J9.11 VERIFICATION OF ECPC'S FIRE CLIMATE AND FIRE DANGER FORECASTS

Hauss J. Reinbold*[1], T. J. Brown[1], J.O. Roads[2], B. L. Hall[1]
[1]Desert Research Institute, Reno, Nevada
[2]Scripps Experimental Climate Prediction Center, UCSD, La Jolla, CA

1. INTRODUCTION

The Experimental Climate Prediction Center (ECPC) at the Scripps Institution of Oceanography has been making extended Regional Spectral Model (RSM) forecasts since September 27, 1997 (Roads 2003; Roads et al. 2003b). This model produces regional 16-week forecasts of common atmospheric elements such as temperature, relative humidity and precipitation every weekend, which are also directly relevant to fire weather meteorologists, fire and fuel specialists and fire management. In addition to these elements, the RSM also calculates fire danger indices for the continental United States. While the skill of the meteorological variables and fire danger indices of this RSM model have been examined (Roads et al. 1991; 2003a), they have been primarily ascertained against the network of observations used to initialize the model. However, the observations used to initialize the model are taken primarily from urban sites and other locations that are not necessarily representative of fire danger areas.

It is therefore of interest to assess and understand the skill of the RSM in comparison to observed atmospheric measurements and fire danger indices. Land managers will, as a result of this analysis, be able to identify the location, time scale, and time of year where the model is most skillful. This will provide an improved understanding of model forecast skill, and help establish a level of trust or confidence to be placed in an RSM forecast for a given time and location. For research meteorologists, this analysis functions as a performance measure that will be helpful in fine-tuning and further development of the model itself.

1.2 RESEARCH OBJECTIVES

The objective of this study is to assess the accuracy of the ECPC weekly, monthly and seasonal RSM forecasts, compared to remote automated weather station (RAWS) observations, with emphasis on the elements most related to fire danger (e.g., temperature, moisture and wind), as well as an evaluation of predicted National Fire Danger Rating System (NFDRS) indices (Bradshaw et al. 1983; Burgan 1988; Deeming et al. 1972; Deeming et al. 1977; NWCG 2002). Specific ECPC forecast atmospheric elements examined include maximum, minimum and average daily surface temperature, maximum, minimum and average daily surface relative humidity, surface wind speed, precipitation amount and precipitation duration. The ECPC forecast fire danger indices that were examined include the Burning Index (BI), Spread Component (SC), Energy Release Component (ERC) and Ignition Component (IC). While ECPC has already performed accuracy tests on both atmospheric and fire danger model output, they have not done so with RAWS data. The analysis in this study complements the skill tests performed by ECPC.

Though the ECPC forecasts cover the continental U.S., the primary RAWS network is currently located in the West, the spatial focus of this study. Geographic sub-regions are individually evaluated to increase the spatial resolution of the analysis. Temporally, the study includes year-round model performance, as well as the distinct summer and winter seasons.

2. DATA

Three primary data sets are used in this study: ECPC RSM forecasts, ECPC RSM validation, and RAWS observations. The spatial domain for all datasets covers the western United States and includes approximately 100ºW to about 125ºW, and 30ºN to 50ºN. All data sets are inclusive of the period from September 27, 1997 through December 31, 2002.

2.1 ECPC RSM FORECAST DATASET

Every weekend, ECPC makes a 16-week RSM forecast for surface temperature (daily minimum, maximum and mean), relative humidity (daily minimum, maximum and mean), precipitation amount, hours of precipitation, mean

* *Corresponding author address*: Hauss J. Reinbold, DRI/DAS/CEFA, 2215 Raggio Parkway, Reno, NV 89512; email: reinbold@dri.edu

afternoon wind speed (defined as 1200 to 1800 hours), IC, SC, ERC, and BI. Model output consists of daily values that are averaged to create weekly means that can then be combined into monthly (four-week) and seasonal (12-week) means. Each extended forecast (275 total from September 27, 1999 through December 28, 2002) was evaluated in the form of twelve one-week means, three one-month means and one seasonal mean (only the first 12-weeks of each 16-week forecasts were examined in this study). These forecasts have a spatial resolution of approximately 0.6 degrees (approximately 60 km) and comprise 58 x 97 grid nodes (covering the entire contiguous U.S.), where each node represents the spatial position of the forecast output elements. Because the majority of RAWS are located in the western US, only the 43 x 39 grid nodes over the West are used in this study.

2.2 ECPC RSM VALIDATION DATASET

Every day ECPC makes one-day RSM forecasts based on the 00 UTC NCEP operational analysis initial conditions. These are referred to as the ECPC validation forecasts. The validation forecasts are not identical to the operational analysis (which uses the latest high-resolution global model) that are based on 6-hour forecasts made four times daily, but can be considered a useful approximation (Roads et al. 2003b; c). As with the extended forecasts, they contain all thirteen atmospheric elements used in this study and are contained within an identical spatial grid. They are archived as weekly averages of daily values and essentially function as validating observations. There were 286 weekly averages of validation data used in this study, including the first eleven weeks of data from 2003. Acquisition of the 2003 data was necessary to evaluate the extended forecasts made in late 2002.

2.3 RAWS

Land and fire management agencies retain an observational network of remote automated weather stations (RAWS) for fire weather related measurements (see http://www.fs.fed.us/raws). They are typically located in wilderness, forest and rangeland areas where it is desired to monitor fire danger. The hourly observations are transmitted to the National Interagency Fire Center (NIFC) using a geostationary operational stationary satellite (GEOS) operated by the National Oceanic and Atmospheric Administration (NOAA). These data are forwarded to the Weather Information Management System (WIMS) for agency use distribution, and to the Western Regional Climate Center (WRCC) for historical archiving. The RAWS data used in this study were obtained from WRCC. From this dataset, RAWS surface measurements of daily minimum temperature, daily maximum temperature, daily mean temperature, wind speed, daily minimum relative humidity, daily maximum relative humidity, daily mean relative humidity, precipitation and hours of precipitation were extracted and used in the analysis. WIMS provides site descriptors (fuel model, slope, climate class, etc.) for each RAWS, which, combined with the above atmospheric elements, allows for the calculation of fire danger indices (BI, IC, ERC, SC). Larry Bradshaw, U.S. Department of Agriculture Missoula Fire Sciences Laboratory, provided the original NFDRS computer software code for calculating the indices that was then adapted to fit the RAWS data format used in this project.

