

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

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12 **Abstract**

13 Airborne light detection and ranging (Lidar) measurements in the southern Sierra Nevada near  
14 peak snow accumulation in 2010, and in the snow-free season, were analyzed for topographic  
15 and vegetation effects on snow accumulation. Point-cloud data were processed from four,  
16 primarily mixed-conifer, forest sites separated by 10 to 64 km with a total surveyed area over  
17 106 km<sup>2</sup>. It was observed that the percentage of pixels with at least one ground return and thus a  
18 snow-depth measurement increases from 65-90% to 99% as the sampling resolution of Lidar  
19 point cloud changes from 1 m to 5 m. With about 28% of the area in dense mixed-conifer forest  
20 in the main snow-producing elevations of 2000-3000 m having no returns at 1-m resolution,  
21 undersampling of snow depth under dense canopies resulted in at least a 10-cm overestimation  
22 error in the average snow depth. The 1-m gridded data show consistent patterns over the four  
23 sites, dominated by orographic effects on precipitation. Elevation explained 43% of snow-depth  
24 variability, with slope, aspect and canopy penetration fraction explaining another 14% over the  
25 elevation range of 1500-3300 m. Although, the relative importance of the four variables varied  
26 with elevation and canopy cover, all were statistically significant over the area studied. The  
27 difference in mean snow depth in open areas versus under canopy increased with elevation in the  
28 rain-snow transition zone (1500-1800 m); and was about  $35 \pm 10$  cm above 1800 m, with the 20-  
29 cm fluctuation range reflecting the effects of other topographic variables.

## 30 **1. Introduction**

31           In the western United States, ecosystem processes and water supplies for agricultural and  
32 urban users depend on the mountain snowpack as the primary source of late-spring and early  
33 summer streamflow (Bales et al., 2006). Knowledge of spring snowpack conditions within a  
34 watershed is essential if water availability and flood peaks following the onset of melt are to be  
35 accurately predicted (Hopkinson et al., 2001). California's multi-billion dollar agricultural  
36 economy as well as multi-trillion dollar urban economy depend on these predictions (California  
37 Department of Water Resources, 2013). Both topographic and vegetation factors are important in  
38 influencing the snowpack conditions, as they closely interact with meteorological conditions to  
39 affect precipitation and snow distribution in the mountains (McMillen, 1988; Raupach, 1991;  
40 Wigmosta et al., 1994). However, mountain precipitation is poorly understood at multiple spatial  
41 scales because it is governed by processes that are neither well measured nor accurately  
42 predicted (Kirchner et al., 2014). Snow accumulation across the mountains is primarily  
43 influenced by orographic processes, involving feedbacks between atmospheric circulation and  
44 terrain (Roe, 2005; Roe and Baker, 2006). In most forested regions, snow distribution is highly  
45 sensitive to vegetation structure (Anderson et al., 1963; Revuelto et al., 2015; Musselman et al.,  
46 2008); and canopy interception, sublimation as well as unloading result in less accumulation of  
47 snow beneath the forest canopies in comparison with canopy gaps (Berris and Harr, 1987;  
48 Golding and Swanson, 1986; Mahat and Tarboton, 2013; Sturm, 1992).

49           The Sierra Nevada serves as a barrier to moisture moving inland from the Pacific, has an  
50 ideal orientation for producing orographic precipitation, and thus exerts a strong influence on the  
51 upslope amplification of precipitation (Colle, 2004; Rotach and Zardi, 2007; Smith and Barstad,  
52 2004). Recent studies provide insight on how orographic and topographic factors affect snow

53 depth in the Alps (Grünewald et al., 2013; Grünewald, et al., 2014; Lehning et al., 2011),  
54 suggesting that similar studies could be extended to the Sierra Nevada. And among the forested  
55 regions of the mountains, the mixed-conifer and subalpine zones cover most of the high-  
56 elevation, seasonally snow-covered area.

57 *In situ*, operational measurements of snow water equivalent (SWE) in the Sierra Nevada  
58 come from monthly manual snow surveys and daily snow-pillow observations (Rosenberg et al.,  
59 2011). Meteorological stations and remote-sensing products also provide estimates of  
60 precipitation and snow accumulation (Guan et al., 2013). Cost, data coverage, accuracy (Julander  
61 et al., 1998) and basin-scale representativeness are issues for *in situ* monitoring of SWE in  
62 mountainous terrain (Rice and Bales, 2010). Satellite-based remote sensing, such as MODIS, has  
63 been used to map snow coverage in large or even global areas. However, it only provides snow-  
64 coverage information in open areas, and no direct information on snow depths (Molotch and  
65 Margulis, 2008). The SNOW Data Assimilation System (SNODAS) integrates data from satellite  
66 and *in situ* measurements with weather-forecast and physically based snow models, providing  
67 gridded SWE and snow-depth estimates (Barrett, 2003). However, since SNODAS has not been  
68 broadly assessed (Clow et al., 2012), its potential for evaluating snow distribution in mountain  
69 areas remains uncertain. Also, owing to its 1-km spatial resolution, the snow depth that  
70 SNODAS provides is a mixed representation of both open and canopy-covered areas.

