~~Orographic~~ Topographic and vegetation effects on snow accumulation in the southern Sierra Nevada: a statistical summary from Lidar~~DAR~~ data

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Abstract

Airborne light detection and ranging (Lidar~~DAR~~) snow-on and snow-off measurements collected in the southern Sierra Nevada near peak snow accumulation and in the snow-free season in the 2010 water year were analyzed for ~~orographic~~ topographic and vegetation effects on snow accumulation ~~during the winter season~~. Combining point-cloud data from four sites separated by 10 to 64 km, ~~and together covering~~ with total surveyed area over 106 km^2, it was observed in that the mixed-conifer forest the percent of pixels with snow-depth measurments is sensitive to the sampling resolution used in processing the point cloud. This is apparently due to Lidar not receiving returns from under the denser canopy. From the 1-m gridded data, it was observed that in addition to elevation effects, snow depth has a strong dependency on slope, aspect and canopy penetration fraction. A multivariate linear model built using all physiographic variables explained 15 to 25% more variability in snow depth than did a univariate linear model with elevation as a single predictor. However, the weight that each physiographic variable exerted on snow depth varied across different elevation ranges, as well as with different canopy-cover amounts. The difference between mean snow depth measured in open area and under canopy increased with elevation in rain-snow transition zone from 1500 to 1800 m and stabilized at about 25 to 45 cm above about 2000 m elevation, with the range reflecting the effects of other topographic variables. ~~area, the 1-m elevation-band-averaged snow depth in canopy gaps as a function of elevation increased at a rate of 15 cm per 100 m until reaching the elevation of 3300 m. The averaged snow depth of the same elevation band from different sites matched up with minor deviation, which could be partially attributed to the variation in other topographic features, such as slope and aspect. As vegetation plays a role in the snow accumulation, the distribution of the vegetation was also studied and shows that the canopy coverage consistently decreased along~~

~~the elevation gradient from 80% at 1500 m to near 0% at above 3300 m. Also, the absolute difference of the averaged snow depth between snow found in canopy gaps and under the canopy increased with elevation, and decreased with canopy coverage disregarding the variation of other topographic features. The influence from the forest density on snow accumulation was quantified based on the snow-depth residuals from 1-m elevation-band-averaged snow depth and the attribute penetration fraction, which is the ratio of the number of ground points to the number of total points per pixel of LiDAR data. The residual increases from -25 cm to 25 cm at the penetration fraction range of 0% to 80%; and the relationship could be modeled by exponential functions, with minor fluctuations along the gradient fraction of canopy and small deviation between sites.~~

1. Introduction

In the western United States, ecosystem processes and water supplies for agricultural and domestic use depend on the mountain snowpack as~~is~~ the primary source of late-spring and early summer streamflow~~ and is associated with agricultural and municipal water supplies~~ (Bales et al., 2006). Knowledge of spring snowpack conditions within a watershed is essential if water availability and flood peaks following the onset of melt are to be accurately predicted (Hopkinson et al., 2001). Both topographic and vegetation factors are important in influencing the snowpack conditions, as they closely interact with meteorological conditions to affect precipitation and snow accumulation distribution in the mountains (McMillen, 1988; Raupach, 1991; Wigmosta et al., 1994). However, the distribution of mountain precipitation is poorly understood at multiple spatial scales because it is governed by processes that are neither well measured nor accurately predicted (Kirchner et al., 2014). Snow accumulation across the mountains is primarily influenced by orographic processes, involving feedbacks between atmospheric circulation and terrain (Roe, 2005; Roe and Baker, 2006). In most forested regions, snow accumulation is highly sensitive to vegetation structure (Anderson, 1963; Revuelto et al., 2015; Musselman et al., 2008), and canopy ~~snow~~ interception, sublimation and unloading result~~s~~ in ~~smaller~~ less accumulation~~s~~ of snow beneath the forest canopies in comparison with canopy gaps (Mahat and Tarboton, 2013).

The Sierra Nevada is ideally suited for studying mountain snow distribution and related hydrologic processes because it serves as a barrier to moisture moving inland from the Pacific, ~~provides~~ has an ideal ~~mountainous region~~orientation for producing orographic precipitation, and thus exerts a strong influence on the upslope amplification of precipitation (Colle, 2004; Rotach and Zardi, 2007; Smith and Barstad, 2004). Recent studies have revealed some insights of snow-depth dependency on orographic and topographic effects in the Alps (Grünewald et al., 2013; Grünewald, et al., 2014; Lehning et al., 2011), suggesting that similar studies could be extended to the Sierra Nevada. And among the forested regions of the mountains, the mixed-conifer and subalpine zones cover most of the high-elevation, seasonally snow-covered area.~~ The geographic, topographic, and vegetation conditions make the Sierra Nevada a natural laboratory in the western United States for studying mountain snow distribution and related hydrologic processes (Grünewald et al., 2013; Grünewald, et al., 2014; Lehning et al., 2011).~~

~~In order to have a better knowledge of precipitation and snow accumulation in the Sierra Nevada, ~~M~~m~~anual snow surveys, one-time surveys, and remote-sensing products are used to estimate precipitation and snow accumulation in the Sierra Nevada~~and analyzed~~ (Guan et al., 2013). *In* ~~-~~*situ*~~ observations ~~, operational measurements of snow water equivalent (SWE) ~~were obtained~~come from monthly manual snow surveys and daily snow pillow observations (Rosenberg et al., 2011). Cost, data coverage, accuracy (Julander et al., 1998) and basin-scale representativeness are issues for *in situ* monitoring of SWE in mountainous terrain (Rice and Bales, 2010). Satellite-based remote sensing, such as MODIS, has been used to map snow coverage in large or even global areas. ~~Fractional snow coverage, grain size and albedo have retrieved from MODIS data (Hall et al., 2002; Painter et al., 2009; Rittger et al., 2013), however the products do not fit catchment-size studies owing to its low spatial resolution. ~~However, i~~I~~t ~~also ~~only provides snow-coverage information in canopy gaps, and no direct information on snow depths (Molotch and Margulis, 2008). There is also the SNOw Data Assimilation Systems (SNODAS) that integrate data from satellite and *in situ* measurements into a physical snowpack model, which provides SWE and snow~~-~~depth ~~information ~~estimates (Barrett, 2003). However, since ~~Since the spatial resolution of ~~SNODAS ~~is 1 km and its products ~~has~~ve~~ not been ~~globally~~

broadly evaluated (Clow et al., 2012), its potential for studying the snow distribution in mountainous areas remains uncertain. Also, owing to its 1-km spatial resolution, the snow depth that SNODAS provides is a mixed representation of both open and canopy-covered areas. ~~SNODAS could not be used for studying the snow distribution on catchment scale in the Sierra Nevada.~~An orographic-lift effect is observable in most of the above data (Howat and Tulaczyk, 2005; Rice et al., 2011), and a binary-regression-tree model using topographic variables as predictors has also been used for estimating the snow depth in unmeasured areas (Erickson et al., 2005; Erxleben et al., 2002; Molotch et al., 2005). However, regression coefficients could not be estimated accurately for most of the predictors, except for elevation, and the consistency of the orographic trend as well as the relative importance of these predictors is still unknown owing to lacking representative measurements across different slopes, aspects and canopy conditions. And the stability of the variance explained by the model also needs to be tested with denser measurements.

In recent years, airborne Lidar~~DAR~~ has been employed for high-spatial-resolution distance measurements (Hopkinson et al., 2004), and has become an important technique to acquire topographic data with sub-meter resolution and accuracy (Marks and Bates, 2000). Therefore, Lidar~~DAR~~ provides a potential tool to help understanding spatially distributed snow depth across mountainous regions. With multiple returns from a single laser ~~beam~~pulse, Lidar~~DAR~~ has also been used to construct vegetation structures as well as observe conditions under the canopy, which helps produce fine-resolution digital elevation models (DEMs), vegetation structures, and snow-depth information. However, the snow depth under canopy can not always be measured because of the signal-intensity attenuation caused by canopy interception (Deems and Painter, 2006; Deems et al., 2006). A recent report applied a univariate-regression model to the snow depth measured in open areas using Lidar; with a high-resolution DEM used to accurately quantify the orographic-lift effect on the snow accumulation just prior to melt (Kirchner et al., 2014). From this analysis it could be expected that Lidar data might also help explain additional sources of snowpack distribution variability in complex, forested terrain.

