Research Article

Modeling Climate-Fire Connections within the Great Basin and Upper Colorado River Basin, Western United States

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ABSTRACT

The specific temporal patterns of antecedent conditions associated with fire occurrence in the Great Basin and Upper Colorado River Basin are poorly understood. Using 25 years of combined fire and climate data, we identified unique antecedent patterns of climate conditions prior to fires in the Great Basin and Upper Colorado River Basin. Five distinct antecedent patterns of climate related to fire were found within the region; with these antecedent patterns we were able to construct models of fire danger. The occurrence of these antecedent patterns varies both spatially and temporally, and appears to be driven by drought severity. We used a Maximum Entropy approach to model the spatial extent and strength of these fire-climate patterns, and the associated fire danger. This approach provides land managers with a practical way to assess fire danger at a relatively fine spatial scale and also gives researchers a tool for assessing future fire danger.

RESUMEN

Los patrones temporales específicos de condiciones que anteceden a la ocurrencia de fuegos en la Gran Cuenca (Great Basin) y la Alta Cuenca del Río Colorado en los EEUU han sido poco estudiados. Usando 25 años de datos combinados de clima y fuego, identificamos patrones de condiciones climáticas previas a incendios en la Gran Cuenca y la Alta Cuenca del Río Colorado. Cinco patrones precedentes del clima relacionados con incendios fueron hallados para la región. Con estos precedentes pudimos construir modelos de peligro de incendio. La ocurrencia de estos patrones precedentes variaron tanto espacial como temporalmente, y parecen estar condicionados por la severidad de la sequía. Utilizamos la aproximación de Máxima Entropía para modelar la extensión espacial y la fortaleza de esos patrones precedentes de clima-fuego y del peligro de incendios asociado. Esta aproximación provee a los gestores de recursos de una manera práctica de evaluar el peligro de incendios en una escala espacial relativamente específica, y brinda a los investigadores una herramienta para evaluar el peligro de incendios a futuro.

Keywords: climate, fire, Great Basin, MaxEnt, Upper Colorado River, western US

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INTRODUCTION

Shaping many of the landscapes throughout the temperate regions of the world, fire is an important ecological component of many ecosystems (Pyne *et al.* 1996). Wildfire occurrence is highly dependent on suitable conditions in order for ignition to occur and combustion to be sustained. Sufficiently dry fuel in quantities large enough to support the persistence of the fire is essential, and is largely dependent on climate. Climate, however, has varied impacts on fuels and fire that vary across space (Westerling *et al*. 2003, Littell *et al*. 2009). Arid regions often do not contain enough fuel to sustain a large persistent fire and fires are often preceded by a moist period to build up sufficient biomass to support fire. On the other hand, alpine regions generally receive more moisture and thus require more severe drought conditions to sufficiently dry out fuels (Swetnam and Betancourt 1998, Westerling *et al*. 2003).

Swetnam and Betancourt (1990) and Holden *et al.* (2007) examined relationships between precipitation and area burned within forests of the southwestern United States. Both found relationships between increased area burned and decreased precipitation during the fire season. Dennison and Moritz (2009) found monthly precipitation fluctuations associated with changes in the timing of fuel moisture decline in southern California, reinforcing the idea of a relationship between precipitation during the fire season and area burned. In northwestern US forests, Trouet *et al.* (2006) and Gedalof (2011) found relationships between increased area burned and increased drought conditions.

Studies that have examined relationships between area burned and climate conditions for regions throughout the western US have found positive relationships between fire and prior year precipitation, and negative relationships between drought conditions and area burned in locations dominated by fine fuel types (e.g., grasses). Fires in areas containing heavier fuels (e.g., forests) were positively associated with drought conditions during the fire season (Westerling *et al*. 2003, Littell *et al*. 2009, Abatzoglou and Kolden 2013). Dennison *et al*. (2014) examined fire and climate trends for nine ecoregions in the western US. Southern and mountain ecoregions with increasing trends in drought severity also experienced the largest increases in number of fires and area burned. Spring temperatures, and thus timing of snowmelt, also have an impact on fire danger (Westerling *et al.* 2006). These previous studies not only suggest that regions are affected by climate conditions differently, but also emphasize the importance of antecedent conditions at least one year prior.

