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Climate and very large wildland fires in the contiguous western USA

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Abstract. Very large wildfires can cause significant economic and environmental damage, including destruction of homes, adverse air quality, firefighting costs and even loss of life. We examine how climate is associated with very large wildland fires (VLWFs ≥50 000 acres, or ~20 234 ha) in the western contiguous USA. We used composite records of climate and fire to investigate the spatial and temporal variability of VLWF–climatic relationships. Results showed quantifiable fire weather leading up and up to 3 weeks post VLWF discovery, thus providing predictors of the probability that VLWF occurrence in a given week. Models were created for eight National Interagency Fire Center Geographic Area Coordination Centers (GACCs). Accuracy was good (AUC > 0.80) for all models, but significant fire weather predictors of VLWFs vary by GACC, suggesting that broad-scale ecological mechanisms associated with wildfires also vary across regions. These mechanisms are very similar to those found by previous analyses of annual area burned, but this analysis provides a means for anticipating VLWFs specifically and thereby the timing of substantial area burned within a given year, thus providing a quantifiable justification for proactive fire management practices to mitigate the risk and associated damage of VLWFs.

Additional keywords: AUC, GACC, logistic regression, niche space, precision, rare events, recall, wildland fire.

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Introduction

Very large wildland fires (VLWFs) have occurred throughout the western contiguous US (also known as CONUS) in the past several years, setting modern records for the largest fires in several states (e.g. High Park, Colorado (2012), Long Draw, Oregon (2012), Wenatchee Complex, Washington (2012), Wallow Fire, Arizona (2011), Whitewater Baldy Complex, New Mexico (2012) and Rim Fire, California (2013); http://www.nifc.gov, September 2013). Such fires may have long-lasting effects including property damage, firefighting costs, loss and degradation of habitat and air quality reductions (Jaffe *et al.* 2008) leading to bronchitis or even premature mortality. Also, fires contribute to global warming, including both direct greenhouse gas emissions and secondary effects of black carbon and other emissions (Bond *et al.* 2013). During VLWFs, particularly if there are multiple VLWFs in a region, firefighting resources within the region may become strained and additional resources may be needed from other areas. More positively, large wildfires have been shown to provide a tool for regional ecological restoration in fire-dominated landscapes and have reduced fuel hazards (Keane *et al.* 2008).

Investigation and quantification of the mechanisms and climatic drivers of VLWFs is a first step towards providing justification for proactive fire management that could mitigate negative effects while encouraging restoration efforts. Past studies have focussed on quantifying factors influencing total annual area burned within a region (Westerling *et al.* 2002; Flannigan *et al.* 2005: Flannigan *et al.* 2009; Littell *et al.* 2009), and the probability of a fire of any size across North America (Parisien *et al.* 2012), or a single-day fire-growth event (Podur and Wotton 2011). Many of these studies have aggregated fires over an entire fire season and have not addressed factors influencing the possibility of individual VLWFs, thus they do not provide as much insight into the timing of large areas burned, which can be useful to develop proactive management strategies, such as fuel reduction or prescribed burning during periods with reduced risk of VLWF occurrence.

Studies investigating fire probability or fire behaviour across a range of fire sizes may fail to capture relationships with VLWFs because VLWFs may behave differently from smaller fires (Alvarado *et al.* 1998) and are often the consequence of uncommon circumstances; for example, extreme fire weather with abundant fuels and limited resources for suppression in their early stages. Studies addressing individual large fires have been geographically specific (Abatzoglou and Kolden 2011: Irland 2013; San-Miguel-Ayanz *et al.* 2013; Tedim *et al.* 2013), not extending across the western CONUS, or have examined only fire danger without linking it to actual events (Liu *et al.* 2013). Our study addresses this knowledge gap by (1) quantifying relationships between climate and the top 2% of fire sizes representing ~33% of all area burned from 1984 to 2010 in the western CONUS, and (2) quantifying intra-annual relationships between preceding and concurrent weather and the probability of VLWF occurrence across the western CONUS.

We analyse and quantify antecedent and concurrent weather and fire danger associations with VLWFs. We hypothesise that VLWFs are associated with an identifiable climatology; that is, individual VLWFs can be quantitatively linked to specific weather both leading up to and during these events. Using climate data (daily and monthly data over the record) and the Monitoring Trends in Burn Severity (MTBS) database of fire perimeters and burn severity, which has fire date of discovery, perimeter and burn severity classifications from 1984 to present, we focus on three questions. (1) What is the spatial and temporal distribution of VLWFs (≥50 000 acres, or ~20 234 ha) from 1984 to 2010 across the western CONUS? (2) Do antecedent and concurrent fuel conditions and fire danger for VLWF occurrence differ from those for other large wildfire (≥10 000 acres, or ≥4047 ha but <20 234 ha) occurrence? (3) How does this spatial and temporal variation affect the probability that a VLWF will occur?

Data and methods

Study area

Our analysis grouped climate and fire information within existing regional, operational management boundaries across the West CONUS (Fig. 1). Specifically, we examined the

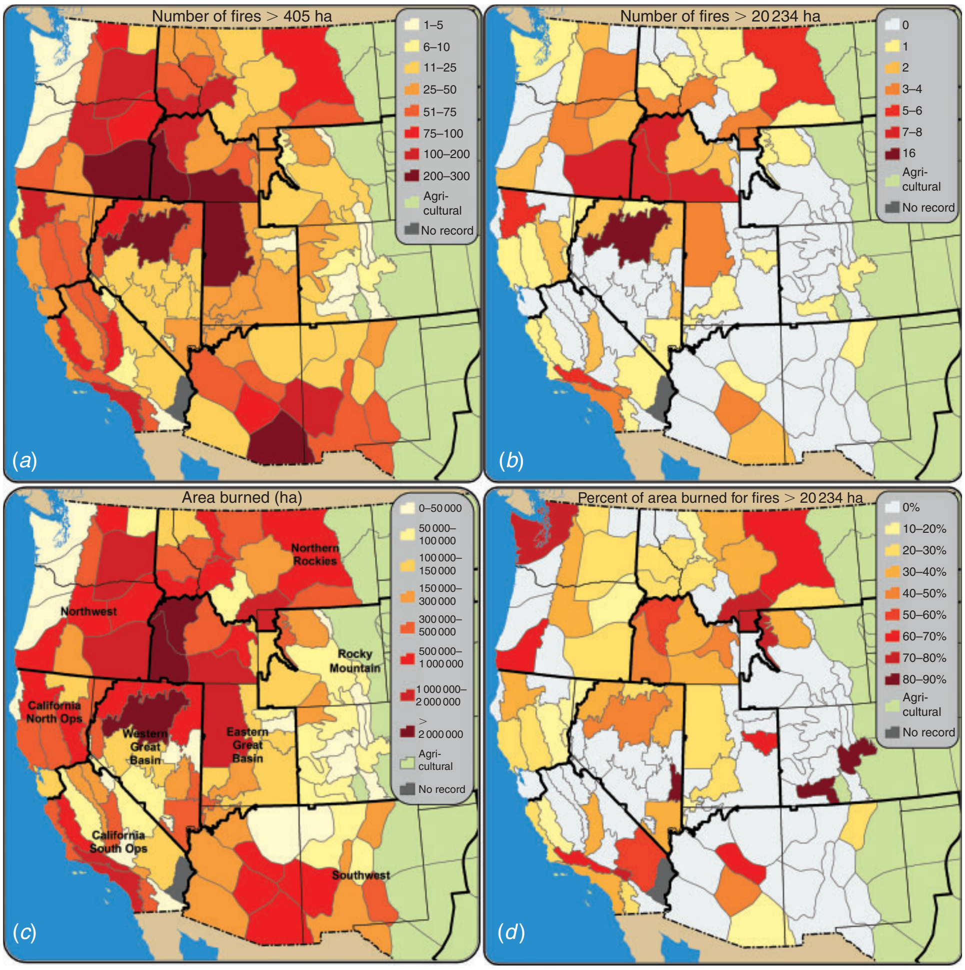

Fig. 1. Spatial patterns of four fire statistics across the study domain from 1984 to 2010. Smaller polygons indicate Predictive Service Areas by which statistics are calculated to show finer scale variability, whereas larger polygons in bold indicate Geographic area Coordination Centers: (*a*) total number of fires in Monitoring Trends in Burn Severity (MTBS) ≥404 ha, (*b*) number of fires in MTBS ≥20 234 ha, (*c*) hectares burned between 1984 and 2010 by all fires and (*d*) total area burned between 1984 and 2010 for fires ≥ 20 234 ha divided by total area burned by all fires.

