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# NCEP–ECPC monthly to seasonal US fire danger forecasts

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**Abstract.** Five National Fire Danger Rating System indices (including the Ignition Component, Energy Release Component, Burning Index, Spread Component, and the Keetch–Byram Drought Index) and the Fosberg Fire Weather Index are used to characterise US fire danger. These fire danger indices and input meteorological variables, including temperature, relative humidity, precipitation, cloud cover and wind speed, can be skilfully predicted at weekly to seasonal time scales by a global to regional dynamical prediction system modified from the National Centers for Environmental Prediction's Coupled Forecast System. The System generates global and regional spectral model ensemble forecasts, which in turn provide required input meteorological variables for fire danger. Seven-month US regional forecasts were generated every month from 1982 to 2007. This study shows that coarse-scale global predictions were more skilful than persistence, and fine-scale regional model predictions were more skilful than global predictions. The fire indices were better related to fire counts and area burned than meteorological variables, although relative humidity and temperature were useful predictors of fire characteristics.

**Additional keywords:** climate models, fire climatology.

## Introduction

Predicting the influence of weather on fire ignition and spread is an operational requirement for national fire planning by the National Interagency Coordination Center (NICC), the US support centre for wildland firefighting. NICC serves federal agencies in the Department of the Interior, including the Bureau of Land Management, National Park Service, Fish and Wildlife Service and Bureau of Indian Affairs, as well as the Department of Agriculture Forest Service. NICC's Predictive Services produce national wildland fire outlook and assessment products at monthly to seasonal time scales, by considering standard Climate Prediction Center seasonal forecasts of temperature and precipitation (Brown *et al.* 2003) along with other factors, including human judgment.

The long-established practice of fire danger assessment in the US follows the procedures of the Forest Service National Fire Danger Rating System (NFDRS; Deeming *et al.* 1977; Cohen 1985; Burgan 1988). 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 duration, temperature and relative humidity. Current fire danger is computed from weather observed over a network of mostly automated stations across the country, and estimated between stations by inverse-distance-squared interpolation. The fire danger maps are automatically updated daily, but they fall precipitously short of the kind of map products required for Predictive Services planning.

Roads *et al.* (2005) previously suggested that NFDRS indices could be dynamically forecast with an experimental global to regional seasonal prediction model, which was essentially an earlier version of the National Centers for Environmental Prediction's (NCEP) seasonal prediction model (Kalnay *et al.* 1996; Kanamitsu *et al.* 2002*a*). Preisler *et al.* (2008) further demonstrated the potential to use such dynamically forecast NFDRS indices in an empirical model to forecast the probability of fire occurrence. The fire danger forecasts are generated by processing the dynamically forecast weather variables through the NFDRS. The seasonal scope of the forecasts matches the planning horizon of Predictive Services.

Recently, NCEP introduced the Climate Forecast System (CFS) (Saha *et al.* 2006), which starts from operational atmospheric and ocean analyses. A coupled ocean–atmosphere model, consisting of a version of the Global Forecast System (GFS) for the atmosphere and the Modular Ocean Model (MOM3) for the ocean, performs the atmosphere–ocean analyses. We used the CFS to initialise atmosphere and land conditions and to provide sea-surface and ice boundary conditions for Global Spectral Model (GSM) forecast runs. The GSM run in turn provided initial (atmosphere and land) and lateral boundary conditions (atmosphere) for higher-resolution Regional Spectral Model (RSM) runs, essentially downscaled global short-term climate forecasts.

Roads *et al.* (2001) reasoned that this type of long-range prediction is feasible when the chaotic atmosphere interacts with slowly varying boundary conditions, especially persistent sea-surface temperature anomalies in the tropics, or locally persistent snow and soil moisture anomalies. In that regard, it should

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be noted that the CFS provides slowly varying boundary conditions through forecast sea surface temperature and sea ice for GSM–RSM predictions. It should also be noted that the GSM–RSM model uses a land surface model similar to that in the CFS.

This paper, following the pilot effort of Roads *et al.* (2005), describes the new NCEP–ECPC downscaling (Experimental Climate Prediction Center) and fire danger forecast experiment, which began in October 2004, for the period 1982–2007. The next section describes the methodology (models, NFDRS, validating analysis, error measures) used for this study. The forecasts of the *US West area means* section evaluates average variations over the US West. The *Geographic variations* section describes geographic variations and evaluations of the forecasts. A summary is presented in the final section.

## Methodology

### Forecast models

The CFS currently starts from the atmosphere–ocean analysis and comprises a triangular 62-wave truncation (200-km physical grid) and 64 vertical-layer (T62L64) atmosphere and 40-level 0.333–1° stretched grids ocean analysis. This analysis is the lower-resolution version of the operational analysis, which uses a T382L64 GFS. Corresponding CFS climatology runs were generated starting on the same calendar month but for previous calendar years (1979–2007) with the T62L28 reanalysis-II (RII) (Kanamitsu *et al.* 2002*b*) and historical 40-level 0.333–1° stretched grids MOM3 ocean analysis.

In turn, we ran a lower-vertical-resolution T62L28 GSM starting from CFS current and historical initial conditions, using the CFS forecast sea surface temperature and sea ice as boundary conditions for the GSM run. These GSM runs required some computer time but were needed to set up the large-scale lateral boundary conditions to drive the RSM (Juang *et al.* 1997). We note that the standard CFS output does not provide sufficient temporal resolution for the required lateral boundary conditions to drive a regional model. The current configuration was deemed the most practical way to generate the needed RSM boundary conditions. These GSM runs required minimal computer time in comparison with the RSM runs.

A 28-level T62 GSM provided the initial state and atmospheric lateral boundary conditions for a 28-level 50-km RSM, from which we obtained an experimental ensemble US regional seasonal forecast (7-month each month). The NCEP RSM US domain covers the conterminous US area and vicinity, from 130° to 65°W and 20° to 55°N with 50-km resolution. It should be noted that other regional domains could also have been set up because the GSM provides global boundary conditions identical in structure to the RII output, which most regional climate models now use. Ideally, the same global forecast system could provide multiregional model ensemble coverage for the US and perhaps several other global regions.

The GSM–RSM produced outputs of weather variables at 6-h intervals on pressure surfaces using the model horizontal Gaussian grid. Standard meteorological output was also enhanced in order to develop the needed input for fire danger forecasts. A rotating disk archive was accessed through the Internet by ECPC to drive the fire danger code, as described below.

The RSM used for this study has previously been used for several regional climate simulation and forecast studies (see e.g. Roads 2004). The RSM was originally developed to emulate the global model but operates at regional scales and is currently in operational use for the 10-km RSM daily weather forecast for Hawaii, and as a member of the 48-km RSM short-range ensemble forecast for the conterminous US area. The RSM physics are currently similar to the CFS physics, but there are several significant physics differences between the GFS and CFS. Plans are currently under way to develop a new CFS reanalysis (to replace the current RII reanalysis) that will once again bring current GFS and CFS physics into closer alignment.

Each month, three 7-month GSM–RSM hindcasts, beginning from CFS initial conditions, are made for each year from January 1982 to December 2006. There were a total of $25 \times 3$ hindcasts available to develop a monthly model forecast climatology. Seven additional forecasts starting on 5 different days at 0000 and 1200 hours (Universal Coordinated Time) were also made as part of a 10-member ensemble forecast (beginning October 2004). More hindcasts (forecasts before October 2004) may be added later in order to construct a more robust 10-member model forecast climatology. These additional members of the ensemble forecasts were not included in the analysis of this study. The number of ensemble members is dependent on available computer time as well as a continual commitment towards running a consistent model. However, as NCEP changes the CFS, similar changes will probably be implemented into the GSM–RSM.

### Forecast evaluation

In this study, we used daily 1-day RSM forecast outputs during the evaluation period as input to NFDRS to derive a surrogate of 'observed' fire danger indices for evaluation of the accuracy of the forecast fire danger indices. Hereafter, we interchangeably call variables derived from these 1-day forecasts as 'validations' or 'observations'. This approach provides better spatial coverage than using indices calculated from the fire weather station network data. However, we recognise that weather model precipitation is usually substandard owing to imperfect model parameterisation of precipitation processes. Instead, an observed precipitation gridded dataset is used, as described by Higgins *et al.* (2000). That study used co-op station data from the National Climatic Data Center and first-order station network along with the precipitation network of the River Forecast Centers to develop a gridded daily precipitation dataset (25-km resolution) for the period 1982–2007. These gridded and quality-controlled US precipitation data from station observations are, in fact, available in near real time.

At the onset of this study, limited observation-based gridded analyses suitable for our fire danger forecast evaluations were available. We therefore developed a continuous set of 1-day RSM forecasts for that purpose (Roads *et al.* 2005). However, we lacked confidence in using the RSM precipitation forecasts as an evaluation standard, and instead used the daily gridded precipitation analyses produced by the Climate Prediction Center (Higgins *et al.* 2000). These serial 1-day RSM forecasts differ from the current NCEP operational analyses, which are based on $4 \times$ daily 6-h forecasts from the latest high-resolution

(T382L64) global model. The reanalysis data are also different, in that they are based on 4 × daily 6-h forecasts with the coarse-scale model used for GSM forecasts. Since this study began, the North American Regional Reanalysis (Mesinger *et al.* 2006) became available as an alternative source of gridded observations for future studies.

As discussed previously by Roads *et al.* (2001) and Reinbold *et al.* (2005), forecasts validated against the 1-day RSM short-range forecasts and observed precipitation are only slightly more skilful than forecasts validated against NCEP's operational analysis and observed precipitation or station observations. Still, we are certainly aware that it would be advantageous to eventually include more independent observations into the validating and initialising fire danger data.

