Dear Mr Brown,

Thanks for handling the review and editing processes of our manuscript. The comments from Reviewer 2 have been carefully re-considered and the manuscript has been revised in response to the comments. Please see the detailed response to each comment below and the revised manuscript submitted. The references of line numbers in responses are based on the revised manuscript without markup. Thank you!

Best regards, Zeshi Zheng

Reviewer 2 comments on revised m/s:

This paper is much improved from the original version, but still needs improvement before I think it should be accepted for publication. The main improvement is to make the results, and their meaning clearer, and to support use the results to support the conclusions more fully.

One thing that will greatly help with clarity is for the authors to review and revise the nomenclature that is being used throughout the text, defining clearly what terms mean, and what is actually being measured. Choose names carefully, then stick to the choice! Consider the use of precipitation, accumulation, snow depth and distribution. Precipitation varies with elevation (orographic lifting). It may also vary with slope and aspect due to squalls and storm tracks moving through basins, but slope and aspect can also effect the snow distribution (as would wind) through direct post-deposition effects, and indirect effects through controls on the vegetation. Depth as revealed by lidar….which includes canopy interception as well as post-deposition processes like avalanching and differential melt….is the product of two very different physical processes. And there is actually a third set of processes that alter depth: snow settlement. The regression equations proposed in the text includes both sets of processes, which is fine, but needs to be stated clearly. Also, while settlement does not affect depth, it does affect SWE. It is completely possible that altitude/slope/aspect driven differences in settlement produces different depths without differences in SWE, another point that deserves discussion.
Response: The use of precipitation, accumulation, snow depth and distribution has been reconsidered throughout the manuscript. And the two processes that physiographic variables could affect snow distribution are stated in the Results section (lines 271-272). However, the settlement effect on SWE could not be discussed because of lacking enough snow density samples to address the effect.

Similar nomenclature issues exist in the paper for the terms related to canopy openings (also called open areas) and under canopy areas, and to the various lidar-derived models (ground DEM, snow depth, canopy etc.) Many of these seem to get called different things at different points in the paper. One simple thing that would help (suggested in my previous review) would be a simple sketch of a tree canopy, a

shrub canopy (less than 2 m high) and the various lidar-derived surfaces, marked on the sketch.
Response: The nomenclatures related to canopy openings are standardized in the manuscript. A figure of sketch showing digital-elevation model, digital-surface model and canopy height model is added in the manuscript.

A second major problem is that the paper does not do a good job of circling back to the stated objectives and three study questions (new) listed page 5. In fact, I would suggest the questions are slightly off target. I think this study really addresses 1) whether using lidar can improve our understanding of the orographic increase in snow depth with height in the Sierras (Yes, because we get so many more data), 2) whether the resolution at which the lidar is used matters (perhaps, but see below), and 3) whether including slope, aspect and some measure of canopy conditions can improve regressions used to predict snow depth (Yes, nicely shown in the paper). Issue 2) remains in doubt and is not addressed well in the paper. The authors show that in order to increase lidar snow depth mapping toward 95% coverage, pixels must be increased to about 5-m, and that doing so tends to favor a bias (though towards + or – is not made clear, and why). But whether the increase in areal coverage leads to a commensurate decrease in actual depth accuracy is either buried away in the text where I missed it, or not addressed. This is an important and practical outcome of the study: it should be addressed more clearly and comprehensively.
Response: We changed the questions in the Introduction part to fit the reviewer's comments. Also, we discussed about the commensurate decrease in snow-depth accuracy from the areal-coverage increase in Section 4.1 (lines 289-295).

Minor Points

I was disappointed that the manuscript at this stage was not more error-free. I would expect it to be so before re-submission. One trivial but indicative point concerning this is the use of the abbreviation Lidar, which in various places also shows up as LiDAR. A recent paper on lidar suggests, just as radar, the all-lower case version is starting to be preferred in the literature. But the point is mistakes like using several versions should be absent by now.
Response: All "LiDAR" are replaced with "Lidar".

Abstract: Line 13: delete "snow-on and snow-off"
Response: Deleted.

Abstract: Lines 25-28 are very awkward.
Response: The sentence was rephrased and it is more informative.

Introduction, Line 38: "…precipitation and snow distribution . . . "
Response: Fixed.

Introduction, Line 45: Surely some knew and published that snow below the canopy is shallower than in a clearer before 2013? In my paper on tree wells (Arctic and Alpine Research, 1992, Vol. 24, pp. 145-152) I cite several papers dating back to 1939 on this topic.
Response: Citation added to the manuscript.

Line 54: Why not cite that Sierra snow fuels a multi-billion dollar agra-business? That's a good reason for the study.
Response: This is a good reason but not really fit to the context here. So we added the reason to the first paragraph of the Introduction part and is properly cited.

Line 69: New paragraph starting with "An orographic-lift effect. . .
Response: Fixed.

Line 73: Predictors: this in the context of the paper are elevation, slope aspect and canopy character, but this gets back to my major comment on being clearer on how the snow depth arises from variations in precipitation, as well as post-depositional processes of redistribution.
Response: The effects on these two processes by the physiographic variables could not be separated in Lidar data. But this time we stated the variations are from precipitation and post-deposition processes in the Results section (lines 271-272), see major comments.

Lines 92: This study doesn't explain or increase our understanding of why the depth varies, but rather how it varies. See above how the questions might be revised. Currently, questions 2 and 3 overlap considerably.
Response: We rephrased the sentence to make it clearer and the questions are changed. See major comments.

Lines 119-120: Poor and confusing sentence.
Response: The sentence is not necessary here and it was deleted.

Lines 138-139: I have no idea what this sentence means.
Response: The sentence is not necessary here and it was deleted.

Equation 1: Specify that north is 0/360°, and that it is measured in degrees.
Response: North direction degree and measurement unit is specified in the manuscript.

Line 152: Too many sentences start with "And. . ." Its OK a few times, but I think it has been over used.
Response: This sentence is verbose and the content was sharpened. We went through the paper and changed a few places to avoid over-using "and".

Lines 155-156: A good example of varying nomenclature: under-canopy. Also why 2 m? Never discussed.

Response: Nomenclature was changed through the manuscript and the reason of using 2 m as the threshold is discussed in the manuscript.

Section 2.4: The reason to define and compute penetration fraction is to be able to examine the impact of canopy on the regression. Fine, but that is never stated.
Response: The first sentence of section 2.4 is the implication of the reason to define penetration fraction. To make the reason explicit, a sentence is added on line 169 to address that it is used to quantify the impact of canopy on snow depth using linear regression.

