

Forest Composition and Structural Controls on Canopy Snow Interception in a Colorado Watershed

Curtis Andregg Beutler

Thesis

Presented to Faculty of M.S. Ecology

Western Colorado University

In Partial Fulfillment of the degree of:

Master of Science

Western Colorado University

Gunnison, Colorado

2024

Copyright by **Curtis Andregg Beutler, 2024**

The thesis committee for the M.S. Ecology Graduate Program certifies that this is the approved
version of the following thesis:

**Forest Composition and Structural Controls on Canopy Snow Interception in
a Colorado Watershed**

By

Curtis Andregg Beutler

Approved By:

Micah Russell

Micah Russell: Thesis Advisor, Interim Dean – Clark School of Environment and Sustainability,
Western Colorado University mrussell@western.edu



Jonathan Coop: M.S. Ecology Program Director – Clark School of Environment and
Sustainability, Western Colorado University jcoop@western.edu



Ian Breckheimer: Adjunct Professor – Clark School of Environment and Sustainability,
Western Colorado University. Research Scientist – Rocky Mountain Biological Lab
ikb@rmbi.org



Kenneth Williams: Senior Scientist – Lawrence Berkeley National Lab. Co. Principal
Investigator - Watershed Function Scientific Focus Area kwilliams@lbl.gov



Mark Raleigh: Assistant Professor – College of Earth, Ocean, & Atmospheric Sciences; Oregon
State University [raleigma@oregonstate.edu](mailto:raleighma@oregonstate.edu)

Acknowledgements

The authors above would like to acknowledge the institutional support of the Western Colorado University M.S. Ecology program faculty and students, Lawrence Berkeley National Lab – U.S Dept. of Energy and the Watershed Function Scientific Focus Area, the Rocky Mountain Biological Laboratory, and the Gunnison National Forest – USFS. Additionally, the lead author would like to acknowledge the support of Rosemary Carroll, Alex Newman, Ken Williams, and Jeff Deems in project realization; and the field support of Austin Shirley, Elin Binck, Russell Penasa, and Owen Parker.

Forest Composition and Structural Controls on Canopy Snow Interception in a Colorado Watershed



*Figure 1: Mixed Conifer Forests at study sites near Crested Butte, CO.
(credit: Jeremy Snyder – Lawrence Berkeley National Lab)*

Curtis Beutler

Western Colorado University - M.S. Ecology

Co-authors / Thesis Committee

Micah Russell

Ian Breckheimer

Kenneth Williams

Mark Raleigh

Abstract

Globally and across the Western United States shifting climate regimes have the ability to propagate change throughout ecosystems and affect their associated hydrologic functions. In mountain regions, which serve as “water towers” for much of humanity, the complex interactions between vegetation and water are especially vulnerable to climate change as they are subject to both ecological and hydrological disturbances. Forests exhibit major controls on the hydrology of mountain systems, of which a primary mechanism is the interception of falling snow in forest canopies which can result in up to 50% of intercepted snow being lost back to the atmosphere through sublimation. Despite being an important driver of forest-snow interactions, scientific inquiry on canopy snow interception has been limited to small spatial scales and limited observations due to the difficult nature of measuring snow in forest canopies. We used Terrestrial Laser Scanning (TLS) to quantify interception rates and interrogate how tree species, forest structure, and weather conditions influence canopy snow interception potential in a high elevation Colorado watershed. Our results represent a step forward in expanding the spatial scale of canopy snow observations and elucidating the differences in interception rates across different tree species, forest compositions, and structures. We compared deciduous tree stands comprised of Quaking Aspen against 3 prevalent coniferous tree species at this altitude (Lodgepole Pine, Engelmann Spruce, and Subalpine Fir) and found that on average conifer forests intercepted an order of magnitude greater snow volume. Analysis of a supplementary dataset on snowpack depth revealed that aspen stands had a 22% greater snow depth on average, despite wide ranges in snow distribution across sites.

Our results indicate that neighboring stand structure, individual conifer crown geometry, and conifer tree species are all significant drivers of interception potential – their effects decreasing in that order. Heterogenous, mid-winter weather events did not significantly affect interception rates across our study dates – implying that a maximum canopy snow load had been approached. The single most predictive structural metrics tested across multiple scales were indices of Rumple (canopy surface area) and Vertical Complexity (vertical evenness of canopy), which demonstrated a trend of high surface area neighboring canopies inhibiting the interception potential of blocked trees - and uneven, vertically diverse canopies intercepting more snow. The most significant difference in interception potential on the basis of tree species was found to be Subalpine Fir, which when accounting for differences in crown size was shown to intercept 0.2 m³ more snow on average than the other coniferous species in this study. These results suggest noteworthy implications for post disturbance forests and successional tree species in a new climate future; where forest composition and structure are in flux and the regeneration of former overstory forests is no longer certain.

Keywords

Forest-Snow Interactions, LiDAR, Canopy Interception, Forest Structure, Forest Composition, Snow Hydrology, Eco-Hydrology

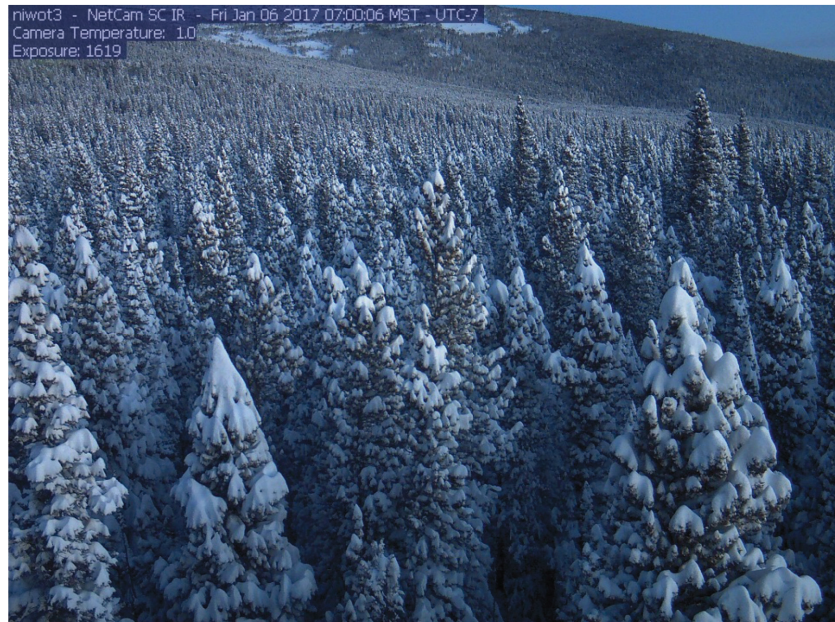
Introduction

Changing Forests

Climate change is having far-reaching effects on mountain regions which serve as “water towers” for much of humanity. Snowpack is the dominant precipitation phase and water resource

in high elevation temperate regions and mediates water availability for 1 billion people globally (Mankin et al. 2015). The storage of winter snowfall and the gradual release of spring/summer snowmelt provides a natural reservoir that many ecosystems and facets of human societies depend on.

Recent studies have shown that the timing and water storage capacity of winter snowpack accumulation/ablation are shifting towards early melt and diminishing storage in the Western U.S. where snow storage has decreased 25% in the last 60 years (Hale et al. 2023). Also, in the Western U.S., Siirila-Woodburn et al. (2021) showed that the impacts of a “low to no snow” future could be catastrophic for societal water supply; as infrastructure and management practices have been built around reliable winter snowfall which could be reduced as much as 35% by the middle of the century. These trends in snowpack timing and magnitude have broad implications for not only societal water needs, but also the species that makeup the many ecosystems that have evolved to thrive under both the dormancy of winter and the sustained release of snowmelt (Slayter et al. 2021). Consequentially, the ecosystem function of many snow-dependent systems is subject to cascading effects due to climate change that will alter the ecohydrology of landscapes in ways that are not well understood currently (Wieder et al. 2022).



*Figure 2: Spruce-Fir forests under a blanket of intercepted snow – Niwot Ridge, CO
 (Phenocam Network: https://phenocam.nau.edu/webcam/sites/niwot3_IR/)*

Changing Snowpack

Global climate change imposes new risks to forest health across the planet, as climate extremes can cause widespread tree mortality events in ecosystems previously considered to be tolerant to severe climate conditions (Hartmann et al. 2022). Due to climate change and resource management legacies that have altered fire, drought, and insect-induced mortality across the Western United States, forests are becoming increasingly susceptible to disturbance-driven conversion (Krawchuk et al. 2020). The eco-hydrologic dynamics of these forest systems are largely driven by forest composition and structure; and the makeup of pine, spruce/fir, and aspen forest types and their associated forest structures are shifting rapidly (McDowell et al. 2020). Some of these shifts may be towards more aspen dominated forests, as Quaking Aspen (*Populus tremuloides*) represent a short-term successional species that can thrive in the wake of disturbance to conifer forests (Alexander et al. 1986). Andrus et al. 2021 showed that shifting disturbance regimes in a warmer climate can allow multiple disturbance types (insect mortality

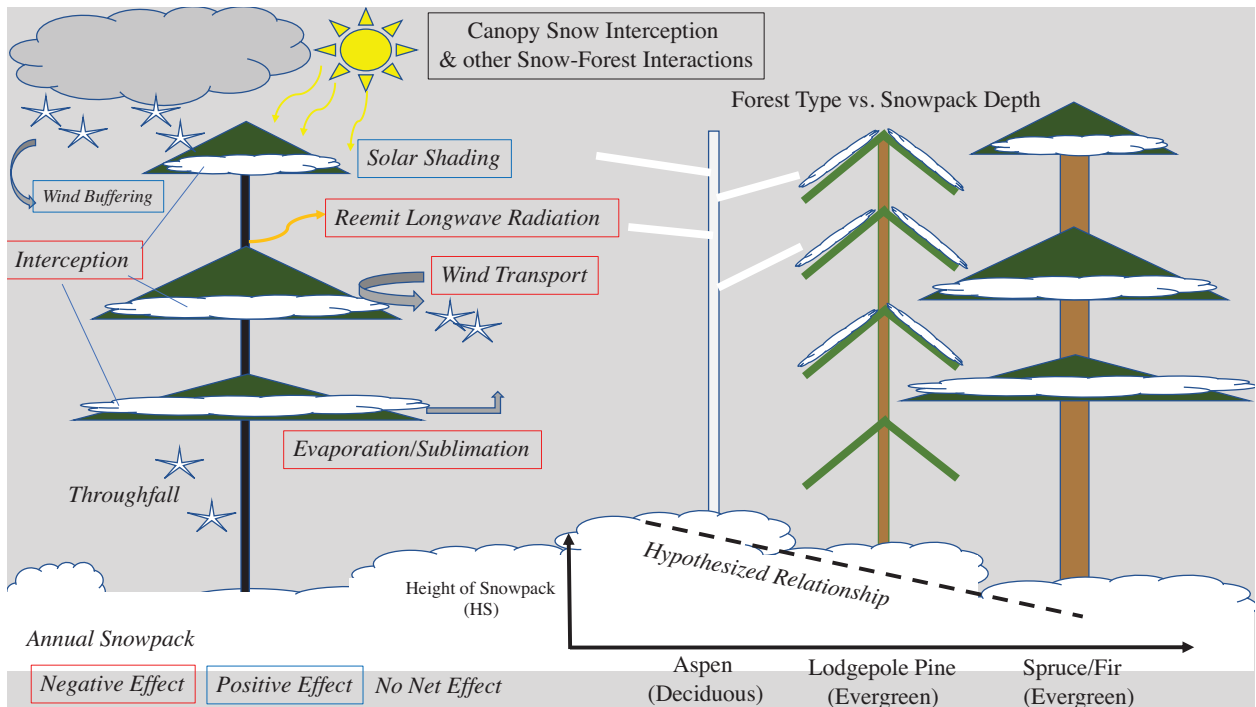
and wildfire) to interact making Spruce-Fir forests more vulnerable to shifts towards an aspen forest type.

Additionally, aspen forests around the Western U.S. are in a state of decline due to pathogenic disturbance and the not well understood phenomena of “Sudden Aspen Decline” (SAD). Worrall et al. showed that in 2010 SAD has impacted nearly 20% of aspen forests in the state of Colorado. In cases of aspen forests, disturbance due to fire, pathogenic disease, and SAD, the transition can be towards a radically altered aspen forest structure or towards a new forest type in the form of conifer species like Spruce-Fir becoming the dominant successional species (Singer et al. 2019). The competing disturbances and trajectories for conifer vs. aspen forests underscore the importance for understanding their associated ecological and hydrological function, as forests in a state of transition pose long-term questions about resource management. Within coniferous forests present in Colorado and the Western U.S., research has shown that different species like *Picea engelmanni* (Engelmann Spruce) & *Abies lasiocarpa* (Subalpine Fir) can succeed *Pinus contorta* (Lodgepole Pine) in subalpine forests altered by insect mortality and wildfire; sometimes transitioning from the antecedent understory species to the dominant post disturbance overstory species (Pelz et al. 2012). These conifer successional trajectories are largely due to species level traits: where Lodgepole Pine are shade intolerant (limiting their understory regeneration) and are known to “live and die” together – whereas Spruce/Fir trees are shade tolerant, often occur together, and able to exist as a sub dominant species in the sub-canopy.

Forest Conversion Impacts on Eco-Hydrologic Function

The eco-hydrologic dynamics of forests are sensitive to disturbance-induced forest conversion that can lead to both positive and negative feedbacks in the relationship between forest

composition/structure and water availability (Harpold et al. 2014). The composition and demography of forests are responsible for different pools and fluxes within an ecosystem's water budget via forest controls on air temperature, soil moisture, evapotranspiration, and many other eco-hydrologic variables (Vose et al. 2016). The importance of forest and water feedbacks in mountain watersheds are underscored by the fact that mountainous systems are bellwethers of climate change – witnessing severe and diverse impacts at a faster rate than most other ecosystems (Williams et al. 2002).



Forest-Snow Interactions

In the northern hemisphere, forests cover an estimated 20% of seasonally snow-covered areas (Rutter et al. 2009) and comprise 17% of global winter freshwater storage (Guntner et al. 2007). Globally, an estimated 4 million km² of mid latitude forests and 11 million km² of high latitude

boreal forests are impacted by seasonal snow (Vuyovich, C. NASA. (2024, May, 24). SnowEx, Nasa.gov, <https://snow.nasa.gov/campaigns/snowex>). A growing body of scientific work suggests that forests that have coexisted with seasonal snowpack for millennia are under threat due to decreases in snow accumulation caused by climate change (Bisbing et al. 2019). The range limits of snow adapted forests vs. the broadening range of species adapted to warmer, drier winters could fuel broad forest composition changes globally (Buma et al. 2017). Forest controls on snowpack accumulation and ablation define the quantity and timing of water delivery to ecosystems, rivers, and communities (Sun et al. 2018). These controls act to both enhance and inhibit the retention of mountain snowpack and many ecosystems have evolved under this regime. Some of these controls include wind buffering (forests' ability to "fetch" blowing snow due to decreased wind speed), shading and the reemission of longwave radiation (which impacts snowpack energy balance), and the interception (and subsequent wind redistribution, sublimation, melt, or unloading) of snowfall by forest canopies.

Forest impacts on the mass and energy balance of mountain snowpacks create a local snow climate unique from unforested areas (Bonner et al. 2022). These differences have been shown to vary drastically across short distances due to heterogenous energy inputs and microclimates. Musselman et al. (2012) showed that canopy metrics pertaining to snowpack energy balance explained up to 58% of the spatial variability of SWE ablation in conifer forests. The dramatic difference in the albedo (absorbed v. reflected radiation) of tree surfaces vs. snowpack surfaces creates a unique environment of sensible and latent heat fluxes, in which small perturbations to forests can have large impacts on snowpack energy balance. Forest disturbances can change the shading of snowpack via tree canopies and snowpack albedo effects via deposited organic

matter, therefore altering total snow amount and disappearance date (Webster et al. 2018).

