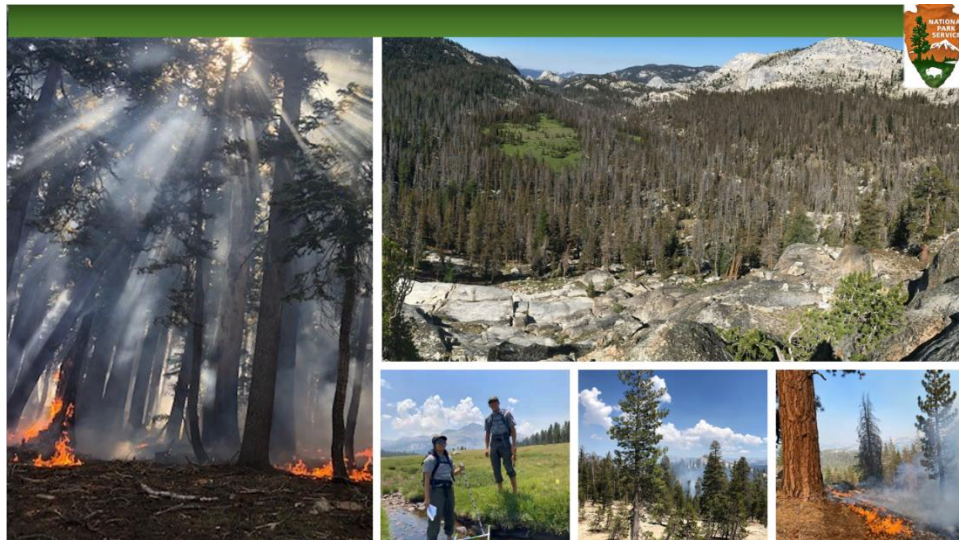


Focused Condition Assessment (FCA) Assessing Landscape Vulnerability to Drought and Megafires using Linked Forest Condition-Water Models to Guide Resilience Planning Final Report

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Executive Summary

Fire suppression in western U.S. mountains has caused the development of dense forests with high water demands. Yosemite National Park has been at the forefront of using fire as a management tool in its fire-adapted landscapes, but it still contains many areas that may be considered in a state of “fire deficit” with heavy fuel loads and unnaturally high water demands. This study takes advantage of the varied fire history within Yosemite National Park to assess how fires have affected the landscape conditions we see today, as well as identify areas with high potential for future change in response to different management actions. The following report describes multiple maps and models to help with future management decisions. The maps below show example outputs of historical conditions (Figure 1) as well as potential future impacts of fire on the landscape (Figure 2).

A combination of remote sensing, field measurements, and modeling showed that areas of dense forest cover generally have higher drought stress and lower snowpack retention compared to more open areas. Restoring wildfire to the landscape has potential to increase soil moisture and runoff while reducing drought stress as well as the intensity of future fires. Fires will not affect all areas of the landscape in the same way, depending on local vegetation cover, soils, fire history, and topography (Figure 2).

A common concern about wildfires is that they will result in increased soil water repellence, and that this will then cause high levels of erosion and surface runoff resulting in flooding and poor water quality. Our field measurements did show increased soil water repellence following fire, but hydrophobicity began decreasing after the first post-fire year, and fell to a minimum approximately 5-10 years post-fire. Our measurements also found strongly hydrophobic soils in areas that had not burned for over 20 years, showing that long periods without fire might also have unwanted impacts on soil properties. Therefore, even though recently burned water-repellent soils can see reduced infiltration and soil moisture in the short term, soils appear able to recover and even improve their ability to infiltrate and retain moisture over multiple years following fire (Figure 3).

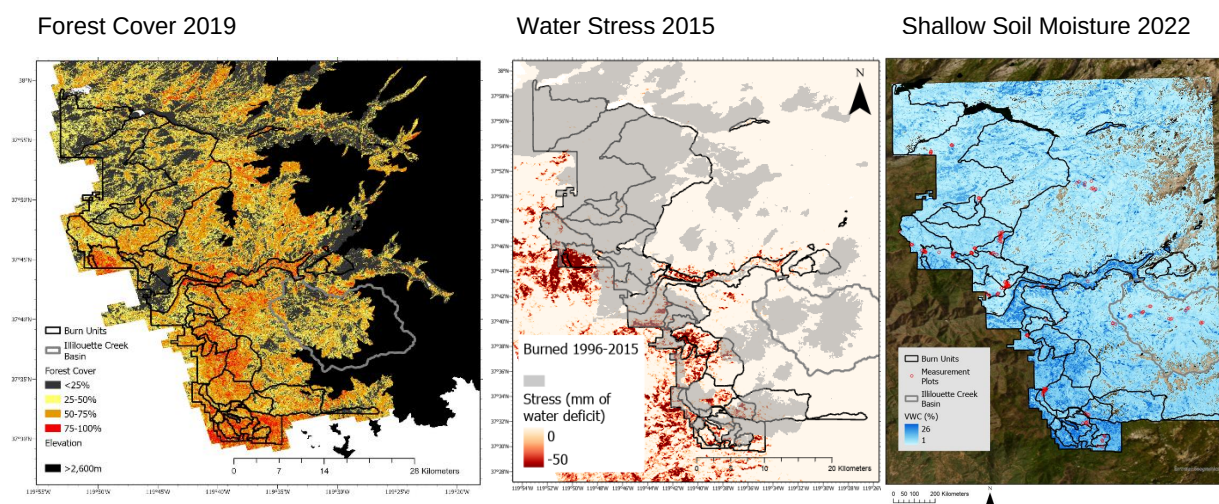


Figure 1. Maps created with various methods show that the southwest regions of Yosemite generally have the greatest forest cover and highest soil moisture, but also experience the most drought stress.

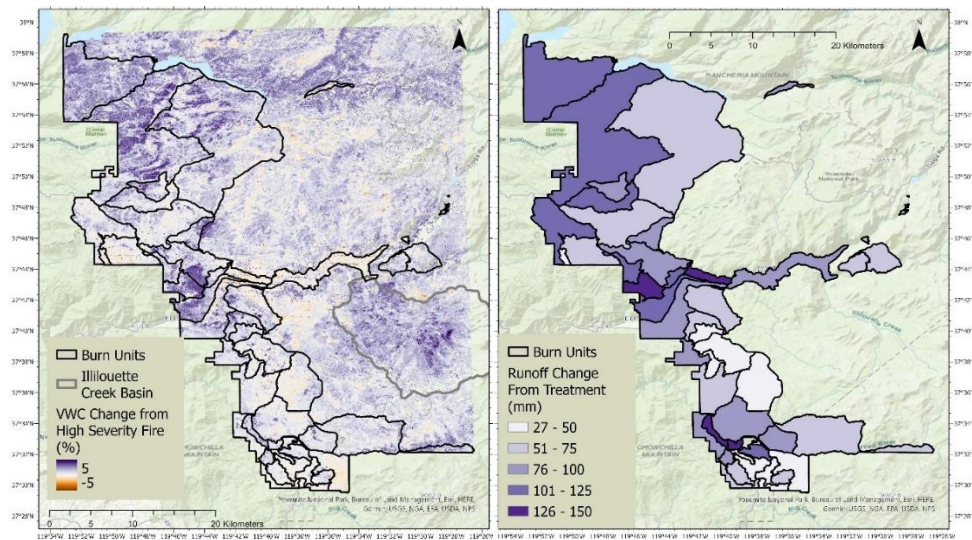


Figure 2. Various types of models can be used to predict the impact of land cover change. These maps show strong overlap between areas where a statistical model predicts increased soil moisture following wildfire (left) and a water balance model predicts greater runoff following forest thinning (right).

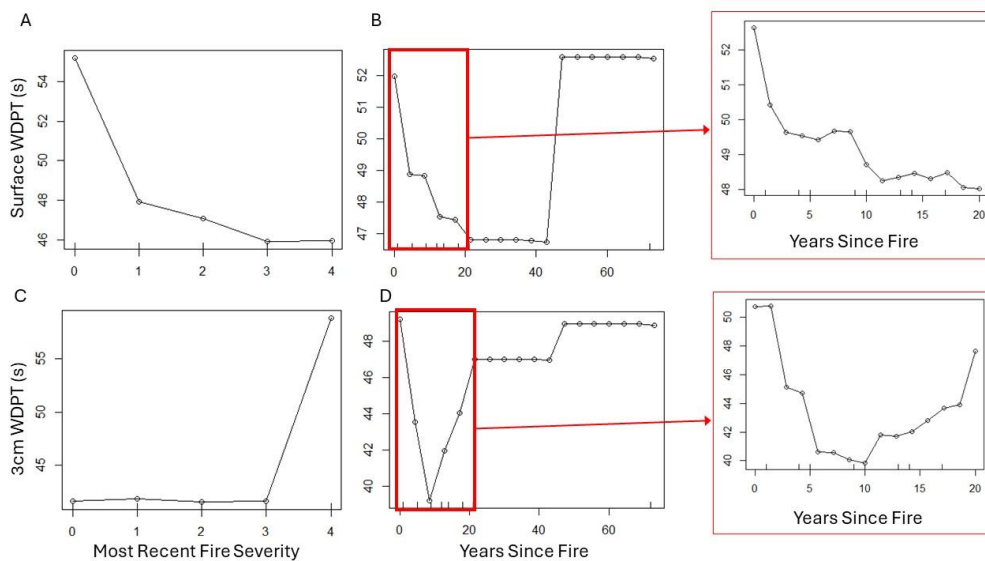


Figure 3. Water drop penetration time (higher values indicate greater water repellence by the soil) at the surface and 3cm depth showed strong relationships to fire history. Low severity fires (severity=0) were associated with higher water repellence on the soil surface, while high severity fires (severity=4) showed water repellence deeper down (A,C). At both depths, water repellence initially decreases and then later increases with time since the most recent wildfire (B and D). The results for 0-20 years since wildfire are shown in red boxes to provide more detail. These plots were created using a random forest model fit to field measurements.

This project led to the creation of a unique dataset of soil properties across a gradient of fire histories and landscapes within Yosemite National Park. This dataset, as well as the files and R code necessary to run the statistical models described in this report, are included in the attached zip files for use by Yosemite National Park researchers and managers. These models can be used to predict which areas are most likely to benefit from various management efforts, according to a wide range of metrics. Given Yosemite's vast area and limited resources for prescribed burns and fuel treatments, directing actions to these areas is critical to optimize efforts.

Project Introduction

Fire suppression in western U.S. mountains has caused the development of dense forests with high water demands (Hessburg et al., 2019; Young et al., 2017). Restoring natural wildfire regimes (i.e. frequent, limited-extent, mixed-severity fires) to these forests can potentially provide multiple co-benefits, including reduced risk of high severity fire, increased snowpack depth and retention, reduced drought mortality, greater habitat diversity, and increased streamflow (Stephens et al., 2021). While forest structure- disturbance-water availability mechanisms are becoming clear, few - if any - parks have been able to apply this learning at a landscape scale to provide a vulnerability assessment and evaluation of past management actions. To address this need, Yosemite National Park (YNP) conducted a landscape vulnerability assessment to understand the effects of forest density on forest health and water availability to inform future management actions. The increasing size and severity of fires in the Sierra Nevada over the past decade (Williams et al., 2023), combined with an unprecedented drought and associated tree mortality from 2012-2016 (Goulden & Bales, 2019), demonstrate that improving the landscape's resilience to change is a vital area of study. Forest condition, water availability, drought, or related factors are listed as a threat in recovery and/or listing documents for the Great Grey Owl, California Spotted Owl, Southern Sierra Nevada Distinct Population Segment of the Pacific fisher, Yosemite Toad, and Sierra Nevada Yellow-legged Frog. The persistence of these species depends on the ability of catchments to provide necessary quantities of water to support habitat as well as use of forest management tools such as thinning and fire to improve and maintain habitat.

The main objective of this project is to create a series of models that can help guide future management decisions by identifying areas within Yosemite that would most benefit from a restored fire regime. Spatially explicit models are used to assess watershed climate vulnerability to mega-fire and drought and identify areas which will be critical to reducing these threats through management actions. Furthermore, this project provides information on the effectiveness of past fire management by comparing areas where fire has been managed versus areas which have been suppressed or have not experienced fires in recent decades. In addition, this project informs management of water use within the park, including for two communities reliant on surface water sources for their domestic supply, and for downstream users. Because various spatially explicit management scenarios (e.g. restored forest condition vs. no action) can be assessed with the models, these results can guide future climate impact assessments and climate mitigation strategies.

Methods:

The project used statistical analysis of the impacts of topography, vegetation density, and weather on soil moisture, snowpack, streamflow, and forest health at multiple spatial scales.

Remote Sensing

Recent vegetation cover was calculated from airborne lidar data collected through the California lidar project's southwest pilot area in collaboration with the U.S. Geological Survey's 3DEP program. Acquisition flights occurred between 7 October 2019 and 23 October 2019. Lidar metrics were developed according to methods outlined in Chamberlain et al. (2021) and summarized to 30-meter pixels (hereafter, all ALS metrics referred to as "ALS-derived").

We also extracted topographic and Forest Service fire history raster data to our field plot locations using ArcGIS Pro 2.9.2. Topographic raster layers such as aspect, elevation (0.5m resolution), and total times burned were extracted from the National Park Service records. Mean percent fire return interval departure (mean PFRID) from historic (1908) return intervals, time since last fire (TSLF) in years (current as of 2021), and fire severity were produced by CAL FIRE et al. (2023) and downloaded from the USDA FSGeodata Clearinghouse. Fire severity (relativized difference normalized burn ratio (RdNBR)) was calculated using methods modified from Parks et al. (2018). As a metric of forest health, summer normalized difference vegetation index (NDVI) values were extracted from 10-m resolution Sentinel-2 imagery captured between June and August of 2016 through 2021.

Field Observations

This project aims to help evaluate the effectiveness of past fire management by comparing areas where fire has been managed versus areas which have been suppressed or have not experienced fires in recent decades. Field sites were chosen to cover a broad range of topography, time since fire, past fire severity, and vegetation density, as well as span a large range of western Yosemite National Park (Figure 4).

We collected new field measurements of shallow soil moisture, soil water repellency, and infiltration rates. Statistical models were then used to relate each of these values to topography, vegetation, and fire history (see subsection on Statistical Models below). Measurements were collected throughout the summers of 2022 and 2023, though the majority were collected in 2022.

A Hydrosense HSII TDR probe was used to measure moisture in the top 12-20cm of soil. We measured water repellency using a simple water drop penetration test. An eyedropper was used to place a clean drop of water on the soil either at the soil surface, 1cm depth, or 3cm depth, and the time for the drop to fully absorb into the soil was recorded to the nearest second. We also used a mini disk infiltrometer to measure infiltration rates of the soil both at the surface and at 3cm depth. This method has been shown to provide useful insights into soil water repellency (Robichaud et al., 2008). At each measurement location, broad soil type categories (e.g. sandy loam, clay loam) were determined using simple tests involving wetting of soil and testing whether the wet soil could form a ball or ribbon. See Appendix A for details of field data collection methods.

temperature of 3°C and a maximum range in daily temperature of 1.5°C, similar to published methods (Dickerson-Lange et al., 2015).

Paired Watershed Study

We downloaded streamflow records for watersheds with varying fire histories from cdec.water.ca.gov, waterdata.usgs.gov, and irma.nps.gov/aqwebportal (Table 1). All records were aggregated to daily mean flows. We compared the distributions of daily mean flows before and after large fires, and evaluated whether the distributions changed in the burned watershed in a manner that was significantly different from control (unburned) watersheds.

Any clearly inconsistent values were removed e.g. a sudden drop in flow in Southern Tuolumne River in September of 2013 suggested that the data preceding it was inconsistent, and this data was excluded from analysis.

For comparisons between watersheds, only dates which had clean data available for both streams were included in the analysis.

Table 1. Watersheds compared in this study. The Data Years columns gives all water years (post-2009, the earliest date of data for STO) when data are available for each watershed. Years of major fires within the watershed post-2009 are listed under “Fire Years”. The data source is either Aquarius webportal data maintained by Yosemite National Park (YNP), the California Data Exchange Center (CDEC), or United States Geological Survey (USGS).

Watershed	Gage Elevation (m)	Data Years	Fire Years	Data Source
Illilouette Creek Basin (ICB)	1796	2012-2023	2017, 2022	YNP
Merced River Above High Sierra Camp (MSC)	2225	2010-2018	NA	YNP
South Fork Tuolumne River (STO)	853	2010-2023 (missing data for 2017-2018)	2013	CDEC
South Fork Merced River at Wawona (SMW)	1207	2010-2023	2017, 2022	CDEC
Cole Creek near Salt Springs Dam (COL)	1804	2010-2022	NA	USGS

Modeling

Spatially explicit models were used to assess watershed climate vulnerability to mega-fire and drought, and identify areas which will be critical to reducing these threats through management actions.

Models were created to indicate locations with varying likelihoods of seeing each of the following outcomes in response to forest management actions: higher soil moisture, lower hydrophobicity (and thus

reduced risk of erosion), greater streamflow, increased resistance to drought, and reduced risk of megafire.

Statistical Models

We created statistical models relating soil moisture and hydrophobicity to land cover, fire history, and topography. We used the random forest package in R (Liaw & Wiener, 2002) using published methods previously used for soil moisture modeling within Illilouette Creek Basin (Boisramé et al., 2018). This model captures nonlinear relationships between predictor and response variables. Inputs to the model were derived from Landsat as well as 2019 lidar flights.

CECS Models

We used spatially explicit process-based models provided by the Center for Ecosystem Climate Solutions (CECS; <https://california-ecosystem-climate.solutions/cecs-decision-support-tools/>) to assess watershed climate vulnerability to mega-fire and drought and identify areas which will be critical to reducing these threats through management actions. These models use land cover estimates derived from Landsat data as input. Roger Bales provided us with mean effects of modeled treatments for each burn unit, which he extracted from the CECS database (<https://california-ecosystem-climate.solutions/cecs-decision-support-tools/>). These effects included reduction in wildfire rate of spread and flame length, as well as impacts on drought stress and runoff. For more information, see: Appendix B. CECS Modeling Details.