Lines 172 ans 177: Repeats. Be more careful!
Response: Fixed.

Line 179: Why 2 m?
Response: We rephrased the sentence so that the reader will know it is the same reason as in the previous text.

Line 188: Is a "survey area" each basin?
Response: Yes. "survey area" is used several times in the manuscript.

Line 207: This needs to go sooner. The whole point of penetration fraction (pf) is to have a useable physiographic variable. To be really acceptable, you would need to show quantitatively that pf is related closely to some physical measure of canopy, and that seems not to have been done, so we have to take this on faith.
Response: We removed the statement here and stated the reason earlier in section 2.4.

Lines 226-227: This seems to warrant more comment. Don't you think it somewhat surprising that these four separate field areas produced such a nicely clustered non-linear function? Why might this be the case?
Response: We discussed about the reason in lines 228-230.

(1) Figures 7a and 7b vs. 5a: Personally, I would lead as Figure 5 with what is currently Figures 7a and b. It is almost the same data, and it is more interesting with the data points actually plotted and coded by aspect. You could readily delete 5a.
(2) Line 230: Here you state the depth is linear with elevation in clearings and under the canopy, but Fig. 5a only shows data from clearings. This is another good reason to replace 5a with 7a and b. Also, I hardly would call the depth-elevation function linear. It can be fit with a line, but it has a strong curve to it.
Response: Answer two comments together. We replaced Figure 5a with Figure 7a and 7b. The interpretation of "linear trend" is now replaced with "increasing trend".

Table 1 needs to have the mean elevation, elevation range, and canopy cover added to it. Table 2 could be deleted if room becomes a problem. We need to readily understand how these basins differed in elevation, area, and so on.
Response: Summary results are added to Table 1.

Lines 235-250: I still would like to see the elevation-depth regression for each area as an equation, before adding in the other explanatory variables.
Response: The regression results are shown in Table 3. We inadvertently forgot to add the reference to Table 3 in this paragraph. We will be more careful. We added the reference of Table 3 in the manuscript. The reason of not showing as equation is that the linear regressions here were based on the averaged snow depth at each elevation band and they were used to qualitatively address the orographic effects. The quantification results were emphasized in the multivariate regression models.

Lines 251 to 267: By their nature, residuals have sign, but we usually mean that an increase in residual can be either positive or negative, while a decrease means the residual absolute value gets smaller.
Response: Increase and decrease in residual are used more carefully. "change" is more frequently used instead of "increase" and "decrease" when the sign of the residual changes.

Lines 264-265: The relative strength of the regression equation coefficients is masked here because the input values differ in scale: elevation ranges from 1500 to 3000, while penetration fraction ranges from 0 to 1. But if you normalized each explanatory variable from zero to 1, then the coefficient magnitudes would suggest the strength of that term.
Response: The equations here are not to show the relative strength of each variable in the regression equations. They are used to quantify how snow depth varies with each variable in their standard unit. If the explanatory variables are normalized from 0 to 1, the objective of showing the equations could not be reached. However, to compensate the discussion of relative strength of each variable, we used the Random Forest Regression algorithm. The strength of each variable is shown in Figure 8 and interpreted in section 3 and section 4.2. This approach is more popular and widely accepted in statistics community than using normalized linear regression because it uses bootstrap to resample the data hundreds of times (the number of times is specified by the user) and the variable is randomized as well, the results of which are more stable and reliable by the nature of the Random Forest algorithm

Line 282: Important and not shown or demonstrated (see above).
Response: Since the laser pulses from the Lidar dataset in this study cannot penetrate dense forest, we were not able to demonstrate how the accuracy is changed when sampling resolution decreases. To do this, we need another set of Lidar data that take more than 1 pt/m^2 *snow depth samples under the canopy so that we could compare these two data sets to address the change of accuracy when the sample resolution changes. From our understanding of the snow-depth difference between open area and under-canopy, we were able to address that it favors a positive bias when the sampling resolution is smaller and we calculated an averaged bias over 2000-3000 m elevation, which is now discussed in Section 4.1.*

Conclusions: Good and clear!

Figure 6: Steeper slopes have less snow than the elevation model predicts. North slopes have more; south slopes less. What does panel c show?
Response: Panel c shows there is more snow when the penetration fraction increases. This is explained on lines 260-261.

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

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Abstract

Airborne light detection and ranging (Lidar)~~ snow-on and snow-off~~ measurements collected in the southern Sierra Nevada near peak snow accumulation in 2010, and in the snow-free season, ~~in the 2010 water year~~ were analyzed for topographic and vegetation effects on snow accumulation. Combining point-cloud data from four sites separated by 10 to 64 km, with total surveyed area over 106 km^2, it was observed that in~~ that~~ the mixed-conifer forest the percent of pixels with snow-depth measurements 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 t~~The 1-m gridded data show that ~~, it was observed that~~ in addition to elevation effects, snow depth depends strongly ~~has a strong dependency~~ on slope, aspect and canopy penetration fraction. A multivariate linear-~~-~~regression model~~ built~~ using all physiographic variables explained 15~~-to~~-25% more variability in snow depth than did a univariate linear-regression 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 in ~~between~~ mean snow depth ~~measured~~ in open areas versus ~~and~~ under canopy increased with elevation in the rain-snow transition zone ~~from~~ (1500~~-to~~-1800 m); and was~~stabilized at~~ about ~~25 to 45~~35±10 cm above ~~about~~ 18~~20~~00 m ~~elevation~~, with the 20-cm fluctuation range reflecting the effects of other topographic variables.

1. Introduction

In the western United States, ecosystem processes and water supplies for agricultural and ~~domestic~~ urban users depend on the mountain snowpack as the primary source of late-spring and early summer streamflow (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). California's multi-billion dollar agricultural economy as well as multi-trillion dollar urban economy depend on these predictions (California Department of Water Resources, 2013). 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 distribution ~~accumulation~~ is highly sensitive to vegetation structure (Anderson, 1963; Revuelto et al., 2015; Musselman et al., 2008);~~,~~ and canopy interception, sublimation ~~and~~ as well as unloading result in less accumulation of snow beneath the forest canopies in comparison with canopy gaps (Berris and Harr, 1987; Golding and Swanson, 1986; Mahat and Tarboton, 2013; Sturm, 1992)~~(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, has an ideal 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~~provide insight~~s~~ on how ~~of snow-depth dependency on~~ orographic and topographic factors ~~e~~affect~~s~~ snow depth 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.