There were 262 RAWS sites in the western U.S. that had sufficient quality data for the years 1997-2003. Observational data through 2003 was needed to verify the seasonal RSM forecasts made in late 2002. Sites were chosen based on three criteria regarding completeness of the data set – 1) no more than two months of missing data in any year, 2) availability of year-round operational measurements, and 3) availability of historical data for the period September 1997 through March 2003. Measurements that were clearly in error (e.g., relative humidity over 100 percent, negative wind speed) were considered missing and excluded from the analysis. There were 477 RAWS with data histories from September 1997 through March 2003 that were missing weeks, months or years of data, mostly due to instrument error or seasonal operation, and therefore were unsuitable for use in this study.

3. METHODS OF ANALYSIS

There are three major components to this study. The first is a comparison of the RAWS observations to the RSM forecast output. The second is a comparison of the RAWS observations to the RSM validating observations. The third is a comparison of the RSM forecasts to the RSM validating observations. Each of these components examines the results for the western U.S. as a whole and then for regions within this area. In addition, these studies are done for the twelve one-week, three one-month and one seasonal mean for every forecast. Comparing the RSM observations to the RSM validations only involves a weekly, monthly and seasonal mean (no forecasted values, just comparing two sets of observations).

A quality control (QC) analysis was performed on the RAWS data for 263 stations that met the initial acceptance criteria described in section 2.3. The data were checked for suspicious values (spikes) through a visual inspection of the time series for each variable and RAWS site. Measurements that were clearly in error (e.g., relative humidity over 100 percent, negative wind speed) were considered missing and excluded from the analysis. One RAWS was removed from the study as a result of this process (leaving 262 total stations for analysis), as it appears to have been physically moved at some point in the last five years. The RSM forecast and validation files did not require a similar QC process, but were visually examined via time series plots to ensure their sufficient internet file transfer from ECPC to local files.

In order to compare the RAWS observations to the RSM forecast or validation data, it was necessary to match the data sets both temporally and spatially. The RSM forecasts are output as weekly averages of daily values out to sixteen weeks (although this study only examines the first twelve weeks of these forecasts for a seasonal emphasis), and are produced every weekend. The RAWS observations include the 1300 local time observations of temperature, humidity and wind speed needed for the calculation of the NFDRS indices, as well as the daily values for maximum and minimum temperature and relative humidity, precipitation, and the mean afternoon wind speed (1200 to 1800 local time).

The first step in matching the datasets was to transform these daily values into weekly averages of daily values. The 1300 local time observations were used to calculate daily values for the four NFDRS indices, while the daily maximums and minimums of temperature and relative humidity were used to calculate daily averages. The weekly mean of these daily values was then calculated with the dates for each weekly mean matching exactly the dates for the RSM forecast weekly means. Weekly means with missing values for three consecutive or four nonconsecutive days were considered missing. The weekly means of all three datasets were then transformed into monthly and seasonal means. For the forecasts, monthly means were calculated by taking the means of weeks 1-4, weeks 5-8, and weeks 9-12 of each twelve-week forecast. Monthly means for the RSM validation and RAWS datasets were computed in the same manner, but using the weekly means for the twelve-week period matching each 12-week forecast. Likewise, forecast seasonal means were computed by taking the mean of all twelve forecast weeks. RAWS and RSM validation seasonal means were computed by taking the mean of the twelve weeks matching each 12-week forecast.

Once the three datasets were matched on a temporal scale, the next step was to match them spatially. The RSM forecast and validation data were output as a grid of values separated by a distance of roughly 60 km. RAWS observations are spatially dissimilar in that they are spaced in an irregular pattern that is not in any way aligned with the model grid output (see Figure 1). Extrapolation of the station data to a grid matching that of the RSM output was ruled out due to potential error in the values at extrapolated grid nodes with no nearby RAWS or that are close to RAWS with missing data. In this case, interpolating the forecast grids to RAWS locations seemed a more accurate method of comparing the datasets. The values in the RSM validation and forecast grids were bilinearly interpolated to match each of the 262 RAWS locations used in this study. This bilinear interpolation algorithm determines values between grid nodes by calculating a distance-weighted average of values at the nearest four nodes. For the sake of consistency, the ECPC validation versus ECPC forecast comparison uses the forecast and validation grid values as they are interpolated to RAWS sites, rather than a direct comparison of the forecast and validation output grid nodes.

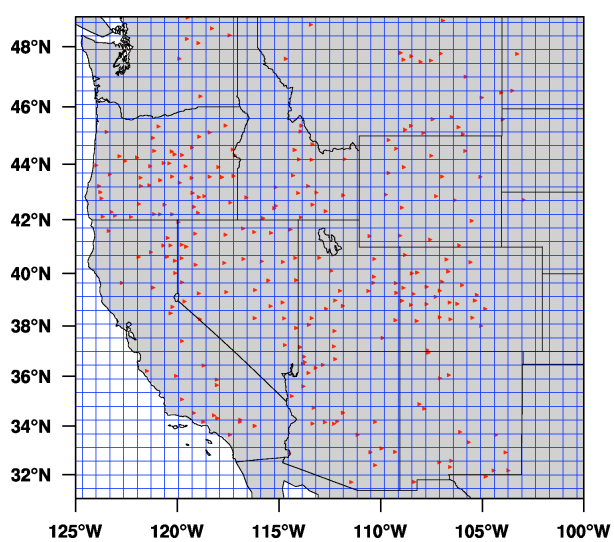

Figure 1 RAWS locations (red triangles) with RSM output grid overlay (blue lines).

The purpose of forecast verification is to determine the quantitative accuracy of the forecast. The statistical methods employed in this study as a means of forecast verification are bias, root mean square error, anomaly correlation, and standard deviation. Due to space constraints, the root-mean square error and standard deviation will not be discussed here.

Bias is a simple calculation of forecast minus observation (Wilks 1995), or

$$bias = f - o, \qquad (1)$$

where f is the forecast value and o is the value of the observation. When shown in graphical form, this calculation has the benefit of revealing under what situations the model is over or under forecasting and by how much. It is also useful in determining potential seasonal characteristics in the errors between the datasets.

