Remote Sensing Analysis on the Impacts of Wildfires on Snow Cover in Sierra Nevada

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ABSTRACT

Mountain snow is a virtual reservoir that stores and releases water, and mountain snow can provide essential water resources for local agriculture. For areas where droughts often occur, water melting from mountain snow has become a very valuable resource for the local farms and ranches (Margulis 2016). However, this water resource is highly seasonal and closely connected to the timing of summer and winter, and also to natural disasters such as fire. The primary research objective behind this study is to find how the megafires would impact the snow cover in the Sierra Nevada mountain range in California, US. Specifically, I want to research whether the melt durations of snow changed in the Sierra Nevada from 2000 to 2016 and whether the severity of megafires relate to the changes of landscapes of snow cover in the Sierra Nevada during that time. I found that the melt duration decreased and with major drops in year with long periods of wildfires. Moreover, the average Snow Water Equivalent value were lower when the fire was more severe, indicating a negative correlation between these two factors. Overall, my study indicates that wildfires have brought many negative effects on the snow cover in Sierra Nevada.

KEYWORDS

snow melting, climate change, environmental disasters, agriculture, snow-water equivalent.

INTRODUCTION

Mountain snow is a virtual reservoir that stores and releases water, and mountain snow can provide essential water resources for local agriculture. For areas where droughts often occur, water melting from mountain snow has become a very valuable resource for the local plantations and ranches (Margulis 2016). However, this water resource is highly seasonal and closely connected to the timing of summer and winter. In normal situations, when a certain region enters summer, mountain snow will melt, and the water will be able to irrigate lands and benefit local agriculture. When the region enters winter, the precipitation is stored as mountain snow as a reservoir for next year. But with the higher frequencies of wildfires in recent years, the amount of water from mountain is decreasing (Margulis 2016), which negatively impact on the local social and economic development. Because mountain snow is so important to the local agriculture, quantitative tools have been designed to observe and monitor the melting water for this seasonal storage and use (Bormann 2018).

Snowpack water storage, measured as Snow Water Equivalent (SWE), is a meaningful and necessary index to track and predict for water resource management (Margulis 2016). SWE is a common measurement used by hydrologists and water managers to gage the amount of liquid water contained within the snowpack (Koch 2019). Most mountainous areas have a regular spatial and temporal pattern of SWE, but other factors slightly influence the pattern. For example, climate change is one main factor that influences the seasonal pattern of SWE. This change is “long-term” (Bormann 2018), and long time series of SWE map can be compared to capture these changes from the global warming accurately. For the recent ten years, the normal period of SWE is gradually lower than the SWE in the past due to the increasing temperatures.

Unlike the long-term changes, sometimes a significant external disturbance, like wildfires, will drastically influence the ratio between water and snow, thus the SWE values in the mountain areas (Margulis 2016). For example, in San Joaquin watershed, in normal summers, the regional average SWE values are around 220-230 millimeters, which means that there is around 220-230 millimeters of water stored in the snow cover. However, in summers with significant wildfires, the average SWE values are around 60-150 millimeters (DOI 2005), which has a lower range than normal situations. Due to the accuracy range of the measuring instruments, researchers typically get a value range of 170 to 200, which underestimate the true value and even not in the actual range, making the further predictions much harder. Therefore, this sudden and drastic disturbance brings technical difficulties for researchers to observe and predict the patterns of SWE under the impacts from wildfires, based on previous fieldwork.

Remote sensing technology then is a tool which can solve the aforementioned issue efficiently because fieldwork is both expensive in terms of time and cost. Researchers can manually measure the SWE by removing cores from the snowpack or installing devices that lie flat on the ground that weighing snow as it accumulates on top of the device (Pomeroy 1998). However, the researchers cannot manually measure the SWE patterns across a large area due to costs of time and money, and snow cover that occurs after wildfires are often in inaccessible and dangerous zones. Another method is to use a non-contact technology, which is named as "CS725", but it must be calibrated under snow-free conditions, which also makes field observations very inconvenient. In contrast, remote sensing can provide high quality geospatial data on a wide range of snow cover. More importantly, electromagnetic radiation from and to Landsat 5-8 satellites can be directly converted into relevant Earth information which can be analyzed though the platform like Python or MATLAB (Margulis 2016). For example, daily change of SWE values in a part of snow cover can be analyzed to track the impacts of wildfires on the snow cover (Mathieu 2018). Currently, remote sensing has been used in modeling the terrestrial water cycling in mountain areas and assimilating data to calculate the impacts of climate changes on snow cover (Margulis 2016). However, this research built numerical models that predict snow with maps of forests from previous years. For major disturbances, such those caused by recent wildfires, much uncertainty and inaccuracy is introduced into the current models and previous because these disturbances make SWE change in a less regular pattern, making these older versions unreliable for the future.