~~Manual snow surveys, one-time surveys, and remote-sensing products are used to estimate precipitation and snow accumulation in the Sierra Nevada (Guan et al., 2013).~~ *In situ*, operational measurements of snow water equivalent (SWE) in the Sierra Nevada come from monthly manual snow surveys and daily snow-~~-~~pillow observations (Rosenberg et al., 2011). Meteorological stations and remote-sensing products also provide estimates of precipitation and snow accumulation (Guan et al., 2013). 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. However, it only provides snow-coverage information in open areas~~canopy gaps~~, and no direct information on snow depths (Molotch and Margulis, 2008). ~~There is also the~~The SNOw Data Assimilation System~~s~~ (SNODAS) ~~that~~ integrates data from satellite and *in situ* measurements ~~into~~ with weather-forecast and ~~a~~ physically based snow~~pack~~ models, ~~which~~ providing~~es~~ gridded SWE and snow-depth estimates (Barrett, 2003). However, since SNODAS has not been broadly assessed ~~evaluated~~ (Clow et al., 2012), its potential for ~~studying~~ evaluating~~the~~ snow distribution in mountain~~ous~~ 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.

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~~explanatory variables, except for elevation;~~,~~ and the consistency of the orographic trend as well as the relative importance of these variables ~~predictors~~ is still unknown owing to the lack~~ing~~ of representative measurements across different slopes, aspects and canopy conditions. Also, ~~And~~ the stability of the variance explained by the model ~~also~~ needs to be tested with denser measurements.

In recent years, airborne Lidar has been ~~employed~~ used 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 provides a potential tool to help understand~~ing~~ spatially distributed snow depth across mountain~~ous~~ regions. With multiple returns from a single laser pulse, Lidar 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 snow~~pack~~ distribution variability in complex, forested terrain.

The objective of this work reported here is to improve our understanding of how~~the~~ topographic and vegetation factors ~~effects~~ affect ~~on~~ snow accumulation in ~~the~~ mixed-conifer forests. We ~~investigated these by using~~used Lidar data collected in four headwater areas in the southern Sierra Nevada and address the following three questions. First, what new information about orographic effects on precipitation versus accumulation is provided by these Lidar data? Second~~First~~, is it possible to have snow-depth measurements in forested mountain terrain from all pixels on a fine sampling resolution (1-~~ to ~~5 m) using Lidar data? If not, how does the percentage of pixels measured change with the sampling resolution. Third~~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?~~

2. Methods

2.1 Study Areas

Our study areas are located in the southern Sierra Nevada, approximately 80 km east of Fresno, California (Figure 1). The four 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 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 southeast of the other three sites (Figure 1) and is located in Sequoia National Park. Both snow-on and snow-off airborne Lidar were flown in 2010 (Table 1) over these sites. The elevation of the survey areas is from 1600-m to 3500-m elevation. Vegetation density generally decreases in high-elevation subalpine forest, with Wolverton also having a large area above treeline (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 mix below 2000 m, where most of Providence is located. The comparison between Providence and the other sites can help in ~~accessing~~ assessing 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 airborne Lidar~~iDAR~~ surveys were performed by the National Center for Airborne Laser Mapping (NCALM) 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~~with 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. Since the snow-on survey required four days to cover the four study areas, time-series *in situ* snow-depth data measured continuously from Judd Communications ultrasonic depth sensors at Providence, Bull and Wolverton were used to estimate changes in snow depth during the survey period. While no snow accumulation was observed, 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 after snow had completely melted out in the study areas.

2.3 Data Processing

Raw 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, including both canopy and ground-surface points, are stored and classified as ground return and vegetation return. ~~Each point is also attributed with the total number of returns and position of all returns from its source laser pulse.~~ The 1-m resolution digital-elevation models, generated from the 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, both in degrees. For aspect angle A, north is either 0° or 360°. 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 1-m resolution canopy-height models ~~vegetation structure~~ from Lidar data, the 1-m digital-elevation models were subtracted from the 1-m digital-surface models that rasterized from the first return of the laser pulses (Figure 2).~~points that are from the first return of the laser pulse are used to generate 1-m gridded digital-surface models. And 1-m resolution canopy-height models were built by subtracting the digital-elevation models from the digital-surface models.~~

The snow depths were calculated directly from the snow-on Lidar data. By referring to canopy-height models, all ground points in snow-on Lidar datasets were classified as under canopy or in open areas~~canopy gaps~~. That is, if the ground point was coincident with canopy of >2-m height, it was classified as under canopy, and otherwise in the open, i.e., a 2-m height was used to classify shrubs versus trees. In this study we assumed the shrubs did not affect the snow depth. ~~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 not all laser pulses that generated canopy-surface returns had ground returns ~~the measurements collected under canopy were insufficient within each pixel~~ (Figure 3~~2~~) and the ground-return percentage 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 open-canopy fraction is a factor that represents the forest density above a given pixel and is used to describe the influence of vegetation on snow accumulation and melt. However there is no algorithm to directly extract this information from Lidar data. Here we use a novel approach we call penetration fraction to approximate the open-canopy fraction from the Lidar point cloud, with which we were able to quantify the impact of canopy on snow depth using linear regression. Penetration fraction is the ratio of the number of ground points to number of total points within each pixel (Figure 4a). Whereas pixels are generally classified as under canopy or in the open (Kirchner et al., 2014), penetration fraction is an index of fraction open in a pixel. Because the electromagnetic radiation from both 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 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 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~~the 2-m 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,~~Since the radius of the Gaussian filter needs to be specified by the user, 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 ~~3~~4b). Therefore, we specified a radius of 5 m in the Gaussian filter.

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~~site. 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 and snow depth retrieved from Lidar measurements, topographic and vegetation effects on snow accumulation were 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 to fit the linear-~~-~~regression model for calculating the residual of snow depth. All snow-depth measurements from Lidar were first separated by either under canopy or in open areas~~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. 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~~ with snow-depth residuals corresponding to each bin of ~~each~~ every physiographic variable ~~were~~ averaged and visualized along the variable gradient to check the existence of these physiographic effects.

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 ~~in~~to all physiographic variables to calculate the regression coefficients, which could be used as ~~the quantification of~~ the effect of that variable on the snow~~pack~~ 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~~having snow-depth ~~data~~ measurements~~d~~ is highly sensitive to the sampling resolution used in processing the Lidar point cloud to produce the raster data.~~, which is~~ The percentage goes from about 65 to 90% across the 4 sites for~~with~~ 1-m resolution and gradually increases to 100% at 5-m resolution (Figure 5~~4~~). Note that the percentage increases in going from the lower to higher elevation sites, consistent with ~~local~~ lower forest density decreasing ~~with~~ at higher elevation.