71 An orographic-lift effect is observable in most of the above data (Howat and Tulaczyk,  
72 2005; Rice et al., 2011), and a binary-regression-tree model using topographic variables as  
73 predictors has also been used for estimating the snow depth in unmeasured areas (Erickson et al.,  
74 2005; Erxleben et al., 2002; Molotch et al., 2005). However, regression coefficients could not be  
75 estimated accurately for most of the explanatory variables, except for elevation; and the

76 consistency of the orographic trend as well as the relative importance of these variables is still  
77 unknown owing to the lack of representative measurements across different slopes, aspects and  
78 canopy conditions. Also, the stability of the variance explained by the model needs to be tested  
79 with denser measurements.

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

94 The objective of the work reported here is to improve our understanding of how  
95 topographic and vegetation attributes affect snow accumulation in mixed-conifer forests. Using  
96 Lidar data from four headwater areas in the southern Sierra Nevada, we addressed the following  
97 three questions. First, in forested mountain terrain what percentage of pixels have ground returns  
98 and thus provide snow-depth measurements at 1-m and coarser sampling resolutions, and what

99 potential error is introduced by undersampling of snow under dense canopies? Second, what new  
100 information about orographic effects on precipitation versus accumulation is provided by these  
101 Lidar data? Third, what is the effect of slope, aspect and canopy penetration fraction on snow  
102 accumulation, relative to elevation; and are effects consistent across sites?

## 103 **2. Methods**

### 104 **2.1 Study Areas**

105 Our study areas are located in the southern Sierra Nevada, approximately 80 km east of  
106 Fresno, California (Figure 1). The four headwater-catchment research areas, Bull Creek,  
107 Shorthair Creek, Providence Creek, and Wolverton Basin were previously instrumented,  
108 including meteorological measurements, in order to have a better knowledge of the hydrologic  
109 processes in this region (Bales et al., 2011; Hunsaker et al., 2012; Kirchner et al., 2014). The  
110 sites were chosen as part of multi-disciplinary investigations at the Southern Sierra Critical Zone  
111 Observatory, and are also the main instrumented sites in the observatory. Wolverton is  
112 approximately 64 km southeast of the other three sites (Figure 1) and is located in Sequoia  
113 National Park. Both snow-on and snow-off airborne Lidar were flown in 2010 (Table 1) over  
114 these sites. The elevation of the survey areas is from 1600-m to 3500-m elevation. Vegetation  
115 density generally decreases in high-elevation subalpine forest, with Wolverton also having a  
116 large area above treeline (Goulden et al., 2012). The precipitation has historically been mostly  
117 snow in the cold and wet winters for elevations above 2000 m, and a rain-snow mix below 2000  
118 m, where most of Providence is located. The comparison between Providence and the other sites  
119 can help in assessing if observed trends are consistent above and below the rain-snow transition.

### 120 **2.2 Data Collection**

121 All airborne Lidar surveys were performed by the National Center for Airborne Laser  
122 Mapping (NCALM) using Optech GEMINI Airborne Laser Terrain Mapper. The scan angle and  
123 scan frequency were adjusted to ensure a uniform along-track and across-track point spacing  
124 (Table 2), with six GPS ground stations used for determining aircraft trajectory. The snow-on  
125 survey date was close to April 1<sup>st</sup>, which is used by operational agencies as the date of peak snow  
126 accumulation for the Sierra. Since the snow-on survey required four days to cover the four study  
127 areas, time-series *in situ* snow-depth data measured continuously from Judd Communications  
128 ultrasonic depth sensors at Providence, Bull and Wolverton were used to estimate changes in  
129 snow depth during the survey period. While no snow accumulation was observed, snowpack  
130 densification and melting observed from the time-series data were taken into considerations  
131 (Hunsaker et al., 2012; Kirchner et al., 2014). The snow-off survey was performed in August  
132 after snow had completely melted out in the study areas.