Anomaly Correlation is commonly used to evaluate extended forecasts. It is designed to reflect good forecasts in the pattern of an observed field, not necessarily the magnitude of the values (Wilks, 1995). There are two different equations, representing the two types of anomaly correlation used in this study. The first is for judging the spatial variation and correlation of the anomalies (Equation 3; Roads et al. 2003b;c). The second is better described as temporal variations in spatial correlations (Equation 4; Wilks 1995). Anomalies are computed by taking the difference between the total forecast (either by region or for the entire Western U.S.) and the climatological monthly means. In other words,

$$A = f - C_f, \qquad (2)$$

where A is the anomaly, f is the forecast and C_f is the climatological mean for that forecast type (weekly, monthly or seasonal mean).

Given that A is a forecast anomaly of any type (weekly, monthly or seasonal mean) and that B is the validating anomaly from observation, the spatial variation in the anomalies is represented by

$$Corr(x,y) = \frac{\sum_{n=1}^{N} A_n B_n - \sum_{n=1}^{N} A_n \sum_{n=1}^{N} B_n \Big/ N}{\left[\left(\sum_{n=1}^{N} A_n^2 - \left(\sum_{n=1}^{N} A_n\right)^2 \Big/ N\right)\left(\sum_{n=1}^{N} B_n^2 - \left(\sum_{n=1}^{N} B_n\right)^2 \Big/ N\right)\right]^{1/2}}, \qquad (3)$$

where N is the total number of forecasts (N = 275 for each forecast type in the complete time period). Similarly, the temporal variations in the spatial anomaly correlations (AC, sometimes known as pattern correlation) are calculated using

$$AC = \frac{\sum_{m=1}^{M} \left[A_m B_m\right]}{\left[\sum_{m=1}^{M} A_m^2 \sum_{m=1}^{M} B_m^2\right]^{1/2}}, \qquad (4)$$

where M is the total number of RAWS in the current region (M = 262 for the western U.S.). Missing values in the observational anomalies for either Equation 3 or 4 reduce the anomaly summations for both datasets by the number of missing values (the missing RAWS values and matching interpolated validation or forecast values are removed).

Computing the anomalies for each dataset requires a calculation of the climatologies for each variable and forecast type in the three separate datasets. Computing and using climatologies for use in determining the anomaly correlations is difficult in that the RSM forecast periods do not reset at the beginning of every year, they just continue making the same forecasts every weekend no matter what time of year it is. This means that the first forecast of one year will not quite match the same dates as the first forecast of another year.

The climatologies for each variable and forecast type were calculated in a manner to solve or at least mitigate this date matching problem. First, rather than try to somehow compare weekly averages that do not span the same dates from year to year, it was decided to compute monthly climatologies for all forecasts beginning in a given month. Thus, the climatology for any given week contains twenty values as opposed to just five. For example, a one-week forecast made in mid-June will be compared to a climatology consisting of all one-week forecasts made in the month of June during the five-year period. Likewise, the fifth week of a twelve-week forecast would be compared to a climatology consisting of all fifth-week forecasts made in June, a one-month forecast mean compared to a climatology of all mean one-month forecasts made in June, and so forth. Of course the two observational datasets (RAWS and RSM validation) do not contain extended forecasts, but the climatologies for the weekly, monthly and seasonal means matching the forecast dates were computed in the same manner.

Finally, the climatologies for each variable and time-span are smoothed in order to increase the accuracy of the anomaly correlation. In other words, the twelve climatologies (January to December) for a given variable and forecast type are interpolated (in this case linearly) to each individual day within each month. For instance, if the March climatology of daily maximum temperature for seasonal forecasts made in March has a value of 70°F and the April value for the same climatology is 80°F, each day between March 15 and April 15 increases by a regular amount from 70°F to 80°F. Therefore, the anomaly computed for a seasonal forecast of maximum temperature made on March 23rd would then use the smoothed climatology value for March 23rd (in this case about 72.66 °F).

Comparisons were also done involving the summer and winter months separately. The performance of the model in summer months is of obvious interest from a fire danger aspect since this is when for most areas in the West the fire season occurs. Wintertime performance of the model, while still having relevance to fire danger in areas with warmer climates (i.e., Arizona and southern California), is done here mostly for comparison and contrast with the summer forecasts. They also demonstrate the response of fire danger indices calculated in the model with seasonally varying atmospheric elements. In summer cases, the study included all weekly forecasts made in June, July or August (JJA), all monthly forecast means that fall within JJA, and the seasonal forecast for each summer (the seasonal mean from the first forecast week in June). The winter analysis likewise included all weekly forecasts made in December, January or February (DJF), all monthly forecast means that fall within DJF, and the seasonal forecast for each winter (the seasonal mean from the first forecast week in December).

4. ANALYSIS

While analyses based on standard deviation, bias and root-mean square errors were performed in this study, only the temporal and spatial analysis for anomaly correlation are presented here. Winter analyses are similarly excluded due to space constraints.

Figures 2 and 3 show for each type of forecast mean the anomaly correlation (AC) performance on a year-round basis of each weekly, monthly and seasonal mean. The RAWS versus forecast (RF), RAWS versus validation (RV) and validation versus forecast (VF) comparisons are all displayed. The solid line represents the AC for forecast weeks 1-12 from the RF comparison. The dashed line is the same but for VF. The average RF (✳) and VF (△) month 1-3 means are listed on weeks 2, 6, and 10 (the midpoint of each monthly mean). The average RF seasonal mean (square) is listed on week 6. The AC of the RV weekly (✡), monthly (▽) and seasonal (o) means are all plotted on week 5 to keep the overlap of symbols to a minimum. The AC for the VF seasonal mean (⊗) is plotted on week 7 for the same reason.

The weekly means, somewhat predictably, start off with high correlation in week one, drop significantly by week two, and level off to a lower, but still positive correlation from weeks 3 through 12. VF atmospheric anomalies show high week one correlation values usually around 0.6 (0.7 or greater for temperature). The fire danger anomalies also maintain an approximate 0.6 correlation for week one. In contrast, RF shows a correlation of 0.6 only for the maximum and average temperature. Minimum temperature, minimum relative humidity and average relative humidity all have values near 0.5, with maximum relative humidity, precipitation amount and precipitation duration all closer to 0.4. Wind speed and the fire danger anomalies show the lowest RF correlation with values of 0.2 or less. Beyond week 3, both RF and VF level out at about the same correlation value for all variables (typically between 0.1 and zero, although the precipitation indices level out closer to 0.15). The weekly mean for RV (✡) is usually below the VF and above the RF week one correlations.