Although the climatic factors associated with fire occurrence have been examined regionally (e.g., Swetnam and Betancourt 1990, Trouet *et al.* 2006, Holden *et al*. 2007, Dennison and Moritz 2009, Gedalof 2011) and across the western United States (e.g., Westerling *et al*. 2003, Littell *et al*. 2009, Abatzoglou and Kolden 2013, Dennison *et al.* 2014), there is an incomplete understanding of the patterns leading to fire occurrence within regions—specifically within the interior portions of the western US. Ecosystems in the interior western US range from deserts to alpine environments, and these diverse environments can be part of differing fire regimes in terms of dominant fuel types and fire frequency. An analysis that examines intraregional relationships is crucial for understanding the connections between climate and fire within complex regions like the interior western US. We used antecedent climate conditions to characterize and model fire danger based on data derived from known fires exceeding 404 hectares (1000 acres) in size between 1984 and 2009. Gridded datasets representing climatic conditions across the study area for this time period were used to construct the models; these datasets included monthly maximum temperature, monthly precipitation, and monthly drought severity. Our analysis revealed both wet and dry patterns of antecedent climate, which vary both spatially and temporally, associated with fire occurrence.

METHODS

Study Area

The location of the study area was delineated using Hydrologic Unit Codes (HUC) developed by the US Geological Survey (Seaber *et al.* 1987) and incorporates the Great Basin (HUC 16) and the Upper Colorado River Basin (HUC 14) (Figure 1). These two watersheds encompass much of the interior western US—the intended focus for this study. Using watersheds to define the study area helps ensure that the inputs from the climate variables, particularly precipitation, are self-contained hydrologically, and makes boundaries simpler in terms of management. This area covers approximately 662 000 km^2, and contains a diverse collection of ecosystems from high elevation deserts to alpine wetlands. The landscapes within the study area are fairly representative of those occurring throughout the interior western US.

Climate, Fire, and Land Cover Data

We used the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (PRISM Climate Group 2010) for the climate variables, which consists of continuous gridded maximum monthly temperature (TMAX) and average total monthly precipitation (PPT). These data are interpolated from weather stations for each month across the United States at a spatial resolution of 2.5 min