~~Even without LiDAR surveys, Erickson et al., (2005) and Erxleben et al., (2002) have used intensive *in situ* SWE measurements with binary regression tree, linear and nonlinear multivariate regression models for studying the topographic and vegetation controls on the spatial distribution of snow in the Colorado Rocky Mountains. But the studying sites were smaller than catchment size, and the results were site dependent as well as the sampling schemes have to be taken into consideration. Recent snow distribution modeling methods developed upon LiDAR measurements have been focused on fractal analysis and linear regression. Even the fractal distributions of snow depth do not vary with sites on local scale from 1 to 1000 m (Deems et al., 2006) and the topographic dependency of spatial snow-depth distribution have been explored (Kirchner et al., 2014), consistency of the topographic and vegetation effects across sites still need to be addressed.~~

The objective of this work reported here is to improve our understanding of the ~~effect of elevation, slope, aspect and canopy cover~~ topographic and vegetation effects on snow accumulation in the mixed-conifer forest. We investigated these by using ~~LiDAR~~ Lidar data collected in four headwater ~~catchments~~ areas in the southern Sierra Nevada and address the following three questions. First, is it possible to have snow-depth measurements in forested mountain terrain from all pixels on a fine sampling resolution (1 to 5m) using Lidar data? If not, how does the percentage of pixels measured change with the sampling resolution. Second, what is the importance of slope, aspect and canopy penetration fraction on snow accumulation, relative to elevation; and are effects consistent across sites? Third, what is the snow-depth difference between open and canopy-covered areas; how does it change with elevation; and is the difference stable with respect to other topographic variables? ~~First, is there a consistent orographic effect on snow accumulation across catchments; and what attributes could account for variability across and within sites? Second, what is the snow-depth difference between canopy gaps, versus under canopy, along elevation; and is binary classification for canopy cover adequate to the differences? Third, how does forest density influence the snow accumulation in canopy gaps and if there are patterns, are they consistent across catchments?~~

2. Methods

2.1 Study Areas

~~The~~ Our study areas are~~is~~ located in the southern Sierra Nevada, approximately 80 km east of Fresno, California (Figure 1). The f~~F~~our headwater-catchment research areas, Bull Creek, Shorthair Creek, Providence Creek, and Wolverton Basin were previously instrumented, including meteorological measurements, in order to have a better knowledge of the hydrologic~~al~~ processes in this region (Bales et al., 2011; Hunsaker et al., 2012; Kirchner et al., 2014). The sites were chosen as part of multi-disciplinary investigations at the Southern Sierra Critical Zone Observatory, and are also the main instrumented sites in the observatory. Wolverton is approximately 64 km ~~away in the~~ southeast ~~direction~~ of the other three sites (Figure 1) and is located in Sequoia National Park. Both snow-on and snow-off airborne ~~LiDAR~~ Lidar were flown in 2010 (Table 1~~, only later date collections were processed~~) over these sites. The elevation of the survey areas ~~covers~~ is from 1600-m to 3500-m elevation.~~,~~ ~~over which~~ V~~v~~egetation density generally decreases ~~with biotic zones of~~in high-elevation subalpine forest~~,~~ ~~and~~ with Wolverton also having a large area above treeline ~~in Wolverton~~ (Goulden et al., 2012). The precipitation has historically been mostly snow in the cold and wet winters for elevations above 2000 m, and a rain-snow ~~transition~~ mix below 2000 m, where most of Providence is located. The comparison between Providence and the other sites can help in accessing if observed trends are consistent above and below the rain-snow transition. Also, various elevation spans of sampling sites is important in understanding the stability of the relative importance of physiographic variables across heterogeneous topography.

2.2 Data Collection

All~~Both~~ airborne LiDAR surveys were performed by using Optech GEMINI Airborne Laser Terrain Mapper. The scan angle and scan frequency were adjusted to ensure a uniform along-track and across-track point spacing (Table 2), and six GPS ground stations were used for determining aircraft trajectory. The snow-on survey date was close to April 1st, which is used by operational agencies as the date of peak snow accumulation for the Sierra~~time~~. Since the snow-on survey ~~lasted~~ required four days to ~~finish data collection over~~cover the four study areas, time-series *in situ* snow-depth data measured continuously from Judd Communications ultrasonic depth sensors ~~of the meteorological stations~~ at Providence, Bull and Wolverton were used to estimate changes in snow depth during the survey period. ~~for checking if precipitation had occurred during survey dates and~~ While no snow accumulation was observed, ~~also taking~~ snowpack densification and melting observed from the time-series data were taken into considerations (Hunsaker et al., 2012; Kirchner et al., 2014). The snow-off survey was performed in August ~~when~~ after snow ~~was~~ had completely melted out in the study areas.

2.3 Data Processing

Raw ~~LiDAR~~ Lidar datasets were pre-processed by NCALM and are available from the NSF Open-Topography website (http://opentopography.org) in LAS format. The LAS point cloud~~s~~, including both canopy and ground-surface points, are stored and classified as ground return and vegetation return.~~;~~ E~~e~~ach point is also attributed with the total number of returns and position of all returns from its source laser pulse~~beam~~. The 1-m resolution digital-elevation models, generated from the ~~LiDAR~~ Lidar point-cloud datasets, were downloaded from the OpenTopography database and further processed in ArcMap 10.2 to generate 1-m resolution slope, aspect, and northness raster products. Northness is an index for the potential amount of solar radiation reaching a slope on a scale of -1 to 1, calculated from:

$$N = \sin(S) \times \cos(A), \quad (1)$$

where N is the northness value; S is the slope angle of the terrain; and A is the aspect angle. Northness is also the same as the aspect intensity (Kirchner et al., 2014) with 0° focal aspect. Since in this analysis the snow-depth comparison is only discussed between north and south facing slopes, northness is used instead of aspect intensity for simplification. To construct the vegetation structure from ~~LiDAR~~ Lidar data, points that are from the first return of the laser pulse~~beam~~ are used to generate 1-m gridded digital~~-~~surface models. And 1-m resolution canopy-height models were ~~was~~ built by subtracting the digital-elevation models from the digital-surface models.

The snow depths were calculated directly from the snow-on ~~LiDAR~~ Lidar data. By referring to canopy-height models, all ground points in snow-on ~~LiDAR~~ Lidar datasets were classified as under canopy or in canopy gaps. That is, if the point was ~~under~~coincident with canopy of >2-m height, it was classified as under canopy, and otherwise in a canopy gap. After classification, snow depths were calculated by subtracting the values in the digital-elevation model from the snow-on point-measurement values. The calculated point snow-depth data were further assigned into 1-m raster pixels, averaged within each pixel, formatted and then gap filled by interpolation with pixel values around it. Since the measurements collected under canopy were insufficient within each pixel (Figure 2) and varied across the transition from the tree trunk to the edge of the canopy, interpolation was not applied to data under the canopy. The error rate of the calculated snow depth should be mainly from the instrumental elevation error, which is about 0.10 m (Kirchner et al., 2014; Nolan et al., 2015).

2.4 Penetration Fraction

The o~~O~~pen-canopy fraction is a factor that represents the forest density above a given pixel and is ~~often~~ used to describe the influence of vegetation on snow accumulation and melt. However there is no algorithm to directly extract this information from ~~LiDAR~~ Lidar data. Here we use a novel approach we call penetration fraction to approximate the open-canopy fraction from the ~~LiDAR~~ Lidar point cloud. Penetration fraction is the ratio of the number of ground points to~~and~~ number of total points within each pixel. Because the electromagnetic radiation from both ~~the LiDAR~~ Lidar and sunlight beams are intercepted by canopies, the open-canopy fraction is used here as an index to represent the fraction of sunlight radiance received on the ground under vegetation. Therefore, penetration fraction of ~~LiDAR~~ Lidar is actually another form of estimating the open-canopy fraction (Musselman et al., 2013). Penetration fraction was calculated as the number of ground points divided by total points in each pixel (Figure 3a). However, under-canopy vegetation can also intercept the ~~LiDAR~~ Lidar beam causing a bias. To eliminate this bias, the canopy-height model was used to check if the pixel was canopy covered by using a threshold value of 2 m; and if not, the local penetration fraction of the pixel was reset to 1 because the open-canopy fraction of a pixel could not be entirely represented by the penetration fraction. A spatial moving-average process was applied using a 2-D Gaussian filter with a radius of 5 m to account for the effect of the vegetation around each pixel. Finally, we tested the sensitivity of smoothing results to the radius of the filter and found it is not sensitive when the radius is greater than 1.5 m (Figure 3b).

