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Key Points:
- Climatic drivers of area burned vary along a gradient from fuel-limited to flammability-limited ecosystems. Most have elements of both
- Climate change is likely to increase area burned more and earlier in flammability-limited systems, less and later in fuel-limited systems
- Climatic projections of area burned are useful for evaluating climate impacts, but excluding humans limits forecasting

Supporting Information:
- Supporting Information S1

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Climate Change and Future Wildfire in the Western United States: An Ecological Approach to Nonstationarity

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Abstract We developed ecologically based climate-fire projections for the western United States. Using a finer ecological classification and fire-relevant climate predictors, we created statistical models linking climate and wildfire area burned for ecosections, which are geographic delineations based on biophysical variables. The results indicate a gradient from purely fuel-limited (antecedent positive water balance anomalies or negative energy balance anomalies) to purely flammability-limited (negative water balance anomalies or positive energy balance anomalies) fire regimes across ecosections. Although there are other influences (such as human ignitions and management) on fire occurrence and area burned, seasonal climate significantly explains interannual fire area burned. Differences in the role of climate across ecosections are not random, and the relative dominance of climate predictors allows objective classification of ecosection climate-fire relationships. Expected future trends in area burned range from massive increases, primarily in flammability limited systems near the middle of the water balance deficit distribution, to substantial decreases, in fuel-limited nonforested systems. We predict increasing area burned in most flammability-limited systems but predict decreasing area burned in primarily fuel-limited systems with a flammability-limited ("hybrid") component. Compared to 2030–2059 (2040s), projected area burned for 2070–2099 (2080s) increases much more in the flammability and flammability-dominated hybrid systems than those with equal control and continues to decrease in fuel-limited hybrid systems. Exceedance probabilities for historical 95th percentile fire years are larger in exclusively flammability-limited ecosections than in those with fuel controls. Filtering the projected results using a fire-rotation constraint minimizes overprojection due to static vegetation assumptions, making projections more conservative.

Plain Language Summary Most people, including many familiar with fire ecology and future climate, assume that the area burned by wildfire will increase in a warmer climate. This depends a lot on what kind of ecosystem we mean. In all ecosystems, fuels must be available to fire for fires to get very big, but the climate controls on those fuels vary widely with vegetation. In wetter forests, it takes an abnormally warm, dry year to make normally wet fuels available. But in many drier ecosystems, fuels are dry enough to burn most years—whether fires get big depends also on whether there is sufficient fuel available to carry fires over large areas. In this kind of vegetation, abnormally wet years in the year prior to fire can create larger or more connected fuels that then lead to larger fires. In this study, we use this concept to investigate how future area burned might be affected by climate change. We found that some ecosystems will burn much more, just as expected. But some will actually burn less. We characterized these futures for 70 different ecosystems around the West. The similarities and differences illustrate the range of futures that might be expected under climate change.

1. Introduction

1.1. Climate-Fire Relationships

Climate-fire relationships have received increasing attention as long-term climate and fire data sets become more available. Recent work compares the utility of fire-related explanatory climate variables (Westerling et al., 2003; McKenzie et al., 2004; Littell et al., 2009; Littell & Gwozdz, 2011; Abatzoglou & Kolden, 2013; Kitzberger et al., 2017), identifies recent trends in area burned (Dennison et al., 2014), attributes the proportion of observed change in area burned due to climate change (Williams & Abatzoglou, 2016), and projects future components of fire regimes statistically given climate change (Kitzberger et al., 2017; Littell et al., 2010; Westerling et al., 2011). Much of this work has focused on forest fires, perhaps in part because the relationships between climate and fire in forests are often statistically stronger and the influence of contrasting climate and vegetation drivers simpler (McKenzie & Littell, 2017). Nonforested vegetation types, spanning more broadly the gradient of aridity to vegetation productivity across the western United States, have received less attention, especially from an ecological, rather than physical, perspective.

The role of climate drivers in fire regimes is ecosystem dependent (Pausas & Bradstock, 2007; Ryan, 1991), and a range of regional climate-fire relationships have been empirically documented across drought, aridity, and productivity gradients (Krawchuk et al., 2009; Krawchuk & Moritz, 2011; Littell et al., 2009; Littell & Gwozdz, 2011; Pausas & Ribeiro, 2013; Westerling et al., 2003). Krawchuk et al. (2009), Littell et al. (2009), and McKenzie and Littell (2017) focused specifically on ecological differentiation of these gradients, proposing resource-based (Krawchuk et al., 2009) and climate-productivity gradient (Littell et al., 2009; McKenzie & Littell, 2017) frameworks for fire variability. Collectively, these studies show that ecosystem response to climatic change can affect fire regimes through changes in fuel availability (productivity), fuel flammability, or both. Although the roles of drought and warming in future fire under climate change receive considerable attention (see reviews in Littell et al., 2016, and Williams & Abatzoglou, 2016), others have noted that regional fuel and climate responses can lead to both increases and decreases in fire activity under future climate. For example, Moritz et al. (2012) described increases more widely than decreases (primarily in the tropics), and Young et al. (2017) showed that boreal and tundra vegetation can respond at different rates. McKenzie and Littell (2017) challenged the dominance of a "drought and warming beget fire" approach to climate and fire in the western United States, arguing that simultaneous nonstationarity in climate, fire, and postfire fuel trajectories limits the predictability of fire area burned. In this paper, we use a concept of stationarity similar to that in Milly et al. (2008), where the assumption that natural systems fluctuate within an "unchanging envelope of variability" is invalidated for water resources problems because human effects on hydrologic systems are directional. Because the probability distribution of fire events (size, severity, or frequency) is changing with climate change, land use and fire suppression effects, landscape and vegetation changes, parameter reference points from historical analyses are unlikely to serve reliably for future predictions. Fire in the 21st century is, and will continue to be, nonstationary.

1.2. Climate-Based Projections of Future Fire

Bowman et al. (2014) argued that projections of future fire activity under climate change should include all the important drivers of fire regimes, implying that considering fire-productivity relationships is only part of the picture. Fischer et al. (2016) described the coupled human-natural system dimensions of fire governance, highlighting that improved projections are merely one dimension of a complex decision context, while Schoennagel et al. (2017) pointed out that increases in fire activity in the western United States will necessarily require adaptation. Wildfire in the western United States is clearly a problem with complex dimensions, including human influences that are not easily quantified and modeled (e.g., Balch et al., 2017; Syphard et al., 2017). For example, fire suppression, land use, and human ignition sources all contribute to the manifestation of fire on real landscapes and are often assumed to play a smaller role than climatic drivers. Nevertheless, given fire sensitivity to climate and the projected rate of climate warming, anticipating and adapting to landscape change in the western United States will depend, at least in part, on understanding future changes in fire regimes in their specific ecological contexts.

The rate of change in wildfire activity in the next several decades will be a product, in part, both of current fuel conditions and their responses to the direct and indirect effects of climate variability and change. Models of this change need to represent processes that are manifest at different spatial and temporal scales (McKenzie et al., 2014). For example, the grid spacing of global climate models is generally orders of magnitude coarser than fire-behavior models, with patch sizes of ecological landscape change somewhere in between (e.g., forest succession and hydrology, and patterns of fire spread constrained by topography). Modeling and projecting wildfire activity therefore involves tradeoffs between the finer resolutions appropriate for fire behavior and fire effects and the coarser resolutions needed to avoid false precision in statistical estimates of climate-fire relationships (McKenzie et al., 2014).

These tradeoffs are illustrated in recent work modeling future fire responses, where the spatial scale chosen for modeling has implications for the flexibility and robustness of projections. Liu and Wimberly (2016) and Kitzberger et al. (2017) evaluated drivers of fire in the western United States with models at relatively fine scales (for the purpose). Kitzberger et al. (2017) produce independent statistical models for each 1 × 1 degree grid cell, whereas Liu and Wimberly (2016) use even finer resolution climate and indirect driving data and individual fire perimeters to calibrate their simulations. Kitzberger et al. (2017) limited their projections universally to mid-21st century, acknowledging that future changes in fire response to climate eventually require simulation of vegetation responses to both climate and disturbance. Liu and Wimberly (2016) instead statistically simulated the role of vegetation change after disturbance and subsequent fire responses. In attempting to account for the complex nature of climate-fire relationships and their spatial variance with fuels or other factors, both these studies use gridded historical climate and fire data and make future projections at the same resolution. These studies therefore assume both that climate-fire relationships are sufficiently resolved at such scales and that they are equally stationary in time as long as vegetation does not change (Kitzberger et al., 2017) or for given combinations of climate, vegetation, and indirect drivers (Liu & Wimberly, 2016). Especially for the approach in Kitzberger et al. (2017), it is difficult to distinguish grid cell climate-fire models that are not significant because the area burned does not respond to variations in climate from those where low historical fire occurrence or short calibration period (a small fraction of many western fire-free periods) limit the ability to detect relationships that actually occur.

Abatzoglou and Williams (2016) go to the other end of the spectrum, building one model for all the forested regions of the western United States combined. For their purpose, attributing the effects of climate change on wildfire proportionally rather than actual regional projections, this coarse-scale approach was more computationally feasible, and probably avoided false precision in their complex attribution process. In our previous work (Littell et al., 2009), we built models at the scale of the Bailey ecoprovinces, one level more aggregated spatially than in this paper. We chose to balance the uncertainties associated with the ecological heterogeneity of the ecoprovinces against the larger sample sizes (number of fires adding up to annual area burned) and more robust representation of climatology (avoiding the possible false precision of characterizing climate at fine spatial scales).