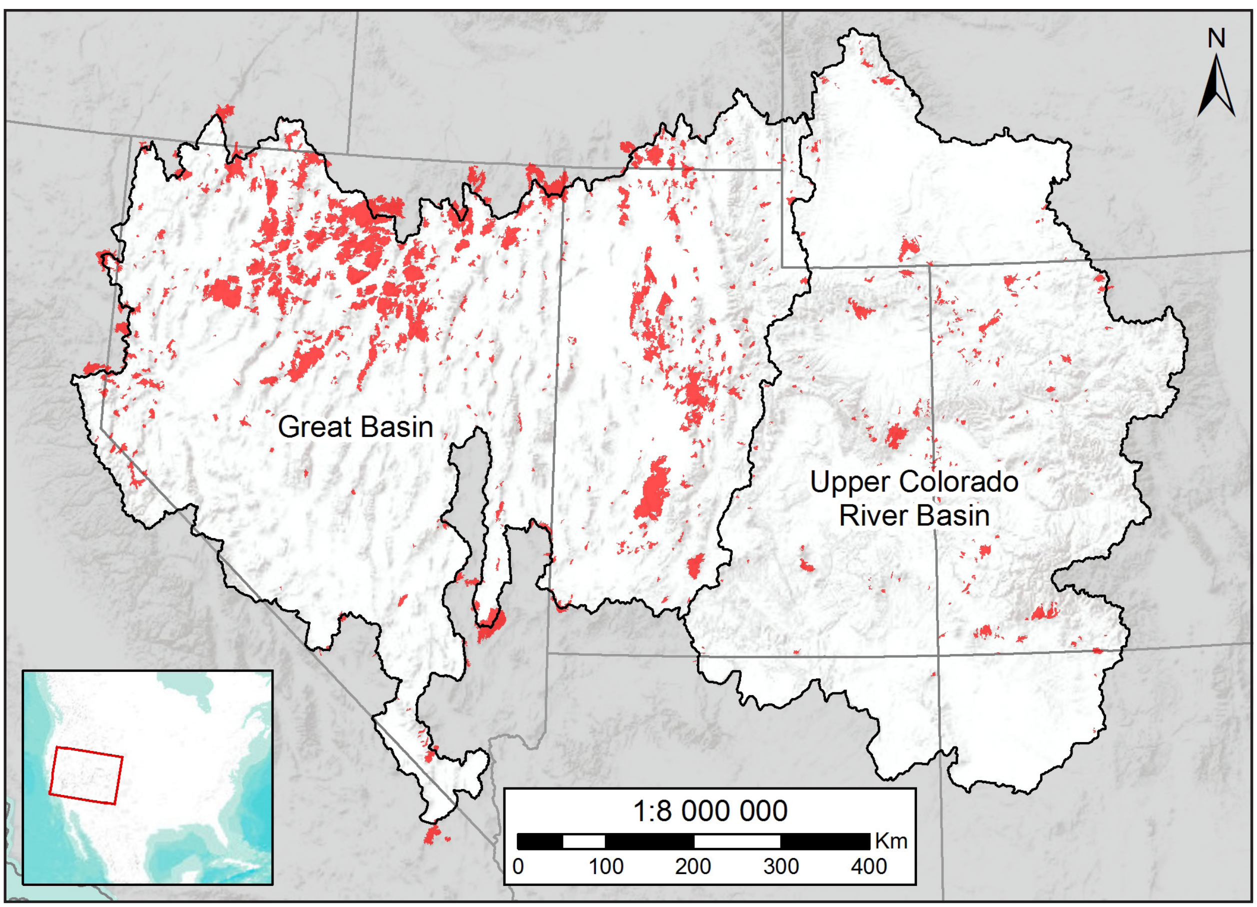

Figure 1. Location of the study area. Red polygons represent the fire perimeters we used for the study.

(≈4 km), and are used extensively for short term regional scale climate studies in the United States (PRISM Climate Group 2010). The sophisticated spatial interpolation methods used by the model consider complex topographic phenomena such as rain shadows and inversions, which are prevalent throughout the highly variable topography of the study area (Daly *et al*. 2000). Although the distribution of weather stations can be relatively sparse in certain areas of the western US, potentially decreasing the accuracy of the interpolation, PRISM performs better in these areas when compared to datasets with a similar spatial resolution (Daly *et al.* 2008).

The PRISM dataset is used in conjunction with the Variable Infiltration Capacity model (VIC) by the Western Regional Climate Center to create a gridded Self-Calibrated Palmer's Drought Severity Index (SCPDSI; Wells *et al.* 2004). The SCPDSI represents a location's water balance compared to that location's historical normal; if the measure is negative, the location is at a water deficit, and a positive value represents a water surplus relative to the past neutral water balance of that location. This measure is based on the traditional Palmer's Drought Severity Index (Palmer 1965) except that the constants used to calculate the index are calibrated for each location as opposed to the regionally derived constants used in the original index. This makes the index more robust and allows for direct comparisons between sites, something that is problematic with the original PDSI since the constants used to determine the water balance are calculated and applied regionally. The regional application of constants is a particular problem for the arid West, given the complex topography and climate. Regional constants are therefore unlikely to reflect local climate, and limit the index's comparability (Wells *et al.* 2004).

We used fire occurrence data from the Monitoring Trends and Burn Severity (MTBS) project. These data provide information for large fires (>400 ha) from 1984 to 2009 at a spatial resolution of 30 meters (Eidenshink *et al.* 2007). There were a total of 1433 large fires used in this study, with an average of 55 fires occurring per year. A maximum of 142 large fires occurred in 2006 and a minimum of 9 large fires occurred in 1990.