2.5 Statistical Analysis

The 1-m resolution snow-depth raster datasets were resampled into 2-m, 3-m, 4-m and 5-m resolution. The percentage of pixels with snow-depth measurements was calculated by using the number of pixels with valid data divided by the total number of pixels inside each survey area. The sensitivity of the percentage changes across different resampling resolutions and the consistency of the percentages across study sites at the same resampling resolution were analyzed by visualizing the percentages against sampling resolutions at all sites.

Using elevation, slope, aspect, penetration fraction~~vegetation structure~~ and snow ~~-~~depth retrieved from ~~LiDAR~~ Lidar measurements, ~~orographic~~ topographic and vegetation effects on snow~~pack~~ accumulation were ~~analyzed statistically~~observed using residual analysis. Owing to orographic effects, there is increasing precipitation along an increasing elevation gradient in this area (Kirchner et al., 2014). Therefore, elevation was selected as the primary variable ~~topographic attribute~~to fit the linear regression model for calculating the residual of snow depth. All snow-depth measurements from ~~LiDAR~~ Lidar were first separated by either under canopy or in canopy gaps, and then were binned by elevation of the location where they were measured, with a bin size of 1-m elevation. As each elevation band had hundreds of snow-depth measurements after binning, the average of all snow depths was chosen as the representative snow depth, and the standard deviation calculated to represent the snow-depth variability within each elevation band. ~~Correlation c~~Coefficients of determination between snow depth and elevation of each site were calculated by linear regression. The fitted linear regression model of each site was applied to the DEM to estimate the snow depth. The residual of snow depth was calculated by subtracting the modeled snow depth from Lidar-measured snow depth. The slope, aspect and penetration fraction were binned into 1° slope, 1° aspect, and 1% penetration-fraction bins. In this study we treat penetration fraction as a physiographic variable and snow-depth residuals corresponding to each bin of each physiographic variable were averaged and visualized along the variable gradient to check the existence of these physiographic effects.~~Northness and slope were also averaged by elevation band for cross comparison. The differences of averaged snow depth between in canopy gaps and under-canopy areas were calculated for each elevation band and cross compared with the vegetation fraction, northness and slope.~~

~~To account for effects other than elevation in the snow depth, a linear regression model of snow depth and elevation was applied to the digital-elevation data to estimate snow depth. The differences between the estimated and LiDAR-measured snow depths were further investigated, with respect to slope, aspect and penetration fraction, by binning the snow-depth difference into 1° slope and aspect bins and 1% penetration-fraction bins. The difference values within each bin were averaged and the standard deviations were calculated.~~

For the variables found to correlate with the snow accumulation, the relative importance of each variable was calculated using the Random Forest algorithm (Breiman, 2001; Pedregosa and Varoquaux, 2011). A multivariate linear regression model was also fitted into all physiographic variables to calculate the regression coefficients, which could be used as the quantification of the effect on snowpack distribution from the variable.

To calculate the snow-depth difference between open and canopy-covered area along an elevation gradient, the 1-m resolution snow-depth data of the two conditions, open and canopy-covered, were smoothed separately against elevation using locally weighted scatterplot smoothing (LOESS) (Cleveland, 1979). The snow-depth difference was then calculated by subtracting the smoothed canopy-covered snow depth from that in open.

3. Results

The percentage of pixels that have snow-depth data measured is highly sensitive to the sampling resolution used in processing the Lidar point cloud, which is about 65 to 90% with 1-m resolution and gradually increases to 100% at 5-m resolution (Figure 4). Note that the percentage increases in going from the lower to higher elevation sites, consistent with local forest density decreasing with elevation.

The snow depth ~~estimated~~ in canopy gaps shows a ~~strong~~ consistent linear trend with elevation across all sites (Figure 5a). The variability (Figure 5b) is highest at about 1500 m, and gradually decreases within rain-snow transition until elevation reaches 2000 m. However, at above 2000 m, the trends of variability changing along elevation gradient vary across sites. ~~ey of distribution patterns and variability across the four sites (Figure 4a, 4b).~~ In general, snow depth is linearly correlated with elevation at all sites, both in the open area and under the canopy. ~~, snow depth under the canopy is consistently less than in the canopy gaps (Figure 5a).~~ Note that values at the upper or lower ends of elevation at each site have few pixels and maybe less representative of the value of physiographic attributes in the study areas (Figure 54c). The forested area, of all four sites combined, spans the rain-snow transition zone in mixed conifer through subalpine forest to significant areas above treeline. ~~The snow-depth difference between canopy gaps and under-canopy varies with elevation, generally increasing from near zero at 1500 m, where there is little snow but dense canopy, to 40 cm in the range of 2000-2400 m, and varying from near zero to 60 cm at higher elevation where snow is deeper and canopy less dense.~~

For each individual site, ~~the~~ a least-squares linear regression~~s~~ of snow depth ~~and~~ versus elevation ~~were~~ was used to investigate the spatial variability of snow ~~-~~depth~~ across sites~~. The median elevation of the three sites increases ~~in going~~ from Providence to Bull to Shorthair. The lowest elevation at Providence Creek is less than ~~goes down to~~ 1400 m, and snow depth increases steeply in this region at a rate of 38 cm per 100 m in ~~canopy gaps~~open areas and 28 cm per 100 m under the canopy. Bull Creek has an elevation range of 2000-2400 meters, which is slightly higher than Providence, and has snow depth increasing at 21 cm per 100 m in ~~canopy gaps~~ open areas and 19 cm per 100 m under the canopy. For Shorthair Creek site, which is the highest of the three, the snow depth increases at 17 cm per 100 m in ~~canopy gaps~~open areas and 16 cm per 100 m under the canopy. Wolverton is 64 km further south and spans a wide elevation range, going from the rain-snow transition in mixed conifer, to subalpine forest, to some area above treeline. The average snow-depth increase is smallest among all four study sites, 15 cm per 100 m in canopy gaps and 13 cm per 100 m under the canopy. Unlike the other three lower-elevation sites, the snow depth at Wolverton site decreases ~~after~~ above 3300-m elevation. ~~However~~ The amount of area above this elevation is relatively small, and factors such as wind redistribution and the exhaustion of perceptible water can also affect snow depth at these elevations (Kirchner et al., 2014).~~ the amount of area above this elevation also drops off steeply.~~

The residuals for the snow in the open areas were further analyzed for effects of slope, aspect and penetration fraction. The snow-depth residual decreases about 10 to 40 cm as slope angle increases from 0° to 60°; and the residual decreases around 50 to 100 cm in going from north-facing to south-facing slopes (Figure 6a, 6b). More interestingly, the topographic effect can be seen from the color pattern of northness observed in the scatterplots (Figure 7a, 7b). The residual increases about 40 to 60 cm as penetration fraction increases from 0% to 80% (Figure

6C). Considering all of these variables together, elevation is the most important variable at all sites except for Shorthair, which has a relatively small elevation range (Figure 8). Aspect exerts a stronger influence than do slope and penetration fraction in open areas. However, for under-canopy areas, penetration is more dominant than aspect at two sites. The multivariate regression model was fitted to the data with aspect transformed into $0°$ to $180°$ range (north to south). Fitted models could be represented as the following two equations for open area and under canopy respectively,

$$SD = 0.0011 \times Elevation - 0.0112 \times Slope - 0.0057 \times Aspect + 0.1802 \times Penetration \quad (2)$$

$$SD = 0.0009 \times Elevation - 0.0128 \times Slope - 0.0046 \times Aspect + 0.9891 \times Penetration \quad (3)$$

where SD is snow depth and p-values of all regression coefficients of the two models are all smaller than 0.01.

The snow-depth difference between open and canopy-covered area was calculated with elevation from locally smoothed snow depth (Figure 7). It ~~The snow-depth difference between canopy gaps and under-canopy varies with elevation,~~ generally increas~~ing~~es from near zero at 1500 m, where there is little snow but dense canopy, to 40 cm in the range of 2000-2400 m, and varies~~ying~~ from near zero to 60 cm at higher elevations where snow is deeper and the canopy less ~~dense.~~dense. It is apparent that the snow-depth difference increases with elevation in the rain-snow transition zone, but lacks a clean pattern along either elevation gradient or penetration-fraction gradient when the elevation is higher.