Studies have shown that change in forest cover/structure post-disturbance can radically alter snow accumulation and streamflow in mixed conifer ecosystems like those found throughout Colorado and Western North America (Pomeroy et al. 2012). The interception of falling snow by forest canopies, and the subsequent loss of snow water equivalent (SWE) from the seasonal snowpack, represents a large unknown in the modelling and remote sensing of snow (Russell et al. 2020; Molotch et al. 2007).

Heterogeneity of Snow Interception

Canopy interception has been shown to be largely heterogenous based on intrinsic and extrinsic factors of forests and their local climates (Russell et al. 2021). Air temperature, humidity, and wind speed/direction extrinsically affect the density, adhesiveness, and cohesiveness of falling snow; and therefore, alter how much snowfall can accumulate on tree branches. Intrinsic forest factors, such as foliar traits, canopy structure, vegetation stiffness, and canopy spacing in turn affect the surface area and geometry of canopy surfaces that can intercept snow (Schmidt & Gluns 1991). Intrinsic and extrinsic factors of forests and their environment impact the overall mass balance of snowpack on the ground, as up to 50% of intercepted Snow Water Equivalent (SWE) never makes it to the ground surface - but is instead lost to sublimation and aeolian wind transport (Lundquist et al. 2021).

Deciduous and coniferous forests have vastly different abilities to intercept falling snow, as the loss of winter Leaf Area Index (LAI) inhibits deciduous trees' ability to accumulate snow on their limbs (LaMalfa et al. 2008). Due to this, most interception studies have focused on conifer

forests. However, quantifying interception rates of deciduous tree stands and comparing subsequent loss/retention of seasonal snowpack to their coniferous counterparts would inform water balance estimates of changing mountain forest types. Also, deciduous trees could be a compelling analog for how post mortality, needleless coniferous trees impact snow processes when providing the shading and wind buffering benefits of a forest canopy, without high interception rates due to the absence of a foliar canopy (Baker et al. 2014). Quantifying the effect of these “standing dead” analogs may offer a glimpse into how the eco-hydrology of conifer forests changes after fire or insect driven mortality (Manning et al. 2020). Studies have found mixed results in using different conifer tree species as the sole predictor of interception rates (Storck et al. 2002; Schimdt & Gluns et al. 1991). Forest structure metrics that can be applied across a range of conifer tree species offer promise in bridging the gap between the direct measurements of intercepted snow and remotely sensed forest structure data (Roth et al. 2019). These emerging metrics from recent publications use remote sensing and new calculations of the 3-dimensional geometries of forest canopies to define the vertical distribution of foliage and branches which show promising relationships to interception efficiency and the net impact on sub-canopy snow (Hojatimalekshah et al. 2021).

Applications of Terrestrial Laser Scanning

Light detection and ranging (LiDAR) has become a hallmark of remote sensing of the environment in the last 15 years, due to its ability to collect high accuracy measurements across previously unprecedented scales (Deems et al. 2013; Harpold et al. 2015). LiDAR technology uses concentrated pulses of (laser) light emitted from and returned to the instrument to quantify the distance and position of environmental media that reflect these waves of energy back to the sensor. The three-dimensional positions of each LiDAR return are combined into a functional

“point cloud” which allows practitioners to investigate the structure, deformation, and spacing of environmental media. Terrestrial Laser Scanning (TLS) is a subset of LiDAR technology (operated at the ground level, typically on a tripod) that has been demonstrated as a highly quantitative technique for collecting very high spatial resolution information that allows for the investigation of nuanced structural differences at the scale of individual trees. The spatial capabilities of Terrestrial LiDAR make it well suited for capturing the intricate structural detail of forests since TLS can be operated below the canopy level. Capturing the horizontal (tree spacing) and vertical (crown geometry) structure of forests with terrestrial LiDAR reveals properties that traditional forestry methods cannot capture, from sophisticated biomass and foliar estimates to vertical complexity and spacing. These interrogations of three-dimensional structure have propelled advancements in the ways forest ecologists understand everything from tree reproduction and allometry to how forest fires interact with standing versus ground fuels (Marcozzi et al., 2023). LiDAR systems have also proven to be a revolutionary technology for the measurement of snowpack, as the spatial resolution and level of detail of LiDAR datasets is well equipped to capture the subtleties of snow distribution, which is known to be highly spatially variable (Deems et al. 2013).

In the field of snow hydrology, canopy interception is a largely understudied phenomenon, in large part due to the difficulty of collecting accurate measurements and scaling up the spatial range of observations (Russell et al. 2020). The implementation of TLS techniques to capture tree volume and shape has been shown as a promising method for collecting high spatial resolution data of both forest structure important to interception and canopy snow volume at the individual tree scale (Russell et al. 2021). Although this application is still its infancy, the data-

rich nature of TLS retrievals means that there are many avenues to explore within a single dataset. Additionally, TLS observations with a diverse sample pool, across multiple tree stands, have the potential to be correlated with broader-scale remote sensing techniques (such as airborne LiDAR) which could inform hydrologic observations/models across an entire forest or on a watershed scale. Previous research utilizing Terrestrial LiDAR to measure intercepted snow volume has not achieved spatial scales and sample numbers necessary to categorize the variance and trends in snow interception across different forest compositions and structures, due to both the challenging fieldwork and high computational requirements necessary to attain such observations.

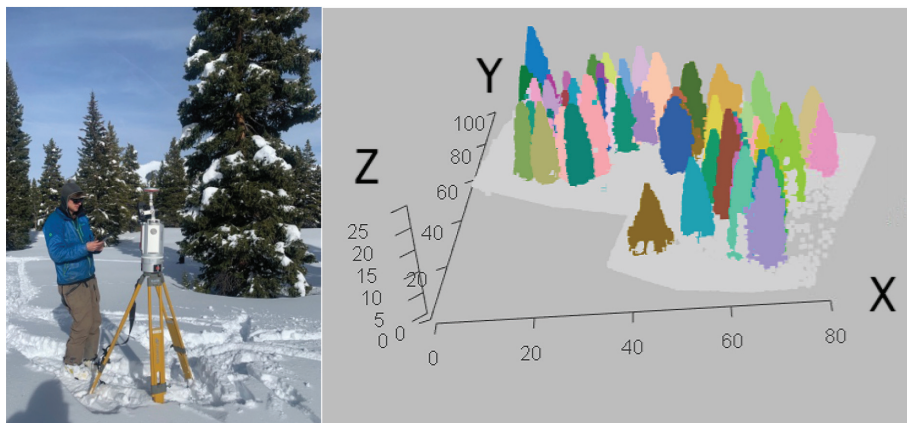


Figure 4: Terrestrial LiDAR scan acquisition and data products

Methodology

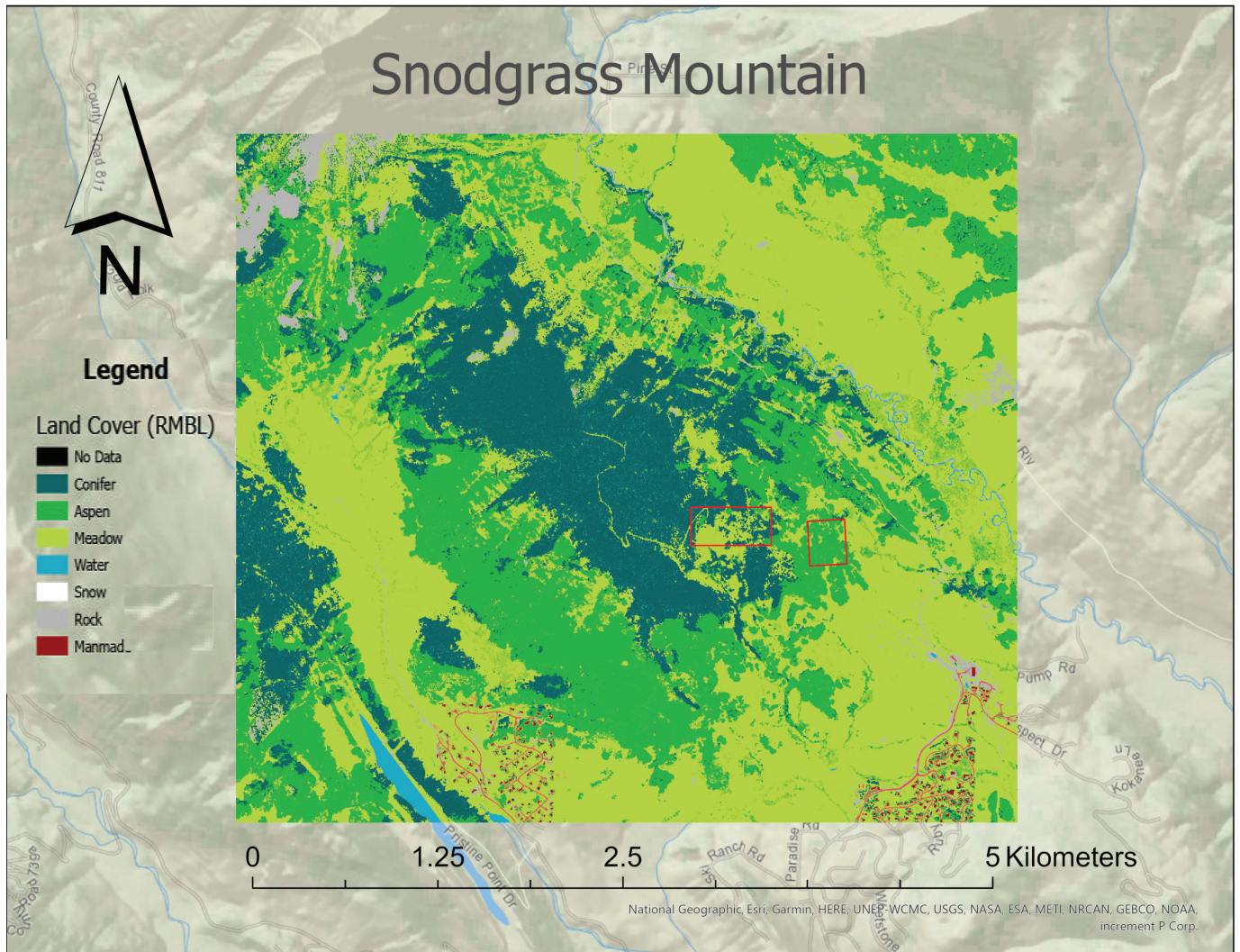
Study Location

Our sites were selected on Snodgrass Mountain, northwest of Mt. Crested Butte within the East River watershed of Gunnison County, Colorado. Snodgrass Mountain represents an ideal location to study forest-snow interactions as ~85% of its slopes are forest covered, all the way to

its summit at 11,100 ft above sea level - just shy of the typical tree-line elevation for this area. Additionally, the geography of Snodgrass Mountain is less complex compared to surrounding peaks in the area, allowing for relatively easier control of slope angle, aspect, and microclimate variables across sites. Furthermore, site access in this area is feasible year-round and is reliably safe during the winter field season, which is vitally important for collecting time sensitive data after storm events which often raise avalanche danger. The subalpine forests of Snodgrass Mountain are representative of the East River watershed as well as many other high elevation watersheds. Forests in the study area are comprised of the four regionally dominant tree species at these elevations: Quaking Aspen (*Populus tremuloides*), Lodgepole Pine (*Pinus contorta*), Engelmann Spruce (*Picea engelmanni*), and Subalpine Fir (*Abies lasiocarpa*). As such, Snodgrass Mountain offers a prime environment to test interception efficiencies across tree species. Due to differences in growing conditions, competition, and fire history, these forests exhibit diverse allometry within tree species, suitable for testing a range of forest structures on interception efficiencies of canopies. The forested slopes of Snodgrass Mountain also represent a high elevation conifer forest poised for, but not yet severely impacted by, the modern severity of woodland disturbances— disturbances that have the potential to alter the species and structural composition of forest ecosystems. These landscape altering disturbances include insect mortality, drought, and wildfire, all of which are intensified by changing climate conditions that can surpass the level of interruption mountain ecosystems have evolved to fully recover from.



Figure 5: The Colorado River Basin with inset of the East River Watershed in Red and Study Location in Green. (ESRI: NatGeo Worldmap)



*Figure 6: Landcover Map of Snodgrass Mountain, CO showing site locations in red squares.
(National Ecological Observatory Network – Rocky Mountain Biological Lab 2018)*

Collection of LiDAR Data

We collected LiDAR scans using a VZ-2000i model Terrestrial Laser Scanner manufactured by Riegl LiDAR in Horn, Austria. This cutting-edge instrument is owned by Lawrence Berkeley National Laboratory (U.S. Department of Energy) and was used in cooperation LBNL and the Watershed Function Scientific Focus Area. The VZ-2000i operates in a Near Infrared wavelength of 1064 nm and has a range of 1 to 2,500 m, with 3mm precision and 5mm accuracy. This unit operates on top of a surveying tripod and shoots a Class 1 strength laser into a spinning

prism which emits pulses of concentrated light that are reflected back to the instrument to create two-way travel times for impacted media. The resulting three dimensional “point cloud” of laser returns has an approximately 5mm accuracy in the X, Y, Z depending on scan conditions. We operated this instrument at a laser pulse repetition rate of 1200 kHz (approximately 500,000 measurements per second), a scan resolution of 40 millidegrees, and with a “Panorama” 360-degree scan pattern. These settings maximized data richness, with a laser footprint of 2.8 cm and an average return spacing of 7 cm (at 100m distance), while striking an efficient balance of the time taken per scan (~45 seconds). We operated the TLS platform with a multiple, discrete return operating system where the peaks of the incoming waveform were interpreted as distinct points (up to 4 returns per laser pulse). Reflectance in the NIR wavelength varies across objects in the environment. Snow surfaces specifically exhibit a range of relatively low reflectance values based on snow grain size; large snow grain sizes typical of warm snow and spring conditions have very low reflectance in the NIR wavelength (Deems et al. 2013). We observed good LiDAR reflection and intensity values off snow surfaces due to our data being collected in mid-winter months, when snow grain sizes were relatively smaller.



Figure 4: Terrestrial LiDAR retrievals of Spruce & Pine trees on Snodgrass Mtn – left v. right image show tree structure and intercepted snow in NIR reflectance v. True Color respectively (lighter colors = higher reflectance, darker colors = lower reflectance)

Geospatial Techniques

We utilized the onboard GNSS system of the Riegl VZ-2000i which achieved an average 2-3 m accuracy with a reliably consistent signal. The internal GPS in combination with geo-positioning “monuments” (explicitly identified/installed to provide geo-referenced markers to correct each timepoint) allowed for correction to a ~50 cm confidence on average. These monuments were erected in Fall of 2023, built of a t-post and 2m tall PVC pipe, and located in nearby clearings where they could be accurately measured with a handheld RTK unit to achieve 1 cm accuracy in position. To back correct for scan data collected during Winter 2023, before monument installation, we were able to identify 1 prominent tree apex per site whose relative position to each site’s monument was calculated and applied to February and March 2023 scans to achieve relative position correction. This technique relied on prominent tree apices being in approximately the same place; we found good agreement between scans corrected with the installed v. identified scan monuments.

Collection of UAS Data and Tree Species Determination

We determined the species identity of all focal trees in our study using a combination of on-the-ground determinations and “heads-up” classification from high resolution imagery from an Uncrewed Aircraft System (UAS). Uncrewed aircraft (drones) have revolutionized the remote sensing of ecosystems and snowpack, as they represent an ideal, user-defined balance of spatial scale versus data resolution. In this study we utilized 1 cm resolution RGB and 5 cm resolution multispectral orthomosaics from a *DJI m300* UAS system equipped with an DJI P1 RGB camera and *Micasense Altum v1* multispectral sensor. Raw images were processed into orthomosaics using Aigsoft Metashape (version 1.7) according to a standard photogrammetry protocol (Tinkham et al. 2021). The UAS was equipped with a high accuracy RTK (real-time kinematic) geo-positioning system that allowed orthomosaics to be co-registered with the TLS point clouds. To identify the species of each tree in our study sites we employed a hybrid method of limited field identification coupled with high resolution, high geo-accuracy aerial imagery which allowed for the timely and confident designation of 240 trees. The motivation for this method came from not only the time saved by not identifying every individual in the field, but also the desire to demonstrate the co-registration capabilities of TLS canopy measurements with other scales/applications of remote sensing. Concurrent with UAV collections we used a high accuracy handheld RTK unit to map polygonal tree canopy areas while identifying tree species via on the ground measurements. The polygon crown areas were then later added to the imagery of the UAV mosaic in a GIS system which allowed for confirmation and visual training of species ID from the aerial imagery.

