7.2 STATISTICAL FORECASTS OF WESTERN WILDFIRE SEASON SEVERITY

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1. INTRODUCTION

Strong associations between observed climate anomalies at lags of one season to years in advance and normalized area burned in the western U.S. wildfire season have recently been described using a newly compiled comprehensive gridded western regional fire history (Westerling et al 2001b). Earlier studies of fire scar dendrochronologies and local fire histories have demonstrated that large-scale climate patterns are linked to the severity of the wildfire season in various regions of the U.S. at similar lead times (Simard *et al*.1985, Swetnam and Betancourt 1990, Balling *et al* 1992, Swetnam and Betancourt 1998, Jones *et al*. 1999). These relationships and the availability of a comprehensive western wildfire history motivate this experimental statistical forecast methodology for the western wildfire season.

Previous work (Westerling et al 2001a & b) has established that lags of the Palmer Drought Severity Index can be used to forecast normalized acres burned at lead times of a season to years in advance, using co-located PDSI values as regressors. This work has also shown that regional indices describing modes of variability in PDSI—represented by leading principal components (PCs) of lagged PDSI values—show similar skill in forecasting western wildfire season severity. Moreover, models based on these regional indices show impressive predictive skill even in locations where strong associations between local PDSI values and normalized acres burned are lacking.

Canonical Correlation Analysis (CCA) offers a method for constructing western wildfire season severity models whose prediction skill derives from spatial and temporal patterns in climate spanning the western U.S. In this example the authors estimate a forecast model using a CCA to calculate linear relationships between principal components of seasonal acres burned on a 1x1 degree lat-lon grid and principal components of lagged U.S. Climatological Division PDSI values (similar to the methodology in Gershunov et al 2000). Jack-knife cross-validation is used to estimate robust measures of forecast skill for a range of choices for the number of principal components and canonical correlations incorporated in the model. A Skill Optimization Surface (SOS) is used to select a parsimonious model maximizing forecast skill over the entire region.

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2. DATA

The fire history used here is composed of seasonal $\log_{10}$ acres burned on a 1 x 1 degree grid extending from 31°N to 49°N latitude and from 101°W to 125°W longitude for 1980 through 2000. These data were compiled from 300000 quality-controlled fire reports of the Bureau of Land Management (BLM), U.S. Forest Service (USFS), National Park Service (NPS) and Bureau of Indian Affairs (BIA). The $\log_{10}$ transformation was used to normalize the data. Only the 330 grid cells averaging at least one fire per fire season are included in the analysis.

For predictors, 110 western U.S. Climate Division PDSI series are used at five different lags: March and December immediately preceding the fire season, August and March one year previous to, and August two years prior to the fire season, for a total of 550 predictor variables (*cf.* Westerling et al 2001a).

3. METHODS

Since a CCA cannot yield a unique solution if the number of predictor or predictand variables is greater than the number of observations, the dimensions of the predictor and predictand data sets were reduced by substituting their principle components (PCs) for each of the two data sets. (For a detailed CCA methodology see Barnett and Preisendorfer 1987, Johnson and

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Wichern 1998, Gershunov et al 2000). The first PC of each data set is the linear combination of all the variables in the data set which has maximum variance. Each subsequent PC is likewise a linear combination of the original variables with its variance maximized subject to the constraint that the PC is independent of each other PC. Thus, each PC summarizes an independent mode of variability in its original data set, and taken together the PCs summarize all the information contained in the original data set. For the predictor data, the first six principal components explain over 70% of total variance. Similarly for the predictands, the first six principal components explain more than 80% of total variance. So, relatively few PCs are needed to convey most of the information contained in these data.

We use a CCA to look for patterns in each of the two PC data sets that are highly correlated with each other. A linear combination of the predictor PCs and a linear combination of the predictand PCs are calculated such that the correlation between the two is maximized. Each subsequent pair is similarly calculated to maximize their correlation subject to the constraint that they be uncorrelated with the other pairs. Since these canonical correlates (CCs) are linear combinations of PCs, which in turn are linear combinations of the original data, we can specify a set of CCs to be our linear forecast model and solve for standardized $\log_{10}$ acres burned, our predictand, given the appropriate lagged PDSI values.

To find a parsimonious CCA model using the specified lags of PDSI, we calculated the Skill Optimization Surfaces (SOS) shown in Figure 1. The x-axis denotes the number of PCs contributed from the predictor and from the predictand data. The number of each are constrained to be equal here to render the solution more tractable. The y-axis denotes the number of CCs included in the model. Note the triangular shape of the shaded area—the maximum number of CCs is limited to the number of PCs included. Thus, in the lower left corner we use only the first principal component, which explains the largest share of variance, from both the predictors and predictands, and as a result are constrained to estimating our model from only the first CC pair. As we move to the right, adding PCs in order of their share of the total variance of their data sets explained, we can choose to move up the y-axis, adding additional CC pairs in our model in order of strength of correlation.