### *Fire danger indices*

The NFDRS fire danger indices (FDI) describe characteristics of fire danger, given ambient conditions of fuel, topography, and weather. The basic inputs to the NFDRS include surface temperature (T), relative humidity (RH), cloud cover (CC) and wind speed (WSP) as well as local fuel characteristics and slope. Slope is important in assessing fire danger because fire generally burns faster spreading upslope than on flat ground. Fuel characteristics describe the attributes of vegetation that influence combustion. Twenty NFDRS fuel models (Burgan 1988) represent the vegetation types across the USA, defining fuel characteristics such as depth, load by live and dead classes, heat content and fuel particle size. Each fuel model in the fire danger rating system covers a rather broad range of vegetation types. The basic vegetation data source was the 1-km resolution land cover map released in 1991 by the Earth Resources and Observation and Science Center. The land cover map was previously converted to an NFDRS fuel model map through classification of satellite data, validated by 2546 ground sample plots scattered across the US, and consultation with fire managers from across the country.

The standard practice to determine current fire danger requires weather input to the NFDRS from weather station data, assumed to be representative of a large area ($\sim 10^3$ ha) in the vicinity of the weather station. Fuel types and slope are also defined for the area covered by each weather station. For example, the Wildland Fire Assessment System (WFAS) features a current fire danger map based on observations mapped to the domain by inverse-distance-squared interpolation. WFAS fire danger forecasts derive either from trend forecasts by danger rating area, or, more recently, from 6-day forecasts from the National Weather Service National Digital Forecast Database (NDFD). Our NFDRS calculations differ from WFAS NFDRS calculations as follows. WFAS uses fuels and topography resolved to a 1-km grid and either interpolates weather data to the same grid from station observations, or it uses the NDFD forecast data and assumes a single fuel type (Model G) to develop the gridded US fire danger forecast maps. Our fuels and slope data were initially defined at 1-km spatial resolution, but the fuel type and elevation at the nearest 1-km grid point were used for each point on our 25-km grid interval.

We focussed on five NFDRS indices: Burning Index (BI), Ignition Component (IC), Energy Release Component (ER), Spread Component (SC), and the Keetch–Byram (KB) drought index (Keetch and Byram 1988). We also included the Fosberg Fire Weather Index (FWI) (Forsberg 1978), which is not an NFDRS index, but has proved informative in past studies (Roads *et al.* 2001, 2005). Fig. 1 shows mean summertime FDI averaged over the past 25 years (1982–2006). We refer to the period from May through September as summertime to consider it the peak fire season over the US West. The high-resolution features of the standard NFDRS FDI (IC, BI, ER, SC) are related to the high-resolution fuel and slope characteristics influencing these particular FDI (Roads *et al.* 2005).

### *Fire activity*

Westerling *et al.* (2002, 2003) developed an extensive database of gridded (1°-grid) monthly fire counts and area burned – which we call fire activity measures (FA) – from fire reports of federal agencies for most of the western states since 1974. Westerling's FA database includes anthropogenic as well as natural fires, although these data include only those fires that were reported and managed and hence are not likely to fully represent all fire counts. Despite some potential limitations, we use this database for assessing an FDI and FA forecast system. Following Westerling *et al.* (2002), the natural logarithm (ln) of the fire counts and area burned (hereafter CN and AC) were used. We doubted the validity of FA for a higher-resolution grid; therefore, we spatially averaged FDI variables to Westerling's 1° US West grid. As shown in Fig. 1, the initialising and validating FDI have an overall relationship with CN and AC, although it is clearly not a one-to-one relationship.

### *Skill measures*

As discussed by Roads *et al.* (2001), skill can be measured in several different ways. We first qualitatively compared the means of the forecasts with the corresponding analyses in order to make sure that the forecast values were reasonable. In fact, the forecasts were quite similar, exhibiting small biases related to the tendency for the forecast model to drift away from the initial state towards a model climatology. Figs 2 and 3 show the RSM summertime biases (forecast minus observed) for the last 5-month means from each 7-month forecast starting 1 March of each year. The maximum amplitudes of the bias range from 40% for IC to 20% for BI, compared with their respective mean values (Fig. 1). Note the strong similarity of the FDI biases (Fig. 2), being positive along the US West Coast, negative over the Great Basin, and positive again over the US East. When compared with the biases in the meteorological variables (Fig. 3), it appears that the FDI biases are inversely related to the RH, precipitation and CC, and directly related to T and WSP variations. GSM FDI and meteorological variables biases are similar (not shown), mainly because the physics in the driving GSM and RSM are similar.

Although the biases are relatively small, they are as large as their corresponding seasonal anomalies and must be removed before assessing the skill of the forecasts. This is accomplished by developing monthly climatologies for each forecast initial state and forecast lag and then only comparing forecast anomalies with validation anomalies.

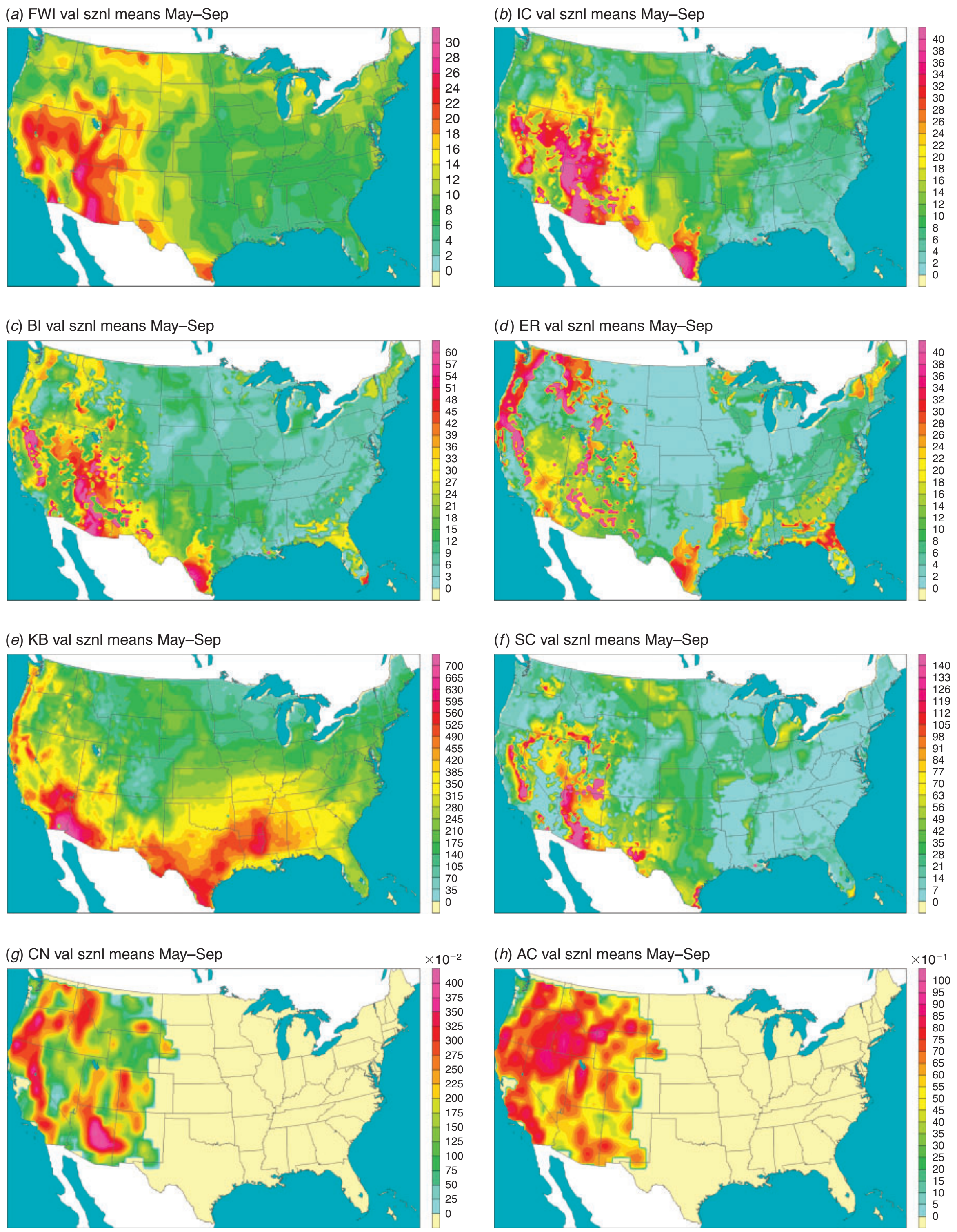


**Fig. 1.** Summer seasonal climatologies of validation fire danger indices (FDI): (*a*) Fire Weather Index, FWI; (*b*) ignition component, IC; (*c*) Burning Index, BI; (*d*) energy-release component, ER; (*e*) Keetch–Byram Drought Index, KB; (*f*) spread component, SC; (*g*) fire counts, CN; (*h*) area burned, AC (acres).