~~A visual inspection of the pattern of snowpack distribution with elevation for all sites shows a consistent pattern (Figure 4). Especially for the elevation range where Providence and Wolverton overlap, the patterns of snow depth change are the same for both sites, with the only difference being Wolverton snow depth is consistently less than that in Providence, which is~~

~~likely due to a small amount of densification that occurred between the two acquisitions (Table 1) observed from depth sensors.~~

~~At higher elevations, vegetation coverage decreases consistent with lower temperature, and soil depth. By cross comparing the vegetation fraction and snow-depth difference (Figure 5a, 5b), similar patterns were observed at all sites along elevation gradient. Also, for most of the elevation range investigated, the snow-depth difference was either increasing or remaining constant, except for 2300 to 2500 m at Wolverton, where the snow-depth difference drops drastically, which may be explained by steeper and more southerly exposed slopes (Kirchner et al., 2014) (Figure 6).~~

~~The snow-depth residual deviation from a linear increase with elevation, investigated versus penetration fraction (Figure 7), indicates how the density of vegetation affects the snow-depth accumulation in canopy gaps. For all sites, the snow-depth residuals increase with penetration fraction, with bias across sites and fluctuations at higher penetration fractions.~~

4. Discussion

4.1 Sensitivity of measurements to sampling resolution

The results of the percentage of pixels with snow depth measured from Lidar data at different sampling resolutions illustrate that even high-density airborne Lidar measurements do not have 100% coverage of the surveyed area at 1-m resolution, especially in densely forested areas. According to the snow-depth difference between snowpack in open areas and under canopy, the trade-off between accuracy and coverage happens when adjusting the resolution; and lower sampling resolutions can introduce overestimation into the results. This is because upon averaging, sub-pixel area under the canopy that was not measured is represented by the open that is measured, introducing an overestimation error into the averaged snow depth of the pixel. Therefore, the sampling resolution for processing the Lidar point cloud needs to be chosen according to the objective and accuracy tolerance of the study.

~~The overall increasing trend of precipitation with elevation observed from airborne LiDAR data is consistent with the orographic effect on precipitation (Roe, 2005; Roe and Baker, 2006) and less snow accumulation was observed under vegetation at all sites. The decrease in under-canopy snow is consistent with previous work using ground-based data (Bales et al. 2011, Musselman et al. 2008, and Varhola et al. 2010). Finally, the penetration fraction explained part of the snow-depth residual of the linear model between snow depth and elevation.~~

~~4.1~~4.2 ~~Orographic~~ Physiographic effect on snow accumulation

Below 3300 m, the increasing trend of snow accumulation with elevation was observed for all sites (Figure 5~~4~~). Linear regression is applicable to model the relationship between snow depth and elevation when the study area has a broad elevation range. This holds true for all of our sites with the exception of Shorthair, where the elevation range is about 200 m and ~~As indicated in Table 3,~~ the ~~correlation~~ coefficient of determination for~~of~~ this linear model ~~used for Shorthair site~~ is much smaller than the other three sites, which have ranges greater than 500 m. ~~The other three sites all have elevation range larger than 500 m; however the elevation spans around 200 m at Shorthair site.~~ The bias of mean snow depth in the same elevation band between different sites is acceptable if the standard error is ~~being~~ added or subtracted from the mean (Figure 5~~4~~a, 5~~4~~b). The data-collection time, spatial variation and variations of other topographic features should introduce bias across sites. However, as data-collection time only differs a few days, *in situ* snow-depth sensor data suggest that the melting and densification effect ~~should be~~was under 2 cm (https://czo.ucmerced.edu/dataCatalog_sierra.html). Spatial variations at

1800-2000 m elevations between Providence and the further-south Wolverton site appear to have a consistent bias, with less precipitation falling in the southerly location. As for other topographic variables, the observation of a slope effect, shown as the trend lines in Figure 6a and the negative regression coefficients of the two linear models, could be explained by steeper slopes having higher avalanche potential, fewer trees and thus more wind; and thus some snow is more likely to be lost from these slopes. Snowpack located in south-facing slopes receives higher solar radiation, with the snowmelt being accelerated (Kirchner et al., 2014). This explains the trends observed in Figure 6b and the negative regression coefficients of the multivariate models. Although Lidar has measurement errors caused by slope and aspect (Baltsavias, 1999; Deems et al., 2013; Hodgson and Bresnahan, 2004), error is not able to be quantified and traced back to each variable and we assumed its influence on the trends could be neglected. As canopy interception results in reduced snow depth under canopy, the snow-depth residuals are found increasing with penetration fraction and the regression coefficients are positive (Figure 6c). The multivariate linear regression model built from the Lidar data is a significant improvement, as the variability of the snowpack distribution could explain 15 to 25% more than the univariate linear regression model with elevation as the only predictive variable (Table 4) and the estimation bias has a narrower distribution (Figure 9a, 9b). Also, fitting an individual linear model for each site is slightly better than using a general model with all sites' data involved (Figure 9c, d) and it might because that an individual model could capture regional micro-climate within the site better than a general model. The opposite trend of the relative importance of predictive variables observed in Shorthair is because it is a relatively flat site (Figure 1, Figure 8), which implies that topographic variables other than elevation need to be focused more when studying about areas with small elevation ranges in future works. ~~For other topographic features,~~

~~Kirchner et al. (2014) proposed that northness and slope should have negative effects on snow accumulation. They noted that northness is positively correlated with solar radiation, and thus ablation, and northeastness deposition from prevailing winds. Steeper slopes also have has higher avalanche potential and snow is more likely to fall off from these slopes. Across the elevation range that we studied, the snow depth is globally smaller at Wolverton than all other sites; however the northness and slope are globally higher at Wolverton, which is consistent with the northness and slope effects on snow accumulation could exist. Also, the separate investigations on slope and aspect (Figure 6) show that smaller snow-depth residuals could be observed on steeper or more southerly exposed slopes, which further proved the existence of the northness effect. From Figure 2 we also need to notice that each site has about 10% to 24% of total surveyed area does not have point return because of canopy interception. Thus the statistical results are representative but not conclusive of surveyed sites.~~

~~4.2~~4.3 Vegetation effects on snow accumulation along elevation

Under-canopy snow distribution is governed by multiple factors that affect the energy environment, as observed by melting (Essery et al., 2008; Gelfan et al., 2004) and accumulation rates (Pomeroy et al., 1998; Schmidt and Gluns, 1991; Teti, 2003). Our results show different responses when comparing the snow-depth difference between open and canopy-covered areas between study sites (Figure 7c). In the rain-snow transition zone from 1500 to 2000 m of Providence we see a sharp linear increase between open and under-canopy accumulation that is likely governed by the under-canopy energy environment and the canopy-interception effect on precipitation, which accelerate snowmelt and prevent accumulation of under-canopy snow. Above 2000 m, the snow-depth difference observed at Bull and Shorthair stabilized around 40 cm and 20 cm respectively, with fluctuations less than 10 cm along elevation.~~The snow depth in open areas is increasing 2 cm / 100m to 12 cm / 100m steeper than snow depth in under-canopy areas (Table 3). Schmidt and Gluns, (1991) found that the snow intercepted by canopy increases with cumulative snowfall and the interception would saturate when the precipitation is heavy enough. Therefore, in our study sites, with more snow intercepted at higher elevation, the snow-depth increasing slope of under-canopy observations is gentler than open areas.~~ Breaking from this pattern, the large dip in snow-depth difference, down to 10 cm, observed at Wolverton at elevations of 2250 - 2750 m deviates from the 35-40 cm plateau. Also, the snow-depth difference at Shorthair stabilizes around 20 cm, which is 20 cm lower than the stabilized value at Bull. Based on the scatterplot in Figure 7a and 7b that color coded by northness, at elevation range of 2300 m to 2700 m, there are a lot more data points with both low snow depth and extremely negative northness in the open area than under the canopy, which implies that anisotropic distribution of other topographic variables is affecting the snow-depth difference. This is further shown by filtering out the data points not within a small certain range (-0.1 to 0.1) of northness, and then reproducing Figure 7c using the filtered data. As presented in Figure 10, it is apparent that the large dip at Wolverton is flattened out to a canopy effect of around 25-45 cm as the topographic effect is filtered out. Thus a sigmoidal function was used to characterize the snow-depth difference changes with elevation excluding topographic interactions. The interactions between topographic variables and vegetation is most likely attributable to the under-canopy snowpack being less sensitive to solar radiation versus snowpack in the open area (Courbaud et al., 2003; Dubayah, 1994; Essery et al., 2008; Musselman et al., 2008, 2012).