The 2006 National Land Cover Dataset (NCLD) was used as a static indication of vegetation types present throughout the study area. The NCLD is produced by classifying Landsat TM imagery acquired circa 2006 based on the spectral reflectance for each location (Fry *et al.* 2011). Although this dataset provided a snapshot of land cover at a specific point in time, it was used to indicate broad spatial and elevational distributions of vegetation types within the study area.

Data Analysis

First, we calculated pixel-wise *z*-scores for TMAX, PPT, and SCPDSI for each month in the study period to reduce autocorrelation and remove the effects of spatial and seasonal variation in absolute values. These standardized values can be directly compared across datasets and between months, allowing the different variables and fires to be analyzed together. The PPT required an additional log10 transformation prior to *z*-score calculation to correct its generally skewed distribution. For each fire, values from each climate variable were extracted for the 24 months prior to the date of fire ignition. Some larger fires encompassed multiple 2.5 minute PRISM pixels; the pixels covering these larger fires were averaged, yielding one set of climate variables per fire.

We compared the set of antecedent climate variables to randomly extracted sets of 24-month time series from across the entire study period to assess if the antecedent conditions showed trends that differed from non-fire climate conditions. In order to preserve the autocorrelation structure of the climate *z*-scores, a block 24-month time series was extracted from all fire locations with a random start date, and the median climate value for the 24 months across all locations was taken. This sampling was done 1000 times and a 95% confidence interval was constructed to assess the random variation in each variable. We observed that prefire SCPDSI had a different temporal structure and was significantly different for the entire 24 months prior to fire, while PPT and TMAX both deviated from the confidence interval generated by the random sampling approximately 6 months prior to fire. On this basis, we retained for analysis only the 6 antecedent months of TMAX and PPT, but the full 24 months of SCPDSI.

We used a Hard Competitive Learning clustering method to group the antecedent conditions. Hard Competitive Learning is similar to *k*-means clustering, with the exception that the initialization of the centers is driven by the data density rather than being entirely random (R Development Core Team 2008). This method has been shown to be more robust in datasets that have varying densities within the data space and prevents the common issue of centers falling into 'local minimums' (Fritzke 1997). The Calinski Criterion, developed by Calinski and Harabasz (1974) to optimize cluster partitioning, was used to determine the appropriate number of clusters for the data. This approach identified five groups of antecedent conditions based on specific temporal patterns in climate anomalies preceding fire occurrence.

Maximum Entropy (MaxEnt) modeling (Phillips *et al*. 2006) was used to predict fire danger based on climate patterns preceding each fire. MaxEnt has been used extensively in ecological research and has multiple advantages over more traditional modeling methods:

(1) MaxEnt is designed to work with presence-only data, which offers an intuitive approach to modeling fire. Since fires don't occur in all places where fire-prone conditions exist, it is difficult to define a true absence. MaxEnt also does not treat background values where fire has not been observed as absences during the modeling process.
(2) Probabilities are generated for predicted areas, which make for more nuanced interpretation as opposed to a binary presence-absence prediction.
(3) Environmental data from across the study area are used to characterize the environment instead of simply using conditions at presence sites (Phillips *et al.* 2006).

Species distribution modeling is generally concerned with predicting areas of potential species occurrence; we use a similar approach here for modeling fires. The results indicate areas with potential for fire occurrence based on similarities to previously observed fires.

As a statistical learning model, MaxEnt does have some potential limitations. Overfitting is a concern with any statistical learning method. As the model becomes increasingly complex, there is the possibility that it matches the data used to calibrate the model too closely, resulting in limited predictive ability outside of the domain used for calibration. MaxEnt addresses this limitation with a method called regularization, which essentially limits the complexity of the model (Phillips and Dudík 2008). The use of presence-only data can also be problematic. Presence-only data is often biased, likely because of access to data collection sites (e.g., near roads, waterways, etc.). This bias can result in models that are incomplete—based only on observations from a particular type of site (Yackulic *et al*. 2013). However, by using the remotely sensed MTBS dataset rather than field-based observations, this set of fires represents the most complete dataset available for the region, reducing sampling bias.