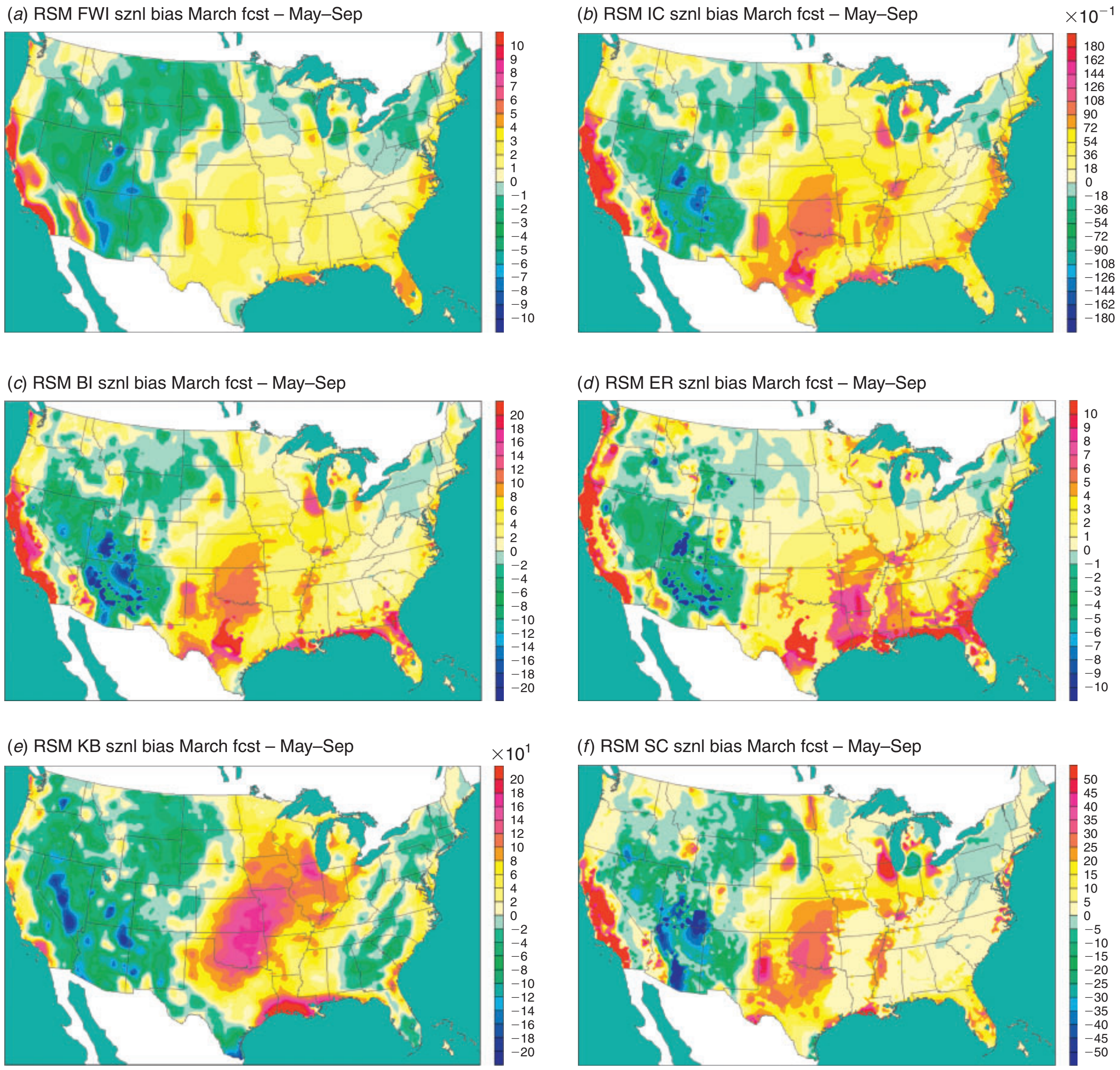


**Fig. 2.** Summer seasonal mean RSM (Regional Spectral Model) Fire Danger Indices biases (forecast – validation): (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC (see Fig. 1 for definitions).

Anomaly correlations of the forecasts with the validating analyses as well as with the fire occurrence and size statistics provide a standard measure of skill

$$\rho = \frac{\sum wA'B'}{(\sum wA'^2)(\sum wB'^2)}$$

where $A$ and $B$ stand for forecast and validating variables respectively, and their deviations from monthly climatologies are marked as $A'$ and $B'$; the summation is over time and space or just time when considering correlations of US West area means. When the summation is over space, a spatial weighting factor, $w$, equivalent to the cosine of the latitude, must also be included.

We also examined Heidke Skill Scores (see e.g. Roads *et al.* 1991), and root mean square errors but did not find any additional insight from these skill measures.

## Forecasts of the US West area means

In this section, we consider the forecast skill of the US West area mean FDI, because these seem to have a relationship to area mean FA. Subsequent to this examination of the area means, we describe our evaluations of regional forecast skill in the *Geographic variations* section.

### *US West seasonal climatology*

Fig. 4 shows the mean seasonal variations of the validating RSM and GSM forecast FDI averaged over the US West for the seventh forecast month. Also shown are the seasonal variations of CN and AC. Clearly, almost all FDI, as well as the CN and AC, tend to be larger during the summer. KB is the exception in that it peaks during the fall. Summertime forecast biases are evident and (owing to cancellation) somewhat smaller than the geographic biases described above. The GSM biases tend to be

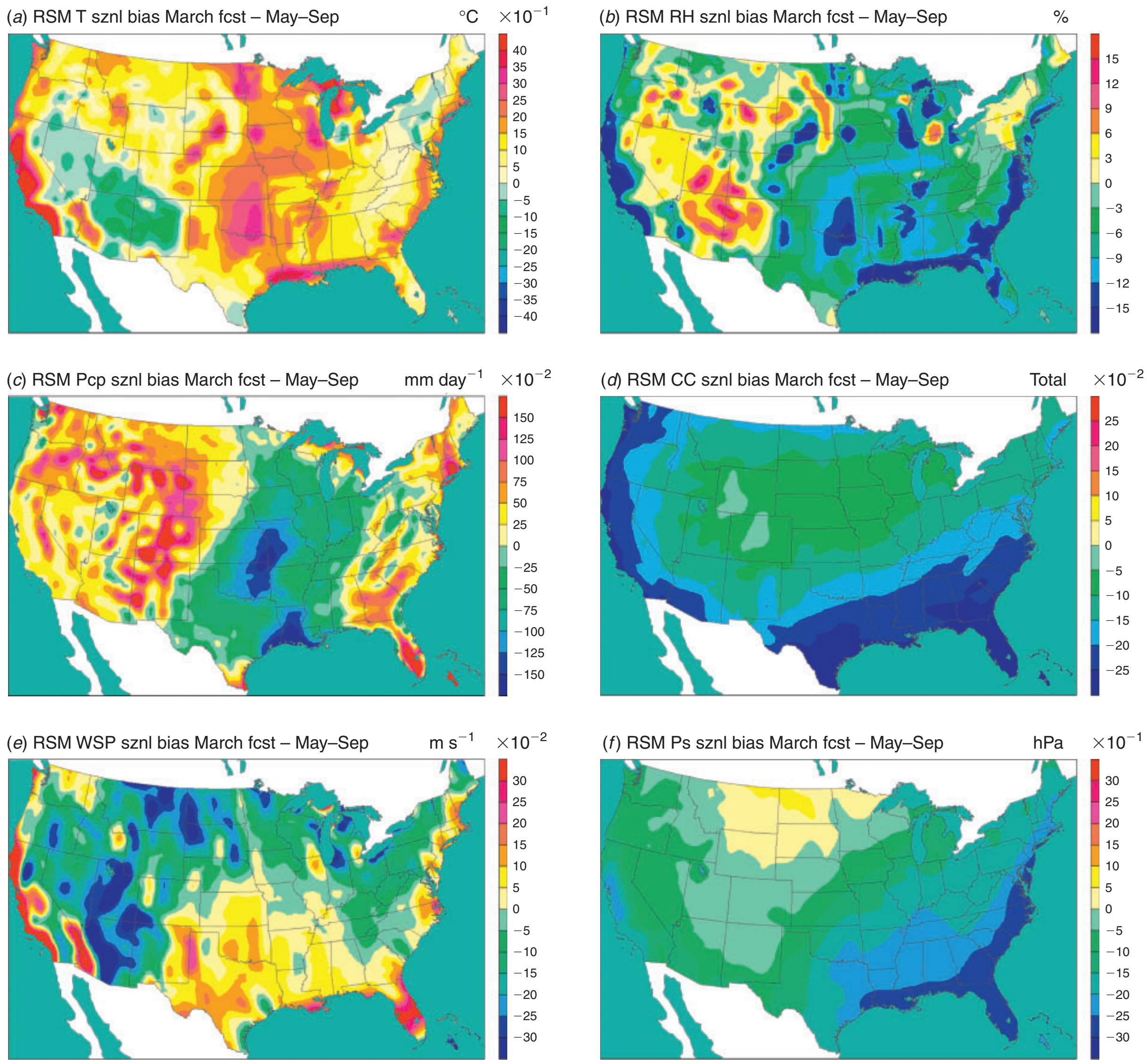


**Fig. 3.** Summer seasonal mean RSM (Regional Spectral Model) meteorological variable biases (forecast – validation): (*a*) surface temperature, T (°C); (*b*) relative humidity, RH (%); (*c*) precipitation, Pcp (mm day$^{-1}$); (*d*) cloud cover, CC (%); (*e*) wind speed, WSP (m s$^{-1}$); (*f*) surface pressure, Ps (hPa).

slightly larger than the RSM biases, at least over the US West. Having removed the biases, we evaluate forecast skill from the forecast and observed temporal anomalies.

### *US West time series*

Fig. 5 shows the US West anomalous time series (running 5-month means are applied for presentation purposes only) for the 5-month forecast (2-month lag) and validating FDI and FA. All anomalous forecast FDI followed well with the corresponding FDI validation. The intradecadal as well as the interannual variations of these FDI forecasts also correlate well with the observed FA shown in the bottom two panels. Tabulated red numbers indicate the correlation between the RSM FDI forecasts and validating fire danger as well as the FA. Green numbers show correlations between the GSM and validating fire danger as well as the FA. Black numbers in the centre of each graph indicate the correlations between the FDI validations and FA. Note that the validating FDI has the strongest relationship with the FA, although the GSM and RSM forecast FDI also have significant relationships. These relationships are in fact much stronger than the relationships with respect to the raw input variables (shown below) providing some reassurance that the focus on the FDI is, in fact, worthwhile.