Thus, the primary research objective of this study is to determine how the megafires would impact the snow cover in the Sierra Nevada using its snow maps. To meet this objective, I identify two sub-questions. The first one is whether the melt durations of snow change in the Sierra Nevada from 2000 to 2016, and the second one is whether the severity of megafires relates to the changes of landscapes of snow cover in the Sierra Nevada. I expect that the melt duration will decrease and with major drops in the year with long periods of wildfires. Moreover, I expect that the average SWE value will lower when the fire is more severe. The first research objective seeks to collect the data of SWE in the research area (Sierra Nevada), the frequency of wildfires in the selected research area, the date of each wildfire. The second research objective aims to collect the data for the fire severity map and the corresponding Snow Water Equivalent (SWE) in the research area.

METHODS

Study site description

The study site is the San Joaquin watershed in the Sierra Nevada, which is in central California. It has a latitude range of 36° to 38° and a longitude range of -120° to -118°. It extends from the Sacramento-San Joaquin River Delta in the north to the Tehachapi Mountain in the south and from coastal regions in the west to the Sierra Nevada in the east. The watershed's primary river is San Joaquin, which drains north through about half of the valley into the river delta (Lundquist 2003). This river is mostly for local agricultural uses and highly depends on the melting of the snow from the mountain top. The San Joaquin watershed is also extremely hot and dry during the summers, and it has experienced a severe drought from 2011 to 2017 (Margulis 2016). These conditions contribute to the spread of wildfires. These years, wildfires happened with high frequency and severity in the San Joaquin watershed, which disordered the local water cycle from the snow cover in mountains (Maxwell 2019).

Data sources

To prepare the SWE dataset for analysis, I cleaned the dataset from Margulis Research Group and clipped them into the specific regions of the San Joaquin watershed in MATLAB 9.10 (MathWorks 2020). First, I downloaded the Sierra Nevada Snow Reanalysis dataset from Margulis Group's website and selected the water years from 2000 to 2015. The reanalysis' method (fully Bayesian), resolution (daily and 90 m), temporal extent (31 years), and accuracy provided a unique dataset for investigating snow processes (Margulis 2016), so I selected this dataset as the main research resources. Then, I verified the data by choosing a specific water year (2010) and loading the data on MATLAB to see whether it works on this platform.

To clip the dataset into San Joaquin watershed. I defined the specific latitude and longitude of the research region, San Joaquin watershed, to be from 36.7250° to 37.7379° and longitude range of -120.3667° to -118.6542° and stored these numeric values as the maximum and minimum of latitude and longitude ranges. I chose this specific region because this part of the San Joaquin watershed has experienced several wildfires in the past, and its snow cover structure and snow melting timing have changed considerably as a result of these major disturbances (Margulis 2016). Then I applied these range values to the original dataset to clip the dataset into my research region in one water year. Finally, I redesigned the function to be recursive to operationalize same clipping analysis on the dataset of all water years. This process resulted in the ready-to-use SWE dataset at the San Joaquin watershed from the water year 2000 to 2015.

I also collected the frequency, level, and date of the wildfires through the files and records from California Government. These records are collected by CAL FIRE, which provides the preliminary number of fires and acres burned in different counties of California on weekly basis (CAL FIRE 2021). I have downloaded the specific data for San Joaquin County from 2000 to 2015 at the preparation stage.