In most cases the RF (✳) and VF (△) monthly means could probably be approximated by the week 2, week 6 and week 10 weekly means, although month 3 correlations tend to fall below these values. The RV (▽) monthly correlation is typically much higher than the other monthly means, and just below the VF weekly correlation.

RF (square) and VF (⊗) correlations for the seasonal forecast means tend to be lower than the week one means, on the order of about 0.2, although the RF seasonal correlations for minimum temperature and wind speed are less than 0.1. The VF seasonal mean correlations are consistently higher than the corresponding RF correlations (by about 0.5), especially for the fire danger anomalies, but with the exception of the relative humidity anomalies. For the fire danger anomalies, the VF seasonal mean correlations are higher compared to the VF atmospheric means (approaching 0.4) while the RF correlations drop to 0.1 or 0.15. RV seasonal mean (o) correlations are very high for the atmospheric anomalies, but drop to the level of the RF seasonal mean correlations for the fire danger anomalies.

The RF anomaly correlations of seasonal means are shown in Figures 4 through 7. For the atmospheric elements, the year-round seasonal means (Figure 4) generally have lower peak correlations compared to summer means (Figure 5). The relative humidity anomalies seem to have the highest correlation in the Southwest (large parts of Arizona, Nevada and California) regardless of the season. The lowest RH correlation occurs in Wyoming, Colorado, and New Mexico. Temperature anomalies have the strongest correlations in the Southwest for the year as a whole, although the minimum temperature correlation is highest only in Arizona and parts of Washington. Maximum temperature also has a high correlation in the Southwest (Arizona and California). New Mexico always has poor temperature anomaly correlations. Precipitation indices have their highest correlation in the Southwest (California and Nevada), including summer. Precipitation correlation is generally poor in Washington, Wyoming, Colorado, and New Mexico. Wind speed has the lowest correlation of all of the atmospheric elements, with virtually no strong correlation over the full year. The correlations of wind speed are best for Washington, Oregon, Colorado and New Mexico during the summer.

Throughout the year (Figure 6) and in summer (Figure 7) the fire danger anomalies have their highest correlation in Nevada and California. Additionally, the BI, IC and SC also have an area of higher correlation in southeastern Montana during the summer and year-round. All four indices perform well in Southern California and Arizona. It is interesting to note that while the highest correlations do not necessarily occur where the highest standard deviation does, they do seem to have higher correlations in areas where the correlations for the relative humidity and precipitation indices are high.

