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How climate change and fire exclusion drive wildfire regimes at actionable scales

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Supplementary material for this article is available online

Abstract

Extreme wildfires are increasing in frequency globally, prompting new efforts to mitigate risk. The ecological appropriateness of risk mitigation strategies, however, depends on what factors are driving these increases. While regional syntheses attribute increases in fire activity to both climate change and fuel accumulation through fire exclusion, they have not disaggregated causal drivers at scales where land management is implemented. Recent advances in fire regime modeling can help us understand which drivers dominate at management-relevant scales. We conducted fire regime simulations using historical climate and fire exclusion scenarios across two watersheds in the Inland Northwestern U.S., which occur at different positions along an aridity continuum. In one watershed, climate change was the key driver increasing burn probability and the frequency of large fires; in the other, fire exclusion dominated in some locations. We also demonstrate that some areas become more fuel-limited as fire-season aridity increases due to climate change. Thus, even within watersheds, fuel management must be spatially and temporally explicit to optimize effectiveness. To guide management, we show that spatial estimates of soil aridity (or temporally averaged soil moisture) can provide a relatively simple, first-order indicator of where in a watershed fire regime is climate vs. fuel-limited and where fire regimes are most vulnerable to change.

1. Introduction

In recent years, ecosystems around the globe have endured increasingly destructive wildfires, accelerating economic and ecological damage and leading to catastrophic loss of property and lives (Calkin *et al* 2014). Increased occurrence of such fires culminates from several, often interacting factors, including anthropogenic climate change (ACC), problematic land management, and suburban expansion into the wildlands (Keyser and Westerling 2017). However, there is still considerable debate over how these factors have contributed to observed changes in fire activity across different regions and ecosystems (Gill *et al* 2013). Despite this ongoing discussion, fuel reduction efforts, including unsuppressed wildfire for resource objectives, controlled burns, and thinning have been proposed to mitigate fire risk. The ecological appropriateness of these efforts depends on how climate and fuels interact, and which driver dominates at actionable scales (i.e. local scales within watersheds where management decisions are implemented). Achieving a finer-scale understanding of climate-fuel interactions will enable us to identify when, where, and under what circumstances fuel management can enhance resilience to environmental change (Stephens *et al* 2013).

Fire regimes—characterized by the frequency, intensity, size, season, and severity of fire over time—exist along an aridity continuum that ranges from being limited by flammability (i.e. climate) to being limited by fuel (Krawchuk and Moritz 2011, Pausas and Paula 2012). In climate-limited systems, there is typically enough fuel for fire to spread, but moisture is too high; these systems are characterized by infrequent, severe fires, which occur during unusually arid conditions. In fuel-limited systems, the climate is relatively arid and conducive to fire, so fire activity is mostly driven by the amount of live and dead plant material present; these systems typically experience frequent, low-severity surface fires.

The sensitivity of fire regimes to drivers such as ACC and fire exclusion is also hypothesized to vary along the climate to fuel-limitation continuum. At large scales, such as across the western U.S., ACC has been shown to directly facilitate changes in the fire environment by increasing fuel aridity and lengthening fire seasons (Abatzoglou and Williams 2016, Westerling 2016, Abatzoglou *et al* 2019). By contrast, local to regional-scale increases in fire size, frequency, and burned area have been associated with changing ignition patterns (Balch *et al* 2017), invasive species (Fusco *et al* 2019), and fire management policies (Allen *et al* 2002). Of these, the legacy of 20th century fire suppression—which led to near-complete exclusion of wildfire—has changed land-cover and fire regimes, most notably in fuel-limited ecosystems adapted to relatively frequent fires (Parks *et al* 2015). In these systems, decades of fire exclusion have led to fuel accumulation and more homogeneous fuel beds (Stephens *et al* 2013, Steel *et al* 2015), while also promoting drought stress through increases in water competition (Gleason *et al* 2017, Voelker *et al* 2019).

Because top-down climate drivers interact with changing fuel loads and continuity across complex terrain, it is difficult to disaggregate their relative influence on wildfire regimes using observations. This is particularly true at actionable/management-relevant scales, where those observations are confounded by interannual climate variability (Abatzoglou *et al* 2018) and covarying factors such as ignition sources (Fusco *et al* 2016), wind patterns (Abatzoglou and Kolden 2011), and forest health (Hicke *et al* 2012). Further, climate change can sometimes shift fire regimes from climate-limited to fuel-limited (Westerling *et al* 2011, Littell *et al* 2018), which may interact with fuel management in complex ways.

Models of fire regimes, and more generally ecosystem process models, have emerged as a tool for estimating the effects of climate change and land use change (Keane *et al* 2004). Useful models, however, must be able to resolve the local controls that drive the aridity continuum including hydrologic dynamics, such as lateral moisture redistribution, and spatial patterns of plant biomass and growth, including overstory and understory canopy layers. Both simple empirical and highly complex physical models are prone to over or underestimate fire activity over time because they do not simulate non-stationarity in climate drivers or important positive and negative feedbacks that influence fire regimes, including the effects of vegetation productivity on local aridity and fuel self-limitation (Littell *et al* 2018, Hurteau *et al* 2019, Tague *et al* 2019). Recent advances in watershed-scale ecohydrological models can help bridge this gap by integrating the mechanisms through which changes in climate and forest structure influence fuel moisture and loads through time.

The Regional Hydro-Ecological Simulation System has recently been coupled with a fire spread model (RHESSys–WMFire), providing an intermediate scale and complexity framework that is well-suited for simulating fire regimes in heterogeneous landscapes (Tague and Band 2004, Kennedy *et al* 2017, Bart *et al* 2020). This framework simulates feedbacks among climate, hydrology, vegetation, fuels, fire spread, and fire effects over decades. As a result, it is designed to project emergent fire regime characteristics as they arise from top-down and bottom-up drivers of watershed ecohydrology (Kennedy *et al* 2017, Bart *et al* 2020). The system predicts plausible distributions of outcomes from different scenarios rather than individual events.

Using this modeling framework, we examined how climate change and fire exclusion influence fire regimes at the scale of actionable management. We conducted a factorial modeling experiment using historical and counterfactual scenarios (i.e. hypothetical or control scenarios, where ACC and fire suppression were removed) using RHESSys–WMFire in two watersheds in the Inland Northwestern U.S. (i.e. Johnson Creek and Trail Creek; supplemental figure 1 which is available online at stacks.iop.org/ERL/16/024051/mmedia). These watersheds are within regions that are strongly and moderately climate-limited with respect to fire (Littell *et al* 2018). Both are primarily federally managed and have been governed by the U.S. fire suppression policies of the last century (Stephens and Ruth 2005). Our goals were to understand the relative contributions of decades of fire suppression (represented as complete fire exclusion) and historical ACC on predicted fire regime characteristics, and whether their contributions differ given the underlying vegetation and historical fire regime context. We hypothesized that the relative roles of climate change and fire exclusion vary even at fine scales within watersheds.