geographic areas defined by the US National Interagency Fire Center as Geographic Area Coordination Center (GACC). GACCs are operation management units used in decision making and regional forecasting for air quality management that do not coincide directly with ecological boundaries or vegetative fuel types. Each GACC is broken into smaller polygons called Predictive Service Areas (PSAs) (http://psgeodata.fs.fed.us/data/gis_data_download/static/PSA_2009.zip, accessed 1 October 2011). To study wildland fires specifically, we excluded PSAs within each GACC for which large fires are primarily agricultural (defined by the Terrestrial Ecoregion L1 boundaries, Olson *et al.* 2001), but wildland fires include fires that burn in non-forested and forested areas. 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). We modelled VLWFs at the GACC scale because the rarity of VLWFs makes finer scale analyses difficult with sample sizes too small to develop predictive models.

Fire data

For fire area, we used fire perimeters from the MTBS dataset produced by the US Forest Service (http://www.mtbs.gov, accessed 1 October 2012). MTBS spans 1984–2010 and includes area burned and burn severity data within nearly 6000 fire perimeters ≥405 ha across the domain. Any areas within the fire perimeter, categorised as 'unburned/unchanged' by MTBS, were excluded in burned area calculations to achieve a more accurate estimate (Kolden *et al.* 2012).

We used past records of fire discovery date to define the core fire season within each GACC and excluded data outside the season from the analysis. Statistical analyses often assume that data classes are balanced, but this is not the case with rare events such as VLWFs (He and Garcia 2009). Consequently, we reduced each year to the core fire season, creating a more balanced dataset and improving inference from statistical analyses. The core fire season was defined for each GACC as the time window within which fires accounting for the middle 95% of the area burned in an average year over the record (Fig. 2; i.e. Abatzoglou and Kolden 2013).

Each week of the core fire season was classified as a 'VLWF week', 'large fire week' or 'no fire week'. Because VLWFs are rare, there were many fewer VLWF weeks than weeks in which no VLWFs occurred (e.g. RM has three VLWF weeks out of 621 weeks available for analysis). Analysis was aggregated to weeks to maintain the fine temporal resolution that makes this analysis so unique. Unfortunately, daily resolution would have created even more of an imbalance in the data and is more subject to temporal autocorrelation. Also, MTBS provides dates of discovery, but there is some uncertainty in that estimate, thus aggregating data to the week made the most sense.

Climate data and derived indices

Climate data were averaged spatially across all pixels (800 m for monthly data, 4 km for daily data) within each GACC perimeter (excluding PSAs within the Great Plains). This aggregation assumes homogeneity of fire regime, vegetation, climate and weather within a GACC. Two gridded climate datasets over the record were considered: (1) monthly temperature (°C) and precipitation from Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly *et al.* 2008), and (2) daily surface meteorological data from Abatzoglou (2013). Multiple biophysical metrics were also available and used for this analysis because, as Abatzoglou and Kolden (2013) suggest, biophysical metrics are more directly linked to fuel flammability than meteorological variables. Furthermore, biophysical metrics provide a means by which short- and long-term effects of moisture in a system are represented in the window of vulnerability that defines the 'VLWF climatology', the focus of this study.

Biophysical metrics used include the Palmer Drought Severity Index (PDSI) and fire danger indices, calculated from the daily surface meteorological data, of the National Fire Danger Rating System (NFDRS) and the Canadian Forest Fire Danger Rating System (CFFDRS). PDSI, calculated from the monthly data, is a time-averaged measure of drought believed to track soil moisture (Mika *et al.* 2005). NFDRS calculations used fuel model G (dense conifer stand with heavy litter accumulation) to maintain consistency with previous studies (Andrews *et al.* 2003) and greenup dates to initiate each year defined as the first day when the normalised growing season index is >0.5 (Jolly *et al.* 2005; M. Jolly, pers. comm.). CFFDRS used greenup defined as when maximum temperature is >12°C for 7 consecutive days. Both CFFDRS and NFDRS are used because each has been shown to be more effective depending on the region (Fig. 3, Xiao-rui *et al.* 2005).

We used six indices from the NFDRS and CFFDRS: (1) NFDRS–100-h fuel moisture (FM100) represents the moisture content of dead fuels 2.5–7.6 cm in diameter or approximately the moisture content of 1.9–10.2 cm of soil; (2) NFDRS–1000-h fuel moisture (FM1000) represents moisture content of dead fuels 7.7–15.2 cm in diameter. Lower values of FM100 and FM1000 represent drier conditions; (3) NFDRS–energy release component (ERC) represents the daily worst-case scenario of total available energy per unit area within the flaming front at the head of a fire; (4) NFDRS–burning index (BI) represents the difficulty of fire control as a function of spread rate and ERC.

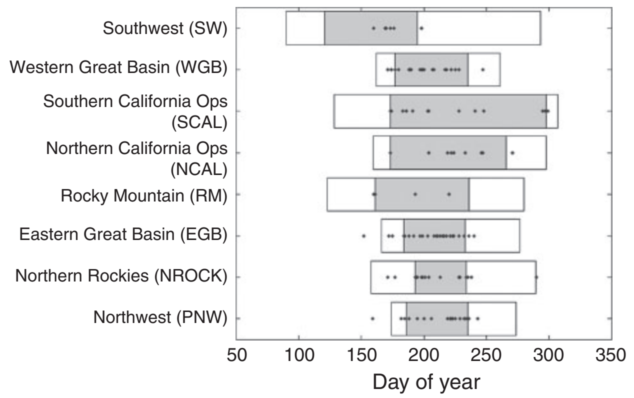

Fig. 2. Core fire season and extended fire season by Geographic Area Coordination Center. Seasons are defined by the average middle 95% of annual area burned (inside white rectangle) in the historical record. The shaded grey region denotes the middle 75% of annual area burned. The points represent very large wildland fire events by discovery date.

Higher values of ERC and BI represent higher fire danger; (5) CFFDRS–fine fuel moisture content (FFMC) represents the relative ease of ignition and flammability of fine fuels; (6) CFFDRS–duff moisture code (DMC) represents average moisture content of loosely compacted organic layers of moderate soil depth. Higher values of FFMC and DMC represent drier conditions. These indices were selected because exploratory data analysis suggested strong associations with the fire data.

Large fire v. *VLWF climatology*

A composite analysis was used to answer our second question: do antecedent and concurrent fuel conditions and fire danger differ for VLWFs than for other large wildfires and for weeks during the fire season without large fires? Composite analysis compares fire climatology between GACCs by showing the climate and fire danger percentiles for fires classified as large *v.* VLWF relative to the date of discovery. As explained under *Fire data*, the analysis is aggregated by weeks, whereby weeks are defined by day of year, for example, week 1 = 1–7 January. This shows the difference in mean (and 95% confidence intervals estimated using bootstrapping with $n = 1000$) of biophysical conditions for all fires within a given classification for a GACC from 10 weeks before and after the discovery of the fire

