EVALUATING THE SNOW-WILDFIRE RELATIONSHIP USING AN ENSEMBLE OF SNOWPACK OBSERVATIONS

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EXTENDED ABSTRACT

Wildfire activity in the United States has increased in recent decades, with documented rises in the number of large fires, burned areas, and the length of the fire season (Westerling, 2016). Fires contribute to carbon emissions, widespread forest mortality, and human morbidity and mortality by posing a direct hazard and from degrading air quality. Wildfire increases are thought to be a product of several interacting factors, including human settlement in fire-prone areas, a legacy of fire suppression, as well as favorable fire weather partly attributable to anthropogenic climate change (Abatzoglou and Williams, 2016). As such, a deeper understanding of the geophysical drivers of wildfire activity can both improve its seasonal predictability and inform expectations about future wildfire under continued warming.

Antecedent snowpacks may be a meaningful predictor of seasonal wildfire activity. For instance, Westerling et al. (2006) showed that the timing of spring snowmelt exerts a strong influence on wildfire activity in the Western United States (WUS), a finding re-emphasized a decade later (Westerling, 2016). Yet the empirical snow-wildfire relationship that underpins this predictability uses proxies for snowpack, such as the timing of peak streamflow in snowmelt-influenced watersheds, computed at a large regional scale (e.g., the entire WUS). As such, it is unclear whether these associations hold at more hydrologically- and decision-relevant scales or if low snowpack itself is a driving factor in wildfires, or is merely associated with something else that drives both low snow and wildfire risks independently. There are also considerable uncertainties in estimates of the magnitude and variability of snowpack (Kim et al., 2021; Mortimer et al., 2020) that may make claims about the snow-wildfire relationship sensitive to data choices. Finally, the ecohydrological consequences of low snowpacks may vary based on meteorological factors: cold winters with limited precipitation, for example, may have different warm season impacts than warm winters with near-normal precipitation (Harpold et al., 2017; Hatchett and McEvoy, 2017). It is not clear how these different meteorological forcings for low snowpack may also shape wildfire risks. Here, we begin to explore these questions using an ensemble of daily snow water equivalent (SWE) estimates and historical burned area data. We address the following questions: First, which CONUS river basins have a robust relationship between antecedent snowpack and burned area? Second, which metrics of snowpack and sets of observations capture this relationship most consistently? And third, how do the meteorological drivers of snowpack differentially select for wildfire activity?

To address the first two questions, we compile an ensemble of 9 daily gridded remote sensing and reanalysis SWE datasets that cover CONUS over our study period, water years (WY) 1984 to 2018 (Table 1). We aggregate daily SWE to the river basin scale using the Global Runoff Data Centre's Major River Basins of the World basin boundaries. We then calculate the maximum value of basin-scale SWE (peak SWE), the date of that maximum (peak date), the basin-scale SWE on 1 April, and a standardized SWE index (SWEI) on 1 April that is based on a 90-day rolling sum of daily basin-scale SWE (see Huning and AghaKouchak (2020)) for each WY. We similarly calculate basin-scale burned area during the following fire season, defined here as May through October, using the Monitoring Trends in Burn Severity (MTBS) database of large (>400ha) fires in the United States (Eidenshink et al., 2007). We log-transform the basin-scale burned area data due to the highly right-skewed nature of the distribution and remove the linear trend and then take the top and bottom terciles (33%) of transformed burned area as our "high" and "low" burned area years. We evaluate the robustness of that difference across the observational ensemble using a robustness metric developed by Knutti and Sedláček (2013), weighing the magnitude of snowpack differences between high and low burned area years against the ensemble agreement in those snowpack estimates.

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Dataset	Method	Ancillary/forcing data	Native resolution	Reference
NASA DayMet	Simple accumulation/melt model	DayMet	1km	Thornton et al. (2020)
ECMWF ERA5-Land	H-TESSEL LSM	ERA5	0.1° x 0.1°	Muñoz-Sabater et al. (2021)
JRA-55	Simple Biosphere Model (SiB)	JRA-55, station data, SSM/I	0.56° x 0.56°	Kobayashi et al. (2015)
NASA MERRA-2	Catchment LSM	MERRA-2	0.5° x 0.625°	Gelaro et al. (2017)
NASA NLDAS	Catchment, Noah, and VIC LSMs	NARR, CPC gauge-based precip.	0.125° x 0.125°	Xia et al. (2012)
Univ. of Arizona	Interpolated in situ	Station data, PRISM	4km	Zeng et al. (2018)
ESA GlobSnow	Satellite passive microwave	Station data	25km	Luojus et al. (2020)

Table 1. Details of datasets used in the observational ensemble.

Lower antecedent snowpack is associated with higher burned area in most CONUS basins (Figure 1, warm colors). The strength of and confidence in that relationship is basin-dependent and highly sensitive to the analytical choice of the metric used to assess a season's snowpack. For instance, in many major basins, including the Colorado, Columbia, San Joaquin, Sacramento, and Great Salt Lake basins, lower SWE measures are seen in years with higher burned areas (Figure 1a-c). Yet evaluation of the robustness of the snow-wildfire relationship across the observational ensemble reveals that even where there is a large signal in the ensemble mean (e.g., April 1 SWE in the Colorado, Sacramento, or San Joaquin basins, Fig. 1b), that difference may not be robust across datasets (as indicated by the hatching in Figure 1). Such uncertainty suggests that snow-wildfire associations are sensitive to data choices.