2. Methods

2.1. Study sites

We conducted our modeling experiment in two mixed-conifer watersheds in Idaho—a region

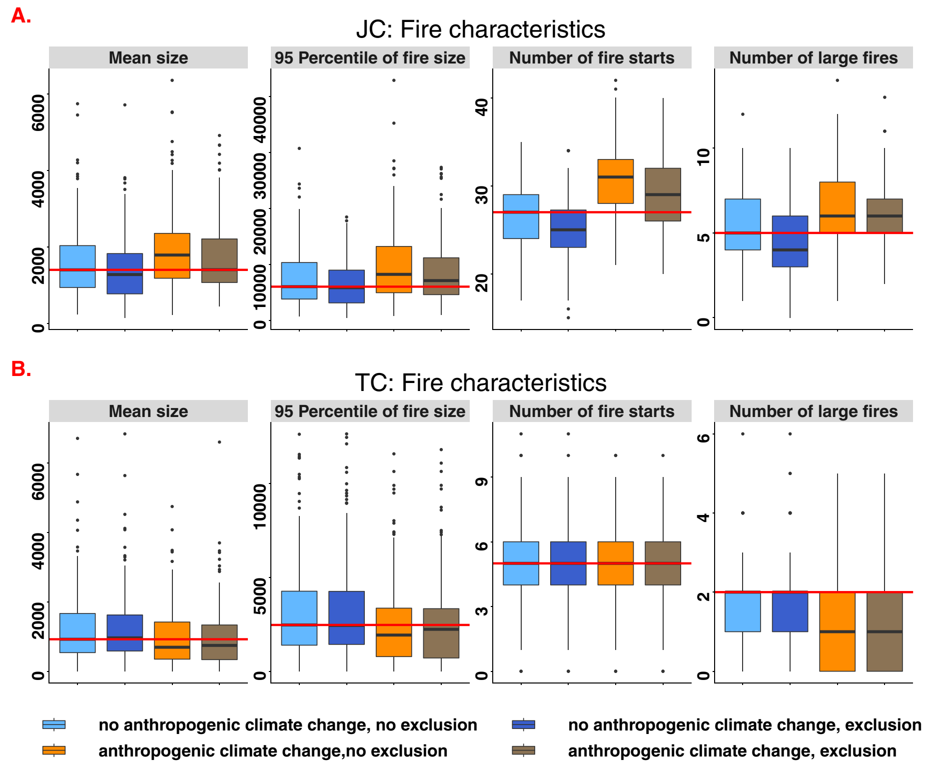

Figure 1. Distribution of fire regime characteristics. Box plots showing median, 25th percentile and 75th percentile values for fire regime characteristics for each scenario in (a) Johnson Creek and (b) Trail Creek during the assessment period. Red line is the median value for the counterfactual scenario (i.e. no climate change, no suppression). Mean and 95th percentile fire sizes are expressed in number of patches burned.

that experienced some of the most intense early suppression efforts following the Great Fire of 1910 (Pyne 2001; supplemental figure 1). The first watershed, Johnson Creek, is representative of watersheds in the Northern Rockies and Idaho Batholith. It is a 565 km^2 sub-catchment of the South Fork Salmon River in central Idaho (44°580 N, −115°30) and includes portions of the Payette and Boise National Forests. The region experiences hot, dry summers and cold winters with heavy snowfall, which constitutes approximately 65% of annual precipitation (Megahan *et al* 1992). Mean annual precipitation is approximately 1175 mm, however precipitation varies between wetter montane forests and semi-arid interior valleys. Johnson Creek is characterized by steep granitic slopes that produce shallow coarse-textured soils (Hyndman 1983). Elevations range from 1429 to 2779 m. Vegetation is dominated by ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) at lower elevations, and lodgepole pine (*Pinus contorta var. latifolia*), grand fir (*Abies grandis*), Engelmann spruce (*Picea engelmannii*), and subalpine fir (*Abies lasiocarpa*) at higher elevations (Arkle and Pilliod 2010). Riparian, shrub, and herbaceous species are also present in the watershed (Homer *et al* 2015). Most contemporary fires in the region are either mixed severity or stand-replacing. Fire regime characteristics for Johnson Creek are described in supplemental text (section 1.1).

The second watershed, Trail Creek is a 167 km^2 sub-catchment of the Big Wood River basin in the Sawtooth National Forest (43.44° N, −114.19° W). This watershed is in the middle Rockies and is representative of transitional watersheds with strong elevation gradients. Such watersheds may be particularly vulnerable to altered fire regimes under climate change because lower elevation species can easily migrate upslope (Romme *et al* 2003). Therefore, increases in fire size and severity may lead to permanent type conversion and further changes in fire activity. Trail Creek has cold, wet winters and warm, dry summers. Mean annual precipitation is approximately 978 mm and 60% of the precipitation falls during the winter season as snow. The soils of the Trail Creek valley are mostly coarse, permeable alluvium (Smith 1960). Elevations range from 1760 to 3478 m. Vegetation can be classified into two main categories based on elevation: lower to middle elevation areas are covered by sagebrush, riparian species, and grasslands, while mid-to-high elevations are dominated by Douglas fir (*P. menziesii*), lodgepole pine (*P. contorta var. latifolia*), subalpine fir (*A. lasiocarpa*), and mixed shrub and herbaceous species (Homer *et al* 2015). Fire regime characteristics for Trail Creek are described in supplemental text (section 1.2)

2.2. Coupled biophysical-fire spread modeling framework

Fire regime models must be both spatially resolved and robust enough to represent fuel conditions and how fuels are distributed in watersheds, while also being simple enough that they can be parameterized over large watersheds. Existing fire models range in complexity from simple statistical models that identify how climate and fuels drive wildfire regimes at large scales (Littell *et al* 2009) to fully physical models that can predict the paths of specific fires (Mell *et al* 2007, Coen *et al* 2013, Andrews 2014). Along this complexity continuum, there are tradeoffs between a model's predictive power and its associated uncertainty. With increased model complexity comes requirements for more detailed and precise data inputs, which are highly uncertain when trying to understand future fuels and wildfire (Keane *et al* 2013, Benali *et al* 2017, Prichard *et al* 2019). Thus, we need simulation tools that operate at actionable, intermediate scales (Littell *et al* 2018). This requires models that are designed to simulate fuel conditions and feedbacks with long-term fire regimes (Keane *et al* 2011, Kennedy *et al* 2017) rather than more complex models that predict spread and intensity of individual fire events.

We ran a factorial modeling experiment using the RHESSys–WMFire framework to understand the relative roles of fire suppression vs. climate change on wildfire activity. The framework couples the watershed scale, ecohydrologic model RHESSys (Regional Hydro-Ecologic Simulation System; Tague and Band 2004) to a stochastic fire spread model (WMFire; Kennedy *et al* 2017), and a model for fire effects (Bart *et al* 2020). In the coupled framework, RHESSys provides spatially explicit, aggregate summaries of fuel structure and loading across a watershed and WMFire is designed to accommodate this representation. WMFire produces fire spread maps over randomized ignitions and stochastic spread, providing probability distributions of fire activity over time. The fire-effects model then accounts for vertical fire spread and consumption through different fuel layers as well as vegetation mortality—this links fire spread to fire severity. Fire effects ultimately feed back into RHESSys by updating postfire stand structure that in turn influences watershed carbon cycling and hydrologic processes, including post-fire recovery of fuels and future fire behavior.

