Plot-Level Quantification of Snow Melt for Old-Growth Forest Plots of the Pacific Northwest Using Low-Cost Temperature Sensors

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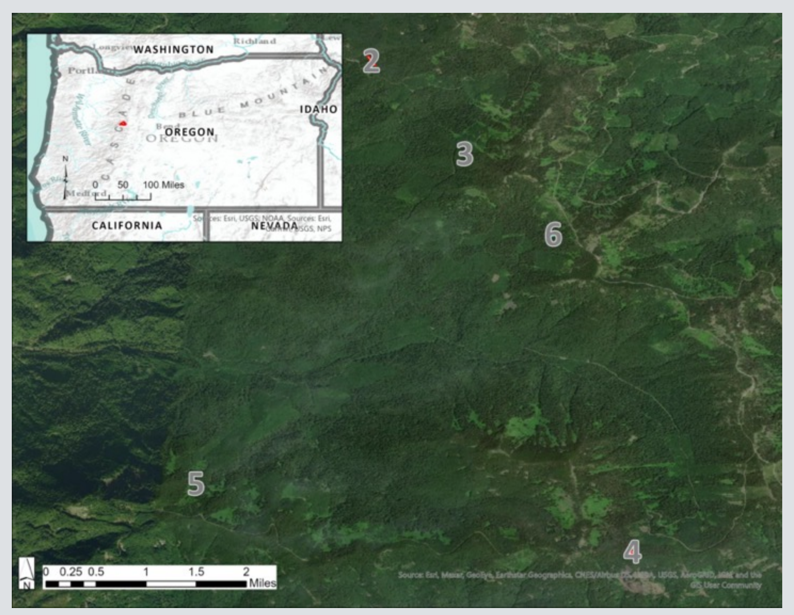
Introduction

An understanding of spring snow melt is foundational to our understanding of hydrologic and ecological response to climate change in mountain environments. Snow melt at high elevations plays a role in the availability of water throughout the summer and helps determine the growing season of small trees in forest ecosystems. Although recent changes in timing and quantity of snow melt have been relatively well documented for mountains of the western U.S., within plot variability is likely to b equally important to forest regeneration processes and has been less studied. The aim of this research was to investigate spatial and temporal trends in seasonal snow melt for old-growth forest plots within the HJ Andrews Experimental Forest in the Cascade Mountains in Oregon.

Data

The raw data for this study was comprised of four daily temperature readings from 122 temperature sensors (HOBOs) placed on five different plots at the HJ Andrews from July 2012 through 2019, as well as two daily images collected during the same period from 11 cameras located on the site, each with 1-3 HOBOs in its frame.