Here we complement this earlier work with a new set of ecologically based projections at the scale of Bailey's ecosections (Bailey, 1995). The rationale for the finer scale of our approach is twofold. First, we have much better characterization of the driving variables in our models at finer scales than for the earlier work (see section 2). Second, we seek results that are more directly "actionable," that is, they represent processes (wildfire) at scales closer to those relevant for watershed and landscape management. We retain the ecosections for their ecological relevance, despite their widely different sizes, rather than using a grid-based approach that ignores the spatial patterns of landscapes.

1.3. Toward Ecologically Based Climate-Fire Relationships

We explore the limits of statistical attribution and projection of climate-driven changes in area burned across biophysical gradients in the western United States. We present what we deem the statistically most defensible climate-fire diagnostic models, and develop an ecologically driven classification of climate-fire relationships. To limit extrapolation far beyond current fuel limitations, we constrain area-burned projections by assuming that as simulated area burned nears ecosection area, vegetation change limits the suitability of statistical models developed on historical vegetation. We interpret the resulting projections of future area burned within the context of expected future climate, and consider practical limitations to the data and models, as well as more subtle uncertainties associated with the nonstationarity of climate-fire relationships (McKenzie & Littell, 2017).

2. Data and Methods

2.1. Fire and Climate Historical Data

For comparison to prior work, and because no update of the required West-wide climatic variables was publicly available beyond 2006 (see below) at the time of analysis, we used the same methods to estimate historical area burned data as Littell et al. (2010), Littell and Gwozdz (2011), and McKenzie and Littell (2017) but expanded the data set to the entire western United States. Briefly, we tabulated annual area burned on federal lands (USBIA, USBLM, USFS, USFWS, and USNPS) from 1980 to 2006, aggregated from individual fires to Bailey's ecosections for the western United States (11 western states, after Littell et al., 2009), but for 70 ecosections rather than the coarser ecoprovinces from Littell et al. (2009) or the smaller number of ecosections explored in Littell and Gwozdz (2011) and McKenzie and Littell (2017). We used time series of interpolated

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historical climate data and modeled ecohydrologic variables (after Elsner et al., 2010; Littell et al., 2011; Littell et al., 2014): potential evapotranspiration (PET), actual evapotranspiration (AET), water balance deficit (DEF, calculated as PET-AET), snow water equivalent (SWE), as well as temperature (TEMP) and precipitation (PREC). Climatic variables were aggregated to ecosection-level time series and seasonally averaged (December to February, DJF; March to May, MAM; June to August, JJA; September to November, SON; as well as October to March, ONDJFM; and April to September, AMJJAS) except for SWE, which we considered only for March, April, or 1 May. Following Littell et al. (2009) and McKenzie and Littell (2017), we considered both lag 1 (L1) and year-of-fire (YO) climate. Longer lagged variables are sometimes significant (e.g., Littell et al., 2009, which considered lag 2), but we eschewed longer lags to limit the number of plausible explanatory variables to those most proximate in their influence on fire.

2.2. Climate-Fire Statistical Models and *F* Index Classification of Ecosections

Following Littell et al. (2009) and Littell and Gwozdz (2011), we used linear regression models to attribute variation in area burned ($\log_{10}$AB) to climate variables, but with some methodological modifications. First, to improve identification of the best predictors from a larger pool of YO and L1 variables, we used the R (R Core Team, 2017) package bestglm (Mcleod & Xu, 2014) to select the best candidate regression models using an all-subsets search algorithm. Best models were determined based on lowest BIC scores and subject to the constraints of p (T) < 0.1 and VIF < 3 (VIF calculations, package "car," v. 2.0-19, Fox et al., 2014). We calculated the Durbin-Watson statistic (package "lmtest," v. 0.9-30, Hothorn et al., 2014) to test for autocorrelation in residuals and used the PRESS statistic to estimate the mean prediction error for each model given the observations. We used package relaimpo (v. 2.2-2, Grömping, 2006) to evaluate the relative importance (i.e., ranging from 0 to 1) of the best regression predictors using methods similar to normalized coefficients but arguably better (Feldman, 2005). Following McKenzie and Littell (2017), we classified ecosection climate-fire relationships based on fuzzy-set theory that defines an ecologically relevant gradient of fire climatologies from fuel limitation to flammability limitation. Ecosections with model terms exclusively indicating positive PREC, SWE, or AET and negative energy or PET were considered purely fuel-limited—these relationships indicate fuel production in the seasons prior to fire. Ecosections with model terms exclusively indicating positive energy (PET and TEMP) and negative PREC, SWE, or AET were considered purely flammability limited. We used the relative importance of the best regression terms (regardless of final model skill) to define the priority of terms in the model and develop a composite fuzzy-set score (*F* index) indicating the position of each ecosection in the historical period along the continuum from fuel to flammability limitation:

$$\begin{aligned} F = {} & 2(\text{relative importance flammability limited variables})/ \\ & (\text{relative importance flammability limited variables} + \text{relative importance fuel limited variables}) - 1 \end{aligned}$$

This produces a continuous variable that describes the climatic controls of fire area burned from completely fuel limited (-1) to completely flammability limited (1).

2.3. Future Fire Projections Based on Future Climate

To estimate the range of future area burned, we developed future climate scenarios using future climate model projections from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel data set statistically downscaled to 1/16th degree for the western United States (see Littell et al., 2014, for further documentation). The scenarios include two climatologies (2030–2059, hereafter "2040s," and 2070–2099, hereafter "2080s") and five forcings (A1B CMIP3 multimodel mean of 10 GCMs and four bracketing GCMs—ECHAM5, MIROC3.2, PCM1, and HadGEM1, Littell et al., 2011, 2014; Mote & Salathé Jr., 2010). The 10 GCM composites consisted of climate models demonstrated in Littell et al. (2011) to perform well over multiple regions of the western United States. The bracketing models include scenarios that represent less warming (annually) and drier (in winter; PCM1), less warming and wetter (ECHAM5), warmer and wetter (MIROC 3.2), and warmer and drier (HadGEM1), compared to the composite. Each of the 10 scenarios consists of temperature and precipitation deltas associated with the future 30-year climatologies applied to the historical 91-year (1916–2006) time series for 1/16th degree cells, resulting in a synthetic projection with historical variability and sequence but with future mean climate. The statistically downscaled TEMP and PREC were in turn used to drive the VIC hydrologic model (see Elsner et al., 2010; Hamlet et al., 2013; Littell et al., 2011, 2014, for details) and derive PET, AET, DEF, and SWE.

Although some progress in both skill and resolution of GCMs has occurred since CMIP3, Knutti and Sedláček (2013) showed that CMIP3 and CMIP5 can be considered as essentially from the same probability distribution, and at the time of analysis, no internally consistent CMIP5 projections with required ecohydrologic variables, especially PET for natural vegetation, were available to us.

The future ecoclimatic variables were then used as predictors in the ecosection statistical climate-fire models to project expected area burned contingent on future climate. From each ecosection's projected area burned, we calculated three metrics of change in fire regime. First, we calculated ecosection fire rotation for the 2040s and 2080s by evaluating the time required to burn a total area equivalent to ecosection area, permuting the calculation 100 times for random sequences of the annual future climate projections to estimate a mean rotation under future climate, including a wide range of plausible sequences of annual climate variables. Simulated fire rotations were averaged over the 100 permutations of the sequence of future climate predictors for each ecosection under each GCM and the composite. If the projected mean composite fire rotation was less than 30 years (the duration of the 2040s and 2080s climatologies, and similar to the time frame of the training data), we assumed use for a later time period would potentially violate the model assumption that vegetation was broadly similar to the historical. That is, if an area equivalent to the ecosection's total area burned during the climatology in question, that ecosection's subsequent projections were considered suspect and especially sensitive to nonstationarity in climate-fire relationships due to expected changes in vegetation composition. Second, we calculated the change in model median (dMed) annual area burned given future climate scenarios and compared it to the historical calibration period. Third, to address changes in extreme fire years, we calculated the change in probability of exceeding the historical 95th percentile area burned year in each of the future time periods.

3. Results

3.1. Climate-Fire Statistical Models

The diagnostic climate-fire models indicate a wide range of climate-fire relationships among the 70 ecosections (Figure 1). All but two (342E [Bear Lake, UT] and 262A [Central Valley, CA]) of the 70 ecosections have climate-fire models that are significant assuming $\alpha = 0.05$, with mean number of predictors 4.0, ±1.4 SD. Model skill varied widely, with the significant models' adjusted R^2 ranging from 0.217 (263A, Northern California Coast) to 0.946 (M331A, Yellowstone Highlands), with a mean of 0.56 (±0.18 SD). The variance explained was somewhat greater (mean R^2 = 0.61, SD 0.16) for Bailey's mountain ("M," often mountainous) ecosections than for non-"M" ecosections (often lower elevation or nonmontane, mean R^2 = 0.51, SD 0.19).