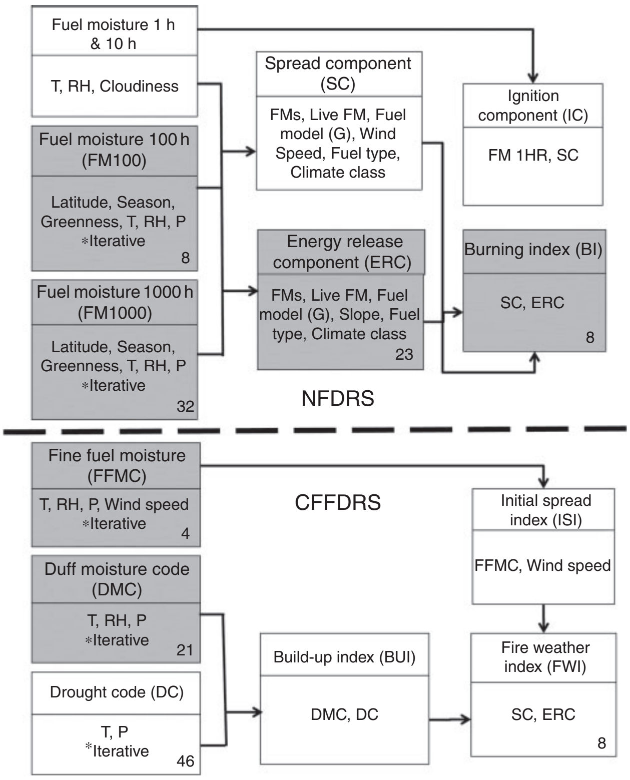

Fig. 3. Computational flow chart of the US National Fire Danger Rating System (NFDRS) *v.* the Canadian Forest Fire Danger Rating System (CFFDRS). Similar positions in the flow charts indicate similar metrics (Xiao-rui *et al.* 2005). The number in the lower right corner represents the residence time in days that any given calculated index has an effect on subsequent calculated indices. Grey shading denotes indices used in this analysis. Note: T, temperature; RH, relative humidity; P, precipitation.

(when the number of weeks before or after discovery (x) is zero, i.e. the week of discovery). Temperature and PDSI were used to examine fire climatologies up to 1 year before discovery and to provide insight into longer term lagged effects of weather.

Probability of a VLWF week

We built logistic regression models for each GACC to estimate the probability of a VLWF week. Predictor variables included climate and fire danger indices as described previously. The hypothesised mechanisms relating each predictor variable to VLWF probability suggest a variety of potential time lags. For example, weather several weeks in advance of ignition could influence fire risk through reduced fuel moisture, whereas weather after ignition could influence VLWF probability by spread from wind and lack of significant precipitation. To allow for these time lags during model building, we used composite graphs to identify predictor variables at multiple time lags. Note that PDSI and temperature (TEMP) are monthly indices that were assigned to all days of the month. Furthermore, explanatory variables used in this analysis were raw values rather than the percentiles applied by managers for fire danger ratings. Percentiles are dependent on the range of values in the model database used to generate them. Thus, using percentiles over-calibrates models to the dataset used to generate them by influencing regression coefficients in the model selection process.

We applied the following binomial logistic regression model selection procedure independently for each GACC. We built models by minimising the Akaike Information Criterion (AIC), then removing insignificant ($P > 0.05$) variables one at a time; re-estimating the model after each elimination. Next, we examined the resultant models for any correlated predictors (Pearsons correlation coefficient $\geq$0.8) retaining the first occurrence of the correlated predictors. We confirmed that all predictor variables retained in the model still met the significance criterion ($P < 0.05$). Forward stepwise regression using AIC avoids corruption of α levels usually associated with forward selection (Anderson *et al.* 2000; Anderson and Burnham 2002; Mundry and Nunn 2009). We used standard odds ratios (OR) to estimate each predictor's influence on the probability of a VLWF week. To understand how sensitive model selection and accuracy statistics were to the choice of VLWF threshold, we built an additional two models for each GACC using alternative definitions of VLWF ($\geq$10,000 acres, or ~4407 ha and $\geq$25 000 acres, or ~10 117 ha).

We evaluated each model using a combination of precision, recall and area under the (receiver operating characteristic) curve (AUC). Precision is 'a measure of exactness' returning the probability of correctly classifying a VLWF, whereas recall is 'a measure of completeness' returning the probability of correctly classifying a VLWF that is actually a VLWF (He and Garcia 2009). There is generally a trade-off between precision and recall. To calculate precision and recall, the model output – probability of a VLWF week – was converted into binary predictions of VLWF week (Table 1). We used a sliding classification criterion, in increments of 0.05, to translate model output into binary VLWF predictions. For example, a classification criterion of probability $\geq$0.5 categorises any probability $\geq$0.5 as a VLWF week. We evaluated model predictive accuracy across all thresholds using AUC, which quantifies the relative trade-offs between true positives (benefits) and false positives (costs) (He and Garcia 2009). An AUC of 0.5 indicates that the model predicts no better than random, whereas a value of 1.0 indicates that the model makes perfect predictions (Harrell 2001).

Results

Large fire v. *VLWF climatology*

In all GACCs, unlike monthly PDSI values, monthly temperature anomalies are highly variable and show limited evidence of meaningful differences in conditions between VLWFs and large fires (Fig. 4). One exception is that fire season temperatures coincident with VLWFs in NROCK and RM have ~2°C warmer temperature anomalies than during large fires. In contrast, PDSI values for VLWFs in several GACCs (most notably in WGB and less so in EGB and SCAL) show a transition from pluvial conditions (PDSI >2 = wet) the year before fire discovery to moisture deficits during the fire season. VLWFs in SW occur during periods of drought and after negative PDSI the summer previously. VLWFs in RM and NROCK appear to occur during drought.

In contrast to the limited and disparate relationships observed for VLWFs using monthly metrics, strong commonality across GACCs was observed in the composite analysis for weekly fire danger indices (Fig. 5). Elevated fire danger generally occurs during and up to 3 weeks following the week of VLWF discovery. Fire danger indices with slower response times (i.e. FM1000, ERC, DMC) sustain conditions in the upper decile in the weeks following the discovery week. For large wildfires, fire danger indices were more moderate and typically subsided the week following fire discovery. In many of the GACCs, there is higher fire danger and drier fuels 2 weeks before the discovery week of VLWF than other large fires. These differences are used to define predictor variables as time durations of calculated indices both before and after fire discovery driving fire growth.

Table 1. Contingency table structure and associated model accuracy statistics precision and recall

Note: TP, true positive; FP, false positive; TN, true negative; FN, false negative. Recall = TP/(TP + FN) = probability of predicting a very large wildland fire (VLWF) that is actually a VLWF. Precision = TP/(TP + FP) = probability of correctly classifying a VLWF

		Observed	
		VLWF	Large fire
Predicted	VLWF	TP	FP
	Large fire	FN	TN

Probability of a VLWF week

Models to predict the probability of a VLWF week and the effect of predictors on the output probability differed by GACC (Tables 2, 3). In general, models predicting VLWF probability for all GACCs included seasonal drought signals (FM100, FM1000, ERC, BI, DMC). Models for EGB and NROCK included short-term, fire weather signals (FFMC). Models for EGB and WGB included long-term moisture signals (PDSI).

The OR (Table 3) demonstrates the effect size of any one predictor variable on the response by holding all other predictors constant. In general, models for all GACCs show that hotter,

