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Regional projections of the likelihood of very large wildland fires under a changing climate in the contiguous Western United States

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Abstract Seasonal changes in the climatic potential for very large wildfires (VLWF≥ 50,000 ac~20,234 ha) across the western contiguous United States are projected over the 21st century using generalized linear models and downscaled climate projections for two representative concentration pathways (RCPs). Significant ($p \leq 0.05$) increases in VLWF probability for climate of the mid-21st century (2031–2060) relative to contemporary climate are found, for both RCP 4.5 and 8.5. The largest differences are in the Eastern Great Basin, Northern Rockies, Pacific Northwest, Rocky Mountains, and Southwest. Changes in seasonality and frequency of VLWFs d7epend on changes in the future climate space. For example, flammability-limited areas such as the Pacific Northwest show that (with high model agreement) the frequency of weeks with VLWFs in a given year is 2–2.7 more likely. However, frequency of weeks with at least one VLWF in fuel-limited systems like the Western Great Basin is 1.3 times more likely (with low model agreement). Thus, areas where fire is directly associated with hot and dry climate, as opposed to experiencing lagged effects from previous years, experience more change in the likelihood of VLWF in future projections. The results provide a quantitative foundation for management to mitigate the effects of VLWFs.

1 Introduction

As the climate warms, we expect increases in lightning ignition (Price and Rind 1994), area burned (Flannigan et al. 2009, Littell et al. 2010), fire intensity (Flannigan et al. 1998, Liu et al.

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2013), and fire severity (Flannigan et al. 2013). Wildfires can have substantial ecological, social, and economic effects. However, the many studies that project annual averages of area burned in an enhanced greenhouse climate (McKenzie et al. 2004, Flannigan et al. 2005, Flannigan et al. 2009, Littell et al. 2010, Westerling et al. 2011) or the potential for fire occurrence (Parisien et al. 2012), do not capture fire-climate relationships at a temporal resolution suitable for predicting individual fires. Predicting the likelihood of individual fires can provide key information necessary for facilitating fire management in mitigating the effects of wildfire. Ecological, social, and economic effects of wildfires include ecosystem effects, property loss, especially along the wildland urban interface (WUI), loss of natural resources, significant degradation of air quality (Jaffe et al. 2008), suppression expenditures (Calkin et al. 2005), and loss of human life. Also, wildfires are a part of a feedback loop between climate, wildfire, and air quality as they produce carbon emissions and aerosols that contribute to global warming (Bond et al. 2013).

Although there are numerous metrics for examining climate-wildfire relationships, most studies have examined annual burned area, which is relatively easy to quantify and often yields strong correlative relationships with climate (Flannigan et al. 2005, Littell et al. 2009, Abatzoglou and Kolden 2013). However, aggregate annual area burned correlations have been shown to be largely influenced by very large wildfires (Stavros et al. 2014). These very large wildland fires (VLWFs) can cause significant damage disproportionate to their area, and are defined in this analysis as wildfires≥50,000 acres~20,234 ha, constituting the top two percent of wildfire sizes in the western contiguous US making them the most “extreme” of fire sizes.

Understanding the potential for future VLWFs is important for both planning and mitigation. VLWFs may be unavoidable, but modeling of VLWF can help identify spatial and seasonal patterns of increased VLWF potential, thereby mitigating risk, enhancing opportunities for management, and developing policy using both direct and indirect strategies. Direct strategies include fuel management, which has successfully reduced economic, social, and environmental damages (Williams 2013). Another direct strategy is fire suppression of smaller fires that might become VLWFs when the likelihood is very high (Podur and Wotton 2011, Tedim et al. 2013) and when suppression resources are available. Indirect strategies to mitigate the smoke and air pollution effects of VLWFs include, for example, reducing anthropogenic emissions (e.g., fossil fuels), so that when there is a wildfire, more emissions must occur before exceeding air-quality standards (Bedsworth 2011).

For this study, we examine three fundamental questions about the future likelihood of VLWF occurrence at scales appropriate for management and policy across the western United States using models developed by Stavros et al. (2014). First, will VLWFs be more likely in the future? Second, will seasons of increased likelihood of VLWF change lengthen in the future? Third, how will key climate predictors of VLWF change in the future?

2 Data and methods

2.1 Study area

The analysis uses regional divisions in the western contiguous United States based on existing operational decision-making and regional forecasting in fire and air-quality management. Regions are defined by the firefighting command centers, Geographic Area Coordination Centers (GACC), run by the U.S. National Interagency Fire Center (acquired 1 Oct 2011 from http://psgeodata.fs.fed.us/download.html/GACC_2009.zip). There are eight GACCs in the study area: Southern California (SCAL), Northern California (NCAL), Pacific Northwest (PNW), Northern Rockies (NROCK), Rocky Mountains (RM), Western Great Basin (WGB), Eastern Great Basin (EGB), and Southwest (SW).