PET was the most frequent leading predictor (24%), followed by seasonal DEF (20%), TEMP (19%), PREC (17%), AET (14%), and SWE (4%). Frequency among all predictors was roughly equal across all predictor variables, ranging between 16% (PET) and 21% (P) for variables other than SWE (9%). Among "M" systems, PET was the most common leading term (33% of models), but among non-"M" systems, it was TEMP (26%). DJF and JJA predictors were the most common (91 and 81 terms respectively), with other seasons demonstrating roughly even representation (ONDJFM = 40 terms, AMJJAS = 34 terms, MAM = 39 terms, and SON = 37 terms). The leading predictor in the best statistical model was from the year prior (L1) in 27% of models overall, but 46% among non-"M" systems. Taken over the ecosections as a whole during the calibration period, a gradient of fire responses to deficit emerges, with mean area burned first increasing with mean warm season deficit, but then decreasing as deficit increases past about 375 mm (Figure 2). Of the significant models, eight models had $R^2 < 0.4$, a self-imposed arbitrary limit of utility, and an additional four models failed DW tests for residual independence, leaving 56 models satisfying the assumptions and requirements for further analysis.

Among the 70 candidate models, there was a clear gradient from almost exclusive fuel limitation to almost exclusive flammability limitation, with most ecosections having some elements of both (Figure 1 and Table 1). Fuzzy set membership identified 14 purely flammability-limited ecosections (F = 1.00), 36 ecosections primarily flammability limited but with some fuel-limited predictors (flammability-fuel, $0.272 < F < 0.931$), nine ecosections with equal dominance ($-0.011 < F < 0.176$), eight ecosections primarily fuel-limited but with some flammability limited predictors ("hybrid," fuel-flammability, $-0.243 < F < -0.778$), and 3 purely fuel limited ecosections ($F = -1.00$). Bailey's "M" and non-"M" classification alone did not separate variance explained or F classification; skill, fuel limitation, and flammability limitation are nearly random relative to ecosystem classification (Figure 3).

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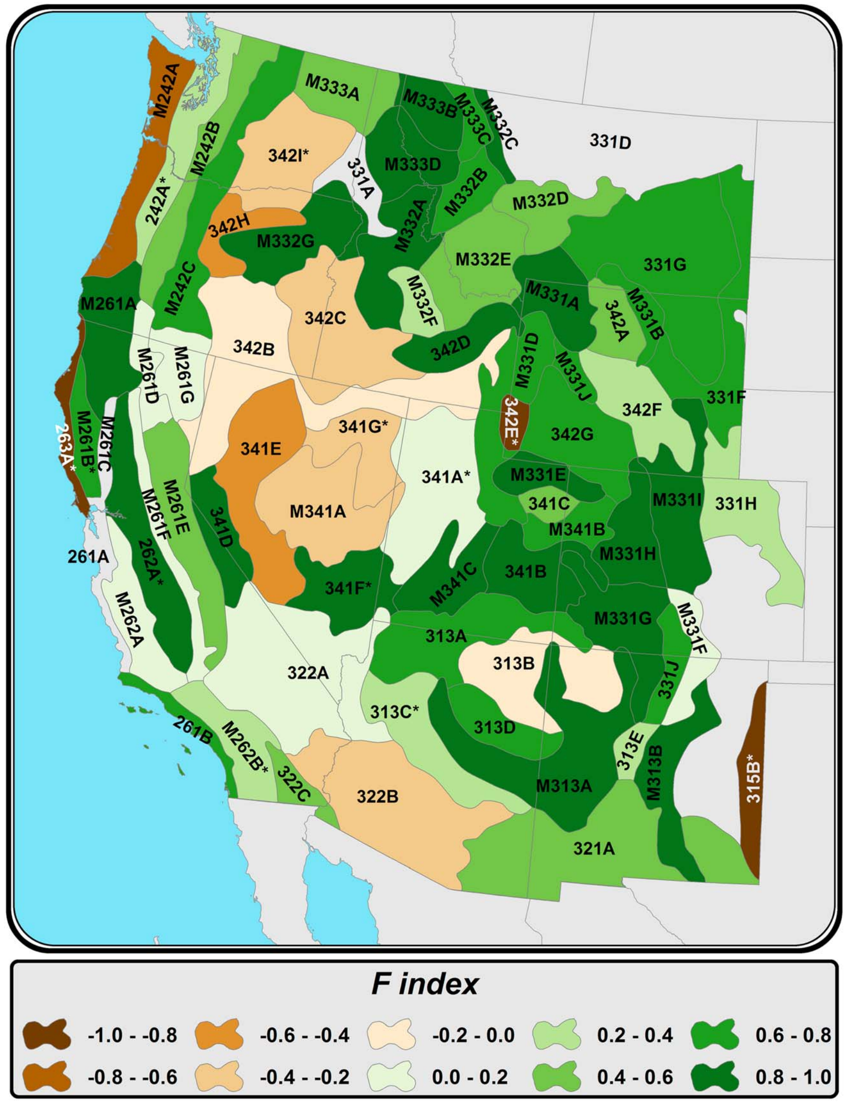

Figure 1. Western U.S. Bailey ecosections classified by climatic controls of area burned according to *F* index, a continuous indicator of fuel-to-flammability limitation determined by the relative importance of climate variables explaining variability in annual area burned (see Table 1 and diagnostics in the supporting information Table S1). Asterisks indicate ecosections for which statistical relationships allowed classification but statistical models were either weak or violated one or more diagnostic tests. Note that ecosection boundaries M313B (Sacramento/Manzano Mountains, NM), 321A (Chihuahuan Basin and Range), 315B (Southwest Texas High Plains), 331F (Northwestern Great Plains), and 331H (Central High Plains) are mapped only for the portion of the ecosection within one or more of the eleven western states from which fire data was extracted.

3.2. Projection Under Future Climate

Given the statistical climate-fire models and projected climate, ecosection area burned responses vary considerably among ecosections (Figure 4). By the 2040s, median area burned is projected to increase among purely flammability limited (ecosection median increase in projected area burned of 132%), flammability-fuel limited (+240%), and equal controls (+43%) ecosections but is projected to decrease (−119%) in fuel-flammability ecosections (Table 2). For the 2080s, area burned increases under all scenarios for the flammability (+770%), flammability-fuel (+442%), and equal control (+139%) ecosections, but decreases (−178%) for fuel-flammability systems.

Projected future fire rotations vary with model sensitivity and therefore also vary considerably across ecosections. Most (68%) ecosections had fire rotations exceeding 91 year (bracketing GCM range 55–80%, Figures 5a and 5b).

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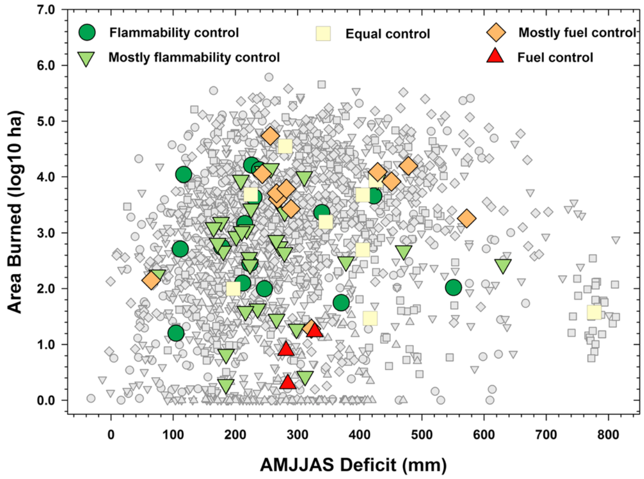

Figure 2. Relationship between fire season deficit and annual area burned across all 70 ecosections. Large colored symbols represent ecosection means for 1980–2006, gray symbols indicate individual years.

Table 1
F Index and Regression Model Skill by Ecosection

Ecosection	*F* index	Adj. R^2	P	Ecosection	*F* index	Adj. R^2	P
263A*	−1.00	0.217	0.01	341C	0.47	0.500	0.00
315B*	−1.00	0.310	0.01	M331B	0.47	0.593	0.00
342E*	−1.00	0.089	0.07	M332D	0.49	0.686	0.00
313B	−0.61	0.894	0.00	M242C	0.50	0.596	0.00
341E*	−0.60	0.479	0.00	M333A	0.52	0.617	0.00
M242A	−0.59	0.555	0.00	341D	0.56	0.455	0.00
342H	−0.54	0.652	0.00	M261E	0.58	0.774	0.00
M262B*	−0.39	0.255	0.02	M332E	0.60	0.735	0.00
322B	−0.37	0.565	0.00	M261B*	0.61	0.268	0.02
M341A*	−0.35	0.385	0.00	M333C	0.63	0.827	0.00
321A	−0.32	0.620	0.00	M331D	0.65	0.709	0.00
342I*	−0.26	0.590	0.00	313A	0.67	0.726	0.00
M262A	−0.26	0.630	0.00	M313B	0.71	0.834	0.00
341G*	−0.25	0.526	0.00	331G	0.74	0.646	0.00
342C	−0.24	0.708	0.00	331F	0.77	0.653	0.00
313C*	−0.24	0.328	0.01	261B	0.77	0.437	0.00
322C	0.02	0.524	0.00	M332B	0.78	0.755	0.00
322A	0.02	0.441	0.00	M341B	0.79	0.483	0.00
M331F	0.03	0.630	0.00	M341C	0.81	0.713	0.00
342B	0.05	0.561	0.00	M333D	0.89	0.639	0.00
M261D	0.05	0.703	0.00	262A*	1.00	0.090	0.07
M261G	0.13	0.469	0.00	341B	1.00	0.435	0.00
341A*	0.14	0.692	0.00	341F*	1.00	0.234	0.02
M261F	0.18	0.426	0.00	342D	1.00	0.425	0.00
342F	0.27	0.665	0.00	M332C	1.00	0.413	0.00
331J	0.29	0.620	0.00	M331E	1.00	0.426	0.00
313D	0.30	0.550	0.00	M332G	1.00	0.486	0.00
242A*	0.31	0.202	0.03	M261A	1.00	0.532	0.00
331H	0.37	0.512	0.00	M331G	1.00	0.542	0.00
342G	0.39	0.706	0.00	M313A	1.00	0.564	0.00
M332F	0.39	0.811	0.00	M333B	1.00	0.639	0.00
313E	0.39	0.581	0.00	M331I	1.00	0.732	0.00
342A	0.40	0.581	0.00	M332A	1.00	0.732	0.00
M331J	0.41	0.637	0.00	M331H	1.00	0.740	0.00
M242B	0.45	0.447	0.00	M331A	1.00	0.946	0.00

Note. Ecosections with asterisks indicate models that did not pass one or more tests of skill or reliability.