### 133 **2.3 Data Processing**

134 Raw Lidar datasets were pre-processed by NCALM and are available from the NSF  
135 Open-Topography website (<http://opentopography.org>) in LAS format. The LAS point cloud,  
136 including both canopy and ground-surface points, are stored and classified as ground return and  
137 vegetation return. The 1-m resolution digital-elevation models, generated from the Lidar point-  
138 cloud datasets, were downloaded from the OpenTopography database and further processed in  
139 ArcMap 10.2 to generate 1-m resolution slope, aspect, and northness raster products. Northness  
140 is an index for the potential amount of solar radiation reaching a slope on a scale of -1 to 1,  
141 calculated from:

$$142 \quad N = \sin(S) \times \cos(A), \quad (1)$$

143 where  $N$  is the northness value;  $S$  is the slope angle and  $A$  is the aspect angle, both in degrees.  
144 For aspect angle  $A$ , north is either  $0^\circ$  or  $360^\circ$ . Northness is also the same as the aspect intensity  
145 (Kirchner et al., 2014) with  $0^\circ$  focal aspect. Since in this analysis the snow-depth comparison is  
146 only discussed between north and south facing slopes, northness is used instead of aspect  
147 intensity for simplification. To construct the 1-m resolution canopy-height models from Lidar  
148 data, the 1-m digital-elevation models were subtracted from the 1-m digital-surface models that  
149 were rasterized from the first return of the laser pulses (Figure 2).

150 The snow depths were calculated directly from the snow-on Lidar data. By referring to  
151 canopy-height models, all ground points in snow-on Lidar datasets were classified as under  
152 canopy or in open areas. That is, if the ground point was coincident with canopy of  $>2$ -m height,  
153 it was classified as under canopy, and otherwise in the open, i.e., a 2-m height was used to  
154 classify shrubs versus trees. In this study we assumed that shrubs did not affect the snow depth.  
155 After classification, snow depths were calculated by subtracting the values in the digital-  
156 elevation model from the snow-on point-measurement values. The calculated point snow-depth  
157 data were further assigned into 1-m raster pixels, averaged within each pixel, formatted and then  
158 gap filled by interpolation with pixel values around it. Since not all laser pulses that generated  
159 canopy-surface returns had ground returns (Figure 3) and the ground-return percentage varied  
160 across the transition from the tree trunk to the edge of the canopy, interpolation was not applied  
161 to data under the canopy. The error rate of the calculated snow depth should be mainly from the  
162 instrumental elevation error, which is about 0.10 m (Kirchner et al., 2014; Nolan et al., 2015).

## 163 **2.4 Penetration Fraction**

164 The open-canopy fraction is a factor that represents the forest density above a given pixel  
165 and is used to describe the influence of vegetation on snow accumulation and melt. However



166 there is no algorithm to directly extract this information from Lidar data. Here we use a novel  
167 approach that we call penetration fraction to approximate the open-canopy fraction from the  
168 Lidar point cloud. With it we were able to quantify the impact of canopy on snow depth using  
169 linear regression. Penetration fraction is the ratio of the number of ground points to number of  
170 total points within each pixel (Figure 4a). Whereas pixels are generally classified as under  
171 canopy or in the open (Kirchner et al., 2014), penetration fraction is an index of fraction open in  
172 a pixel. Because the electromagnetic radiation from both Lidar and sunlight beams are  
173 intercepted by canopies, the open-canopy fraction is used here as an index to represent the  
174 fraction of sunlight radiance received on the ground under vegetation. Therefore, penetration  
175 fraction of Lidar is actually another form of estimating the open-canopy fraction (Musselman et  
176 al., 2013). However, under-canopy vegetation can also intercept the Lidar beam, causing a bias.  
177 To eliminate this bias, the canopy-height model was used to check if the pixel was canopy  
178 covered by using the 2-m threshold value; and if not, the local penetration fraction of the pixel  
179 was reset to 1 because the open-canopy fraction of a pixel could not be entirely represented by  
180 the penetration fraction. A spatial moving-average process was applied using a 2-D Gaussian  
181 filter to account for the effect of the vegetation around each pixel. Since the radius of the  
182 Gaussian filter needs to be specified by the user, we tested the sensitivity of smoothing results to  
183 the radius of the filter and found it is not sensitive when the radius is greater than 1.5 m (Figure  
184 4b). Therefore, we specified a radius of 5 m in the Gaussian filter.

## 185 **2.5 Statistical Analysis**

186 The 1-m resolution snow-depth raster datasets were resampled into 2-m, 3-m, 4-m and 5-  
187 m resolution. The percentage of pixels with snow-depth measurements was calculated by using  
188 the number of pixels with at least one ground return divided by the total number of pixels inside

189 each site. The sensitivity of the percentage changes across different resampling resolutions and  
190 the consistency of the percentages across study sites at the same resampling resolution were  
191 analyzed by visualizing the percentages against sampling resolutions at all sites.