Development of novel computing approach

Given the high resolution and relatively large spatial scale of Terrestrial LiDAR and UAS datasets, an imperative goal of this study was to expand the computing framework described by Russell et al. 2021 to allow for measurements across tree stands of both forest structure and intercepted snow volume. To accomplish this, we employed a host of existing R packages (*lidR*, *alphashape3d*, etc.) that allowed for both automated tree detection and point cloud segmentation, wherein the geometry of the individual trees could be calculated from the point cloud segments using the alpha shape method of generalizing convex hull “alpha” shapes from non-convex objects in order to connect discontinuous points, such as those generated from LiDAR. The “ashape3d” package (Lafarge et al. 2023) is also useful in this application in its feature to calculate the entire volume of the interpolated alpha shapes; this feature was utilized in calculations of “Snow-Off” versus “Snow-On” trees, which allowed for the quantification of added volume from intercepted snow. While LiDAR data is incredibly rich in structural detail and information – the size of and “noise” within LiDAR datasets can pose substantial challenges to accurately processing data. Thus, it is vitally important to use well thought out data categorization and manipulation practices in the processing code to parse out meaningful calculations and trends in observed data. We implemented a noise filtering tool from the *lidR* package which identified and omitted LiDAR returns in the point cloud that did not contain 5 neighboring points within a distance equal to 5x the 3-dimensional standard deviation of all points in the point cloud; this allowed for the reduction of noise from sources like blowing snow.

Individual Tree Detection

As previously noted, one of the challenges of measuring the interception potential of individual tree canopies is obtaining enough measurements to have a sample size that is statistically representative of the forest a project seeks to study. To address this issue of representativeness and maximize the number of individual trees analyzed in this study, we utilized existing automated tree detection and point cloud segmentation algorithms to develop a novel computing workflow that both analyzes trees and calculates tree/snow volume using multiple methods. The code generated in this project builds upon the *lidR* coding package – a primarily aerial LiDAR (ALS) optimized set of tools (Roussel et al. 2024) in *R* (R Core team 2023). Since TLS data produces similar point clouds to ALS (typically denser overall – especially in the Z dimension) we were able to carefully use many of the tools within the “lidR” package while avoiding features that could misinterpret our terrestrial instead of aerial LiDAR returns. One of the package tools we utilized was “locate_trees” in combination with the algorithm described in Dalponte et al. 2016 that uses a rasterized canopy height model to identify individual tree apices. These tools were applied to the Snow-Off TLS point clouds and demonstrated an impressive ability to identify individual treetops when executed with the appropriate settings. Although individual tree crowns can be visually identified from the UAV imagery and LiDAR point clouds alone, it was especially useful to use automated tree detection to confirm visually assessed tree crowns for densely forested stands and aspen canopies, where at the height of the growing season deciduous leaves obscure tree apices and overlap with nearby canopies.



Figure 7: Workflow process Left-Right: Raw UAS imagery, point cloud generated tree tops + ground truth species ID, manual crown polygon clips according to species, final clipped tree.

Given the tight spacing and uneven shapes of some conifer canopies, we chose to overlay the code generated treetops onto the ortho-imagery within QGIS then use a layer clipping tool to manually delineate the crown polygons. With high confidence geo-accuracy and identical spatial datums/coordinate reference systems, this approach allowed us to use the high-resolution aerial imagery to clip tree crowns according to tree species for each site. Another important consideration was the TLS coverage of each tree crown, as the most densely spaced tree stands occlude 3-dimensional coverage of some tree crowns; ortho-imagery assisted in the clipping of tree crowns completed by the TLS operator who was aware of individual scan positions/coverage. Infrequently, crown clipping resulted in erroneous crown delineation – in these cases the issue and solution was obvious from point cloud visualization in R and allowed for a quick correction in QGIS. Our approach was slightly different for aspen canopies, as the reliable canopy shape and spacing of aspen stands allowed for more straightforward automation of the crown delineation process. These methodological differences can be found in our supplementary information.

Calculation of Structural Metrics

The 3-dimensional resolution of LiDAR data and its ability to penetrate and return highly accurate structural detail of forest canopies makes it one of the best remote sensing tools for calculating horizontal and vertical forest structure. From our Snow-Off dataset we were able to calculate 15 forest and canopy structure metrics using tools developed from the *lidR* team and LaRue et al. (2018) that describe the geometry and density of individual tree canopies as well as the spacing and orientation of an entire forest stand. A table of metric definitions and coding pedagogy is included in our results.

Metric	Description	Function & Scale
<i>Maximum canopy height</i>	Maximum height within the plot area from CHM	lidR : grid_canopy() <i>Stand Scale</i>
<i>Mean canopy height (H)</i>	Mean of return heights within the plot generated from CHM	lidR : grid_canopy() <i>Stand Scale</i>
<i>Deep gaps (DG)</i>	The number of 1 m ² canopy gaps in the plot	lidR : grid_canopy() <i>Stand Scale</i>
<i>Deep gap fraction (DGF)</i>	Fraction of 1 m ² canopy gaps in the plot	lidR : grid_canopy() <i>Stand Scale</i>
<i>Cover fraction (CF)</i>	1 minus deep gap fraction (inverse of deep gap fraction)	lidR : grid_canopy() <i>Stand Scale</i>
<i>Gap fraction profile (GFP)</i>	Distribution of gaps in the point cloud 3 m above the ground.	lidR : gap_fraction_profile() <i>Stand Scale</i>
<i>Top rugosity (TR)</i>	The standard deviation of pixel values in chm: measure of outer canopy roughness	lidR : grid_canopy() <i>Stand Scale</i>

Table 1: Descriptions and coding tools for horizontal + vertical metrics applied to neighboring trees

Metric	Description	Function & Scale
<i>Rumple (Rumple)</i>	Area of canopy surface relative to plot area : ratio of outer canopy surface area to ground surface area.	lidR : index() <i>Crown & Stand Scale</i>
<i>Vertical SD</i>	Standard Deviation of LiDAR returns for entire tree	lidR : cloud_metrics() <i>Crown & Stand Scale</i>
<i>SD of vertical SD (StdStd)</i>	Plot level- standard deviation of the standard deviation of heights within 1 m ² voxels in plot	lidR : grid_metrics() <i>Crown & Stand Scale</i>
<i>Entropy (Entropy)</i>	Diversity and evenness of heights within the crown or plot	lidR : entropy() <i>Crown & Stand Scale</i>
<i>Height SD (StdH)</i>	Standard deviation of heights within the plot	lidR : las_metrics() <i>Crown & Stand Scale</i>
<i>Vertical complexity index (VCI)</i>	Normalization of diversity and evenness (entropy) of height within the plot	lidR : VCI () <i>Crown & Stand Scale</i>
<i>Vegetation area index (VAI)</i>	Sum of the 1 m horizontal slices (starting 3 m above the ground) of leaf area density in the plot	lidR : LAD () <i>Crown & Stand Scale</i>
<i>Taper</i>	Average difference in Leaf Area Density dividing crown by 10 height bins	lidR : std.metrics : LAD () <i>Crown Scale</i>

Table 2: Descriptions and coding tools for vertical metrics applied at crown + stand scale.

Realignment of Point Cloud Data

The geospatial techniques used across multiple acquisition dates, no matter how precise, require correction via permanent monuments or relative positioning from common object(s) shared

across different LiDAR retrievals. For instance, a survey grade real-time kinematic (RTK) GPS unit can achieve 3-dimensional accuracies of 2-3 cm, but when this is compounded by the accuracy limits of the Riegl Terrestrial LiDAR and other field collection methods this number can grow to 10+ cm, at which point realignment of target objects (trees) must be conducted to assure the best possible alignment of trees in the x, y, and z dimensions. To satisfy the inconsistencies in geospatial positions between TLS acquisitions, we employed a method of common landmark identification that allowed for the realignment of LiDAR data across different time points. This method allowed individual treetops to be co-registered to the point where specific tree apices were identified as the same individual across time points. As mentioned previously, a coarse accuracy with the onboard GPS coupled with the medium accuracy of TLS monuments allowed us to scale from <3 m to <0.5 m geospatial accuracy. At this point, a fine realignment was performed within each R script where each individual Snow-Off and Snow-On tree apex (defined as all LiDAR returns from the top 1% of each tree) was averaged in 3 dimensions, and the entire Snow-On tree was corrected to the Snow-Off position. This method is similar in principle to the technique described by Ferraz et al. 2018 who used tree apices as Aerial LiDAR monuments to merge data between ALS flights. Although averaging ~100 points from the top 1% of each tree is a generalized approach, visual results show that the average apex position works well for correcting trees to the same position (Figure 8). Each iteration of this process produced a plotted visualization of the combined point cloud with color indicating the point cloud ID; this allowed for time efficient visual quality control to ensure the tree timepoints lined up in position and overall shape. Other methods of quality assurance/quality control included flagging erroneously high and negative values of intercepted snow, the result of which was individual observation omission or manual filtering/realignment of point clouds.

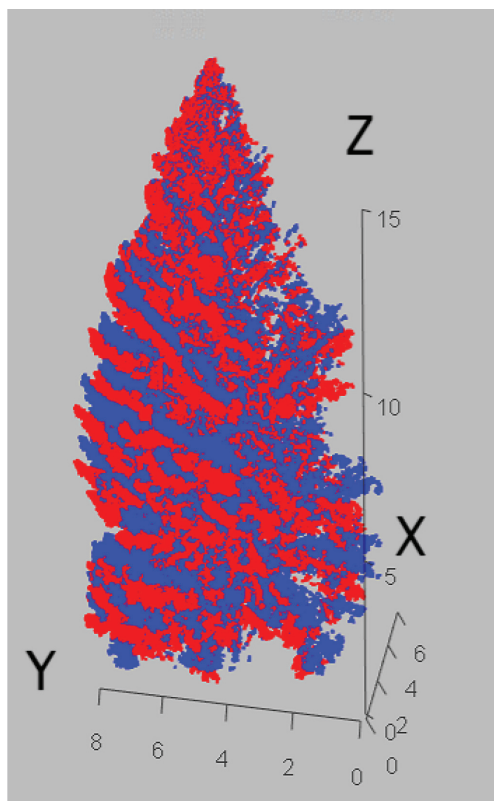


Figure 8: Co-registered and combined Snow-Off (blue) v. Snow-On (red) point clouds via Tree apex fine realignment.

Methods of Intercepted Snow Calculation

An important nuance of using TLS acquisitions to quantify canopy/snow volumes that Russell et al. 2020 found is the deformation of tree branches under the load of intercepted snow. This deformation causes the circumference and area of a tree canopy to shrink as branches become closer to the tree trunk when they are pressed down under the weight of snow. This tree deformation from a canopy under load poses a large problem for the measurement of tree or snow volume via remote sensing, as a smaller area tree canopy will return inaccurately small volumes given the reduced geometry of its deformed limbs. Russell et al. 2020 found a solution to this problem by combining the point clouds of “snow-on” and “snow-off” trees, which allows for overlapping points (the main tree mass) to make up a similar volume as a “Snow-Off” tree, while the non-overlapping points (primarily intercepted snow masses) represent additional

volume to the combined point cloud. The outcome of this method is that, when the estimated volume of the “Snow-Off” point cloud is subtracted from that of the combined “Snow-Off” and “Snow-On” point cloud, the resulting volume represents the added geometry of intercepted snow present during the “Snow-On” TLS scans. This method was developed by Russell et al. 2020 who used an automated LiDAR unit to scan artificial hanging trees attached to continuously monitored load cells to compare the LiDAR retrieval volume directly to intercepted snow mass. The authors found “good” agreement (R^2 0.69; RMSE 0.91 kg) between this “combined” point cloud method and the actual added mass measured on the study trees. We calculated canopy snow volume via the Russell et al. 2020 “combined” point cloud method, sub-setting individual tree canopy point clouds above the 75th percentile according to total tree height to exclude tree sections occluded by seasonal snowpack as well as ice formation that can occur on lower canopy limbs. The upper $\frac{3}{4}$ of the tree is thought to be more consequential for canopy interception which makes this subsection of the canopy more representative of canopy snow processes.

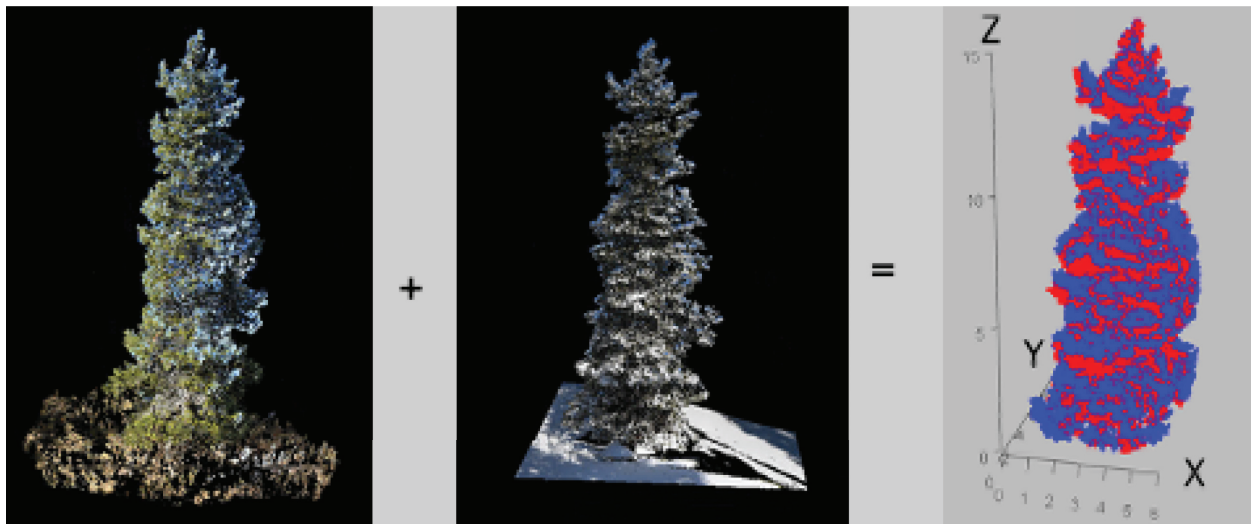


Figure 9: Co-registering of Snow-Off & Snow-On datasets via combined point cloud method.

Statistical Analysis

For statistical analyses we implemented generalized linear modelling and a model selection approach using the *lme4* package described in Bates et al. 2015. This allowed our model selection to parse out which species, structural traits, and weather variables exhibited the most predictive ability in terms of intercepted snow volume for our study trees. Model statistics in this section are reported according to outputs from the *lme4* package in the following format: LMM (Linear mixed model: fit by maximum likelihood: t-tests use Satterthwaite's method), df (degrees of freedom), X^2 (Wald Chi Squared test statistic, p (p - probability value of null hypothesis being true).

Results

One of our primary goals in designing this study was to obtain an adequate number of samples and time points so that a host of predictor variables (forest composition, forest structure, and antecedent weather conditions) were sufficiently compensated for statistically by the number of total samples vs. the number of covariates. These statistical goals, to adequately determine the probability of rejecting versus assessing our null hypothesis, were achieved (variable to observation ratios $\geq 1:40$), with the exception of total weather events to span the 7 variables we hoped to test (variable to observation ratios $> 1:0.5$). Weather events suitable for LiDAR acquisitions for this project were somewhat rare in that they required large snow events immediately followed by calm, dry weather where operation of the TLS was feasible. In all, we analyzed 65 conifer and 58 aspen trees across 4 timepoints for a total of 468 observations of calculated intercepted snow volume after implementing quality control measures to omit trees partially occluded in individual scans. The number of observations in our study kept our

observation to variable ratio well below the 1:5 threshold common recommended for sampling diverse populations (Hair et al. 2018), with the exception of weather variables vs. storm events.