RHESSys has demonstrated skill in simulating processes that control fuel loading and fuel moisture, including plant productivity, evapotranspiration, and streamflow (examples in the Pacific and Inland Northwest include: Garcia and Tague 2014, Garcia et al 2013, Hanan et al 2018, Tague et al 2013). It has also been used to examine how these dynamics respond to climate change and wildfire (Chen et al 2020, Hanan et al 2017). RHESSys–WMFire has demonstrated further skill in replicating spatial patterns of fire spread (Kennedy and McKenzie 2017), fire regime characteristics (Kennedy *et al* 2017) and fire effects for low and mixed-high-severity fire regimes across multiple landcover types (Bart *et al* 2020). These include shrublands, open-canopy forests, and closed canopy forests. The framework also includes methods for using remote sensing products such as leaf area index and forest structure metrics to initialize fire histories (Hanan *et al* 2018). RHESSys–WMFire provides a significant advancement in fire modeling because fire regime characteristics emerge from feedbacks among climate, hydrology, vegetation, fuels, fire spread, and fire effects. Thus, it is robust to non-stationarity in climate conditions and to positive and negative feedbacks that drive wildfire activity (Kennedy *et al* 2017). Details of the model system (including an exposition of how we represent fuels and a description of the relevant scope and model domain) can be found in supplemental text (section 2, and also in Kennedy *et al* 2017, Kennedy and McKenzie 2017, Bart *et al* 2020).

2.3. Datasets and model inputs

Data layers and inputs for initializing, parameterizing, calibrating, validating, and running RHESSys–WMFire are outlined in supplemental table 2. These include daily, high-resolution (1/24th degree or ~4-km) gridded meteorological data (from gridMET), including maximum and minimum temperatures, relative humidity, radiation, and wind speed, for the water years 1980 to 2017. Meteorological inputs for historical scenarios were developed by extending gridMET records back in time (1900–1978) using ERA-20C daily reanalysis data (1900–2010; Poli *et al* 2016) interpolated to gridMET's horizontal resolution. Daily data were bias-corrected to the gridMET fields using quantile matching separately for each month spanning the period of data overlap (water years 1980–2010). This ensured compatibility in distributions between the two records. We further bias-corrected resultant monthly meteorological records using data derived from PRISM (Daly *et al* 1994) while preserving the intramonthly variability from ERA-20C.

We developed counterfactual (i.e. control) scenarios that exclude the first-order modeled influence of ACC from the observational record. Following Abatzoglou *et al* (2020), we approximated the anthropogenic contribution to local and monthly climate variables using a pattern scaling approach that accounts for local changes in individual climate variables per degree change in global mean temperature. Local scaling functions were derived from the ensemble median change of monthly fields from 23 GCMs from the Coupled Model Inter-comparison Project 5 (CMIP5; Taylor *et al* 2012) between two 30 year periods (1850–1879 and 2070–2099), the latter using the relative concentration pathway 8.5. We defined the ACC

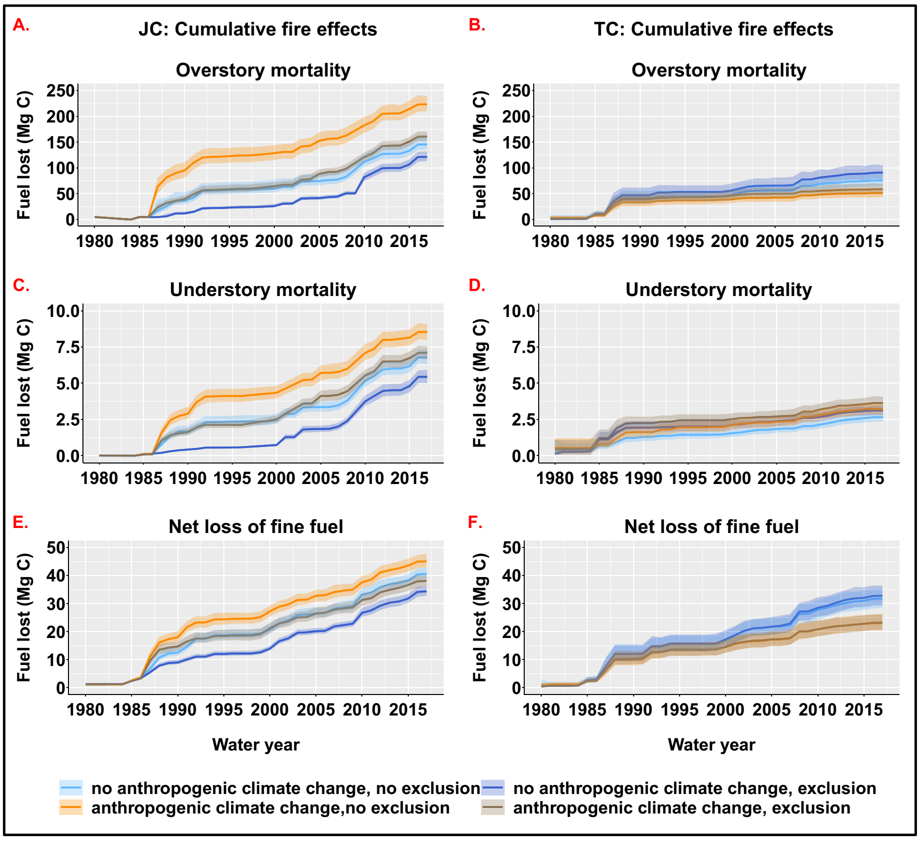

Figure 2. Cumulative fire severity: (left) cumulative mortality in Johnson Creek with respect to carbon lost from (a) overstory fuel layers and (b) understory fuel layers; (c) net changes in fine fuel (i.e. litter) carbon following fine fuel consumption and the deposition of residual dead carbon from understory and overstory layers. (Right) cumulative mortality in Trail Creek with respect to carbon lost from (d) overstory fuel layers and (e) understory fuel layers; (f) net changes in fine fuel (i.e. litter) carbon following fine fuel consumption and the deposition of residual dead carbon from understory and overstory layers. We used a bootstrapping approach to calculate 95% confidence windows for each scenario.

signal for monthly variables by multiplying the monthly varying pattern scaling function by an 11 year moving average of model-simulated changes in the global mean temperature anomaly (1850–1879 baseline climate). Counterfactual meteorological data from 1895 to 2017 was derived by removing the monthly ACC signal from daily observations (e.g. Williams *et al* 2015, Abatzoglou and Williams 2016). We note that this counterfactual scenario does not account for changes in dynamics such as longer dry spells that are projected to arise in response to anthropogenic forcing (Polade *et al* 2014). RHESSys–WMFire model calibration and validation approaches are described in supplemental text (section 3).