Our results highlight the importance of an ensemble-based approach to assess robustness across observations, as such analysis can help identify operationally-useful metrics in particular locations. For instance, there is not a robust association between the timing of basin-scale peak SWE and wildfire activity in any basins except the San Joaquin and Colorado (though notably of opposite signs) (Figure 1d). This finding complicates previous work suggesting the timing of spring snowmelt is directly tied to wildfire activity (Westerling, 2016; Westerling et al., 2006). We note, however, that this does not mean that the timing of peak SWE has no association with wildfire. Instead, it implies that estimates of the timing of peak SWE at the basin scale are inconsistent across datasets. Measures like SWEI, based on a 3-month rolling sum, may exhibit better agreement due to the long integration smoothing out the effects of individual storm or melt events that may vary considerably by product. Broadly speaking, adopting analytical practices that the climate modeling community uses for multi-member ensembles of opportunity can provide valuable insights from noisy observations such as snowpack data.

Finally, we ask whether the meteorological drivers of snowpack differentially select for wildfire activity, as that knowledge could aid in wildfire forecasting and deepen our understanding of the sensitivity of wildfire to further warming. To address this question, we calculate November-March cumulative precipitation and average temperature (detrended) for the seasonally snow-covered area in each basin from the PRISM reanalysis (PRISM Climate Group, 2004), and estimate the joint probability distribution before high burned area years in this temperature-precipitation space (Figure 2). Overall, the combination of warm and dry winter conditions is associated with increased burned area across all WUS basins (Figure 2). Some 39% of years with high burned areas follow

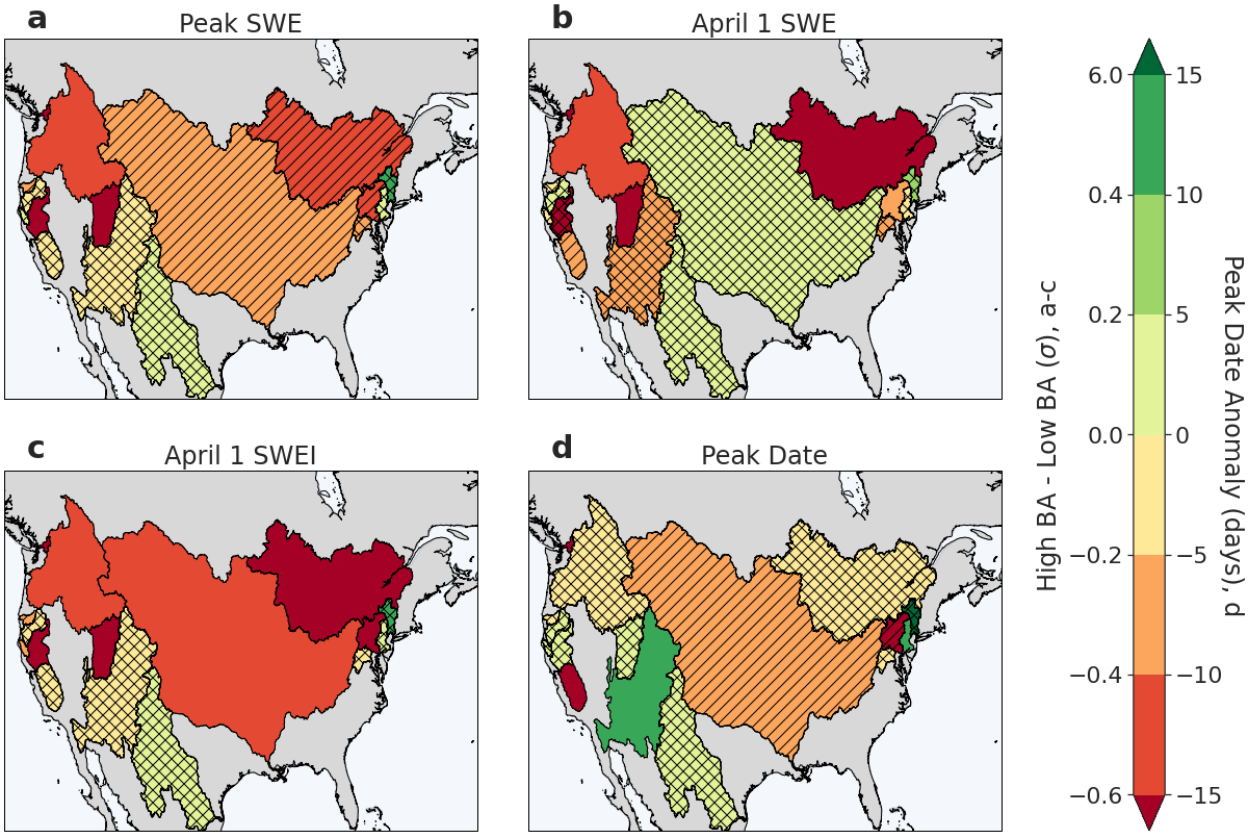

Figure 1. Ensemble mean difference in average peak SWE anomaly (a), April 1 SWE anomaly (b), SWEI (c), and date of peak SWE (d) between top and bottom terciles of burned area in each river basin. Redder colors signify lower snowpack (or earlier peak snowpack, d) being associated with more burned area. Bidirectional hatching indicates basins in which the difference in snowpack between high and low burned area years is not robust across the observational ensemble (R<0.5, see Knutti and Sedláček (2013)), and unidirectional basins with moderate robustness (0.5<R<0.8). No hatching indicates R>0.8.