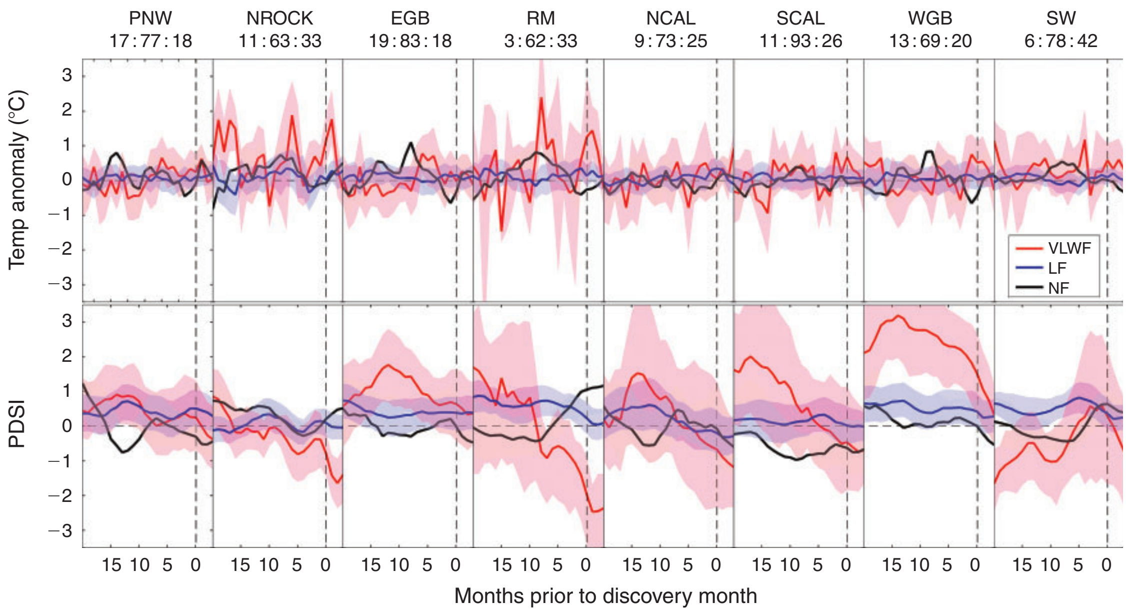

Fig. 4. Monthly composite plots of temperature anomaly and Palmer Drought Severity Index up to 21 months before and 2 months post the month of discovery. Solid lines denote mean conditions where red is very large wildland fires (VLWFs), blue is all other large fires (LF, ≥405 ha) and grey is weeks in the fire season with neither VLWF nor LF – 'no fire'. The dashed line is the VLWF month. The numbers at the top are the ratios of the number of VLWF months to number of large fire months to number of VLWF months with no fire. Note: EGB, Eastern Great Basin; NCAL, Northern California; NROCK, Northern Rocky Mountains; PNW, Pacific Northwest; RM, Rocky Mountains; SCAL, Southern California; SW, Southwest; WGB, Western Great Basin.

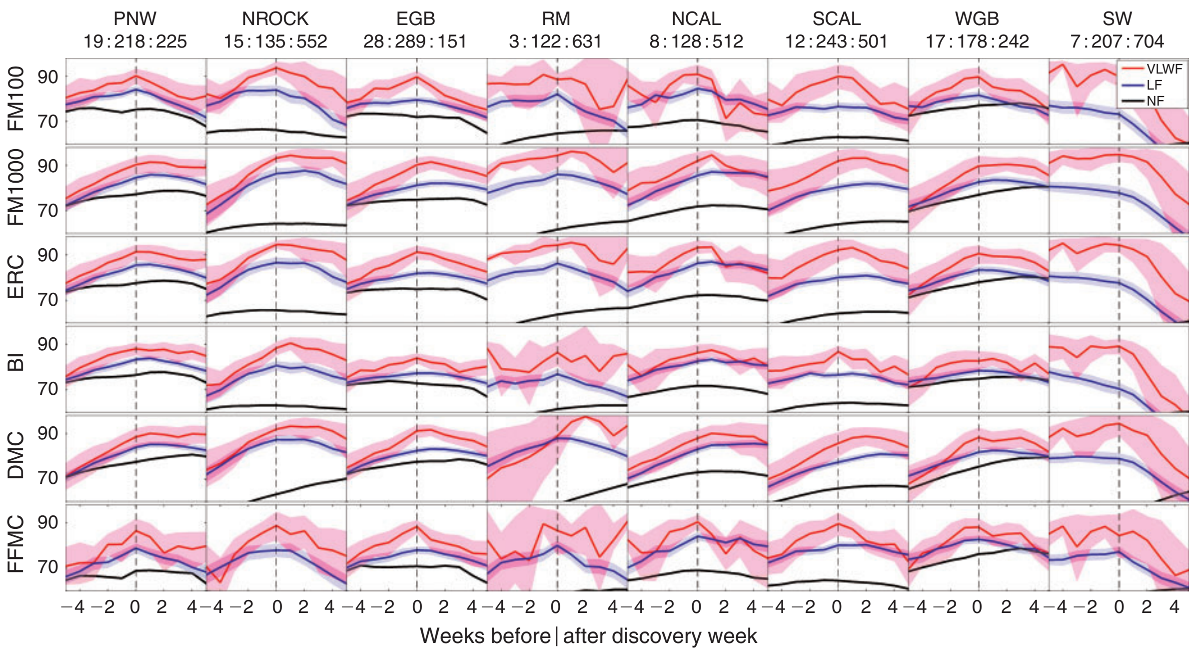

Fig. 5. Weekly composite plots from 6 weeks before discovery of fire and 6 weeks following. Solid lines denote mean conditions where red is very large wildland fires (VLWFs), blue is all other large fires (LF, ≥405 ha) and grey is weeks in the fire season with neither VLWF nor LF – 'no fire'. The shaded regions represent a 95% confidence interval. The dashed line is the VLWF week as defined by day of year, with week 1 = 1–7 January. The *x*-axis shows weeks from discovery week. The lighter shaded regions denote the 95% confidence interval of the mean. The numbers at the top are the ratios of number of VLWF weeks to number of large fire weeks to number of weeks with no fire. Note: EGB, Eastern Great Basin; NCAL, Northern California; NROCK, Northern Rocky Mountains; PNW, Pacific Northwest; RM, Rocky Mountains; SCAL, Southern California; SW, Southwest; WGB, Western Great Basin.

Table 2. Models by Geographic Area Coordination Center (GACC) to calculate the probability of conditions during a given week being conducive for fire growth to very large wildland fire (VLWF) size

AUC is the area under the receiver operating characteristic curve. Note: we defined explanatory variables as the calculated index averaged over the suffix such that '.1' denotes the week before 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; FM1000, 1000-h fuel moisture; ERC, energy release component;and BI, Burning index

GACC	VLWF size (ha)	$P(VLWF) = 1/(1 + e^b)$ where b =	AUC
EGB	20 234	31.033 − 0.226 × FFMC.0 − 0.260 × TEMP.0 − 0.015 × DMC.n3 − 0.238 × PDSI.n1	0.84
NCAL	20 234	−8.500 + 1.290 × FM1000.n1	0.86
NROCK	20 234	−13.951 − 0.309 × BI.n3 + 0.672 × FM100.0 + 0.334 × FFMC.n1 + 0.026 × DMC.0 − 0.366 × TEMP.1	0.93
PNW	20 234	6.664 − 0.514 × TEMP.n1 + 0.468 × FM1000.n1	0.86
RM	20 234	11.930 − 0.057 × DMC.n3	0.97
SCAL	20 234	18.660 − 0.193 × ERC.n1	0.80
SW	20 234	8.430 − 0.017 × DMC.0	0.92
WGB	20 234	−4.532 + 1.279 × FM100.0 − 0.392 × PDSI.0	0.86

drier conditions increase the probability of a VLWF week. EGB and WGB show PDSI with an OR >1, thus increased long-term moisture increases the probability of a VLWF week. The NROCK model also includes FFMC and DMC, which have OR <1, indicating that wetter conditions increase the probability of a VLWF.

Models for all GACCs have AUC >0.8, suggesting that the models have high predictive ability (Harrell 2001), but examining the trade-offs between precision and recall demonstrates that model probabilities are classified as zero above low threshold probabilities (Fig. 6). Because of the large zero inflation, the model can achieve reasonably high predictive ability by simply predicting a probability of zero. This phenomenen is most obvious when the percentage of non-VLWF weeks ≥98 (e.g. NCAL, SCAL and SW at 20 234 ha and RM at 10 117 and 20 234 ha).