### *US West time series correlations*

Figs 6 and 7 summarise the seasonal forecast skill for the area mean FDI and meteorological variables. Note first of all that the correlation of the forecast area mean FDI and meteorological variables with respect to the validating area mean FDI and meteorological variables (marked Val or Fcst) is comparable with the correlation of the validating FDI and FA (CN-Val or AC-Val). However, it is clear that the forecast FDI and

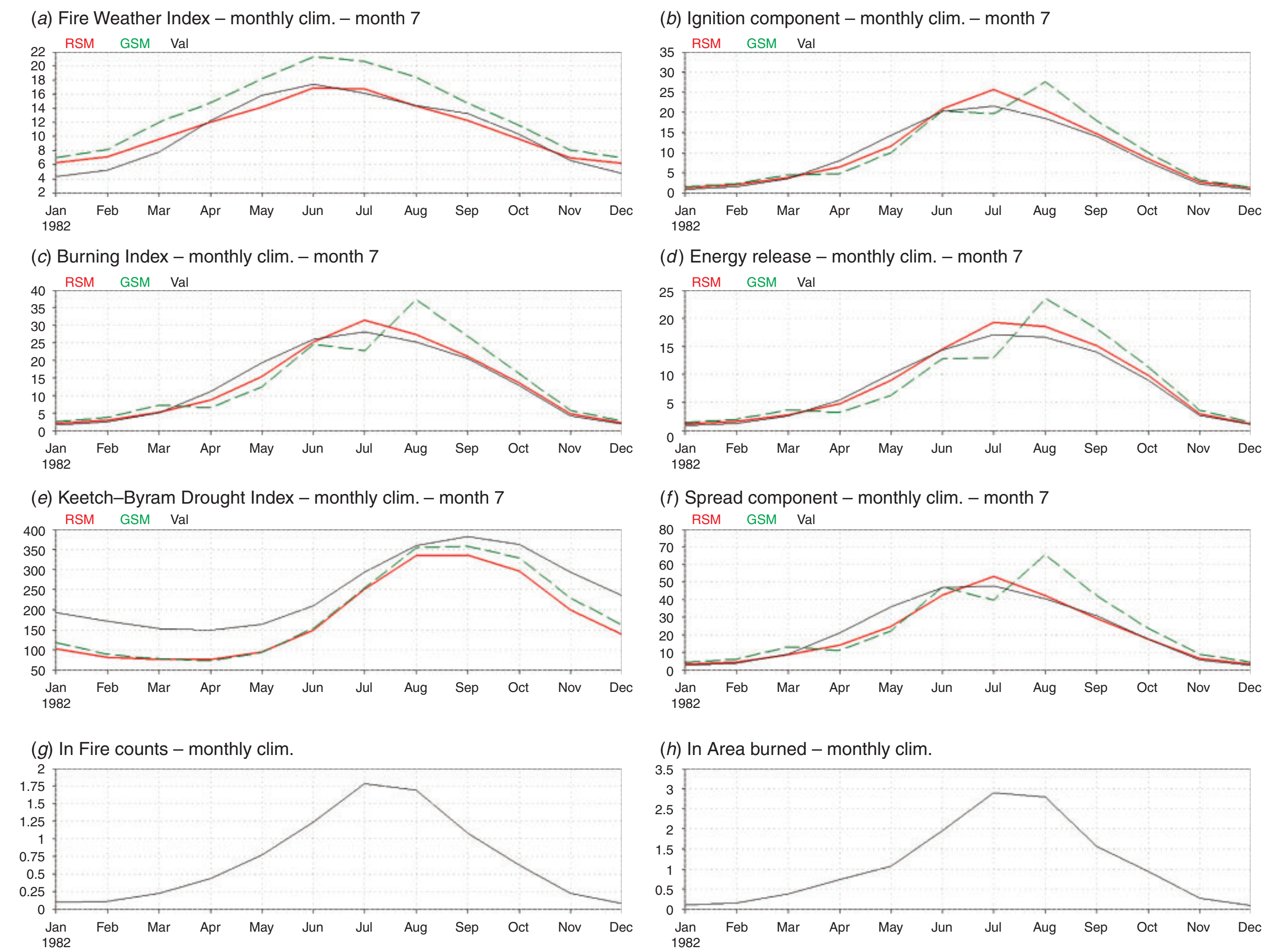


**Fig. 4.** Monthly mean US West climatologies for the RSM (Regional Spectral Model; red solid), GSM (Global Spectral Model; green dashed), validation (black solid) FDI: (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC; logarithm of (*g*) CN; and (*h*) AC (see Fig. 1 for definitions).

meteorological variables (except WSP) have less correspondence than the validating one to the FA, perhaps indicating that further improvements in forecast skill are likely to lead to improved seasonal forecasts of FA. These figures also indicate that the GSM adds skill to persistence forecasts (the first bar of each colour group), that the RSM (the third bar) provides even higher skill, and in some cases the skill of the combined (RSM + GSM) provides the best forecast skill, although for the most part, the RSM provides the highest skill. All of the FDI have good correspondence with the FA, with the ER slightly better than the remaining FA. Although all FDI demonstrate least correlation in persistence forecast, KB is the only exception, showing better skill validating against itself and comparable skill when compared with GSM or RSM forecast FA.

The FDI mostly have greater correspondence to the FA than the meteorological variables, indicating the validity of calculating the FDI through the non-linear relationships to the meteorological variable inputs. However, it is also clear that validating and forecast RH have good correspondence with FA. It is also interesting that forecast WSP has a larger correspondence than validating WSP with FA. We attribute these differences to statistical uncertainty involved with comparing average time series with few degrees of freedom. As will be shown later when we examine the behaviour of a large number of gridpoints, the validating WSP has a higher correlation with the FA than does the forecast WSP.

## Geographic variations

Fig. 8 shows the spatial variation in the temporal correlations at each grid point for the 3–7-month summer forecasts. It is apparent that the FDI forecasts demonstrate better skill over the western portion of the US than the Midwest and US East. With respect to the meteorological variables (Fig. 9), the strongest correlations appear to be related to the ability of the model to forecast T, RH, and CC, which is dependent on RH. Forecasts are less accurate for precipitation, Pcp, and WSP, especially over the US Midwest, which likely erodes the FDI forecast skill there compared with that over the US West. During the validation months, the US West is, in fact, in the summer dry season.

Figs 10 and 11 show the grand correlations (summation over time and space) for all of the forecast lags and averaging periods for all of the FDI and all of the input meteorological variables