The snow depth in open areas and under canopy ~~canopy gaps~~ show~~s a~~ consistent increasing~~linear~~ trends with elevation across all sites (Figure ~~5~~6a, 6b). Although orographic effects may vary between individual storms across sites, these data suggest that the effect of the 4 main snowfall events prior to the Lidar data collection date (Kirchner, 2013) resulted in similar patterns. The variability within an elevation band for open area (Figure 6c~~5b~~) is highest at about 1500 m, and gradually decreases within the rain-snow transition ~~until~~ up to 2000-m elevation ~~reaches 2000 m~~. However, at above 2000 m, the ~~trends~~ pattern of variability ~~changing along~~with increasing elevation ~~gradient~~ varies~~y~~ across sites. ~~In general, snow depth is linearly correlated with elevation at all sites, both in the open area and under the canopy.~~ 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 6d~~5e~~). 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.

For each individual site, a least-squares linear regression of averaged snow depth versus elevation was used to investigate the spatial variability of snow depth (Table 3). The median elevation of the three sites increases from Providence to Bull to Shorthair. The lowest elevation at Providence Creek is less than 1400 m, and snow depth increases steeply in this region at a rate of 38 cm per 100 m in 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 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 open areas and 16 cm per 100 m under the canopy. Wolverton is 64 km further south and spans a wider 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 open areas ~~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 above 3300-m elevation and these high-elevation data were not modeled with the linear regression. 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 residuals for the snow in the open areas were further analyzed for effects of slope, aspect and penetration fraction. The snow-depth residual ~~de~~increases negatively about 10 to 40 cm as slope angle increases from 0° to 60°; and the residual ~~decreases~~ changes from positive 0-50 cm to negative 20-60 cm ~~around 50 to 100 cm~~ in going from north-facing to south-facing slopes (Figure 7a, 7b~~6a, 6b~~). ~~More interestingly, the~~The topographic effect can also be seen from the color pattern of northness observed in the scatterplots (Figure ~~7~~5a, ~~7~~5b). The residual also changes from negative 20-40 cm to positive 20-40 cm ~~increases about 40 to 60 cm~~ as penetration fraction increases from 0% to 80% (Figure 7~~6~~c~~C~~). 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~~ can 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 effects quantified in these two equations are mixtures of influences that exerted during both precipitation processes and post-deposition processes.

The snow-depth difference between open and canopy-covered area was calculated with elevation from locally smoothed snow depth (Figure 9~~7~~). It generally increases from near zero at 1500 m, where there is little snow but dense canopy, to 40 cm in the range of 1800-2000 ~~2000-2400~~ m, and varies from near zero to 60 cm at higher elevations where snow is deeper and the canopy less 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.

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. In order to estimate that bias for each pixel, we would need more under-canopy snow-depth measurements at 1-m resolution. In our survey areas, 10-35% of the total areas need to be densely measured. Besides, an average overestimation bias could be estimated over the main snow-producing elevation range of 2000-3000 m. Since using open rather than under-canopy values would introduce a bias of about 35 cm over 20-35% of the area, a 2-m mean snow depth in 2000-3000 m elevation will have about 10 cm or 5% overestimation. Therefore, the sampling resolution for processing the Lidar point cloud needs to be chosen according to the objective and accuracy tolerance of the study and the average overestimation bias needs to be corrected for the study results.

4.2 Physiographic effect on snow accumulation

Below 3300 m, the increasing trend of snow accumulation with elevation was observed for all sites (Figure 6~~5~~). 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 the coefficient of determination for this linear-regression ~~-~~model is much smaller than the other three sites, which have ranges greater than 500 m. The bias of mean snow depth in the same elevation band between different sites is acceptable if the standard error is added or subtracted from the mean (Figure 6~~5~~a, 6~~5~~b, 6c). 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 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 ~~6~~7a and the negative regression coefficients of the two linear-regression 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 ~~6~~7b 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 changing from negative to positive ~~increasing~~ with penetration fraction and the regression coefficients are positive (Figure ~~6~~7c). The multivariate linear-~~-~~regression model built from the Lidar data is a significant improvement, as the variability of the snow~~pack~~ 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 ~~9~~10a, ~~9~~10b). Also, fitting an individual linear-regression model for each site is slightly better than using a general model with all sites' data involved (Figure ~~9~~10c, 10d) 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.

4.3 Vegetation effects on snow distribution ~~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 9a~~7e~~). In the rain-snow transition zone from 1500 to 2000 m of Providence we see a sharp linear increase between open and under-canopy snow depth ~~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. 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 6~~7~~a and 6~~7~~b 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 9a~~7c~~ using the filtered data. As presented in Figure 11~~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.

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.

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Table 1. Lidar data collection information

	Bull	Shorthair	Providence	Wolverton
Snow-off flight date	August 15, 2010	August 13, 2010	August 5, 2010	August 13-15, 2010
Snow-on flight date	March 24, 2010	March 23, 2010	March 23, 2010	March 21-22, 2010
Area, km^2	22.3	6.8	18.4	58.9
Mean elevation, m	2264	2651	1850	2840
Elevation range, m	1925-2490	2436-2754	1373-2207	1786-3523
Canopy cover, %	50.3	43.4	63.2	38.6

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	±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-regression 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