Calculating melt durations

To explore the extent of influences of wildfires on snow cover, I calculated the melt durations change from 2000 to 2015. I expected that the melt durations did change from 2000 to 2016, and the melt duration would be shorter annually since there was a higher frequency of wildfires from 2010 to 2016. I prepared the data of SWE in the San Joaquin watershed, the frequency of wildfires in the selected research area, and the date of each wildfire. I had already cut the SWE dataset into the research area using the MATLAB models that I designed.

The frequency and date of the wildfires in San Joaquin watershed have been extracted through the files and records from CAL FIRE. For the melting duration calculations, the specific goal was to find the date with the maximum SWE numeric value and the first date with the minimum SWE numeric value in a water year. The reasoning behind this process is that when all the possible snow cover has melted into water, the water amount should be the maximum of the year at this time, and it means that the SWE will also be the maximum at this time. This period should be around July or August, which is hot summer (Margulis 2016). When all the possible water has frozen into snow and ice, the water amount should be a minimum of the year at this time, so is the SWE. This period should be around December or next year's January to February, which is cold winter (Margulis 2016). I conducted the analysis on MATLAB to find the dates with maximum SWE values and minimum SWE values in each water year recursively, and I recoded the specific dates into numeric days in a year (For example, January 13th is day 13 in a year). I then calculated the melt durations simply minus the date of maximum SWE value with the date of minimum SWE value. Finally, I checked the trend of the snowmelt durations from 2000 to 2015 and compared it with the frequency trend of local wildfires to look periods with decreasing trends. The melt durations would be in a decreasing trend and with major drops in the year with long periods of wildfires.

The relationship between fire severity and SWE

To determine the relationships between fire severity and changes of SWE, I randomly selected 150 points in the research area and compared the corresponding SWE values and fire severity index. My hypothesis is that the severity of megafires relates to the changes of SWE in the San Joaquin watershed, and when the fire is more severe, the snow cover area will be smaller and shallower (smaller SWE values).

I collected the data for the fire severity map and the SWE dataset in the research area for this part of the analysis. The fire severity data is prepared and stored by the CA Government CAL FIRE website (CAL FIRE 2021). This data is mainly stored in the forms of maps, and it is categorical as “None”, “Moderate”, “High”, and “Very High”. I selected the data from 2000 to 2010 because the data is only available for this period, and I added layers of fire severity over the research area in ArcGIS. After clipping the SWE data into the range of the San Joaquin watershed, I randomly selected 50 points for three groups (150 points in total) on this area and calculated and recorded their average SWE values. For the random selection, I used a website named “GeoMidpoint-Random Point Generator” and defined the region inside the San Joaquin watershed. This platform directly helps me choose ten exact spots on a certain region with their latitudes and longitudes. The random selection ensured the whole research process was objective. Then, I recorded the fire severity category of each spot.

Finally, to find the relationships between fire severity and SWE values, I drew the regression map for these two sets of values. Specifically, I first stored random spots into the three fire severity categories and then calculated the average SWE values in each category. Then, I applied the same analysis process to each spot group. Last, I plotted line graphs for these three groups for visualization. I expected the fire severity to relate to the landscapes of the SWE, and when the fire is more severe, the average SWE value will be higher.

RESULTS

Data summaries

I used clipped SWE tiff files (Figure 1) for every day in each water year as key inputs for the melt duration analysis and a full dataset of wildfires frequency, level, and date (Table 1) around San Joaquin watershed in Sierra Nevada. I found that for mountains in the San Joaquin watershed, mountaintops had the highest values of SWE, and plain areas have zero SWE values because there was no snow cover on this area for this time. I also found that during summer (May to September), the average SWE values were higher than other areas. I also saw that wildfires are very common during summers in Sierra Nevada regions and typically with very high levels of severity. Moreover, the frequency of wildfires showed an increasing trend annually, and in 2015 to 2020, the wildfire frequencies are much higher compared to other years of record.