Across these GACCs are two main fire regimes: fuel-limited and flammability-limited. Fuel-limited fire regimes typically need a wet period in the year preceding fire occurrence to increase fuel connectivity and facilitate fire spread (Veblen et al. 2000). On the other hand, flammability-limited fire regimes have enough fuel to burn under the conditions that promote combustion (Littell et al. 2009). Although all GACCs have finer-scale variable creating mosaics of fuel and flammability limited regimes largely dependent on the variation in dominant ecosystems (Littell et al., 2009), generally PNW is a flammability-limited system and WGB is fuel-limited (Stavros et al. 2014). The SW has finer scale variability, but is unlike the other GACCs with mixed fire regimes in that the likelihood of VLWF dramatically falls with the onset of the Southwest monsoon (Stavros et al., in press).

2.2 Climate data

The study uses observed climate data over 1979–2010 and modeled climate data from 14 Global Climate Models (GCMs) over 1950–2099 with future projections of representative concentration pathways (RCPs) beginning in 2006. Observed climate data from 1979–2010 come from two gridded data sets: (1) 800-m monthly temperature and precipitation from Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly et al. 2008), and (2) 4-km daily surface meteorology from Abatzoglou (2013).

Climate predictions have three sources of uncertainty: model uncertainty, scenario uncertainty, and internal variability (Hawkins and Sutton 2009). To address model uncertainty, this analysis uses 14 global climate models (GCMs, Table 1) and to address scenario uncertainty, this analysis uses two RCPs 4.5 and 8.5. RCPs are back-engineered from cumulative radiative forcing in 2,100, in watts per square meter (van Vuuren et al. 2011). In RCP 4.5, total radiative forcing is stabilized before 2,100. In RCP 8.5, greenhouse gas emissions continue to increase through the 21st century. Daily output from these climate models was downscaled using the Multivariate Adaptive Constructed Analogs method (Abatzoglou and Brown, 2012) using the observational datasets across the geographic domain. Downscaled outputs included daily maximum and minimum temperature and relative humidity, accumulated precipitation, daily averaged wind speed and downward shortwave radiation at the surface for model years 1950–2,100.

From the gridded climate datasets, the Palmer Drought Severity Index (PDSI, Kangas and Brown 2007) and six indices from the United States National Fire Danger Rating System (NFDRS, using fuel model G) and the Canadian Forest Fire Danger Rating System (CFFDRS) were calculated (Abatzoglou and Kolden 2013). Indices from NFDRS include the moisture content of fuels 2.5-7.6 cm in diameter (100-h fuel moisture- FM100), the moisture content of fuels 7.6–15.2 cm in diameter (1,000-h fuel moisture- FM1000), how hot a fire could burn (energy release component- ERC), and the potential difficulty of controlling a fire as a function of spread rate and ERC (burning index- BI). Indices from CFFDRS include the relative ease of ignition and flammability of fine fuels (fine fuel moisture content- FFMC), and the average moisture of loosely compacted organic layers (duff moisture code- DMC). For all indices but FM100 and FM1000, the higher the index value, the higher the fire danger.

Bias correction ensured that the statistical distributions for individual variables (e.g., daily precipitation, temperature) over the modeled historical period (1950–2005) are mapped to those of the observed record (1979–2010). However, bias correction is applied independently across variables thus potentially resulting in multi-dimensional biases across variables (e.g., temperature

Table 1 The 14 GCMs used in this analysis, listed in descending order of most to least total relative error as a sum of relative errors from many metrics over the PNW as calculated by Rupp et al. (2013)

GCM	Reference
CNRM-CM5	Voldoire et al. 2013
GFDL-ESM2M	http://www.gfdl.noaa.gov/earth-system-model
CanESM2	http://www.atmos-chem-phys-discuss.net/11/22893/2011/acpd-11-22893-2011.pdf
MIROC5	Watanabe et al. 2010
HadGEM2-ES	Martin et al. 2011
GFDL-ESM2G	http://www.gfdl.noaa.gov/earth-system-model
HadGEM2-CC	Martin et al. 2011
CSIRO-MK3-6-0	Collier et al. 2011
inmcm4	Volodin et al. 2010
MIROC-ESM	Watanabe et al. 2011
MIROC-ESM CHEM	Watanabe et al. 2011
bcc-csm 1-1	
MRI-CGCM3	Yukimoto et al. 2012
BNU-ESM	http://esg.bnu.edu.cn/BNU_ESM_webs/htmls/data_acc.html