Results and Discussion:

Remote Sensing of Forest Health

The CECS dataset uses satellite imagery combined with a water balance model to calculate plant water stress (the amount of plant water demand that is unmet by precipitation and stored soil water). During the drought year of 2015, this dataset shows higher plant water stress in the southwest portion of YNP, especially in areas that had not experienced fire in over 20 years (Figure 5).

Water Stress 2015

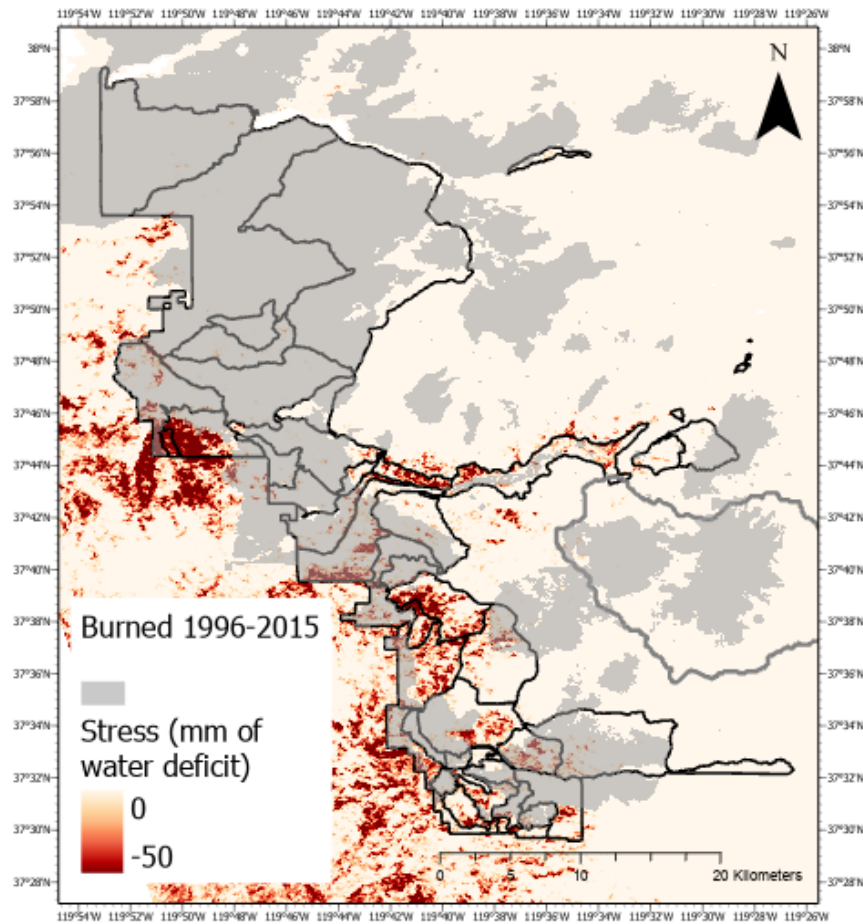


Figure 5. Water stress during the extreme drought year of 2015, according to the CECS modeled data (using satellite imagery from 2015 as an input). Areas within YNP which burned between 1996 and 2015 are shown in grey, demonstrating that many water stressed areas (more negative numbers) had gone over 20 years without fire. Black outlines indicated prescribed burn units, while the grey outline shows Illilouette Creek Basin.

Remote Sensing of Fire Effects

Shrub cover fraction was defined as the proportion of Lidar returns between 0.5m and 2m height, while forest fraction is the proportion of Lidar returns above 2m height. Fire severity in the preceding 5 years was strongly related to both shrub and forest fraction (Figure 6). In order to capture this in our modeling, we used the median shrub and forest cover values from a given fire severity as the cover fraction under that severity in model scenarios.

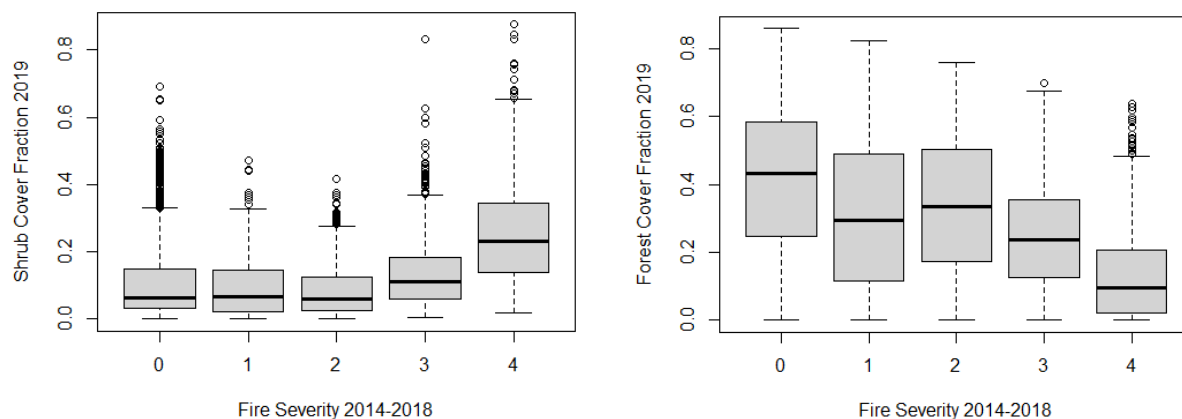


Figure 6. Impact of fire severity (0 = unburned, 1= low severity, 4=high severity) in the previous 5 years on shrub and forest cover fractions. These boxplots exclude locations mapped as either meadow or rock.

Field Observations

The Washburn fire burned through four of the measurement plots in early July of 2022 (fire perimeter shown in lower right portion of Figure 4). Although we had originally planned to only take field measurements in the summer of 2022, we repeated measurements in a subset of locations in 2023 in order to capture the short-term impacts of the Washburn fire by comparing measurements from the summers immediately before and after the fire. Repeat measurements were performed in all plots burned by the Washburn fire, as well as a subset of sites outside of the fire for comparison. Including unburned sites for comparison was especially important for disentangling the effects of weather on soil properties, as the winter of 2022-2023 experienced 2.6X more precipitation than the winter of 2021-2022 (according to PRISM precipitation data; PRISM Climate Group, 2014) as well as a substantially deeper and more persistent snowpack (cdec.water.ca.gov). The April 1st snowpack in the Merced and Tuolumne watersheds was 241% and 244% of average, respectively, compared to 41% in 2022 (cdec.water.ca.gov). Average air temperatures in March-June in the Sierra region were also 2.5°C lower in 2023 than in 2022 (wrcc.dri.edu). The deep snowpack and moderate temperatures caused snow to persist on the landscape in 2023 well beyond the snow off date in 2022, with the USGS gage on the Merced River at Pohono displaying a diurnal snowmelt signal through the summer into early August 2023 as opposed to mid-June in 2022 (waterdata.usgs.gov).

Soil moisture was more likely to be lower in 2023 in sites that had burned in the 2022 Washburn fire, suggesting a short-term decrease in shallow soil water storage in this high-severity fire (Figure 7). This lower water storage could be due to increased evaporation and/or increased soil hydrophobicity (as indicated by higher water drop penetration time in Figure 8).

Water drop penetration time (WDPT; a higher value indicates greater hydrophobicity) was much more likely to increase in 2023 in areas that had burned in late 2022 (labeled with “Yes” in Figure 8) compared to unburned. This suggests that these high severity 2022 burns led to increased hydrophobicity for at least the first year following fire, especially below the soil surface. In 2023, water drop tests were performed on the surface of ash recently deposited at one site which had been burned the previous week in a prescribed fire. These tests showed that black ash surfaces generally had high hydrophobicity (WDPT>5

minutes) while white and brown ash was hydrophilic ($WDPT \leq 1s$), demonstrating that hydrophobicity of surfaces can be highly heterogeneous within a burned area.

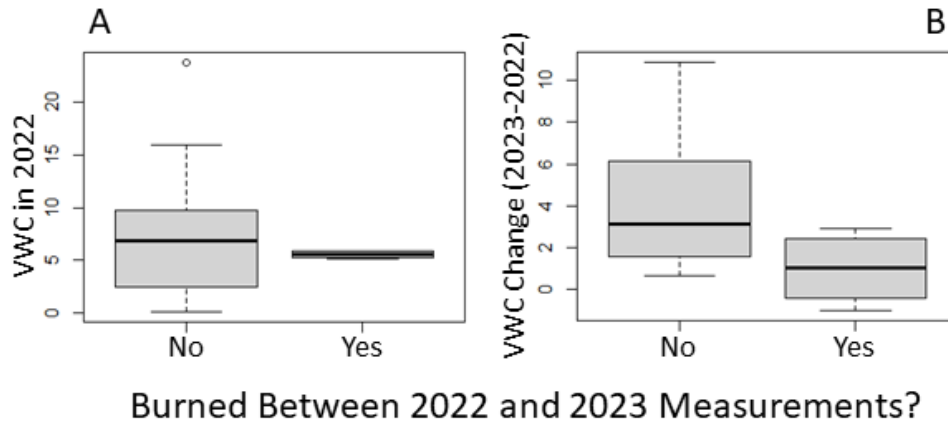


Figure 7. A: Box-and-whisker plot showing the range and median (thick horizontal lines) of shallow soil moisture (measured as volumetric water content, VWC) in late spring of 2022 for all plots that were then re-measured in late spring of 2023. B: Change in shallow soil VWC between 2022 and 2023 for all sites that were measured in late spring of both years. A “No” denotes the site did not burn in 2022, whereas a “Yes” indicates it burned after the 2022 measurements were taken. Only plots without snow in either year are included. Before the fire, all plots that would later burn fell within the soil moisture range of other plots that would remain unburned. All unburned plots experienced higher soil moisture in 2023 compared to 2022, whereas some burned plots had lower soil moisture in 2023.

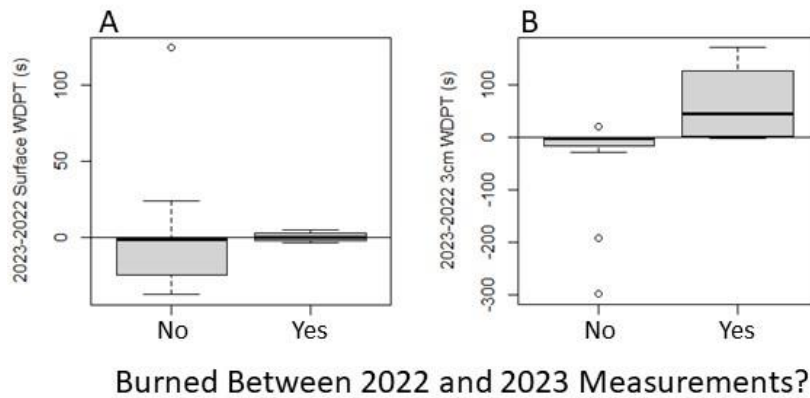


Figure 8. Change in water drop penetration time (WDPT) between 2022 and 2023 for sites that were measured in late spring of both years, both at the soil surface (A) and 3cm below the surface (B). Positive numbers indicate that WDPT was longer in 2023, suggesting higher hydrophobicity. A “No” on the x axis denotes the site did not burn in 2022, whereas a “Yes” indicates it burned after the 2022 measurements were taken.

Infiltration rate also increased post-fire, which might seem to contradict the finding of increased hydrophobicity, but this higher infiltration may be due to drier post-fire soils and thus greater sorptivity. Although there was a negative correlation between infiltration rate and WDPT (-0.2 for both surface and 3cm depth), infiltration rate showed high variability at low WDPT values (Figure 9). This could be due to the fact that infiltration is influenced by soil moisture.

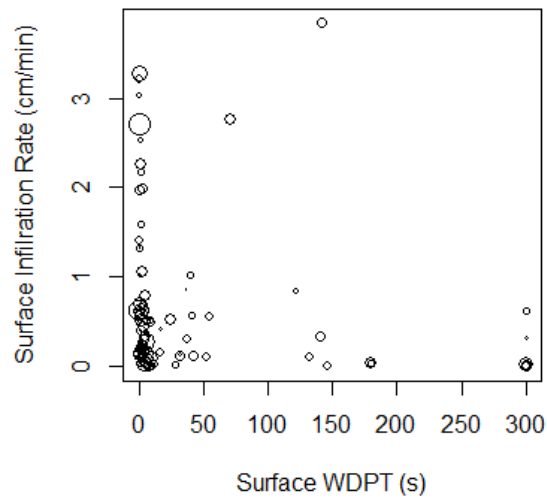


Figure 9. Relationship between infiltration rate (measured using a mini disk infiltrometer) and water drop penetration time at the soil surface. Circle size is proportional to soil moisture, showing that the wettest soils often have low WDPT and infiltration.

Infiltration is highly influenced by soil type, with greater infiltration in sandy soils and the lowest median infiltration in clay loam (Figure 10). While there are broad maps of soil type available (e.g. SSURGO), soils can be very spatially heterogeneous and these maps may not capture local variations, which adds uncertainty to any upscaled maps of infiltration.

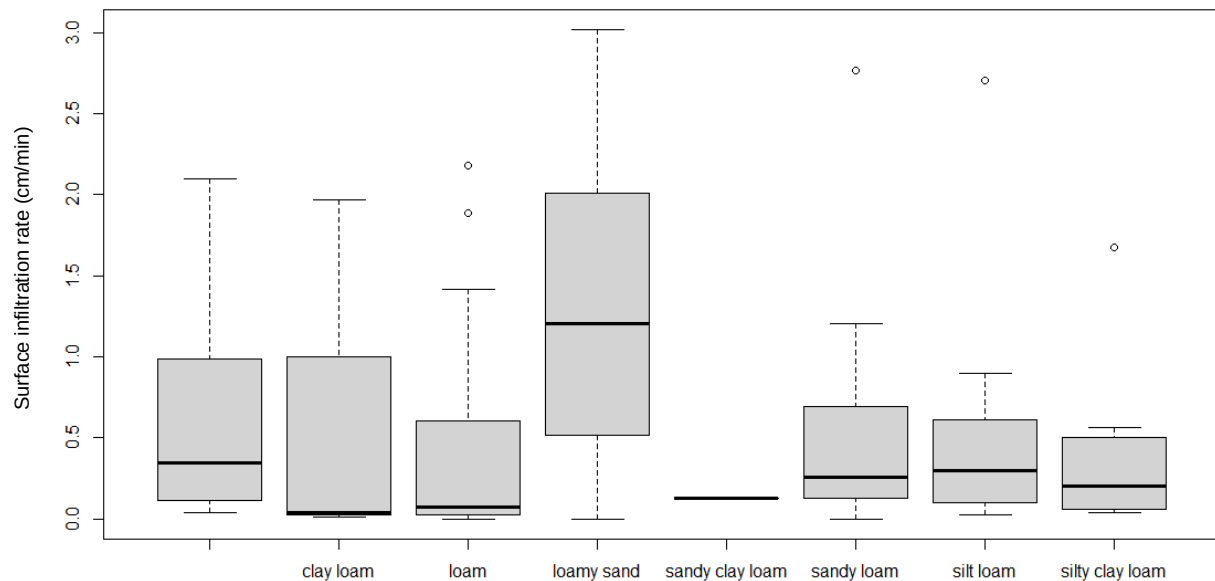


Figure 10. Boxplot showing the range of infiltration rates within each soil category (in cm/minute). Dark horizontal lines show the median for each soil type.

In May of 2023 there was still snow present at some plots (elevations 1843-1896m). We took the opportunity to measure snow depth and relate it to canopy cover (Figure 11). On average snow was deeper in open areas compared to under canopy, consistent with the other snow datasets discussed in this report.

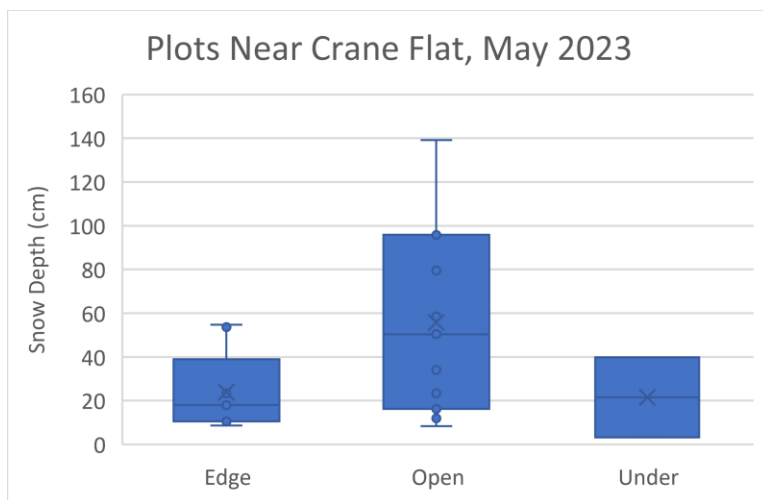


Figure 11. Distribution of snow depths measured under the canopy drip edge (Edge), in the open (Open), or under forest canopy (Under).

Analysis of Observed Snow and Soil Moisture Time Series

Previous work has shown that snow will generally persist longer in areas with more open canopy in regions with relatively warm winters (Lundquist et al., 2013). This is largely due to the longwave radiation emitted from dark tree surfaces causing more snowmelt than the shortwave radiation from sunlight hitting the exposed snowpack. This is partially due to the low sun angles during the period when snow is generally melting in these regions. We used multiple datasets of snowpack observations to verify that snow persisted longer in open canopies within the study area. We were also able to show the relationship between snow persistence and soil moisture, providing insights into snowpack's relationship to drought stress.