In spite of filtering the topographic effect, there is still about a 20-cm magnitude of fluctuation in the snow-depth difference, which might be attributed to various clearing sizes of open area at different locations and various vegetation types in the forests (Hedstrom and Pomeroy, 1998; Pomeroy et al., 2002; Schmidt and Gluns, 1991), however, these features of the sites are not able to be explored from this Lidar data set.

~~The difference of averaged snow depth between open and under-canopy areas increases with elevation as vegetation coverage decreases (Figure 5a, 5b). We found that a high density of vegetation exerts a negative influence on snow accumulation in canopy gaps, which makes the snow-depth difference less significant at lower elevations. With precipitation increasing along the elevation gradient, the difference of snow depth between open and canopy-covered areas also increases; and in more densely forested areas, even though the open area does not have canopy right above the ground (Hedstrom and Pomeroy, 1998; Pomeroy et al., 2002; Schmidt and Gluns, 1991) they can still be influenced by the canopies around them. Golding and Swanson (1986) found that the difference increased with clearing size, caused by snow ablation as well as direct solar radiation reaching the snowpack. Another cause of this effect could be traced back to how precipitation drops on the ground. As precipitation has both horizontal and vertical velocities, in a densely forested area a small fraction of snowflakes or raindrops would be intercepted by the vegetation, not only vertically, but also horizontally. Therefore, the snow accumulated in the open area that is surrounded by dense vegetation would actually be smaller than the snow accumulated in a wide-open area. This is also consistent with the finding that areas at the drip edge have snow-depth values, intermediate between under canopy and in the open (Bales et al., 2011). Thus in the more-open forests at higher elevation, the under-canopy and in-canopy-gap allow for greater snow-depth differences. Since the differences could change in different forest conditions and also under the effect of drip-edge transitions, binary classification of in canopy gaps and under-canopy does not work for quantifying differences in snow accumulation.~~

~~Furthermore, the pattern could be altered as some other topographic feature varies. We observed a sudden drop of snow-depth difference in the elevation range of 2300-2500 m at Wolverton from Figure 5a. By visually inspecting the vegetation-pixel percentage, northness, and slope along the elevation gradient (Figure 4d, 5b, 5c), it is observed that the vegetation pixel percentage decreases constantly at a low rate and northness decreases from positive to negative (north dominant to south dominant); while the slope kept increasing significantly in this elevation range. Dubayah (1994), Courbaud et al. (2003), and Essery et al. (2008) found that slope is a dominant factor in modeling the solar radiation received by the soil when canopy structures remain constant, and more solar radiation would be received on steeper south facing slopes, which could be the cause of the snow-depth difference decrease that we observed.~~

~~4.3 Quantify vegetation effects on snow accumulation~~

~~In the previous section, we reasoned that vegetation reduces snow accumulation in canopy gaps by blocking the snow that in a less-dense forest would fall to the ground. Vegetation density is a significant factor (Teti, 2003), as we observed that snow-depth difference increases when vegetation fraction decreases. Figure 7 shows the quantification of the vegetation-density effects on the snow-depth accumulation. Considering the blocking of snow from vegetation (Pomeroy et al., 1998; Schmidt and Gluns, 1991), the vegetation density should be transformed into open fraction that one could see from the given pixel. In this case, penetration fraction was applied to represent percentage opening. As is shown in Figure 7a, the snow-depth residual differed from the linear increase with elevation is highly correlated with penetration fraction, which implies that penetration fraction is a good indicator of vegetation effects on snow accumulation. Moreover, the ranges of the snow-depth residual are similar and the patterns of snow-depth residual changing against penetration fraction are consistent across sites, as the~~

~~studied sites share similar vegetation structures and climate conditions (Fites-Kaufman et al., 1970). The consistency of changing patterns supports the idea of modeling the relationship between vegetation density and snow depth so that the effects from vegetation on open area snow accumulation could be quantified.~~

5. Conclusions

As an advanced and promising remote-sensing technology, Lidar is able to measure snow depth of 100% survey area at 5-m sampling resolution however the accuracy is still left to be evaluated because of lacking enough representative measurements under the canopy. A 1-m resolution processed Lidar data set is more accurate but the percentage of pixels with measurements is much less than 100%.

Using processed Lidar data sampled at 1-m resolution, averaged snow depth within each 1-m elevation band shows a strong correlation with elevation at all sites, indicating that snow accumulation in the southern Sierra Nevada is primarily affected by orographic lift. Snow-depth residuals calculated by de-trending the elevation dependency are correlated with slope, aspect and penetration fraction, which shows the effect of additional physiographic variables on snow accumulation other than elevation. The relative importance of these variables in predicting snow depth implies that other than elevation, aspect affects snow-accumulation and retention more in open areas, while penetration fraction is as important as aspect for snow under the canopy. More significantly, a multivariate linear regression model fitted with variables for slope, aspect and canopy penetration fraction explains 15 to 25% more snow-depth variability than using elevation as the only predictive variable, suggesting multiple predictive variables will be more effective for quantifying the water equivalent in the Sierra Nevada at peak snow accumulation.

The snow-depth difference between open and canopy-covered areas increases in the rain-snow transition elevation range and then stabilized around 25 to 45 cm at high elevation. Large magnitude of fluctuations are presented at certain elevation ranges in Wolverton and Shorthair, which is partially due to interactions from other topographic variables, evidence of which is found by filtering the northness into a narrow band and which causes the fluctuations flattening out.~~The regression analysis of snow depth versus terrain and vegetation attributes that are extracted from LiDAR show that snow accumulation in the southern Sierra Nevada is strongly affected by both the orographic effect and vegetation factors, and are consistent across the four sites studied. Comparing these results across sites reveals that the altitudinal effects on snow accumulation are consistent and globally linear, with a lapse rate of approximately 15 cm per 100 m. By cross comparing between snow depth and other topographic features along the elevation gradient, we confirmed that the variability of snow depth, after de-trending the altitudinal effect, could be further explained by attributes such as slope and aspect. The characterization of snow-depth difference between open and canopy-covered area, together with vegetation fraction, not only suggests that the snow-depth-difference increase along the elevation gradient is because of vegetation density decreasing, it also suggests that, penetration fraction can be used to quantitatively study vegetation effects on snow accumulation. Moreover, the analysis of the snow-depth residual from the altitudinal trend and penetration fraction reveals that the vegetation effects on snow accumulation are consistent across the four study-sites, implying that the effects could be quantified and modeled mathematically.~~

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Table 1. LiDAR data collection information

	Snow-off flight date	Snow-on flight date	Area, km^2
Bull	August 15, 2010	March 24, 2010	22.3
Shorthair	August 13, 2010	March 23, 2010	6.8
Providence	August 5, 2010	March 23, 2010	18.4
Wolverton	August 13-15, 2010	March 21-22, 2010	58.9

Table 2. Flight parameters and sensor settings

Flight parameters		Equipment settings	
flight altitude	600 m	wavelength	1047 nm
flight speed	65 m s^{-1}	beam divergence	0.25 mrad
swath width	233.26 m	laser PRF	100 kHz
Swath overlap	50%	scan frequency	55 Hz
point density	10.27 p m^{-2}	scan angle	$\pm$14°
Cross track res	0.233 m	scan cutoff	3°
Down track res	0.418 m	scan offset	0°

Table 3. Linear regression of averaged snow depth vs. elevation in four sites

	Bull	Shorthair	Providence	Wolverton
Open R^2	0.968	0.797	0.931	0.914
Vegetated R^2	0.978	0.737	0.921	0.972
Open slope, cm per 100 m	21.6	16.1	37.8	15.3
Vegetated slope, cm per 100 m	19.9	13.1	26.0	13.4