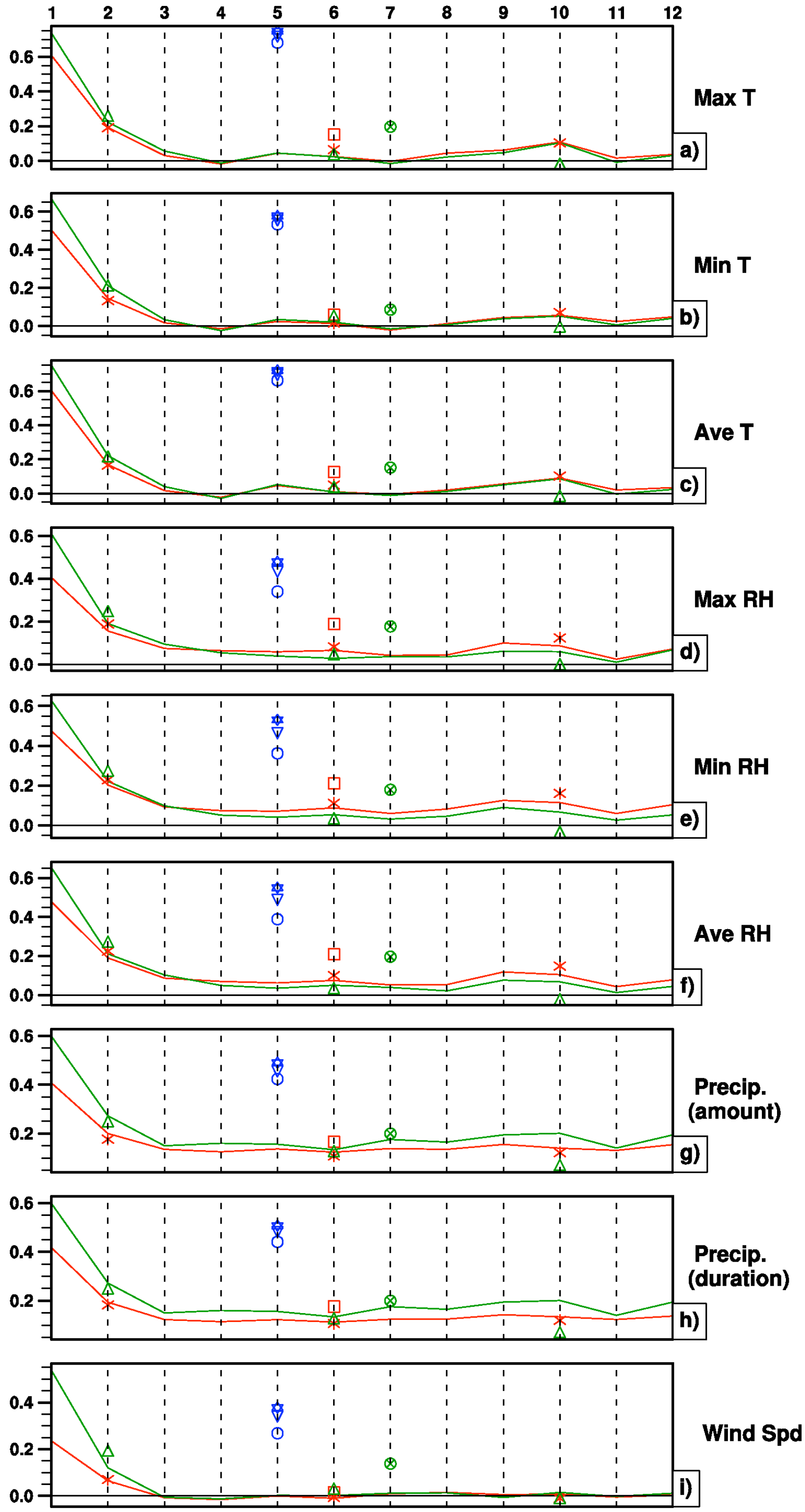

Figure 2 RF weekly (red line), monthly (✳), seasonal (square), VF weekly (green line), monthly (△), seasonal (⊗), and RV weekly (✡), monthly (▽), and seasonal (o) anomaly correlations. Monthly and seasonal values are plotted at the center points (i.e. week 2 for month 1, week 6 for RF seasonal, week 5 for RV values and week 7 for VF seasonal). Atmospheric elements are (a) Max T; (b) Min T; (c) Ave T; (d) Max RH; (e) Min RH; (f) Ave RH; (g) Precip Amt; (h) Precip Dur; (i) Wind Spd.

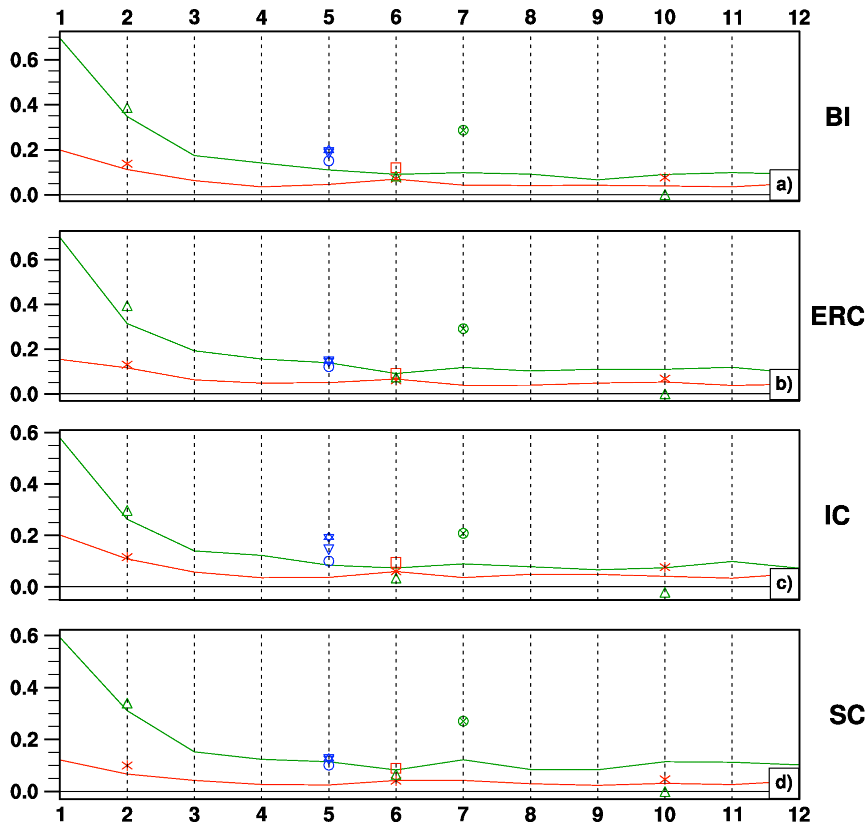

Figure 3 RF weekly (red line), monthly (✳), seasonal (square), VF weekly (green line), monthly (△), seasonal (⊗), and RV weekly (✡), monthly (▽), and seasonal (o) anomaly correlations. Monthly and seasonal values are plotted at the center points (i.e. week 2 for month 1, week 6 for RF seasonal, week 5 for RV values and week 7 for VF seasonal). Fire danger indices are (a) BI; (b) ERC; (c) IC; (d) SC.