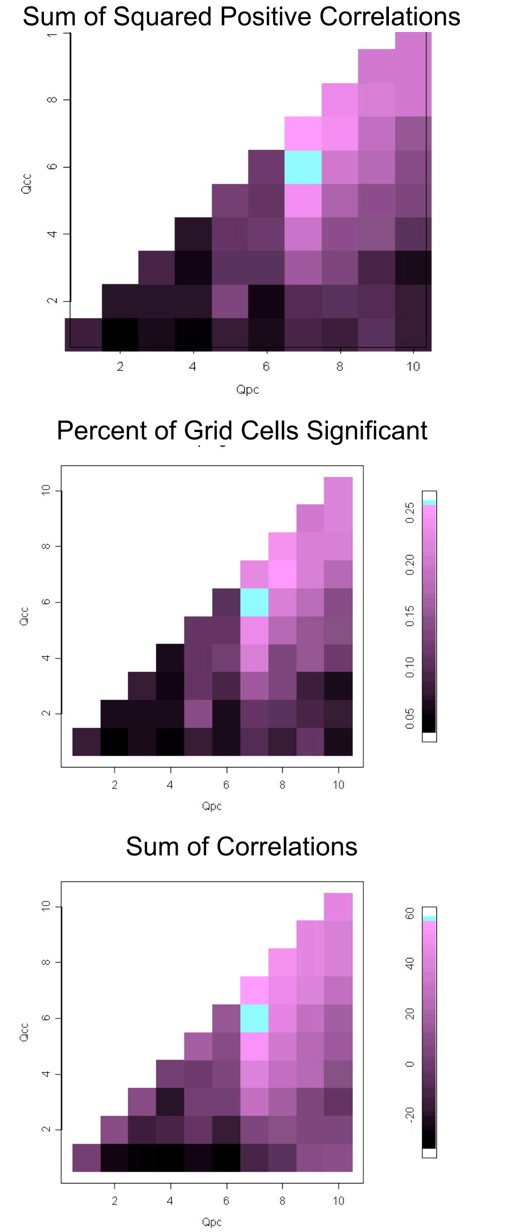

Figure 1: Skill optimization surfaces showing model skill calculated for the entire western U.S. together (330 grid points) using 3 different metrics comparing cross-validated forecast and observed transformed acres burned: *top:* sum of the squared positive correlations, *middle:* percentage of grid cells with significant correlations, and *bottom:* sum of correlations. Each skill optimization surface shows skill calculated for a cross-validated series of models with the indicated dimensions—the number of principal components is on the x-axis, the number of canonical correlations is on the y-axis. Darker shading indicates higher skill.

The shading in each SOS denotes the over-all skill of the forecast, calculated here using three different metrics. The first (*Figure 1, top*) is the sum of squared positive correlations between the cross-validated series of model estimates and the observed predictand for all 330 grid cells with one or more fires per year on average. Negative correlations indicate no skill and were excluded. This metric gives more weight to models with a small percentage of grid cells with high forecast skill. In the second metric, the percentage of grid cells with correlations within the 95% confidence interval of the t-distribution are included. This metric tends to favor models with moderate skill over a wide area over those with high skill in a few grid cells. Finally, in the third metric, the sum of correlations is used. Negative, correlations, indicating no skill, are more costly in this metric than in the others. Note that in each case, the model dimensions showing the greatest skill—six canonical correlations composed of seven principal components—are the same for this example.

To avoid an inflated estimate of the skill achieved in this exercise, model diagnostics here are all for results using jack-knifed cross-validation. That is, for each time step of the model, a forecast is made using model coefficients estimated on the subset of the data excluding that time step. This removes the potential for false statistical skill in the diagnostic measures reported here using Pearson's correlations. In the context of our CCA models, jack-knife cross-validation requires not only that at each time-step the coefficients of our forecast model be estimated on the subset of the data excluding that time step, but also that the loadings on the principal components and canonical correlations be recalculated at each time-step on that subset as well. Thus, for each time-step and number of PCs and CCs we are calculating a different model. The SOS does not help us to select an exact, fixed model, but rather the dimension or level of complexity of model which gives the best result. In this example, the SOS shows a maximum in skill at 7 PCs and 6 CCs, so we further examine the properties of a cross-validated series of models using these dimensions.

3. RESULTS

Figure 2 shows the skill, expressed as the correlation between cross-validated model estimates and observed transformed acres burned for a CCA using 7 principal components from the predictor and predictanddata sets to construct 6 canonical correlations. The model appears to do particularly well in the Intermountain West and parts of the Rockies. It also shows high skill in the Southwest along the California-Arizona border and central Arizona. It performs rather poorly in coastal southern and central California, where our data are sparse. The eastern-most grid-cells in an arc up from the Mexico-New Mexico border are also poorly represented in the fire history data. The wet Pacific Northwest is better represented in our data, but shows lower skill in this model.

These results show that useful skill can be achieved in forecasting fire season severity using lags of the PDSI. Acres burned aggregated over a one-degree grid may be too noisy to fully exploit the potential forecast skill for fire season severity using climate indices such as the PDSI. Elsewhere (Westerling et al. 2001a & b) we achieve better forecast skill for areas such as the Great Basin and Sierra Nevada by aggregating fire activity over larger regions with similar vegetation and climate. In future work will explore a combination of these approaches, using this CCA methodology for indices of fire season activity aggregated over larger areas with common characteristics.

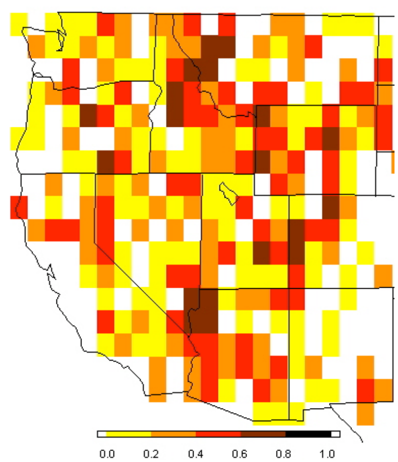

Figure 2: Model skill represented as correlation between forecast and observed transformed acres burned on a 1 x 1 degree grid. Forecasts are from a cross-validated series of models using 7 principal components and 6 canonical correlations. Darker shading represents higher correlations (skill), while white areas indicate grid cells with either no skill or no data.

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