Roche et al. data shows later snow disappearance date (SDD) and deeper peak SWE in the open compared to under canopy (Figure 12). The sites in the legend are ordered from highest (Olmsted Quarry at 2612m) to lowest elevation (Merced Grove at 1792m). Note that Merced Grove (lowest elevation site) had the earliest SDD of all sites and also the greatest difference between open and under canopy SDD.

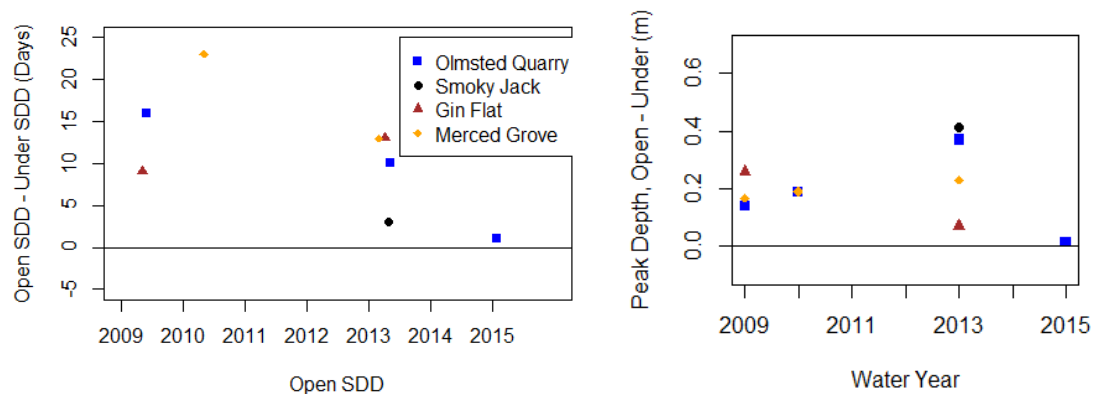


Figure 12. Influence of canopy cover on snow disappearance date (SDD) and annual peak snow depth. A positive “open-under” value indicates that snow remains on the ground longer (for SDD) or gets deeper (for Depth) in the open spaces between trees compared to under the canopy.

Multiple studies have shown fire to be detrimental to snowpack accumulation and retention due to black carbon reducing albedo and thus increasing melt rates (Gleason et al., 2013; Koshkin et al., 2022). However, these studies are generally from isolated, high severity fires. Observations and modeling in areas of Illilouette Creek Basin (ICB) with frequent burns show that snow can persist in open, recently burned areas longer than in adjacent dense forests (Boisramé et al., 2019). Recent data show snow persisting longer in open areas (sites that had burned at high severity and regrown with non-tree vegetation) compared to nearby forested areas (sites that had burned at low severity and retained a dense tree canopy) for 4/7 locations measured in 2023, including one location where the open plot had burned at high severity in the 2022 Red Fire (Figure 13). The difference in snow cover was less than 10 days for those sites where snow persisted longer in forest, whereas in other sites snow persisted up to 40 days longer in the open site. It is possible that the fire history in ICB makes the snowpack less susceptible to negative impacts of wildfire compared to locations with denser fuels that might generate more black carbon post-fire. In general, snow melts earlier in forested areas in the locations measured; this relationship is less strong at the highest elevations which could be due to the influence of the Red Fire burning the high elevation sites or due to colder temperatures altering the energy balance dynamics at these higher elevations (Figure 14).

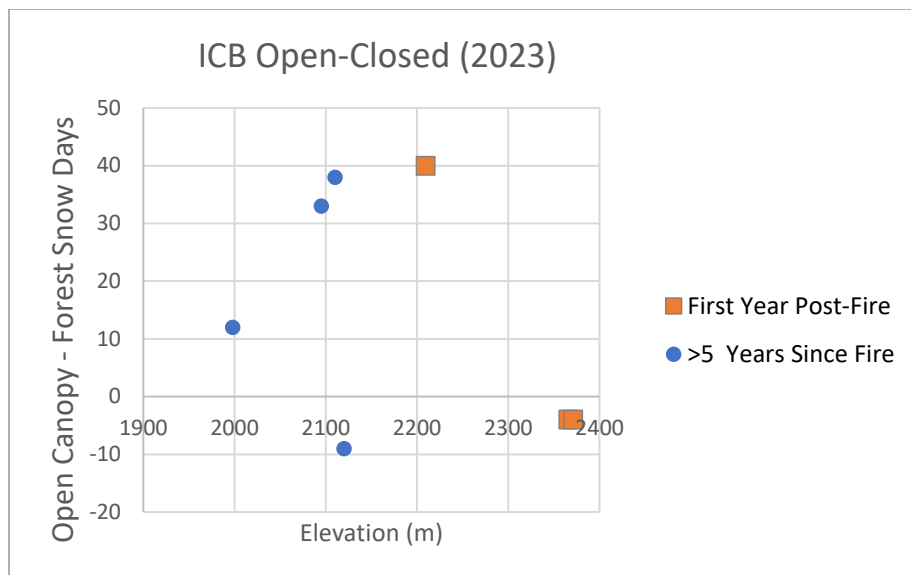


Figure 13. Difference in the number of days with snow cover in 2023 between open areas (shrub or meadow) and nearby forested areas at a range of elevations within Illilouette Creek Basin. Orange squares indicate sites that had burned in the 2022 Red Fire.

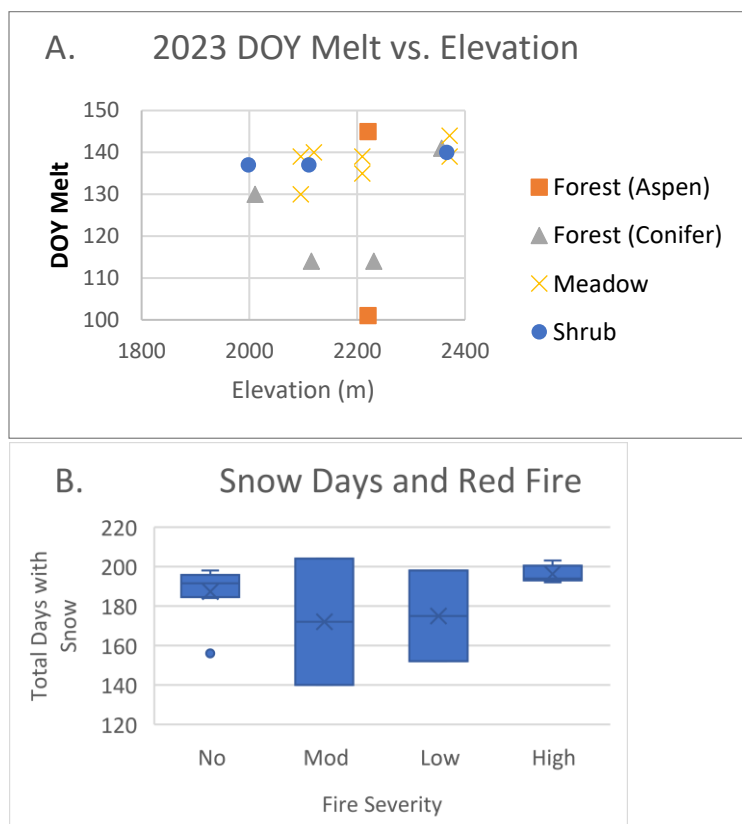


Figure 14. A: Observations of the date of snowmelt within Illilouette Creek Basin show that vegetation cover explains more variability in snow persistence than elevation does, and conifer forests generally have earlier meltout dates compared to meadows or shrubfields. B: The highest elevation sites had all burned in the 2022 Red Fire, but areas with high fire severity still had some of the most days with snow cover.

In the Roche et al. dataset, greater snow accumulation and persistence in the open areas sometimes appears to translate into higher soil moisture in the open the following summer, especially in wetter years (Figure 15). An eight year record of snow disappearance date and soil moisture at a site in Illilouette Creek Basin shows that later snow disappearance is associated with greater summer soil moisture (Figure 16). These both show that forest management to increase snow retention can also help soil moisture and therefore drought resistance.

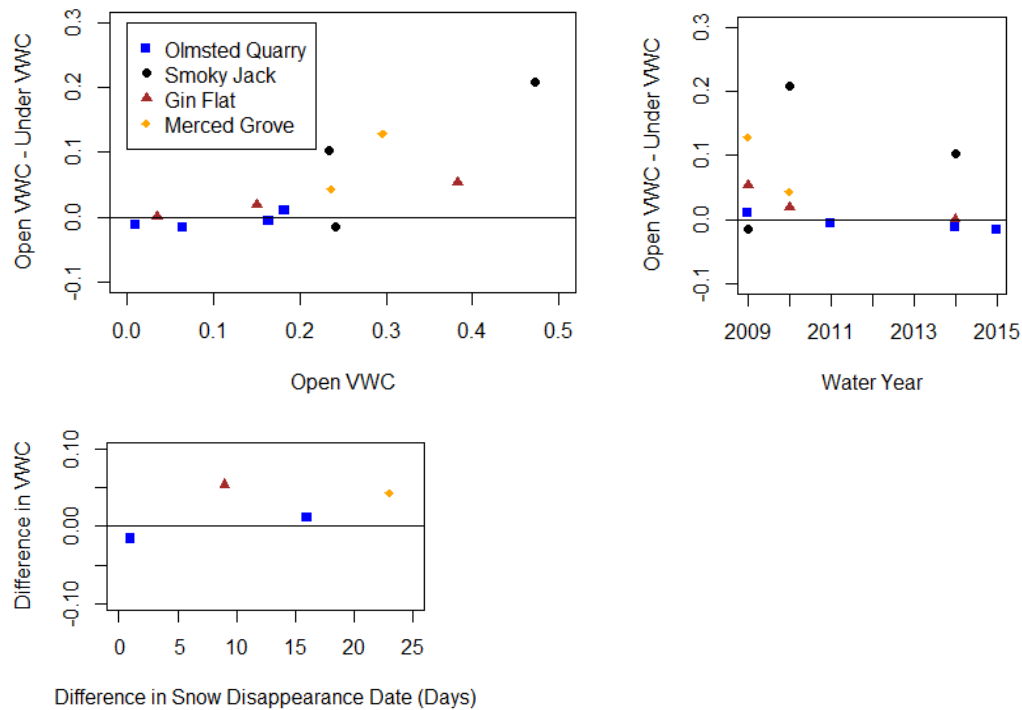


Figure 15. Soil moisture differences (mean for May-September) between open areas and under canopy.

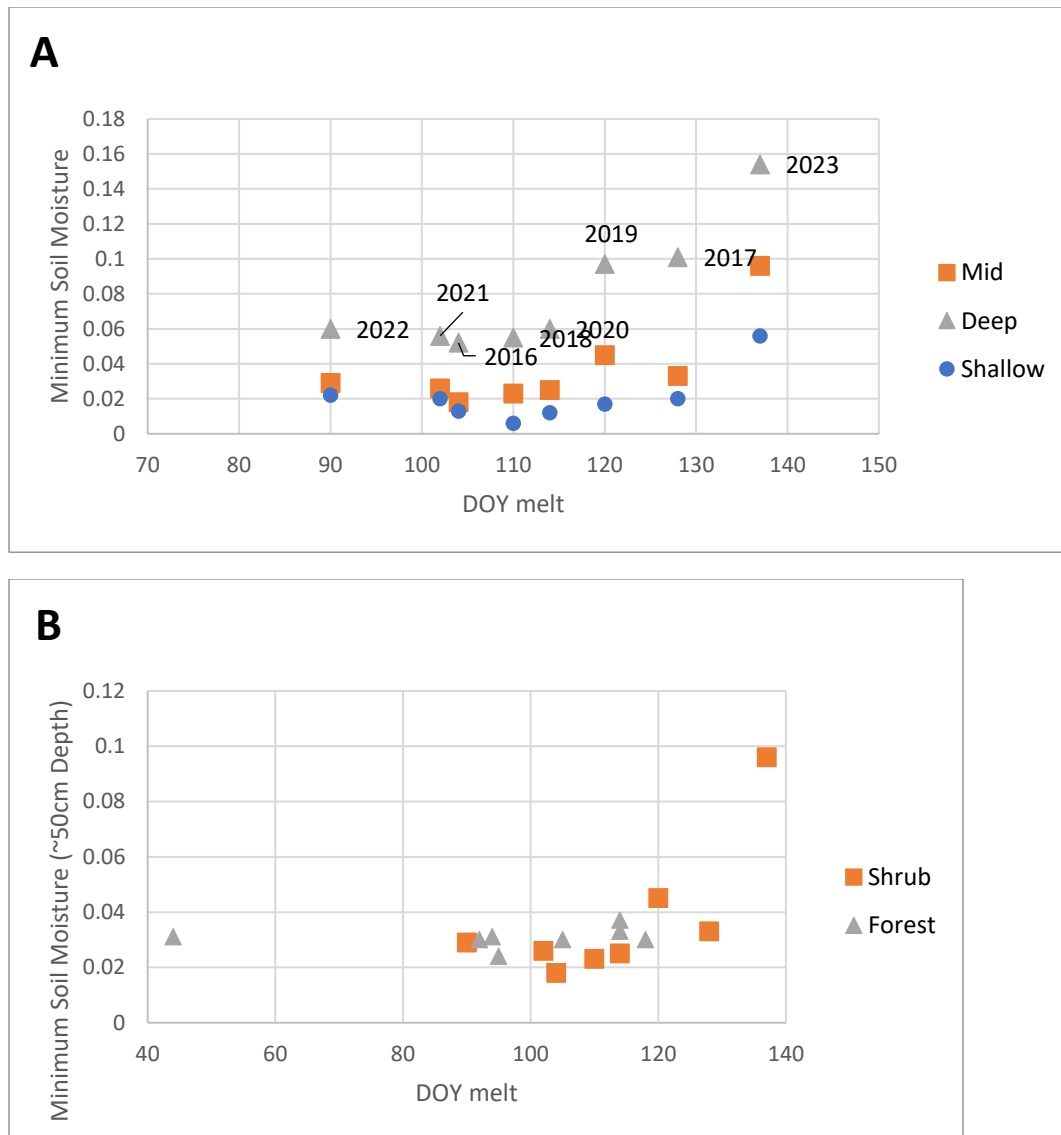


Figure 16. Relationship between the day of year (DOY) of total snowmelt on the following summer's minimum soil moisture at instrumented sites in the Illilouette Creek Basin. A: Minimum soil moisture at three depths within a shrub-dominated site; shallow soil moisture probe is 12cm below soil surface, and deep is approximately 1m below. B: Comparing the mid-depth soil moisture vs. day of melt for two sites (one shrub-dominated and one forested) on the same hillside and same elevation. Both sites burned in 2004 and 2017 (at different severities) and data ranges from 2016-2023. Starting with a melt date around April 10 (DOY=100), later melt dates generally indicate higher minimum moisture levels both within the same site (A) and between two sites with similar topography but different vegetation cover (B).

Figure 17 shows areas that have the greatest potential for increasing snowpack persistence by reducing canopy cover (e.g. through moderate severity fire) in red. Note that the Illilouette Creek Basin, which has experienced 50 years of a restored fire regime, has very little areas mapped in red, and thus theoretically has achieved relatively healthy levels of forest cover in terms of snowpack. Figure 18 shows the same data as Figure 17 but averaged within each burn unit, showing that most of the burn units that would benefit the most from reduced canopy cover are located south of 37°46'N.

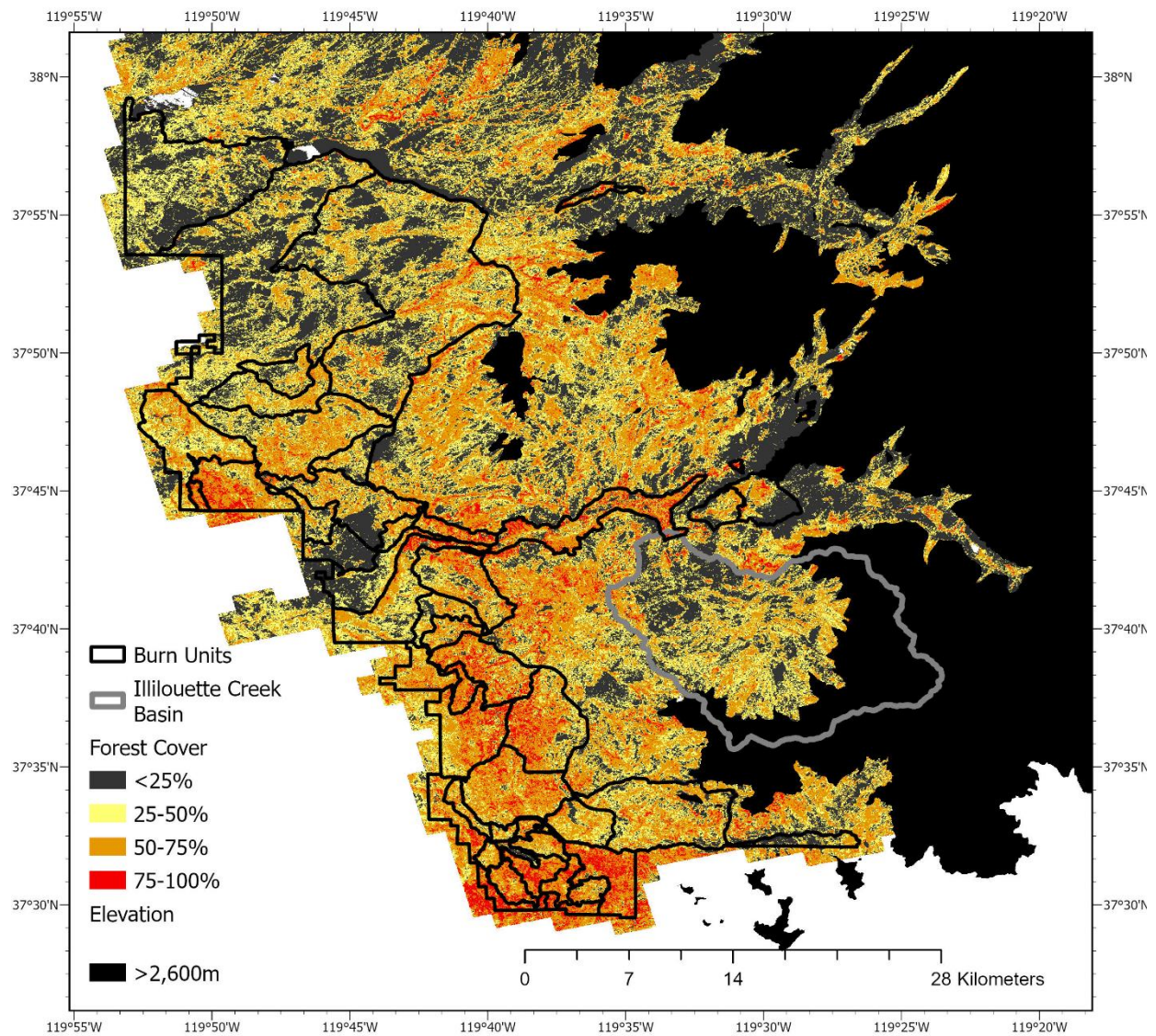


Figure 17. 30 meter-resolution map of YNP showing areas with high forest density (measured as proportion of lidar returns above 2m in 2019 lidar flight) that would likely see long term snow retention benefits with canopy cover reduction. Grey areas already have fairly low forest cover (<25%) and thus are unlikely to see a large snow benefit from further canopy reduction. Yellow through red indicates increasingly dense canopy and thus an increasing potential benefit from reducing canopy cover. Black areas are higher elevation than our highest snow observations, and thus likely colder and snowpack may respond differently to canopy thinning.