Intercepted Snow Volume

We found intercepted snow volumes ranging from 0 to 0.5 m³ for individual aspen trees, and 0.2 to 4.2 m³ for conifer trees. Co-located weather station data allowed us to calculate individual canopy values of snow water equivalent (SWE) by applying storm-event snow density values to the volumes of intercepted snow. Storm snow depth values allowed us to calculate canopy snow depth from intercepted snow volume, which ranged from 0 to 0.30 m when averaged across individual canopy areas (i.e. the effective area of ground individual canopies covered). These values translated to area normalized (crown area at 25th percentile height) canopy SWE volumes ranging from 0 to 0.003 m for aspen trees and 0 to 0.03 m for conifer trees. Another noteworthy application of canopy snow volume was the calculation of precipitation SWE percent from each storm event that was captured in the canopy; these calculations yielded mean values of 0.4 % for aspen and 14 % for conifer individuals. These percentages are actually higher in regard to SWE that stays in the snowpack. This is because of the rate of moisture loss in new fallen snow, which varies widely from 10 to 90% due to thermodynamic instability of freshly fallen snowflakes and the loss of SWE to sublimation and other processes. This study did not analyze the fate or rates of SWE loss in canopy snow, but previous research has shown that up to 50 % of intercepted SWE is lost to sublimation due to the increased surface area, snow ventilation, and exposure to energy fluxes of canopy snow (Lundquist et al. 2021).

Metric	Aspen	Conifer
<i>Total Snow Volume</i>	0 – 0.5 m ³	0.2 – 4.2 m ³
<i>Mean Snow Volume & SD</i>	0.10 m ³ ; 0.15 m ³	1.7 m ³ ; 0.7 m ³
<i>Total Snow Depth</i>	0 – 0.03 m	0.0003 – 0.30 m
<i>(by area)</i>		
<i>Total SWE (by area)</i>	0-0.003 m	0* - 0.03 m
<i>Mean Percent of Storm SWE</i>	0.4 %	14%

Table 3: Summary of Aspen & Conifer Canopy Snow Calculations.

To see how strongly correlated intercepted snow was across different storm events we performed a Principle Components Analysis of the individual-level snow volumes across the 4 events and observed that >80% of overall variance was described by PC1 (Figure 10). The high level of explanatory power found in PC1 gives us confidence that reproducible interception patterns were present across our calculations of individual crown snow volume. However, the 10% of variance described in PC2 poses an interesting question about what processes led to slightly different interception patterns in the data from February and March – which exhibited roughly equal variance along the axes of PC1 & PC2.

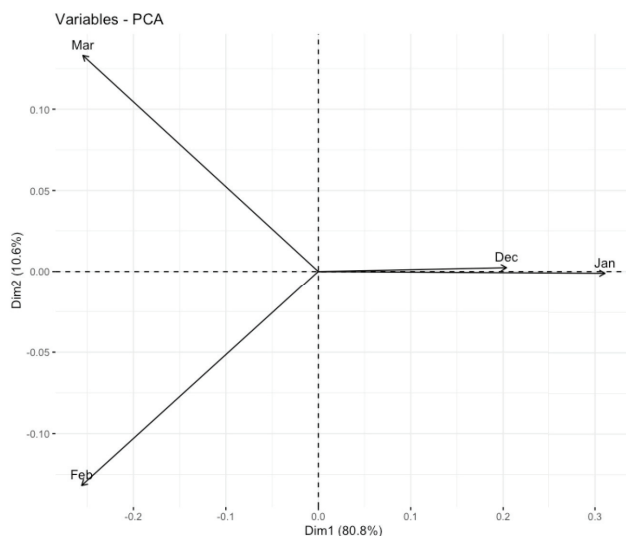


Figure 10: PCA Biplot showing correlation of collection date and individual snow volumes for all conifer samples and sites.

Difference Across Aspen & Conifer Forests

Linear mixed model results revealed that intercepted snow volume in aspen v. conifer trees were significantly different (LMM, $df = 434$, $X^2 = 31.8$, $p < 0.0001$). On average, aspen trees intercepted an order of magnitude less snow than conifer species, and TLS derived maps of snowpack depth showed that aspen sites had 22% greater snow depth on average (0.15 - 0.34 m across dates) compared to the conifer plots. The limited interception rates coupled with the snow retention benefits of decreased wind speed and incoming solar radiation enhance snow depth in aspen forests during the accumulation season compared to conifer stands.

To determine statistical significance across the different groups in our study, it was most appropriate to use the model generated p-values from the linear mixed model fit by maximum likelihood using Satterthwaite's method. These tests were used in lieu of traditional T-Tests and ANOVA, which were less appropriate given our data structure.

Data Group	Statistical Test	P value	Statistical Difference
<i>Intercepted Snow by Conifer Site</i>	Linear Mixed Model	0.2 – 0.4 ($X^2 = 0.18$)	No
<i>Intercepted Snow by Date</i>	Linear Mixed Model	0.06 – 0.20	No
<i>Intercepted Snow by Conifer Species</i>	Linear Mixed Model	0.10 (Spruce-Fir) 9e-4 (Lodgepole-Fir)	Yes, Fir trees different than Lodgepole
<i>Intercepted Snow by Vertical Structure</i>	Linear Mixed Model	Rumple 0.06 Taper 0.01 VCI 0.05	Yes (3/9)
<i>Intercepted Snow by Horizontal Structure</i>	Linear Mixed Model	<i>Neighbors</i> Rumple 1.46e-11 uMCH 1.01e-09 Top Rugosity 1e-05	Yes (7/12)

Table 4: Analysis groups and significance levels

Conifer Tree Species

Species level differences lead to diverging trends in how structural metrics and tree size correlated with intercepted snow volume. To investigate this issue, we chose to incorporate our

size term in an interactive, fixed effect with tree species: “crown area * tree species”; the resulting models gave us strong support for a modelling approach that included “area * species”, yielding p values of 0.01 & 9e-4 respectively, well below our desired significance level of $p < 0.05$. The categorical variable of 3 conifer species built each model using Subalpine Fir trees as the reference case which in turn produced a low but insignificant p-value of 0.10 for Engelmann Spruce trees and a very low, significant p-value of 9e-4 for Lodgepole Pine samples. These p-values indicate the probability that our null hypothesis is true: “Conifer tree species alone *does not* have a statistically significant effect on intercepted snow volume, when included as an interactive term with crown area”; which we are able to reject for observations of the conifer species of Subalpine Fir.

Between the three conifer species we sampled across our sites, only one tree species, Subalpine Fir, was shown to intercept significantly different volumes of snow than other select conifer tree species when tree size was included in our statistical models. Volumes of intercepted snow in Subalpine Fir canopies were 1.84 m³ on average compared to 1.77 m³ and 1.66 m³ for Engelmann Spruce and Lodgepole Pine respectively. Overall, the mean and median raw volumes of intercepted snow followed a trend of Fir > Spruce > Lodgepole all with similar wide spreads of values in the interquartile range (1.05 – 1.15) compared to their means.

<u>Random Effects</u>	Groups	Statistic	Variance	Std.Dev.	Obs:Groups
	Site:Date	(Intercept)	0.05255	0.2292	
		Residual	0.47684	0.6905	247 : 16
<u>Fixed Effects</u>	Estimate	Std. Error	df	t-value	Pr(> t)
<i>(Intercept)</i>	1.499596	0.180089	200.366057	8.327	1.29E-14
<i>area25_off</i>	0.014697	0.006094	232.749793	2.412	0.016647
<i>speciesL</i>	0.838173	0.250012	242.997043	3.353	0.000929
<i>speciesS</i>	0.413959	0.251946	240.326166	1.643	0.101681
<i>Crown area:speciesL</i>	-0.027344	0.006829	236.694009	-4.004	8.33E-05
<i>Crown area:speciesS</i>	-0.018391	0.00724	233.538876	-2.54	0.011728

Table 5: Regression Table for Crown Area * Species Interactions.

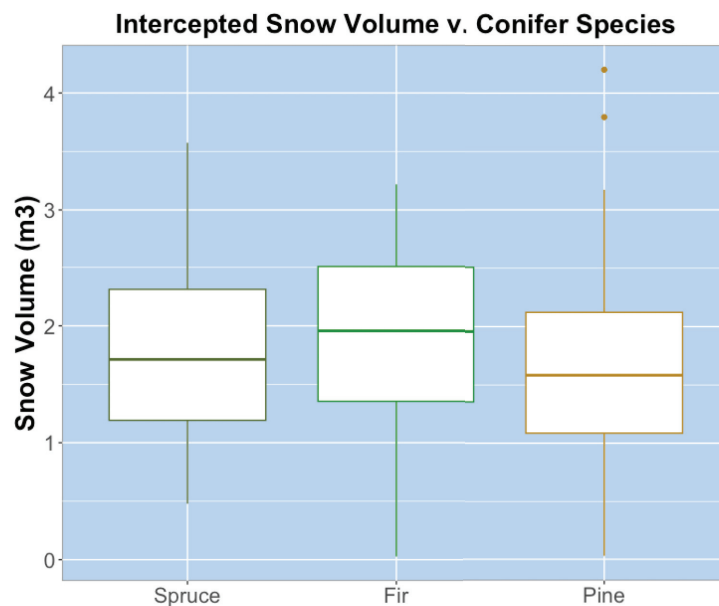


Figure 11: Intercepted Snow Volume versus Conifer Species.

Individual Canopy Structure

Our first scale of structural analysis encompassed calculating 7 metrics to describe vertical structures of individual tree canopies, with these. These structural metrics (defined in Table 2) describe different aspects of how tree mass is distributed throughout the canopy and can be applied to individual trees or averaged across entire forest stands. In this first scale of application, metrics are derived from individual study trees above a height known to be covered by average annual snowpack. We constructed 13 linear mixed effects models in order of complexity to test these structural metrics with the random effect of site and date, then sorted each model result according to its respective AIC (Akaike Information Criterion) model rank.

Equation	lmer(SnowVolume ~ 1 + <i>METRIC</i> + area*species + (1 Site:Date), REML=FALSE)						
Description	Package/Function = lme4 : lmer()						
Where <i>METRIC</i> is 1 distinct LiDAR derived metric from rows below							
Metric	K	AICc	Delta	AICc	Cum.	LL	Pseudo
			AICc	Wt	Wt		R ²
							(Cond)
<i>Rumple</i>	9	536.49	0	0.61	0.61	-258.86	0.21
<i>Taper</i>	9	538.49	2	0.22	0.83	-259.86	0.2
<i>VCI</i>	9	541.52	5.03	0.05	0.88	-261.37	0.18
<i>Area*Species</i>	8	541.77	5.28	0.04	0.93	-262.58	0.18
<i>Vertical</i>	9	543.19	6.7	0.02	0.95	-262.21	0.18
<i>Entropy</i>							
<i>vert.sd</i>	9	543.43	6.94	0.02	0.97	-262.33	0.18
<i>VAI</i>	9	543.73	7.24	0.02	0.98	-262.48	0.17

<i>sd.sd</i>	9	543.92	7.43	0.01	1	-262.57	0.18
<i>Area</i>	4	549.49	13	0	1	-270.66	0.12
<i>Area+Species</i>	6	553.63	17.14	0	1	-270.64	0.12
<i>constant</i>	3	556.3	19.81	0	1	-275.1	0.09
<i>Species</i>	5	557.95	21.46	0	1	-273.85	0.1

Table 6: Individual Conifer Crown Metrics Model selection based on AICc with generic equation & R code included.

The 3 significant metrics that were ranked at the top of our individual canopy models, including all 3 conifer species, were: Rumble – the outer surface area of the canopy compared to underlying 2d ground area; Taper – the mean difference in leaf area density across canopy divided into 10 height bins; and Vertical Complexity Index (VCI) – a fixed normalization of vertical entropy across 1 m slices of the tree canopy. Together, these 3 metrics describe the effective canopy size, the distribution of vegetation density vertically, and the unevenness of canopy structure in the Z dimension.

The results of the Generalized Linear Mixed Models and their pseudo R^2 values were calculated according to Bates et al. (2015) using the following equations:

- Marginal R^2_{GLMM} denotes the variance explained by the fixed effects as calculated from the equation: $R^2_{\text{GLMM (m)}} = \sigma_f^2 / (\sigma_f^2 + \sigma_\alpha^2 + \sigma_\tau^2)$
- Conditional R^2_{GLMM} can be interpreted as the variance explained by both the fixed and random effects as calculated from the equation: $R^2_{\text{GLMM (c)}} = (\sigma_f^2 + \sigma_\alpha^2) / (\sigma_f^2 + \sigma_\alpha^2 + \sigma_\tau^2)$
- Where “ σ_f^2 ” is the variance of the fixed effect components, “ σ_α^2 ” is the variance of the random effects, and “ σ_τ^2 ” is the “observation-level” variance.

Analysis of interception values across each individual conifer species revealed that no two tree species shared a top ranked structural metric – here we describe the top ranked metrics and their relative conditional pseudo R^2 values for each species:

Species	Top	K	AICc	Delta	AICc	Cum.	LL	Pseudo	Equation
	Metric			AICc	Wt	Wt		R ²	
<i>Spruce</i>	Rumple	5	189.45	0	0.79	0.79	-89.36	0.22	lmer(SnowVolume ~ 1 + Rumple + Area + (1 Site:Date), REML=FALSE)
<i>Pine</i>	Rumple	5	203.67	0	1	1	-96.52	0.41	lmer(SnowVolume ~ 1 + Rumple + Area + (1 Site:Date), REML=FALSE)
<i>Fir</i>	Taper	5	118.04	0	0.93	0.93	-53.38	0.46	lmer(SnowVolume ~ 1 + Taper+ Area + (1 Site:Date), REML=FALSE)

Table 7: Individual Crown Metric Model Regression table based on AICc for Conifer Species.

Subalpine Fir trees ranked Taper as the most predictive metric, with a pseudo R^2 value of 0.46 and RMSE of 0.62 m³. Taper was a novel metric we calculated that divides a tree crown vertically into 10 even height bins, then calculates the mean difference in Leaf Area Density (LAD) between each successive bin using the equation: $Taper = u(\sum^{10} \Delta$

LAD). Taper describes how tree mass decreases or “Tapers” moving vertically through the crown, where lower negative values indicate greater tapering and higher values closer to zero indicate less tapering vertically. Fir trees exhibited a positive correlation between intercepted snow volume and Taper, implying that for this species the more even branch & needle area is along the Z axis, the more snow Fir canopies intercept.

