Impacts of Wildfire on Snowpack in the Western U.S. Based on SNOTEL Observations

Jeremy Giovando

U.S. Army Engineer Research and Development Center, Cold Regions Research and Engineering Laboratory



Wildfire & Western U.S. Ecosystems

- Wildfires have been part of the landscape in the western U.S. for thousands of years (Calder et al. 2015)
- The land surface impacts vary by location and burn severity, but increases in surface temperature nearly always occur (Liu et al. 2019)
- The abrupt changes energy and water balances are from net radiation, sensible and latent heat fluxes changes (Prater and Delucia 2006; Sanches et al. 2015; Hallema et al. 2017)
- Climate change continues to increase fire activity and add complexity in our ability to understand long-term impacts from wildfire (Westerling et al. 2006; Dennison et al. 2014; Stavros et al. 2014)



Prescribed burn near Flagstaff, AZ Photo courtesy of Brandon Oberhardt

Climate Change & Snowpack

- Decreasing trends have been observed across western U.S. at 90% of snow course and SNOTEL sites (Mote et al. 2018)
- Observed average 41% decrease in peak snow water equivalent (SWE and 34 days earlier meltout between 1982 and 2016) (Zeng et al. 2018)
- Snow droughts are projected to increase from 6% to 42% of years by mid-21st century (Marshall et al. 2019)
- Snowfall frequency expected to decrease with climate change especially in transition watersheds (Catalano et al. 2019)



Figure 7. Correlation of monthly (and seasonal for winter, November through May, and summer, June through September) precipitation trend vs temperature trend from Snowpack Telemetry (SNOTEL) stations, divided by (a) west stations (Clow; orange group); and (b) east stations (Clow; purple group); The correlation of (c) first of the next month's snow water equivalent (SWE) trend and (d) change in monthly SWE trend are presented as bubble size, divided into increasing (blue) and decreasing (red) for all stations on the plots of precipitation trend vs temperature trend.

Rocky Mountain National Park SWE and climate trends Fassnacht et al. (2018)

Snowpack & Canopy Disturbances

- Canopy disturbances including drought, insect mortality, clear cutting, and wildfire are often grouped together, but the response in surface energy balance does vary (Boon 2009)
- Nine studies in northern U.S. and Canada generally found higher SWE after disturbance while four had variable responses (Goeking and Tarboton 2020)
- At lower latitudes in western U.S., the postdisturbance SWE is more variable (Goeking and Tarboton 2020)
- Several studies suggest topographic aspect controls the effects trees have on snowmelt via its effects on shortwave radiation (Goeking and Tarboton 2020)



Cameron Peak Burn Area, CO November 2020

Research Needs

- 1. There is limited understanding of what snowpack changes will occur following wildfire and how this change varies across the different ecoregions of the western U.S.
- 2. Snowpack vulnerability from wildfire has not been quantified and locations of vulnerability have not been identified for the western U.S.
- 3. Forecasting snowmelt changes using models requires an understanding of how model parameter change after wildfire.

Study Objectives

- The overall goal of this study is to understand the impact of wildfires on snowpack for different ecoregions across the Western U.S.
- This goal includes quantifying:
 - 1. Wildfire impacts on snowpack phenology in a changing climate within the western U.S.
 - 2. Regional snow vulnerability to wildfire and changing climate within the western U.S.
 - 3. Wildfire impacts for temperature index snowmelt model parameters

Wildfire Impacts for Snow Phenology in a Changing Climate within the Western U.S.