Under the 2040s projected ensemble climate, roughly a third of ecosections had fire rotations shorter than the 91-year simulation period (Figure 6). Sixteen percent of ecosections under the composite scenario (GCM range 13–23%) had mean rotations between 30 and 91 years, and 16% (range 5–21%) exceeded one fire rotation within our 30-year limit, indicating very short rotations that suggest nonstationarity in the late 21st century. No clear relationships between the time required to reach one fire rotation and ecosection flammability/fuel limitation index, Bailey ecosystem classification (non-"M" versus "M"), or warm season water balance index were evident. However, the mean *F* index was lower for ecosections with fire rotation >91 (0.430, SD 0.45, *n* = 38,) than for ecosections with fire rotation <91 but >30 (0.570, SD 0.47, *n* = 9) or fire rotation <30 years (0.587, SD 0.45, *n* = 9), indicating that ecosections with elements of flammability limitation were somewhat more likely to exceed historical fire rotations in the future than those dominated by fuel limitation but also that considerable variation exists among ecosections with similar *F*. Eighteen ecosections (Figure 6) exceeded one fire rotation in 91 years or less under the composite 10 GCM scenarios, and nine of those exceeded fire rotation in 30 years or less. Of the former, 13 had *F* index >0.5, and only two had *F* index <0, indicating that flammability limited ecosections dominate this response. Even when the projected median area burned is filtered for ecosection area already burned in the models (e.g., excluding models that exceed the fire-rotation restriction), statistical climate-fire models project large increases in area burned except in fuel-flammability ecosystems, where decreases are clear. It is worth noting that individual ecosections often have composite trends that differ in sign from the fuel class that their climate-fire regression models suggest. For example, seven (331H, 342A, M331J, M331B, M332D, M261E, and M341B—largely drier, lower elevation central Rocky Mountain ecosections) of the 29 ecosections in the flammability-fuel class have modestly decreasing (−133.5% for 2040s composite) median area burned under all scenarios, while one (313B—Navajo Canyonlands Section of the Colorado Plateau) of the seven fuel-flammability ecosections has rapidly increasing median area burned under all scenarios.

Unfiltered increases in exceedance probability of the historical 95th percentile for the 2040s and the 2080s are largest in exclusively flammability-limited ecosections (2040s composite 0.33, scenario range 0.24–0.44, 2080s composite 0.71, range 0.34–0.77) compared with other fuel controls (composites 0.19, 0.26, and 0.27; Table 3 and Figure 7). Between the 2040s and 2080s, exceedance probabilities increase and diverge among flammability and fuel limitation classes, and there is a clear gradient from smaller exceedance probabilities in fuel limited ecosections to larger exceedance probabilities in flammability-limited ecosections (Figure 8). Filtered (restricted to those ecosections with <1 fire rotation) increases are generally smaller but follow a similar pattern.

The warmer, drier summer climate model (MIROC 3.2) produces the largest increases in exceedance probability in flammability limited and flammability-fuel systems except in the filtered 2080s, where many of the projections are excluded by the fire rotation filter. Among the fuel flammability limited systems, by the 2080s, the projected exceedance probabilities for all but the PCM1 climate model are similar to or

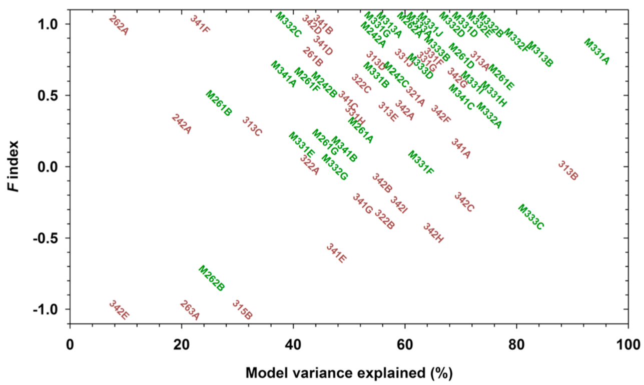

Figure 3. Relationship between *F* index (fuel/flammability control) and model variance explained for ecosections. Colors indicate Bailey "-" (brown) versus "M" (green) classification. To facilitate plotting and minimize overlap, especially among ecosections with *F* ~ 1, slight jitter was applied.

lower than historical, likely due to increasing temperature and decreasing precipitation influences on the productivity of those systems. Filtering for fire rotation to minimize the effect of fire-driven changes in vegetation decreases the exceedance probabilities, but the future increases are still very large. For flammability-limited systems, the 1-in-20 event year becomes a roughly 1-in-8 year under the filtered 2040s composite, but a 1-in-3 under the unfiltered 2040s composite. For fuel-flammability limited systems, the 1-in-20 event year becomes a roughly 1-in-7 year under the filtered 2040s composite, but a 1-in-4 under the unfiltered 2040s composite. For the unfiltered composites the probability of exceeding the 95th percentile event at least doubles for the 2080s for all fuel classes except fuel flammability; filtered composites still increase for all fuel classes except fuel flammability, which decreases, but the absolute increases are not as large—1-in-3 for flammability-limited, 1-in-5 for flammability fuel, 1-in-7 for even controls, and 1-in-20 for fuel flammability. Regardless of which metric is used to classify future changes in area burned, the ecosection-level statistical models project a wide range of future area burned. Even when the model projections are filtered to eliminate over-prediction, the projected increases in area burned in flammability and flammability fuel systems is very large, and the exceedance probability clearly increases with increasingly positive *F* index membership (Figure 8).

4. Discussion

4.1. Statistical Models and Future Projections

The diversity of drivers and skill evident in our statistical climate-fire models for landscapes of the western United States is remarkable, and the implied role of climate in fire regimes clearly varies with ecological context in consistent and expected ways. If the statistical models of climate-fire relationships are robust to

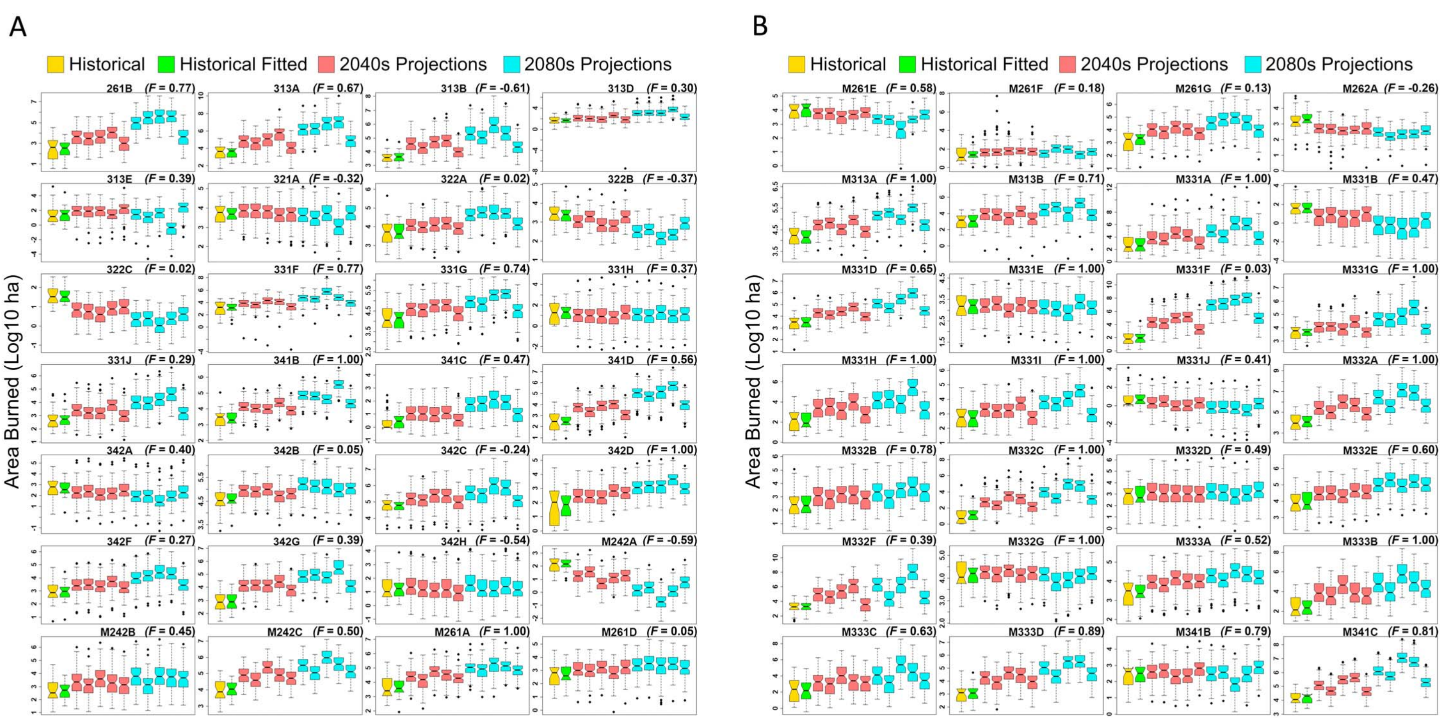

Figure 4. (a) Boxplots of historical, 2040s projected, and 2080s projected area burned by ecosection. Future scenarios, left to right, are 10 GCM composites, ECHAM5, HadGEM1, MIROC3.2, and PCM1. (b) Same as in Figure 4a.