and precipitation) originating from GCM biases. Likewise, GCM biases in serial correlation (e.g., sequences of dry days) are not corrected for in typical bias correction routines. Collectively, these uncorrected biases manifest in metrics that integrate across variables and time such as PDSI and fire danger indices resulting in apparent differences between historical modeled data and observed data. To overcome some of these limitations we perform a secondary bias correction of all variables using a non-parametric quantile mapping transformation (Michelangeli et al. 2009) that matches quantiles of modeled data over the historical forcing period to the observational record. The same transformation was applied to indices calculated from future-climate projections with the assumption that any biases are stationary in time, thereby ensuring unbiased estimation of the differences between the projections and historical model runs. We note however, that the secondary bias correction eliminates multi-dimensional biases across predictor variables (e.g., PDSI and ERC, supplementary online material (SOM Table 1).

2.3 Data analysis

To investigate the three questions posed for this analysis, we used existing VLWF models built by Stavros et al. (2014) (see Table 2), defined per GACC, and projected the probability that in a given week, a VLWF will occur, onto future climate space. VLWF models were developed by defining explanatory variables as the average fire danger index value for the weeks before and after fire discovery, as defined in the Monitoring Trends in Burn Severity (MTBS) database. Comparing fire danger indices for large fires and VLWFs in the weeks before and after the discovery of fire showed windows of unmanageable fire growth. These windows defined the temporal window (s) for explanatory variables used in generalized linear models (GLMs) of the binomial family. Model selection was based on minimizing the Akaike Information Criterion (AIC). MTBS is a database of fire perimeters with burn severity and data of discovery for fires $\geq$1,000 ac~404 ha covering the contiguous United States 1984–2010, fires in the Great Plains were excluded from model development to focus on wildfires rather than agricultural fires. Models were assessed using Area Under the [receiver operating characteristic] Curve (AUC,

Table 2 Models by GACC to calculate the probability of VLWF event. Models taken fromStavros et al. (2014). AUC represents the Area Under the [receiver operating characteristic] Curve, a metric of model sensitivity to false positives whereby a value of 0.5 is totally random prediction and a value of 1 is a perfect prediction. Note: Explanatory variables are denoted as the calculated index averaged over the suffix such that ".1" denotes the week prior to discovery, ".0" is the discovery week, and ".n#" is the number of weeks post discovery week. PDSI=Palmer drought severity index, TEMP=mean temperature, FFMC=fine fuel moisture code, DMC=duff moisture code, FM100=100-h. fuel moisture, FM1,000=1000-h. fuel moisture, ERC=energy release component, and BI=Burning Index

GACC	P (VLWF)=1/(1+e^b) where b =	Classification threshold	AUC
EGB	31.033–0.226*FFMC.0–0.260*TEMP.0–0.015*DMC.n3–0.238*PDSI.n1	0.225	0.84
NCAL	−8.500+1.290*FM1000.n1	0.125	0.86
NROCK	−13.951–0.309*BI.n3+0.672*FM100.0+0.334*FFMC.n1+0.026*DMC.0–0.366*TEMP.1	0.275	0.93
PNW	6.664–0.514*TEMP.n1+0.468*FM1000.n1	0.175	0.86
RM	11.930–0.057*DMC.n3	0.200	0.97
SCAL	18.660–0.193*ERC.n1	0.125	0.80
SW	8.430–0.017*DMC.0	0.125	0.92
WGB	–4.532+1.279*FM100.0–0.392*PDSI.0	0.225	0.86

Table 2), precision, and recall (He and Garcia 2009). AUC is a metric of model accuracy averaged over all possible classification thresholds (0,1), precision is a measure of prediction exactness (i.e. number of predicted VLWFs that are actually VLWFs), and recall is a measure of prediction completeness (i.e., number of VLWFs of all predicted VLWFs). Using three different thresholds to define VLWF showed model selection to be insensitive to a wide range of thresholds for VLWFs, suggesting the robustness of our threshold of 20,234 ha.

The observed (1979–2010) likelihoods of VLWF were compared to both the modeled historical (1950–2005) and future (2006–2099) likelihoods of VLWF using both time series of the normalized probability of VLWF defined as the proportional change in probabilities from the baseline mean and Welch's t-tests. For each RCP ensemble from 1950 to 2099 and for the observed 1979 to 2010, we used 5-year moving averages, each divided by the mean of the observed record, to determine the normalized probability. Because the probabilities of these rare events are low by definition, results were normalized to simplify comparison of current and future changes in the likelihood of VLWF. Normalized probabilities for 2031–2060 were compared for individual GCMs and the multi-model mean to the historical modeled (1950–2005) normalized probability using Welch's pairwise *t*-test assuming unequal variances. We chose 2031–2060 to capture differences between a radiative forcing of 4.5 and 8.5 Wm^{-2}. Although the differences between RCP4.5 and RCP8.5 become more acute in the latter half of the 21st century, vegetation shifts and their feedback to fire climatology might change the climate-VLWF associations used to build the models in this analysis (McKenzie and Littell 2011). Nevertheless, time series were extended to 2,100 to capture the full potential difference in probability of a VLWF between RCP scenarios.