Table 4. Coefficients of determination of univariate and multivariate linear models

	Univariate model R^2	Multivariate model R^2
Bull	0.23	0.37
Shorthair	0.06	0.32
Providence	0.39	0.53
Wolverton	0.16	0.38
All sites	0.43	0.57

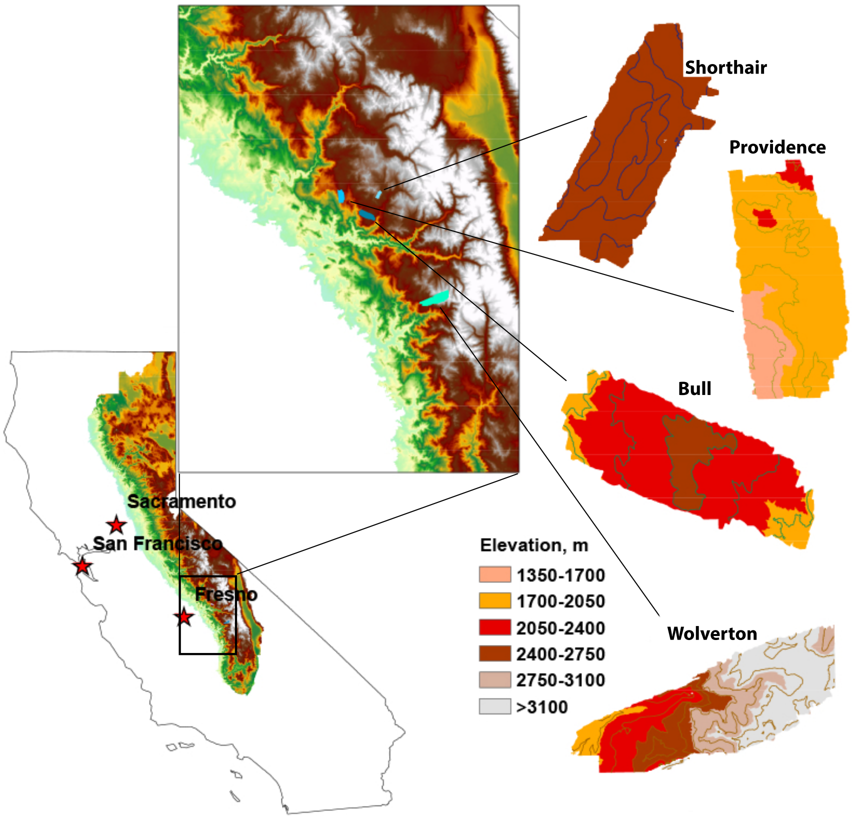

Figure 1. Study area and Lidar footprints. (Left) California with Sierra Nevada. (Center) Zoomed view to show the locations of Lidar footprints. (Right) Elevation and 200-m contour map (100-m for Bull) of LiDAR footprints

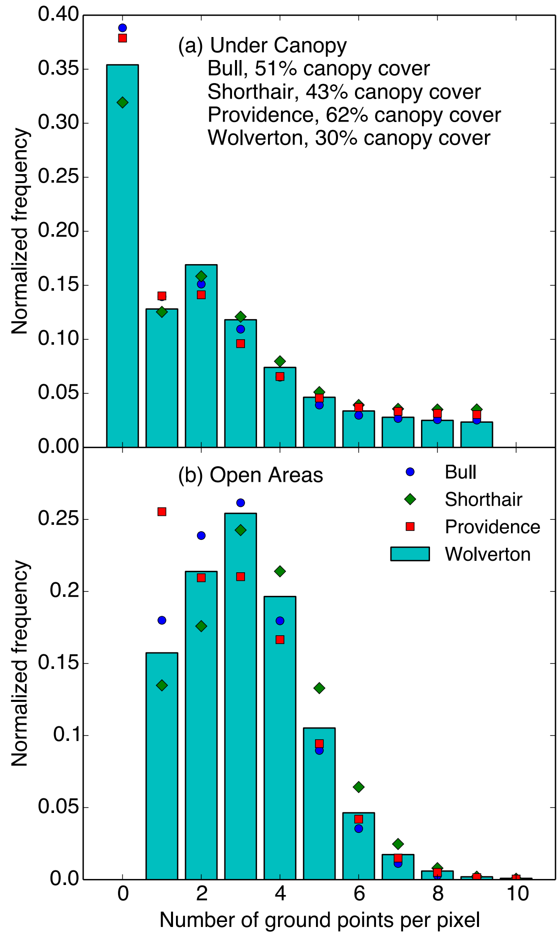

Figure 2. (a) Normalized histogram of the number of ground points for under canopy pixels. (b) Normalized histogram of the number of ground points in open pixels.

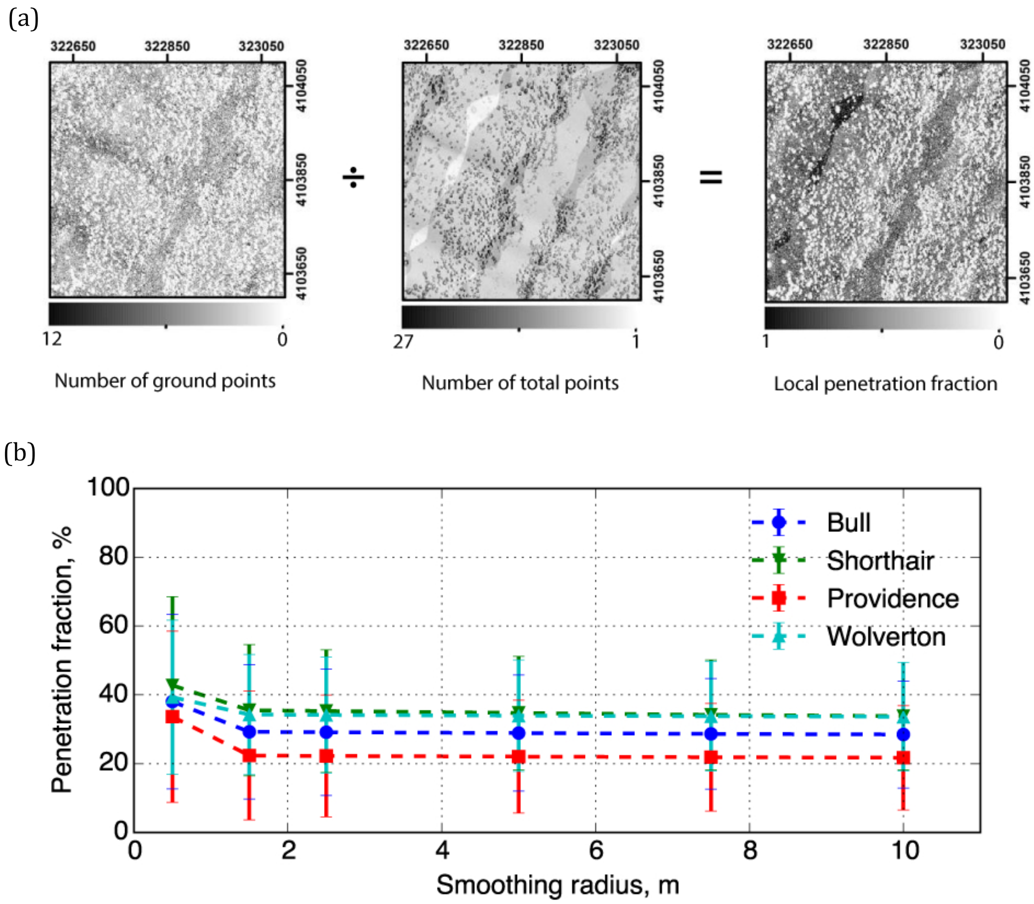

Figure 3. (a) Dividing the number of ground points of each 1-m pixel by the total number of points in the pixel will result the penetration fraction of the local pixel. (b) Sensitivity of the smoothed penetration fraction to the smoothing radius, showing that the result is not sensitivity as the radius is larger than 1.5 m.