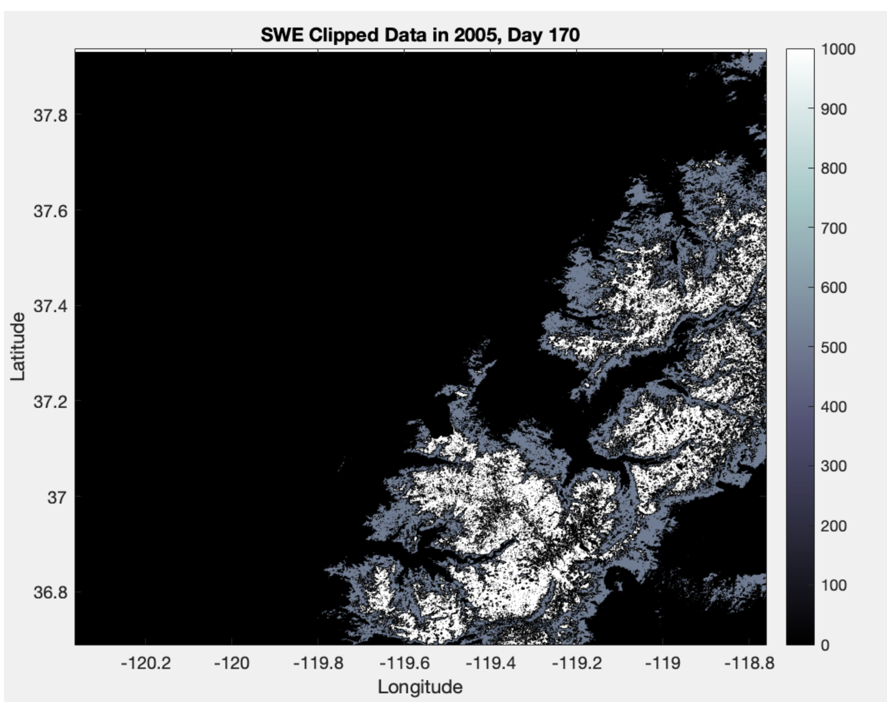

Figure 1. A sample clipped SWE graphs on Day 170, 2005, in San Joaquin watershed. In summer, there were large areas of high SWE values (in white colors), which distributed through the mountain tops. In plain areas, the SWE values were nearly zero (black) because there was no snow cover on this area.

Table 1. Dataset of Wildfires in Sierra Nevada. Parameters include Level of Severity, Date of the Wildfires, and Frequency of the Wildfires in This Period.

Wildfire Parameters / Area	Level	Date	Frequency
Sierra Nevada	Moderate	2000 Summer	Below 3 Per Month
Sierra Nevada	High	2002 Fall	Below 3 Per Month
Sierra Nevada	High	2002 Summer	Below 3 Per Month
Sierra Nevada	Moderate	2003 Summer	Below 3 Per Month
Sierra Nevada	None	2004 Winter + Spring	N/A
Sierra Nevada	Very High	2004 Summer	Above 3, Below 10 Per Month
Sierra Nevada	Very High	2004 Fall	Below 3 Per Month

Melting durations calculation results

I found that snow melt durations in a water year were decreased on annual basis (Figure 2), and it was also noticeable that compared to the SWE values from 2000 to 2004, the SWE values from 2012 to 2016 were overall lower (Figure 3). Starting from water year 2000, the melt duration was 203 days. When it came to water year 2003, the melt duration decreased to 145 days, but in water year 2004, the SWE values increased to 216 days. From water year 2012 to water year 2016, the melt durations decreased more significantly. The difference of melt durations between water year 2012 and water year 2016 was 69 days. Although the melt durations increased to 235 days in water year 2016, it was still lower than the melt durations in water year 2012.

Furthermore, the overall SWE values from water year 2012 to 2016 were lower than the values from water year 2000 to 2004. The maximum regional average SWE values from water year 2000 to 2004 was 228 mm. However, the counterpart from 2012 to 2016 was 182 mm. By averaging the max SWE values in each water year, the water year group from 2012 to 2016 also had much lower SWE values (107 mm) than the water year group from 2000 to 2004 (188 mm). I also found that in water year group from 2012 to 2016, the max SWE values in each year were also in a decreasing pattern annually.

Finally, I have also conducted a T-test to illustrate the significance of the differences of SWE values between these two groups of water years. My null hypothesis is that there are no differences of the average melt durations between these two groups, and my alternative hypothesis is that there are differences in the average values of these two groups. My p-value is 0.05, and my t-table value is 2.228. Upon calculations, I found that my t-value is -2.74, which is numerically bigger than the t-table value. Therefore, I would reject my null hypothesis, and there are differences between these two groups of water years.