Two other analyses included (1) changes in the timing and duration of VLWF seasons and (2) the spatial distribution of the change in climate space from the observed record to the future. First, we examined seasonality by plotting the probability of a VLWF against week of year, and testing, using Welch's *t*-test, the difference in mean VLWF season start week, end week, and length of the observed, historical modeled, and future scenarios. The mean is defined as the average (e.g., start week) over the record for each year for each model. A week is classified as a VLWF week if the probability for that week exceeds the threshold for classifying a VLWF, which is defined as the intersection of model evaluation statistics precision and recall (Table 2, Stavros et al. 2014). Thus, “start week” and “end week” are defined as the first and last VLWF week of the season. Notably, the observed baseline coincides with the last phase of negative PDO, however the difference in mean temperature between the modeled over the observed record and historical modeled from 1950 to 2005, by which future scenarios were compared, is an order of magnitude less than the differences modeled for the future (SOM Table 2), thus changes in probability VLWF are not merely a result of natural variation associated with PDO. Second, we examined projected changes in climatic and fire-danger extremes across the domain from the baseline conditions (1950–2005) to the more conservative future RCP 4.5 scenario for 2031–2060. Because VLWF have a proclivity for occurring during extreme conditions, we examined changes in the frequency of ERC, BI, FFMC, DMC and Temperature exceeding the historical observed top decile from June to August and below the historical bottom decile for PDSI, FM100, and FM1000. We qualify regions where at least 10 of the 14 models agree on the sign of change.

3 Results

3.1 Projected changes in VLWF probability

The baseline period from 1950 to 2005 showed no significant (α=0.05) difference between the historical modeled ensemble and the observed probabilities in any GACC except WGB. These results were not only true for ensembles, but also most models (≥12 of 14) tested independently, thus providing high confidence in these findings. Despite bias correction on biophysical metrics used to develop the explanatory variables used in the VLWF probability models, the difference between the observed and modeled in WGB show that the models are slightly over-predicting VLWF probabilities.

The normalized mean probabilities for the future (2031–2060) is significantly different (α= 0.05) from the historical normalized probability of the modeled mean for all GACCs. In all but the SW, means increased from the historical modeled probabilities to RCP 4.5 (2031–2060) and then to RCP 8.5. However, for all GACCs, the likelihood of VLWF is greater under RCP 8.5 than RCP 4.5 by the end of the century. For all GACCs, there is strong model agreement (≥11 of 14 GCMs) that significant differences exist between future scenarios and the historical observed. Although all GACCs show significant increases over the 21st century for both RCPs (Fig. 1), four of the eight GACCs, EGB PNW, RM, and SW, show at least a 200 % increase in probability of a VLWF (SOM Table 1). These four GACCs have large inter-model variability in the normalized probability of VLWF.

There is variation in how the probability of VLWF will change by GACC, but in general there is a statistically significant increase in the frequency of VLWF weeks (defined in Section 2.3) for the future than from the baseline (Fig. 2 and SOM Table 1) except under RCP 4.5 in NCAL and NROCK.

3.2 Seasonal changes in VLWF potential

Both quantitative and qualitative assessments of the probability of VLWF show changes in fire season specifically for VLWFs and for the “vulnerable fire season”. We define vulnerable fire season as an increase in the future probability for a given week of year from the baseline (Fig. 2), but not necessarily exceeding the threshold for classifying a VLWF week. The VLWF fire season is defined by the first and last VLWF week in a year, means of all years from all GCMs are shown in SOM Table 1. SOM Table 1 provides a quantitative assessment of how