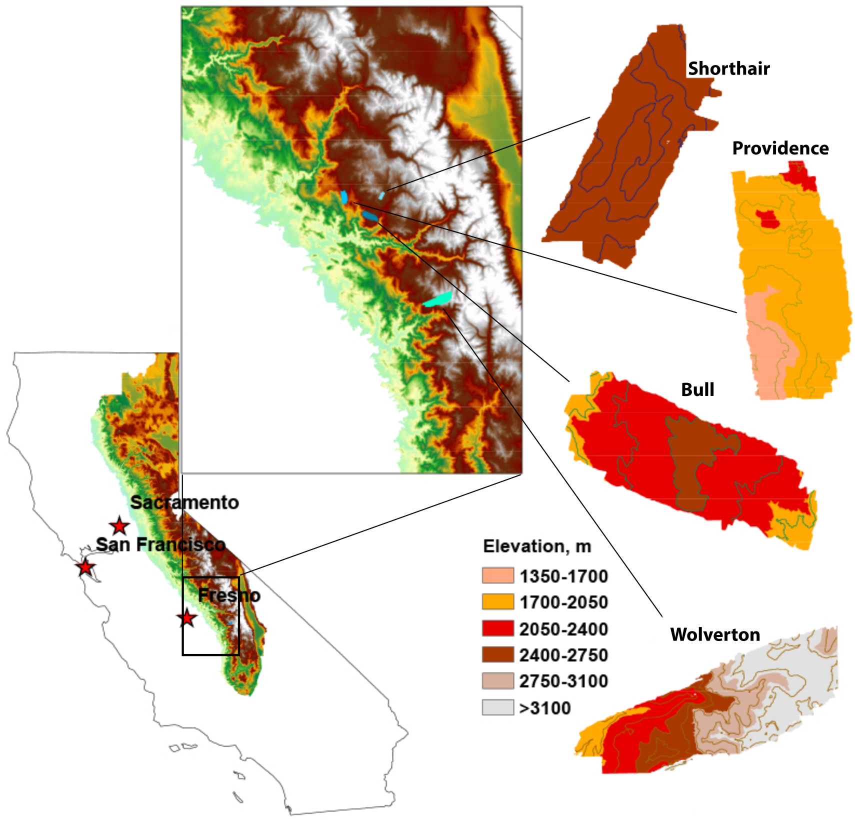


Figure 1. Study area and Lidar footprints. (Left) California with Sierra Nevada. (Center) Zoomed view to show the locations of Lidar footprints. (Right) Elevation and 200-m contour map (100-m for Bull) of Lidar footprints

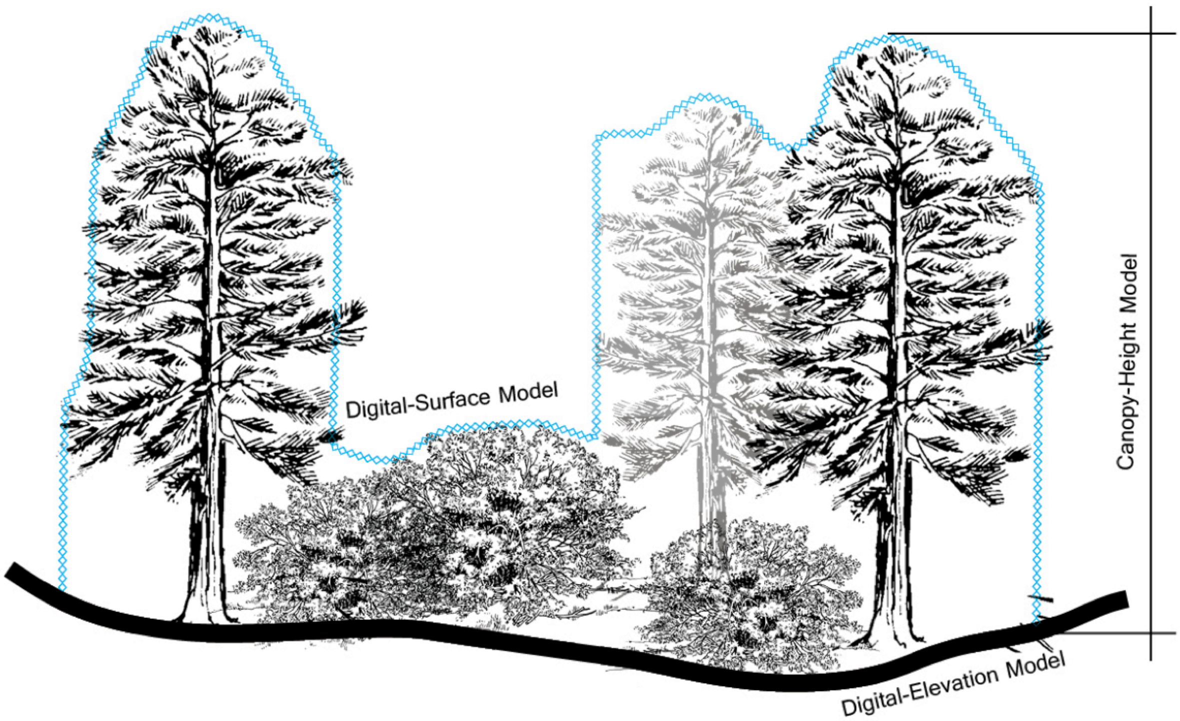


Figure 2. Subtracting the digital-elevation model from the digital-surface model will result in the canopy-height model. In this study the height of shrub vegetation is assumed smaller than 2 m while tree vegetation is taller than 2 m.

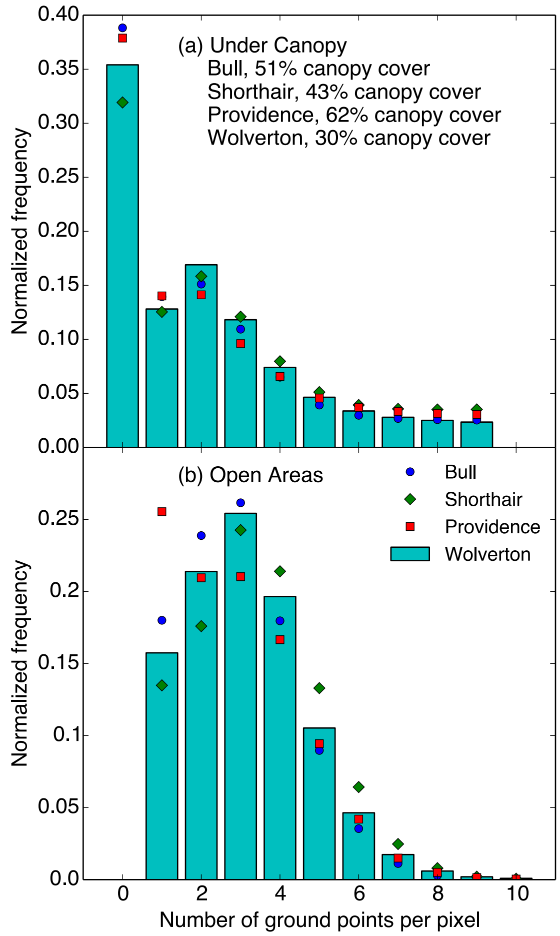


Figure 3. (a) Normalized histogram of the number of ground points for under canopy pixels. (b) Normalized histogram of the number of ground points in open pixels.