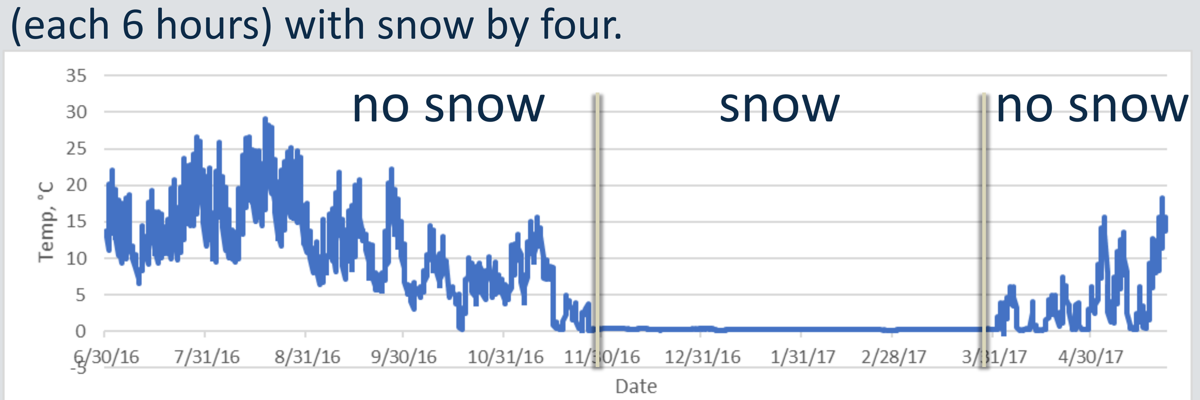
Location of plots

11 Cameras

122 HOBOs

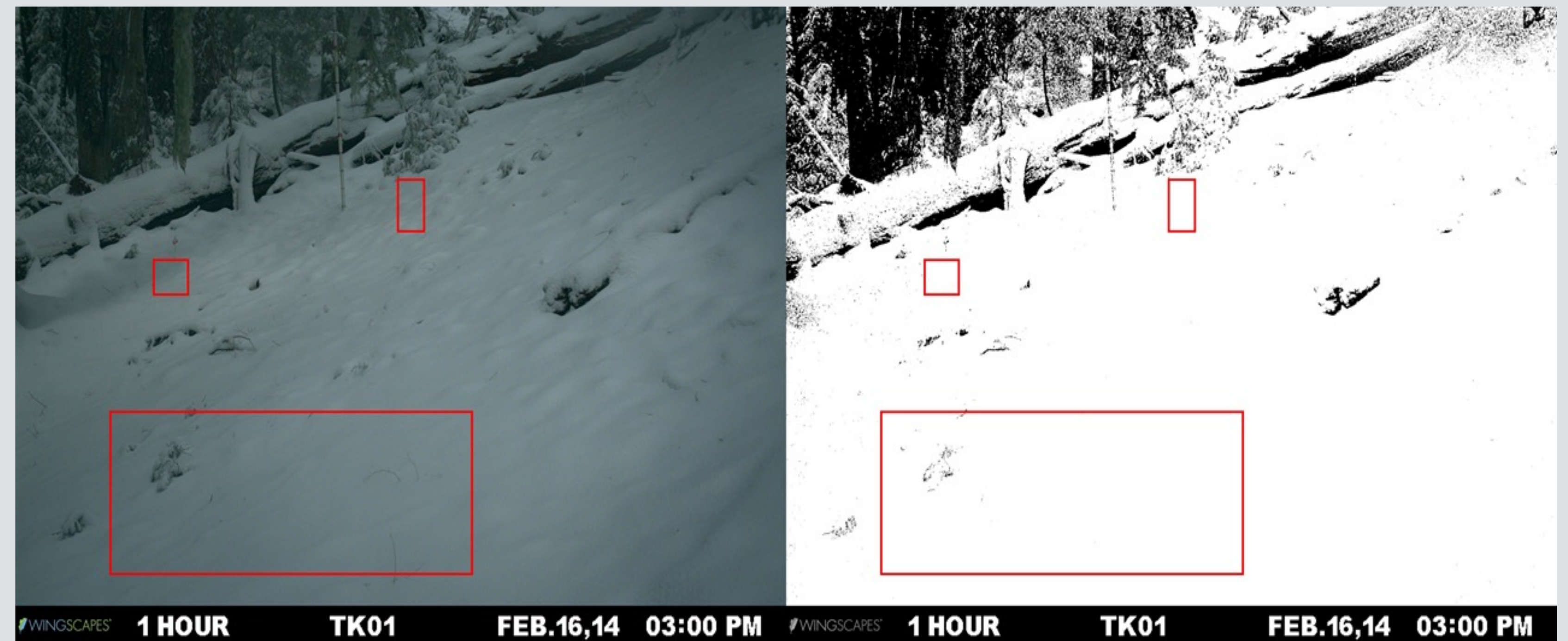
Analysis of HOBOs

A sustained reading (of at least four consecutive recordings) of temperatures within one degree of 0 °C was interpreted as insulation under snow cover. Using a script, the time of the last snow for each HOBO in each water year was obtained. The number of snow days during the melt season (March 21-June 30) was obtained by dividing the total number of time periods (each 6 hours) with snow by four.