Table 2
Percent Changes in Median Area Burned by Fuel/Flammability Class (Median of Available Ecosections)

	Filtered			
Scenario	Fuel.Flam	Even	Flam.Fuel	Flam only
2040s COMP	−119	43	240	132
2040s ECHAM5	−100	12	174	147
2040s HadGEM1	−130	75	167	24
2040s MIROC 3.2	−170	26	368	520
2040s PCM1	−125	56	54	59
2080s COMP	−178	139	442	770
2080s ECHAM5	−184	319	151	1,024
2080s HadGEM1	−183	179	320	1,143
2080s MIROC 3.2	−183	38	180	2,089
2040s PCM1	−107	86	221	319

climate change, expected future trends in area burned range from massive increases, primarily in flammability limited systems near the middle of the water balance deficit distribution, to substantial decreases, in drier nonforested systems in which fuel limitation controls area burned. Most of the western United States is between these two futures, however. The frequency with which ecosection area burned is projected to exceed the observed 1-in-20 event varies jointly with ecosection-level controls on the climate-fire relationship and the climate scenario considered (Table 2). Filtering the most sensitive regression models for those exceeding a fire rotation in 30 years decreases the projected changes in exceedance probabilities but does not change the general pattern in most fuel limitation types (Figure 7). Overall, our models portend continually increasing regional area burned, but the outcomes on real landscapes depend on the simultaneous responses of fuel accumulation in the years prior to fire season and the fuel availability (dominated by precipitation and water availability via AET) and flammability in the year of or year prior to fire (dominated by temperature and energy via PET). The *F* index classification presented above clearly captures the differences in projected future fire response to climate and, in general, provides an indicator of an ecosection's proximity to thresholds of change in fuel response given change in climate.

4.2. Fuel and Flammability Limitations on Area Burned

While intuitive and useful, the *F* index calculation bears more scrutiny because it is dependent on our interpretation of climate variables' effect on fuels. For most variables, there exists a body of literature showing the sign and magnitude correlation across different regions (e.g., Abatzoglou & Kolden, 2013; Keeley & Syphard, 2017; Littell et al., 2009; Littell & Gwozdz, 2011; McKenzie & Littell, 2017; Westerling et al., 2003), but some are more challenging to interpret. For example, an increase in AET implies either an increase in PET with sufficient water in the environment to meet the demand, or an increase in available water to meet demands of a given PET. Calculating DEF accounts for this, but independently, the consequences of these two scenarios may be different in different ecosystems and for different fuels. In the former, for a montane forest, available surface

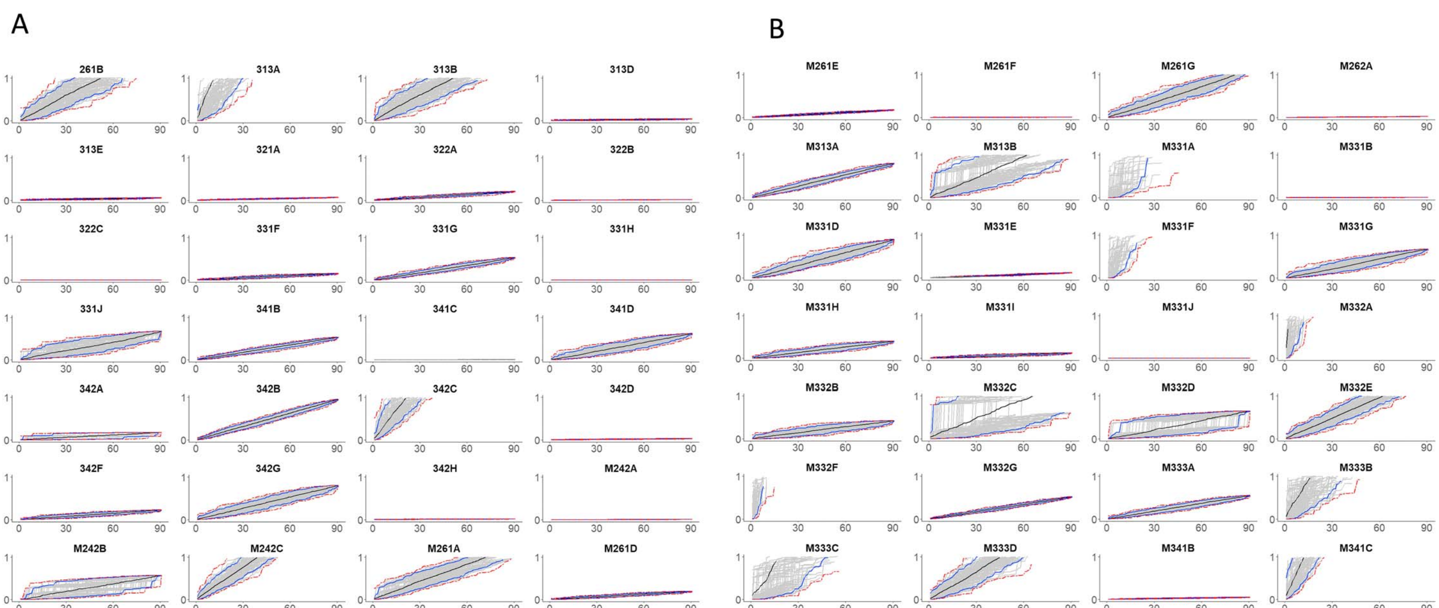

Figure 5. (a) One hundred permuted simulations of the first fire rotation for 28 ecosections using 2030–2059 10 GCM composites climate. Red lines indicate maximum (fastest approach to fire rotation) and minimum (slowest approach to rotation), blue lines indicate estimated fifth and 95th percentile runs, and black indicates median of all runs. (b) Same as Figure 5a, but for an additional 28 ecosections.

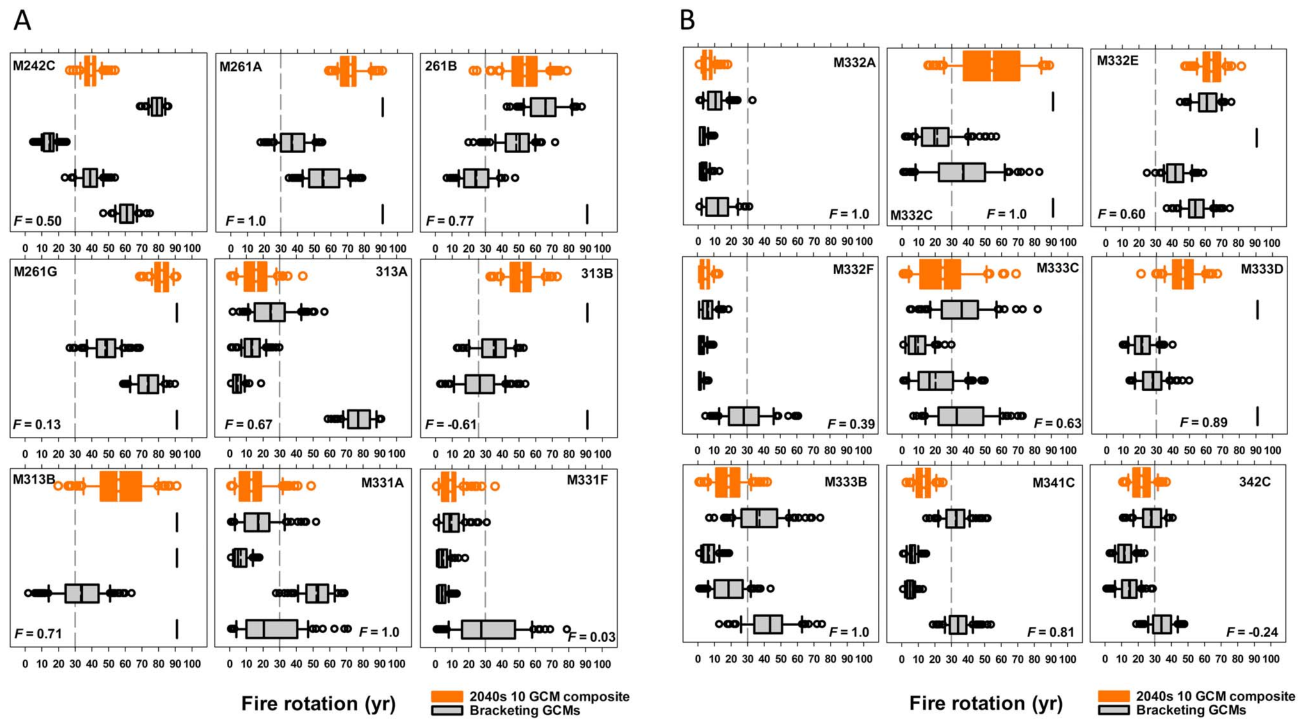

Figure 6. Boxplots of projected future fire rotations under the 2040s climate for 18 ecosections with composite (in orange) mean fire rotation less than the 91 years permuted in the simulations. Gray boxplots indicate bracketing GCMs (from top to bottom: ECHAM5, HadGEM1, MIROC 3.2, and PCM1). Vertical bars in place of boxplots indicate bracketing models in which all fire rotations exceeded 91 years. *F* index describes a range from fuel (−1) to flammability (1) control (see text).