192         Using elevation, slope, aspect, penetration fraction and snow depth retrieved from Lidar  
193 measurements, topographic and vegetation effects on snow accumulation were observed using  
194 residual analysis. Owing to orographic effects, there is increasing precipitation along an  
195 increasing elevation gradient in this area (Kirchner et al., 2014). Therefore, elevation was  
196 selected as the primary variable to fit the linear-regression model for calculating the residual of  
197 snow depth. All snow-depth measurements from Lidar were first separated by either under  
198 canopy or in open areas, and then were binned by elevation of the location where they were  
199 measured, with a bin size of 1-m elevation. As each elevation band had hundreds of snow-depth  
200 measurements after binning, the average of all snow depths was chosen as the representative  
201 snow depth, and the standard deviation calculated to represent the snow-depth variability within  
202 each elevation band. Coefficients of determination between snow depth and elevation of each  
203 site were calculated by linear regression. The fitted linear-regression model of each site was  
204 applied to the DEM to estimate the snow depth. The residual of snow depth was calculated by  
205 subtracting the modeled snow depth from Lidar-measured snow depth. The slope, aspect and  
206 penetration fraction were binned into 1° slope, 1° aspect, and 1% penetration-fraction bins with  
207 snow-depth residuals corresponding to each bin of every physiographic variable averaged and  
208 visualized along the variable gradient to check the existence of these physiographic effects.

209         For the variables found to correlate with the snow accumulation, the relative importance  
210 of each variable was calculated using the Random Forest algorithm (Breiman, 2001; Pedregosa

211 et al., 2011). A multivariate linear-regression model was also applied to quantify the influence of  
212 the various physiographic variables on the snowpack distribution.

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

### 218 **3. Results**

219 The percentage of pixels having snow-depth measurements is sensitive to the sampling  
220 resolution used in processing the Lidar point cloud to produce the raster data. Values go from  
221 about 65-90% across the 4 sites for 1-m resolution and gradually increase to 99% at 5-m  
222 resolution (Figure 5). Note that the percentage increases in going from the lower- to higher-  
223 elevation sites, reflecting lower forest density at higher elevation.

224 The snow depths in open areas and under canopy show consistent increases with  
225 elevation across all sites (Figure 6a, 6b). Although orographic effects may vary between  
226 individual storms across sites, these data suggest that the cumulative effect of the 4 main  
227 snowfall events prior to the Lidar flight (Kirchner, 2013) resulted in similar patterns. The  
228 variability within an elevation band for open areas (Figure 6c) is highest at about 1500 m, and  
229 gradually decreases within the rain-snow transition up to 2000-m elevation. However, above  
230 2000 m the pattern of variability with increasing elevation varies across sites. Note that values at  
231 the upper or lower ends of elevation at each site have few pixels and thus may not have a  
232 representative distribution of other physiographic attributes (Figure 6d). The forested area of all

233 four sites combined spans the rain-snow transition zone in lower mixed-conifer forest through  
234 snow-dominated subalpine forest, with significant areas above treeline higher up.

235 For each individual site, a least-squares linear regression of averaged snow depth versus  
236 elevation was used to investigate the spatial variability of snow depth (Table 3). The median  
237 elevation of the three sites increases from Providence to Bull to Shorthair. The lowest elevation  
238 at Providence Creek is less than 1400 m, and snow depth increases steeply in this region at a rate  
239 of 38 cm per 100 m in open areas and 28 cm per 100 m under the canopy. Bull Creek has an  
240 elevation range of 2000-2400 meters, which is slightly higher than Providence, and has snow  
241 depth increasing at 21 cm per 100 m in open areas and 19 cm per 100 m under the canopy. For  
242 Shorthair Creek site, which is the highest of the three, the snow depth increases at 17 cm per 100  
243 m in open areas and 16 cm per 100 m under the canopy. Wolverton is 64 km further south and  
244 spans a wider elevation range, going from the rain-snow transition in mixed conifer, to subalpine  
245 forest, to some area above treeline. The average snow-depth increase is smallest among all four  
246 study sites, 15 cm per 100 m in open areas and 13 cm per 100 m under the canopy. Unlike the  
247 other three lower-elevation sites, the snow depth at Wolverton decreases above 3300-m elevation  
248 and these high-elevation data were not included in the linear regression. The amount of area  
249 above this elevation is relatively small, and factors such as wind redistribution and the  
250 exhaustion of perceptible water can also affect snow depth at these elevations (Kirchner et al.,  
251 2014).