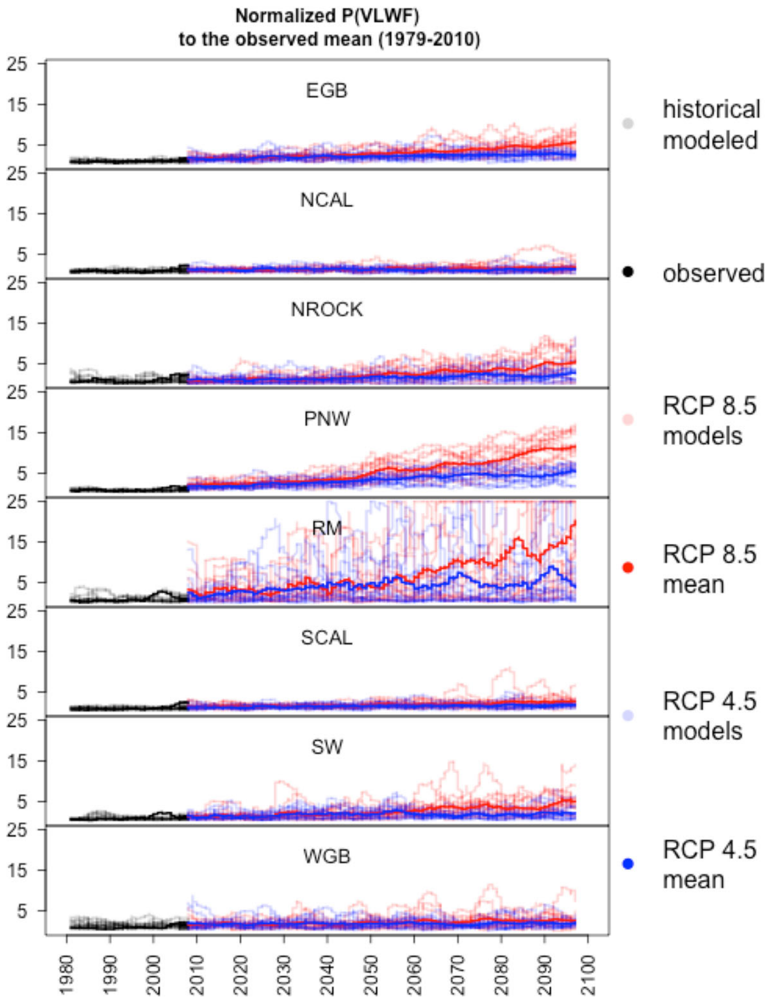

Fig. 1 Proportional change (from observed) of the probability that in a given week a VLWF will occur. The plots show a 5-year moving average. Dashed vertical lines mark the transition from modeled values over the observed period (1979–2010) to those for the future (2011–2099). Each shaded line denotes one of 14 GCMs used, and the bold line denotes the ensemble mean of all 14 models

the frequency of VLWF weeks and the VLWF fire season change under different future scenarios. In general the fire season start week is significantly (α<0.05) different and advances relative to the historical baseline with the exception of NROCK and SW under RCP 4.5, and RM and SCAL under both scenarios. The fire season end week is significantly later than the baseline in all GACCs except NROCK and RM under RCP 4.5 and under either scenario for WGB. These differences in start and end week for the fire season show all GACCs have VLWF fire seasons significantly different from the baseline. SOM Table 1 also shows an increase in the number of weeks classified with at least one VLWF occurring. In further agreement, Fig. 2 provides a qualitative confirmation that the vulnerable fire season will change across time for each GACC. Generally, the probability of VLWF increases under RCP 4.5 and is even more pronounced under RCP 8.5 than from the baseline. NCAL, as the