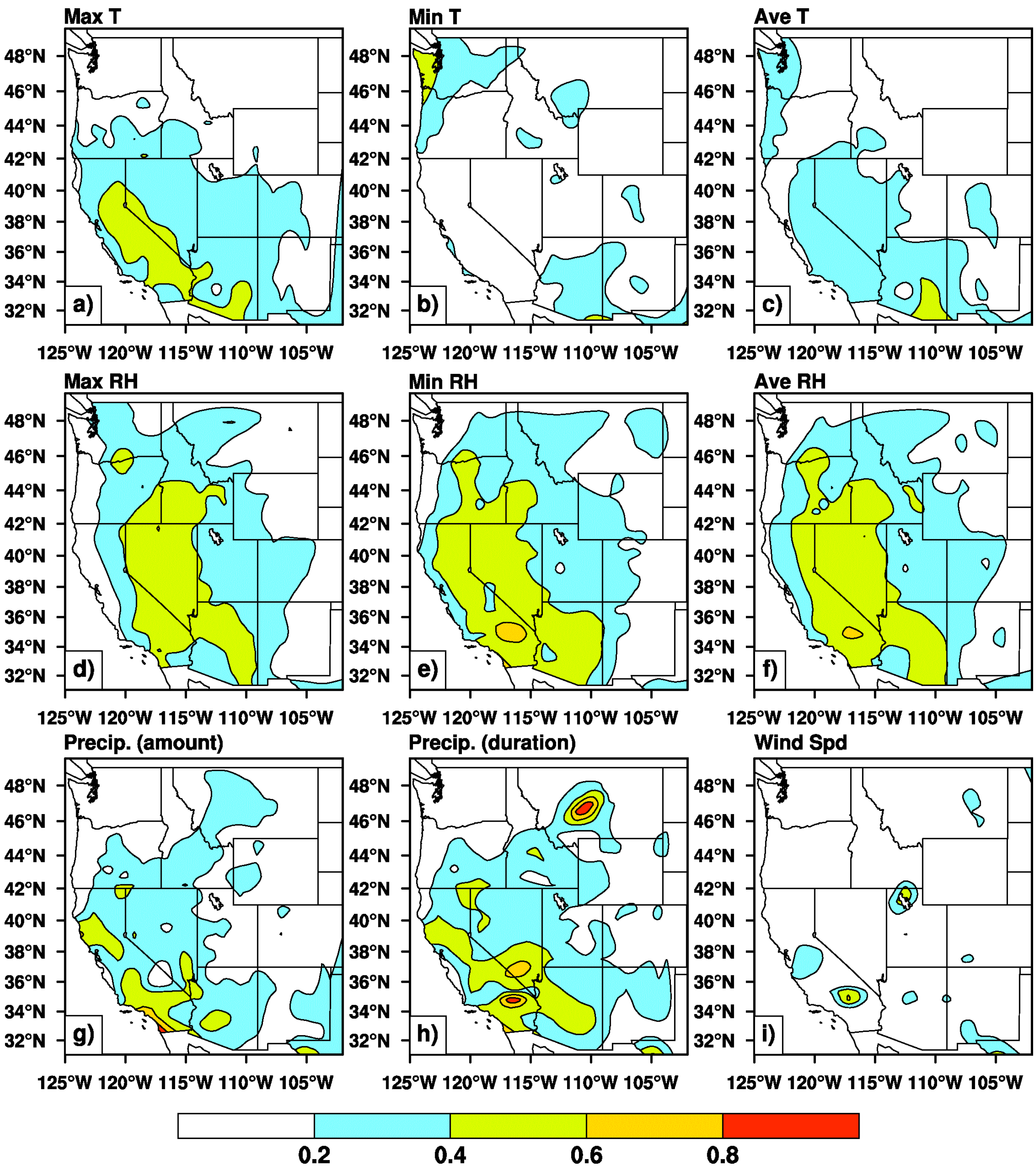

Figure 4 RF seasonal mean correlations for (a) Max T; (b) Min T; (c) Ave T; (d) Max RH; (e) Min RH; (f) Ave RH; (g) Precip Amt; (h) Precip Dur; (i) Wind Spd.

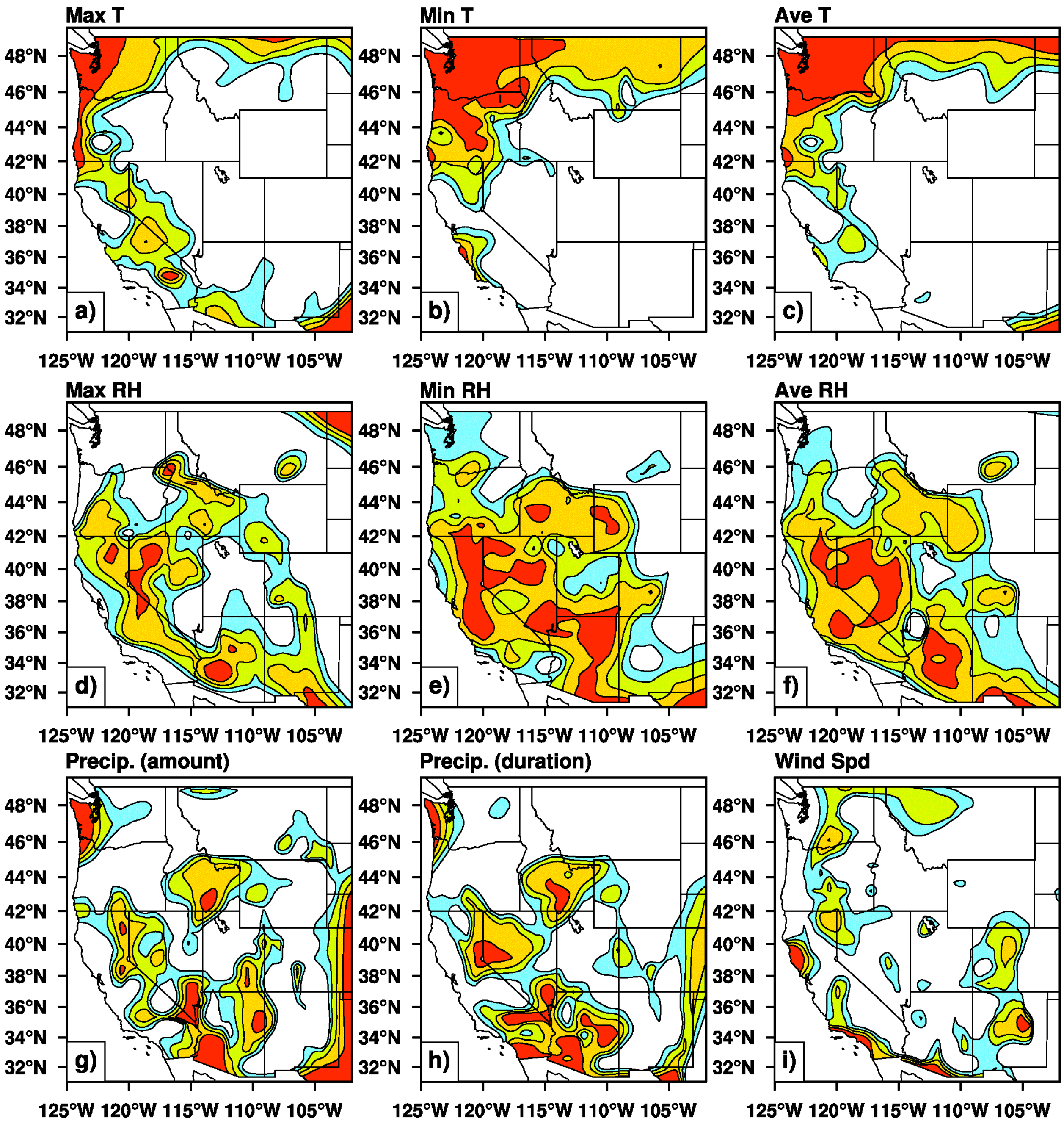

Figure 5 RF summer (JJA) season mean correlations for (a) Max T; (b) Min T; (c) Ave T; (d) Max RH; (e) Min RH; (f) Ave RH; (g) Precip Amt; (h) Precip Dur; (i) Wind Spd.