2.4. Modeling scenarios

To disentangle the relative and combined influence climate change and fire suppression (modeled as complete exclusion) on fire regimes, we implement historical and counterfactual modeling scenarios in a factorial design. We examined the extent to which seven decades of fire exclusion (water years 1911–1979) and historical anthropogenic climate change have interacted to influence potential fire regime characteristics over the last four decades (water years 1980–2017; supplemental figure 2). The goal was not to replicate the past 40 years of fire activity in the watersheds, as this has resulted from other exogenous factors such as fire suppression and ignitions. Rather, we examined the individual and combined effects of these drivers to estimate the relative potential fire activity in this time frame. Previous climate-fire studies have largely focused on area burned (e.g. Littell *et al* 2009, Dennison *et al* 2014, Abatzoglou and Williams 2016, McKenzie and Littell 2017, Hurteau *et al* 2019), which we do here in conjunction with the probability of fire activity in a given area (to scale down to unique subsystems within the larger watersheds). We also show how climate change and fire exclusion influence other fire regime characteristics in the two watersheds, including the mean distribution of fire sizes, fire frequency, and fire severity.

WMFire is stochastic; Kennedy (2019) recommended at least 157 replicates to distinguish fire regime characteristics. Using that guideline as a lower limit, we ran 200 iterations of the coupled model for each of the four scenarios in a 2×2 factorial design: (a) a counterfactual scenario, (b) a scenario with ACC, no exclusion, (c) a scenario with exclusion, no ACC, and (d) a scenario with both ACC and exclusion. Our modeling study included three phases:

2.4.1. Preliminary spin-up

We initialized vegetation and fuel loads using a historic spin-up period of 300 years. For this period, we looped our reconstructed climate record after removing the ACC signal; this was a period of pre-human interference.

2.4.2. Scenario initialization

Following the preliminary spin-up, we ran the model for 68 years (water years 1911–1979) to initialize each scenario (with and without historical ACC and/or fire exclusion; supplemental figure 2). For the two fire exclusion scenarios, we ran simulations without fire spread from 1911 to 1979. RHESSys without wildfire is deterministic, so this required a single model run for the two fire exclusion scenarios. For the scenarios without exclusion, we included fire spread and effects and ran the model stochastically (i.e. 200 iterations for each of the 2 scenarios). This enabled us to capture potential fire regime variability during the 1911–1979 period and how it influenced fuel loads. The initial conditions established at the end of the 1979 hydrologic year were then used to initialize the four corresponding scenarios in our factorial design (supplemental figure 2).

2.4.3. Assessment period

Simulations for the assessment period were conducted using climate from water years 1980 through 2017 with fire spread and effects turned on for all scenarios. In our experimental design we assumed either complete fire exclusion or no exclusion for the initialization climate period prior to 1980, then no fire exclusion during our 1980-2017 assessment period. As a result, the effects of prior fire exclusion are isolated in the simulations. For scenarios with prior fire exclusion, we simulated the assessment period both with and without ACC using 200 independent simulation replicates. For scenarios without prior fire exclusion, we continued the 200 initialization replicates to comprise our 200 assessment replicates both with and without ACC. All scenarios were run with the same 200 individual random seeds to ensure consistency in the ignition sequences.

2.5. Analysis

Following the three phases of simulation, we estimated fire regime characteristics, including mean fire size, 95th percentile fire size, the number of fire-starts (i.e. fires that burned more than 30 patches, where a patch represents the smallest spatial unit in a watershed), and the number of large fires (i.e. fires that burned > 1000 patches) over space and time in two study watersheds. For mean fire size, we first calculated the mean for each replicate and then evaluated the distribution of means across replicate simulations for each scenario. For all other fire characteristics, we identified the values first within each replicate for a given scenario and then compared the distribution of those characteristics among scenarios. Our goal was not to predict actual values for these metrics, but to compare their relative patterns among scenarios.

To examine fine-scale spatial variation, we also calculated burn probability (i.e. how likely a fire is to occur at a specific location in a given simulation year) for each pixel across the two watersheds. We estimated the likelihood of fire (P_{burn}) as:

$$P_{\text{burn}} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{N} F_{ij}}{n \times N} \tag{1}$$

where n is the number of years in the simulation, N is the number of simulation replicates, and F_{ij} is the number of times the patch burned in a given year in a given replicate. This represents the proportion of times a given patch burned across all simulations.

To summarize the effects of ACC and fire exclusion (EX) over the 38 year assessment period, we calculated cumulative area burned (CAB) across all 200 simulations for each scenario and then calculated the percent change in burned area due to each driver as:

$$\text{Percent}\Delta_{\text{ACC}} = \frac{(\text{CAB}_{\text{ACC,EX}} + \text{CAB}_{\text{ACC,noEX}}) - (\text{CAB}_{\text{noACC,EX}} + \text{CAB}_{\text{noACC,noEX}})}{(\text{CAB}_{\text{noACC,EX}} + \text{CAB}_{\text{noACC,noEX}})} \times 100 \tag{2}$$

$$\text{Percent}\Delta_{\text{EX}} = \frac{(\text{CAB}_{\text{ACC,EX}} + \text{CAB}_{\text{noACC,EX}}) - (\text{CAB}_{\text{ACC,noEX}} + \text{CAB}_{\text{noACC,noEX}})}{(\text{CAB}_{\text{ACC,noEX}} + \text{CAB}_{\text{noACC,noEX}})} \times 100. \tag{3}$$

We also examined how the role of climate change and fire exclusion varied with aridity. We selected soil moisture (SM) as a proxy for local aridity because it responds to both top-down and bottom-up drivers (such as climate and topography, respectively), while also influencing multiple fire regime drivers, including fuel moisture and fuel loads. We calculated mean fire season (June–September) soil moisture (SM_{fs}) over the entire 38 year assessment period by selecting a single simulation (with the same random seed to avoid any differences due to stochasticity) for each scenario (SM_{fs} did not vary significantly among replicate simulations):

$$SM_{fs} = \frac{\Sigma\left(SM_{June} + SM_{July} + SM_{August} + SM_{September}\right)}{4 \times 38}. \tag{4}$$

This enabled us to compare spatial differences in site aridity to burn probability over the 38 year assessment period for each scenario. We also calculated mean fire season litter C and mean fire season fuel aridity using the same formula.

3. Results

3.1. Effects of climate change and fire exclusion on fire regimes

Results from the scenario initialization period are presented in supplemental text (section 4) and results from the assessment period are presented below. In Johnson Creek, ACC increased predicted mean fire size, 95th percentile fire size, number of fires, and number of large fires across the watershed (figure 1(a)). Fire severity was also higher in climate change scenarios for all fuel layers (figures 2(a), (c), and (e)). However, fire severity appeared to be self-limiting—cumulative overstory mortality increased rapidly with climate change over the first two decades of simulation and then remained steady for multiple decades while fuels recovered (figure 2(a)). When summed over the 38 year assessment period, there was a 40% increase in burned area compared to scenarios that did not include climate change. Fire exclusion on the other hand increased initial fuel loading (supplemental figure 2(b)), which promoted larger fires during the first five years of the assessment period (table 1). However, over the course of the full assessment period, scenarios with prior exclusion experienced a cumulative 15% decrease in burned area compared to the scenarios without exclusion.