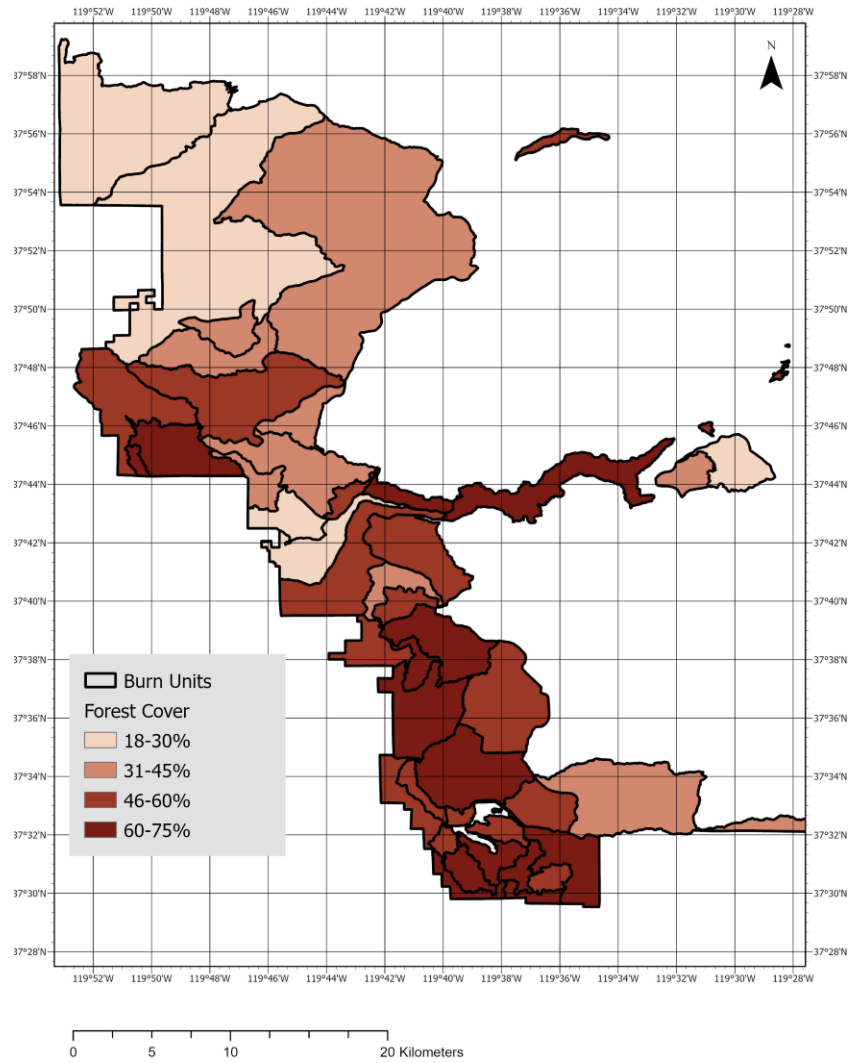


Figure 18. Total forest percent cover (measured as proportion of lidar returns above 2m in 2019 lidar flight) within each burn unit.

Paired Watershed Study

This analysis was limited by a shortage of overlap in clean streamflow data between burned and unburned gages (Figure 19), but we were still able to make some comparisons.

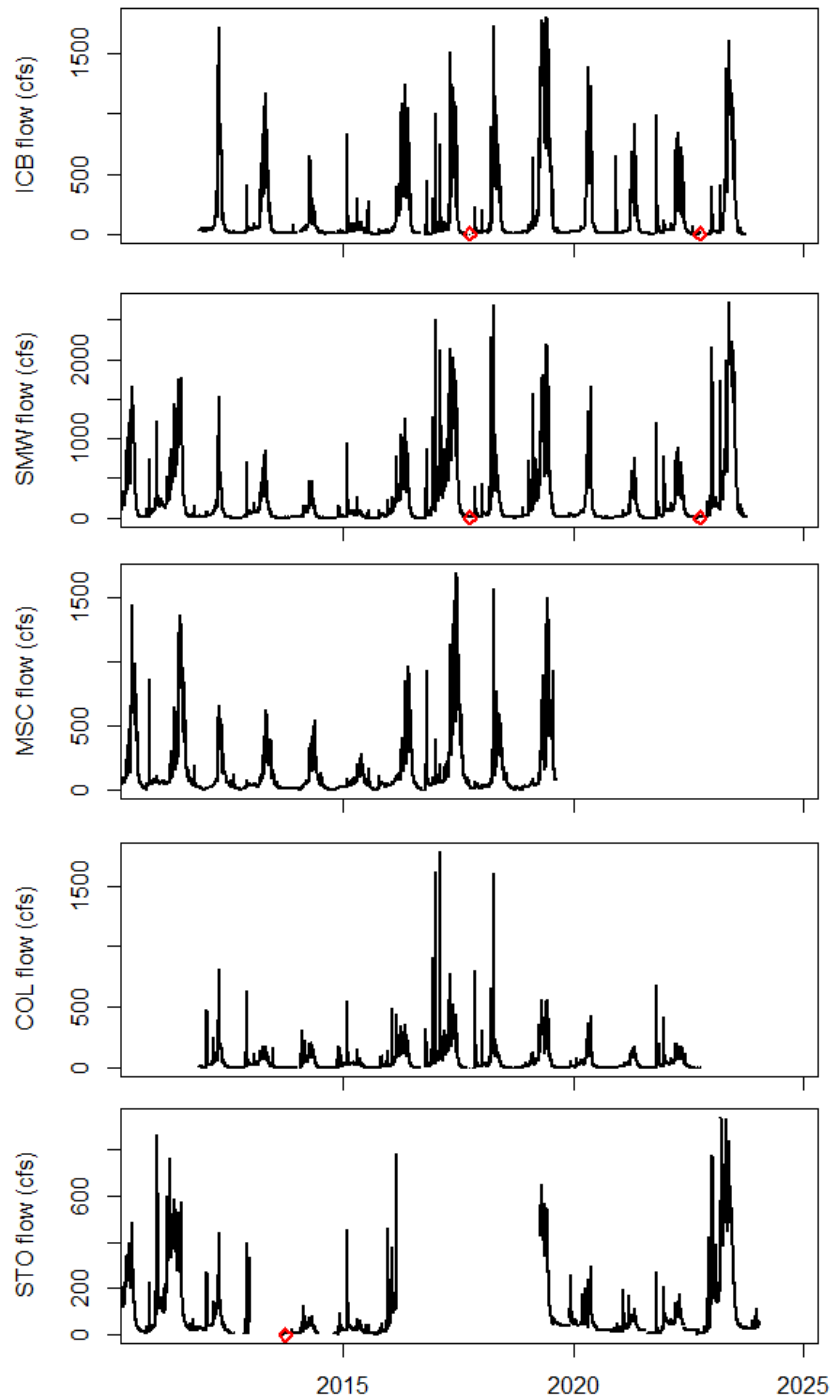


Figure 19. Daily streamflow values for the gages described in Table 1. Red diamonds show approximate fire dates.

Both ICB and SMW appear to experience an increase in their lowest flow levels following fire in 2017, which is not observed in unburned watersheds. The likelihood of high flows may also have increased slightly, but this was also observed in the unburned Merced River gage above Merced Lake High Sierra Camp. Overall, the 2017 fires in ICB and SMW do not appear to have dramatically altered their flow distributions. (Figure 20, Figure 21). This could be partially due to the fact that both ICB and SMW have much of their streamflow originating in high elevation areas dominated by exposed bedrock, and such areas are not impacted by wildfire.

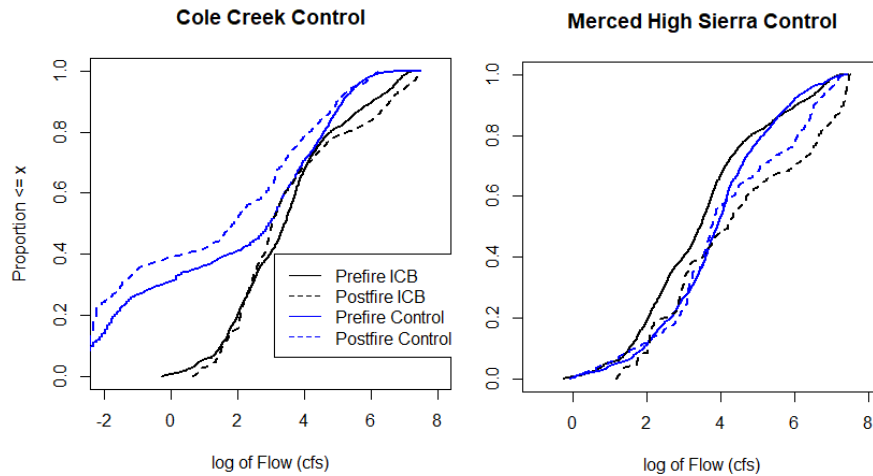


Figure 20. Distribution of daily streamflow volumes in ICB and two unburned control watersheds both before (solid line) and after (dashed line) the 2017 Empire Fire which burned a portion of ICB. This plot includes only data through summer 2022 to avoid capturing effects of the Red Fire in Illilouette Basin. Control watersheds are: Cole Creek, and the Merced River Above Merced Lake High Sierra Camp. In each comparison, only days when data is available for both Illilouette Creek and the control are included which is why the ICB lines are not identical between plots.

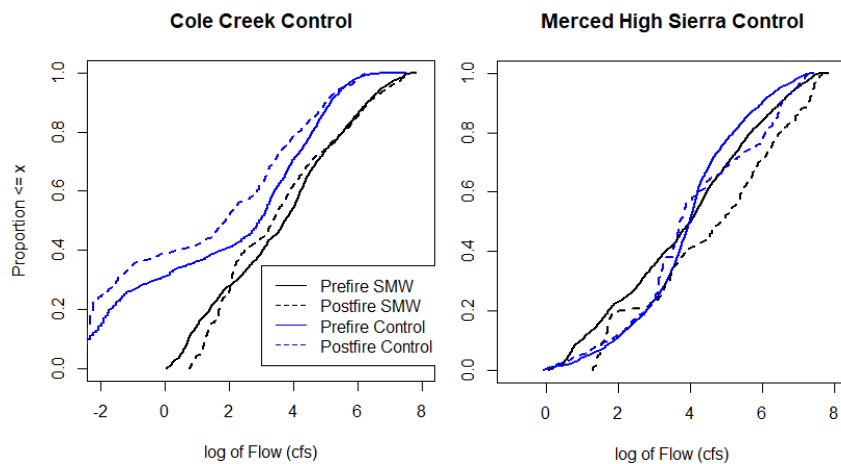


Figure 21. Distribution of daily streamflow volumes in SMW and two unburned control watersheds both before (solid line) and after (dashed line) the 2017 South Fork Fire which burned a portion of SMW. This plot includes only data through summer 2022 to avoid capturing effects of the Washburn Fire. Control watersheds are: Cole Creek, and the Merced River Above High Sierra Camp. In each comparison, only days when data is available for both Illilouette Creek and the control are included which is why the SMW lines are not identical between plots.

The South Fork Merced River (SMW) saw a large shift in its flow distribution for water year 2023 compared to 2011-2017 flows, while the shift for ICB was less extreme (Figure 22). However, it is unclear how much of these differences can be attributed to the different fire behaviors in each watershed in 2022 versus differences in how their hydrology responded to the record snowpack of the 2022-2023 winter. In addition, the earlier period of comparison encompasses the 2012-2016 drought, which included a three-year period estimated to be the most severe drought in California in the last 1200 years (Griffin and Anchukaitis, 2014). Water years 2019 – 2022 was also an extremely dry three year period in California (ncei.noaa.gov).

Figure 23 shows that in the first two years after 2017 and 2022, when both watersheds burned, the South Fork Merced (SMW) had higher flows compared to what would be expected from flows at ICB. Higher flows in SMW are likely due to a combination of reduced interception, reduced infiltration, and reduced evapotranspiration in SMW following this fire. The fact that flows increased in SMW more than in ICB is potentially due to differences in the size and severity of the fires in each watershed. ICB has a history of frequent, mixed severity fire which has led to reductions in individual fires' severity and extent (Collins et al., 2009). This fire history may have kept the 2017 fire from affecting its streamflow as much as the South Fork Merced's.

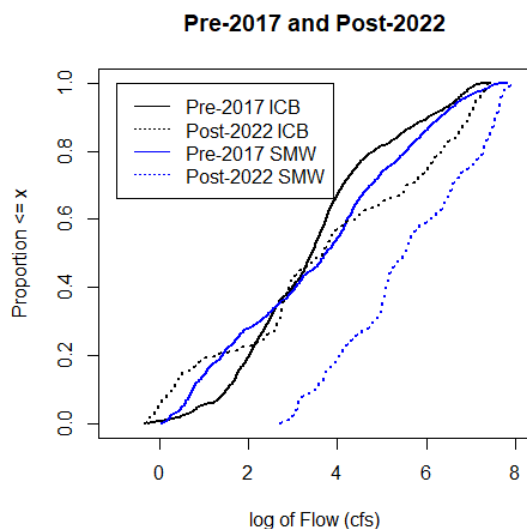


Figure 22. Distribution of daily streamflow in ICB and SMW for 2011-2017 (a period without major fires in either watershed) and water year 2023 (the first year of data available following the 2022 fires that burned portions of each watershed). Both watersheds saw increases in the upper 50th percentile of their flows, likely due to the very wet winter of 2022-2023. SMW saw a large increase in its low flows as well, while ICB saw a decrease in its low flows; it is unclear whether this discrepancy is due to different reactions to fire or due to differences in how low flows in winter and summer were affected by the high snowpack.

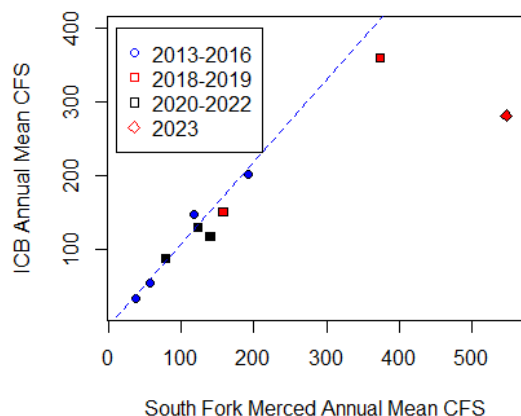


Figure 23. Mean annual flow rates for Illilouette Creek (ICB) versus the South Fork Merced at Wawona for each water year when complete data are available. Different symbol shapes indicate breaks across years when fires burned through portions of both watersheds in 2017 and 2022. There is a strong linear relationship between these flows (dashed blue line) for 2013-2016.

Additional analyses related to the Rim fire, which did not show strong impacts on the Southern Tuolumne watershed, are shown in Appendix C.

Statistical Models of Soil Properties

Random forest models were trained on field observations of soil moisture, water drop penetration time, and infiltration rate. These models allowed us to explore the field observations in more detail by providing insights into the individual impacts of different predictors on soil properties. We also used these models to upscale our observations and to simulate soil conditions under different vegetation and fire scenarios.

The final predictors used in the random forest models are: Date, % Open Land Cover 2019, % Shrub Cover 2019, % Forest Cover 2019, NDVI 2016, Latitude, Longitude, Meadow (categorical), Times Burned, Time Since Fire, Most Recent Fire Severity, Maximum Fire Severity, Slope, Aspect, Mean Canopy Height 2019, Elevation, Curvature at 30m resolution, Uphill flow accumulation at 30m resolution. Basal area was also tested but did not improve model fit.

The random forest model for soil moisture explained 50% of the variance in observations, and the root mean squared error was 21. The correlation between observations and model values was 0.96, and the model tended to underpredict soil moisture at the wettest measured sites. The infiltration models were only able to explain 16% (for 3cm depth) and 19% (for soil surface) of data variance, but the modeled values had high correlation with observations (0.93 for both surface and 3cm depth). There was much greater uncertainty in the random forest model for water drop penetration time (WDPT, a measure of hydrophobicity), but the model values still had a 0.95 correlation with observations at the soil surface and 0.88 correlation at 3 cm depth. (Figure 24)

NDVI was found to be very important in predicting both volumetric water content and infiltration rates (Figure 25). We verified that using NDVI from a single year (2016) was still predictive even for areas that burned post-2016 by showing that higher 2016 NDVI values were associated with wetter soils regardless of fire year (Figure 26). This is likely because NDVI in that one year is capturing information about the potential amount of vegetation that can be supported in a given area, which is related to the amount of moisture that can be held there.