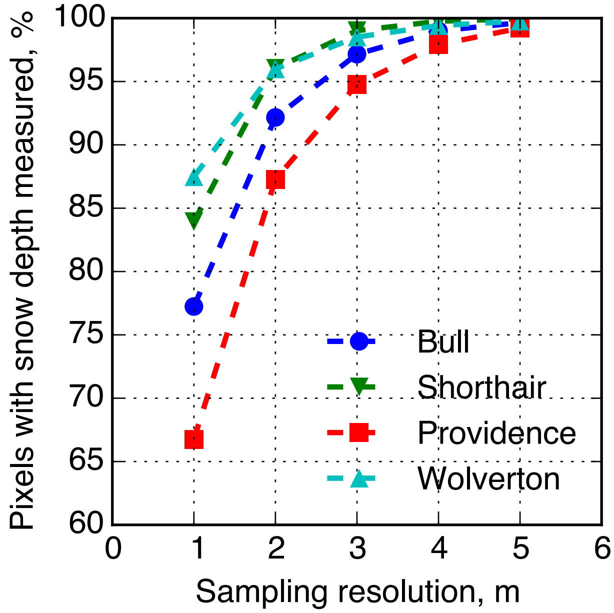

Figure 4. Sensitivity of the percentage of pixels with snow depth measured to the sampling resolution used in processing the Lidar point cloud at each site.

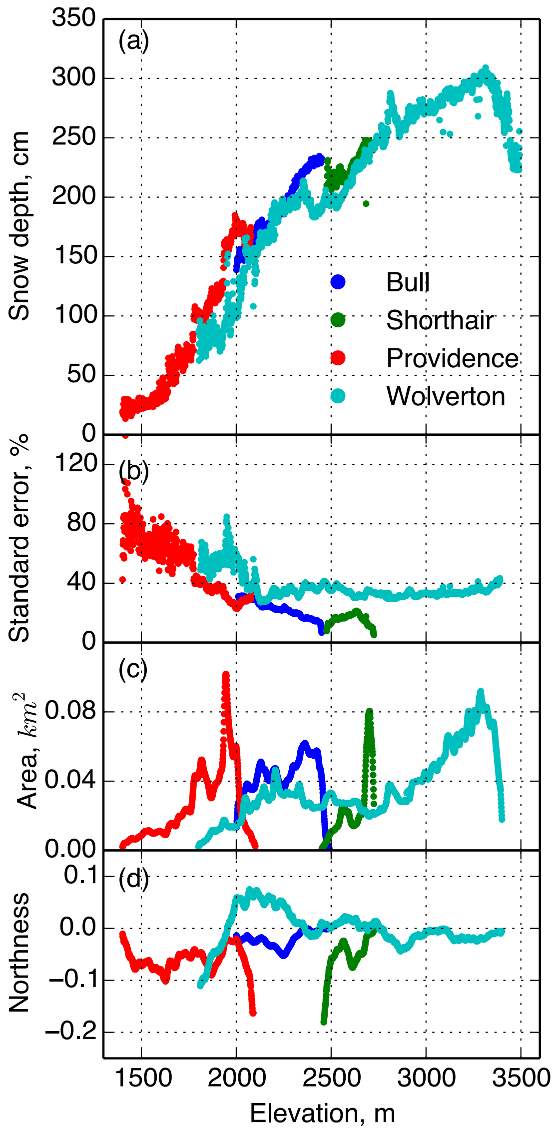

Figure 5. (a) Averaged snow depth from snow-on and snow-off Lidar data versus elevation for pixels in the open at the four sites. (b) Standard error of the snow depth within each 1-m elevation band. Values above 3400 m not shown, where there are few data. (c) Total area of averaged data within each elevation band. (d) Averaged northness of each elevation band from four sites.

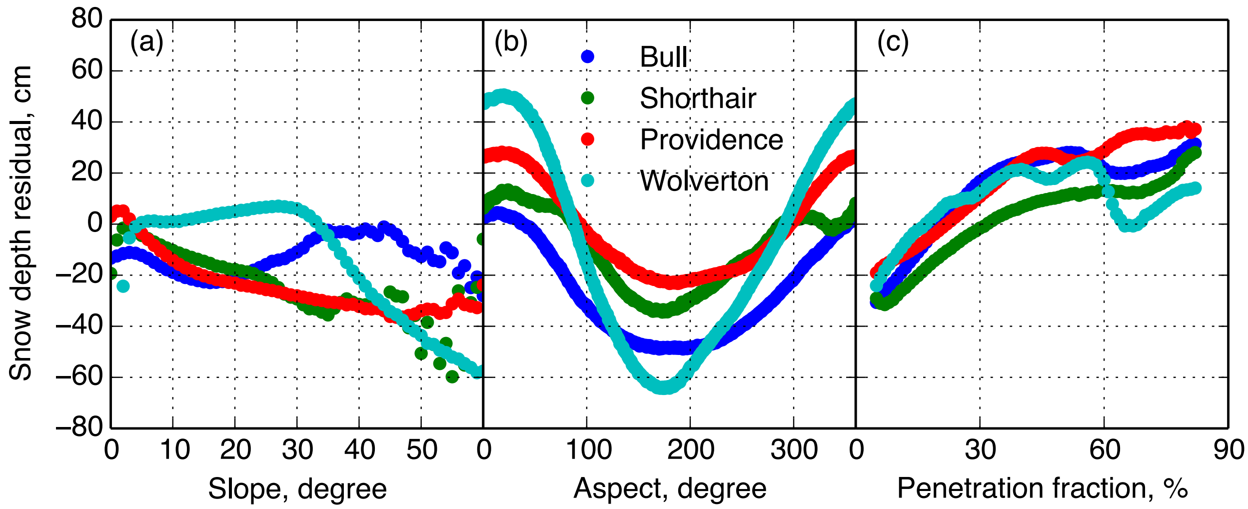

Figure 6. (a) Averaged snow-depth residual along slope. Raw snow-depth residual was calculated from Lidar measured snow depth and estimated snow depth from the linear regression model (open areas). (b) Averaged snow-depth residual along aspect. (c) Averaged snow-depth residual along penetration fraction.

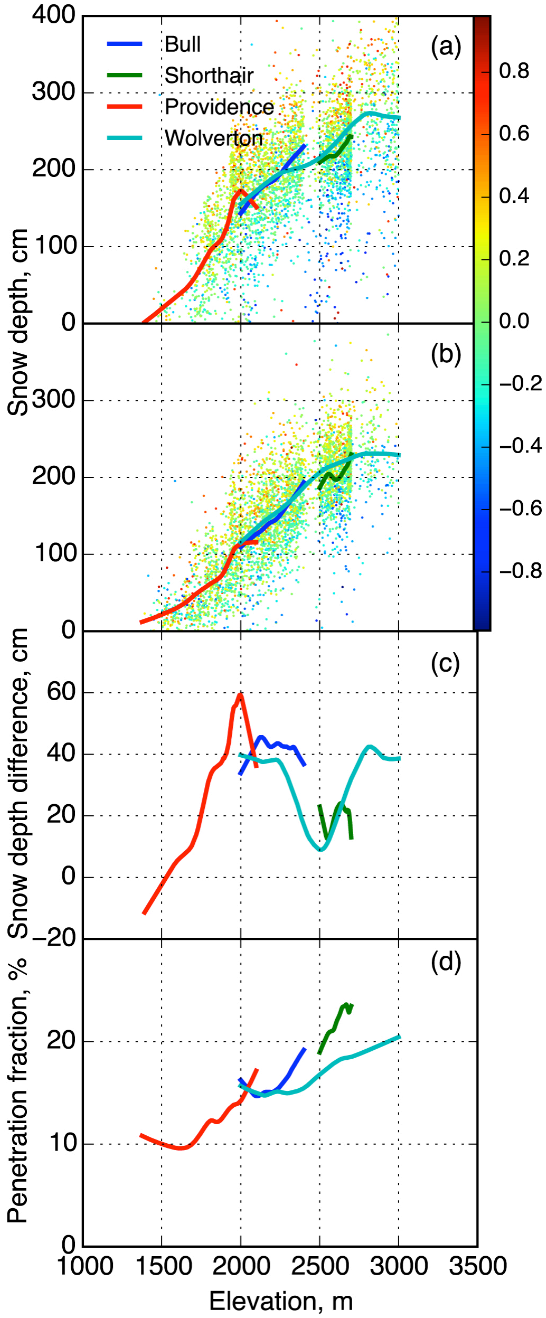

Figure 7. LOESS smoothed snow depth with northness color coded scatterplot of raw-pixel snow depth against elevation for (a) open area (b) canopy-covered area. (c) Snow-depth difference along elevation calculated from the LOESS smoothed snow depth. (d) Averaged penetration fraction.