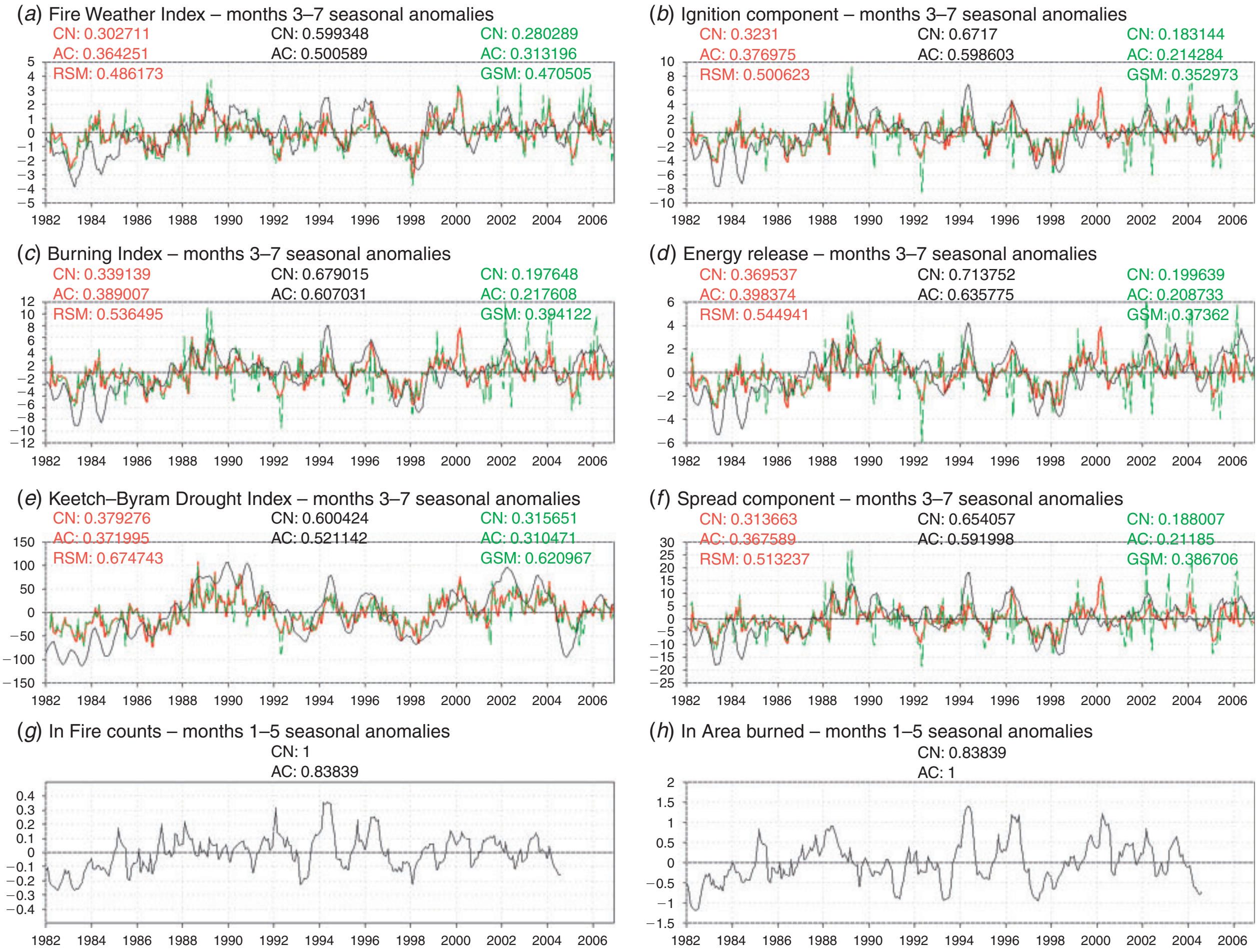


**Fig. 5.** Five-month running mean US West anomalies for the RSM (Regional Spectral Model; red solid), GSM (Global Spectral Model; green dashed), validation (black solid) FDI (fire danger index): (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC (see Fig. 1 for definitions). Text (RSM, red solid; GSM, green solid) on the figures represents the correlations between the forecasts and validations as well as the correlations between the forecast FDI and CN (fire counts) and AC (area (acres) burned). Also shown are the correlations between the CN and AC to validating FDI in black text. The corresponding anomalies of (*g*) CN and (*h*) AC are also given at the bottom two panels.

from the GSM and RSM in comparison with persistence. Persistence is difficult to beat, especially for the KB, where persistence provides the greatest skill. With the exception of KB, however, GSM forecasts are definitely better than persistence. Also, RSM forecasts are mostly better than GSM forecasts, and the (RSM + GSM) combinations are almost always better, which presumably indicates the possible skill increase using larger ensembles. All of the forecasts have significant skill, although the initial weekly to monthly forecasts have the greatest forecast skill and the final weekly to monthly forecasts have the lowest skill. Some of the meteorological forecasts, such as T and RH, have fairly high correlations, while others, like Pcp and WSP have low correlations. Apparently, most of the skill in prediction of the FDI relies on good temperature and relative humidity forecasts, and the future improvement of the FDI forecast skill should focus on the improvement of the modelled precipitation and wind speed.

In contrast to the relatively high skill in the area mean FDI depiction of area mean FA, there is a much weaker relationship with the validating and forecast FDI and FA at individual grid points. Fig. 12 shows the correlation of the validating FDI with CN. Note the relationship is strongest in the northern Front Range, Southern Utah, and northern Sierras. KB also shows some relationship in the New Mexico region. There is poor correlation between FDI and FA in the Arizona, southern California, and Great Basin regions. We suspect this geographical contrast in skills can be attributed to the imperfect model forecast of the North American summer monsoon over the south-west US. Similar relationships are apparent with the meteorological variables shown in Fig. 13: relatively high correlations with respect to temperature, relative humidity, and precipitation in the northern and eastern domains, but much less in the south-west.

Fig. 14 summarises the grand correlations for the validations and forecasts of FDI and their relationship to FA. Once again, despite low skill in forecasting FA, the FDI are forecast well everywhere. Note that the grand correlations at each grid point or, more to the point, the correlation of the time and space

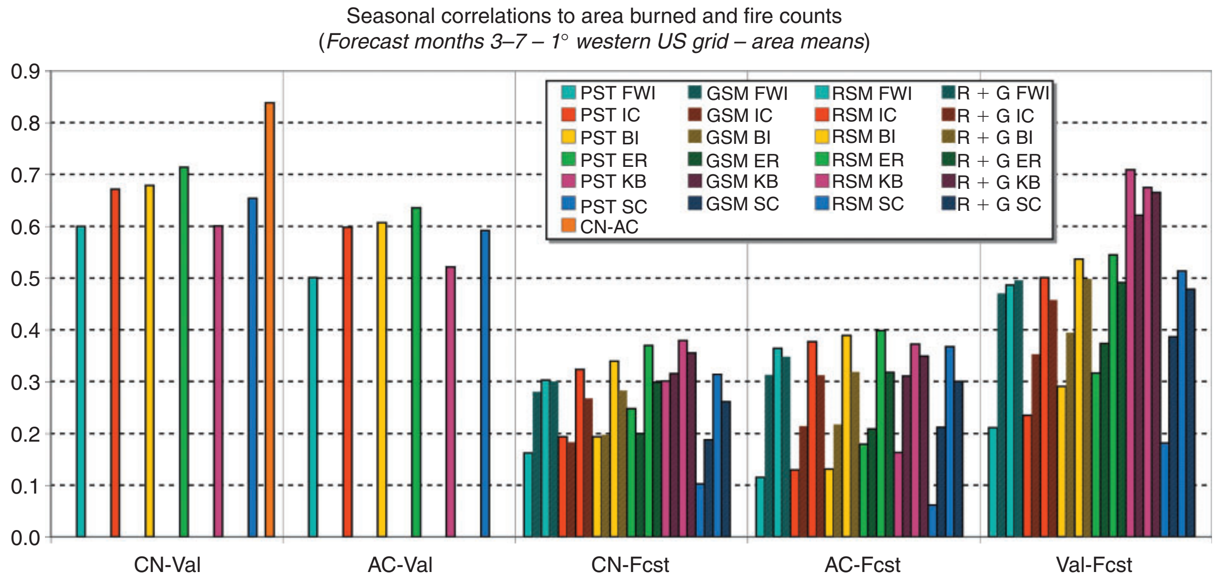


**Fig. 6.** The 3–7-month seasonal FDI (fire danger index) forecast (Fcst) correlations with FDI validations (Val), CN, and AC. Also shown are the correlations of the FDI validations with the CN and AC. Forecasts include persistence of the initial day (PST), GSM (Global Spectral Model), RSM (Regional Spectral Model), and the average of the RSM and GSM (R + G). FDI include FWI, IC, BI, ER, KB, SC (see Fig. 1 for definitions).

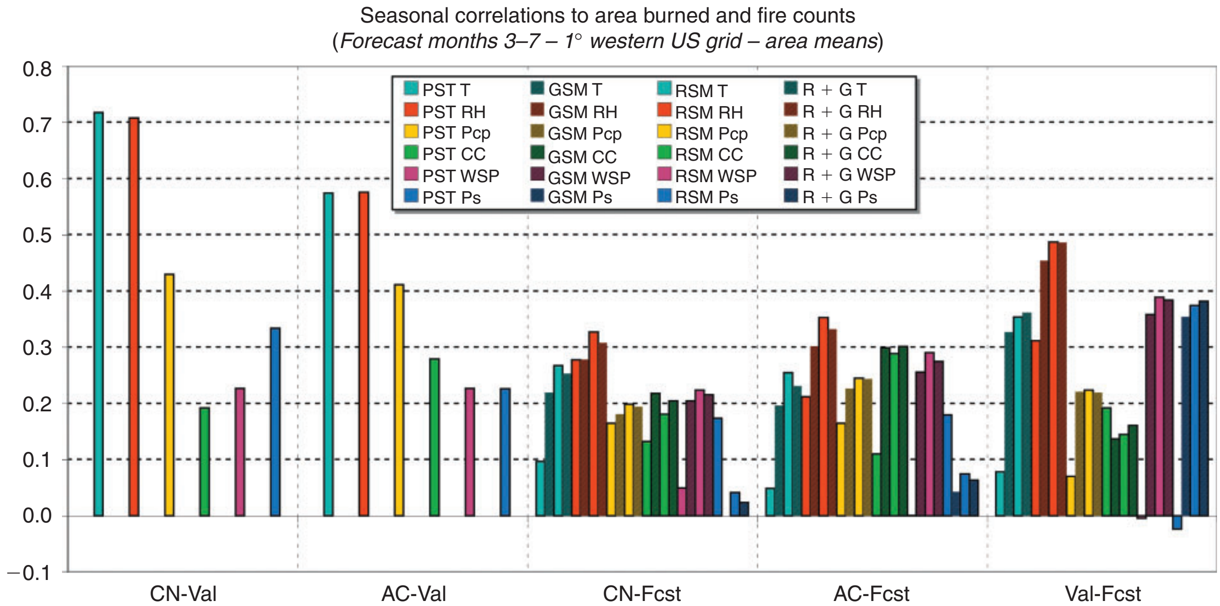


**Fig. 7.** The 3–7-month seasonal meteorological variables forecast (Fcst) correlations with validations (Val), CN, and AC. Also shown are the correlations of the meteorological variable validations with the CN and AC. Forecasts include persistence of the initial day (PST), GSM (Global Spectral Model), RSM (Regional Spectral Model), and the average of the RSM and GSM (R + G). Meteorological variables include T, –RH, –Pcp, –CC, WSP, Ps (see Fig. 1 for definitions).

ensemble, is somewhat less than the correlation of the forecast validating area means shown previously in Figs 6 and 7. Also note that the GSM adds value to the persistence forecast, the RSM adds value to the GSM forecast, and the combination of the RSM and GSM is mostly marginally better than either one alone, with some exceptions. Again, KB persistence is always better than any forecast KB. Despite the high correlation between CN and AC, CN appears to be slightly better forecast than AC. One reason for this could be that the extent of AC depends on the fire management actions and not entirely on weather. FWI and ER apparently provide the best forecast of CN. It is noteworthy that the FWI assumes no spatial fuel variation, yet it is still among the best FDI predictors, consistent with the finding of Preisler *et al.* (2008).