We created separate models for each cluster of antecedent conditions, and ran each 100 times, leaving out a random 25% of the data for validation. The variables for each model included 6 months of antecedent PPT and TMAX, 24 months of antecedent SCPDSI, and the raw value of TMAX at lag 0 (the month of the prediction). This raw maximum temperature value was included to inform the model about the season since the use of *z*-scores for the other variables removed seasonality from the dataset.

We chose one month outside (August 2011) and one month within (June 2007) the study period to test the predictive skill of the fire danger model. Each pixel in the study area was classified into one of the clusters of antecedent conditions based on the lowest Euclidean distance between the pixel's time series and the cluster centers. The distances were retained to give a quick assessment of prediction uncertainty. To assess the goodness-of-fit for the 100 model runs for each cluster, the Area Under Curve (AUC) score was used in addition to an error matrix comparing observed fires to the calculated fire danger of the fire's location. The AUC score reflects the ability of a model to discriminate between the group being tested (climate patterns associated with fire) and the other data. An AUC of 0.5 means that the model does no better than random at distinguishing the test group from the rest of the data. As the AUC increases, the model's ability to separate the two groups is improved.

The raw probability values from each model are not directly comparable to other models. The variation in the probability values between models is partly due to varying model performance in addition to the characteristics of the group being modeled (Phillips *et al.* 2006). Thresholds based on model performance provide a way to assign common values to different models, and these were used to determine classes of fire danger. A confidence interval was calculated for each pixel by creating a probability distribution function of the predicted probability values from the 100 model runs. We then compared the probability distribution to the thresholds associated with the fire danger classes (Table 1). The highest fire danger category with a threshold value below the 95th percentile of the distribution was assigned to the pixel. The final classification was created by taking the predicted danger class from the pixel's assigned cluster.

The clustering of antecedent conditions revealed five distinct patterns present in the months prior to fire (Figure 2A). These five groups may be more generally characterized as having predominately wet or predominantly dry antecedent conditions, but are further separated by the magnitude and timing of these wet and dry periods. Cluster 1 was wetter than baseline over most of the 24 months prior to fire occurrence, but trended towards drier than baseline and became slightly drier than baseline around 2 months prior to fire occurrence. Cluster 2 showed 12 months of increasing wet conditions that then remained relatively con-

Table 1. Descriptions of fire danger assignment.

Fire danger class	Threshold	Threshold description
Very Low	<Minimum training presence	Predicted value was less than any training fire's predicted value.
Low	Minimum training presence	Predicted value was at least the minimum value predicted for a training fire.
Moderate	Equal	A value which balances commission error (false negative) with omission error (false positive) for the training fires.
High	5th percentile training	Predicted value was in the 5th percentile of training fire predicted values.