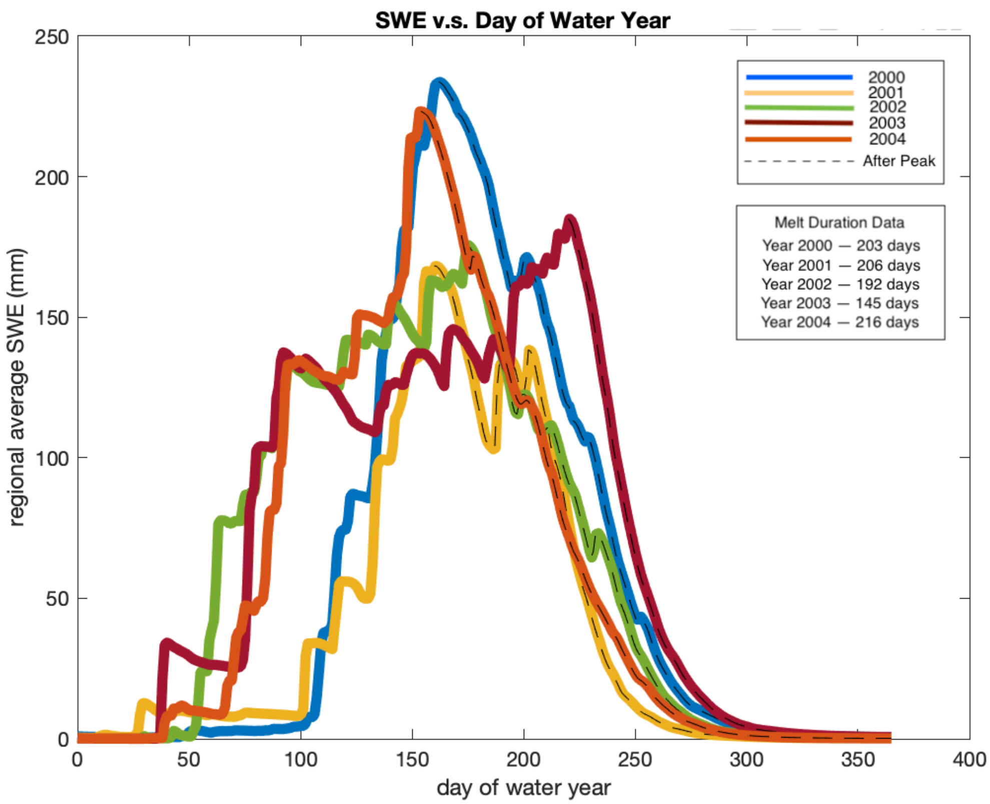

Figure 2. Water year group from 2000 to 2004. Different colors represent different water years, and the dashed line contained in each curve represents the period after peak in SWE values.