Models predicting the odds of a VLWF using smaller fire size thresholds with more fire weeks are more balanced (smaller

Table 3. Table of odds ratio (OR, i.e. effect size) of explanatory variables for each Geographic Area Coordination Center (GACC) model
OR >1 indicates a positive relationship that an increase in the predictor results in an increase in the probability of a very large wildland fire (VLWF) week. OR < 1 indicates a negative relationship that an increase in the predictor results in a decrease in the probability of a VLWF week. Note: CI, confidence interval. We defined explanatory variables as the calculated index averaged over the suffix such that '.1' denotes the week before 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; FM1000, 1000-h fuel moisture; ERC, energy release component; BI, Burning Index

GACC		Explanatory variable OR				
EGB	variable	FFMC.0	TEMP.0	DMC.n3	PDSI.n1	
	OR	1.25	1.3	1.01	1.27	
	95% CI	(0.98,1.61)	(1.05,1.60)	(1.00,1.03)	(1.02,1.58)	
NCAL	variable	FM1000.n1				
	OR	0.28				
	95% CI	(0.12,0.64)				
NROCK	variable	BI.n3	FM100.0	FFMC.n1	DMC.0	TEMP.1
	OR	1.36	0.51	0.72	0.97	1.44
	95% CI	(1.14,1.63)	(0.28,0.92)	(0.58,0.89)	(0.96,0.99)	(1.06,1.97)
PNW	variable	TEMP.n1	FM1000.n1			
	OR	1.67	0.63			
	95% CI	(1.15,2.43)	(0.44,0.89)			
RM	variable	DMC.n3				
	OR	1.06				
	95% CI	(1.02,1.10)				
SCAL	variable	ERC.n1				
	OR	1.21				
	95% CI	(1.10,1.33)				
SW	variable	DMC.0				
	OR	1.02				
	95% CI	(1.01,1.02)				
WGB	variable	FM100.0	PDSI.0			
	OR	0.28	1.48			
	95% CI	(0.15,0.50)	(1.15,1.90)			

portion of zeros), and may be more robust because they included a larger sample of VLWFs. We identified similar predictor variables for models across the three fire size thresholds within a region in all GACCs except NCAL and PNW (Tables 2, 4).

Discussion

VLWFs across space and time

The spatial and temporal distributions of VLWFs show three patterns. First, mapping the number of fires and percentage area burned by VLWFs (Fig. 1) shows fine-scale variability at the PSA scale such that many PSAs have no VLWF occurrence, PSAs with the most fires also have the most VLWF occurrences and PSAs with VLWFs have a substantial percentage of annual fire area burned by VLWFs. Second, fire seasons are qualitatively different among GACCs (Fig. 2) and, with the exception of SW, VLWFs occur throughout the fire season. Third, years with the most annual area burned are years with not only a substantial fraction of hectares burned by VLWFs (Fig. 7), but also an increased number of VLWFs (Fig. 8).

VLWF climate space

This analysis is unique in that it specifically examines large wildfire events and thus provides insight into what drives individual VLWFs. We focus on the climate space (i.e. climate–VLWF relationships), because although there are other controls on fire size – such as fuel abundance and connectivity, and topographic complexity (Hessburg *et al.* 2000; Littell *et al.* 2009; Kennedy and McKenzie 2010) – extreme climate and weather can neutralise the effects of other controls (Turner and Romme 1994; Bessie and Johnson 1995). We compared findings from this analysis to those for annual area burned in previous studies because similar broad-scale ecological mechanisms were associated with VLWFs, thus suggesting that the VLWF size class may substantially influence associations found in aggregate analyses.

Identifying the VLWF climate space requires both examining the fire climatologies and interpreting the effect of predictors on the probability of a VLWF week. Fire climatologies provided qualitative assessment of both short- and long-term fire danger preceding and post-fire discovery across a variety of time lags (Figs 4, 5). From these climatologies, we determined windows of vulnerability during which fire weather leading up to and following the discovery of fire is important for determining fire growth to VLWF size. These qualitative findings provided a foundation from which to develop quantitative models of VLWF probability. Using these models and ORs (Table 3), we interpret the effect of predictors on the probability of a VLWF week despite incomplete independence between predictors – a result of nonlinear relationships between meteorological data and the biophysical metrics used to generate the predictors. Because predictors are not completely independent, the sign and

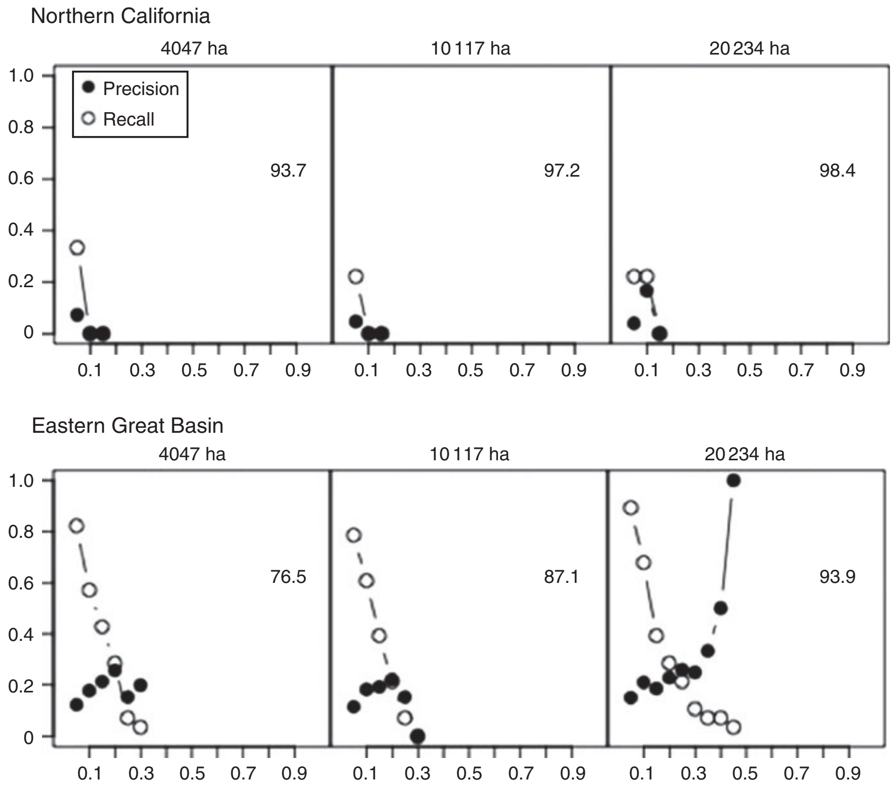

Fig. 6. Trade-offs between precision and recall of two characteristic Geographic Area Coordination Centers: Eastern Great Basin and Northern California, for each of the three very large wildland fire (VLWF) size thresholds. The *x*-axis is the probability threshold for classifying a VLWF (i.e. a probability >0.2 is a VLWF). Solid circles represent normalised precision (how well do the models predict VLWFs) and hollow circles represent recall (how often do the models miss VLWFs that actually happened). The numbers on the right of each graph denote the percentage of non-VLWF weeks. For a complete list of precision and recall values, see Table A1 in the Appendix.

Table 4. Models by Geographic Area Coordination Center (GACC) to calculate the probability of conditions during a given week being conducive for fire growth to very large wildland fire (VLWF) size for alternate size thresholds defining VLWF

AUC is the area under the receiver operating characteristic curve. Note: we defined explanatory variables as the calculated index averaged over the suffix such that '.1' denotes the week before 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; FM1000, 1000-h fuel moisture; ERC, energy release component; BI, Burning Index

GACC	VLWF size (ha)	P(VLWF) = 1/(1 + e^b) where b =	AUC
EGB	10 117	0.004 + 0.501 × FM1000.n3 − 0.165 × TEMP.n1 − 0.181 × PDSI.n3	0.78
	4047	−1.393 + 0.550 × FM1000.n2 − 0.161 × TEMP.n1 − 0.202 × PDSI.0	0.80
NCAL	10 117	64.410 − 0.594 × FFMC.0 − 0.120 × BI.0	0.84
	4047	12.211 − 0.153 × ERC.0	0.79
NROCK	10 117	4.67 − 0.158 × BI.n3 + 0.567 × FM100.0	0.93
	4047	−8.822 − 0.192 × BI.n2 + 0.133 × FM100.0 + 0.278 × FFMC.n1 − 0.021 × DMC.n3 − 0.199 × TEMP.n1	0.93
PNW	10 117	3.759 + 0.584 × FM100.0 − 0.322 × TEMP.n1 − 0.010 × DMC.n3	0.88
	4047	0.761 + 0.450 × FM100.0 − 0.103 × BI.n3	0.81
RM	10 117	9.640 − 0.045 × DMC.n1	0.93
	4047	1.450 − 0.033 × DMC.n2 + 0.483 × FM1000.1	0.92
SCAL	10 117	−1.53680 − 0.158 × ERC.n1 + 0.175 × FFMC.1	0.75
	4047	10.460 − 0.141 × ERC.n1 + 0.101 × TEMP.n3	0.74
SW	10 117	−2.938 + 0.753 × FM1000.n2	0.89
	4047	−1.500 + 0.599 × FM1000.n1 − 0.080 × TEMP.n3	0.86
WGB	10 117	14.596 − 0.012 × DMC.0 − 0.180 × TEMP.n2 − 0.345 × PDSI.0 − 0.080 × BI.n2	0.81
	4047	40.910 − 0.366 × FFMC.0 − 0.296 × PDSI.0 − 0.069 × BI.n2	0.76