fuels and foliar moisture may respond differently during the fire season. In contrast, the latter scenario in more water-limited vegetation is consistent with fine fuel production in the year prior to fire (e.g., Swetnam and Betancourt, 1998). Some models yield surprising relationships. For example, M242A (western Cascades) is classified as fuel limited with some flammability limitation, largely because "fuel limited" variables (lag year negative spring TEMP anomalies and lag year positive spring PREC anomalies) explain 41% of the variability in subsequent fire. While M242A rarely fails to have some fire in it during the calibration period, small total areas burned are often recorded (<1,000 to ~2,500 ha). Ecosections 242A (Puget/Willamette lowlands), 315B (NM portion of Texas High Plains), 331J (Upper Rio Grande), 341C (Uinta Basin), and 342E (Bear Lake, UT) similarly have low area burned, and this lack of variance sometimes results in poor models

Table 3
Mean Exceedance Probabilities for 95th Percentile Historical (1980–2006) Area Burned by Climate-fire Limitation Class; 0.05 Represents no Change From Historical

	Filtered					Unfiltered		
Scenario	Fuel.Flam	Even	Flam.Fuel	Flam only	Fuel.Flam	Even	Flam.Fuel	Flam only
2040s COMP	0.14	0.05	0.15	0.13	0.26	0.19	0.27	0.33
2040s ECHAM5	0.10	0.05	0.15	0.17	0.23	0.19	0.21	0.30
2040s HadGEM1	0.14	0.08	0.15	0.10	0.27	0.21	0.33	0.38
2040s MIROC 3.2	0.02	0.04	0.22	0.27	0.30	0.18	0.38	0.44
2040s PCM1	0.08	0.06	0.14	0.10	0.08	0.06	0.17	0.24
2080s COMP	0.04	0.14	0.20	0.36	0.31	0.39	0.53	0.71
2080s ECHAM5	0.03	0.16	0.23	0.45	0.30	0.40	0.50	0.70
2080s HadGEM1	0.03	0.16	0.23	0.29	0.31	0.40	0.58	0.62
2080s MIROC 3.2	0.03	0.13	0.26	0.26	0.30	0.38	0.59	0.77
2080s PCM1	0.12	0.06	0.17	0.15	0.12	0.20	0.37	0.34

Note. Models with insufficient skill were excluded from both filtered and unfiltered means. Filtered means contain only models with mean fire rotations >30 years; unfiltered means contain all models regardless of fire rotation results. Fuel. Flam = Fuel limited with some flammability limitation; Even = even control; Flam.Fuel = Flammability limited with some fuel limitation; Flam only = flammability control.

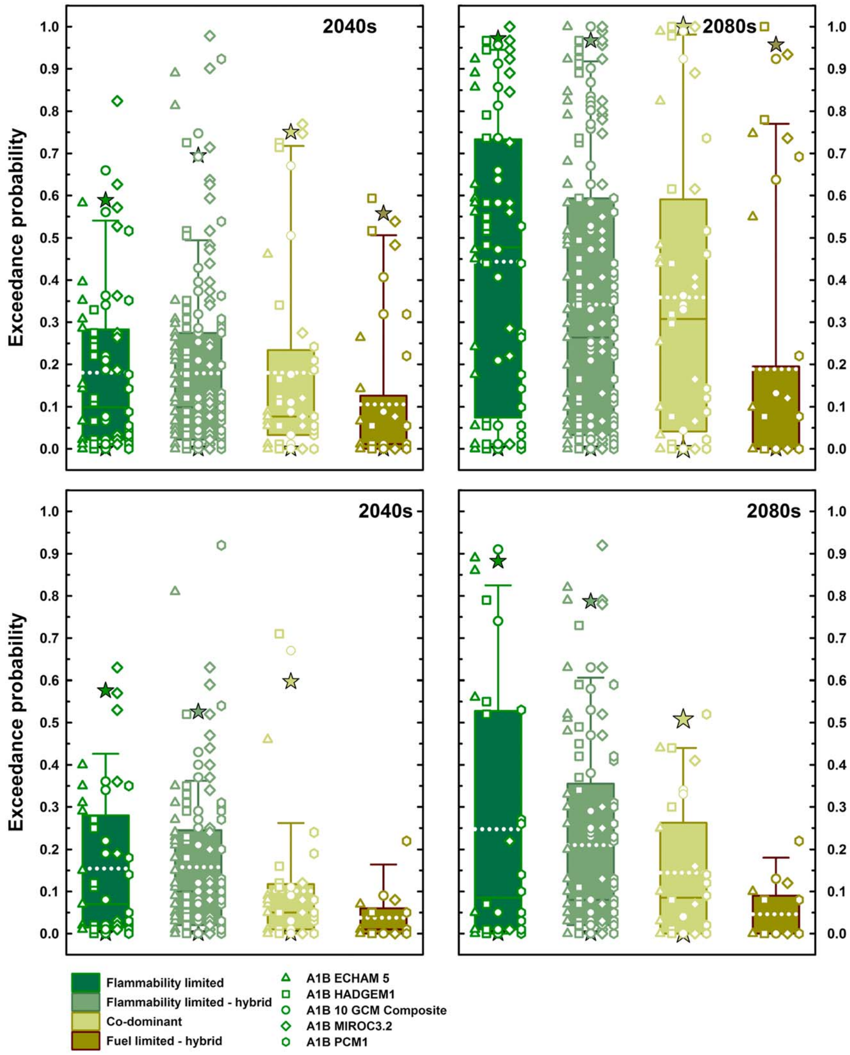

Figure 7. Exceedance probability of historical 95th percentile area burned under projected climates by fuel—flammability class; 0.05 is equivalent to historical. (Top) Unfiltered (projections include all future area burned regardless of fire rotation). (Bottom) Filtered to exclude those models exceeding 1 fire rotation in <30 years. Starred values indicate 95th percentile of the box and whiskers distribution for the 10 GCM composites. Models with poor diagnostics or exceeding fire rotation limits not included. Completely fuel limited ecosections not pictured because no models passed regression diagnostic requirements.

(see Figure 1 and Table 1). The short time period of analysis also contributes to this caveat; some ecosections are sufficiently data sparse (possibly due to low fire activity or frequency, small ecosection area, or other factors) that statistical inference is limited. In any case, for maximum utility, the *F* index classification should be seen as additional aggregate metric of the variability of the models, along with the models' relative goodness-of-fit and their expected robustness to future projections as measured by the fire-rotation constraint.

4.3. Potential Ecosection Responses

For ecosections projected to exceed historical extreme years and fire rotations frequently, our approach highlights where expected climatic changes may lead to no-analog fire regimes by the mid-21st century. For the purposes of this paper, no-analog fire regimes are those with which we have no prior management experience (i.e., the 20th century and especially the calibration period for the models). There is also less uncertainty in these projections because emissions scenarios do not diverge notably until after that time. These are primarily, but not exclusively, flammability-limited ecosections, implying that increases in fuel flammability

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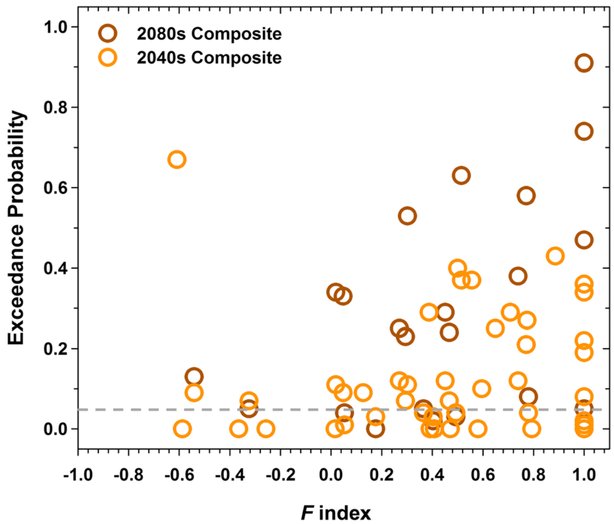

Figure 8. Relationship between *F* index (fuel-to-flammability control) and 2040s and 2080s probability of exceeding the historical (1980–2006) estimated 95th percentile annual area burned (dashed line is 0.05 annual probability).