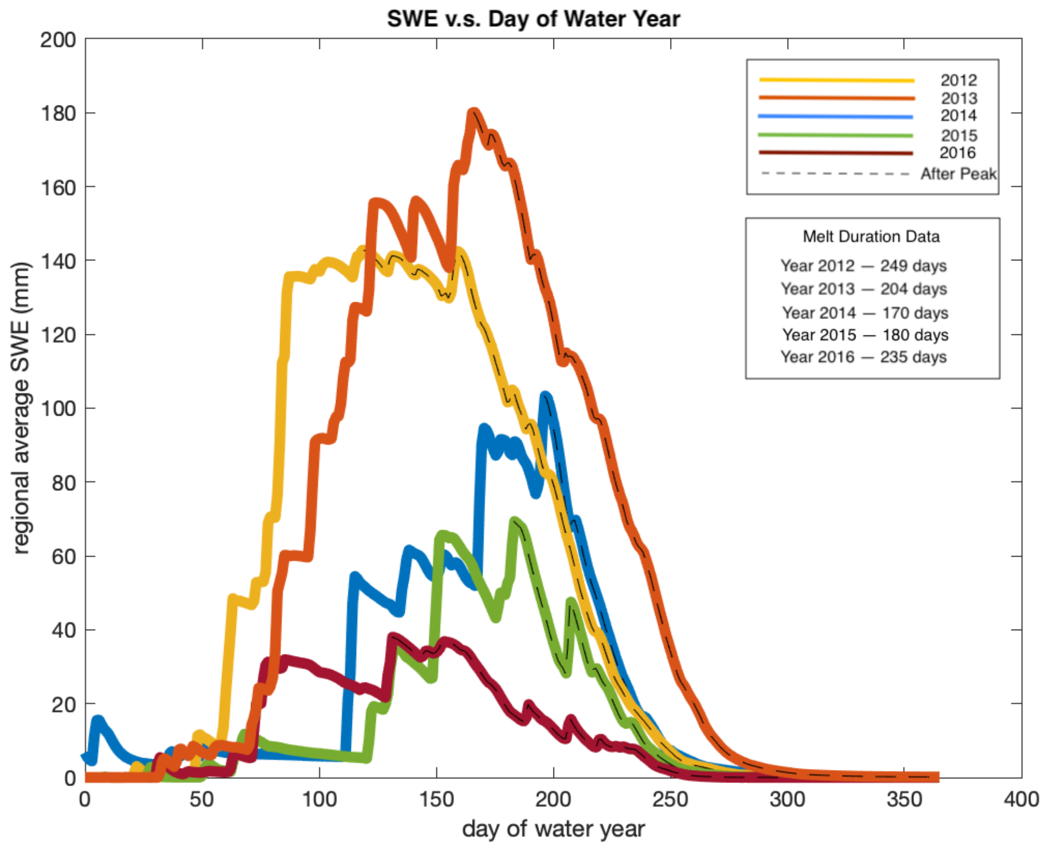

Figure 3. Water year group from 2012 to 2016. Different colors represent different water years, and the dashed line contained in each curve represents the period after peak in SWE values.

Correlation between fire severity and SWE

I found there were strong correlations between the fire severity and the values of SWE (Table 2). For the areas with "Moderate' fire severity, the fire severity index and SWE values have relatively weak positve relationship (correlation coefficient was 0.31) (Figure 4). For areas with "High" fire severity, the fire severity index and SWE values have strong postive relationship (correlation coefficient was 0.82) (Figure 5). For areas with "Very High" fire severity, the fire severity index and SWE values have nearly perfect positive relationship (correlation coefficient was 0.96) (Figure 6).

Furthermore, I found that with higher level of fire severity, the relationships between fire severity index and SWE values were stronger, and the average SWE values were also higher in that category.

Table 2. Results of Correlation Between Fire Severity Index and SWE values, and Average SWE Values for Each Category. Points in Each Category were randomly generated by "GeoMidpoint-Random Point Generator", and Average Values Were Calculated through Them.

Fire Severity Category	Moderate	High	Very High
Average SWE values (mm)	82.64	41.08	12.30
Correlation Coefficient Between Fire Severity Index and SWE Values	0.31	0.82	0.96

(a) **(b)** **(c)**

Figure 4. Scatter diagram between SWE values and fire severity index. a. Correlation Scatter Diagram and Its Linear Correlation Graph in "Moderate" Fire Severity Category; b. Correlation Scatter Diagram and Its Linear Correlation Graph in "High" Fire Severity Category; c. Correlation Scatter Diagram and Its Linear Correlation Graph in "Very High" Fire Severity Category.

DISCUSSION

I found that the amount of snow and the resulting melt durations in San Joaquin watershed correlate closely with local wildfire severity. With higher fire severity, melt durations decreased sharply, and compared to past trends from 2000 to 2004, the current melt durations of snow cover in San Joaquin watershed are lower due to the higher frequencies and severity of wildfires in recent years. Wildfires also seem to be related in changes in snow melt timing. If this timing can be monitored and predicted, it would provide benefits and convenience to the local farmers for the irrigation. My findings suggest that with frequent wildfires, the begin date of the melting process moves to earlier dates each year. This could have critical implications on agriculture and ranching in the San Joaquin valley that relies on this water.