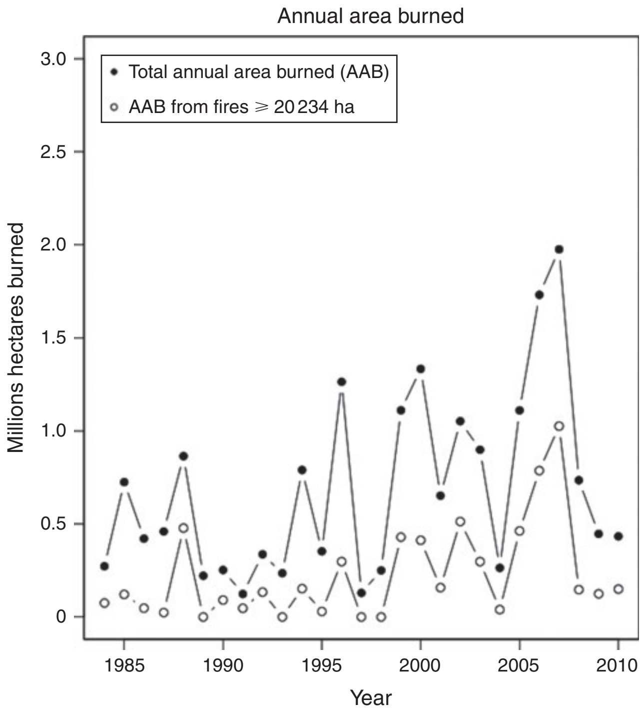

Fig. 7. Proportion of annual area burned across the western contiguous US by very large wildland fires (VLWFs; grey) and by all large fires including VLWFs (black), by the criteria defined on this study. This illustrates that in many years, the largest fires constitute a substantial proportion of the annual area burned.

magnitude of coefficients cannot be used to compare the relative influence of predictors directly.

Confirming our hypothesis that VLWFs are associated with an identifiable climatology, the climate space of VLWFs across the West CONUS shows very different fire danger leading up to and during discovery of VLWFs than with large wildfires. Despite commonality among GACCs, there is variability that reflects either fuel-limited or flammability-limited fire regimes. Fuel-limited fire regimes in extremely hot, dry climates are enabled by fuel accumulation and connectivity developed during wet conditions the year prior to fire (Veblen *et al.* 2000). Flammability-limited fire regimes in more moderate climates and forested vegetation (Littell *et al.* 2009) have sufficient fuel to burn under the right conditions. It is difficult to classify a fire regime for entire GACCs because of finer scale variability of climate, ecotypes (i.e. groupings of similar ecosystems) and fire regimes within them (Fig. 1; Littell *et al.* 2009; Littell *et al.* 2010).

The composite plots (Figs 4, 5) show that mountainous and Northern regions are generally flammability limited, in agreement with the conceptual model of annual area burned and climate (Littell *et al.* 2009). For example, in PNW, the most influential predictor (defined using the magnitude of the OR) is temperature the week following discovery. In agreement with findings from Littell *et al.* (2010), which show annual area burned increase with low summer precipitation and high temperature, the probability of VLWF increases under hotter (OR = 1.67) and drier (OR = 0.63) conditions (Table 3). In NROCK, our models and the composite graphs suggest that

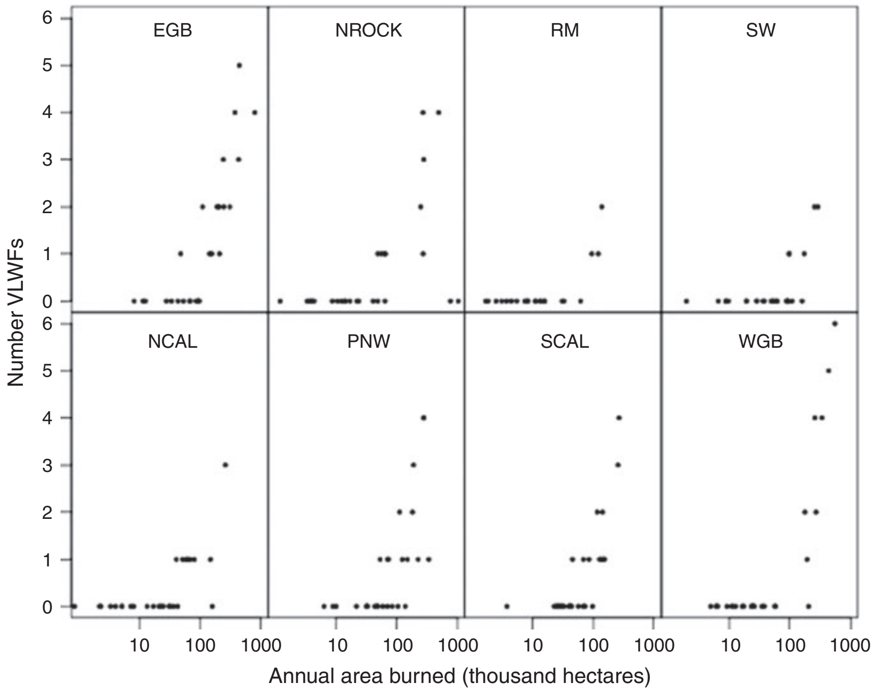

Fig. 8. Scatterplot of annual area burned and number of VLWFs for each Geographic Area Coordination Center. Note: EGB, Eastern Great Basin; NCAL, Northern California; NROCK, Northern Rocky Mountains; PNW, Pacific Northwest; RM, Rocky Mountains; SCAL, Southern California; SW, Southwest; WGB, Western Great Basin.

drying of medium-sized fuels (FM100, OR = 0.51) during the discovery week and increased temperature leading up to it (OR = 1.44), as well as increased heat and rate of fire growth (BI, OR = 1.36), increase the probability of occurrence of VLWFs. Counter-intuitively, when FFMC and DMC increase (i.e. drier conditions), the probability decreases. An increase in FFMC probably decreases the probability because the model uses both FM100 and FFMC, which are sufficiently correlated (Pearsons correlation coefficient = 0.55) to have interacting effects on the predicted probability, but not enough so to be excluded from the model. Although an increase in DMC decreases the probability of a VLWF, the OR for DMC is very close to 1 and thus does not heavily influence the output probability. In RM and NCAL, drying of fuels increases the probability of VLWF occurrence.

NROCK and RM experience periods of warmer temperature in the winter preceding VLWF occurrence, and it could be argued that this relates to timing of snow melt and consequent associations with fire incidence (Westerling *et al.* 2006). Although the relationship between winter temperature anomalies and timing of snow melt is beyond the scope of this investigation, it is worth noting that PDSI does not discriminate between snow and rain precipitation, thus examining the timing of temperature anomalies and PDSI could provide some insight into how the timing of snow melt affects moisture conditions in the system. However, neither NROCK nor RM models select PDSI as a dominant predictor and thus no conclusions can be reliably drawn from this analysis relating snow melt and winter temperature anomalies. It could be argued that a direct measure of snow melt (i.e. snow water equivalent (SWE)) should have been included in the analysis because it has been shown to correlate with area burned during the first half of the fire season for these areas (Abatzoglou and Kolden 2013). However, preliminary analyses used to identify predictor variables for model development showed no strong qualitative relationship between VLWF occurrence and SWE, thus excluding SWE as a predictor variable for the quantitative portion of this work. Lack of a relationship between SWE and VLWF may be a result of aggregating all VLWFs into one fire season rather than looking at how VLWF climatology varies within a fire season, an analysis that is not feasible because of limited samples of VLWFs in some regions (notable RM).