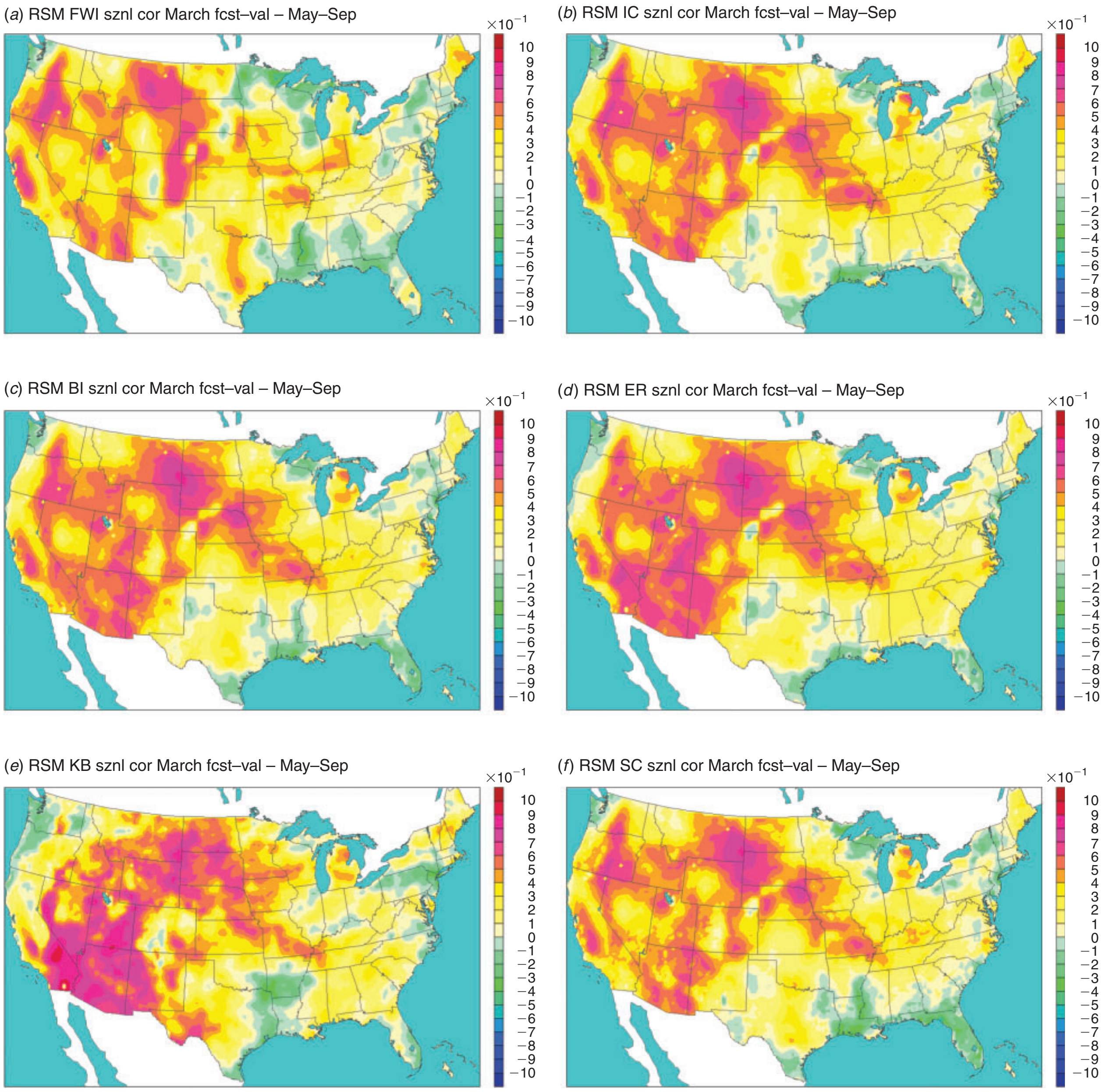


**Fig. 8.** Temporal correlation of summertime forecast FDI with FDI validation: (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC (see Fig. 1 for definitions).

## Summary

During the past decade, seasonal forecasts have become more commonplace, although more development is still needed for the fire management community. Clearly, NFDRS users require more than forecasts of standard monthly mean temperature and precipitation for long-range planning. They need dynamical predictions of these and other meteorological variables, such as relative humidity and wind speed. This study attempted to make dynamical seasonal fire danger forecasts fully compatible with current fire danger applications, and to suggest how daily to seasonal forecasts of temperature, relative humidity, wind speed, and precipitation can be used to forecast FDI and, through statistical relationships, fire activity.

Confirming the previous pilot experiment of Roads *et al.* (2005), there is significant seasonal forecast skill for all of the NFDRS FDI (IC, BI, ER, KB, SC) as well as the FWI, which had previously been used by Roads *et al.* (2001) to forecast global fire danger. Persistence forecasts were evaluated and found somewhat inferior to these dynamical forecasts. It was further shown that the FDI were somewhat better related than the input meteorological values to fire counts and area burned, especially when the validating rather than forecast output was used.

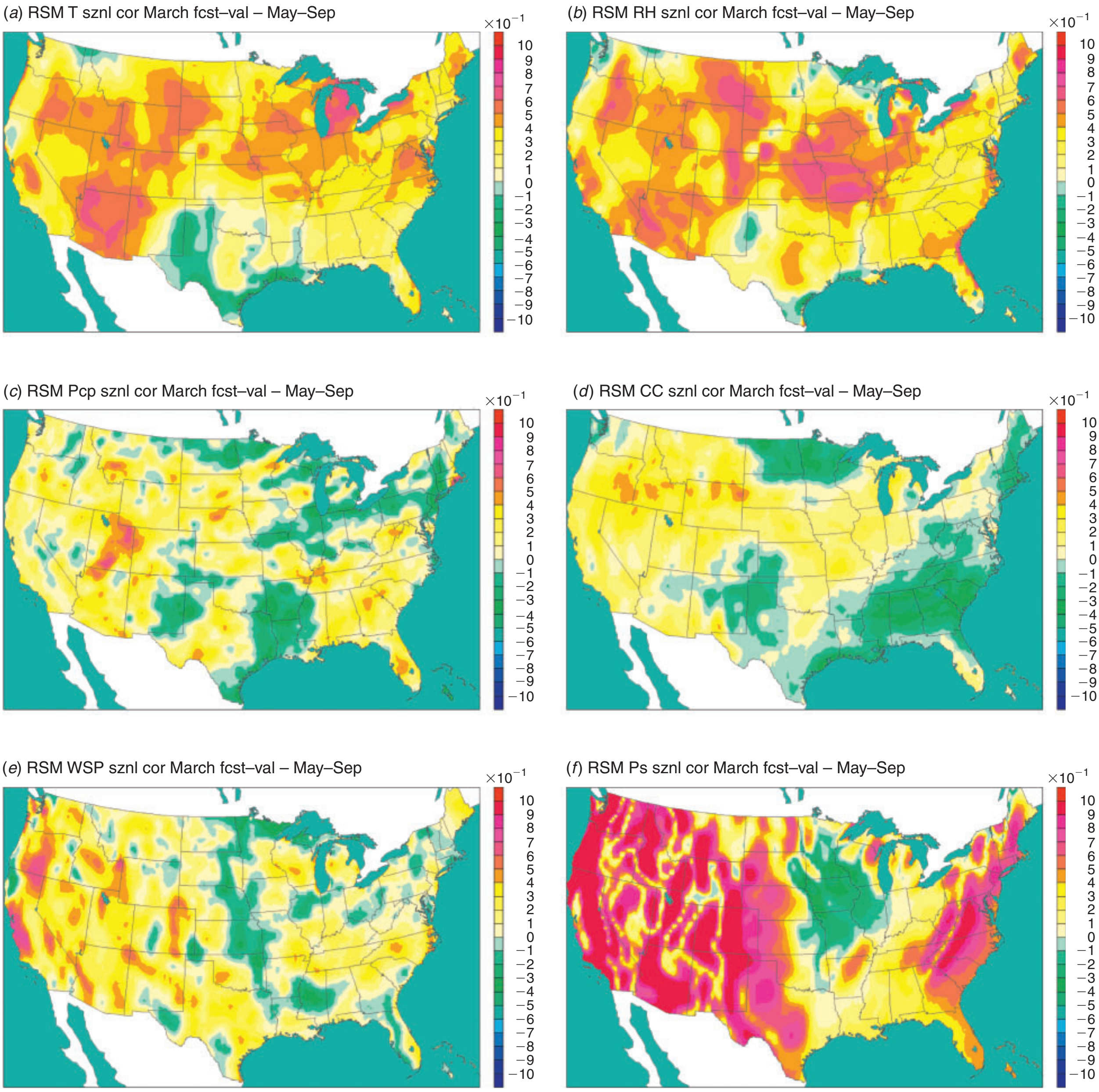


**Fig. 9.** Temporal correlation of summertime forecast meteorological variables with validation: (*a*) T; (*b*) RH; (*c*) Pcp; (*d*) CC; (*e*) WSP; (*f*) Ps (see Fig. 1 for definitions).

The forecast relationships are certainly weaker than the correlations with the FDI validation data, especially on a local scale, for the obvious reason that forecasts diverge farther from reality as the forecast time increases. But we suspect the major reason that the validating fire danger dataset had a high degree of correlation with observed fire activity measures is due to our use of observed rather than forecast precipitation. Accurate forecasting of precipitation over time is critical to KB and to ER for large fuel types. This assertion is supported by the geographical contrast in FDI forecast showing higher skills over the entire US West during the summer fire and dry season. Therefore further improvements in forecast skill should still be possible if precipitation parameterisation in the weather models can be substantially improved.