Shortened Melting Durations

The decreased melt durations from 2000 to 2016 suggest the negative impacts of the wildfires on snow cover in San Joaquin watershed. As we can see from the Figure 3, the decrease in melt durations in each water year was straightforward for both 2000-2004 period and 2012-2016 period. However, the gap of melt durations between each water year in 2012-2016 period was larger than that of 2000-2004 period, suggesting a more drastic and frequent wildfire occurrences during the 2012-2016 period. This coincides with a study in the San Joaquin watershed from 2015, which found that wildfires in California are much more frequently now than 20 years ago (Mathieu 2014). Other than wildfires, there are also other factors which will cause shortened melting durations of snow. For example, global warming temperature is also a catalyst in the faster snow melt, which are directly caused by climate changes (Musselman 2020). Moreover, positive feedback loop is also a factor shortening the melt durations. Positive feedback loop enhances changes. Therefore, with more snow melted, the average albedo of earth surface decreases, causing more and more snow to melt faster than before (Jakobs 2021).

Unexpected Impacts on Local Agriculture and More

When melt durations decrease, more water enters the water cycle faster and earlier in the season. This can increase short-term local water resources, at the expense of long-term snowpack resources. Other studies have also found that shorter melt durations are associated with higher snowmelt discharge in the San Joaquin watershed. This increased maximum discharge has been found to provide more water resources for local farmers (Pausas 2019), but since farmers often do not have the infrastructure to store this water, there are water shortages later in the year. This is one major consequence of climate change and wildfire on snow: earlier melt durations mean that during the summer drought, the vast reservoir of snow that slowly releases water over time is depleted long before it becomes necessary. Additionally, studies have shown that the randomness of water supply will make the local environment too harsh for species to live there (Archibald 2018).

Correlation Between Fire Severity and Snow Cover Landscapes

I found a strong positive correlation between the wildfire severity and snow cover landscapes, which are the geographical structures of the snow land, suggesting that the wildfires can change the landscapes of snow cover. This happens because when the wildfires are more severe, SWE values will be higher, meaning there is more water contained in the snow, then the snow cover is denser, heavier, and more compact (Painter 2016). However, if the SWE values are low, then the landscape structures will be light and sparse because there is more snow (Painter 2016). Since SWE values are closely related to the geographical structures of snow land (Zhong 2021), I can determine the change of structures by the trend of SWE values.

Rethinking the Impacts of Wildfires on Snow Cover

I found that wildfire had a direct impact on local SWE values in the San Joaquin watershed. As fire severity increased, SWE also increased. This relationship also disturbs the ecology of the San Joaquin watershed. First, the wildfires have shortened the snow melting durations, which brought uncertainty to the local agricultures and other biological activities (Archibald 2018). What is more, the wildfires increase SWE values, changing the landscapes of the snow cover. As a result, this change makes the local environment fragmented, and possibly disrupts processes and habitats that harbor native species (Archibald 2018). As the climate changes, droughts become more persistent, and megafire becomes more common in California, the relationships between fire and snow will become more critical to understand (Goss 2020). My study highlights how fire is connected to melt timing and duration, and to SWE, but it is also critical to think about the broader ecological consequences of changing mountain environments.

Limitations

Since my data sources are limited to the region of San Joaquin watershed, I cannot apply my conclusions to other regions. We need to research on other regions if we want to apply the trends and relationships between wildfire severity and SWE values. Moreover, the methodology of my research focuses on analyzing wildfires, without considerations on other factors like climate changes and global warming. There has been plenty of evidence on the impacts of climate change on mountain environments (Bormann 2018). Although the impacts of climate changes on melt durations and SWE values are small, they still exist and may influence my explanations on the results (Margulis 2016).

Future Directions

This study could be improved by incorporating other factors, such as climate changes, human activities, and ecological change, and analyze how these factors influence melt durations and SWE values. More importantly, we should design a set of practical tools to predict the melt durations and early and final dates of the melt process through this analysis. Converting this knowledge into specific tools will help local farmers and ranchers benefit from this research and be able to predict the effect of the fire on snow and its subsequent impacts on water availability.