Dry, fuel-limited areas such as WGB and parts of EGB show similar dominant predictors with both long- and short-term precipitation influencing the occurrence of VLWFs, in agreement with findings from previous studies (Westerling and Swetnam 2003; Littell *et al.* 2009). In WGB, seasonal drought (i.e. dry conditions over the season, FM100, OR = 0.28) peaking the week of discovery, and increased long-term moisture signals (PDSI, OR = 1.48) increase the probability of VLWF occurrence. Similarly, in EGB, increased short-term (FFMC, OR = 1.25) and seasonal drought (DMC, OR = 1.01) during and up to 3 weeks post the discovery week, as well as increased temperature (OR = 1.3) and long-term moisture signal (PDSI, OR = 1.27), increases the probability of VLWF. Although an increase in long-term moisture signal (PDSI) to increase the likelihood of VLWF may initially seem counter-intuitive, this represents the fuel-limited fire regime over the regions. Because PDSI values are influenced by values up to 10 months earlier (Cook *et al.* 2007), increased values of PDSI indicate wet conditions in the months preceding discovery of VLWF. Although PDSI was designed for agricultural purposes in the Midwestern US (Palmer 1965), and was not intended as a panacea for long-term moisture stress, the composite plots show positive PDSI for at least 1 year prior in WGB and EGB for a year to 6 months before the month of VLWF discovery confirming preceding wet conditions. Previous studies have shown area burned in non-forested areas of EGB and WGB had significant correlations with the previous year's moisture (Littell *et al.* 2009; Abatzoglou and Kolden 2013). EGB also showed significant correlations between area burned in forested areas and in-season fire danger (Abatzoglou and Kolden 2013), thus demonstrating the mixed fire regime of EGB between fuel and flammability limited.

Similar to EGB, SW has an intermediate fire regime (Swetnam and Baisan 1996; Littell *et al.* 2009). In concurrence, our model shows that increased seasonal drought (DMC, OR = 1.02) peaking the week of discovery increases the probability of VLWF occurrence. There is a sharp decline in fire danger indices the month following discovery of all fires in the dataset for SW, especially VLWFs (Fig. 5), which is likely attributable to monsoonal moisture responsible for curtailing fire growth. In correspondence, Fig. 2 shows that most VLWFs occur in the hot, dry months before the monsoon. It could be argued that if precipitation events, such as monsoon, can occur during periods of long-term drought and concurrent with fire (thus affecting the likelihood of that fire growing to VLWF size) they should be included as predictors in model development independent of biophysical metrics. However, the time scale of moisture variability not captured by biophysical metrics (e.g. FFMC) is finer (e.g. diurnal) than this analysis examines for the likelihood of VLWF occurrence (Viney 1991). Thus, although short-term precipitation might indeed influence the likelihood of VLWF occurrence, it would require a separate analysis at the daily time scale, instead of weekly, which was selected here to avoid uncertainties with autocorrelation (see *Fire data*). Although biophysical metrics are most appropriate for this analysis, which examines weekly time scales leading up to and directly post-fire, evidence that VLWFs in the SW could be influenced by the onset of monsoon warrants further investigation of precipitation as a predictor of fire growth to VLWF size, at the daily time scale.

Drivers of wildfire in SCAL differ from the rest of the CONUS. In general, wildfires are driven by either Foehn-type winds known as Santa Anas (Sergius *et al.* 1962; Westerling *et al.* 2004; Keane *et al.* 2008; Parisien and Moritz 2009) or decreased spring precipitation (Littell *et al.* 2009). Our models do not include wind as a direct predictor, rather a component of the calculated indices (e.g. BI) used to define explanatory variables. Nevertheless, in agreement with the understanding that seasonal drought influences the occurrence of wildfire, our models found that the potential for how hot the fire burns (ERC, OR = 1.21), a function of seasonal drought the week following the discovery week, has a positive relationship with the probability of a VLWF week.

All of the models had higher accuracy (AUC $\geq$0.8) at the highest VLWF size threshold than with smaller fire size thresholds. However, similarity in models across fire size definitions provides confidence that our models are robust to the specification of particular VLWF thresholds and to heavy zero inflation. With this confidence in model output, we can now use preceding and concurrent weather to predict specific fire growth to VLWF size, and we can investigate intra-annual timing of VLWFs.

Domain of model applicability

Besides the intrinsic difficulties of modelling rare events (Alvarado *et al.* 1998; Coles 2001), other factors limit the domain of applicability of these models. First, these models assume that area burned approximately equates to fire effects. VLWFs are not always the most environmentally and socially costly (Kasischke *et al.* 2005) as costs include lives lost, structures destroyed, economic cost and degradation of air quality. Second, wildfires are controlled and driven by other factors besides short- (i.e. concurrent) and long-term (i.e. up to a year previous) weather. VLWFs can occur because of large areas of continuous fuels, merging of multiple fires, time available for spread, and ineffectiveness of suppression (Gill and Allan 2008), which can be taxed if there are multiple coincident wildfires. In all GACCs, there was at least one VLWF week in which more than one VLWF burned, but there are no indices or metrics in this analysis that account for preparedness or availability of suppression resources. Third, the biophysical metrics used here to regress the binary occurrence of a VLWF in a given week do not include all climate influences, for example, atmospheric stability (Werth *et al.* 2011). Fourth, there is an element of uncertainty in these models associated with ignitions and discovery date. Our models do not account for proximity to the wildland–urban interface or the time between the fire start and initial attack of suppression efforts (Gill and Allan 2008), which can vary widely depending on the number of concurrent fires. Multiple ignitions in different locations can merge into one large fire (Gill and Allan 2008), referred to as a complex fire, thus there is some uncertainty about classifying the discovery date of a VLWF. Lastly, these models were developed at the scale of the GACC as this is useful for management, but there is much fine-scale variability both in vegetation type (e.g. in reference to application of Fuel Model G for NFDRS calculations) and fire regime that could affect the applicability of these models at a finer resolution.

These confounding factors limit the domain of applicability of these models to the coarse scale of the GACC. Predicting VLWFs at finer scales will require explicit fire spread modelling, whether probabilistic or mechanistic, and acceptance of even greater uncertainty about factors producing a VLWF. Nonetheless, our models provide a foundation to begin investigating ecological drivers and timing of specific VLWFs, rather than using aggregate statistics such as annual area burned.

Conclusions

Because large wildfires have lasting ecological and social effects, and future projections under a changing climate estimate increased annual area burned (Flannigan *et al.* 2009; Littell *et al.* 2010) and certain types of weather and climate extremes (Coumou and Rahmstorf 2012), there is a need to understand how climate influences the occurrence of VLWFs. This analysis not only assesses, but also quantifies the spatial and temporal domain of VLWFs and related climate patterns. In general, hotter, drier conditions both leading up to and during a VLWF increase the probability of a fire being identified as a VLWF in the West CONUS. Climate drivers of VLWFs are similar to (but not the same as) those of annual area burned, which is largely attributable to broad-scale ecological mechanisms driving wildfire. Years with large area burned have more VLWFs and a substantial portion burned by VLWFs, thus demonstrating how annual aggregates can be influenced by individual events.

A focus on individual fires can identify not only intra-annual timing of large annual area burned that can aid managerial preparedness – for example, to keep smaller fires small when the probability of a VLWF week is high (Tedim *et al.* 2013) – but also the specific conditions that support fire growth to VLWF size. Short-term operational fire management uses fire danger indices (Xiao-rui *et al.* 2005) or the probability that fire will spread in a given day (Podur and Wotton 2011). The application of these models is that they quantify what we intuitively know about VLWF (e.g. hotter and drier is more risky) and as such, provide a quantifiable justification for *proactive* fire management and policy. The predictive capability of these models allows us to plan for the future by not only understanding intra-annual timing of VLWFs, but also how weather leading up to and during the event can support fire growth to VLWF size. Proactive fire management includes carefully placing fuel reductions averting the climatic potential of a VLWF occurrence (Williams 2013) and controlled burns during times of year with lower VLWF risk.