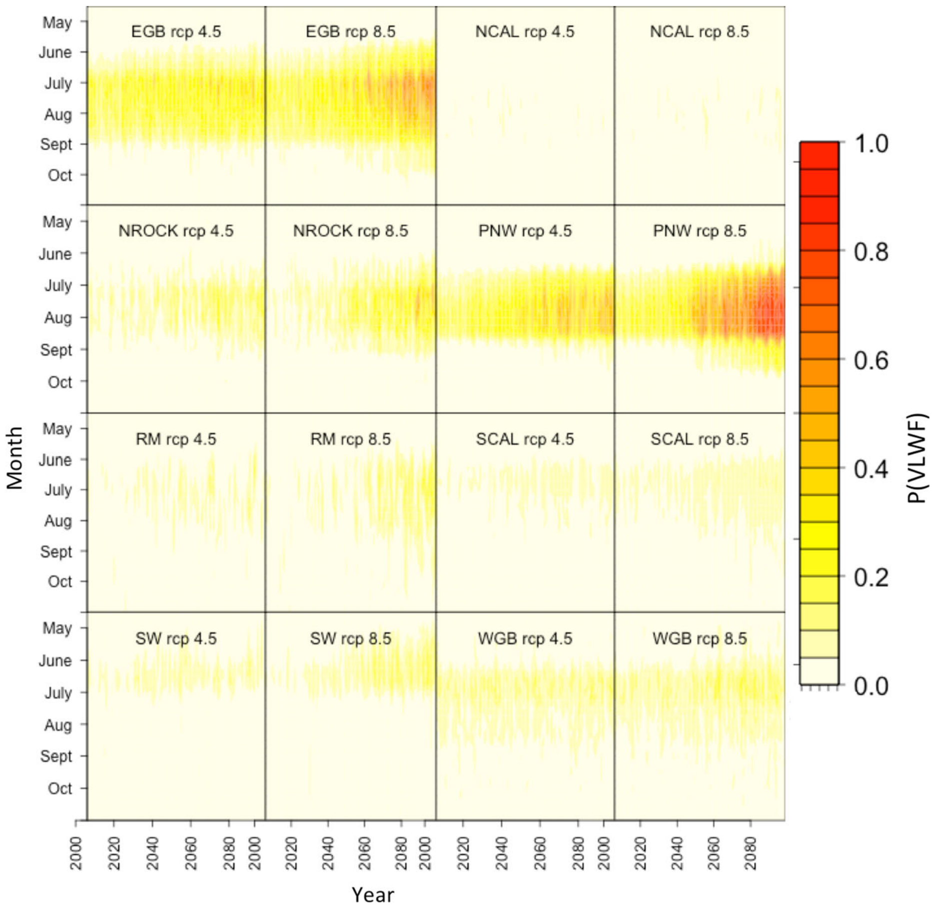

Fig. 2 The seasonality of P (VLWF) from 1979–2099. The historical modeled ensemble is used for 1979 to 2010. The ensemble mean of the14 GCMs is used for scenarios RCP 4.5 and RCP 8.5 from 2011 to 2099

exception, shows no indication under either RCP 4.5 or RCP 8.5 that the vulnerable fire season length or probability of VLWF will change.

3.3 Changes in the climate space

We examined spatial patterns of the change in frequency of extreme conditions as these are thought to increase the chance of an extreme event like VLWF. Generally, the frequency of days or months classified as having extreme climate (i.e., exceeding the decile threshold classified as "extreme" from 1979–2010 to 2031–2060 (Fig. 3)), especially with respect to high temperature and drought, will increase. There are areas, however, where more than three of the 14 GCMs disagree on such increases, particularly for: 1) BI in PNW, NCAL, NROCK, EGB, and RM, 2) FM1000 in EGB and RM, and 3) DMC for SCAL, WGB and EGB. GCMs predictions for temperature are more robust than for wind and relative humidity, consequently biophysical metrics that most linearly relate to temperature (e.g., FFMC and PDSI) have better model agreement than biophysical variables with more complicated derivations (BI, ERC, DMC, FM100, and FM1000).