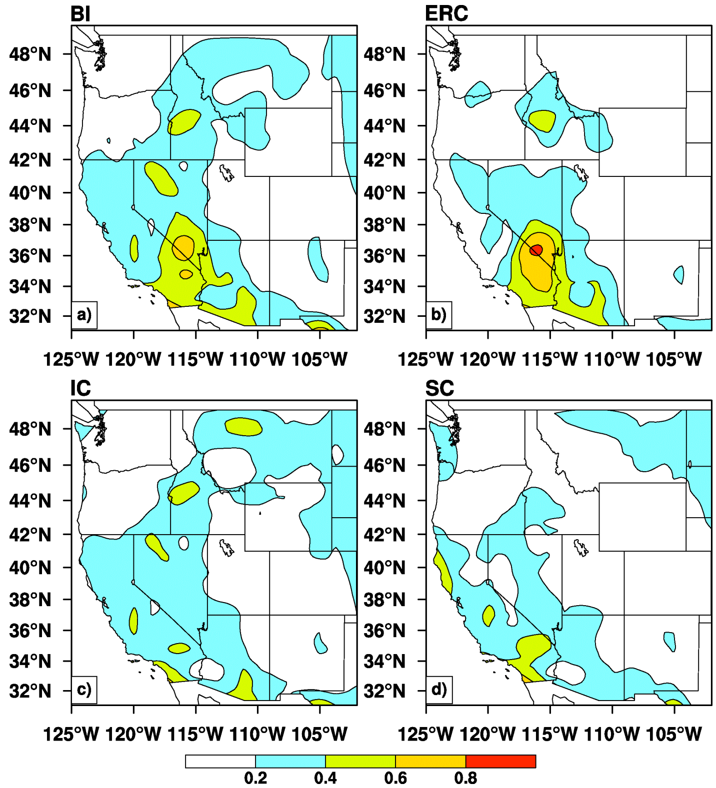

Figure 6 RF seasonal mean correlations for (a) BI; (b) ERC; (c) IC; (d) SC.

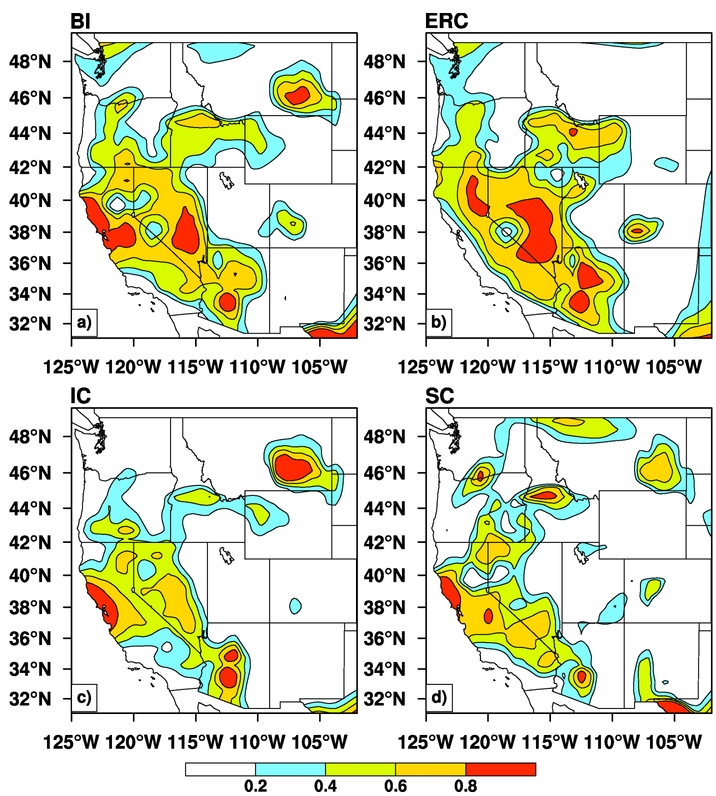

Figure 7 RF summer (JJA) season mean correlations for (a) BI; (b) ERC; (c) IC; (d) SC.

5. DISCUSSION AND CONCLUSION

The goal of this study was to test the skill of a dynamical forecast model producing seasonal forecasts of weather elements and fire danger rating indices that are important to fire management. Since fire danger indices rely largely on weather elements that have predictability to varying skill depending on the time scale, it seems that fire danger indices should also have a corresponding level of skill. In an effort to make these forecasts more useful in application to land managers, a set of observations from RAWS were used to determine model skill from the period September 1997 through December 31, 2002.

All biases, both atmospheric element and fire danger index, between the RAWS observations and RSM forecasts and validations have a greater magnitude than the biases between the elements of the RSM forecasts and RSM validations. Overall, the relative humidity biases are the largest. For the nine atmospheric elements assessed, this is likely due, at lease in part, to differences between RAWS observations and the NCEP data used to create the validation files. RAWS are generally located in forest, wilderness and rangeland areas while atmospheric soundings and surface data incorporated into the NCEP analysis grids are usually gathered from locations unrepresentative of where wildfire occurs. Additional sources of bias may stem from the fact that the RSM validations (which are 1-day forecasts) are themselves only close approximations of the NCEP data (Roads 2003; Roads et al. 2003a; b), and that the RSM surface grid is interpolated to RAWS sites for this study. Using a more advanced interpolation algorithm, reducing output grid size or increasing the number of RAWS in the study could reduce bias due to interpolation. Bias in the fire danger indices may also be due to differences between RAWS and ECPC site descriptions (fuel model, slope) that are used in the NFDRS equations. The ECPC fire danger indices are calculated on 100 km fuel model and slope grids, and then interpolated to 60 km grids for comparison to the atmospheric RSM indices. The fire danger indices calculated from RAWS observations are based on the WIMS descriptions of each RAWS site, not grids. Additional bias comes, of course, from consistent errors within the model itself.

Bias can interfere with measures of forecast accuracy that are based on a direct comparison of forecast and observational values such as the root-mean square error. In order to minimize the bias between the RAWS observations and RSM output, correlations between datasets are computed using anomalies (deviations from climatology) rather than the original forecast or observational values. At a weekly time scale, the RAWS overall daily maximum and average temperature indices are shown to correlate with the validating observations (RV) with a value of 0.7. The remaining temperature, relative humidity and precipitation elements have correlations closer to 0.5, with wind speed correlations closer to 0.4. Correlations between RAWS observations and the RSM forecasts (RF) at week 1 are not quite as high, with 0.6 for the maximum and average temperature elements, 0.5 for minimum temperature, and minimum and average relative humidity, 0.4 for maximum relative humidity and the precipitation elements, and 0.25 for wind speed. In all instances, the RSM validation versus RSM forecast (VF) atmospheric correlations are greater than the other two comparisons and greater than 0.6. Month 1 and seasonal correlations for the RF and VF comparisons drop to values close 0.2 for most atmospheric indices, excluding minimum temperature in which both RF and VF correlations drop below 0.1 and wind speed in which the RF correlation is closer to 0.05. The RV monthly and seasonal correlations remain comparable to the weekly correlations for maximum, minimum and average temperature, and typically drop by no more that 0.15 for the other elements.