Datasets

Snow Water Equivalent (SWE)

- From Snow Telemetry (SNOTEL) (NRCS, 2021)
- 45 burned sites were identified using information from NRCS
 - Avg. pre-fire period 23 years
 - Avg. post-fire period is 12 years
- For each burned site, at least two similar unburned sites were identified in same ecoregion
 - 80% were within 50 km and ±300 m



Datasets

Burned Site Characteristics

- Elevation (SNOTEL)
- Precipitation (SNOTEL)
- Dominant tree genus (2017 USDA Forest Inventory and Analysis) (Burrill et al., 2018)
 - Pine (Pinus)
 - Fir (*Abies* and *Pseudotsuga*)
 - Spruce (*Picea*)
 - Hemlock (*Tsuga*) / other
- Change in leaf area index (LAI) (from early October values MODIS 8-day averages) (Myneni et al. 2015)
- Categorical burn severity (based on differenced Normalized Burn Ratio from Monitoring Trends in Burn Severity program) (Eidenshink et al., 2007)



Methods

- At **burned** sites, changes between post-fire and pre-fire periods → **Combined Signal** (climate and wildfire)
- At **unburned** sites, changes between post-fire and pre-fire periods → **Climate Signal**
- Calculate differences between the changes at burned and unburned sites → Wildfire Signal



Stillwater Creek, CO 2014 (Photo courtesy of NRCS Snow Survey-Colorado)



Stillwater Creek, CO 2020 (Photo courtesy of NRCS Snow Survey-Colorado)

Results: Melt-out Date



- Unburned sites: 78% of had earlier melt-out dates (post-fire period vs pre-fire period)
- **Burned sites:** 93% of had earlier melt-out dates
- **Burned sites:** 84% had larger changes than the associated unburned sites

Results: Date of Peak SWE



- Unburned sites: 56% of had earlier peak SWE date
- Burned sites: 78% of had earlier peak SWE date

Results: Peak SWE



- Unburned sites: 38% of had a decrease in peak SWE for the post-fire period
- Burned sites: 60% of had decreases in peak SWE

Results: Peak Normalized SWE (nSWE)



- Unburned sites: 49% had decreases in peak nSWE
- Burned sites: 67% had decreases in peak nSWE

Magnitude of Changes

Combined Signal

Post-Fire Minus Pre-Fire at Burned Sites

Climate Signal				
Post-Fire Minus Pre-fire at Unburned Sites				
	Melt-Out	Peak	Peak	Peak
	Date	SWE	SWE	nSWE
	[d]	Date [d]	[%]	[%]
Average	-6	-4	-2	-1
Median	-5	-2	1	-1

	Melt-Out	Peak	Peak	Peak
	Date	SWE	SWE	nSWE
	[d]	Date [d]	[%]	[%]
Average	-15	-11	-15	-8
Median	-13	-10	-14	-8

Wildfire Signal					
	Burned Diff. Minus Unburned Diff.				
	Melt-Out	Peak	Peak	Peak	
	Date	SWE	SWE	nSWE	
	[d]	Date [d]	[%]	[%]	
Average	-9	-7	-13	-7	
Median	-9	-8	-12	-7	

Results: Burn Severity

- The wildfire effect occurs for all three burn severity categories
- No clear dependence on burn severity is observed



Results: Leaf Area Index (LAI)

- The burned sites typically had earlier melt-out and peak SWE dates than the unburned sites irrespective of the LAI change
- Greater reductions in peak SWE and nSWE are observed when LAI decreased more



Results: Tree Genus

- The wildfire effect is observed for all tree genera
- Largest changes in melt-out date and peak SWE occur for the hemlock/other category



Results: Years Since Fire

- The effect of the wildfires persists beyond 10 years
- For SWE and nSWE, the greatest wildfire impacts are observed beyond 10 years



Results: Site Elevation

• Wildfire effects are most substantial at the lowest elevations



Conclusions

For the dataset considered:

- Wildfires produced earlier melt-out dates for all ecoregions.
- Wildfires produced earlier peak SWE dates for all ecoregions except the Northern Rockies and the Arizona-New Mexico Mountains.
- Wildfires produced **lower peak SWE** values for most ecoregions.
- Wildfire impacts on snowpack exhibited no clear dependence on burn severity category and persisted beyond 10 years
- Wildfire impacts on snowpack are greater for large LAI reductions and lower elevations

Regional snow vulnerability to wildfire and changing climate within the western U.S.