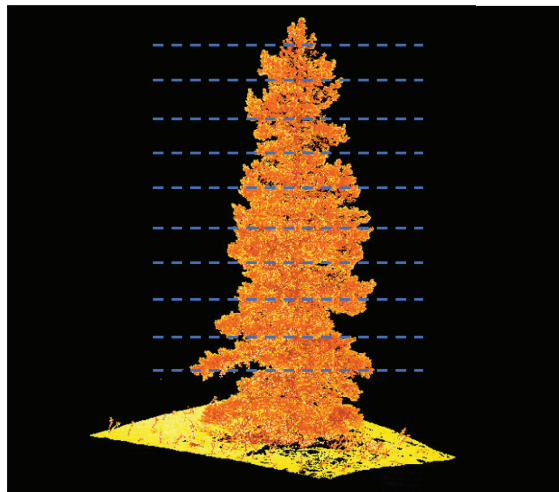


Figure 12: Visualized TLS Point Cloud with height bins used for calculating Leaf Area Density and Taper

Lodgepole Pine metrics ranked “Rumple Index” as the highest performing model, with a pseudo R^2 value of 0.41 and an RMSE of 0.54 m^3 . Interestingly, canopy snow volumes in Lodgepole Pine were negatively correlated with increases in tree size (area, surface area, and height), implying that Lodgepole lose interception potential as they mature and grow. The highest ranked model variable, “Rumple Index”, is a calculation of outer canopy surface area compared to effective 2D ground area below the canopy. Our hypothesis to why Lodgepole trees intercept less snow as they grow larger is that the lack of branch width taper in their allometry forms roof structures over lower branches – limiting interception. Lodgepole individuals that are not crowded by other trees tend to grow wide

canopies even at the top of the tree crown, which may inhibit canopy snow capture. An additional theory is that the wider Lodgepole canopies grown, and the longer branches become, the less consolidated branch material like sub-branches (twigs) and pine needles are spaced; therefore limiting the adhesion and subsequent cohesion of incoming snowflakes. A caveat to this observation is that many of the Pine trees included in this study lacked diversity in size class and presumably age (following the adage that Lodgepole Pine “live together & die together” uniformly); this means that of the Lodgepole Pine in our studied size class, those that grew wider saw decreases in interception potential.

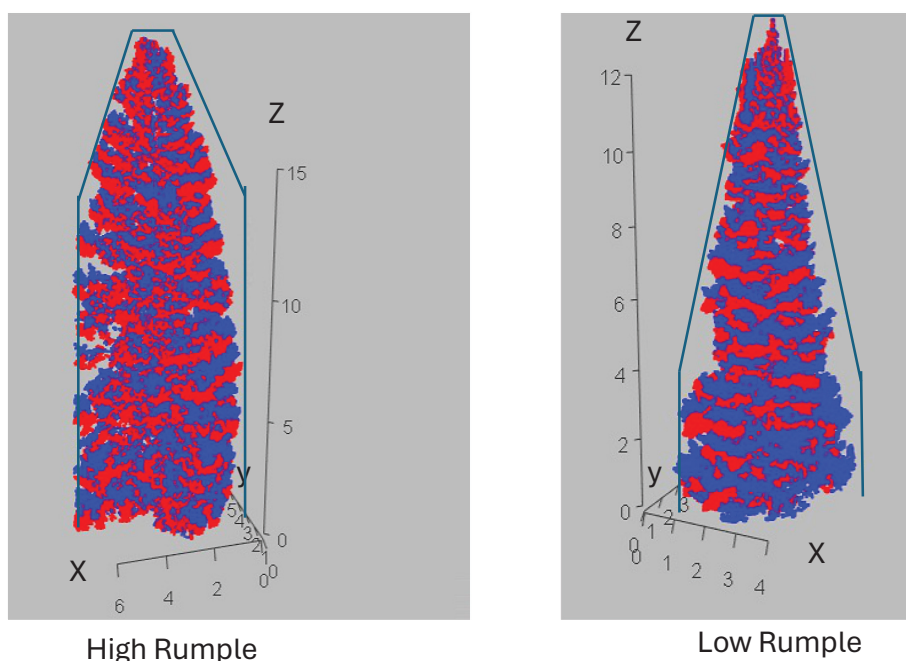


Figure 13: Merged Snow-Off (blue) & Snow-On (red) point clouds showing High v. Low surface area trees which translate to Rumple Index values.

Engelmann Spruce trees also demonstrated a counterintuitive trend in losing interception potential as they grew larger. The highest AIC ranked individual canopy metric for Spruce trees was also Rumple Index, which each described an estimated ~22% of variance in canopy snow volumes, with an RMSE of 0.6 m³. Once again Rumple had a

negative correlation with intercepted snow volume, suggesting that more dense and compact Spruce crowns would intercept more snow than trees spread out wider, with a higher surface area. Another high performing metric for spruce trees was “Taper” which yielded similar R^2 & RMSE value to Rumpel. In contrast to the effect of Taper on interception potential in Fir trees, Spruce trees exhibited a negative correlation with Taper values, indicating that Spruce crowns with more vertical Taper intercept more snow.

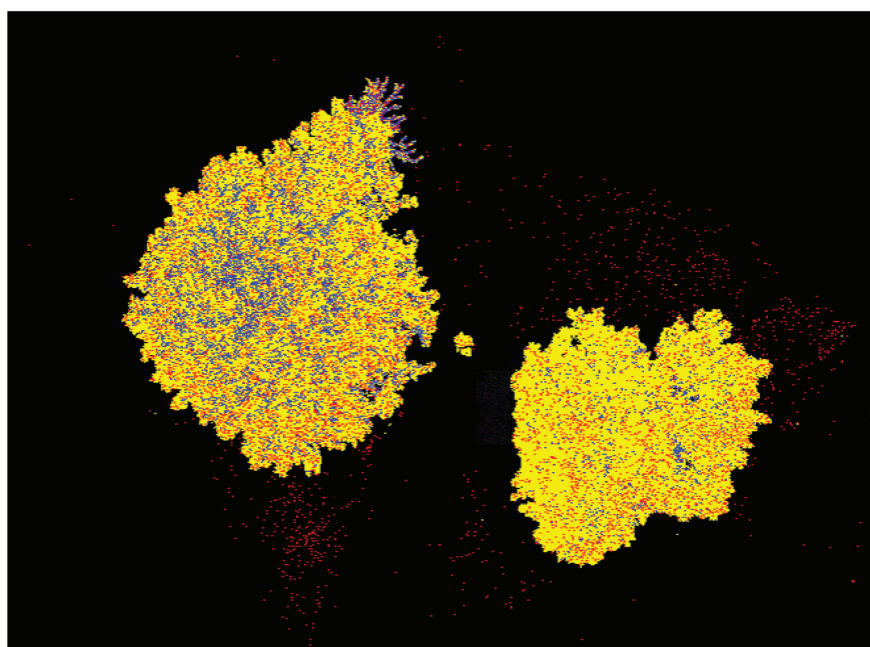


Figure 14: Birdseye view of LiDAR retrievals visualized in Near Infrared Reflectance for a relatively wide (left) vs. thin (right) crown. Darker Colors indicate higher reflectance values typical of tree matter not occluded by snow.

When we ran the model selection purposefully without including conifer species, we saw a slight rearranging of 3 prior top metrics and a meaningful reduction of our pseudo R^2 values:

Metric	K	AICc	Delta	AICc	Cum.	LL	Pseudo
			AICc	Wt	Wt		R2

Taper	5	539.04	0	0.91	0.91	-264.39	0.17
VCI	5	544.72	5.68	0.05	0.96	-267.23	0.13
vert.sd	5	548.43	9.4	0.01	0.97	-269.09	0.12
Rump	5	549.01	9.97	0.01	0.97	-269.38	0.13

Metric	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	2.407216	0.161437	160.645097	14.911	2.60E-16
Taper	2.558495	0.711488	232.722726	3.596	0.000395
Voll	-0.009137	0.00213	237.886887	-4.29	2.60E-05

Table 8: Model Selection Results & Model Regression Table for top performing metrics when excluding Conifer species.

Neighboring Canopy Structure

The next scale of forest structure metrics we chose to test expanded structural analysis in a circle around each individual study tree with a radius equal to the total height of that tree. This approach of measuring neighboring trees has been used in seed dispersal and allometric studies, as the effective radius represents nearby trees most likely to influence different processes specific to each individual tree. We chose to omit the “focal” study tree from each buffer as to collect details on surrounding canopy structure independent of the sample tree. We used 13 metrics described in the methods section, half of which are scaled-up versions of the 7 vertical metrics for individual tree crowns described above – but applied to all surrounding trees to describe average structure of neighboring trees. In a similar mixed effects model approach to the individual-scale analysis, we tested each neighboring tree structure variable with the fixed, interactive effect of tree area * species built on top of the strongest, 3 metric model of Individual

Crown variables. We also included the original, individual canopy metrics in our list of models to directly test their performance against the neighboring tree variables.

Metric	K	AICc	Delta	AICc	Cum.	LL	Pseudo
			AICc	Wt	Wt		R²
RumpN	12	488.13	0	0.98	0.98	-231.39	0.37
ENTRON	12	496.05	7.92	0.02	1	-235.35	0.34
uMCN	12	501.79	13.66	0	1	-238.22	0.36
VAIN	12	506.26	18.13	0	1	-240.45	0.31
GFPN	12	508.51	20.38	0	1	-241.58	0.3
SDN	12	509.24	21.11	0	1	-241.94	0.33
VCIN	12	509.57	21.44	0	1	-242.11	0.32
TRN	12	513.53	25.4	0	1	-244.09	0.32
MCHN	12	514.33	26.2	0	1	-244.49	0.3
VsdN	12	518.34	30.2	0	1	-246.49	0.3
CFN	12	518.85	30.72	0	1	-246.75	0.3
DGFN	12	518.85	30.72	0	1	-246.75	0.3

Table 9: Neighbor Conifer Crown Metrics Model selection

Best Model Equation	lmer(SnowVolume ~ 1 + RumpN + RumpL + Taper +
(Using top Neighbor and top 3 Individual metrics)	VCI + area*species + (1 Site:Date), REML=FALSE)

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	4.018444	0.687273	103.834914	5.847	5.85E-08
RumpN	-0.166586	0.029004	241.552344	-5.744	2.77E-08
rumpL	-0.018235	0.04308	238.688943	-0.423	0.672461
Taper	3.845679	1.040955	184.059737	3.694	0.000291
VCI	-1.25749	0.940005	85.66318	-1.338	0.184519
Area	-0.001643	0.006181	232.592055	-0.266	0.790666
speciesL	0.866084	0.25534	242.389897	3.392	0.00081
speciesS	0.302613	0.243501	241.557789	1.243	0.215161
Area:speciesL	-0.021294	0.006642	235.983932	-3.206	0.001531
Area:speciesS	-0.010793	0.006923	240.685624	-1.559	0.120326

Table 10: Conifer Metrics Model Regression Table - built on best Individual Crown Metrics & top Neighbor combined model.

The resulting model table showed that the majority of neighboring forest metrics outperformed all but 3 individual canopy metrics (RumpL, Taper, and VCI) and that RumpL, and more broadly, the size of neighboring trees was negatively correlated with intercepted snow. RumpL of Neighbors (RumpN) yielded a pseudo R^2 value = 0.34 (RMSE 0.61 m³) which outperformed the estimated predictive ability of any individual vertical canopy metric. A handful of other neighboring metrics were highly ranked and showed a modest predictive ability as well. There were, however, somewhat expected high levels of multicollinearity amongst these top variables – as they were all influenced by the size of neighboring trees. One exception was “EntroN” – the

entropy of neighboring canopies, which had one of the more limited correlations with RumpN ($R^2 = 0.34$) and was positively correlated with interception potential across all tree species with an estimated $R^2 = 0.24$ (RMSE 0.65 m^3).

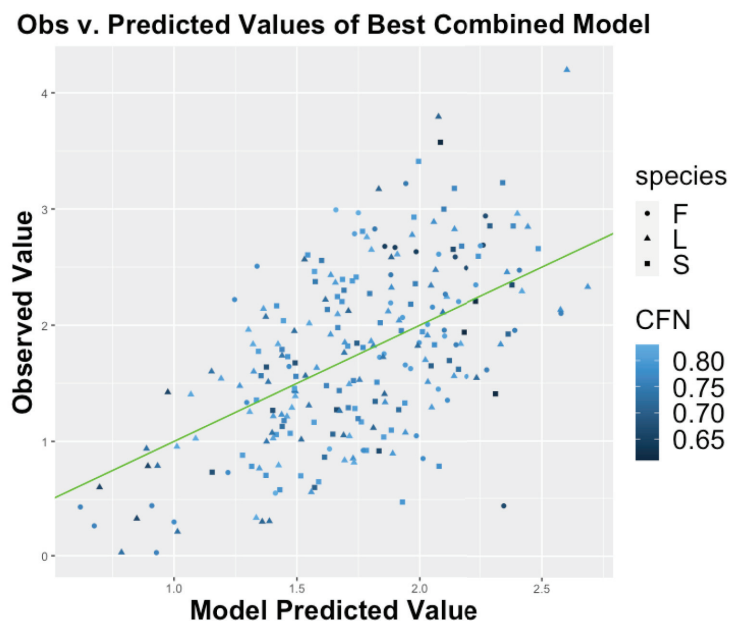


Figure 15: Results for Mixed Effects model using Neighbor Canopy RumpN & 3 best Individual Crown Metrics ($R^2 = 0.37$); green trendline = 1:1 line. With species and Cover Fraction of Neighboring tree stand (CFN) visualized.

A noteworthy observation from the comparison of individual canopy vs. neighboring tree metrics is that the trends of highly ranked neighboring tree metrics were shared across all conifer species, unlike the individual canopy metrics, which varied in importance across species. Additionally, models combining the effects of different structural metrics revealed that adding the 3 top ranked individual canopy metrics bolstered estimated model R^2 values and demonstrated a significant model improvement using a likelihood ratio test (package *lme4* : *lrtest*). This was a pronounced difference from neighboring metrics, as adding together the top ranked effects of the surrounding canopy did not improve model performance significantly (likelihood ratio p-values > 0.05).

However, adding the 3 top ranked individual tree metrics and the top ranked neighboring metric allowed a combined model to reach an estimated R^2 value of 0.37 (RMSE = 0.59 m³).

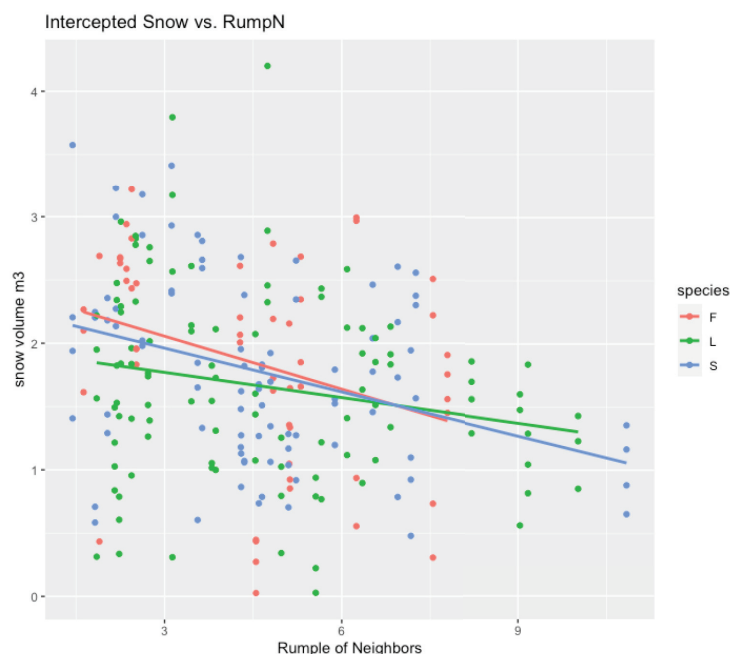


Figure 16: Shared trends in Neighbor Canopy RumpN v. Interception Potential across all Conifer Tree Species.

Analysis of Isolated Trees

Our results vary drastically from those found by Russell et al. 2021, but a primary difference in our study is the inclusion of trees that are part of continuous forest stands rather than isolated tree specimens. When we completed an identical analysis on a subset of study trees that were devoid of neighboring canopies, we found much higher estimated R^2 values of 0.60 (RMSE 0.48 m³) for the highest rank model variable of VCI. This boost in predictive power yields similar model strength to Russell 2021 with a similar number of samples, except that the metrics the Russell study found to be most predictive were Canopy Base Height & Maximum Canopy Height; we found that VCI had a higher AIC rank and a higher estimated R^2 value for our dataset.