In Trail Creek, basin-scale wildfire regimes responded differently. At the watershed scale, mean fire size, 95th percentile fire size, and the number of large fires all decreased in scenarios that included climate change, while the number of fires was not affected (figure 1(b)). Fire severity was also lower in climate change scenarios for all fuel layers (figures 2(b), (d), and (f)). This occurred because climate change increased plant competition for water, which reduced net primary productivity and fine fuel loads in both the prior exclusion and no prior exclusion scenarios (supplemental figure 2(d)). Reduced fuel loads resulted in a cumulative 19% decrease in predicted burned area compared to scenarios without climate change. Scenarios with prior fire exclusion experienced smaller fires during the first 5 years of the assessment period (table 1), corresponding to lower fine fuel loading (supplemental figure 2), though at the watershed scale, fire exclusion increased burned area by 2% over the full assessment period. We note that the distribution of fire sizes (figure 1) does not account for area burned outside the watershed boundaries. Thus, fire size distributions that are not truncated to individual watersheds could be significantly larger.

3.2. Effects of aridity on the climate-fuel continuum

Soil moisture influences multiple fire-relevant variables, including both fuel aridity and fuel loads (figures 3(c)–(f)). We found that these interacted to predict the probability of wildfire in complex ways between the two watersheds (figures 4 and 5). For example, climate change generally increased fuel aridity and therefore burn probability in locations where mean fire season soil moisture (SM_{fs}) was above 35%. In locations where SM_{fs} was below 25% on the other hand, climate change decreased burn probability by reducing fuel loads (figure 3). At intermediate SM_{fs} (i.e. between 25% and 35%) burn probability and the effects of climate change varied in response to local trade-offs between aridity and productivity, which yield a compromise between flammability and fuel load (figures 4 and 5).

In Johnson Creek, when fuel loads were sufficiently high (i.e. above 0.5 g C m^{-2}), burn probability responded mostly to fuel aridity (figure 4). For example, in locations where SM_{fs} was above 35%, climate change increased burn probability regardless of whether or not exclusion had occurred (figure 3(a)) and the largest increases in burn probability occurred in locations where fuel load was high and fuel aridity was low (figures 4(c) and (f)). At a given SM_{fs} in these wetter areas, climate change increased fuel aridity (calculated as 1-AET/PET of the understory vegetation) by increasing PET relative to AET (figure 3(c)). Although climate change also reduced fine fuel loads (figure 3(b)), burn probability still increased in many locations because the watershed was not generally fuel-limited and responded more to drying.

Fuel loads played a more prominent role in Trail Creek, where SM_{fs} and fuel moisture were both generally lower (figures 3(b), (d), and (f)). Burn probability increased with fuel load as would be expected in a fuel-limited system. However, when fuel load was greater than 0.6 g C m^{-2}, fuel limitation was somewhat alleviated and burn probability was more sensitive to fuel aridity (figures 5(a), (b), (d), and (e)). These effects were most pronounced in scenarios that did not include historical ACC however (figures 5(b) and (e)), suggesting that climate change is increasing fuel-limitation. In arid locations, where SM_{fs} was below 35%, climate change decreased net primary productivity, thus reducing fuel loads (figure 3(d)) and burn probability (figure 3(b)).

Table 1. Fire size characteristics during the first 5 years of the assessment period for scenarios with and without anthropogenic climate change (ACC) and with and without historical fire exclusion. In Johnson Creek, historical exclusion scenarios (in italicized bold type) had larger fires early in the assessment period compared to no exclusion scenarios. Trail Creek had the opposite response, with larger fires in no-exclusion scenarios.

Watershed	Scenario	Mean fire size (# patches)	Fire starts	95th percentile fire size
Johnson Creek	No ACC, no exclusion (counterfactual)	92.7	99	194.3
	No ACC, exclusion	***118.9***	***82***	***351.1***
	ACC, no exclusion	76.0	105	184.2
	ACC, exclusion	***100.5***	***97***	***221.2***
Trail Creek	No ACC, no exclusion (counterfactual)	275.1	48	1110.6
	No ACC, exclusion	***203.7***	***40***	***781.9***
	ACC, no exclusion	261.8	55	1109.5
	ACC, exclusion	***226.6***	***43***	***663.9***