Temperature readings of one HOBO over one year. A consistent reading of 0 °C was interpreted as snow cover on the HOBO

Analysis of Cameras

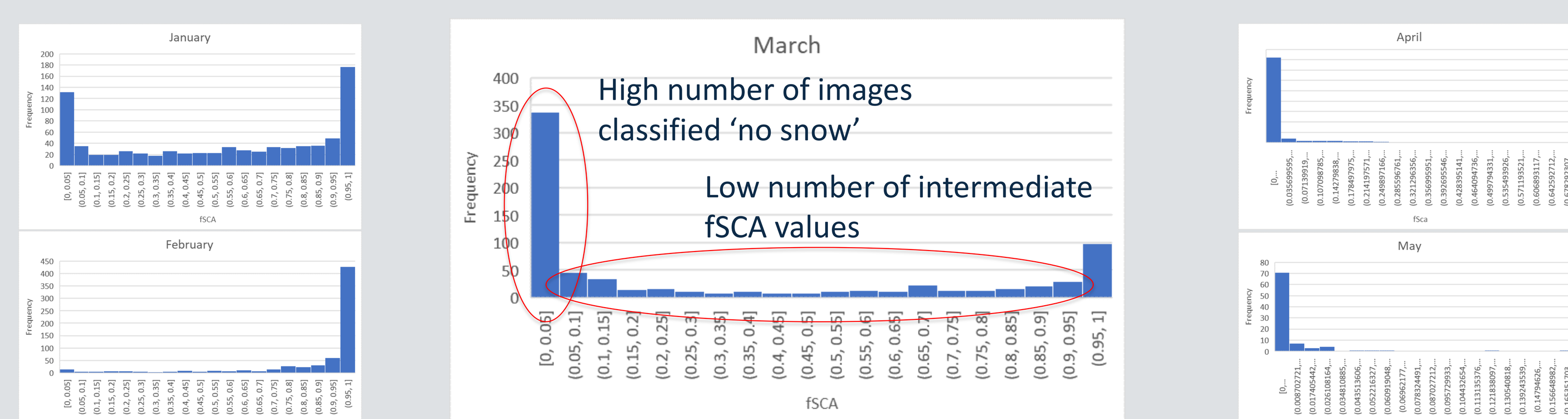


Camera images could be used to verify the accuracy of the HOBOs in determining snow cover. An automated image classification was also attempted to automate the verification process as well as to provide fractional snow-covered area (fSCA) as an additional metric. Regions of Interest (ROI) were drawn around each HOBO in the image, as well on a large area with homogenous ground cover. The classification converted the colored image to black and white. Pixels in each ROI were counted to obtain fSCA.

Results of Camera Classification

	HOBO Snow	HOBO No Snow
Camera Snow	2667	186
Camera No Snow	1889	5892
Observed Agreement	8559	
Expected Agreement	5670	
Kappa	**0.58**	

Confusion Matrix of agreement between HOBOs and image classification. A threshold of fSCA>0.25 was used to classify snow for the cameras.



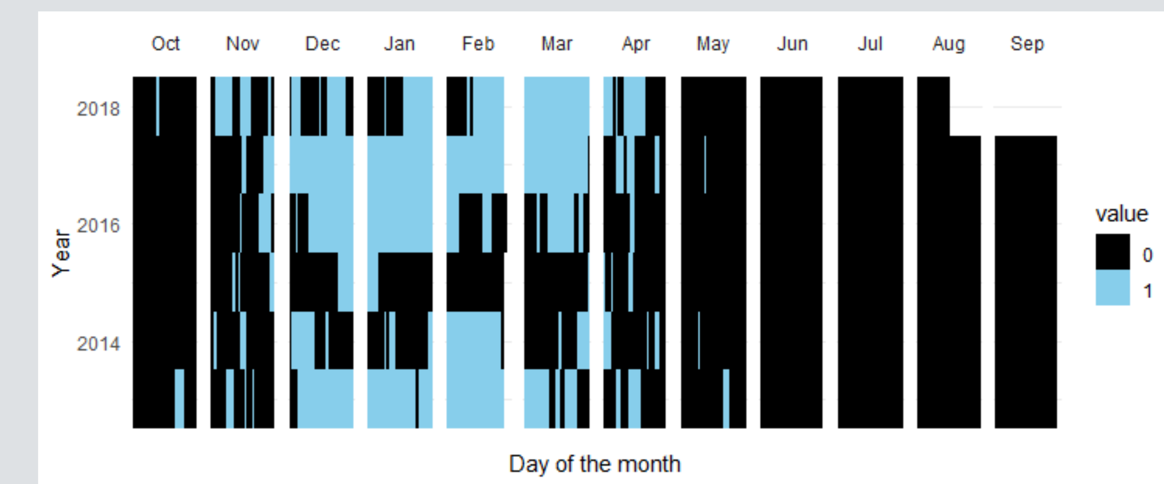
fSCA of all visible HOBOs from January to May of each year when HOBOs record snow. Although the classifier was able to accurately classify binary snow/no snow values for images during the peak (Jan/Feb) and trough (April/May) seasons, the higher incidence of false negatives during the shoulder season (March) and the low incidence of intermediate fSCAs overall suggest that the classifier did a poor job of accurately detect fractional snow cover. As a result, we classified the images by eye for our final comparison with the Snow estimates derived from the HOBO sensors.