alone are sufficient to drive the change given late-20th century fuel availability. But there are also ecosections (largely but not exclusively fuel limited) with projected exceedance probabilities and fire rotations that indicate area burned similar to—or lower than—historical, and climatically driven changes in area burned alone are not projected to change landscapes radically. It is also clear from the fire rotation calculations that the order of climate years used to drive the fire responses matters. For example, ecosections M242B (western Cascades), M332C (Rocky Mountain Front, MT), and M333C (Northern Rockies, MT) show threshold (abrupt changes past some point in time) behavior in most runs (Figure 5), but the timing of major events accumulating toward the fire rotation varies with the sequence of climate years. This underscores a point evident in the observed record, namely, that there is sufficient stochasticity in the sequence of climatic anomalies and sufficient fire sensitivity to the order of those anomalies that projections have a wide time window over which they might manifest. Decadal and interannual climatic variability add temporal persistence to the order of these anomalies and therefore can either exacerbate or attenuate the mean responses for extended periods. Conversely, it is also true that one exceptional season can override considerable periods of climate either favorable to or limiting fire. In any case, the rotation calculations suggest that the stationarity of the climate-fire relationships we have observed is limited and that the rate of disturbance and subsequent landscape vegetation change are an indicator of when the climate-fire models will likely fail to describe the dynamics of interest. Williams and Abatzoglou (2016) argue that refinements in both statistical and process model projections are needed to more accurately project fire regime responses to climatic change. However, as climate continues to change, the underlying dynamics of statistical fire models will be nonstationary (McKenzie & Littell, 2017) and must eventually fail to describe the conditions in future ecosections. Statistical climate-fire models therefore cannot be expected to simulate "no-analog" dynamics (those with a distribution partially or wholly unlike the historical reference) accurately and explicitly. Instead, we have shown they can be used to identify limits (such as the fire rotation) beyond which the ecosection in question changed sufficiently that the model projections can no longer be assumed tenable. For example, as the total area burned approaches most of a landscape and the fire frequency increases, some vegetation types with incompatible life histories will become less dominant, although it is possible that some extant vegetation types could remain resilient to shorter fire rotations. Our approach is not a solution for nonstationarity, but it does provide a hedge on it that varies with the observed dynamics of each ecosection and therefore provides climatically and ecologically tailored information about when no-analog conditions could plausibly be expected.

4.4. Limitations of Our Approach and Application

There are some concrete limitations to the projections presented here. Although the historical decades used for model calibration are those arguably most similar to the next several decades of climate in the western United States, the historical record on which these climate-fire relationships were developed does not reflect the full range of climate variability known to have occurred in the 20th century. Others (Higuera et al., 2015; Littell et al., 2009) have shown that statistical relationships between area burned and climatic predictors vary with the longer climate record. Therefore, it is likely that variability in climate, fuels, or both leads to transience and that statistical climate-fire models should be considered projections and not forecasts.

Another caveat is that even though the area burned in most ecosections is driven by large fires that escape suppression, the landscape as a whole—and the fire regimes from which the relationships between climate and fire are derived—is still influenced by suppression efforts and human ignitions. The effects of fire suppression vary across ecosystems, with influence inversely proportional to the expected pre–Euro-American mean fire return interval, but in all cases a fire deficit of some magnitude exists during the period for which the models were trained (Marlon et al., 2012). Radeloff et al. (2018) demonstrate that increasing wildland-urban interface increases wildfire risk, both due to more ignitions and due to the potential for catastrophic fire (i.e., fires affecting life and property). Syphard et al. (2017) demonstrate that proximity to population centers decreases the area burned variance explained by climate variables alone. Balch et al. (2017) provide analysis that clearly shows that the fraction of human ignitions in much of the western United States is low compared to natural ignitions, with notable exceptions in southern California, southernmost Arizona, and coastal Oregon and Washington. These regions overlap with some of those where our statistical models perform poorly. Taken together, these papers illustrate that there are trends both in fire hazard and fire risk, and their interactions will determine the impacts of future fire regimes. It is also possible that changes in fuel availability, flammability, or both could change the sensitivity of ignition and area burned to climate at the ecosection scale, for example, as a result of human activity or invasive species. The total area burned for a given climatic anomaly may therefore change with time given the relative influence of fire suppression or changes in species composition. Statistical models project the central tendency of area burned given a climatic anomaly—years with extreme climate but with relatively moderate area burned occur (such as with lack of ignitions), as do years in which fire weather not reflected in climatic anomalies produces large area burned for less-than-extreme climate anomalies.

It is also critical to evaluate the source data for these statistical climate-fire models (and others presented elsewhere) objectively. As noted earlier, there is a necessary tradeoff between fine-scale resolution (such as in even finer gridded fire and climate data) and adequate representation of the climate-fire processes on the landscape. Although these “errors” might be expected to average out over longer periods and larger areas, such behavior is indicative of a real-world complexity not captured in statistical models like those we present, and the time period represented here is relatively short for a complex process.

Given this apparent impasse, there is a temptation to substitute space for time and look to other places (or other times) in the western United States with historical climates like those expected for the future in a location of interest and apply the historical climate-fire relationships to obtain future projections (e.g., Parks et al., 2017). Such an approach is valid for prediction purposes only if we are convinced that the aggregate distribution of vegetation and climate-fire relationships converges to a limited set of configurations that are transferrable. Lacking such a fortuitous convergence, this space-for-time analog approach is not likely to generate accurate future projections. Historical and future vegetation trajectories, land-use histories, local responses to changes, eco-climatic teleconnections (Stark et al., 2016), and rates of disturbance all vary sufficiently among ecosections that historical climate-fire analogs (even if they were equilibrium) cannot be assumed to be valid predictors of future fire regime characteristics. The evidence we present above suggests that although there are broad similarities in the variables that predict area burned for ecosections with similar ecological classifications, the details of seasonality, interannual sequences of climate influences, and other factors that differentiate similar ecosections result in dynamics that tend more toward divergence, transience, and variation than they do toward equilibrium. The most-limiting factors for area burned, even among relatively similar ecosections, are not stationary.

Finally, climate and biophysical drivers are not the only factors affecting fire, historically or in the future. Humans have used and managed fire on western U.S. landscapes for most of the Holocene, if not before, and a complete understanding of the likely future fire regimes in ecosections of the western United States would incorporate economic and management policy, perhaps in an agent-based approach. Our results are necessarily restricted to the impacts of climate change.

5. Conclusions

We have presented an ecologically informed classification of climate-fire relationships that clearly shows a continuum of climatic influences on fire area burned driven by differences in fuel limitation and flammability. This classification cannot be expected to remain stationary. The relatively slow ecosystem processes that create the fuels that carry fire interact with the relatively fast climatic influences that make those fuels available to burn, resulting in a transient nexus of climate and fire conditions. Both have trajectories that can be projected, but if history serves, they can be expected to evolve in often surprising ways. In that case, what do these projections tell us? Statistical projections of future climate-fire relationships based on historical dynamics are useful because they provide a relatively quick and simple approach to measure the relative sensitivity and potential for change in different ecosystems. They also likely have high skill in projecting short-term changes in area burned (e.g., next 3–5 decades) before the altered climate-fire regime resets landscape-level fuel loads, and as such are useful in anticipating and adapting to likely large increases in fire area burned in much of the western United States. However, because future conditions eventually radically exceed the calibration domain, the models do not represent long-term forecasts. A limit, such as a fire rotation, can be used to determine when the transition from this domain is likely to occur, allowing a more precise estimate of when a no-analog future potentially emerges from the historical variation. Until that time, our findings indicate that area burned will likely increase considerably in ecosystems where fuels are abundant and their flammability is most sensitive to climate variations. In ecosystems where fuels are chronically limiting, the usually slower rate of fuel accumulation under novel future climates is the limiting factor; fuels will still be flammable, perhaps for longer fire seasons, in most years. In ecosystems where flammability is chronically limiting, the climatic potential to render existing fuels available to burn is the limiting factor; fuels will still be present, and likely flammable more frequently and for longer fire seasons. Finally, it is plausible to anticipate that changes in human approaches to fire, including fire and vegetation management, land use, and population driven effects such as prevalence of ignitions could modify the controls we detected and push fire regime trajectories in directions we have not anticipated.

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References

Abatzoglou, J. T., & Kolden, C. A. (2013). Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire*, *22*(7), 1003–1020. https://doi.org/10.1071/WF13019

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(42), 11,770–11,775. https://doi.org/10.1073/pnas.1607171113

Bailey, R. G. (1995). Description of the ecoregions of the United States (2nd ed.). Misc. Pub. No. 1391, Map scale 1:7,500,000. USDA Forest Service.

Balch, J. K., Bradley, B. A., Abatzoglou, J. T., Nagy, R. C., Fusco, E. J., & Mahood, A. L. (2017). Human-started wildfires expand the fire niche across the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(11), 2946–2951. https://doi.org/10.1073/pnas.1617394114

Bowman, D. M. J. S., Murphy, B. P., Williamson, G. J., & Cochrane, M. A. (2014). Pyrogeographic models, feedbacks and the future of global fire regimes. *Global Ecology and Biogeography*, *23*(7), 821–824. https://doi.org/10.1111/geb.12180

Dennison, P. E., Brewer, S. C., Arnold, J. D., & Moritz, M. A. (2014). Large wildfire trends in the western United States, 1984-2011. *Geophysical Research Letters*, *41*, 2928–2933. https://doi.org/10.1002/2014GL059576

Elsner, M. M., Cuo, L., Voisin, N., Deems, J. S., Hamlet, A. F., Vano, J. A., et al. (2010). Implications of 21st century climate change for the hydrology of Washington State. *Climatic Change*, *102*(1–2), 225–260. https://doi.org/10.1007/s10584-010-9855-0

Feldman, B. (2005). Relative importance and value. Unpublished manuscript. https://doi.org/10.2139/ssrn.2255827

Fischer, A. P., Spies, T. A., Steelman, T. A., Moseley, C., Johnson, B. R., Bailey, J. D., et al. (2016). Wildfire risk as a socioecological pathology. *Frontiers in Ecology and the Environment*, *14*(5), 276–284. https://doi.org/10.1002/fee.1283

Fox, J., Weisberg, S., Adler, D., Bates, D., Baud-Bovy, G., Ellison, S., et al. (2014). car: Companion to applied regression. *In: R Package Version 2.0-21*, 1–157.