Finally, as development proceeds to improve NFDRS FDI forecasts, it should again be emphasised, as it was in Roads *et al.* (2005) and reconfirmed in the current study, that the fire danger rating of an area is an imperfect predictor of fire activity. As experienced fire managers know, fire danger predictions must be considered in light of uncertainties in the prediction process.

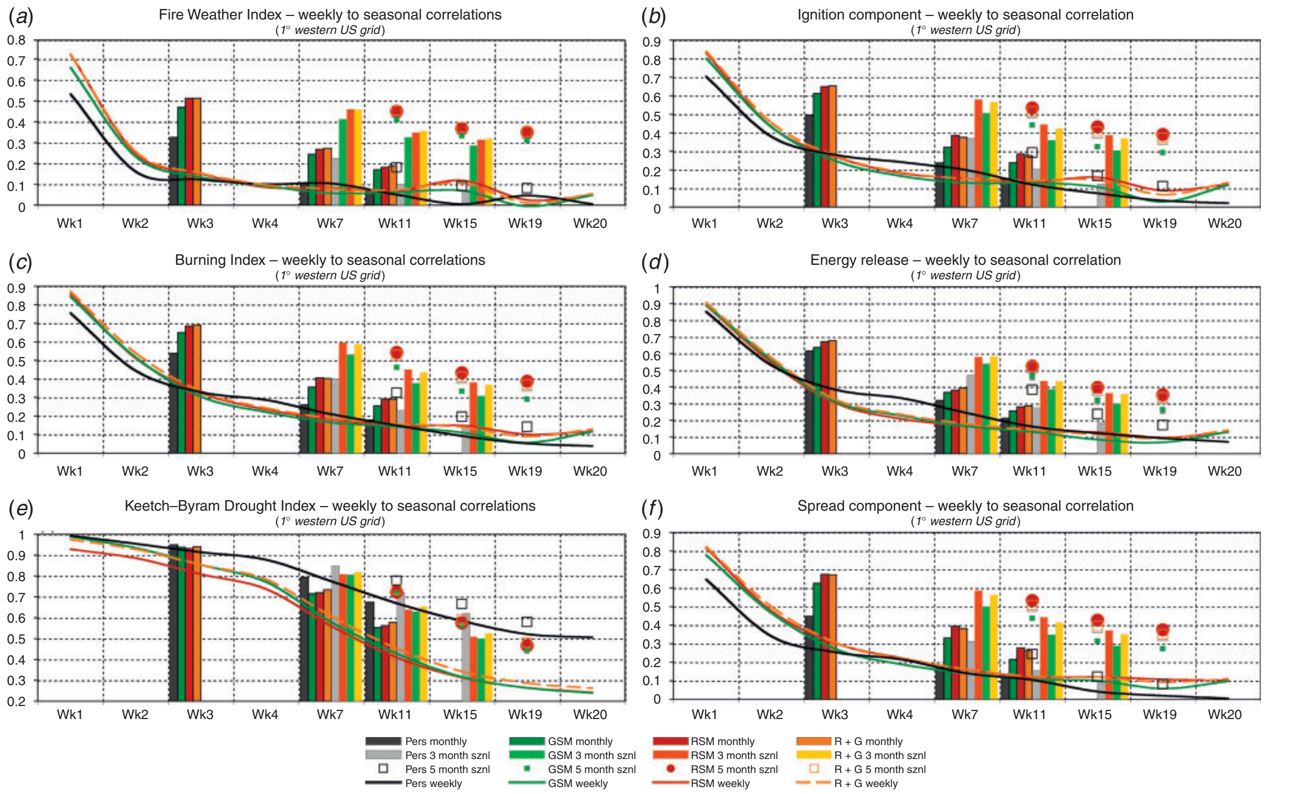


**Fig. 10.** Grand (summation over time and space) correlations for weekly (lines), monthly (bars), 3-monthly (bars), 5-monthly (markers) persistence, GSM (Global Spectral Model), RSM (Regional Spectral Model), (RSM + GSM) forecasts: (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC (see Fig. 1 for definitions).

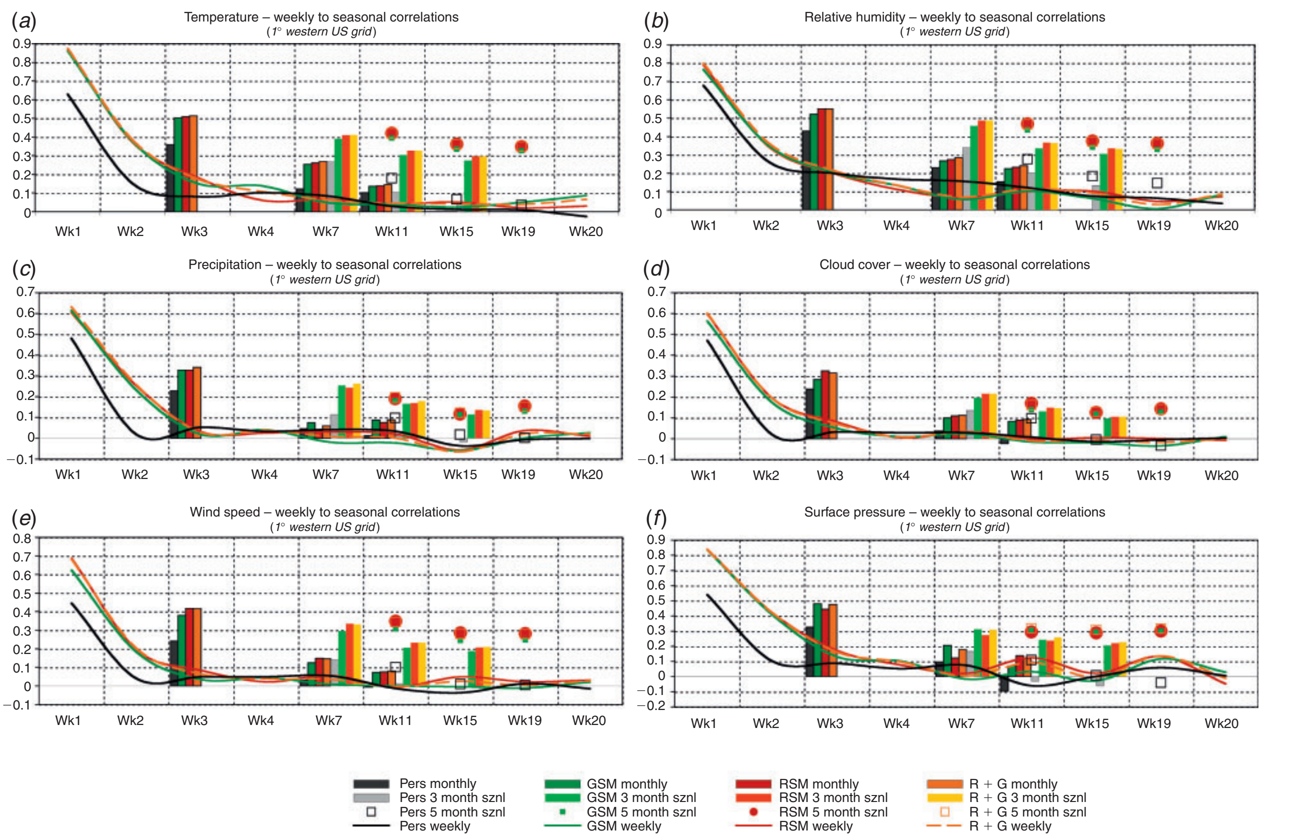


**Fig. 11.** Grand (summation over time and space) correlations for weekly (lines), monthly (bars), 3-monthly (bars), 5-monthly (markers) persistence, GSM (Global Spectral Model), RSM (Regional Spectral Model), (RSM + GSM) forecasts: (*a*) T; (*b*) RH; (*c*) Pcp; (*d*) CC; (*e*) WSP; (*f*) Ps (see Fig. 1 for definitions).