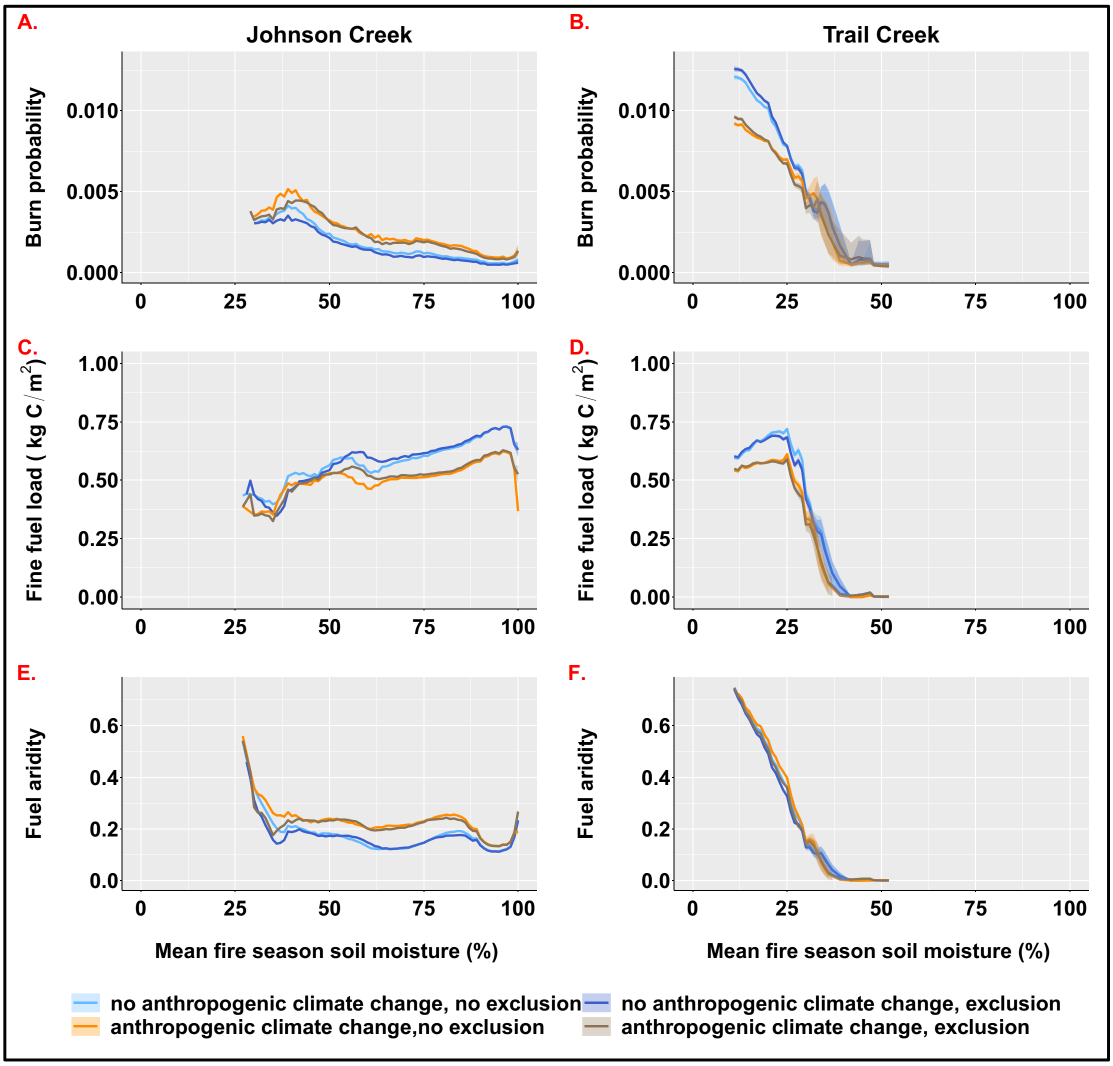

Figure 3. SM_{fs} effects on burn probability, fuel load, and fuel aridity. Top: relationship between SM_{fs} and annual burn probability (Pburn) calculated over the 1980–2017 assessment period in (a) Johnson Creek (JC) and (b) Trail Creek (TC). Middle: relationship between SM_{fs} and litter C (i.e. surface fuel loads) in (c) JC and (d) TC. Bottom: relationship between SM_{fs} and fuel aridity in (e) JC and (f) TC. In TC, more than 99% of patches had SM_{fs} below 50%. Therefore, we masked patches with >50% SM_{fs} from the analysis. Data were aggregated and smoothed using moving windows of 0.03 and 0.05 for JC and TC, respectively.

Climate change reduced burn probability to the greatest extent in locations where fuel aridity was high (figures 5(c) and (f)).

The effects of aridity on wildfire drivers are also confounded with vegetation cover. In the more-mesic Johnson Creek watershed, the climate change effect

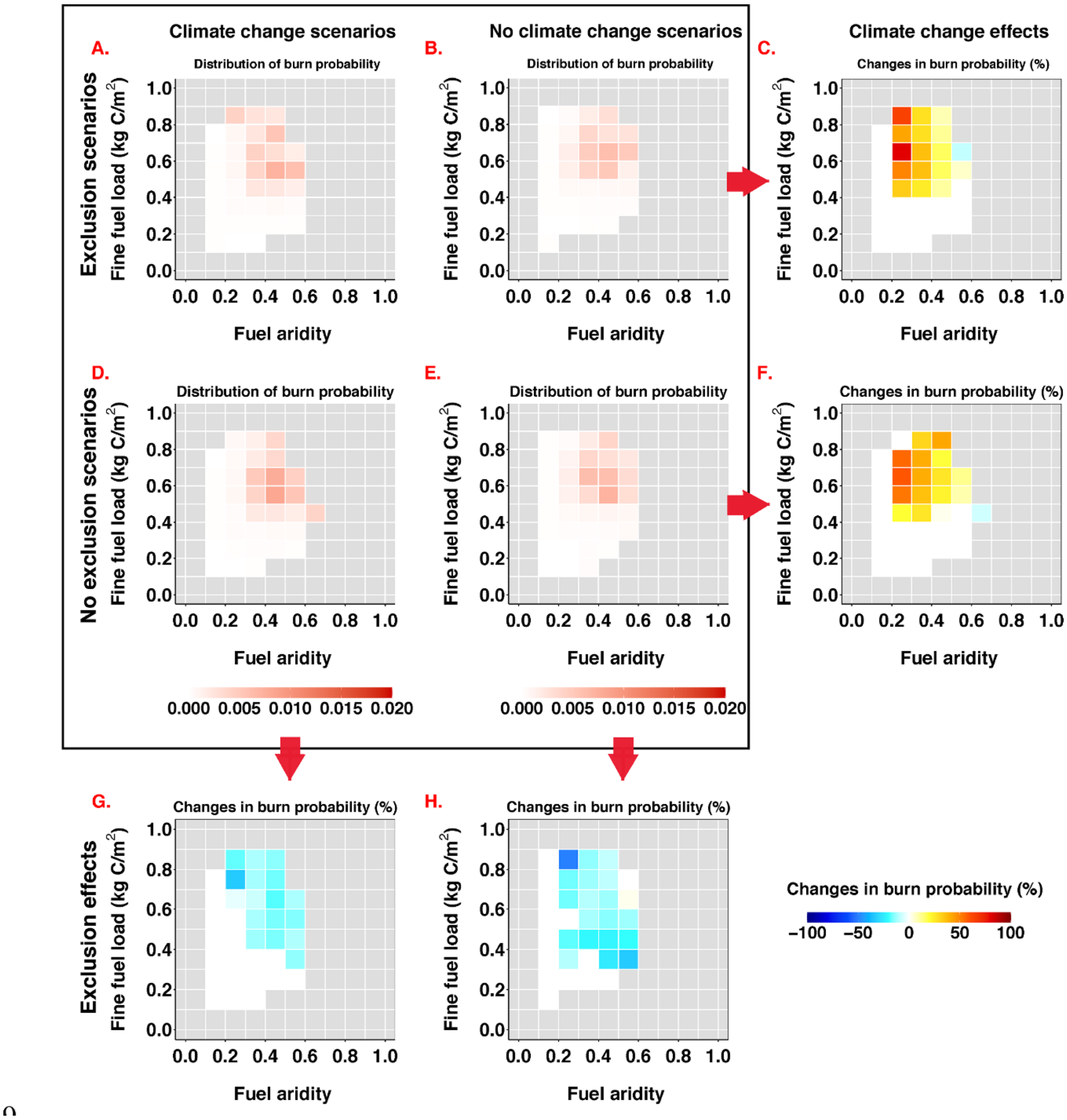

Figure 4. Effects of fuel aridity and fine fuel load on burn probability for each scenario in Johnson Creek. Scenarios include: (a) climate change, exclusion, (b) no climate change, exclusion, (d) climate change, no exclusion, and (e) no climate change, no exclusion. Right: percent changes (±) in burn probability due climate change for (c) no exclusion and (f) exclusion scenarios. Bottom: percent changes (±) in burn probability due exclusion for (g) no climate change and (h) climate change scenarios. No data and very small sample sizes (i.e. <600 pixels for JC) are masked in grey.

was most pronounced for pine trees, while trees, shrubs, and grasses all responded similarly to fire exclusion (supplemental figures 3(a) and (b)). In the more arid Trail Creek, burn probability decreased with climate change to the largest extent for shrubs and trees (supplemental figures 3(c) and (d)).