Grömping, U. (2006). R package relaimpo: Relative importance for linear regression. *Journal of Statistical Software*, *17*(1), 139–147. https://doi.org/10.1016/j.foreco.2006.08.245

Hamlet, A. F., Elsner, M. M., Mauger, G. S., Lee, S.-Y., Tohver, I., & Norheim, R. A. (2013). An overview of the Columbia Basin Climate Change Scenarios Project: Approach, methods, and summary of key results. *Atmosphere-Ocean*, *51*(4), 392–415. https://doi.org/10.1080/07055900.2013.819555

Higuera, P. E., Abatzoglou, J. T., Littell, J. S., & Morgan, P. (2015). The changing strength and nature of fire-climate relationships in the northern Rocky Mountains, U.S.A., 1902-2008. *PLoS One*, *10*(6), e0127563. https://doi.org/10.1371/journal.pone.0127563

Hothorn, T., Zeileis, A., Fare-brother, R. W., Cummins, C., & Millo, G. (2014). lmtest: Testing linear regression models. *In: R Package Version 0.9-30*, 1–46.

Keeley, J. E., & Syphard, A. D. (2017). Different historical fire–climate patterns in California. *International Journal of Wildland Fire*, *26*(4), 253. https://doi.org/10.1071/WF16102

Kitzberger, T., Falk, D. A., Westerling, A. L., & Swetnam, T. W. (2017). Direct and indirect climate controls predict heterogeneous early-mid 21st century wildfire burned area across western and boreal North America. *PLoS One*, *12*(12), e0188486. https://doi.org/10.1371/journal.pone.0188486

Knutti, R., & Sedláček, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, *3*(4), 369–373. https://doi.org/10.1038/nclimate1716

Krawchuk, M. A., & Moritz, M. A. (2011). Constraints on global fire activity vary across a resource gradient. *Ecology*, *92*(1), 121–132. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/21560682

Krawchuk, M. A., Moritz, M. A., Parisien, M.-A., Van Dorn, J., & Hayhoe, K. (2009). Global pyrogeography: The current and future distribution of wildfire. *PLoS One*, *4*(4), e5102. https://doi.org/10.1371/journal.pone.0005102

Littell, J. S., & Gwozdz, R. B. (2011). Climatic water balance and regional fire years in the Pacific Northwest, USA: Linking regional climate and fire at landscape scales (pp. 117–139). https://doi.org/10.1007/978-94-007-0301-8_5

Littell, J. S., Mauger, G. S., Salathe, E. P., Hamlet, A. F., Lee, S.-Y., Stumbaugh, M. R., et al. (2014). Uncertainty and extreme events in future climate and hydrologic projections for the Pacific Northwest: Providing a basis for vulnerability and core/corridor assessments. Retrieved from https://pubs.er.usgs.gov/publication/70100634 Data: https://www.sciencebase.gov/catalog/item/54dd5e58e4b08de9379b3905 Stumbaugh, M., Mauger, G.S. 2014, https://doi:10.5066/F7KS6PMF.

Littell, J. S., McGuire Elsner, M., Mauger, G. S., Lutz, E. R., Hamlet, A. F., & Salathé, E. P. (2011). Regional climate and hydrologic change in the Northern U.S. Rockies and Pacific Northwest: Internally consistent projections of future climate for resource management. Final project report, USFS JVA 09-JV-11015600-039. Retrieved from https://digital.lib.washington.edu/researchworks/handle/1773/38434

Littell, J. S., Mckenzie, D., Peterson, D. L., & Westerling, A. L. (2009). Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. *Ecological Applications*, *19*(4), 1003–1021. https://doi.org/10.1890/07-1183.1

Littell, J. S., Oneil, E. E., McKenzie, D., Hicke, J. A., Lutz, J. A., Norheim, R. A., & Elsner, M. M. (2010). Forest ecosystems, disturbance, and climatic change in Washington State, USA. *Climatic Change*, *102*(1–2), 129–158. https://doi.org/10.1007/s10584-010-9858-x

Littell, J. S., Peterson, D. L., Riley, K. L., Liu, Y., & Luce, C. H. (2016). A review of the relationships between drought and forest fire in the United States. *Global Change Biology*, *22*, 2353–2369. https://doi.org/10.1111/gcb.13275

Liu, Z., & Wimberly, M. C. (2016). Direct and indirect effects of climate change on projected future fire regimes in the western United States. *Science of the Total Environment*, *542*, 65–75. https://doi.org/10.1016/J.SCITOTENV.2015.10.093

Marlon, J. R., Bartlein, P. J., Gavin, D. G., Long, C. J., Anderson, R. S., Briles, C. E., et al. (2012). Long-term perspective on wildfires in the western USA. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(9), E535–E543. https://doi.org/10.1073/pnas.1112839109

McKenzie, D., Gedalof, Z., Peterson, D. L., & Mote, P. (2004). Climatic change, wildfire, and conservation. *Conservation Biology*, *18*, 890–902.

McKenzie, D., & Littell, J. S. (2017). Climate change and the eco-hydrology of fire: Will area burned increase in a warming western USA. *Ecological Applications*, *27*(1), 26–36. https://doi.org/10.1002/eap.1420

McKenzie, D., Shankar, U., Keane, R. E., Stavros, E. N., Heilman, W. E., Fox, D. G., & Riebau, A. C. (2014). Smoke consequences of new fire regimes driven by climate change. *Earth's Future*, *2*, 35–59. https://doi.org/10.1002/2013ef000180

Mcleod, A. I., & Xu, C. (2014). bestglm: Best subset GLM v. 0.34. Retrieved from https://cran.r-project.org/package=bestglm

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Climate change. Stationarity is dead: Whither water management? *Science*, *319*(5863), 573–574. https://doi.org/10.1126/science.1151915

Moritz, M. A., Parisien, M.-A., Batllori, E., Krawchuk, M. A., Van Dorn, J., Ganz, D. J., & Hayhoe, K. (2012). Climate change and disruptions to global fire activity. *Ecosphere*, *3*(6), art49. https://doi.org/10.1890/ES11-00345.1

Mote, P. W., & Salathé, E. P. Jr. (2010). Future climate in the Pacific Northwest. *Climatic Change*, *102*, 29–50. https://doi.org/10.1007/s10584-010-9848-z

Parks, S. A., Holsinger, L. M., Miller, C., & Parisien, M.-A. (2017). Analog-based fire regime and vegetation shifts in mountainous regions of the western US. *Ecography*, *41*, 910–921. https://doi.org/10.1111/ecog.03378

Pausas, J. G., & Bradstock, R. A. (2007). Fire persistence traits of plants along a productivity and disturbance gradient in mediterranean shrublands of south-east Australia. *Global Ecology and Biogeography*, *16*(3), 330–340. https://doi.org/10.1111/j.1466-8238.2006.00283.x

Pausas, J. G., & Ribeiro, E. (2013). The global fire-productivity relationship. *Global Ecology and Biogeography*, *22*(6), 728–736. https://doi.org/10.1111/geb.12043

R Core Team (2017). R Core Team (2017). R: A language and environment for statistical computing. In. *R Foundation for Statistical Computing* Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-Project.org/

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., et al. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(13), 3314–3319. https://doi.org/10.1073/pnas.1718850115

Ryan, K. C. (1991). Vegetation and wildland fire: Implications of global climate change. *Environment International*, *17*(2–3), 169–178. https://doi.org/10.1016/0160-4120(91)90099-C

Schoennagel, T., Balch, J. K., Brenkert-Smith, H., Dennison, P. E., Harvey, B. J., Krawchuk, M. A., et al. (2017). Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(18), 4582–4590. https://doi.org/10.1073/pnas.1617464114

Stark, S. C., Breshears, D. D., Garcia, E. S., Law, D. J., Minor, D. M., Saleska, S. R., et al. (2016). Toward accounting for ecoclimate teleconnections: Intra- and inter-continental consequences of altered energy balance after vegetation change. *Landscape Ecology*, *31*(1), 181–194. https://doi.org/10.1007/s10980-015-0282-5

Syphard, A. D., Keeley, J. E., Pfaff, A. H., & Ferschweiler, K. (2017). Human presence diminishes the importance of climate in driving fire activity across the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(52), 13,750–13,755. https://doi.org/10.1073/pnas.1713885114

Westerling, A. L., Gershunov, A., Brown, T. J., Cayan, D. R., & Dettinger, M. D. (2003). Climate and wildfire in the Western United States. *Bulletin of the American Meteorological Society*, *84*(5), 595–604. https://doi.org/10.1175/BAMS-84-5-595

Westerling, A. L., Turner, M. G., Smithwick, E. A. H., Romme, W. H., & Ryan, M. G. (2011). Continued warming could transform Greater Yellowstone fire regimes by mid-21st century. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(32), 13,165–13,170. https://doi.org/10.1073/pnas.1110199108

Williams, A. P., & Abatzoglou, J. T. (2016). Recent advances and remaining uncertainties in resolving past and future climate effects on global fire activity. *Current Climate Change Reports*, *2*(1), 1–14. https://doi.org/10.1007/s40641-016-0031-0

Young, A. M., Higuera, P. E., Duffy, P. A., & Hu, F. S. (2017). Climatic thresholds shape northern high-latitude fire regimes and imply vulnerability to future climate change. *Ecography*, *40*(5), 606–617. https://doi.org/10.1111/ecog.02205