Broader Implications

This study brings important insights for local farmers, environmental agencies, and other researchers about major natural disturbances, such as wildfires, which make environmental changes less predictable. However, with the aid of remote sensing and MATLAB, we can quickly plot and measure these changes with high accuracy and efficiency. These results can form a pattern that can assist the local farmers to understand timeframe of water supply, and they can adjust their irrigation plans according to this analysis. Moreover, my visualization process of the wildfires can also act as a sample for other environmental researchers to explore the impacts from other major environmental disturbances. As climate change and wildfire continue to increase in California and across the world, understanding the impacts of fire on snow are critical for fully understanding and mitigating the consequences of climate change.

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REFERENCES

Archibald, S., C. E. R. Lehmann, C. M. Belcher, and W. J. Bond. et al. 2018. Biological and geophysical feedbacks with fire in the Earth system. Environmental Research Letters 13: 033003.

Bormann, K. J., R. D. Brown, and C. Derksen. 2018. Estimating snow-cover trends from space. Nature Climate Change 8: 924-936.

CAL FIRE. 2022. State of California. <fire.ca.gov>

DOI [United States Department of Interior]. 2005. Snowmelt Discharge Characteristics Sierra Nevada, California. A Report of the U.S. Geological Survey (SIR-2005-5056). DOI, Washington, D.C., USA.

Goss, M., D. L. Swain, J. T. Abatzglou, and A. Sarhadi. et al. 2020. Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. Environmental Research Letters 15: [DOI: 10.1088/1748-9326/ab83a7].

Jakobs, C. L., C. H. Reijmer, M. R. van den Broeke, and W. J. van de Berg. et al. 2021. Spatial Variability of the Snowmelt-Albedo Feedback in Antarctica. Journal of Geophysical Research: Earth Surface 126: [DOI: 10.1029/2020JF005696].

Koch, F., P. Henkel, F. Appel, and L. Schmid. et al. 2019. Retrieval of Snow Water Equivalent, Liquid Water Content, and Snow Height of Dry and Wet Snow by Combining GPS Signal Attenuation and Time Delay. Water Resources Research 55: [DOI: 10.1029/2018WR024431].

Lundquist, J. D., D. R. Cayan, and M. D. Dettinger. 2004. Spring Onset in the Sierra Nevada: When Is Snowmelt Independent of Elevation? American Meteorological Society 5: 327-342.

Margulis, S. A., G. Cortes, M. Girotto, and M. Durand. 2016. A Landsat-Era Sierra Nevada Snow Reanalysis (1985–2015). American Meteorological Society 1203: [DOI: 10.1175/JHM-D-15-0177.1].

Mathieu, E. C. 2014. The Effects of Fire on Snow Accumulation, Snowmelt and Ground Thaw on a Peat Plateau in Subarctic Canada. Thesis, University of Ottawa, Ottawa, Ontario, Canada.

MATLAB Team. 2010. MATLAB version 7.10.0 (R2010a). The MathWorks Inc, Natick, Massachusetts, United States.

Maxwell, J. and S. S. Clair. 2019. Snowpack properties vary in response to burn severity gradients in montane forests. Environmental Research Letters 14: 124094.

Musselman, K.N., M. P. Clark, and C. Liu. 2017a. Slower snowmelt in a warmer world. Nature Climate Change 7: [DOI: 10.1038/NCLIMATE3225].

Musselman, K., N. Addor, J. Vano, and N. Molotch. 2021b. Winter melt trends portend widespread declines in snow water resources. Nature Climate Change 10: [DOI: 10.1038/s41558-021-01014-9].

O'Leary, D. S., T. D. Bloom, and J. C. Smith. 2016. A new method comparing snowmelt timing with annual area burned. Fire Ecology 12: [DOI: 10.4996/fireecology.1201041].

Painter, T. H., D. F. Berisford, and J. W. Boardman. 2016. The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. Remote Sensing of Environment 184: 139-152.

Pausas, J. G. and J. E. Keely. 2019. Wildfires as an ecosystem service. Front Ecol Environ 17(5): 289–295.

USDA [United States Department of Agriculture]. 2008. Sierra Nevada Fire Severity Monitoring 1984-2004. A Report of the USDA Forest Service (R5-TP-027). USDA, Washington, D.C., USA.

Zhong, X. Y., T. J. Zhang, S. Hang, and X. X. Xiao. et al. 2021. Impacts of landscape and climatic factors on snow cover in the Altai Mountains, China. Advances in Climate Change Research 12: 95e1.