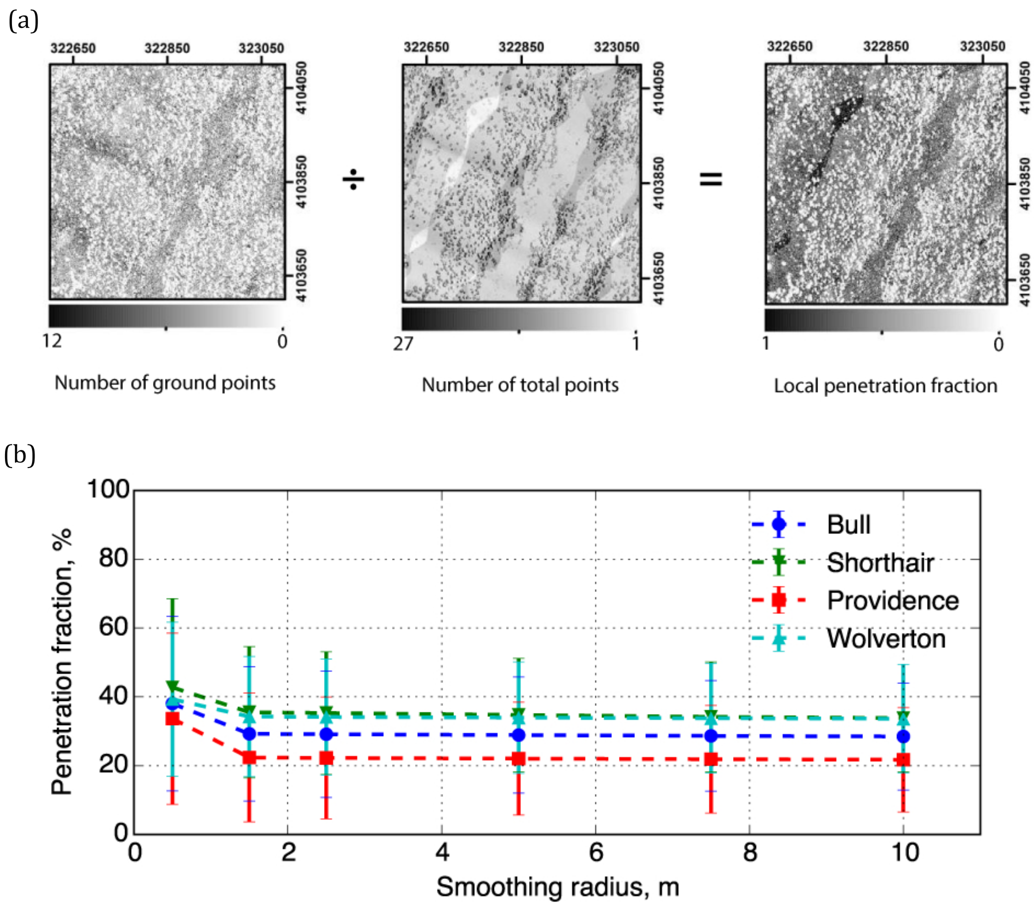


Figure 4. (a) Dividing the number of ground points of each 1-m pixel by the total number of points in the pixel will result the penetration fraction of the local pixel. (b) Sensitivity of the smoothed penetration fraction to the smoothing radius, showing that the result is not sensitivity as the radius is larger than 1.5 m.

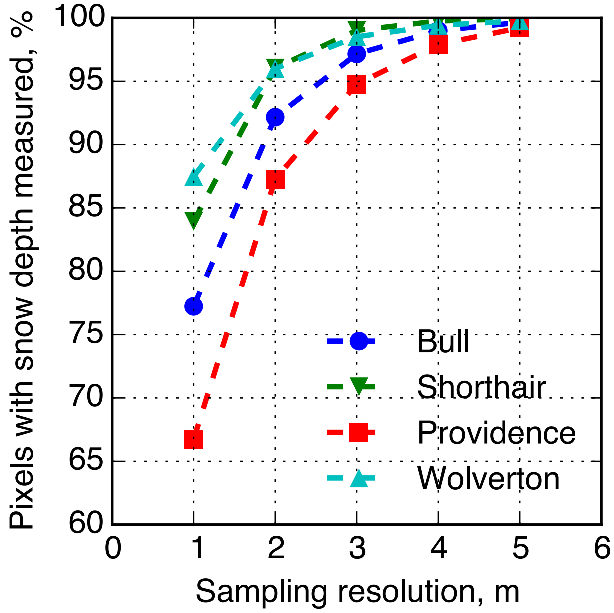


Figure 5. Sensitivity of the percentage of pixels with snow depth measured to the sampling resolution used in processing the Lidar point cloud at each site.

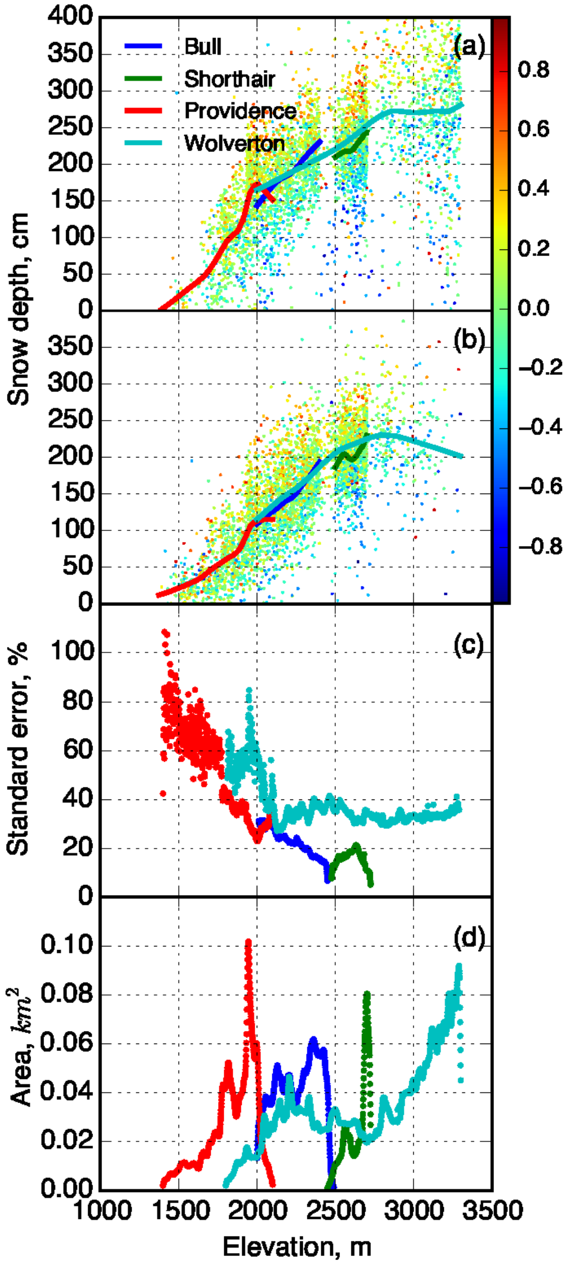


Figure 6. LOESS smoothed snow depth with northness color coded scatterplot of raw-pixel snow depth against elevation for (a) open area (b) under-canopy area. (c) Standard error of the snow depth within each 1-m elevation band for open area. (d) Total area of each elevation band for both open and under-canopy area. Values above 3300 m not shown, where there are few data.