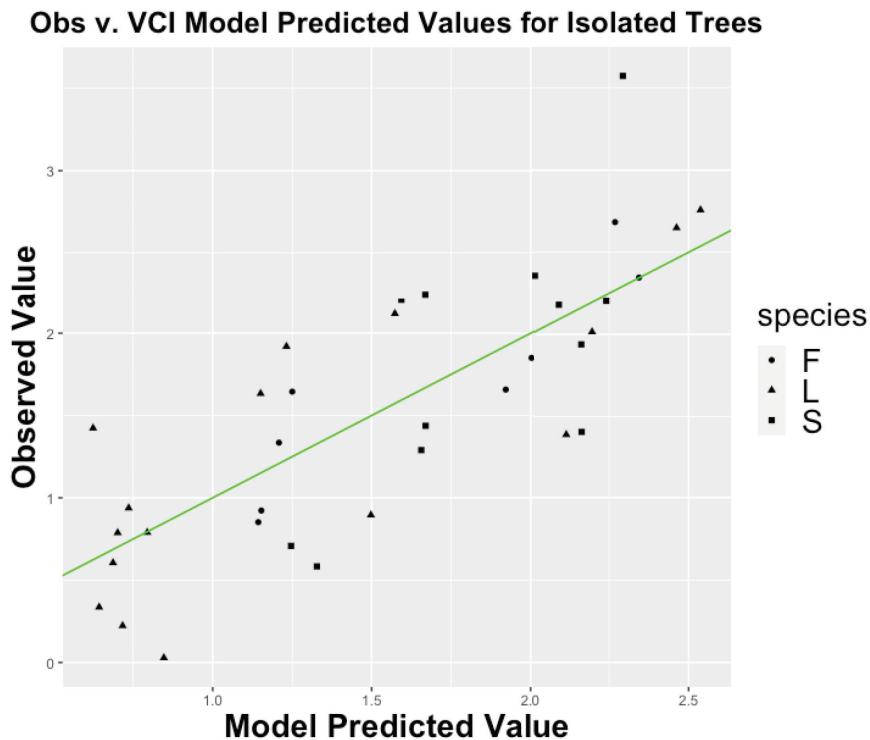


Figure 17: VCI Model Results for Isolated Conifer Crowns; green trendline = 1:1 line.

Similarly to individual canopy metrics applied across the entire sample pool, the trends for VCI versus. Intercepted Snow for isolated trees exhibited competing directionality depending on conifer tree species. For Spruce and Pine trees, vertical complexity was positively correlated with intercepted snow (since lower values = more complex), indicating that the more diverse vertical canopy spacing resulted in more intercepted snow. Fir trees however showed an opposing trend, where more even vertical canopy spacing promoted greater interception potential.

Analysis of Weather Variables

The nearby Snodgrass “Open” Weather station (operated by Oregon State University and the Watershed Function SFA) provided QA/QC verified hourly weather variables that quantify meteorologic, precipitation, and snowpack properties. We chose 7 weather station variables

(Table 12) to describe weather conditions antecedent to and concurrent with our TLS collections; these variables summarize the previous storm event and air temperature at the time of post storm LiDAR acquisition. Although the number of LiDAR acquisition timepoints were not enough to satisfy a statistical observation to variable of 5:1 or greater, the weather station data nonetheless provides a characterization of storm events and a glimpse into what weather variables may influence canopy snow interception.

Variable Name	Description
ΔHS	Change in Snow Height on ground pre/post storm
Total SWE	Total precipitation SWE from Storm Event
New Snow Density	Density of snow from storm event (ΔHS /Total SWE)
Max Wind Speed	Maximum Wind Gust Speed during Storm Event
Mean Storm Temp	Average Air Temperature during Storm Event
Mean Storm RH	Average Relative Humidity during Storm Event
Collection Temp u	Average Air Temperature during TLS Collection post-storm

Table 12: Weather Variables Tested

	<u>ΔHS</u>	<u>ΔSWE</u>	<u>Density</u>	<u>Max Wind</u>	<u>Mean Storm</u>	<u>Mean</u>	<u>Mean</u>
				<u>Speed</u>	<u>Temperature</u>	<u>Storm</u>	<u>Collection</u>
						<u>RH</u>	<u>Temperature</u>
Dec	<u>37.81</u>	<u>5.35</u>	<u>0.14</u>	<u>4.76</u>	<u>-8.75</u>	<u>86.80</u>	<u>-4.60</u>
Jan	<u>56.39</u>	<u>6.30</u>	<u>0.11</u>	<u>5.17</u>	<u>-11.36</u>	<u>89.35</u>	<u>-11.43</u>
Feb	<u>25.23</u>	<u>1.94</u>	<u>0.08</u>	<u>8.45</u>	<u>-8.58</u>	<u>81.04</u>	<u>-14.07</u>
Mar	<u>53.63</u>	<u>8.43</u>	<u>0.16</u>	<u>14.69</u>	<u>-5.26</u>	<u>86.02</u>	<u>-2.47</u>

Table 13: Summary Table of the 4 storm events captured in this study.

Of the weather variables tested, Average Storm Temperature was the highest rank model variable in a linear mixed effects model of all interception observations that included Site as a random

effect. In our generalized statistical models, our results *did* produce a significant difference between the lowest intercepted snow date (Jan 2024) and the highest date (Mar 2023), with the Jan date being the coldest storm temperature and Mar being the warmest. Due to limited observations, we did not pursue additional analysis of these differences, but note that the most apparent meteorological distinction between the two significantly different collection dates was average air temperature during the storm events.

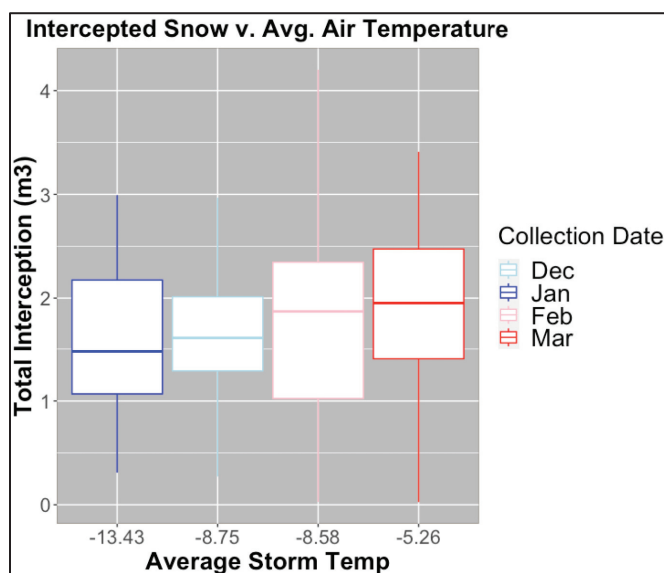


Figure 18: Top model ranked weather variable (Average Storm Air Temperature) vs. total canopy snow volume across all Conifer samples & sites.

Discussion

This study sought to capture rates and characteristics of canopy snow interception, a first order component of forest-snow interactions, in a mountain watershed representative of many high elevation areas throughout the Colorado River Basin. At sites of similar elevation, aspect, and geographic position we observed an order of magnitude less intercepted snow in the canopies of aspen versus conifer trees, while observing relatively similar volumes of intercepted snow across 3 conifer tree species. When volumes of intercepted snow were normalized by the effective 2-dimensional area they cover, we were able to estimate that aspen and conifer canopies

intercepted up to 3 mm vs. 3 cm of snow water equivalent (SWE) respectively across the observed timepoints. These estimates of canopy SWE translate to aspen and conifer trees intercepting 0.4% and 14% of total precipitation SWE by effective canopy area on average from the 4 storm events we quantified.



Figure 19: Terrestrial Laser Scanner amongst the mixed conifer forests at Site 3.

Crown size and tree species were shown to be important factors in interception potential and were therefore included as terms in our statistical models that showed both individual crown metrics and neighboring canopy metrics were significantly correlated with canopy snow volumes. Our three top ranked individual canopy metrics (Rumple, Taper, and VCI) describe the canopy surface area, vertical taper in vegetation density, and the vertical complexity of tree matter and explain approximately 1/3 of variance of interception when included together in a

combined model. Likewise, our top ranked metrics of neighboring forest structure had an upper predictive threshold at an estimated R^2 of 0.34, given that it did not add statistical power to add multiple neighbor metrics to combined model. When appropriate individual and neighboring metrics were included in the same model, they could explain up to 37% of the variance in interception for 120 individual trees across all sites, dates, and conifer tree species included in this study.

Deciduous v. Coniferous Trees Implications

The drastic difference in interception rates of the deciduous trees (Quaking Aspen) versus the coniferous trees (Engelmann Spruce, Lodgepole Pine, and Subalpine Fir) in our study carry significant implications for forest disturbance and changing forest types. The heterogeneity of disturbance varieties and responses, along with competing pathologies specific to different forest compositions, implies that uncertainty about aspen versus conifer dominance across mountain watersheds translates to uncertainty whether there will be more or less water resources from snow accumulation. Generally, aspen dominated forest stands can be expected to accumulate more snow depth and SWE due primarily to less canopy snow interception, which we found to be an order of magnitude less than conifer forests.

Conifer Tree Species Implications

Similar to previous studies who found limited variability in interception across different conifer tree species (Satterland & Haupt 1970; Schmidt & Gluns 1991; Storck et al. 2002), we found that Engelmann Spruce and Lodgepole Pine trees did not intercept significantly different volumes of falling snow (although mean interception was higher for Spruce trees). However, we did find that the inclusion of conifer tree species and tree size was a statistically important factor in building

models to predict the volume of intercepted snow. This is because Subalpine Fir trees had significantly different interception potential compared to Lodgepole Pine trees *and* because of a disparity in geometry/size versus interception trends present in Fir versus Spruce/Pine trees. The size and allometry of the Fir trees in this study may represent a stage in Fir tree growth where trees are primed to intercept greater volumes of snow respectively – which could explain why these results deviate from previous studies (Schmidt & Gluns 1991), where Fir trees were equal or greater in size to Spruce/Pine trees. Conversely, Fir tree specific characteristics due to foliar traits and allometry may promote higher interception potential beyond the growth/prominence of Fir trees in this study, in which case our results are markedly different than previous studies who used different techniques to measure intercepted snow amounts. Although the number of trees in our study (of each local species) represents a step forward for observations of interception, we were limited to a relatively smaller sample pool of Fir trees due to their low abundance at our sites compared to Spruce and Pine trees. We analyzed a total of 15 Fir trees compared to ~22 Spruce and Pine trees.

Our analysis of conifer species suggests that there are important species level trends regarding not only intercepted snow volume but also interspecific structural metrics important to canopy interception rates. We found conflicting trends between species for a number of metrics that our model selection deemed significant, these disparities in trends are likely due to differences in the internal structure and allometry of conifer tree species we studied. These trends complicate the large-scale remote sensing of forest structure important for canopy interception, as individual crown level species ID is difficult to extract using common remote-sensing observations, especially.

One example of opposing trends across species was the metric: “Rumple” index (outer canopy surface area versus effective 2-dimensional ground area below the canopy), the overall highest ranked model variable for conifers. Individual crown geometry. Lodgepole Pine and Engelmann Spruce trees exhibited a counterintuitive negative correlation between Rumple and intercepted snow volume, whereas Subalpine Fir trees showed a positive correlation between canopy surface area and interception. Our hypothesis to why Pine/Spruce trees intercept less snow as they grow larger is that the lack of branch width taper in their allometry forms roof structures over lower branches – limiting interception. These canopies can grow very wide when not competing with other tightly spaced nearby canopies, even at the top of the tree crown, which may inhibit canopy snow capture. An additional theory is that the wider Pine/Spruce canopies grow and the longer branches become, the less consolidated branch material like sub-branches (twigs) and pine needles are spaced, therefore limiting the adhesion and subsequent cohesion of incoming snowflakes. A caveat to this observation is that many of the Pine trees included in this study lacked diversity in size class and presumably age (following the adage that Lodgepole Pine “live together & die together” uniformly); this means that of Lodgepole Pine in our studied size class, those that grew wider saw decreases in interception potential.

In our attempts to determine how important conifer species ID was for our results we found that the interactive term of species * crown area alone could explain up to 18% of interception differences. Likewise, in our final 4-metric model for all samples, we found that removing the species term dropped our pseudo R^2 from 0.37 to 0.30. Potential next steps for disentangling these species-structure trends could be determining what aspects of interspecific structure

interact and/or “binning” trees by structure to then apply specific metrics thought to be most influential according to structural category.

Conifer Tree Structure Implications

Individual canopy and neighboring tree structure metrics were found to be nearly equally predictive in this study, which suggests both are important factors of canopy snow interception. We found that the size and surface area of neighboring trees inhibits the interception of canopy snow. We hypothesize this is because of reduced wind speeds, which limit the horizontal vector of falling snow, therefore reducing the total canopy surface area it interacts with (Hedstrom & Pomeroy 1998).

We explored the effect of tree structure, size, and species on canopy interception potential and explained 37% of variation across our samples. This result poses the question of what additional effects could be investigated to better predict interception? This question is underscored by our additional analysis on only the isolated trees in our study, where we found that a single structural metric (Vertical Complexity Index) could explain 60% of intercepted snow variation in our smaller sample pool of trees without neighboring canopies. It is possible that a large proportion of the unexplained variation in interception is due to complex spatially dependent effects of neighboring trees. To investigate this hypothesis, we attempted both an aspect classification and subset analysis of neighboring trees in the dominant wind direction of focal trees but did not identify significant trends. Potential avenues for future research on the effects of neighboring canopies, and tree stand position on interception potential, should focus on more sophisticated variables like the directionality of wind during storm events and the orientation of focal trees relative to meadows and the edge of the tree stand (Staines et al. 2023). Novel neighboring

canopy metrics from LiDAR or other remote sensing datasets may also prove useful in identifying elucidating impacts of the local environment on canopy interception.

Extrinsic Weather Variables important for Interception

Our study included limited observations of different weather events due to the limitations of collecting post storm data. However, from the observations we did collect, “average storm temperature” was the highest rank variable. A weak trend was present in the data to suggest that higher air temperatures during storm events is correlated with higher volumes of intercepted snowfall. This conclusion is consistent with previous studies that have shown air temperature has the strongest influence on heterogeneity of canopy snow loading events (Roth et al. 2019; Storck et al. 2002). However, other studies (Storck et al. 2002) have also noted that differences in interception rates are relatively low storm to storm, which was also apparent in our dataset in that just one collection date showed significantly different canopy snow volumes. This could be due to a “maximum loading” threshold in the canopy, where branches and entire tree crowns reach capacity for holding snow caused by either canopy unloading, or perhaps a geometric limitation in how snow accumulates in the canopy due to space available or the actual cohesive properties of the intercepted snow masses (Satterland & Haupt 1967; Hedstrom & Pomeroy 1998).

Successional Species and Changing Structure

The starkest difference in interception rates across the groups we tested was between aspen and conifer trees, with; this dynamic particularly interesting within the context of succession of tree species succession following disturbance. As a fast-growing early successional species, aspen can quickly come to dominance in mixed conifer areas altered by wildfire or other disturbances. In the case of conifer forests converting to aspen forest types, our results suggest significant

increases in SWE availability due to an order of magnitude less canopy interception. An estimate from our intercepted snow totals suggests that a 10% increase in peak snowpack SWE would be reasonable in an aspen versus conifer climax site with the same environmental parameters and total crown area. Leafless winter aspen canopies responsible for limited interception in turn provide less shading effects for an ablating snowpack. This means that we would expect higher SWE totals but earlier snowmelt in aspen versus conifer forests. Future research questions about snowmelt timing for aspen and conifer forests should seek to quantify how earlier or later forest snowmelt influences the relative runoff efficiency of each forest type. “Runoff efficiency” refers to how effectively snowmelt runoff becomes surface water streamflow in the spring via surface and subsurface level pathways. With increased solar radiation under aspen canopies, we would expect runoff from aspen forests to be “flashier” (defined by higher amplitude, but shorter peak) and therefore more efficient as faster snowmelt has been associated with higher runoff efficiency (Musselman et al. 2017).



Figure 20: Interspersed aspen and conifer forests near our sites in the East River Watershed

(credit: Jeremy Snyder – Lawrence Berkeley National Lab).