Although fire history did not rank among the most influential variables in predicting soil moisture (see low “importance” of time since fire, fire severity, etc. in Figure 25), we do see that volumetric water content has some complex relationships with fire history. For example, areas that have burned more than 3 times were associated with the highest soil moisture, on average (Figure 26). This suggests that repeated burns may be needed to achieve soil moisture benefits. Areas that had not burned for multiple decades were also associated with high soil moisture, but this is likely due to the fact that the wettest meadows are unlikely to burn rather than indicating that fire exclusion is beneficial for soil moisture (Figure 26).

Infiltration rate is generally highest in areas with low vegetation (Figure 27), which may be related to sandy soils that do not retain enough moisture to support dense vegetation.

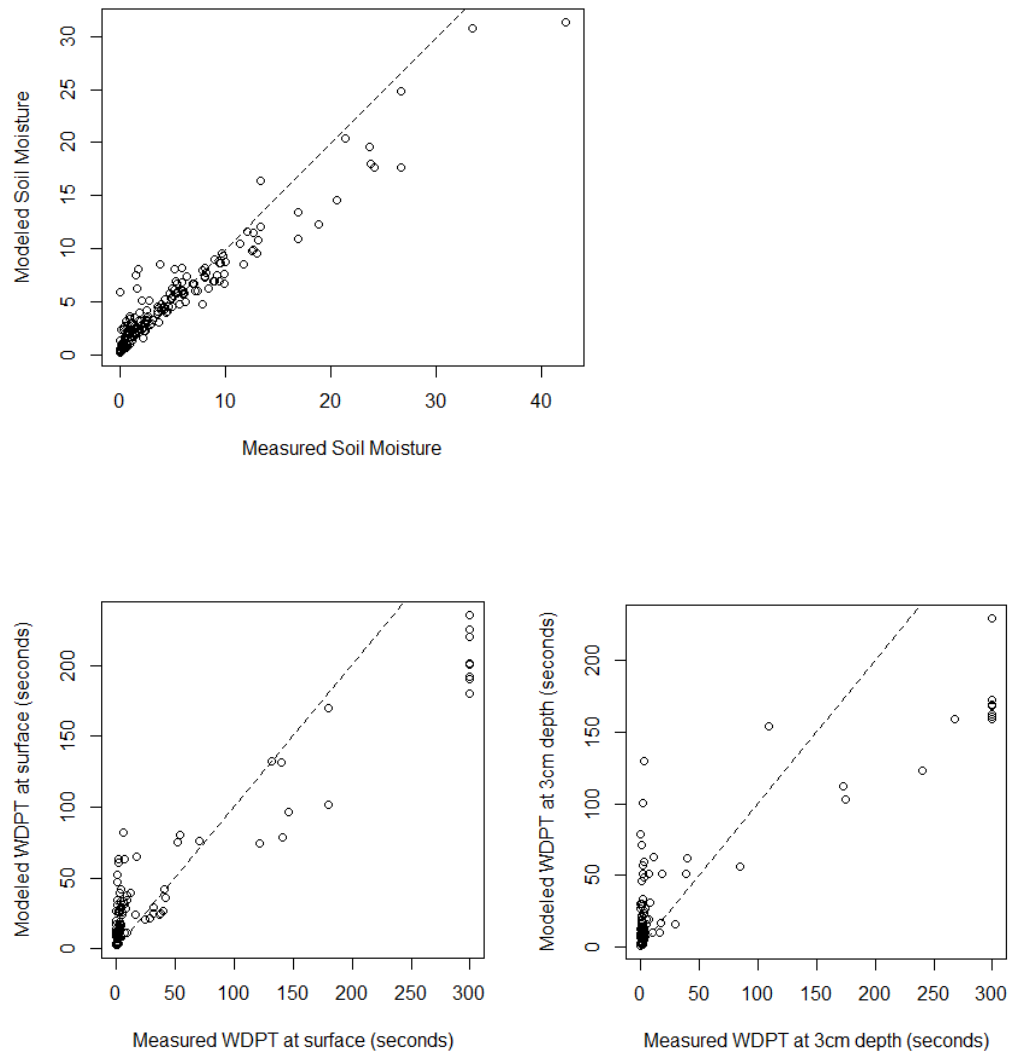


Figure 24. Validation of random forest models for soil moisture (measured as % water content of the soil), water drop penetration time (WDPT), and infiltration rate. Dashed lines show the 1:1 line that would indicate perfect fit.

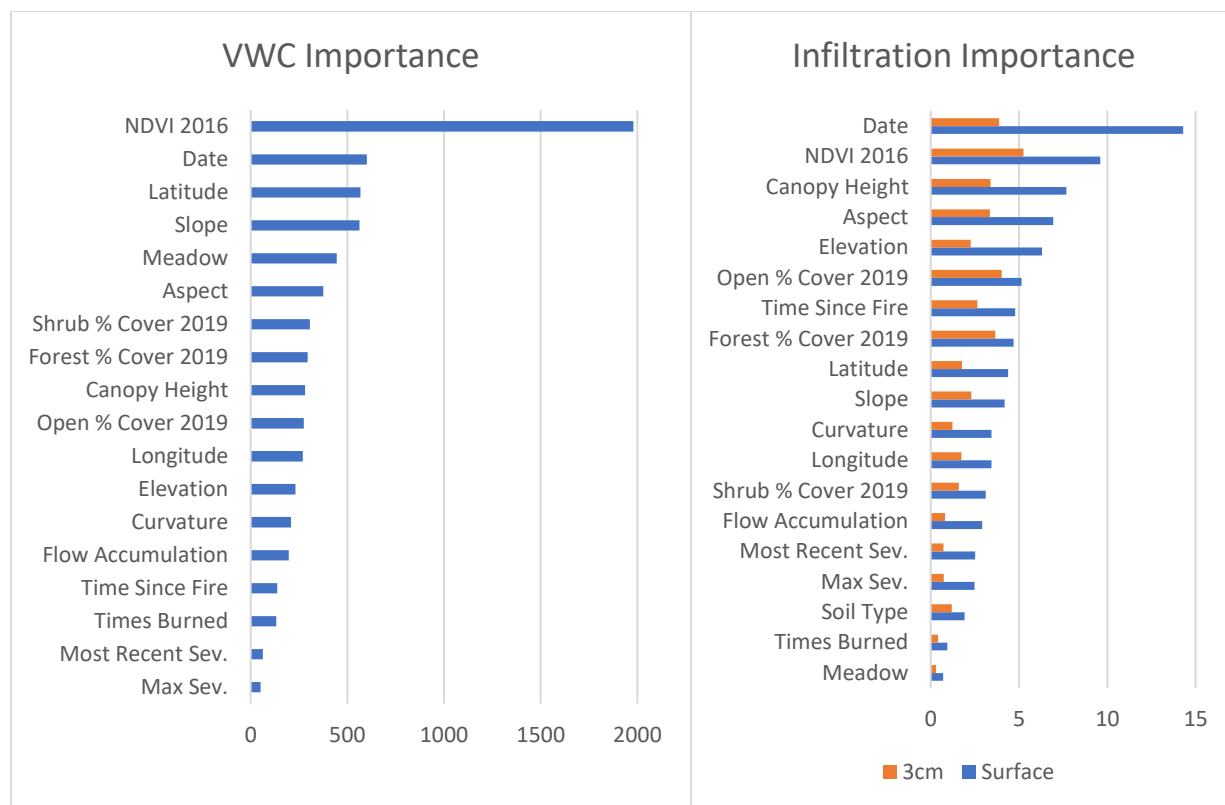


Figure 25. Relative importance of each variable in predicting VWC and infiltration rates (both at the soil surface and 3cm depth) using random forest models. A higher importance indicates that the model error increases more if that variable is omitted.

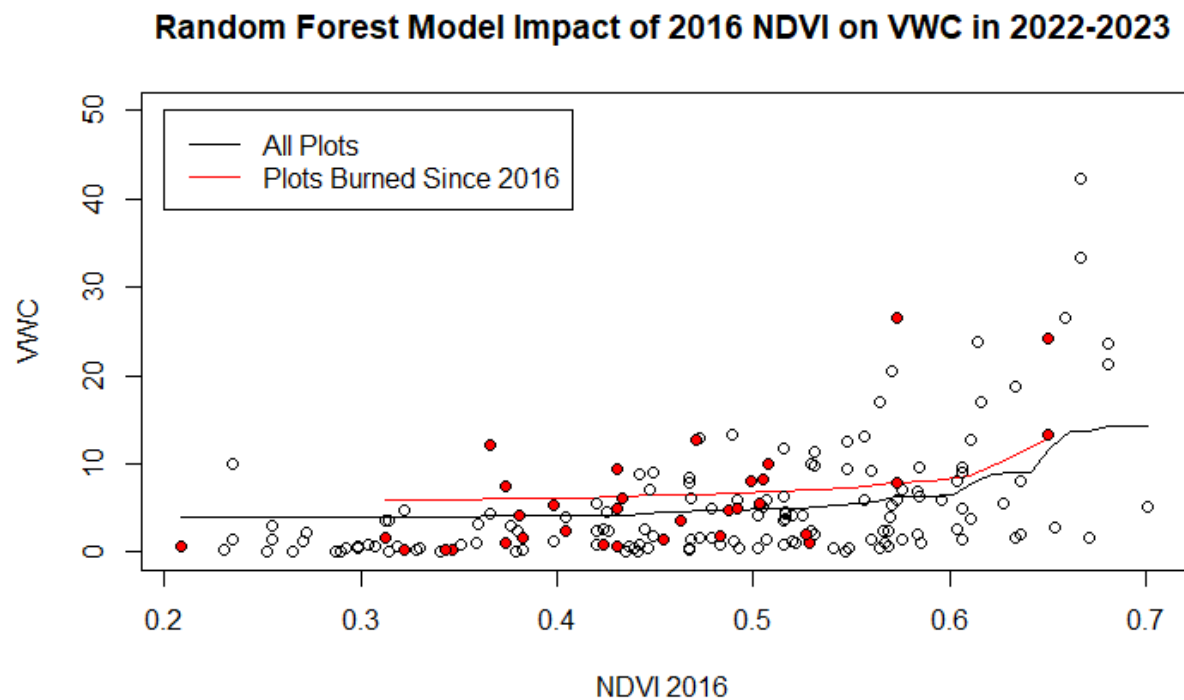
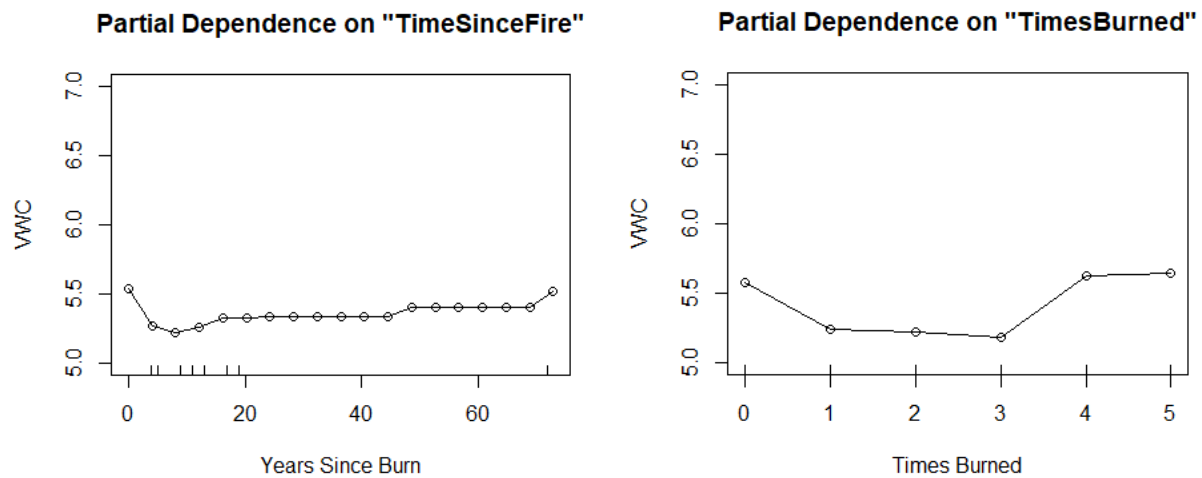


Figure 26. Volumetric water content (VWC) of the shallow soil is highest either in unburned sites or sites that burned very recently and/or were burned more than 3 times. A higher NDVI in 2016 predicted wetter soils, even in sites that had burned since 2016 (and thus presumably have lower NDVI).

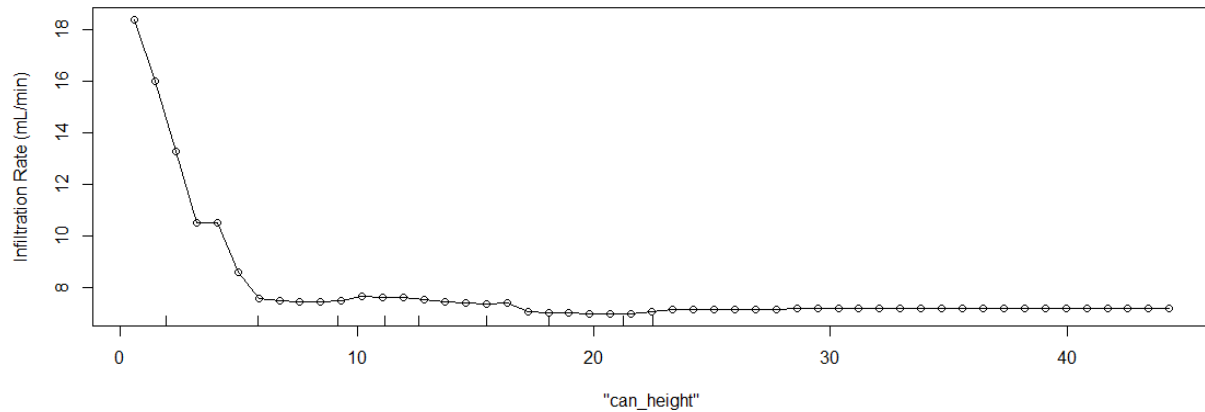


Figure 27. Infiltration rate is generally highest in areas with low vegetation. The x axis gives mean canopy height in meters (according to 2019 lidar at 30m resolution).

Figure 28 shows that high severity fires can increase hydrophobicity (which reduces infiltration and increases erosion potential) for several years post-fire, but that long-unburned landscapes can also have a high level of hydrophobicity (and associated negative impacts on soil). Surface soils are most likely to be hydrophobic in long-unburned locations (Figure 28A), though areas that burned in very recent years also generally have high hydrophobicity (Figure 28B). At 3cm depth, hydrophobicity increases with fire severity and decreases with time since fire up to a minimum at 10 years post-fire, at which point hydrophobicity begins to rise with time since fire (Figure 28D). These results are consistent with other work which has shown that high severity fires can lead to surface temperatures that are so high that they volatilize hydrophobic compounds, but below the soil the temperatures during fire are amenable to creation of a new hydrophobic layer (Debano, 2000).

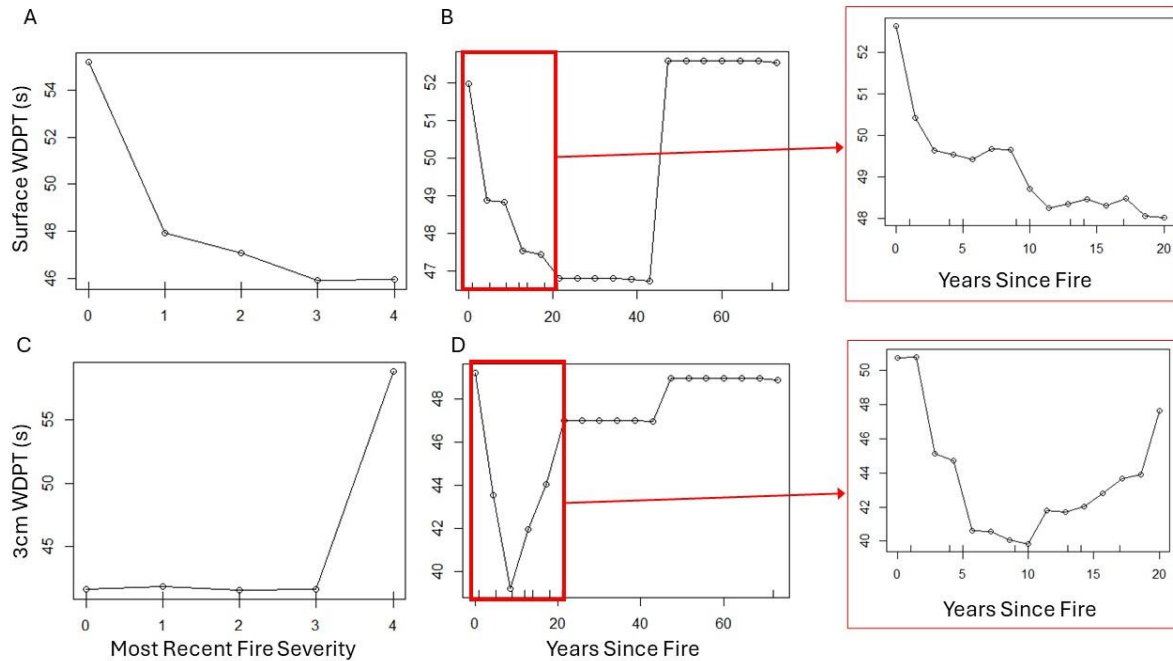


Figure 28. Partial dependence plots showing the relationship between water drop penetration time (WDPT) and fire variables, according to the random forest model. The fire variables shown here are most recent fire severity (A and C, where 4 is high severity and 0 is unburned)) and years since the most recent wildfire (B and D). The results for 0-20 years since wildfire are shown in red boxes to show more detail.