4. Discussion

The effects of climate change and prior suppression varied within and between the two Inland Northwest watersheds. Although fuel loads in both watersheds were primed for less extreme fires in climate change scenarios (supplemental figures 2(b) and (d)), this did not play out in Johnson Creek, which was climate rather than fuel limited. In Johnson Creek, scenarios with ACC and no prior exclusion resulted in the highest mean fire size, the largest 95th percentile fire size, more fire starts, and more large fires, whereas scenarios with no climate change and prior exclusion resulted in the lowest overall values (figure 1(a)). For a given exclusion scenario, climate change resulted in both larger and more frequent fires, and for a given climate change scenario, exclusion resulted in smaller and less frequent fires. Fire severity was also higher in climate change scenarios for all fuel layers.

Historical suppression increased initial fuel loading in Johnson Creek (supplemental figure 2(b)), leading to larger fires early in the assessment period (table 1). Yet, over the course of the entire assessment period, prior exclusion decreased mean wildfire size, frequency, and burned area (figure 1(a)). This

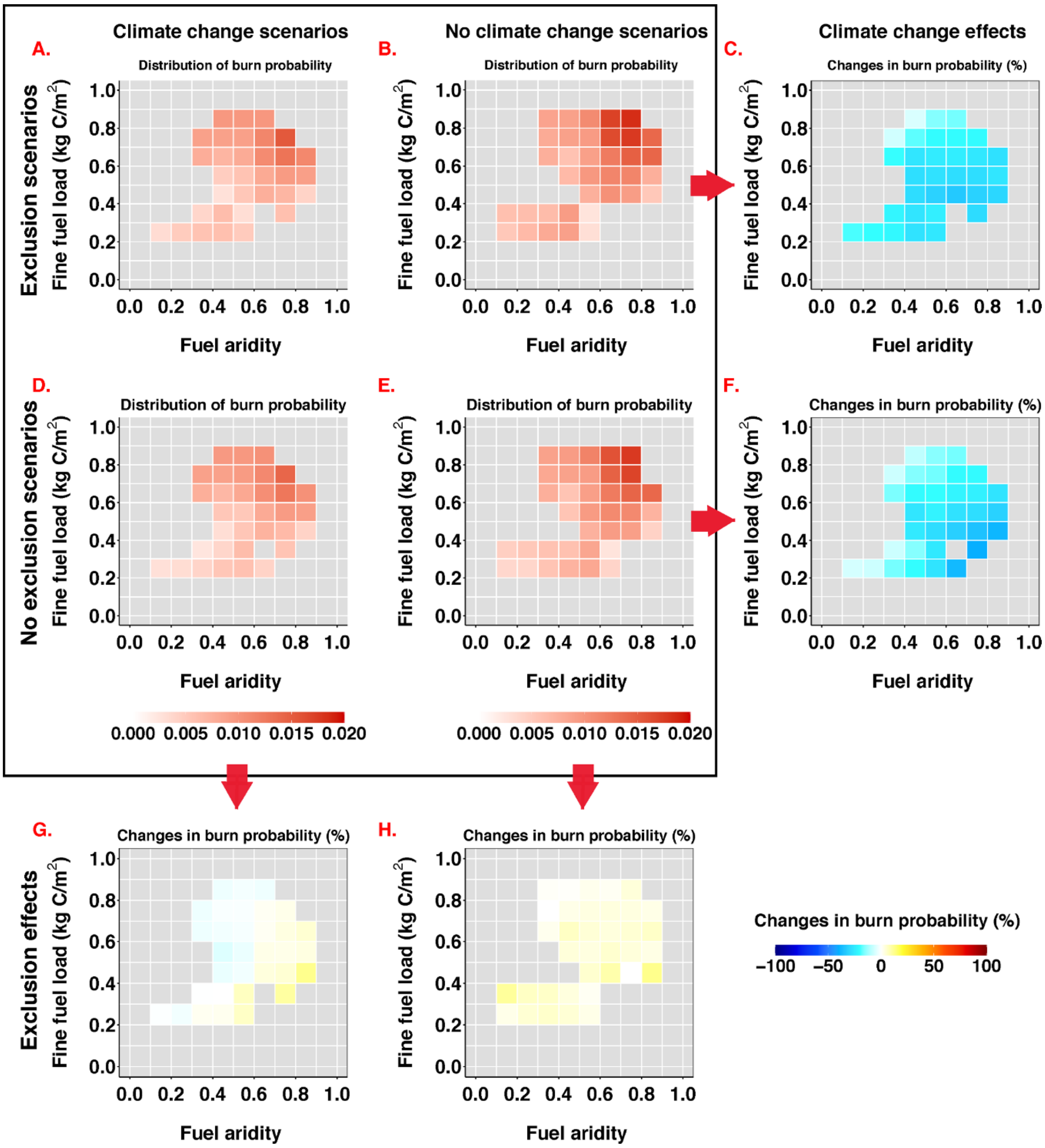

Figure 5. Effects of fuel aridity and fine fuel load on burn probability for each scenario in Trail Creek. Scenarios include: (a) climate change, exclusion, (b) no climate change, exclusion, (d) climate change, no exclusion, and (e) no climate change, no exclusion. Right: percent changes (±) in burn probability due climate change for (c) no exclusion and (f) exclusion scenarios. Bottom: percent changes (±) in burn probability due exclusion for (g) no climate change and (h) climate change scenarios. No data and very small sample sizes (i.e. <50 pixels for TC) are masked in grey.

occurred for a few reasons. In many areas, initial increases in fire size and severity due to exclusion contributed to subsequent decreases in fuel loading and continuity. In other areas, exclusion increased overstory canopy density, which provided shading and reduced ET in sub-canopy layers. Similarly, field observations have shown that solar radiation and wind are less able to penetrate closed canopies, leading to lower sub-canopy temperatures and greater humidity (Agee *et al* 2000, Meyer *et al* 2001, Whitehead *et al* 2006). These sub-canopy effects can reduce surface fuel accumulation (Swetnam and Baisan 1994, Schoennagel *et al* 2004) and promote greater moisture retention (Harrington 1982, Estes *et al* 2012). Overall, we found that climate change was the dominant force influencing fire activity in Johnson Creek and the role of exclusion was relatively minor (figures 3(a) and 4).

In Trail Creek, findings were more similar to fuel-limited fire regimes in the southwestern U.S. where warmer temperatures and drought have been shown to reduce forest productivity (McDowell *et al* 2016). We found that climate change decreased fire size and severity by increasing aridity and therefore decreasing, productivity and fine fuel loading (figures 1(b), 2(b), and 5). However, the projected effects of climate change varied spatially. In the northern, more mesic portion of the watershed, climate change increased burn probability in a few locations where local aridity was relatively low (figure 3(b)). In the southern, more arid portion of the watershed, which contained a mosaic of mixed pine and sagebrush patches, fire regime was strongly fuel-limited and climate change reduced burn probability by increasing fuel limitation.