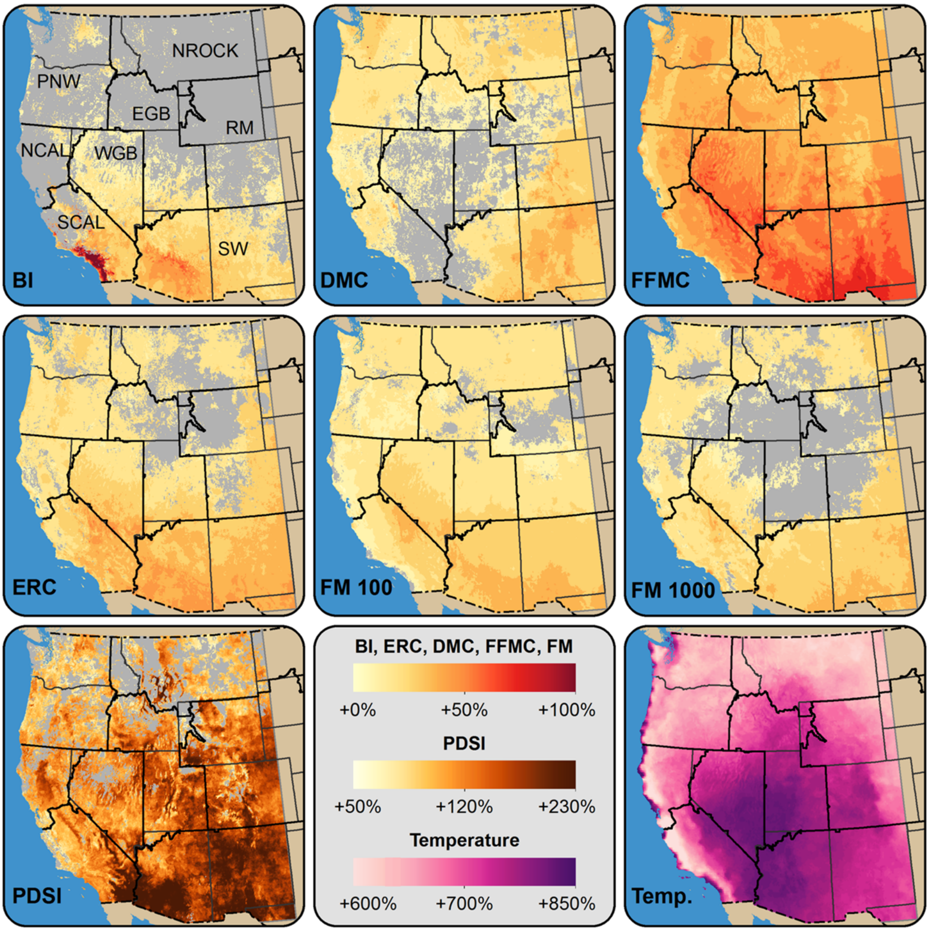

Fig. 3 Projected changes, under RCP 4.5, in the number of days or months that exceed the threshold defined by the upper/lower decile of days or months from 1979–2010 to 2031–2060 for each index. Changes are expressed as a percentage change from baseline conditions (e.g., +100 means a doubling). Regions where the signal is not robust, i.e. regions of high uncertainty across models, areas with <11 of 14 model agreement are gray. For ease, examining the spatial distribution of changes in FM100 and FM1,000 used inverted categorized color spectrums. FM100 and FM1000 decrease with increased fire danger, in contrast to all other variables, which increase with increased fire danger. Therefore, the color spectrums used for spatial investigation of the changes in climate space represent the same for all indices such that red denotes increased fire danger. Note: PDSI=Palmer drought severity index, TEMP=mean temperature, FFMC=fine fuel moisture code, DMC=duff moisture code, FM100=100-h. fuel moisture, FM1000=1000-h. fuel moisture, ERC=energy release component, and BI=Burning index

4 Discussion

4.1 Long-term trends and seasonal change

Understanding the effect of climate on the occurrence of VLWFs specifically, rather than annual-scale projections of area burned, provides insight into how the timing and seasonality of these events may change. All GACCs show an increase in the probability (Fig. 2) of VLWFs, and a significant (α=0.05) increase in their frequency (SOM Table 1), from the historical modeled (1950–2005) to the future (2031–2060) under RCP 4.5 and even more so under RCP 8.5. Periodic fluctuations in climate are reflected in the changing probability of a VLWF, although attributing probabilities to specific future years would constitute false precision that ignores the stochastic nature of climatic variability. Mapping the normalized probability of a VLWF across 14 GCMs (Fig. 1) shows the range of variability among GCMs. GACCs with the most inter-model variability of projected proportional change, PNW and RM, not only have the most models that agree that VLWFs will be more likely in the future, but also that the proportional change in probability of VLWF is the largest among GACCs.

A unique feature of this study is that it specifically projects the likelihood of VLWFs rather than fire-danger indices separate from their relationship to actual events (Liu et al. 2013), the less informative simple likelihood of a fire start (Preisler and Westerling 2007, Krawchuk et al. 2009, Parisien et al. 2012), or the aggregate statistic of annual area burned (Flannigan et al. 2005, Littell et al. 2009, Abatzoglou and Kolden 2013). Because VLWFs, defined in this study as the top two percent of fire sizes over the observed record (1984–2010), influence aggregate statistical relationships such as that between climate and annual area burned (Stavros et al. 2014), it is necessary to asses the seasonality of these events. The models used in this study enable more timely anticipation of rare VLWF events and show that not only can we project future increases in the probability of VLWF, but also longer VLWF seasons and vulnerable fire seasons.

By examining projected changes in key extremes that coincide with historical VLWF occurrence, we better explain regional variations in projected changes in VLWF probability. Generally, all GACCs project at least a 30 % increase in the mean normalized probability of a VLWF (SOM Table 1) and are expected to have more days and months with “extreme” conditions (i.e., high fire danger or low fuel moisture) than the observed period (Fig. 3). Understanding the influence of key predictors (Table 2) on changes in the probability of VLWF (SOM Table 1) is not straight forward (Stavros et al. 2014), but examining all indices of the climate space provides a broader foundation from which to develop hypotheses for further investigation. For example, areas that show the most increase in normalized probability of VLWF, the PNW, are flammability-limited (Littell et al., 2009; Stavros et al. 2014). Fire in these areas is directly associated with hot and dry weather, so it follows logically that as the climatic extremes of hot and dry become more likely in these areas, there will also be more fire.