Maps of Soil Properties Created Using Random Forest Models

The following maps give examples of the extrapolation and hypothesis testing possible using our statistical models of soil properties. These models will be made available to YNP researchers and managers for use in testing potential management strategies.

Soil moisture maps follow expected spatial patterns, with flat areas near streams and wetlands having higher soil moisture than uplands (Figure 29).

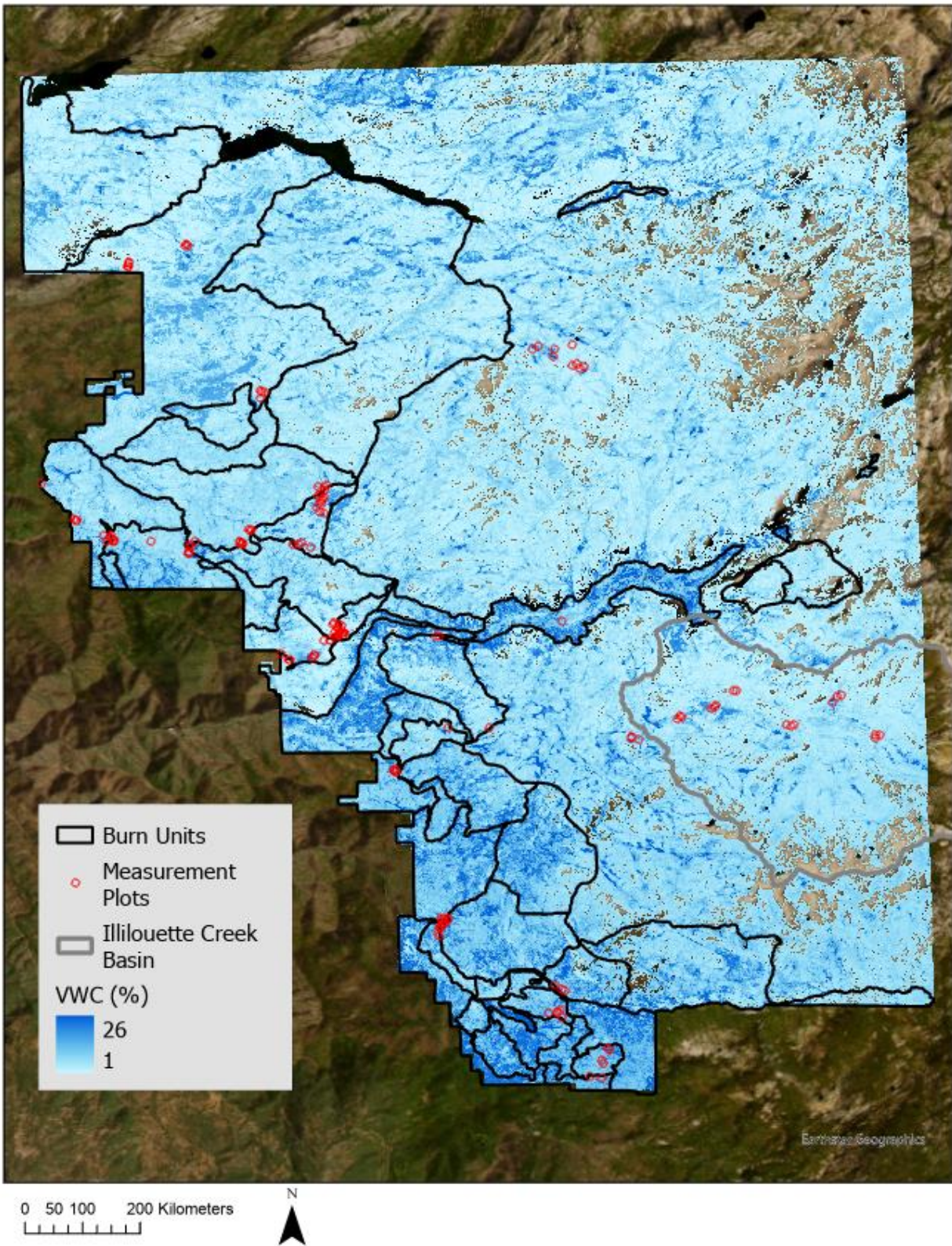


Figure 29. Modeled soil moisture (measured as volumetric water content, or VWC) across the entire study area for June of 2022. Red circles indicate location of measurements used to train the model. Black outlines show prescribed burn units, and the grey outline indicates the Illilouette Creek Basin.

Figure 30 shows expected changes to June soil moisture (compared to actual 2022 conditions) one year following the fourth in a sequence of moderate-low severity fires, compared to soil moisture following an isolated high severity fire. The moderate-low severity fires would have less impact overall (varying between a few percentage points increase or decrease depending on location), but high severity fires might actually have the potential to greatly increase soil moisture in certain areas. The modeled increases in soil moisture post-fire within Illilouette Creek Basin are consistent with previous studies (Boisramé et al., 2018, 2019).

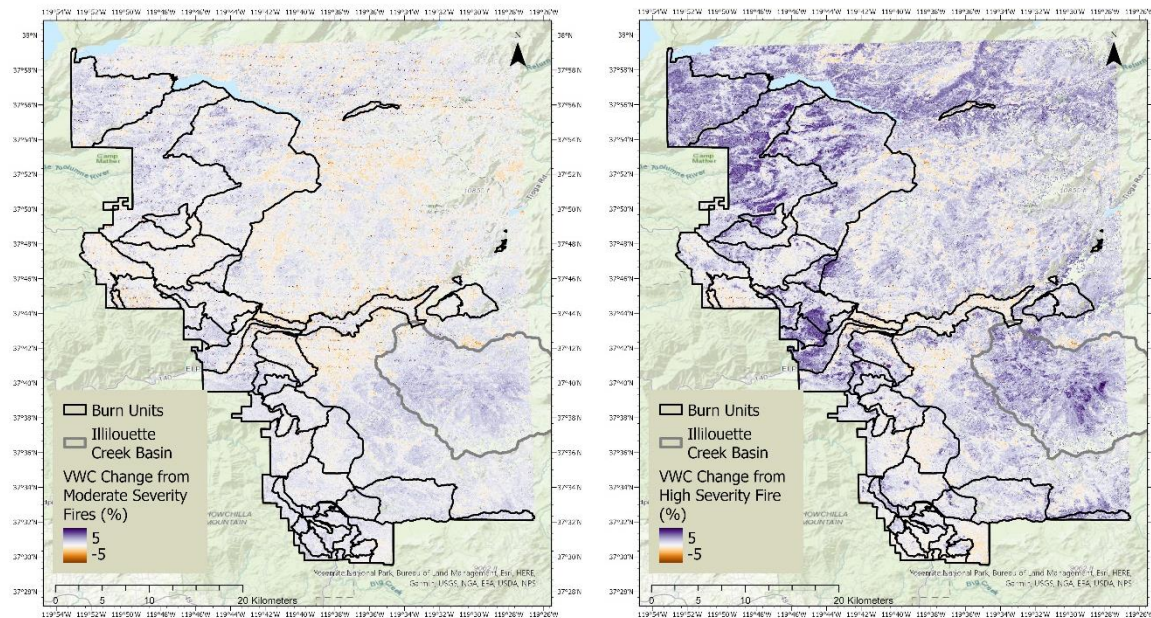
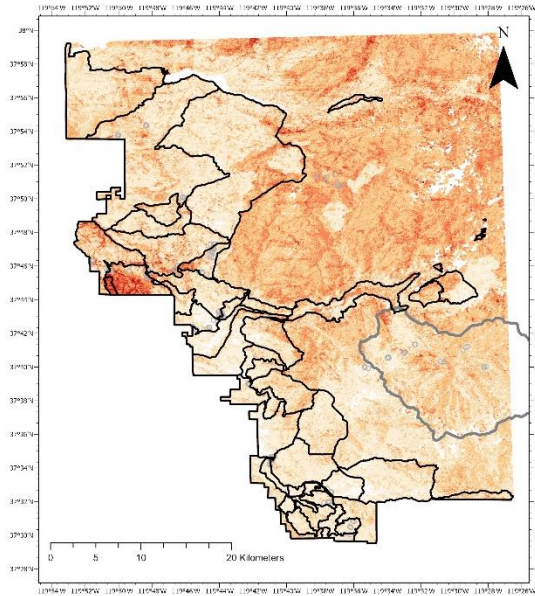


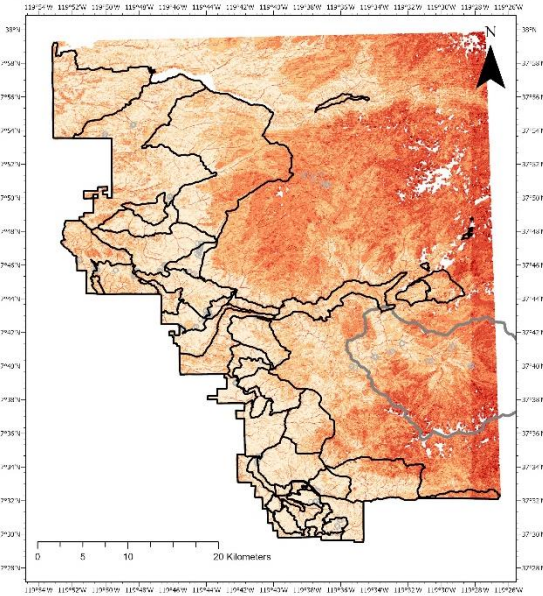
Figure 30. Maps of expected changes to June soil moisture (measured as difference in volumetric water content, VWC, from the current conditions model shown in Figure 29) one year post-fire for two fire scenarios: Repeated moderate-low severity burns, with the most recent fire being low severity (left), and a single high severity fire (right). This model assumes a water year similar to 2022.

Maps of water drop penetration time and infiltration rates were created assuming a universal soil cover of loam (the most common soil type) but could be improved with maps of spatially-varying soil type. These two measurements of soil hydrophobicity give very different spatial patterns, making interpretation of these maps more complicated (Figure 31). Some of these differences may be due to interactions between soil moisture and both WDPT and infiltration rate.

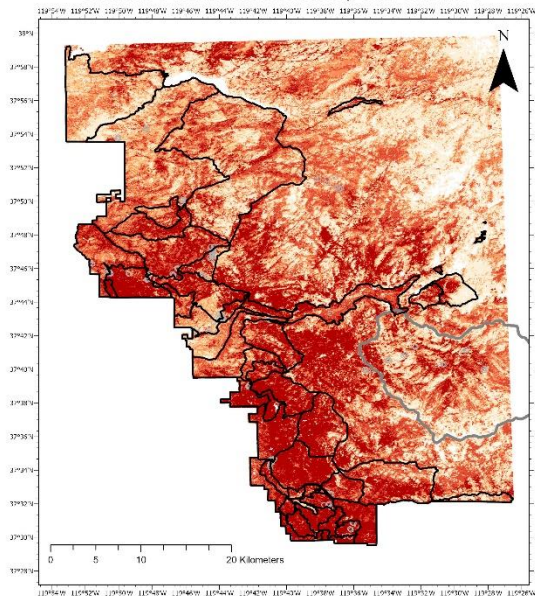
Relative Water Drop Penetration Time, Soil Surface



Relative Water Drop Penetration Time, 3cm Depth



Relative Infiltration Rates, Soil Surface



Relative Infiltration Rates, 3cm Depth

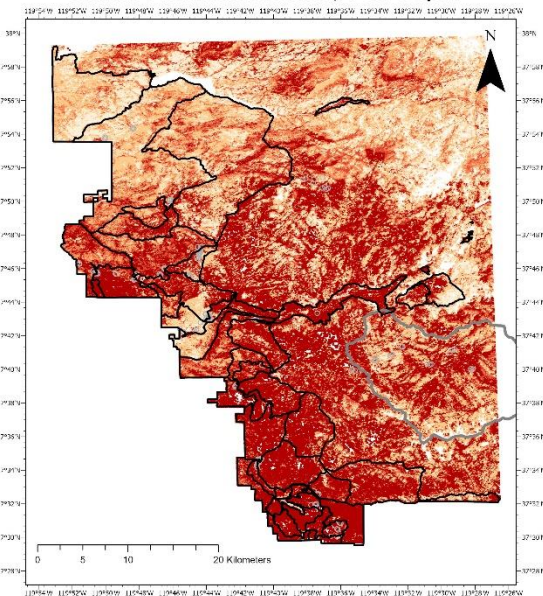


Figure 31. Maps of water drop penetration time and infiltration rate, assuming 2022 conditions. These maps could also be generated to represent different post-fire scenarios as with the soil moisture maps above. In all plots, **red indicates the highest hydrophobicity** (high WDPT or low infiltration rate) while light pink indicates soils that can easily absorb water (and thus are less prone to erosion and flooding). Other symbols are the same as Figure 29, except measurement locations are shown as grey circles. Note that these predicted values do not use spatially-varying soil type data, but are predicted based on topography, vegetation cover, and fire history.

Mapping Using Process-Based Models of Fire and Hydrology

Validation of CECS Dataset

Tree proportional cover from YNP 2019 Lidar estimates (using 4m as cutoff height for tree) was compared to CECS proportional tree cover. On average, Lidar tree cover was 1.1X CECS tree cover (Figure 32). Most of the points where CECS apparently identified high tree cover while Lidar cover was near 0 occurred in shrubby or meadow areas. The opposite occurred in steep areas (potentially Lidar errors on steep slopes)

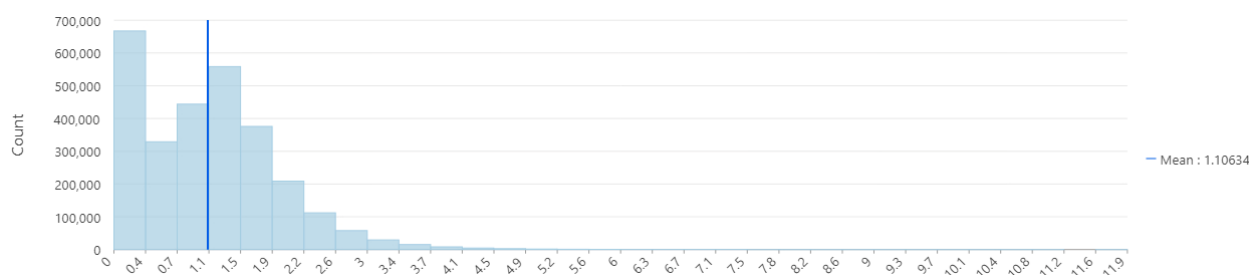


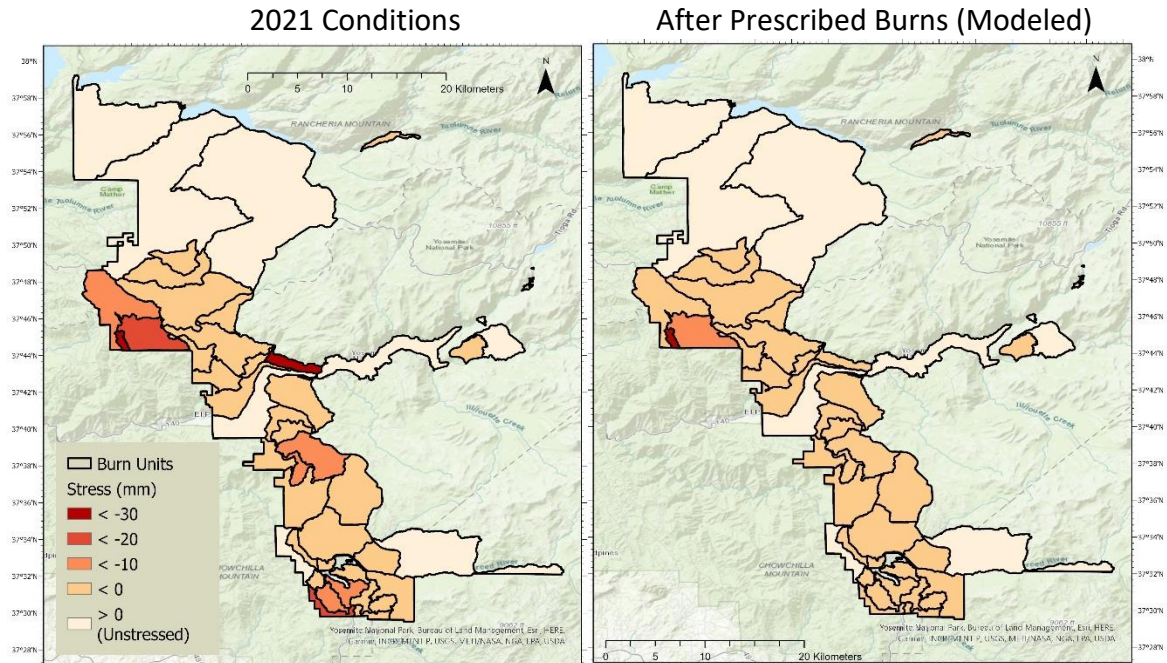
Figure 32. Histogram of lidar-derived tree cover divided by CECS tree cover for each 30m pixel of overlap. Vertical dark blue bar at $x=1.1$ indicates the mean proportion of lidar to CECS tree cover.

Defining shrubs in YNP lidar as being anything between 0.5m and 2m high, on average the Lidar shrub cover was 40% of CECS shrub cover. Overestimates by CECS especially occur in very steep areas.