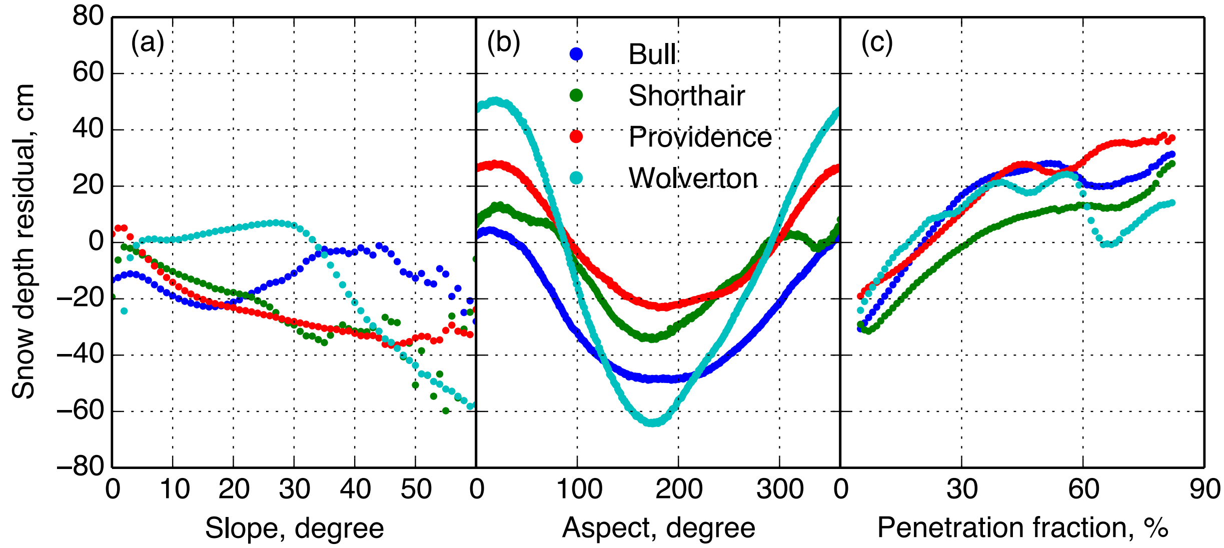


Figure 7. (a) Averaged snow-depth residual along slope. Raw snow-depth residual was calculated from Lidar measured snow depth and estimated snow depth from the linear-regression models (open areas). (b) Averaged snow-depth residual along aspect. (c) Averaged snow-depth residual along penetration fraction.

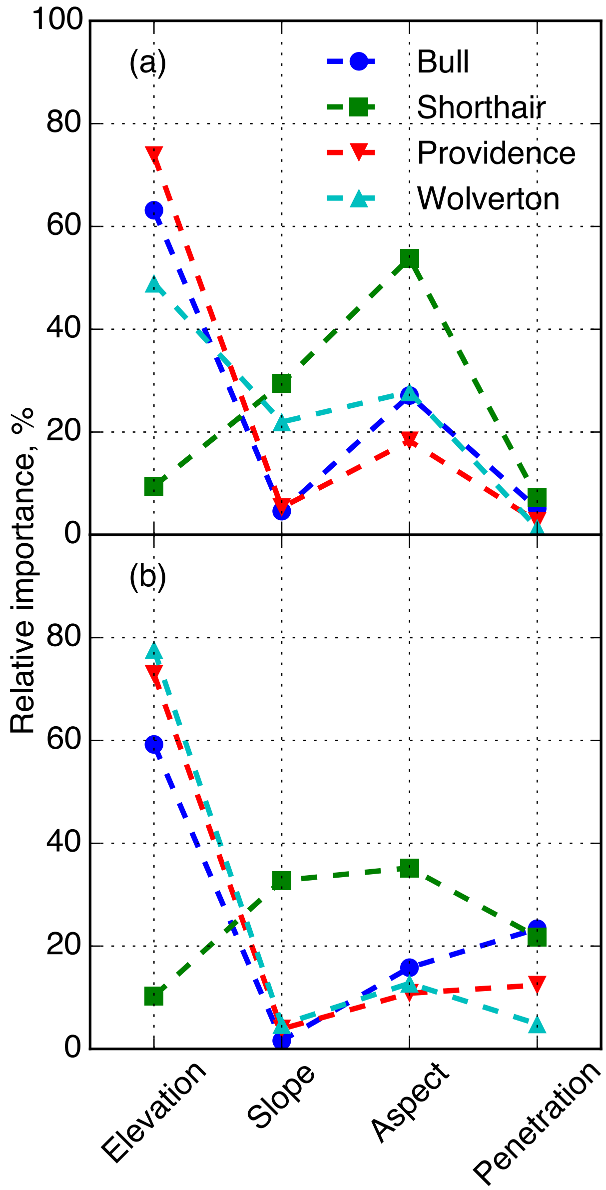
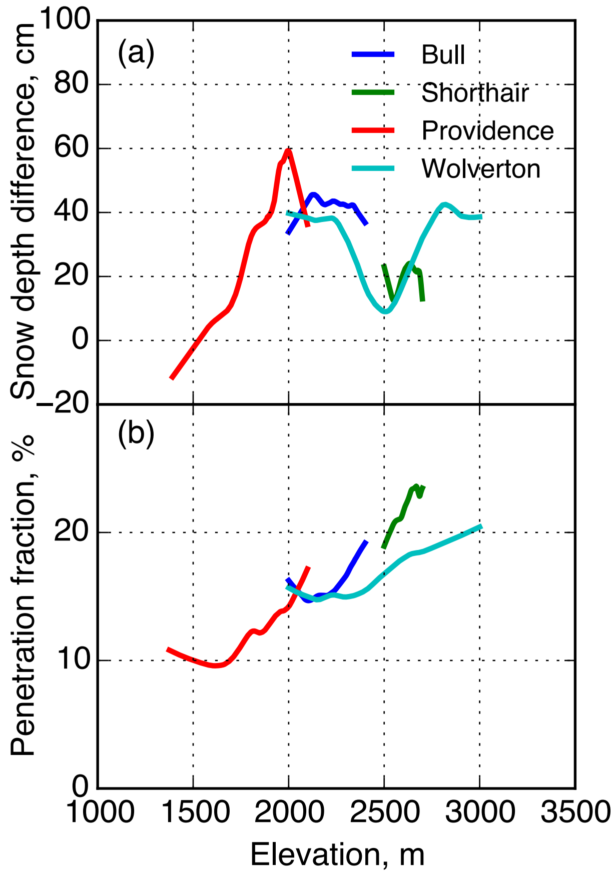


Figure 8. Relative importance of each physiographic variable in predicting the snow depth from each site for (a) open area (b) under-canopy area

37 

38 Figure 9. (a) Snow-depth difference along elevation for each site calculated from the LOESS smoothed
39 snow depth. (b) Averaged penetration fraction along elevation gradient for each site.