On the other hand, areas that are fuel-limited, such as non-forested parts of SCAL and NCAL, and most of WGB (Littell et al., 2009; Abatzoglou & Kolden, 2013; Stavros et al. 2014) may experience reduced fuel abundance as warmer climate reduces the productivity of water-limited vegetation (McKenzie and Littell 2011) thus affecting fuel connectivity (Littell et al. 2009, Stavros et al. 2014), reducing area prone to fire (Krawchuk et al. 2009, Batllori et al. 2013) and possibly even the likelihood of VLWF. Consequently the likelihood of VLWF in these systems may not increase as much as in flammability-limited systems with a warming climate.

Our projections of longer seasons of high fire potential are similar to those from other studies (Liu et al. 2013). Because fire regimes are variable within GACCs, further investigation at finer spatial resolution is necessary to confirm or refine our understanding of the sensitivity of projected probabilities to the climate space, and to identify within-GACC heterogeneity in fire climatology.

4.2 Projection considerations

There are three limitations to our projections including (1) complications projecting downscaled biophysical variables, (2) non-stationarity in relationships used to develop VLWF models, and (3) lack of consideration in human impact on the occurrence of VLWF. First, biophysical variables provide may better correlations for fire potential than do meteorological variables like temperature and precipitation (Abatzoglou and Kolden 2013), but they require integrating variables over an extended time period. Temporal autocorrelation and inter-model biases in the simulation of meteorological variables may limit the direct application of downscaled data to future projections and exist even after downscaling and bias correction. Biases in modeled VLWF probabilities in the historic runs are likely a consequence of biases in the joint probability of predictor variables for multivariate logistic models, however a secondary downscaling of integrated metrics significantly reduced modeled biases between the historical model runs and observations for all GACCs except WGB (SOM Table 1). Further investigation of persistent bias in WGB showed modeled PDSI values higher than the observed, consequently models using PDSI may not accurately predict the probability of VLWF. Although both EGB and WGB models use PDSI, EGB has four explanatory variables, which may dampen the effect PDSI has on the final VLWF probability, thus explaining why WGB is the only model that over-predicts VLWF probability from the observed record.

Second, model development assumes stationarity both in climate-vegetation relationships and in the covariance structure used in statistical downscaling methods for climate data. The response of vegetation and wildfire patterns to climate change is not simple. For example, extreme environments are unsuitable for wildfire (Parisien and Moritz 2009), e.g., very hot and dry climates that lack fuel connectivity to carry wildfire or cold and wet climates where fuels are rarely flammable. Uncertainty exists about how vegetation, and the fire regimes it supports (Abatzoglou and Kolden 2013), will change VLWF-climate correlations (McKenzie and Littell 2011), thus weakening or changing the predictors used to calculate the probability of VLWF. Not only are VLWF-climate correlations subject to change in the future, but also statistical downscaling methods used on the climate data are contingent on relationships between stationarity in the covariance structure of coarse- to fine-scale patterns of climate. Changes in land-surface feedback processes (e.g., snow-albedo feedback) may modify the local energy budget and change the intrinsic covariance structure that was developed using observational data, thereby violating stationarity and introducing additional uncertainty in our downscaling approach. Such uncertainties are one motivation for using a multi-model approach rather than relying on the results of a single or few model experiments.

Third, the models used in this analysis are not spatially explicit and only account for climatic influence on the likelihood of VLWF, thus they exclude considerations of resource allocation for suppression. Because much of the United States experienced nearly a century of fire suppression, further analyses should distinguish climatic effects from those associated with fire management and changes in land use.

5 Conclusions

Because VLWFs have lasting effects socially and environmentally, understanding future changes can inform decision makers on how best to prepare for such events. This analysis, the first of its kind over the western US, addresses key questions about how the likelihood of rare VLWFs is projected to change both seasonally and over the 21st century. In general, across the western US, the likelihood of a VLWF will increase over the long-term, in duration of VLWF season, and in frequency of occurrence throughout the fire season. Areas with cooler and wetter climate (i.e., flammability limited systems like PNW or mixed regimes like RM) have higher increases in the likelihood of VLWF in the future than those with hotter and drier climate.

These results can be used to shape new fire policy, including fuel and air-quality management. For example, areas with previous fuel treatments have reduced tree mortality, fire behavior and spread rates, thereby proactively offsetting suppression costs, private property loss, environmental damages, and fatalities from VLWFs (Williams 2013). This work also informs air-quality policy because it matches the broad spatial extent but fine temporal resolution of air-quality modeling frameworks, e.g. BlueSky (Larkin et al. 2009), given that VLWFs are a principal cause of air-quality exceedances (Jaffe et al. 2008). Projections from this study may be a useful baseline for policy and management, by identifying regions of particular concern (i.e., where VLWFs are projected to increase greatly), and for future research that considers finer-scale variability in environmental gradients, ecosystem types, and large-fire potential.

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