CECS Model Outputs

According to the CECS models, applying prescribed fire across all burn units would reduce drought stress (Figure 33) and increase surface water runoff (Figure 34, Figure 35), though these effects would be felt to different degrees in different locations. This is consistent with published work showing that repeated mixed severity fires in Illilouette Creek Basin have increased streamflow and reduced drought stress compared to hypothetical unburned conditions (Boisramé et al., 2017, 2019). Prescribed fire would also reduce the likelihood of megafire by reducing fire rate of spread and flame length (Figure 35 - Figure 37).

Further maps like the ones below, as well as maps of spatially-distributed conditions such as annual evapotranspiration, runoff, and water stress for years 1985-2021 (see Figure 5 for an example), can be created using the data provided in the “CECS_Data” folder attached.



Stress Reduction from Prescribed Fire

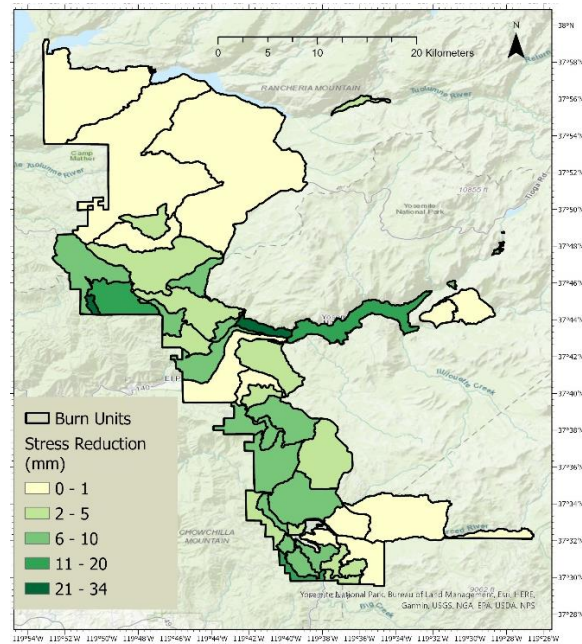


Figure 33. Modeled water stress within each burn unit for 2021 assuming actual conditions (top left) or prescribed burning (top right). Stress is defined as the amount of plant water demand that is unmet by precipitation and stored soil water (negative numbers indicate greater stress). The difference between the top two maps (prescribed fire versus no action) is shown in green, with darker green indicating a greater stress reduction following prescribed fire (bottom right).

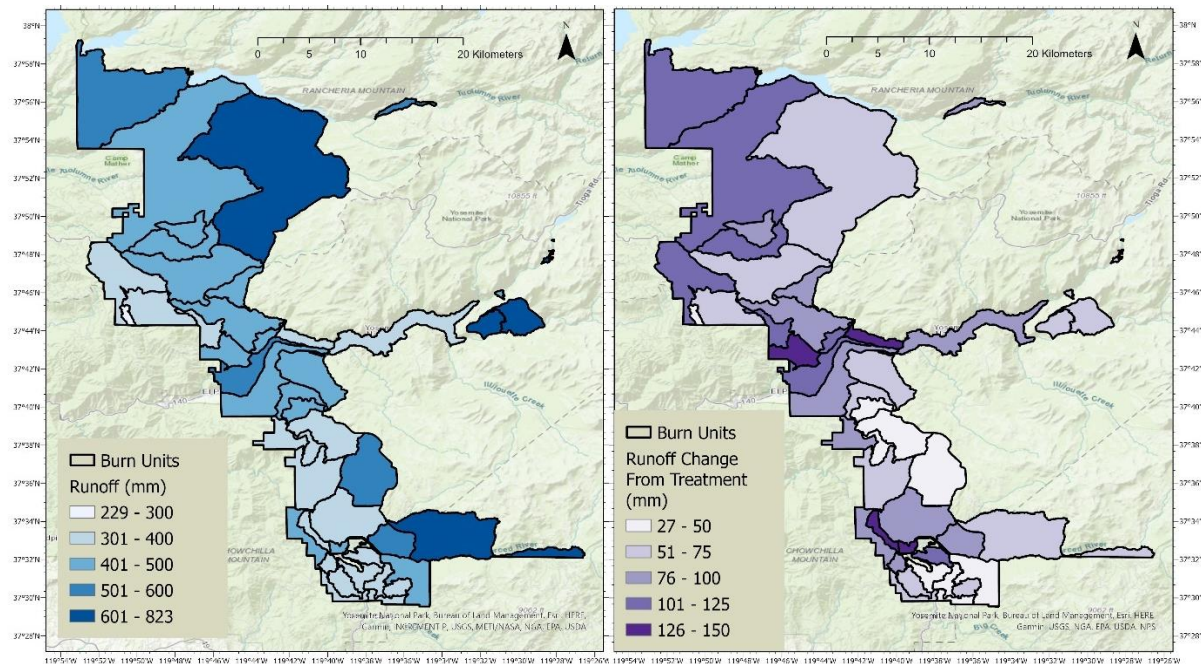


Figure 34. Modeled total runoff (mm; total runoff volume divided by land area) from each burn unit under 2021 actual conditions (left). The modeled increase in runoff (mm) due to prescribed fire is shown on the right.

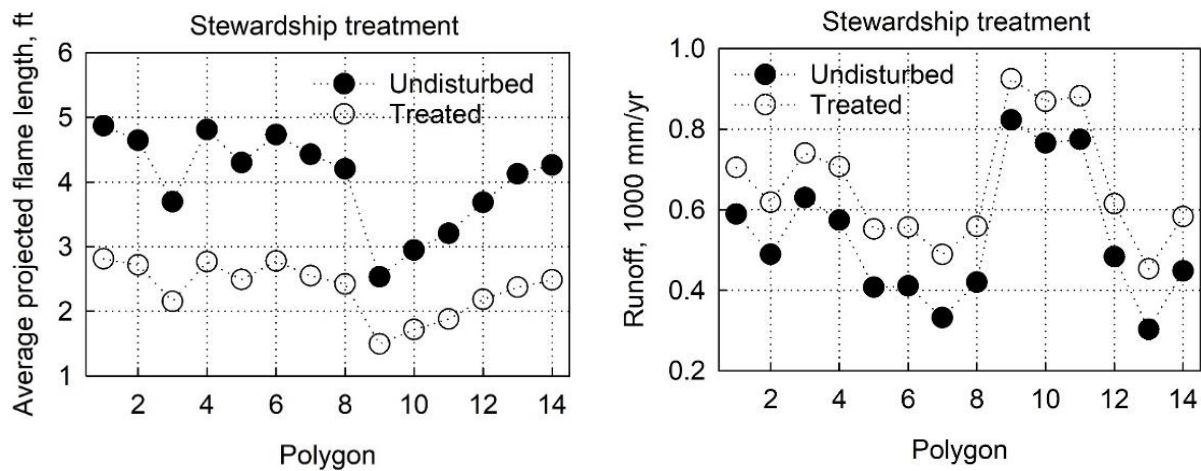


Figure 35. Results of the "stewardship" treatment, which removes some overstory as well as much of the understory, on projected flame length and runoff. Each polygon is a separate burn unit. All burn units are expected to experience decreases in flame length and increases in runoff following this treatment.

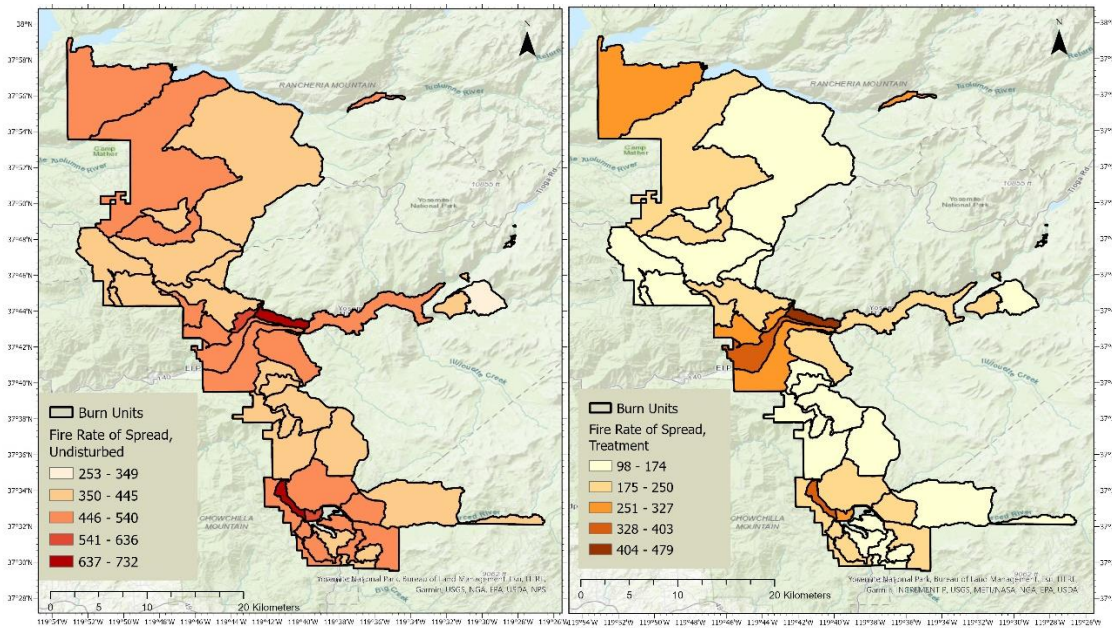


Figure 36. Modeled mean potential fire rate of spread (m/hr) within each burn unit, both under 2021 vegetation conditions (left) and following prescribed fire (right). Note different scales for each map; the prescribed fire theoretically reduces all rates of spread to below the minimum rate modeled for 2021 forest conditions.

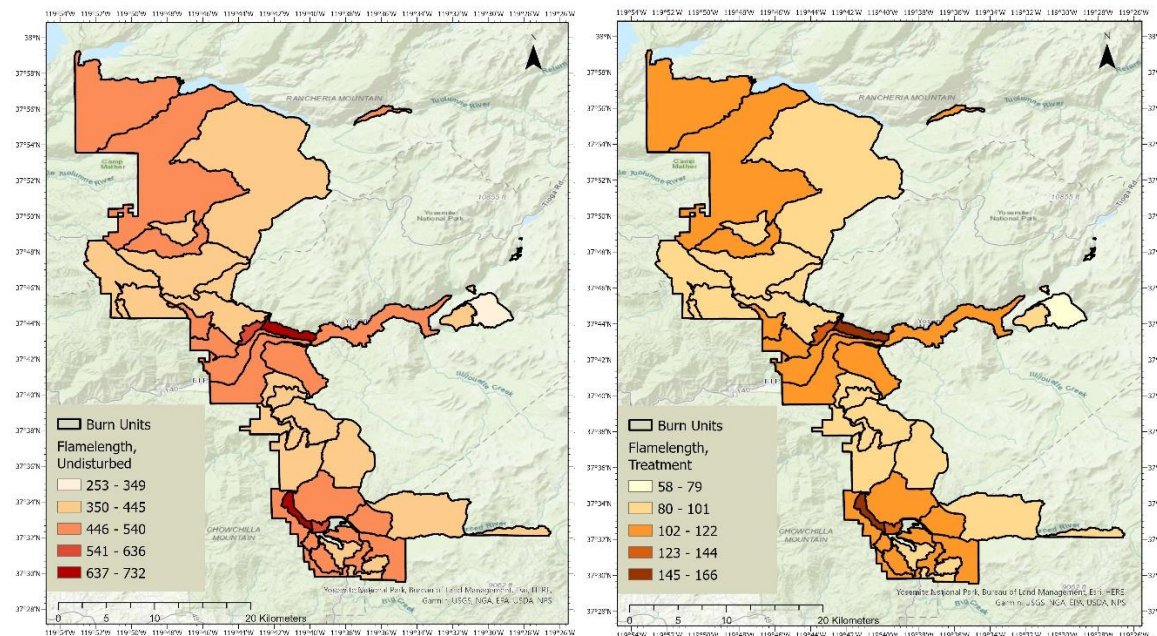


Figure 37. Modeled potential fire flame length (hundredths of feet; 100 = 1ft) in 2021, both under current conditions (left) and following prescribed fire (right). Note different scales for each map; the prescribed fire theoretically reduces all rates of spread to below the minimum rate modeled for 2021 under existing forest conditions. Wind velocity is set at 20 ft/min and wind direction is upslope.

Conclusions

Our assessment shows that areas with less tree cover in western Yosemite National Park generally have greater snowpack storage and less drought stress. Statistical models fit to field observations suggest that increasing the presence of wildfire on the landscape could reduce the negative impacts of fire on soil properties and alleviate drought stress through increased soil moisture. Process-based models also show the potential to increase streamflow, reduce fire intensity, and reduce drought stress through prescribed fire. We have created maps demonstrating areas that would most benefit from increased low-moderate severity fire according to a variety of metrics. Given Yosemite's vast area and limited resources for prescribed burns and fuel treatments, directing actions to these areas is critical to optimize efforts.

A paired watershed study showed uncertain impacts of past fire on streamflow volume. The full impact of recent fires on streamflow can be better assessed once additional years of post-fire data have been collected that encompass a range of wet and dry years. It is therefore important to continue collecting streamflow data with as much accuracy and consistency as possible.

This project led to the creation of a unique dataset of soil properties across a gradient of fire histories and landscapes within Yosemite National Park. Further work will expand on the analysis of this dataset to create more sophisticated models of fire impacts on the landscape. This dataset, as well as the files and R code necessary to run the statistical models described in this report, are included in the attached zip files for use by Yosemite National Park researchers and managers. These models can be used to predict how various management scenarios are most likely to affect different areas.

Data Availability

All spatial data analyzed and mapped in this report is available in the accompanying zip folders, as well as metadata and instructions for its use.

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Appendix A. Field Protocols for Field Measurements

Fire Hydrology Measurements

Measurement sites have been randomly selected to cover as broad as possible a range of fire history, topography, and vegetation cover. Sites are all located within 500m of a trail, road, or other infrastructure in places with <30 degrees slope. A list of sites gives each a priority, with 4 being the highest priority (most important to measure) and 0 being the lowest priority (only measure if you are already traveling very near this site and you have a little extra time).

It is possible that the exact location may be inaccessible (e.g. too rocky for soil measurements, requires a dangerous creek crossing, would take hours of bushwhacking, or somewhere that is unsafe to walk for any reason). It's also possible that due to map accuracy errors the site's coordinates are too close (within 50m) of a trail or road. If the site's GPS location is inaccessible or too close to a trail/road, then use your best judgement to locate a nearby area (within ~100m) with similar characteristics and be sure to note the coordinates of the new location. If nowhere nearby is accessible, note the reason for skipping the site in your field notebook and move on to the next one.

Soil Moisture Measurements:



Figure A1: TDR

Measure a 30m transect running uphill-downhill, centered on the provided GPS point. If the ground is perfectly flat, then run the transect perpendicular to the nearest creek, or run it north-south if there is no creek nearby.

Standing at the center of the transect, **take photos** looking approximately N, E, S, W, and straight up. Make sure the clock time on your camera is correct in order to facilitate matching of photos with sites.

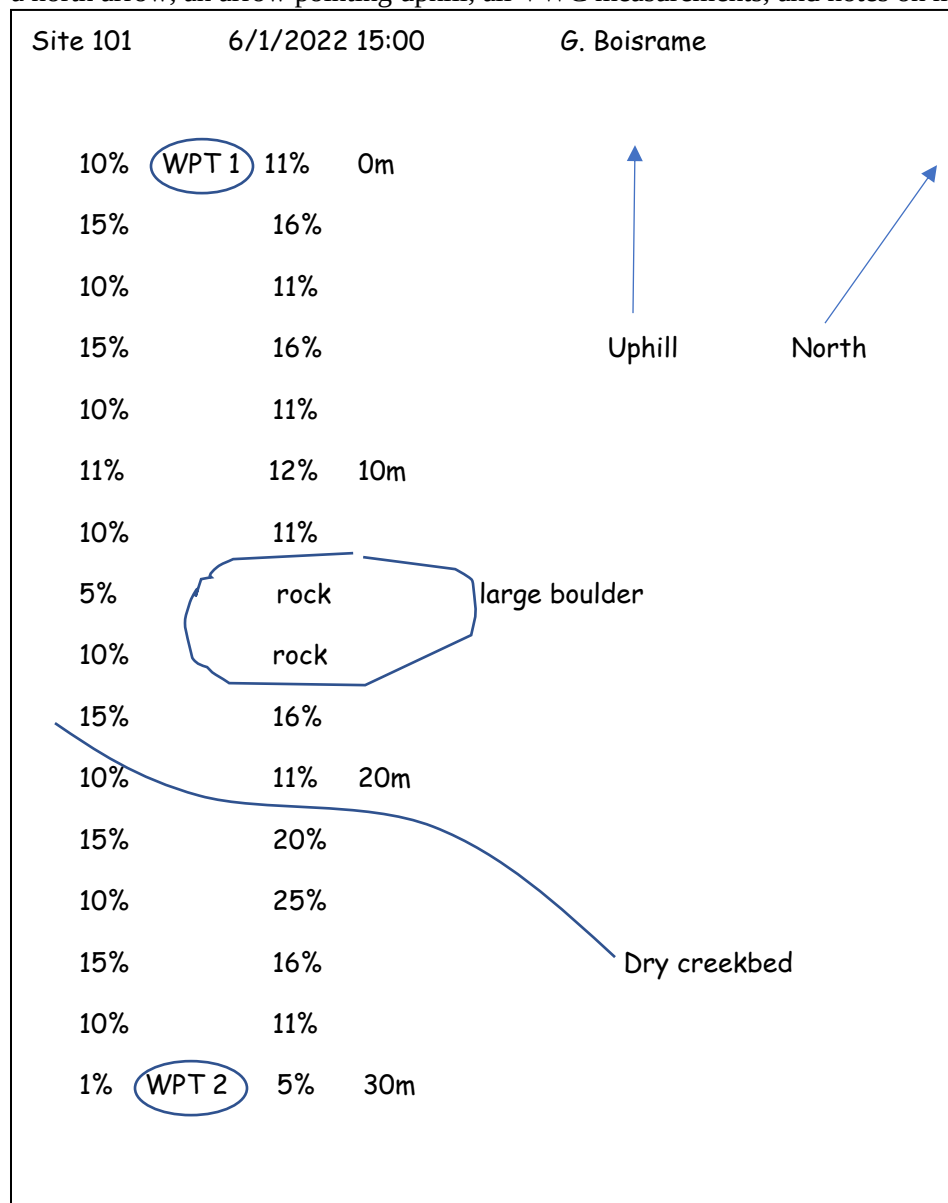
At each end of the transect, mark the GPS location (**mark a waypoint** on your GPS)

In notebook, write the site name, date, time, and your name at the top of the page. Sketch the site in notebook, noting location of major landmarks (e.g. large boulder, creek), shifts in veg cover, or breaks in slope. Include a north arrow, and an arrow pointing in the uphill direction. Write the GPS waypoint numbers (or full coordinates if you prefer) at either end of the transect in your sketch. Leave room to write soil moisture measurements on sketch (or write on adjacent page if needed). See sample notebook sketch below.