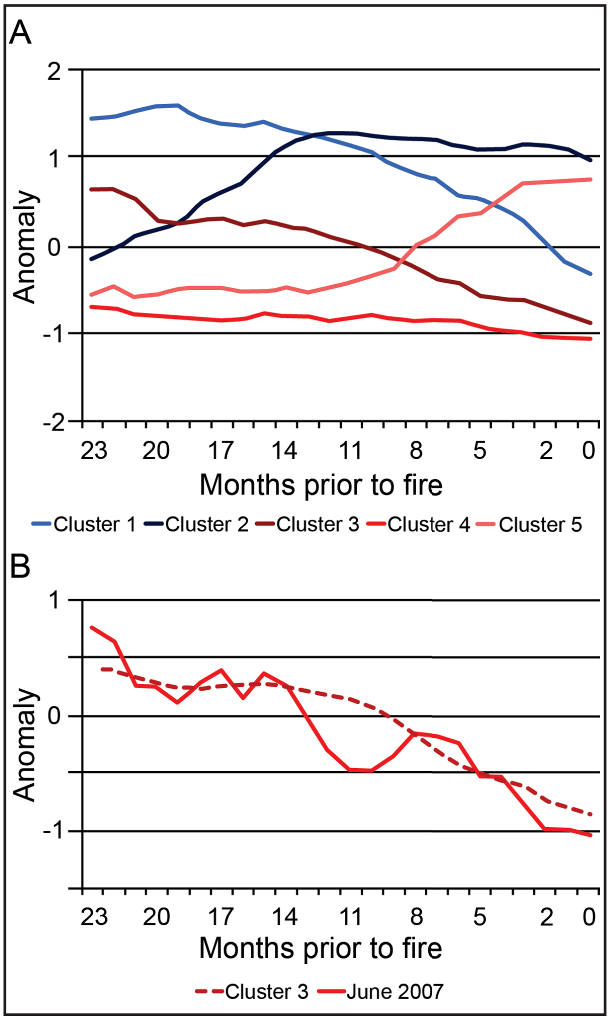

Figure 2. (A) Cluster centers for drought severity (SCPDSI). Blue lines denote fires in which conditions preceding fire are characterized by generally wetter than baseline while red lines are associated with antecedent conditions that are drier than baseline. (B) Median climate pattern observed during June 2007 compared to Cluster 3. The expectation is that fire danger will be well predicted by the model due to the similarity in the two patterns.

sistent for the remaining 12 months. Cluster 3 looked similar to Cluster 1 in terms of trend, but overall conditions were drier. Cluster 3 crossed over to drier than baseline approximately 10 months prior to fire occurrence. Cluster 4 showed consistent drought for the entire 24 month period. Cluster 5 was almost the opposite of Cluster 2 with consistent drought for the first 12 months followed by increasingly wet conditions beginning 12 months before fire occurrence.

The 'wet' clusters (1 and 2) were at significantly lower elevations (P-value = 5.74E-10), 1768 m on average, and were composed of significantly more shrubland compared to the mid-elevation (1930 m) clusters (3 and 5), which had more mixed composition. Cluster 5 had more shrubland and Cluster 3 had more evergreen forest. The highest elevation (2034 m) cluster (4) exhibited the most severe antecedent drought trend and was predominantly composed of conifer forest.

Variation in the abundance of individual clusters varied over space and time. For example, multiple clusters (wet and dry) were present during a given month as opposed to a single cluster dominating the study area based on average conditions within the region. Fires with antecedent wet conditions appear in a cyclical pattern throughout the study period, compared to a fairly consistent occurrence of fires with antecedent dry conditions (Figure 3A). The occurrence of fires with antecedent wet conditions corresponds well to periods of positive regional SCPDSI (i.e., wetter conditions).

The MaxEnt models successfully identified areas with antecedent climate patterns similar to those that have resulted in fire in the past (e.g., Figure 2B). The average AUC for all clusters was 0.945 and remained consistent between the months tested. This consistency is expected, and results from using the same training data for each prediction. Since the AUC measures the ability of the model to distinguish antecedent patterns of climate associated with fire from everything else, the variation in AUC from month to month should be minimal.

A test dataset of fires that occurred in August 2011 was compared with the model predictions of those areas. Out of the 16 fires that occurred during this month, 38 % of fire locations were classified as high danger areas and 63 % were either moderate or high danger. Another comparison was done with the model