Both the RF and RV BI and IC indices have small correlations with RAWS observations, even in the first week (close to 0.2). ERC and SC correlate even lower at 0.15 and almost 0.12 respectively. In contrast, the overall VF week 1 correlations are 0.6 or higher for all four indices. RF and RV seasonal forecasts are comparable with the week 1 correlation for SC; lower by 0.1 for BI and IC and 0.05 for ERC. In contrast, the VF correlations are greater for all fire danger indices at week one with a value of 0.6 and seasonally with a value of 0.25 or 0.3.

While it is clear that the RF seasonal (and some of the week one) correlations do not reach 0.6, this does not necessarily mean that the forecasts are absent of skill entirely. In most cases (except for wind speed and minimum temperature), the RF seasonal correlations in the atmospheric and fire danger indices are still higher than the weekly means after week 3. This indicates that there is skill in the seasonal forecasts of these elements.

For modelers, these results are additional encouragement that fire danger indices can be skillfully forecast by this RSM at seasonal time scales, even if the current skill is not high. These results also serve as a useful contrast of RSM skill when compared to RAWS observations rather than the validating observations. The skill when compared to RAWS is much lower than when compared to validation, especially for the precipitation, wind speed and fire danger indices. However, even indices with lower overall correlation may have high correlation in specific locations, especially during a given season. For instance, seasonal wind speed correlates with values at or above 0.6 in parts of Washington, Oregon, New Mexico and Colorado during the summer. The results for the RSM forecasts versus RSM validation comparison are comparable to studies performed at ECPC for the fire danger indices (Roads et al. 2003b). The VF precipitation correlations in this study are slightly higher than the correlations found in a similar study at ECPC (Roads 2003).

The RSM model output can be useful for land managers and fire weather meteorologists. The one-week forecasts of the atmospheric indices, especially temperature, show significant skill and could likely be incorporated into short-range fire weather forecasts. Seasonal forecasts of atmospheric indices and fire danger ratings show low skill as an overall average, but can have much higher skill in specific regions and during specific seasons. For instance, the spatial analysis indicated higher correlations of seasonal forecasts in all indices for southern California, Arizona and Nevada.

5.1 SPECIFIC RECOMMENDATIONS

Modelers:

- Re-evaluate the algorithm used to output fire danger indices, focusing on elements like fuel moisture and carry-over values.
- Incorporating RAWS into the initialization of the model (perhaps even as part of the NCEP/NCAR operational analysis or reanalysis), would likely aid in the upgrading model skill with reference to RAWS.

Fire Managers:

- The skill of most of the week-one forecasts of atmospheric indices (especially temperature) is very high. These values should be useful in making short-term management decisions.
- While seasonal skill as an overall average is low, especially for the fire danger forecasts, most indices still show some potentially useful regional skill.

Future work on this topic might include a more in-depth examination of the large biases and low overall correlation between the RAWS observations and the ECPC forecasts. Also, performing a similar study between the ECPC GSM forecasts and RAWS observations would be helpful. Generating fire danger indices locally from ECPC forecasts of weather elements and comparing them to the fire danger indices output by ECPC would be beneficial. Upgrading the GSM and RSM to the latest incarnations of each would hopefully improve the forecasts of precipitation and wind speed; with possible increases in fire danger forecast skill as a result. It may also be of additional benefit to fire management to examine the potential of this RSM to forecast for specific RAWS.

6. ACKNOWLEDGEMENTS

This work was supported by the Bureau of Land Management national Office of Fire and Aviation under cooperative Assistance Agreement number 1422RAA000002.

7. REFERENCES

Bradshaw, L. S., J. Deeming, R. Burgan, J. Cohen 1983: *The National Fire-Danger Rating System: Technical Documentation*. USDA Forest Service General Technical Report INT-169, 44 pp.

Burgan, R. E., 1988: *1988 Revisions to the 1978 National Fire-Danger Rating System*. Res. Pap. SE-273. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station, 39 pp.

Deeming, J. E., J. Lancaster, M. Fosberg, R. Furman, M. Schroeder, 1972: *National Fire-Danger Rating System*. Res. Pap. RM-84, Fort Collins, CO, U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station, 165 pp.

Deeming, J. E., R. Burgan, J. Cohen, 1977: *The National Fire-Danger Rating System-1978*. Gen. Tech. Rep. INT-39. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, 63 pp.

NWCG, 2002: *Gaining an Understanding of the National Fire Danger Rating System*. P. Schlobohm and J. Brain (Eds.), National Wildfire Coordinating Group. NFES 2665, PMS 932, Boise, Idaho, 78 pp.

Roads, J. O., K. Ueyoshi, S. Chen, J. Alpert, F Fujioka, 1991: Medium-Range Fire Weather Forecasts. *International Journal of Wildland Fire,* **1**, 159-176.

Roads, J. O., S. Chen, F. Fujioka, M. Kanamitsu, H. Juang, 1997: Global to Regional Fire Weather Forecasts. *International Forest Fire News (BAHC),* **17**, 33-37.

Roads, J. O., S. Chen, F. Fujioka, 2001: ECPC's Weekly to Seasonal Global Forecasts. *Bulletin of the American Meteorological Society,* **82**, 639-658.

Roads, J., S. Brenner, 2002: Global Model Seasonal Forecasts for the Mediterranean Region. *Israel Journal of Earth Sciences,* **51** (1), 1-16.

Roads, J. O., 2003: Experimental Weekly to Seasonal, Global to Regional US Precipitation Forecasts. *Journal of Hydrology* (submitted).

Roads, J. O., F. Fujioka, R. Burgan, 2003a: Fire Danger Forecasts. *International Journal of Wildland Fire* (submitted).

Roads, J., S. Chen, M. Kanamitsu, 2003b: US Regional Climate Simulations and Seasonal Forecasts. *Journal of Geophysical Research-Atmospheres* (in press).

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences*. Academic Press, 467 pp.