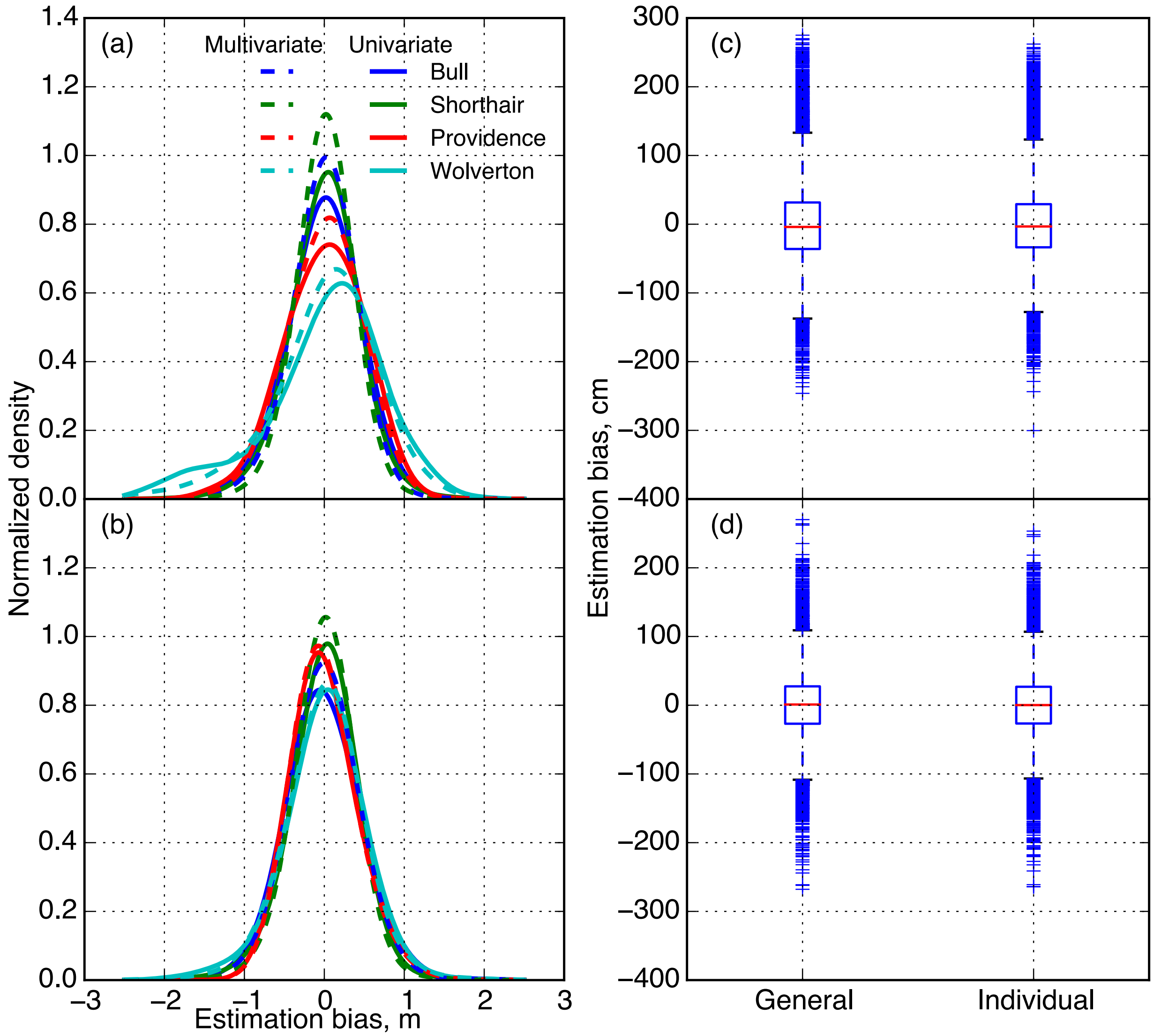


Figure 10. Normalized density of estimation bias for (a) open area (b) under-canopy area; Estimation bias boxplots of using one general linear-regression model with all sites' data combined and four linear-regression models of each individual site for (c) open area (d) under-canopy area.

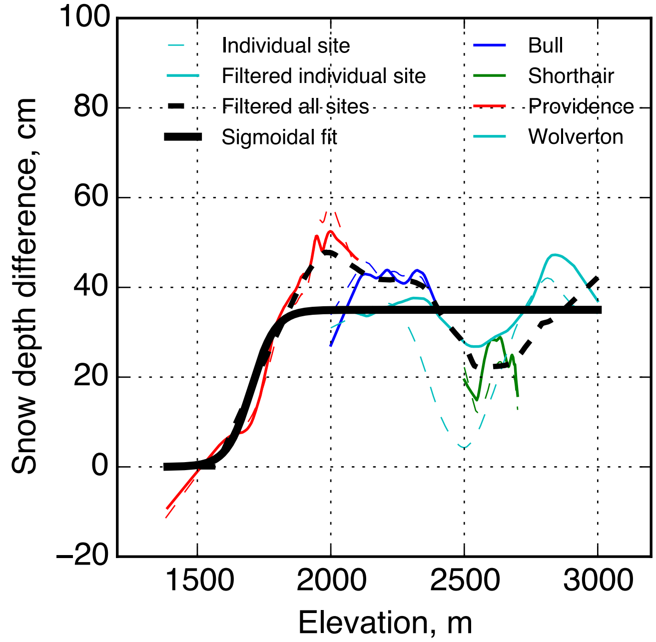


Figure 11. Snow-depth difference between open and under-canopy area: comparison between using raw 1-m pixel snow depth and northness-filtered 1-m pixel snow depth, together with the sigmoidal fit of the snow-depth difference changing with elevation