts. *International Journal of Wildland Fire* **1**, 159–176.

Roads J, Chen S-C, Fujioka F, Kanamitsu M, Juang H (1997) Global to regional fire weather forecasts. *International Forest Fire News [BAHC]* **17**, 33–37.

Roads JO, Chen S-C, Kanamitsu M, Juang H (1999) Surface water characteristics in the NCEP global spectral model and reanalysis. *Journal of Geophysical Research* **104**, 19 307–19 327. doi:10.1029/98JD01166

Roads JO, Chen S-C, Fujioka F (2001*a*) ECPC's weekly to seasonal global forecasts. *Bulletin of the American Meteorological Society* **82**, 639–658. doi:10.1175/1520-0477(2001)082<0639:EWTSGF>2.3.CO;2

Roads J, Rockel B, Raschke R (2001*b*) Evaluation of ECPC's seasonal forecasts over the BALTEX region and Europe. *Meteorologische Zeitschrift* **10**, 283–294. doi:10.1127/0941-2948/2001/0010-0283

Roads J, Chen S-C, Kanamitsu M (2003*a*) US regional climate simulations and seasonal forecasts. *Journal of Geophysical Research* **108**, 8606

Roads JO, Chen S-C, Cocke S, Druyan L, Fulakeza M, LaRow T, Lonergan P, Qian J, Zebiak S (2003*b*) The IRI/ARCs regional model intercomparison over Brazil. *Journal of Geophysical Research* **108**, 4425.

Roads J, Chen S-C, Ritchie J (2003*c*) ECPC's March 2003 atmospheric forecasts. *Experimental Long-Lead Forecasts Bulletin* **12**. Available at http://grads.iges.org/ellfb/Mar03/roads/roads.htm [Verified 19 January 2005]

Westerling A, Cayan D, Gershunov A, Dettinger M, Brown T (2001) Statistical forecast of the 2001 western wildfire season using Principal Components Regression. *Experimental Long-Lead Forecasts Bulletin* **10**. Available at http://grads.iges.org/ellfb/Mar01/west.htm [Verified 19 January 2005]

Westerling A, Gershunov A, Cayan D, Barnett T (2002) Long lead statistical forecasts of area burned in western US wildfires by ecosystem province. *International Journal of Wildland Fire* **11**, 257–266. doi:10.1071/WF02009

Westerling A, Cayan D, Gershunov A, Dettinger M, Brown T (2003*a*) Statistical forecasts of the 2003 western wildfire season using canonical correlation analysis. *Experimental Long-Lead Forecasts Bulletin* **12**. Available at http://grads.iges.org/ellfb/Mar03/leroy/leroy.htm [Verified 19 January 2005]

Westerling A, Brown T, Gershunov A, Cayan D, Dettinger M (2003*b*) Climate and wildfire in the western United States. *Bulletin of the American Meteorological Society* **84**, 595–604. doi:10.1175/BAMS-84-5-595