Using the TDR, **measure the soil's volumetric water content (VWC)** every 2 m along transect, 1 m to each side (total of 32 measurements). If highly homogeneous (measurements not varying by more than 2 percentage points after the first 10 meters) you may increase to every 5 m for remainder of transect. **Save measurements on TDR** (by pressing "store" after each measurement) and write them in the notebook in their approximate locations on your sketch. If there is an obstruction (like a boulder or log) that keeps you

from measuring within about 1m of the desired spot, just note it in your notebook (e.g. write “rock” or “log” where you would have put the measurement) and skip to the next measurement.

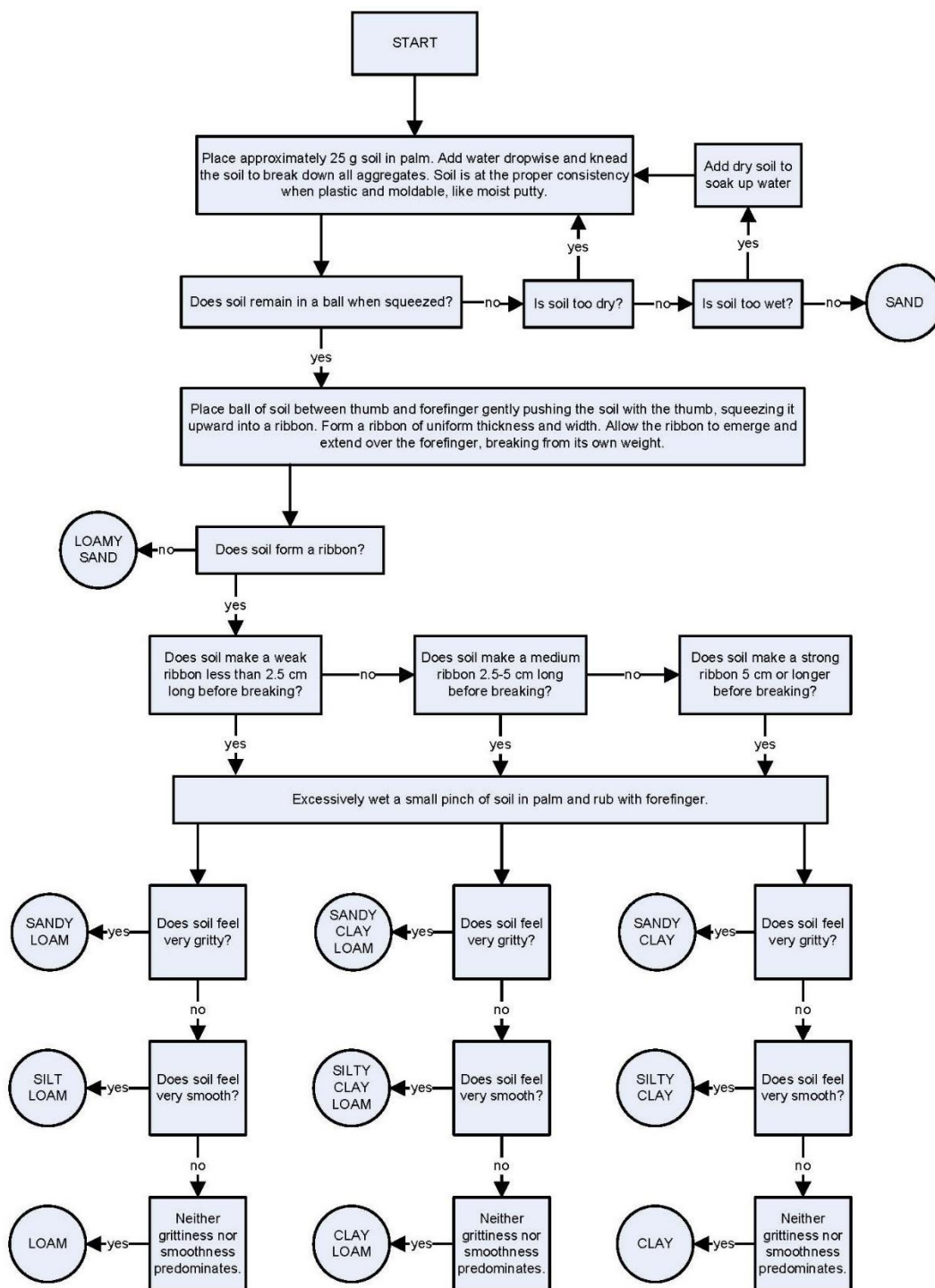
Your field notebook entries should look something like this, with the site number, date, time, your name, a north arrow, an arrow pointing uphill, all VWC measurements, and notes on major landmarks:



At each transect, also **fill out the “soil type and moisture” datasheet**. If you try to get to a site and decide to skip it because it’s not accessible, still mark that site on the datasheet and write the reason for not measuring it under “notes” (e.g. could not access due to high creek water level).

Soil Characterization

Use the NRCS soil type guide below to classify soil as sand, sandy loam, etc. and note soil type on the data sheet.



Source: <https://www.nrcs.usda.gov/sites/default/files/2022-11/texture-by-feel.pdf>

Take the following measurements at the center of the transect.

Soil Hydrophobicity

Remove litter, ash, etc. until you reach mineral soil. Note the approximate depth of material removed on the “Hydrophobicity Water Drop Tests” data sheet.

Use the eyedropper to place a droplet of water on the soil, and time how long it takes for it to seep into the soil (up to 5 minutes). Note times on data sheet. If still beaded up after 5 minutes, mark “>5 min” on the data sheet.

Test at mineral soil surface, 1cm depth, and 3cm depth. Do 5 repetitions at each depth (If the water infiltrates slowly, you can do all the droplets at the same time rather than one at a time).

Methods similar to <https://www-sciencedirect-com.unr.idm.oclc.org/science/article/pii/S0022169414002984?via%3Dihub>

Infiltration Rates



Use the mini disk infiltrometer to measure infiltration in the same area that you cleared for the water drop test, both at the surface and at 3cm depth, at least 30cm apart from each other (so the wetted soil from one measurement doesn’t affect the other). Make sure there is a smooth surface to place the infiltrometer on; if there are too many little rocks keeping the whole base from making complete contact with the soil then the measurements won’t work. If needed, take some fine soil from a nearby area and sprinkle it over the site to make sure the soil surface is smooth enough.

Fill the bottom (larger) portion of the infiltrometer with water (creek water is fine as long as it’s not too dirty) up to at least 40mL. On the Infiltration data sheet, note the initial water level. Make sure there is a gap between the ends of each tube and any surfaces so that air can move in and out of them.

Once you place the infiltrometer on the soil, start your stopwatch. Note the water level on your data sheet every 30s up to 5 minutes. If you don’t see bubbles coming out of the tube in the water after one minute, jiggle the infiltrometer a little to make sure it has good contact with the soil. If 40mL infiltrates in less than two minutes, repeat the measurement (on a nearby spot that is not wetted from your previous measurement) and record the water level every 10 seconds.

Detailed notes on using the TDR to measure soil moisture:

Turn on TDR by holding down the power/menu button for 3 seconds



Insert metal prongs all the way into the soil, making sure they are fully buried up to the white plastic. You may need to clear twigs and leaves out of the way in order to make sure the prongs are fully in contact with the soil.

Press the Read/OK button to take a measurement



The screen should now look like this:

```
10/11/2011 22:51:08
NOT IN A ZONE
VWC 10.0%
PER 1.000us
CS658 20cm
Lt19°15.000'S Ln146°45.000'E
```

The number next to “VWC” (10.0% in this example) is the main value we care about. Write this number on your sketch in the field notebook. Sometimes in very wet soils the TDR cannot determine water content and will just show a dashed line next to “VWC.” In this case, still save the measurement on the TDR and write “saturated” in your notebook at the measurement location.

Press “Store” to save the measurement along with its GPS location.



If the screen displays “Not in a Zone” when you hit “store,” follow the prompts to create a new zone and make the zone’s radius as large as possible.

Tips: Make sure the date and time are correct before you start taking measurements. Turn off Bluetooth to save battery life while in the field. If the unit will not turn on, use a screwdriver to open up the back cover and replace the batteries.

Appendix B. CECS Modeling Details

The Center for Ecosystem Climate Solutions (CECS) has produced a California-wide database of model outputs describing conditions in natural landscapes. Contributing CECS researchers include: Michael Goulden, Jon Wang, and James Randerson of UC Irvine, John Battles (UC Berkeley), and Toby O'Geen (UC Davis).

The CECS website provides the following information about their predictions of management impacts:

“Data layers are sourced from Landsat (30-m grids) and transformed into ecosystem services with transparent physical units using our natural ecosystem modeling Data Engine to track water, vegetation stress, fire, and carbon as a wholistic web of tightly-linked ecological conditions. This allows for apples-to-apples comparisons across space and time. CECS data products are created with scientific software on the leading edge of reproducibility, rapid refresh, and continuous improvement.

More information is available online at <https://california-ecosystem-climate.solutions/>.”

The Natural Climate Solutions Toolbox Guide (unpublished, provided by Roger Bales) gives the following definitions for the CECS models' outputs of forest conditions:

“Effects of drought on tree stress - Millimeters (mm) of water shortfall in a given water year, representing unmet precipitation needs relative to plant demand (evapotranspiration) and stored water available in the soil.

Effects of drought on water supply - Total water available for runoff in millimeters (mm) in a given water year, calculated as precipitation surplus relative to plant demand (evapotranspiration) and soil storage.

Predicted wildfire flame length - Predicted wildfire flame length in feet (ft) in a given water year if a given 30 by 30-meter pixel had burned. Predicted using the Rothermel surface fire spread model. This includes surface fuels, topography, wind speed, and wind direction. Wind velocity is set at 20 ft/min and wind direction is upslope.

Predicted wildfire rate of spread - Predicted rate of spread of wildfire in meters per minute (m/min) in a given water year if a given 30 by 30 meter pixel had burned. Predicted using the Rothermel surface fire spread model. This includes surface fuels, topography, wind speed, and wind direction. Wind speed is set at 20 ft/min and wind direction is upslope.”

The online CECS Data Atlas tool (<https://cecs.ess.uci.edu/data-atlas/>) allows users to visualize the impact of land management actions on the conditions described above by specifying percent changes to canopy cover, shrub cover, and dead surface fuel. For this report, we used outputs from a predefined set of fuel changes designed using expert opinion (Figure B 1). We primarily focused on the prescribed fire scenario, which maintains most of the tree cover while reducing shrubs and ground fuel by 70%.

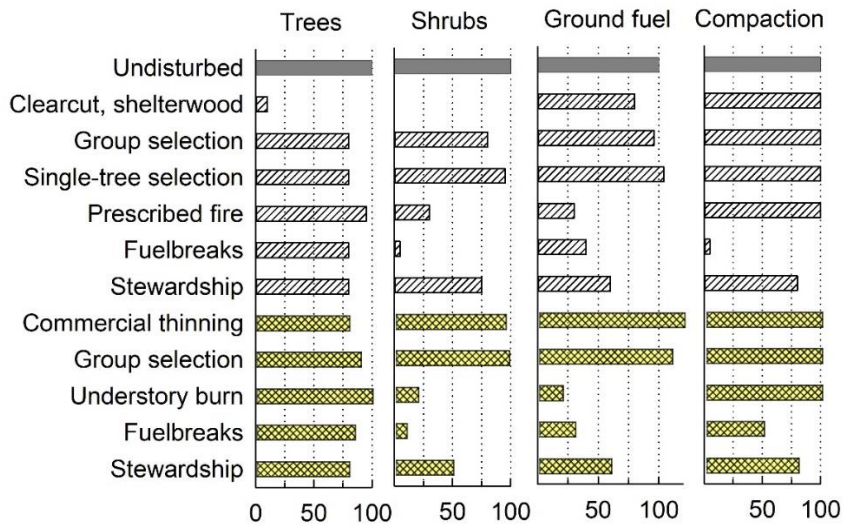


Figure B 1. Changes to different fuel loads under the various management scenarios available in the model.

Appendix C. Additional Paired Watershed Study Results

The South Fork Tuolumne gage showed reductions in flow following the Rim Fire, but this was also seen in control watersheds since the years immediately following the Rim Fire experienced extreme drought (Figure C1). There was no clear change in annual flows following the Rim Fire according to the data analyzed here (Figure C2).

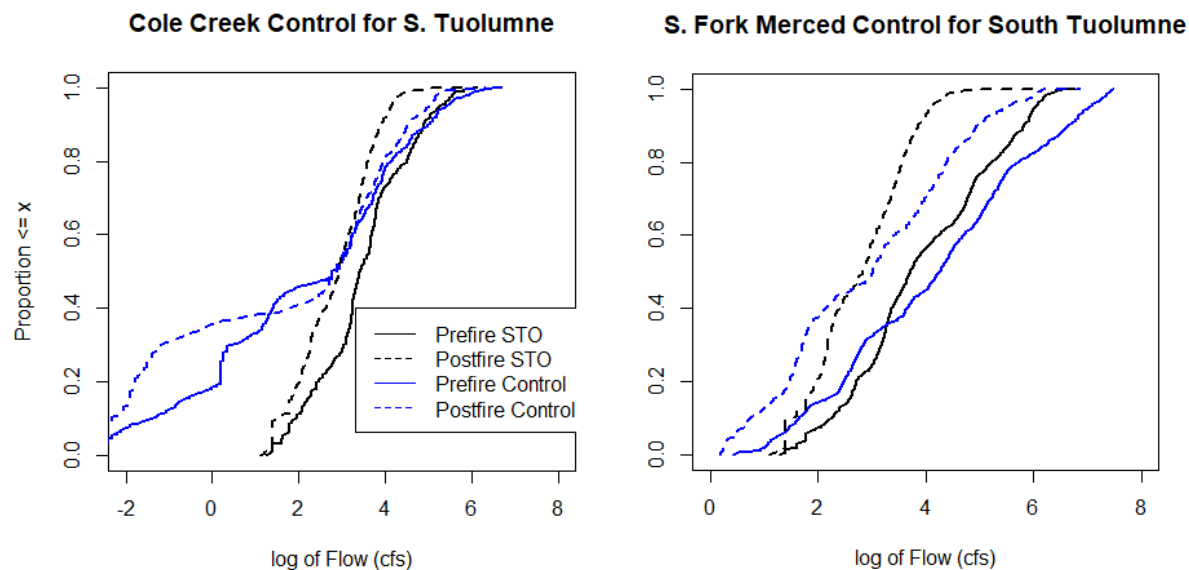


Figure C1. Comparison of South Fork Tuolumne (STO) before and after the 2013 Rim Fire, compared to either Cole Creek or South Fork Merced as control watersheds that did not burn. Post-fire period only extends through water year 2015 due to missing data in STO in subsequent years. This short post-fire period encompasses two very dry years, which is why flows decrease for both the burned and control watersheds.

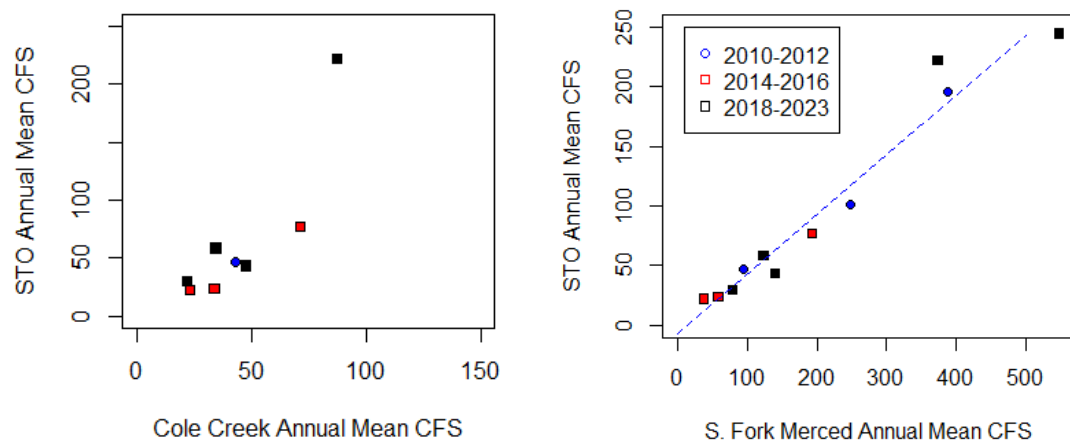


Figure C2. Same data as previous plot but summarized by mean flow within each water year. Blue diamonds are from before the Rim fire (which burned part of STO), while squares are from post Rim Fire. Dashed blue line for the STO versus Merced plot shows a linear fit to flow prior to the Rim Fire.