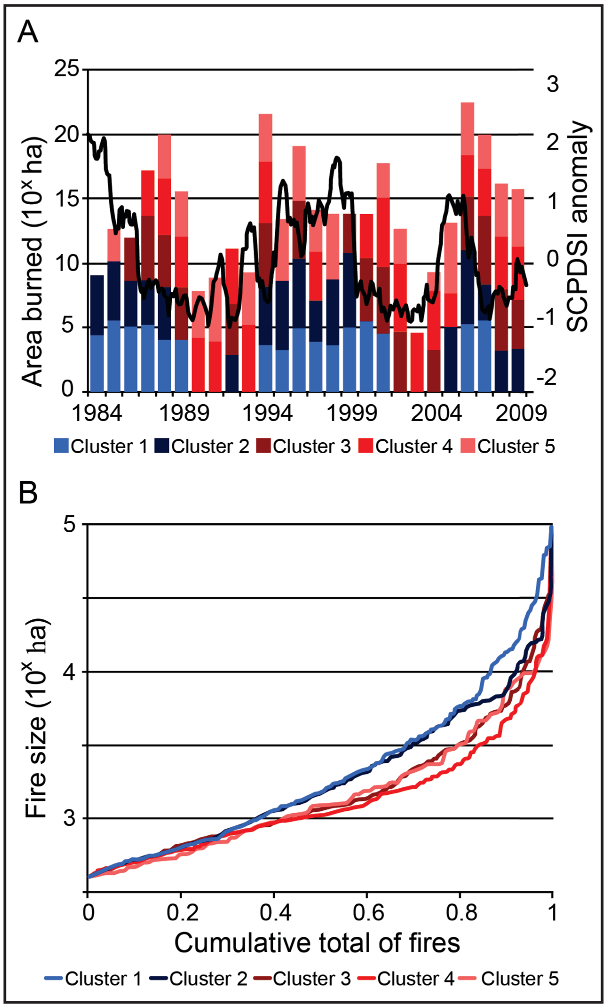

Figure 3. (A) Area burned per year by each cluster. Drought severity (SCPDSI) is overlaid to show how area burned is associated with fluctuations in drought severity. Fires preceded by anomalously dry conditions (red bars) remain relatively constant, while fires preceded by anomalously wet conditions (blue bars) appear during and after periods of anomalously high SCPDSI (low drought severity). (B) Comparison of fire sizes between clusters. Blue lines are associated with clusters characterized by antecedent wet conditions, while red lines are associated with antecedent dry clusters. Fire size is calculated as the log10 of the fire size in hectares. Fires that were preceded by wet conditions tended to be larger than those preceded by dry conditions.

output from June 2007 to assess model predictions for months within the study period. The classification results showed 50 % of observed fire locations classified as having a high danger and 83 % of the locations were classified as either moderate or high danger.

DISCUSSION

The antecedent climate patterns we found support observations made in previous studies (Westerling *et al.* 2003, Littell *et al.* 2009, Whitlock *et al.* 2010) that attributed the relationship between antecedent dry vs. antecedent wet fires to climate-limited vs. fuel-limited fire regimes, with wetter conditions increasing fuel loads in fuel-limited areas, and drier conditions affecting fuel moisture in climate-limited locations (Westerling *et al.* 2003).

This idea of climate-limited vs. fuel-limited regimes is reinforced when the average land cover composition and elevation are compared between the clusters. Clusters 3 to 5 have land cover and elevation consistent with a climate-limited regime, meaning that fuel is always abundant enough to support a large wildfire, but the typical climate in these areas does not often support the conditioning of fuels required for fire. In the interior western US, these areas would most often be higher elevation locations, which generally receive more precipitation and are dominated mostly by forest when compared to lower elevations, which are often composed of mostly grass and shrubland. In contrast, clusters 1 and 2 are fuel-limited (i.e., the climatic conditions are frequently sufficient for fuel conditioning but the sparse vegetation often results in insufficient fuel to support a large fire). An antecedent wet period increases the fine fuel biomass and connectivity in these areas, and higher fuel loads are readily dried out when conditions return to baseline.

Fuel type may explain differences in the distribution of fire size within each cluster (Figure 3B), where antecedent wet clusters had larger fires relative to antecedent dry clusters. Topography may also contribute to the differences in fire size distributions. Within the study area, lower elevation locations are often less complex topographically compared to higher elevations. Complex topography can impede fire spread due to variations in slope with respect to wind direction and physical barriers (e.g., riparian areas, steep slopes, etc.). The slowing of fire spread may, however, result in an increase in fire severity as the fire burns longer in a particular location (Pyne *et al*. 1996).