Methods: Overview of Modeling Process





Methods: Random Forest

- RF is derived from decision trees (i.e. Classification and Regression Tree (CART))
- RF are ensemble of CART models and error based on average across entire ensemble (Breiman 2001)
- RF Development process:
 - 1. Training/Validation data split and used 5-fold cross validation
 - 2. Iteration of variable importance: variable with lowest sequentially removed
 - 3. Final set of predictor variable based on lowest cross-validation values



Colorado State University

Datasets: Predictor Variables

Freezing Degree-day

FDD =min(Ta,0)

Temperature Index TI=max(Ta,0)

Ta =daily mean air temperature (°C)

Variable Name	Variable Description	Data Source
Aspect (degrees)	Land surface aspect at 30 m spatial resolution	LANDFIRE
Slope (m/m)	Land surface slope at 30 m spatial resolution	LANDFIRE
Elevation (m)	Land surface slope at 30 m spatial resolution	LANDFIRE
Latitude (degrees)	Land surface slope at 30 m spatial resolution	LANDFIRE (extracted from elevation file)
Latitude (degrees)	Land surface slope at 30 m spatial resolution	LANDFIRE (extracted from elevation file)
Total Basal Area (m²)	Resampled to 30 m spatial resolution from 240 m total basal area dataset using nearest neighbor value	FIA
Tree Genera	Classified from resampled 30 m spatial resolution from 240 m dominant stand index species dataset using nearest neighbor value	FIA
Mean Temperature (°C)	Mean Oct-Apr daily temperature values	PRISM
Mean ATI (°C - Days)	Mean of annual accumulated TI between Oct-Apr	PRISM
Mean LT0 (days)	Mean of annual accumulated count for days less than 0 °C between Oct-Apr	PRISM
Mean AFFD (°C -Days)	Mean of annual accumulated freezing degree days between Oct-Apr	PRISM
Mean Oct-Apr Total ppt (m <u>m)</u>	Mean annual total precipitation between Oct-Apr	PRISM

Results: Predictor Variable Importance

- Topographic aspect is most important variable for fire signal SWE and peak date changes
- Tree genera is used for all fire signal models but in only one combined signal (melt-out)
- All RF models use at least one topographic and one climatic variable

Model	RMSE (train)	R ² (train)	RMSE (Val)
SWE-FS	21%	0.41	29%
SWE-CS	16%	0.54	27%
nSWE-FS	21%	0.10	18%
nSWE-CS	18%	0.24	18%
Peak-FS	9.8 d	0.32	9.3 d
Peak-CS	9.9 d	0.47	9.0 d
Melt-FS	8.5 d	0.15	6.3 d
Melt-CS	7.5 d	0.35	8.4 d



Results: Snowpack Measure Changes by Ecoregion

- Median (point) and inter-quartile range (error bars) for all grid cells within each ecoregions
- Reduced peak SWE is likely for most ecoregions using both signals
- Both peak SWE date and melt-out date are earlier for both signals
- Peak SWE has relatively large spatial variability
- Post-wildfire measurements for peak SWE changes in limited locations may not represent larger domains



Combined Signal 💻

Signal

Results: SWE Vulnerability Location-Fire Signal



- Vulnerable locations are areas that predicted change exceeds the model error (RMSE 21%)
- North and northwest aspects are most vulnerable
- Fires between 2015 through 2020 show SWE impacts from wildfire vary substantially between fires

Results: SWE Vulnerability Location-Combined Signal



- Vulnerable locations are areas that predicted change exceeds the model error (RMSE 16%)
- The combined signal has both increasing and decreasing locations
- Moderate to steep slope areas along with north and northwest aspects indicate increases
- Fires between 2015 through 2020 show SWE impacts from wildfire vary substantially between fire

Results: SWE Vulnerability Location (Sprague Fire 2017)

Variable Important-#1

Variable Important-#2

Percent Change peak SWE (fire)



Results: SWE Vulnerability Location (Sprague Fire 2017)