Results HOBO Analysis

	Eye Snow	Eye No Snow
HOBO Snow	656	2
HOBO No Snow	53	1553
Observed Agreement	2189	
Expected Agreement	1309	
Kappa	**0.94**	

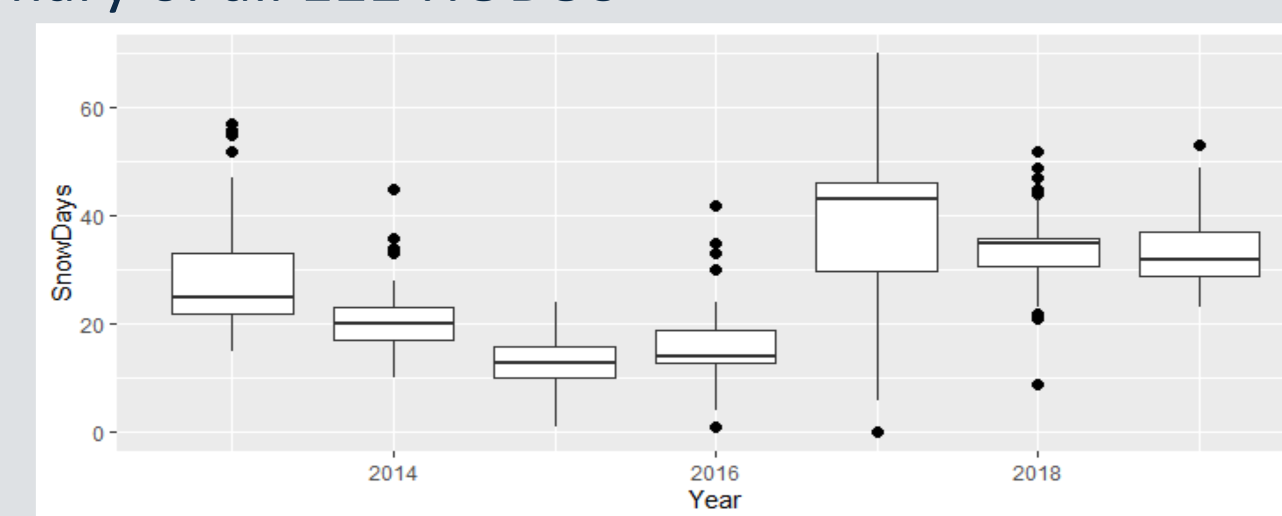
Confusion Matrix of agreement between HOBOs and snow cover determined by eye using the images. The results suggest that HOBOs accurately record snow cover.

Single HOBO



Graph represents when a single HOBO recorded snow (blue) or no snow (black) during a six-year period. The graph indicates a relatively consistent snowcover from Dec – Feb, with the exception of 2015. Snow is absent from May-Oct. Spatial and temporal variability was generally greatest in March.

Summary of all 122 HOBOS



The boxplot shows the number of days of snow each HOBO recorded each year between March 21 and June 30. A two-tailed t-Test between the years 2014-2016, years with high El Niño values, and 2013, 2017-2019 was significant ($t(584)=-9.47$, $p=2.88E-20$), suggesting that El Niño may have influenced snow totals.

Conclusion

- Snow patterns are more strongly influenced by shorter-term teleconnections such as El Niño Southern Oscillation than longer-term trends associated with climate change.
- The HOBOs provided more accurate data for snow cover than than image classification
- The shoulder season in late March/early April can be relatively well quantified using the HOBO technology.