In many fuel-limited forested systems, extensive fire suppression has increased forest density, allowing ladder fuels to develop and dead materials to accumulate, which can in turn increase fire severity and its spread into the canopy (Hurteau and Brooks 2011). While exclusion increased fire size and frequency in some locations in Trail Creek, it had no effect in others. For fire exclusion to increase fuel accumulation and burn probability, there must be sufficient moisture to enhance growth (Taylor and Skinner 2003), which was not the case in the more arid parts of the watershed. Thus, at the whole-watershed scale, fire suppression only increased burned area by 2% during the 1980–2017 assessment period. Similarly, in Central Oregon mixed pine forests, Merschel *et al* (2014) found that fire exclusion enabled ladder fuels to accumulate to the greatest extent in relatively moist locations while arid locations were relatively resistant to changes in understory structure.

Our findings illustrate how fire regimes can vary within and among watersheds in regions that are thought to be at least moderately climate-limited (Littell *et al* 2018). However, it is not enough to simply identify that relative climate and fuel-limited conditions can vary at fine scales. Instead, we need to discern simple, first-order metrics that can indicate when and where fire regimes may shift from climate to fuel limited. While previous studies show that climatological dryness can influence the drivers of fire regimes at large scales (Higuera *et al* 2015), at smaller scales, vegetation and fuels do not always respond linearly to these indices. Thus, soil moisture has been used as a proxy for aridity metrics—particularly live-fuel moisture—in an increasing number of studies (Qi *et al* 2012). In the current study, we found that temporally averaged soil moisture (SM_{fs}) was a useful proxy for local aridity more generally, because it integrates top-down and bottom-up drivers such as climate and topography, respectively.

In Johnson Creek, low aridity (i.e. wetter soils) promoted a strongly climate-limited fire regime, similar to other systems in the Northern Rockies (Schoennagel *et al* 2004). This climate limitation can wane with warming, which increases vapor pressure deficit and often corresponds with lower fire-season precipitation (Calder *et al* 2015). We found that climate change decreased fuel load but increased fuel aridity in Johnson Creek (figures 3(a) and (e)), which increased burn probability. These results agree with recent studies showing a correlation between fuel aridity and the number of large fires occurring in forests across the western U.S. (Abatzoglou and Williams 2016, Westerling 2016).

As with other fire regime characteristics, Trail Creek responded inversely. Climate change decreased burn probability (figure 3(b)) by decreasing fuel loading (figure 3(d))—this response was most pronounced in arid locations where SM_{fs} was low. Findings in Trail Creek demonstrate that the watershed is highly fuel limited and similar to transitional (aka hybrid forest-desert) ecoregions, where climate change is expected to further increase fuel-limitation and decrease burn probability (McKenzie and Littell 2017).

A unique strength of the RHESSys–WMFire framework is its ability to capture non-stationarity in fire regimes, which are an emergent property of the system. When isolating the effects of each scenario for the most recent decades (i.e. 1999–2017), we found that the most arid locations in Johnson Creek shifted to become more fuel-limited. In these locations, climate change scenarios began to reduce burn probability while prior exclusion scenarios began to increase it (supplemental figure S4). This is corroborated by projections for lodgepole pine forests in the Greater Yellowstone ecosystem, where future warming is projected to increase aridity and shift fire regimes from climate-limited to fuel-limited (Westerling *et al* 2011).

5. Implications for management

Fire regimes vary over space and time across the globe, and while climate change is a major factor increasing the frequency of large wildfires (Mouillot *et al* 2002, Abatzoglou and Williams 2016), there are still many regions where suppression has played a dominant role (Calkin *et al* 2014). Forest density reduction is often used in historically fuel-limited forests where decades of fire exclusion have substantially increased fuel loads (Allen *et al* 2002, Stephens *et al* 2012). However, density reductions can sometimes have unintended consequences, particularly when vegetation growth is enhanced by treatment, leading to greater ET and ultimately drier conditions (Tague *et al* 2019). We observed this type of drying for non-excluded (i.e. naturally fire-thinned) scenarios in Johnson Creek and in some parts of northern Trail Creek, suggesting that feedbacks among local environmental conditions, wildfire behavior, and watershed recovery should be factored into management decisions.

In Johnson Creek, we found convincing evidence that there has already been a clear climate signal above and beyond the effects of fuels (figure 1(a)), suggesting that with future climate change, the risk of large wildfires will likely continue to increase. However, even though climate change is currently the strongest driver of wildfire size, frequency, and occurrence in Johnson Creek, the strength of the climate-fire relationship varies with position in the watershed (figure 4) and local aridity (figure 3(a)) and appears to be changing as the climate continues to warm (supplemental figure S4). This is congruent with past studies showing that topo-edaphic gradients, which influence aridity and productivity (Abella *et al* 2015), can give rise to unique fire regimes at sub-regional and/or subwatershed scales (Heyerdahl *et al* 2001, Bigio *et al* 2016, Merschel *et al* 2018). Thus, local-scale adaptive management is critical as we move into a warmer, drier future (Schoennagel *et al* 2017).

To inform management, we found that spatial estimates of soil aridity (or SM_{fs}) can help identify where in a watershed fire regime is climate-limited (e.g. SM_{fs} greater than 35% in the current study) vs. fuel-limited (e.g. SM_{fs} less than 25%) and where spatial patterns are most vulnerable to change (e.g. intermediate SM_{fs} between 25% and 35%). These results can inform future research that examines how specific management practices affect fire regimes in locations where fuel treatments are most likely to mitigate extreme wildfire risk.

6. Conclusions

Understanding the connection between climate, fire exclusion, and wildfire behavior is critical for managing risk and guiding climate change adaptation. It also has key implications for public perception, policy, and decision-making. Although we are beginning to understand the role of climate at large (e.g. sub-continental) scales, disentangling and attributing the role of climate and fuels at finer-scales has been much more challenging. This challenge arises because extreme wildfires are rare at regional and sub-regional scales, resulting in low statistical power and small climate change signals are often outstripped by larger interannual variability (Stott *et al* 2010). Because fuel management often occurs at local or landscape scales (Jain *et al* 2012), spatially explicit fire regime models that can account for climate effects on hydrology, vegetation, and fuels are needed to project how different management units within a watershed are likely to respond to fire exclusion or fuel treatments under a new climate paradigm.

We found that local responses to climate change and fire exclusion vary with aridity at fine scales. Thus, even in mixed pine regions that have been defined as climate-limited, fire exclusion and fuel accumulation can still have local effects. Similarly, in regions that are defined as fuel-limited, climate change-driven increases in local aridity may limit fuel accumulation and its effects on the probability of fire. These findings highlight the importance of considering both spatial heterogeneity and non-stationary climate in policy and management planning. They also reveal a need to test and reevaluate management goals in the context of the dominant role that climate change is playing in many managed landscapes across the western U.S. and globally.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://osf.io/26x5r/.

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