Variable Important-#1

Variable Important-#2

Percent Change peak SWE (combined)



Results: Peak SWE Volume Changes by Ecoregion





- Peak SWE volume changes are negative for all ecoregions for 2015-2020 fires
- Changes in total streamflow volume are beyond the scope of this study and are not quantified

Conclusions

For the model considered:

- **Most important variable** for peak SWE change is **aspect. Temperature** is most important variable for combined signal.
- **Peak SWE percent differences are spatially variable** within each ecoregion and generally indicate decreases. This would suggest that locations for post-fire SWE measurements should be considered carefully.
- Vulnerable locations for peak SWE decreases due to wildfire are north and northwest facing slopes.
- Average of **8% peak SWE volume reduction** from wildfires occurring between 2015-2020.



Wildfire Impacts for Temperature Index Snowmelt Model Parameters



Snowmelt Variables and Parameters for TI Snowmelt Model

- Variables:
 - Temperature Index (TI) is the difference between the observed air temperature and a base temperature which is the melting point reference (usually 0 °C); minimum of zero and always positive
 - Antecedent Temperature Index (ATI) is the total of the TI values during the ablation season
- Parameters:
 - **Px Temperature [accumulation/ablation]** is threshold air temperature which defines the transition between rain and snow.
 - **ATI-Melt Rate Function [ablation]** is the melt-rate magnitude based on ATI and physically represents the varying energy fluxes into the snowpack from late winter to early summer. Can be constant or time varying (most realistic) when parameterized.



Methods: Px Temperature Estimation Process



Results: Px Temperature Differences and Adjustment Equations

 Px temperature adjustments variable within ecoregions

Site

SNOTEL

- Significant change are concentrated within specific ecoregions
- GLM based on exhaustive evaluation of predictor variable combination to find combination with lowest cross-validation error





Methods: Melt Rate Function Estimation Process



Methods: Step 2 Melt-Rate Function Estimation



Methods: Step 3 Melt-Rate Function Structure



- Melt-rate is continuous function however for model implementation best fit lines are used to estimate values over ATI ranges
- To determine best fit lines continuous functions were fit to each water year at every SNOTEL site
 - Linear, linear piece-wise, nonlinear (quadradic and log-linear)
- A generalized linear model (GLM) was developed for each component (k-fold cross validation) based difference between average pre- and post-fire values

Results: Observed Melt-Rate Difference



Site

IOTEL

SN

- Late season melt-rate has more significant changes for increased melt rates
- The ATI change point for the meltrate function increases (higher ATI) for northern and decreases midlatitude

Results: Equations for Adjusting Melt-Rate Function Components



- GLM produced equations that can be used by practitioners modeling snow regions after a fire
- The GLM results produce a multiplying factor which can be used by modelers to adjust melt-rate functions
- GLM based on exhaustive evaluation of predictor variable combination to find combination with lowest cross-validation error

Conclusions

For the dataset considered:

- Wildfire impacts on Px Temperature are site specific.
- Wildfires produced **higher melt-rates later in the ablation season** when sun angle is larger and more shortwave radiation reaches the snow surface.
- Early season melt-rate changes are variable and local topographic conditions are likely more important.
- The ATI values increases at the northern sites and decrease at mid-latitude sites.

Summary

- Significance:
 - Understanding of snowpack changes after wildfire occurs using set of consistent measurements across the western U.S.
 - Predictive model to identify vulnerable snowpack locations following a wildfire
 - Predictive equations for practitioners to adjust snowmelt model parameters
- Challenges, Limitations, and Opportunities:
 - Very limited observational data for post-fire snowpack changes
 - Pre- and post-wildfire periods vary between sites
 - Vulnerability model results should be used for larger regional evaluation
 - Post-wildfire sampling plans for snowpack can be informed by vulnerability model
 - Testing of melt-rate and Px temperature equations within the context of post-wildfire hydrology modeling

Recognition

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"Life is beautiful." J.A. Ramirez