Given the importance of antecedent climate in determining fire danger, we used the cross-correlation function (Venables and Ripley 2002) to examine synchronous and lagged correlations between SCPDSI and multiple broad scale synoptic patterns, including the North American Monsoon, El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and 500 hPa geopotential height anomalies. No significant correlations were found between these synoptic patterns and SCPDSI within the study area. Wise (2010) describes a 'Precipitation Dipole Transition Zone.' This transition zone lies between two regions (the southwestern US and Pacific Northwest) that are highly affected by these larger patterns, but in opposite directions. For example, a positive ENSO anomaly is typically associated with decreased cool season precipitation in the southwestern US, but is also associated with increased cool season precipitation in the northwestern US. Since a large portion of our study region lies in this transition zone, synoptic patterns do not have a clear impact on climate, and are unlikely to have strong correlations with fire activity. Also, relationships between fire and synoptic indices, like those found by Collins *et al.* (2006), may not be apparent due to the limited length of the MTBS time series.

In addition to climate, Westerling *et al*. (2006) addressed the notion that land use change may play a role in the increase of area burned by wildfires over the past decades, showing that even areas that have seen little to no land use change since the mid-1980s have experienced this increase in area burned—particularly in the Rocky Mountains. While management plays a role in fire occurrence, climate has a strong connection as well (Littell *et al.* 2009, Dennison *et al.* 2014).

MaxEnt does exhibit some difficulty in identifying novel climate patterns different from those used to develop the model. Using MaxEnt, a prediction was made into July 2012. The results showed very low danger of fire across Utah, despite 2012 being an above average fire year (National Interagency Fire Center 2014). The poor performance during this time period is understandable as antecedent conditions for July 2012 show a much more exaggerated and abrupt change from wet to dry when compared to the antecedent conditions represented by the antecedent wet clusters. As more data become available, these extreme patterns can be incorporated and better identified within the model. The distances calculated during the modeling process can also be used to examine where these novel patterns are located.

When the correspondence between predictive antecedent conditions and those used to calibrate the model is high, MaxEnt produces useful information regarding the implications for fire danger associated with those conditions. This information could be readily utilized by land managers to inform decisions related to dangerous fire conditions. The quality and availability of climate data makes the use of these data for fire danger assessment an attractive option. Another powerful application of these models is their use in conjunction with long-term projections made by climate models (Liu *et al.* 2013). If relationships between climate and fire can be assumed to persist as climate changes, MaxEnt fire danger models could provide an indication of the prevalence of fire-associated climate patterns under different change scenarios. While climate projections would be limited by an assumption of stationary land cover, they would still yield valuable information related to the future of fire occurrence in the region.

As the climate continues to shift, the patterns currently associated with fire provide insight into the potential changes in fire regime that can be expected in response to the changing climate. Projections from the Coupled Model Intercomparison Project (CMIP3 global climate) archive for the western United States under a moderate emission scenario (A1B) describe increasing drought throughout the region (Gutzler and Robbins 2011). Increasing drought may result in more dry fires (clusters 3 to 5), which tend to occur at higher elevations in locations with abundant heavy fuels. However, drought may also reduce the number of lower elevation grass fires as biomass and fuel connectivity are reduced.

Our investigation into the climatic conditions prior to fires within the interior western US identified clear and distinct patterns associated with fire, including wet and dry antecedent conditions. Five clusters of antecedent climate conditions were further discriminated by land cover composition and elevation. These distinctions appear related to fuel vs. climate-limited fire regimes with unique interactions with climate. Models built using these relationships provide a good indication of fire danger within our study region, but their predictive ability declines when these antecedent conditions are markedly different from those used in model calibration. As more data become available to describe these novel conditions, we expect the model performance to improve. The current results do, however, illustrate the models' utility for predicting and characterizing fire danger.

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