The pronounced difference in interception potential of Subalpine Fir trees could lead to enhanced stand/forest wide interception rates when forests reach Spruce/Fir climax states after Lodgepole Pine disturbance, a phenomenon which has long been documented in Colorado and mountain regions (Alexander et al. 1986). Spruce and Fir trees are shade tolerant and can grow as a sub-dominant species in the understory of Lodgepole Pine forests. Spruce/Fir successional trajectories often involve becoming the dominant forest type after Lodgepole Pine disturbances like wildfire and insect mortality. In these secondary successional states, we would expect elevated interception rates and relatively diminished SWE values in seasonal snowpack.

Another interesting trend in the data was an unexpected relationship between the size of Spruce and Lodgepole trees and volumes of intercepted snow. For both species we observed a weak, but significant negative correlation in intercepted snow volume with the total height and area of the tree. We attribute this counterintuitive trend to the decreases in vegetation density and complexity as these trees reach their maximum heights in this area. That we did not witness this trend in Fir trees (which were generally smaller and less dominant in our study area) implies that there may be an inflection point in interception potential as these conifer trees mature, -- a threshold that most Fir trees in our study had not yet reached. This could also explain the difference in our results as compared to Schimdt and Gluns et al. 1991 who found a) that these 3 species intercepted insignificantly different amounts of snow in Colorado and British Columbia, and b) that the overall ranking was Spruce > Lodgepole > Fir where the largest tree species by area in their study was Subalpine Fir. Future studies should seek to better elucidate the size

allometry effects on interception rates by collecting observations across a wider range of crown sizes for each conifer tree species.

Assumptions and Uncertainties

Given the variable nature of canopy snow and the complexities of measuring canopy snow volume with LiDAR datasets, our study built upon necessary assumptions of our measurements to attain the spatial and temporal scales of observations we achieved. In measuring *interception potential* we deliberately chose not to investigate the residence time and fate of canopy snow and snow water equivalent, instead making the assumption that canopy snow across our study groups goes through similar processes. Future studies could seek to quantify the processes by collecting iterative measurements across shorter timescales to measure changes to canopy snow.

Additionally, the use of snow sampling and stable water isotope analysis may offer insights into the rates of phase change and metamorphoses canopy snow undertakes. We utilized the *combined point cloud* method developed by Russell et al. (2020) to calculate canopy snow volume while accounting for branch deformation and occlusion of LiDAR pulses by snow. This method comes with assumptions and uncertainties, but the original authors attempted to address this by validating the method with direct measurements of snow mass & density yielded a strong correlation with LiDAR calculated snow volume. We attempted to develop our own method by testing several novel methods of TLS based snow volume calculations (including changes to crown circumference/surface area and filtering LiDAR returns by intensity), but found that the level of noise and uncertainty introduced by these novel techniques was prohibitive. Studies in the future could: a) seek to further validate the combined point cloud method with a new scale of

comparable measurements, or b) develop a novel technique that reduces the assumptions needed to calculate canopy snow.

Conclusions

Shifting climate regimes in the 21st century have the ability to propagate change throughout landscapes and ecosystems thereby, impacting the ecosystem services they provide for flora, fauna, and humanity. Mountain regions, which serve as “water towers” for much of society and the natural world, are experiencing the effects of global climate change in a more intense and faster manner than many other landscape types. The ecological and hydrological changes to these landscapes (like mountain forests) that are spurred by changing climate regimes can interact with and amplify one another making for an uncertain future for the natural services these systems provide.

Studying canopy snow interception and forest-snow interactions is a nuanced and challenging field due to the myriad competing effects and the fast-changing nature of snow conditions in and below the forest canopy. This study represents an important addition to the existing body of literature on canopy snow interception that dates back to the 1920s (Bates et al. 1922) and proposes the novel goal of testing the effects of forest composition, forest structure, and weather conditions on canopy interception rates by accomplishing TLS measurements of snow in tree canopies rather than on the ground from the individual crown to tree stand level. One of the primary objectives of this endeavor was to advance the Terrestrial Laser Scanning techniques developed by Russell et al. 2020, 2021 by broadening the spatial and temporal scale of

observations, as well as designing a semi-automated, reproducible computing workflow to allow for greater sample sizes and diverse observations.

Our novel comparison of intercepted snow volumes between the primary deciduous vs. coniferous tree species in this area revealed that Quaking Aspen canopies intercept an order of magnitude less snow than conifer Forests. This implies that, as a short-term successional species, Quaking Aspen becoming dominant in the wake of conifer forest disturbance will lead significantly greater SWE accumulation in forest environments.

Our results indicate that vertical crown structure, neighboring stand structure, and conifer tree species are all integral controls on canopy snow interception. Additionally, our findings revealed that the primary weather condition that influences interception rates is storm temperature; however, our results indicate that, overall, weather variables play a relatively minor role in major mid-winter interception rates. Unlike conifer species identification, metrics and indices of vertical canopy structure can be attained via multiple scales of remote sensing and applied across broader spatial domains to improve modelling estimates of canopy snow interception.

The results of our analysis of interception potential using Terrestrial Laser Scanning and linear mixed modelling deviate from existing literature, suggesting that there can be significant differences in interception rates between conifer tree species, with Subalpine Fir having the greatest interception potential. However, our results suggest that the age and overall size of conifer trees play a nuanced role in interception potential and that mature trees may see an

inflection point wherein their interception potential no longer increases but may instead decrease with size.

The management of pre- and post-disturbance forests in the Anthropocene poses a unique challenge and opportunity for forest and water managers, as shifting ecologic and hydrologic functions. A predictive understanding of forest composition and structural trajectories and their associated interactions with snow and water gives resource managers a roadmap to new climate realities *and* the potential opportunity to proactively manage forests according to the ecologic and hydrologic futures best suited for ecosystems and society.

Works Cited

- Alexander, R. R. (1986). Silvicultural systems and cutting methods for old-growth spruce-fir forests in the central and southern Rocky Mountains (Vol. 126). US Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station
- Andrus, R. A., Hart, S. J., Tutland, N., & Veblen, T. T. (2021). Future dominance by quaking aspen expected following short-interval, compounded disturbance interaction. *Ecosphere*, 12(1), e03345. <https://doi.org/10.1002/ecs2.3345>
- Baker, E. H., Raleigh, M. S., & Molotch, N. P. (2014, December). Quantifying widespread canopy cover decline through the course of a beetle kill epidemic in Colorado with remote sensing of snow. In AGU Fall Meeting Abstracts (Vol. 2014, pp. H51H-0704).
- Bates, C. G., & Henry, A. J. (1921). STREAMFLOW AT WAGON WHEEL GAP, COLO. ¹. *Monthly Weather Review*, 49(12), 637–650. [https://doi.org/10.1175/1520-0493\(1921\)49<637:SAWWGC>2.0.CO;2](https://doi.org/10.1175/1520-0493(1921)49<637:SAWWGC>2.0.CO;2)

- Bates D, Mächler M, Bolker B, Walker S (2015). “Fitting Linear Mixed-Effects Models Using lme4.” *Journal of Statistical Software*, **67**(1), 1–48. [doi:10.18637/jss.v067.i01](https://doi.org/10.18637/jss.v067.i01).
- Bisbing, S. M., Buma, B. J., Oakes, L. E., Krapek, J., & Bidlack, A. L. (2019). From canopy to seed: Loss of snow drives directional changes in forest composition. *Ecology and Evolution*, **9**(14), 8157–8174. <https://doi.org/10.1002/ece3.5383>
- Bonner, H. M., Smyth, E., Raleigh, M. S., & Small, E. E. (2022). A Meteorology and Snow Data Set From Adjacent Forested and Meadow Sites at Crested Butte, CO, USA. *Water Resources Research*, **58**(9), e2022WR033006. <https://doi.org/10.1029/2022WR033006>
- Broxton, P. D., Harpold, A. A., Biederman, J. A., Troch, P. A., Molotch, N. P., & Brooks, P. D. (2015). Quantifying the effects of vegetation structure on snow accumulation and ablation in mixed-conifer forests. *Ecohydrology*, **8**(6), 1073–1094. <https://doi.org/10.1002/eco.1565>
- Bruggisser, M., Hollaus, M., Kükenbrink, D., & Pfeifer, N. (2019). COMPARISON OF FOREST STRUCTURE METRICS DERIVED FROM UAV LIDAR AND ALS DATA. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, **IV-2/W5**, 325–332. <https://doi.org/10.5194/isprs-annals-IV-2-W5-325-2019>
- Buma, B., Hennon, P. E., Harrington, C. A., Popkin, J. R., Krapek, J., Lamb, M. S., Oakes, L. E., Saunders, S., & Zeglen, S. (2017). Emerging climate-driven disturbance processes: Widespread mortality associated with snow-to-rain transitions across 10° of latitude and half the range of a climate-threatened conifer. *Global Change Biology*, **23**(7), 2903–2914. <https://doi.org/10.1111/gcb.13555>
- Calders, K., Adams, J., Armston, J., Bartholomeus, H., Bauwens, S., Bentley, L. P., Chave, J., Danson, F. M., Demol, M., Disney, M., Gaulton, R., Krishna Moorthy, S. M., Levick, S. R., Saarinen, N., Schaaf, C., Stovall, A., Terryn, L., Wilkes, P., & Verbeeck, H. (2020).

- Terrestrial laser scanning in forest ecology: Expanding the horizon. *Remote Sensing of Environment*, 251, 112102. <https://doi.org/10.1016/j.rse.2020.112102>
- Currier, W. R., & Lundquist, J. D. (2018). Snow Depth Variability at the Forest Edge in Multiple Climates in the Western United States. *Water Resources Research*, 54(11), 8756–8773. <https://doi.org/10.1029/2018WR022553>
- Dalponte, M., & Coomes, D. A. (2016). Tree-centric mapping of forest carbon density from airborne laser scanning and hyperspectral data. *Methods in ecology and evolution*, 7(10), 1236-1245.
- Deems, J. S., Painter, T. H., & Finnegan, D. C. (2013). Lidar measurement of snow depth: A review. *Journal of Glaciology*, 59(215), 467–479. <https://doi.org/10.3189/2013JoG12J154>
- Ferraz, A., Saatchi, S., Bormann, K. J., & Painter, T. H. (2018). Fusion of Multiple Low-Resolution NASA Airborne Snow Observatory (ASO) Lidar Data for Forest Vegetation Structure Characterization. *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 7532–7535. <https://doi.org/10.1109/IGARSS.2018.8518983>
- Hale, K. E., Jennings, K. S., Musselman, K. N., Livneh, B., & Molotch, N. P. (2023). Recent decreases in snow water storage in western North America. *Communications Earth & Environment*, 4(1), 170. <https://doi.org/10.1038/s43247-023-00751-3>
- Harpold, A. A., Marshall, J. A., Lyon, S. W., Barnhart, T. B., Fisher, B. A., Donovan, M., Brubaker, K. M., Crosby, C. J., Glenn, N. F., Glennie, C. L., Kirchner, P. B., Lam, N., Mankoff, K. D., McCreight, J. L., Molotch, N. P., Musselman, K. N., Pelletier, J., Russo, T., Sangireddy, H., ... West, N. (2015). Laser vision: Lidar as a transformative tool to advance critical zone science. *Hydrology and Earth System Sciences*, 19(6), 2881–2897. <https://doi.org/10.5194/hess-19-2881-2015>

- Hartmann, H., Bastos, A., Das, A. J., Esquivel-Muelbert, A., Hammond, W. M., Martínez-Vilalta, J., McDowell, N. G., Powers, J. S., Pugh, T. A. M., Ruthrof, K. X., & Allen, C. D. (2022). Climate Change Risks to Global Forest Health: Emergence of Unexpected Events of Elevated Tree Mortality Worldwide. *Annual Review of Plant Biology*, 73(1), 673–702. <https://doi.org/10.1146/annurev-arplant-102820-012804>
- Hartzell, P. J., Gadomski, P. J., Glennie, C. L., Finnegan, D. C., & Deems, J. S. (2015). Rigorous error propagation for terrestrial laser scanning with application to snow volume uncertainty. *Journal of Glaciology*, 61(230), 1147–1158. <https://doi.org/10.3189/2015JoG15J031>
- Hedstrom, N. R., & Pomeroy, J. W. (1998). Measurements and modelling of snow interception in the boreal forest. *Hydrological Processes*, 12(10–11), 1611–1625. [https://doi.org/10.1002/\(SICI\)1099-1085\(199808/09\)12:10/11<1611::AID-HYP684>3.0.CO;2-4](https://doi.org/10.1002/(SICI)1099-1085(199808/09)12:10/11<1611::AID-HYP684>3.0.CO;2-4)
- Helbig, N., Moeser, D., Teich, M., Vincent, L., Lejeune, Y., Sicart, J.-E., & Monnet, J.-M. (2020). Snow processes in mountain forests: Interception modeling for coarse-scale applications. *Hydrology and Earth System Sciences*, 24(5), 2545–2560. <https://doi.org/10.5194/hess-24-2545-2020>
- Hojatimalekshah, A., Uhlmann, Z., Glenn, N. F., Hiemstra, C. A., Tennant, C. J., Graham, J. D., Spaete, L., Gelvin, A., Marshall, H.-P., McNamara, J. P., & Enterkine, J. (2021). Tree canopy and snow depth relationships at fine scales with terrestrial laser scanning. *The Cryosphere*, 15(5), 2187–2209. <https://doi.org/10.5194/tc-15-2187-2021>
- Karna, Y. K., Penman, T. D., Aponte, C., & Bennett, L. T. (2019). Assessing Legacy Effects of Wildfires on the Crown Structure of Fire-Tolerant Eucalypt Trees Using Airborne LiDAR Data. *Remote Sensing*, 11(20), 2433. <https://doi.org/10.3390/rs11202433>

- Krawchuk, M. A., Meigs, G. W., Cartwright, J. M., Coop, J. D., Davis, R., Holz, A., Kolden, C., & Meddens, A. J. (2020). Disturbance refugia within mosaics of forest fire, drought, and insect outbreaks. *Frontiers in Ecology and the Environment*, 18(5), 235–244.
<https://doi.org/10.1002/fee.2190>
- Lafarge T, Pateiro-Lopez B (2023). `_alphashape3d`: Implementation of the 3D Alpha-Shape for the Reconstruction of 3D Sets from a Point Cloud_. R package version 1.3.2, <https://CRAN.R-project.org/package=alphashape3d>
- LaMalfa, E.M., Ryle, R. Differential Snowpack Accumulation and Water Dynamics in Aspen and Conifer Communities: Implications for Water Yield and Ecosystem Function. *Ecosystems* 11, 569–581 (2008). <https://doi.org/10.1007/s10021-008-9143-2>
- López-Moreno, J. I., Revuelto, J., Alonso-González, E., Sanmiguel-Valladolid, A., Fassnacht, S. R., Deems, J., & Morán-Tejeda, E. (2017). Using very long-range terrestrial laser scanner to analyze the temporal consistency of the snowpack distribution in a high mountain environment. *Journal of Mountain Science*, 14(5), 823–842. <https://doi.org/10.1007/s11629-016-4086-0>
- Lundquist, J. D., Dickerson-Lange, S., Gutmann, E., Jonas, T., Lumbrazo, C., & Reynolds, D. (2021). Snow interception modelling: Isolated observations have led to many land surface models lacking appropriate temperature sensitivities. *Hydrological Processes*, 35(7), e14274. <https://doi.org/10.1002/hyp.14274>
- Mankin, J. S., Viviroli, D., Singh, D., Hoekstra, A. Y., & Diffenbaugh, N. S. (2015). The potential for snow to supply human water demand in the present and future. *Environmental Research Letters*, 10(11), 114016. <https://doi.org/10.1088/1748-9326/10/11/114016>