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Appendix

Table A1. Tables of each Geographic Area Coordination Center (GACC) providing the numerical values of precision and recall given different probability thresholds for classifying a very large wildland fire (VLWF)

Percentage imbalance is the percentage of non-VLWF weeks in the analysis. Note: EGB, Eastern Great Basin; NCAL, Northern California; NROCK, Northern Rocky Mountains; PNW, Pacific Northwest; RM, Rocky Mountains; SCAL, Southern California; SW, Southwest; WGB, Western Great Basin

Accuracy statistic		Precision	Recall	Precision	Recall	Precision	Recall
VLWF size (ha)		20 234		10 117		4047	
GACC				EGB			
Percentage imbalance		93.9		87.1		76.5	
Probability Threshold (for classifying a VLWF)	0.05	0.15	0.89	0.18	0.9	0.28	0.98
	0.1	0.21	0.68	0.23	0.85	0.34	0.94
	0.15	0.19	0.39	0.27	0.78	0.37	0.88
	0.2	0.23	0.29	0.3	0.59	0.39	0.8
	0.25	0.26	0.21	0.34	0.41	0.43	0.76
	0.3	0.25	0.11	0.37	0.29	0.45	0.69
	0.35	0.33	0.07	0.32	0.17	0.49	0.61
	0.4	0.5	0.07	0.4	0.1	0.53	0.48
	0.45	1	0.04	0.29	0.03	0.57	0.39
	0.5			1	0.02	0.59	0.31
	0.55					0.64	0.23
	0.6					0.55	0.11
	0.65					0.64	0.08
	0.7					0.6	0.03
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				NCAL			
Percentage imbalance		98.4		97.2		93.7	
Probability Threshold (for classifying a VLWF)	0.05	0.04	0.22	0.21	0.69	0.12	0.86
	0.1	0.17	0.22	0.14	0.31	0.15	0.53
	0.15	0	0	0.14	0.13	0.2	0.36
	0.2			0.17	0.06	0.21	0.19
	0.25			0.5	0.06	0.33	0.14
	0.3			1	0.06	0.25	0.03
	0.35					0	0
	0.4						
	0.45						
	0.5						
	0.55						
	0.6						
	0.65						
	0.7						
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				NROCK			
Percentage imbalance		97		94.4		91.5	
Probability Threshold (for classifying a VLWF)	0.05	0.18	0.81	0.23	0.9	0.27	0.89
	0.1	0.26	0.75	0.29	0.8	0.33	0.78
	0.15	0.32	0.69	0.37	0.73	0.39	0.72
	0.2	0.42	0.59	0.39	0.63	0.46	0.7
	0.25	0.35	0.44	0.42	0.57	0.51	0.65
	0.3	0.5	0.38	0.44	0.5	0.55	0.63
	0.35	0.67	0.25	0.52	0.47	0.54	0.56
	0.4	0.67	0.25	0.62	0.43	0.58	0.5
	0.45	0.8	0.25	0.67	0.4	0.63	0.48

(*Continued*)

Table A1. (Continued)

Accuracy statistic		Precision	Recall	Precision	Recall	Precision	Recall
VLWF size (ha)		20 234		10 117		4047	
	0.5	0.8	0.25	0.64	0.3	0.71	0.44
	0.55	1	0.25	0.56	0.17	0.83	0.41
	0.6	1	0.25	0.67	0.13	0.81	0.37
	0.65	1	0.19	0.6	0.1	0.88	0.3
	0.7	1	0.06	1	0.1	0.92	0.26
	0.75	1	0.06	1	0.07	1	0.17
	0.8					1	0.11
	0.85					1	0.09
	0.9						
	0.95						
	1						
GACC				PNW			
Percentage imbalance		95.8		91.7		80.8	
Probability Threshold (for classifying a VLWF)	0.05	0.12	0.83	0.21	0.94	0.25	0.95
	0.1	0.18	0.61	0.24	0.78	0.29	0.9
	0.15	0.21	0.33	0.27	0.61	0.35	0.86
	0.2	0.21	0.17	0.32	0.53	0.38	0.78
	0.25	0.22	0.11	0.33	0.39	0.44	0.71
	0.3	0	0	0.34	0.33	0.46	0.58
	0.35	0	0	0.44	0.33	0.51	0.53
	0.4			0.5	0.31	0.51	0.39
	0.45			0.53	0.25	0.57	0.31
	0.5			0.83	0.14	0.61	0.27
	0.55			0.75	0.08	0.61	0.13
	0.6			0.67	0.06	0.6	0.07
	0.65			1	0.03	0.6	0.04
	0.7					0	0
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				RM			
Percentage imbalance		99.5		98.9		96.9	
Probability Threshold (for classifying a VLWF)	0.05	0	0	0.13	0.57	0.2	0.84
	0.1	0	0	0.13	0.29	0.25	0.74
	0.15	0	0	0.22	0.29	0.29	0.58
	0.2	0	0	0	0	0.29	0.32
	0.25			0	0	0.33	0.26
	0.3			0	0	0.4	0.21
	0.35			0	0	0.5	0.21
	0.4					0.5	0.16
	0.45					0.5	0.11
	0.5					0.5	0.11
	0.55					0.33	0.05
	0.6					0.33	0.05
	0.65					0.33	0.05
	0.7					0.5	0.05
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				SCAL			
Percentage imbalance		98		95.4		90.2	
Probability Threshold (for classifying a VLWF)	0.05	0.09	0.5	0.1	0.72	0.14	0.93
	0.1	0.27	0.29	0.18	0.41	0.17	0.67
	0.15	0.29	0.14	0.28	0.22	0.2	0.44
	0.2	0.2	0.07	0.39	0.16	0.28	0.3

(*Continued*)

Table A1. (Continued)

Accuracy statistic		Precision	Recall	Precision	Recall	Precision	Recall
VLWF size (ha)		20 234		10 117		4047	
	0.25	0	0	0.17	0.03	0.31	0.16
	0.3			0	0	0.35	0.1
	0.35					0.46	0.07
	0.4					0.38	0.04
	0.45					0.5	0.01
	0.5						
	0.55						
	0.6						
	0.65						
	0.7						
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				SW			
Percentage imbalance		99.1		97.4		90.9	
Probability Threshold (for classifying a VLWF)	0.05	0.13	0.43	0.12	0.76	0.21	0.93
	0.1	0.18	0.29	0.1	0.29	0.27	0.87
	0.15	0.17	0.14	0.1	0.14	0.29	0.68
	0.2	0.25	0.14	0.23	0.14	0.31	0.53
	0.25	0.33	0.14	0.5	0.1	0.32	0.43
	0.3	0.33	0.14			0.35	0.37
	0.35	0	0			0.36	0.28
	0.4					0.41	0.19
	0.45					0.57	0.16
	0.5					0.69	0.12
	0.55					0.88	0.1
	0.6					1	0.03
	0.65						
	0.7						
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						
GACC				WGB			
Percentage imbalance		96.3		92.6		84.2	
Probability Threshold (for classifying a VLWF)	0.05	0.12	0.67	0.15	0.9	0.19	0.98
	0.1	0.21	0.47	0.21	0.6	0.23	0.89
	0.15	0.27	0.4	0.25	0.4	0.27	0.73
	0.2	0.31	0.33	0.31	0.37	0.3	0.59
	0.25	0.3	0.2	0.32	0.27	0.39	0.5
	0.3	0.5	0.13	0.4	0.2	0.52	0.34
	0.35	0.33	0.07	0.33	0.1	0.47	0.22
	0.4	0.33	0.07	0.33	0.1	0.5	0.14
	0.45	0	0	0.33	0.07	0.43	0.09
	0.5	0	0	0	0	0.4	0.06
	0.55			0	0	0.17	0.02
	0.6					0	0
	0.65					0	0
	0.7					0	0
	0.75						
	0.8						
	0.85						
	0.9						
	0.95						
	1						