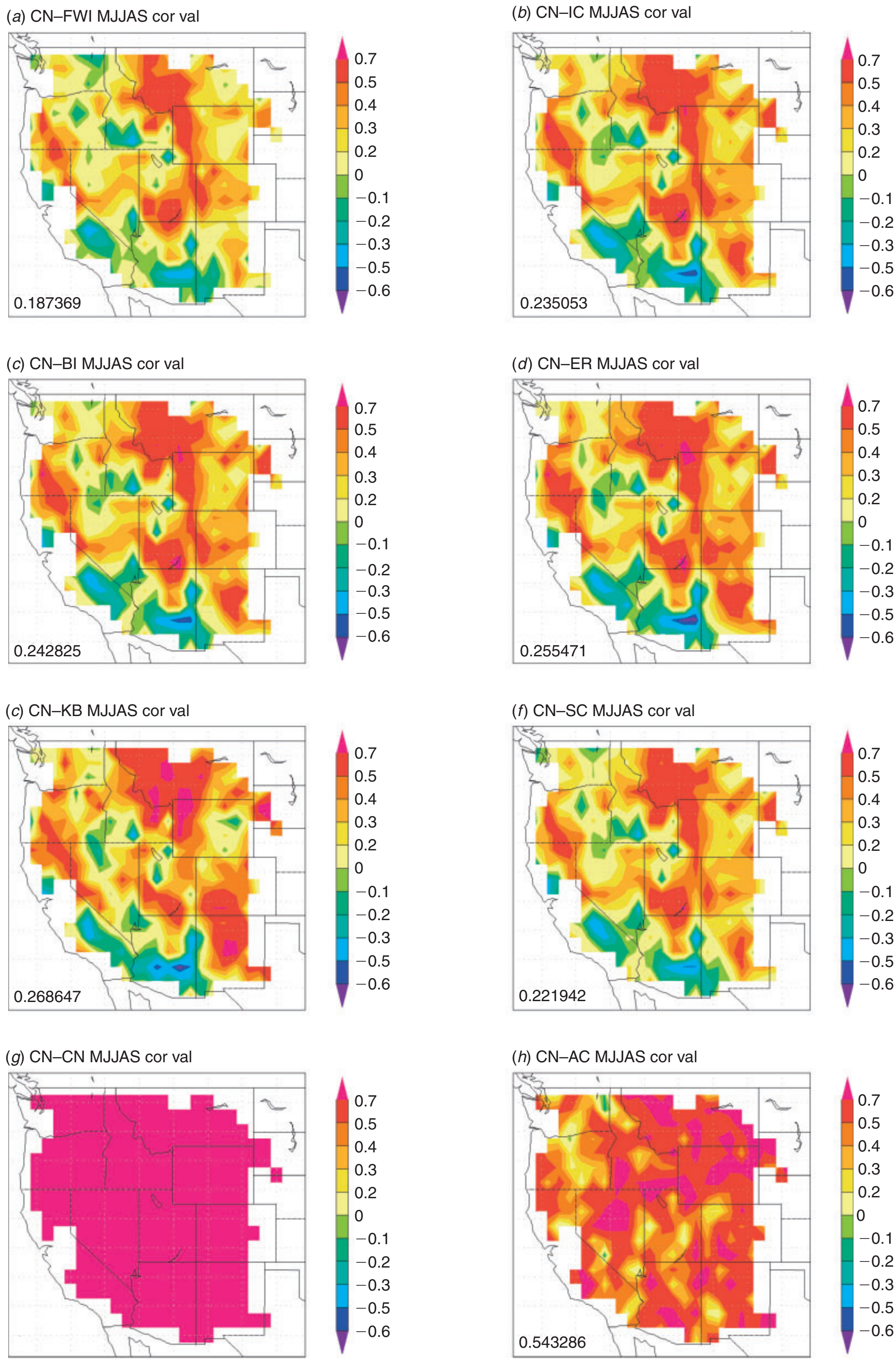


**Fig. 12.** Temporal correlation of summertime validation FDI (fire danger index) with CN: (*a*) FWI; (*b*) IC; (*c*) BI; (*d*) ER; (*e*) KB; (*f*) SC; (*g*) CN); (*h*) AC (see Fig. 1 for definitions).

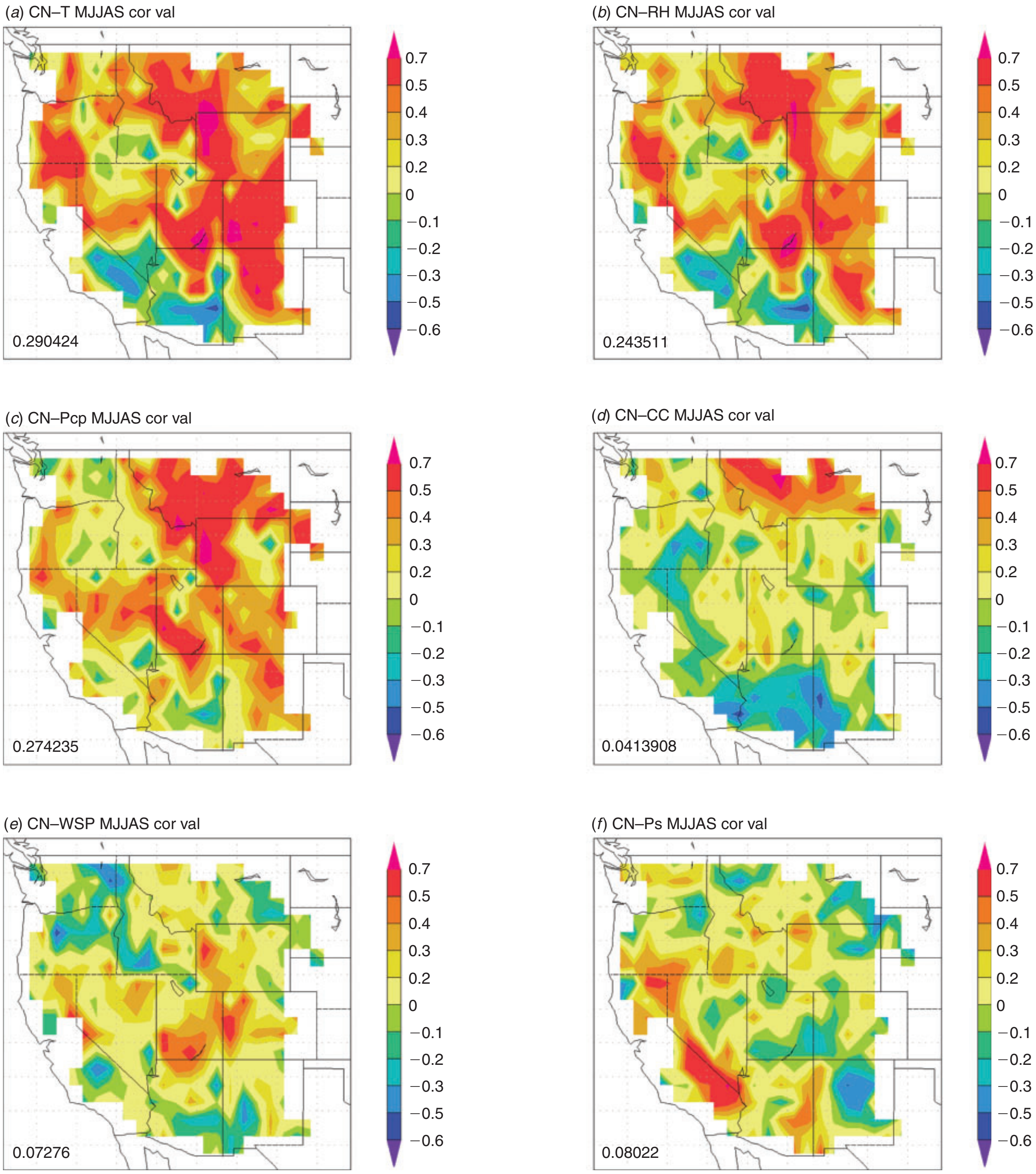


**Fig. 13.** Temporal correlation of summertime validation meteorological variables with CN: (*a*) T; (*b*) –RH; (*c*) –Pcp; (*d*) –CC; (*e*) WSP; (*f*) Ps (see Fig. 1 for definitions).

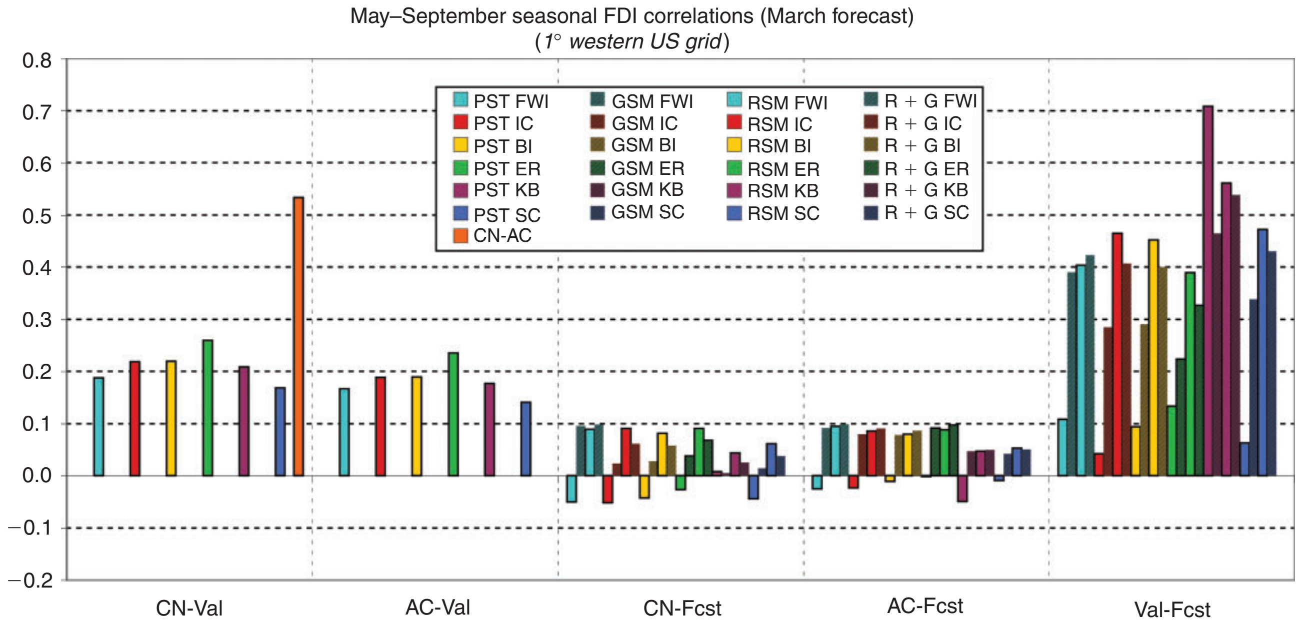


**Fig. 14.** The 3–7-month summer seasonal FDI (fire danger index) forecast (Fcst) ensemble correlations with FDI validations (Val), CN, and AC. Also shown are the ensemble correlations of the FDI validations with the CN and AC. Forecasts include persistence of the initial day (PST), GSM (Global Spectral Model), RSM (Regional Spectral Model), and the average of the RSM and GSM (R + G). FDI include FWI, IC, BI, ER, KB, SC (see Fig. 1 for definitions).

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