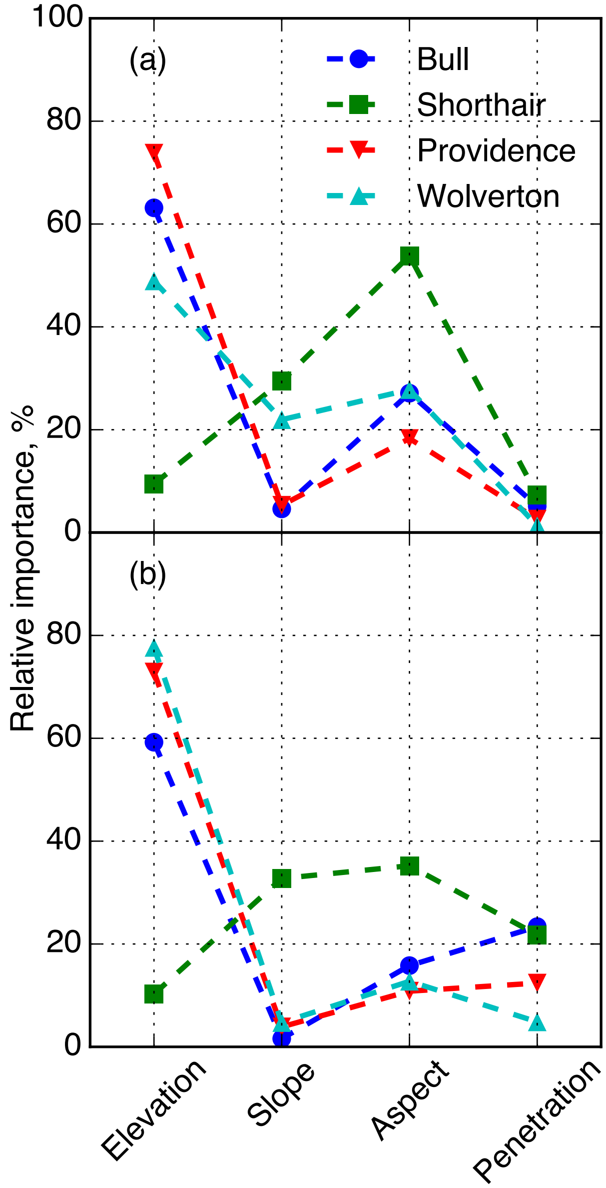

Figure 8. Relative importance of each physiographic variable in predicting the snow depth from each site for (a) open area (b) canopy-covered area

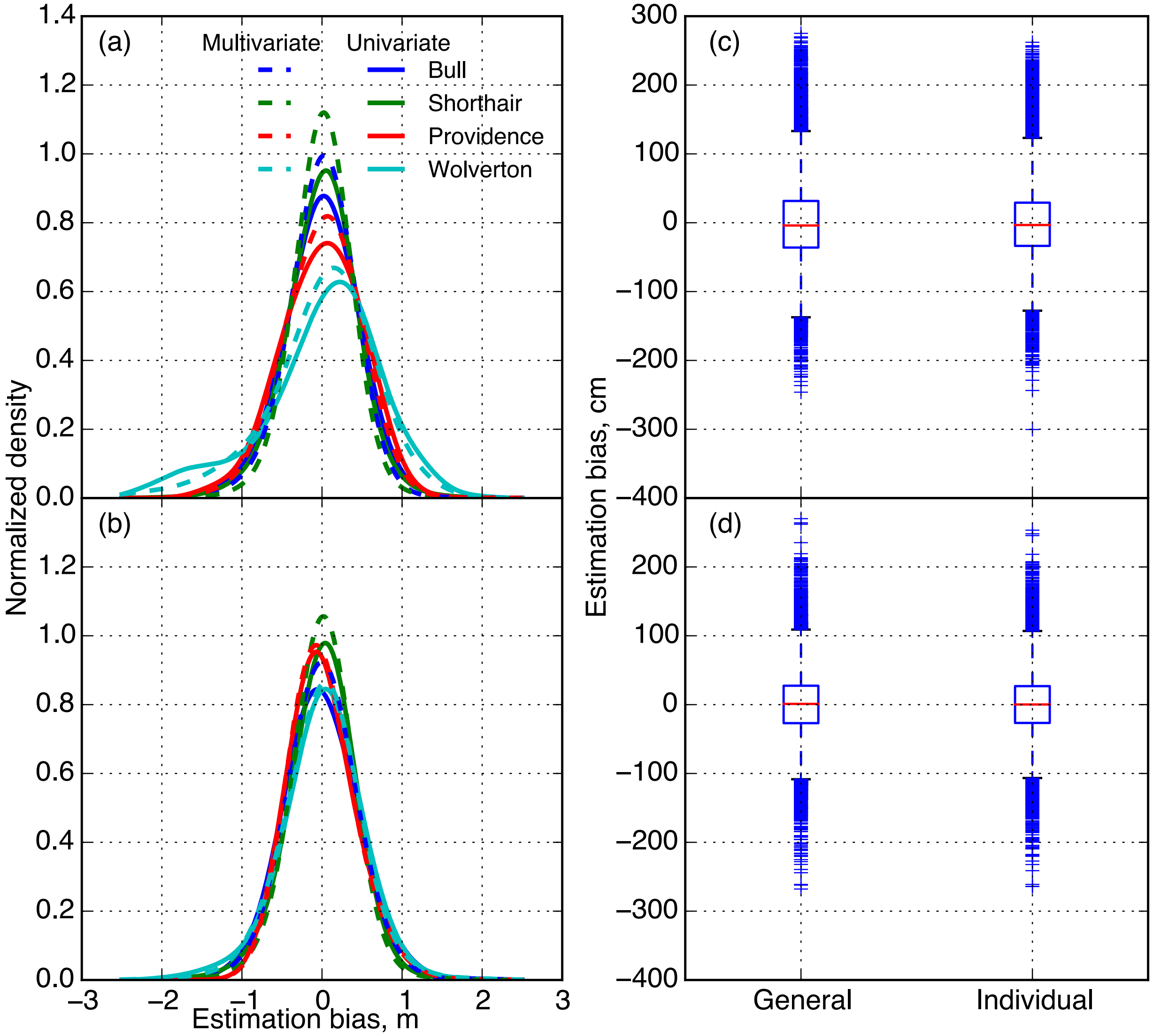

Figure 9. Normalized density of estimation bias for (a) open area (b) canopy-covered area; Estimation bias boxplots of using one general linear model with all sites' data combined and four linear models of each individual site for (c) open area (d) canopy-covered area.

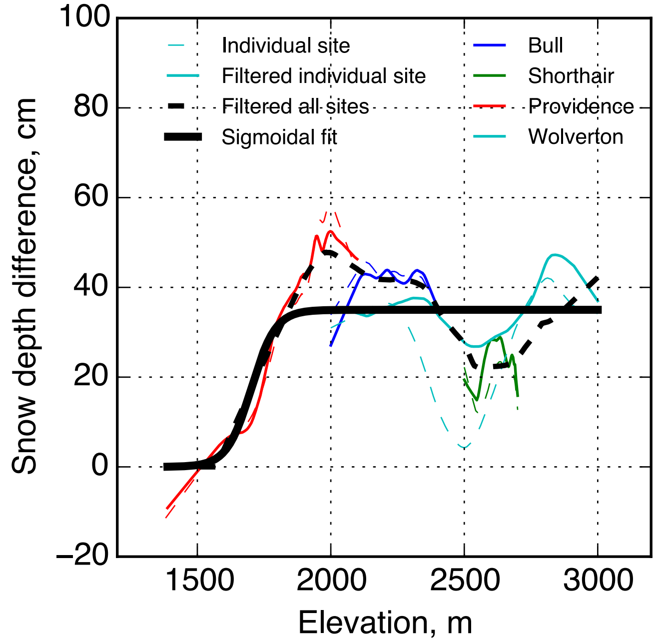

Figure 10. Snow-depth difference between open and canopy-covered area: comparison between using raw 1-m pixel snow depth and northness-filtered 1-m pixel snow depth, together with the sigmoidal fit of the snow-depth difference changing with elevation