winters with both above-average temperatures and below-normal precipitation (Figure 2a). Neither high temperatures nor low precipitation seems to be more discriminating for wildfire across all basins, as 59% of bad fire seasons follow warm winters and 64% dry. At the scale of individual basins, however, many different combinations of winter temperature and precipitation are associated with increased fire activity (Figure 2b). For instance, in the Sacramento River basin, low precipitation is associated with high burned areas, with 83% of bad fire years following dry winters, with little influence from temperature variability. In the Skagit, on the other hand, every single high burned area year in the study period followed an anomalously warm winter, with precipitation roughly evenly distributed between wet and dry. In others still, such as the San Joaquin and Great Salt Lake, there seem to be multiple centers of mass, one cold and dry, one warm and wet. Writ large, the variability both within and between basins suggests a number of pathways through which winter meteorology and the resulting snowpack may influence warm-season wildfire risks, with different mechanisms predominating in different locations. Detailed process tracing is needed to identify these mechanisms — for instance, increased vegetation water stress due to lower soil water availability (Harpold and Molotch, 2015) or increased warm-season temperature and aridity due to warming and drying land-atmosphere interactions (Groisman et al., 1994; Seneviratne et al., 2010) — and the conditions under which they predominate. (KEYWORDS: wildfire, ensembles, snow water equivalent, climate change)

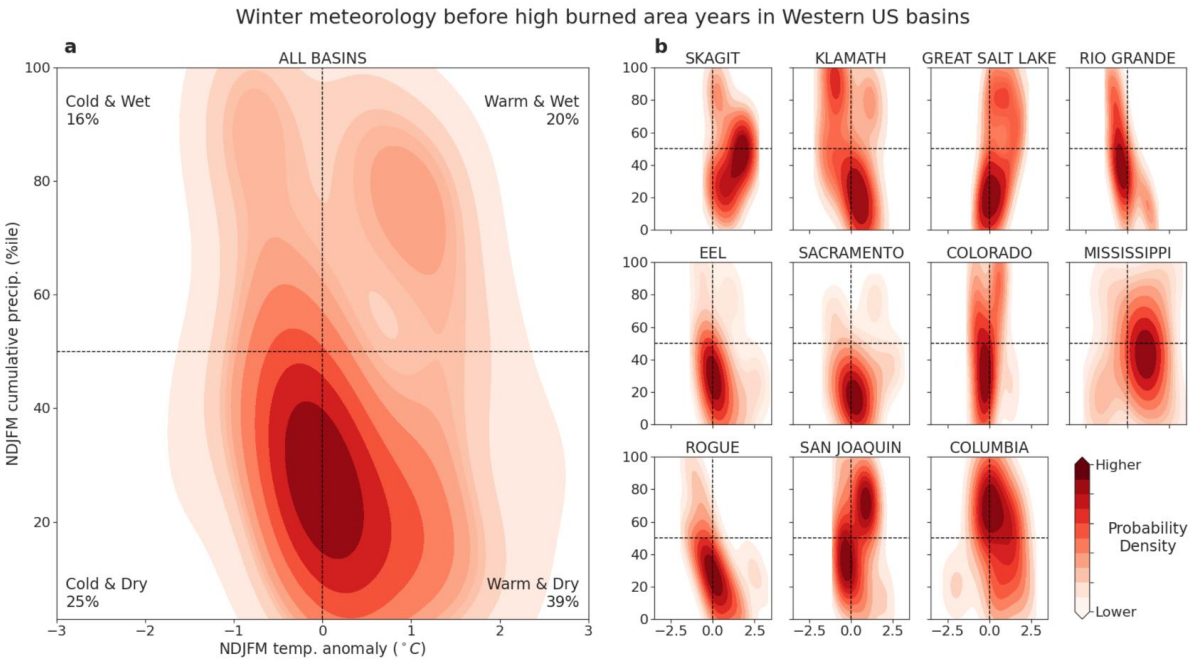

Figure 2. Joint probability distribution of November-March cumulative precipitation and average temperature over seasonally snow-covered area in top tercile of burned area years in all WUS basin-years (a) and individual WUS basins (b). The probability distribution is estimated using a 2-dimensional Gaussian kernel density estimate and bandwidth chosen according to Scott's rule. Seasonally snow-covered area is defined as all grid cells in the snowpack ensemble with non-zero SWE for more than 2 weeks in the majority of ensemble members.

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