- Manning, A. L., Harpold, A., & Csank, A. (2022). Spruce Beetle Outbreak Increases Streamflow From Snow-Dominated Basins in Southwest Colorado, USA. *Water Resources Research*, 58(5), e2021WR029964. <https://doi.org/10.1029/2021WR029964>
- Marcozzi, A. A., Johnson, J. V., Parsons, R. A., Flanary, S. J., Seielstad, C. A., & Downs, J. Z. (2023a). Application of LiDAR Derived Fuel Cells to Wildfire Modeling at Laboratory Scale. *Fire*, 6(10), 394. <https://doi.org/10.3390/fire6100394>
- Marcozzi, A. A., Johnson, J. V., Parsons, R. A., Flanary, S. J., Seielstad, C. A., & Downs, J. Z. (2023b). Application of LiDAR Derived Fuel Cells to Wildfire Modeling at Laboratory Scale. *Fire*, 6(10), 394. <https://doi.org/10.3390/fire6100394>
- Mazzotti, G., Currier, W. R., Deems, J. S., Pflug, J. M., Lundquist, J. D., & Jonas, T. (2019). Revisiting Snow Cover Variability and Canopy Structure Within Forest Stands: Insights From Airborne Lidar Data. *Water Resources Research*, 55(7), 6198–6216. <https://doi.org/10.1029/2019WR024898>
- Mazzotti, G., Essery, R., Moeser, C. D., & Jonas, T. (2020). Resolving Small-Scale Forest Snow Patterns Using an Energy Balance Snow Model With a One-Layer Canopy. *Water Resources Research*, 56(1), e2019WR026129. <https://doi.org/10.1029/2019WR026129>
- Mazzotti, G., Webster, C., Quéno, L., Cluzet, B., & Jonas, T. (2023). Canopy structure, topography, and weather are equally important drivers of small-scale snow cover dynamics in sub-alpine forests. *Hydrology and Earth System Sciences*, 27(11), 2099–2121. <https://doi.org/10.5194/hess-27-2099-2023>
- McDowell, N. G., Allen, C. D., Anderson-Teixeira, K., Aukema, B. H., Bond-Lamberty, B., Chini, L., Clark, J. S., Dietze, M., Grossiord, C., Hanbury-Brown, A., Hurtt, G. C., Jackson, R. B., Johnson, D. J., Kueppers, L., Lichstein, J. W., Ogle, K., Poulter, B., Pugh, T. A. M.,

- Seidl, R., ... Xu, C. (2020). Pervasive shifts in forest dynamics in a changing world. *Science*, 368(6494), eaaz9463. <https://doi.org/10.1126/science.aaz9463>
- Moeser, C. D., Broxton, P. D., Harpold, A., & Robertson, A. (2020). Estimating the Effects of Forest Structure Changes From Wildfire on Snow Water Resources Under Varying Meteorological Conditions. *Water Resources Research*, 56(11), e2020WR027071. <https://doi.org/10.1029/2020WR027071>
- Moeser, D., Mazzotti, G., Helbig, N., & Jonas, T. (2016). Representing spatial variability of forest snow: Implementation of a new interception model. *Water Resources Research*, 52(2), 1208–1226. <https://doi.org/10.1002/2015WR017961>
- Moeser, D., Morsdorf, F., & Jonas, T. (2015). Novel forest structure metrics from airborne LiDAR data for improved snow interception estimation. *Agricultural and Forest Meteorology*, 208, 40–49. <https://doi.org/10.1016/j.agrformet.2015.04.013>
- Moeser, D., Stähli, M., & Jonas, T. (2015). Improved snow interception modeling using canopy parameters derived from airborne L i D A R data. *Water Resources Research*, 51(7), 5041–5059. <https://doi.org/10.1002/2014WR016724>
- Molotch, N. P., Blanken, P. D., Williams, M. W., Turnipseed, A. A., Monson, R. K., & Margulis, S. A. (2007). Estimating sublimation of intercepted and sub-canopy snow using eddy covariance systems. *Hydrological Processes*, 21(12), 1567–1575. <https://doi.org/10.1002/hyp.6719>
- Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K., & Rasmussen, R. (2017). Slower snowmelt in a warmer world. *Nature Climate Change*, 7(3), 214–219. <https://doi.org/10.1038/nclimate3225>

- Musselman, K. N., Molotch, N. P., & Brooks, P. D. (2008). Effects of vegetation on snow accumulation and ablation in a mid-latitude sub-alpine forest. *Hydrological Processes*, 22(15), 2767–2776. <https://doi.org/10.1002/hyp.7050>
- Musselman, K. N., Molotch, N. P., Margulis, S. A., Kirchner, P. B., & Bales, R. C. (2012). Influence of canopy structure and direct beam solar irradiance on snowmelt rates in a mixed conifer forest. *Agricultural and Forest Meteorology*, 161, 46–56. <https://doi.org/10.1016/j.agrformet.2012.03.011>
- Vuyovich, C. NASA. (2024, May, 24). SnowEx, Nasa.gov, <https://snow.nasa.gov/campaigns/snowex>
- Pelz, K. A., & Smith, F. W. (2012). Thirty year change in lodgepole and lodgepole/mixed conifer forest structure following 1980s mountain pine beetle outbreak in western Colorado, USA. *Forest Ecology and Management*, 280, 93–102. <https://doi.org/10.1016/j.foreco.2012.05.032>
- Pomeroy, J., Fang, X., & Ellis, C. (2012). Sensitivity of snowmelt hydrology in Marmot Creek, Alberta, to forest cover disturbance. *Hydrological Processes*, 26(12), 1891–1904. <https://doi.org/10.1002/hyp.9248>
- Prokop, A. (2008). Assessing the applicability of terrestrial laser scanning for spatial snow depth measurements. *Cold Regions Science and Technology*, 54(3), 155–163. <https://doi.org/10.1016/j.coldregions.2008.07.002>
- R Core Team (2023). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- Raleigh, M. S., Gutmann, E. D., Van Stan, J. T., Burns, S. P., Blanken, P. D., & Small, E. E. (2022). Challenges and Capabilities in Estimating Snow Mass Intercepted in Conifer

- Canopies With Tree Sway Monitoring. *Water Resources Research*, 58(3), e2021WR030972. <https://doi.org/10.1029/2021WR030972>
- Revuelto, J., López-Moreno, J. I., Azorin-Molina, C., & Vicente-Serrano, S. M. (2015). Canopy influence on snow depth distribution in a pine stand determined from terrestrial laser data. *Water Resources Research*, 51(5), 3476–3489. <https://doi.org/10.1002/2014WR016496>
- Roth, T. R., & Nolin, A. W. (2019). Characterizing Maritime Snow Canopy Interception in Forested Mountains. *Water Resources Research*, 55(6), 4564–4581. <https://doi.org/10.1029/2018WR024089>
- Russell, M., Eitel, J. U. H., Link, T. E., & Silva, C. A. (2021). Important Airborne Lidar Metrics of Canopy Structure for Estimating Snow Interception. *Remote Sensing*, 13(20), 4188. <https://doi.org/10.3390/rs13204188>
- Russell, M., U. H. Eitel, J., J. Maguire, A., & E. Link, T. (2020). Toward a Novel Laser-Based Approach for Estimating Snow Interception. *Remote Sensing*, 12(7), 1146. <https://doi.org/10.3390/rs12071146>
- Rutter, N., Essery, R., Pomeroy, J., Altimir, N., Andreadis, K., Baker, I., Barr, A., Bartlett, P., Boone, A., Deng, H., Douville, H., Dutra, E., Elder, K., Ellis, C., Feng, X., Gelfan, A., Goodbody, A., Gusev, Y., Gustafsson, D., ... Yamazaki, T. (2009). Evaluation of forest snow processes models (SnowMIP2). *Journal of Geophysical Research: Atmospheres*, 114(D6), 2008JD011063. <https://doi.org/10.1029/2008JD011063>
- Schmidt, R. A., & Gluns, D. R. (1991). Snowfall interception on branches of three conifer species. *Canadian Journal of Forest Research*, 21(8), 1262-1269.

- Slatyer, R. A., Umbers, K. D. L., & Arnold, P. A. (2022). Ecological responses to variation in seasonal snow cover. *Conservation Biology*, 36(1), e13727.
<https://doi.org/10.1111/cobi.13727>
- Stahelin, R. (1943). Factors influencing the natural restocking of high altitude burns by coniferous trees in the central Rocky Mountains. *Ecology*, 24(1), 19-30.
- Staines, J., & Pomeroy, J. W. (2023). Influence of forest canopy structure and wind flow on patterns of sub-canopy snow accumulation in montane needleleaf forests. *Hydrological Processes*, 37(10), e15005. <https://doi.org/10.1002/hyp.15005>
- Storck, P., Lettenmaier, D. P., & Bolton, S. M. (2002). Measurement of snow interception and canopy effects on snow accumulation and melt in a mountainous maritime climate, Oregon, United States. *Water Resources Research*, 38(11). <https://doi.org/10.1029/2002WR001281>
- Sun, N., Wigmosta, M., Zhou, T., Lundquist, J., Dickerson-Lange, S., & Cristea, N. (2018). Evaluating the functionality and streamflow impacts of explicitly modelling forest–snow interactions and canopy gaps in a distributed hydrologic model. *Hydrological Processes*, 32(13), 2128–2140. <https://doi.org/10.1002/hyp.13150>
- Tinkham, W. T., & Swayze, N. C. (2021). Influence of Agisoft Metashape parameters on UAS structure from motion individual tree detection from canopy height models. *Forests*, 12(2), 250. <https://doi.org/10.3390/f12020250>
- Uhlmann, Z. (2018). *Correlating the Spatial Distribution of Snow Depth to Forest Canopy Parameters Derived from Terrestrial Laser Scans* [Boise State University].
<https://doi.org/10.18122/td/1498/boisestate>

- van Ewijk, K. Y., Treitz, P. M., & Scott, N. A. (2011). Characterizing Forest Succession in Central Ontario using Lidar-derived Indices. *Photogrammetric Engineering & Remote Sensing*, 77(3), 261–269. <https://doi.org/10.14358/PERS.77.3.261>
- Varhola, A., Coops, N. C., Alila, Y., & Weiler, M. (2014). Exploration of remotely sensed forest structure and ultrasonic range sensor metrics to improve empirical snow models: REMOTELY SENSED FOREST METRICS, ULTRASONIC SENSORS AND SNOW INDICATORS. *Hydrological Processes*, 28(15), 4433–4448. <https://doi.org/10.1002/hyp.9952>
- Varhola, A., Coops, N. C., Bater, C. W., Teti, P., Boon, S., & Weiler, M. (2010). The influence of ground- and lidar-derived forest structure metrics on snow accumulation and ablation in disturbed forests. *Canadian Journal of Forest Research*, 40(4), 812–821. <https://doi.org/10.1139/X10-008>
- Varhola, A., Frazer, G. W., Teti, P., & Coops, N. C. (2012). Estimation of forest structure metrics relevant to hydrologic modelling using coordinate transformation of airborne laser scanning data. *Hydrology and Earth System Sciences*, 16(10), 3749–3766. <https://doi.org/10.5194/hess-16-3749-2012>
- Vose, J. M., Miniati, C. F., Luce, C. H., Asbjornsen, H., Caldwell, P. V., Campbell, J. L., ... & Sun, G. (2016). Ecohydrological implications of drought for forests in the United States. *Forest Ecology and Management*, 380, 335–345. <https://doi.org/10.1016/j.foreco.2016.03.025>
- White, J. C., Coops, N. C., Wulder, M. A., Vastaranta, M., Hilker, T., & Tompalski, P. (2016). Remote Sensing Technologies for Enhancing Forest Inventories: A Review. *Canadian*

Journal of Remote Sensing, 42(5), 619–641.

<https://doi.org/10.1080/07038992.2016.1207484>

Wieder, W. R., Kennedy, D., Lehner, F., Musselman, K. N., Rodgers, K. B., Rosenbloom, N., Simpson, I. R., & Yamaguchi, R. (2022). Pervasive alterations to snow-dominated ecosystem functions under climate change. *Proceedings of the National Academy of Sciences*, 119(30), e2202393119. <https://doi.org/10.1073/pnas.2202393119>

Williams, M. W., Losleben, M. V., & Hamann, H. B. (2002). Alpine Areas in the Colorado front Range as Monitors of Climate Change and Ecosystem Response*. *Geographical Review*, 92(2), 180–191. <https://doi.org/10.1111/j.1931-0846.2002.tb00003.x>

Siirila-Woodburn, E. R., Rhoades, A. M., Hatchett, B. J., Huning, L. S., Szinai, J., Tague, C., ... & Kaatz, L. (2021). A low-to-no snow future and its impacts on water resources in the western United States. *Nature Reviews Earth & Environment*, 2(11), 800-819. <https://doi.org/10.1038/s43017-021-00219-y>

Worrall, J. J., Marchetti, S. B., Egeland, L., Mask, R. A., Eager, T., & Howell, B. (2010). Effects and etiology of sudden aspen decline in southwestern Colorado, USA. *Forest Ecology and Management*, 260(5), 638–648. <https://doi.org/10.1016/j.foreco.2010.05.020>

Supplementary Information

Aspen Crown Delineation

As noted in the methods section: scanning aspen stands was a much higher ability to attain 3-dimensional coverage of many trees with relatively few scan positions. Therefore, each aspen site had approximately 40 – 100 identified trees, about half of which had good point cloud coverage and were unobscured by the surrounding environment. Here we ran our aspen specific

code to not only identify each tree apex, but also segment the entire point cloud according to individual tree canopies. This approach is remarkably powerful for calculating individual tree metrics, but must be attentively quality controlled, especially with TLS data, as raster CHM derived point cloud segmentation can include multiple trees or cut of parts of tree crowns. Our solution to this was to query the script to plot each individual tree at the end of apex identification and canopy segmentation; the results of which we then quickly filtered in a visual QC process. Since we only needed ~15 aspen trees per site to match the sample number of conifer trees in this study we were able to select the individual tree crowns most accurately segmented by the code. To be confident in the reproducibility of this method we had to craft a novel method of applying code generated point cloud segmentation to different timepoints, i.e. different point clouds. Given the complexity of point cloud data and limitations to the tree identification/segmentation algorithm, the code based approach could not be trusted to identify individual trees the same way across different timepoints. The solution to this was to generate a convex hull geometry from the original Snow-Off, quality-controlled point cloud segments which could be reapplied to each Snow-On timepoint to essentially clip the point cloud in a reproducible manner. This novel computing method is exciting in the sense that it could allow users to sort through hundreds of trees within point cloud data in rather short order; then quickly apply the filtered results across a timeseries. This method could be applied to conifer forests like the ones in this study, however, special attention would be needed to compensate for the increased occlusion of point cloud data by conifer canopies. Calculating intercepted snow values in aspen trees had to be approached differently than conifer trees because the apex and geometry of aspen trees was not pronounced enough to realign and combine point clouds for accurate estimation of canopy snow. However, the rudimentary method of subtracting Snow-Off from

Snow-On values produced reliable results with thoughtful QA/QC because of the lack of aspen branch deformation/occlusion under the mass of (minimal) intercepted snow. Differences in Snow-Off/Snow-On volumes were consistently very low and many were negative, but within an acceptable margin (-0.001 to -0.5) where approximating a zero value for intercepted snow was reasonable when confirmed with visual QA/QC methods.

ProQuest Number: 31328394

INFORMATION TO ALL USERS

The quality and completeness of this reproduction is dependent on the quality and completeness of the copy made available to ProQuest.



Distributed by ProQuest LLC (2024).

Copyright of the Dissertation is held by the Author unless otherwise noted.

This work may be used in accordance with the terms of the Creative Commons license or other rights statement, as indicated in the copyright statement or in the metadata associated with this work. Unless otherwise specified in the copyright statement or the metadata, all rights are reserved by the copyright holder.

This work is protected against unauthorized copying under Title 17,
United States Code and other applicable copyright laws.

Microform Edition where available © ProQuest LLC. No reproduction or digitization of the Microform Edition is authorized without permission of ProQuest LLC.

ProQuest LLC
789 East Eisenhower Parkway
P.O. Box 1346
Ann Arbor, MI 48106 - 1346 USA