252 The residuals for snow in open areas were further analyzed for effects of slope, aspect  
253 and penetration fraction. The snow-depth residuals are negative and larger in magnitude on  
254 steeper slopes, i.e. less snow on steeper slopes (Figure 7a). The residual also changes from  
255 positive to negative with aspect, reflecting deeper snow on north-facing versus south-facing

256 slopes (Figure 7b). The topographic effect can also be seen from the color pattern of northness  
257 observed in the scatterplots (Figure 6a, 6b). The residual also changes from negative 20-40 cm to  
258 positive 20-40 cm as penetration fraction increases from 0% to 80%, reflecting less snow under  
259 canopy (Figure 7c). Considering all of these variables together, elevation is the most important  
260 variable at all sites except for Shorthair, which has a relatively small elevation range (Figure 8).  
261 Aspect exerts a stronger influence than do slope and penetration fraction in open areas. However,  
262 for under-canopy areas, penetration is more dominant than aspect at two sites. The multivariate  
263 regression model was fitted to the data with aspect transformed into 0° to 180° range (north to  
264 south). Fitted models can be represented as the following two equations for open area and under  
265 canopy respectively:

$$266 \quad SD = 0.0011 \times Elevation - 0.0112 \times Slope - 0.0057 \times Aspect + 0.1802 \times Penetration \quad (2)$$

$$267 \quad SD = 0.0009 \times Elevation - 0.0128 \times Slope - 0.0046 \times Aspect + 0.9891 \times Penetration \quad (3)$$

268 where *SD* is snow depth and p-values of all regression coefficients of the two models are all  
269 smaller than 0.01. The effects quantified in these two equations are mixtures of influences that  
270 affected both precipitation and post-deposition processes.

271         The snow-depth difference between open and canopy-covered areas was calculated with  
272 elevation from locally smoothed snow depth. It generally increases from near zero at 1500 m,  
273 where there is little snow but dense canopy, to 40 cm in the range of 1800-2000 m, and varies  
274 from near zero to 60 cm at higher elevations where snow is deeper and the canopy less dense  
275 (Figure 9). It is apparent that the snow-depth difference increases with elevation in the rain-snow  
276 transition zone, but lacks a clean pattern along either elevation gradient or penetration-fraction  
277 gradient when the elevation is higher.

## 278 **4. Discussion**

## 279 **4.1 Sensitivity of measurements to sampling resolution**

280           The results of analyzing the percentage of pixels with snow depth measured by Lidar at  
281 different sampling resolutions illustrate that even high-density airborne Lidar measurements do  
282 not have 100% coverage of the surveyed area at 1-m resolution, especially in densely forested  
283 areas. According to the snow-depth difference between snowpack in open areas and under  
284 canopy, a trade-off between accuracy and coverage happens when adjusting the resolution; and  
285 lower sampling resolutions can introduce overestimation into the results. This is because upon  
286 averaging, sub-pixel area under the canopy that was not measured may be represented by the  
287 open area that is measured, introducing an overestimation error into the averaged snow depth of  
288 the pixel. In order to estimate that bias for each pixel, we would need more under-canopy snow-  
289 depth measurements at 1-m resolution. In our survey areas, 28% of the total area in the main  
290 snow-producing elevations of 2000-3000 m has no returns at 1-m resolution. Assuming that  
291 using open rather than under-canopy values would introduce a bias of at least 35 cm for these  
292 unmeasured areas, a 2-m mean snow depth will have about 10 cm or 5% overestimation over the  
293 whole area. The overestimation could be higher if the area with no returns represents denser  
294 canopy with less snow than the under-canopy areas measured; and could also be more significant  
295 for shallower snowpacks. It would also be higher for a less-dense point cloud, which would  
296 introduce uncertainty into both percentage canopy cover and open versus under-canopy snow-  
297 depth differences. Therefore, the sampling resolution for processing the Lidar point cloud needs  
298 to be chosen according to the objective and accuracy tolerance of the study and the average  
299 overestimation bias needs to be corrected for the study results.

## 300 **4.2 Physiographic effects on snow accumulation**

301 Below 3300 m, the increasing trend of snow accumulation with elevation was observed  
302 for all sites (Figure 6). Linear regression is applicable to model the relationship between snow  
303 depth and elevation when the study area has a broad elevation range. This holds true for all of  
304 our sites with the exception of Shorthair, where the elevation range is about 200 m and the  
305 coefficient of determination for this linear-regression model is much smaller than for the other  
306 three sites, which have ranges greater than 500 m. The bias of mean snow depth in the same  
307 elevation band between different sites is acceptable if the standard error is added to or subtracted  
308 from the mean (Figure 6a, 6b, 6c). The data-collection time, spatial variation and variations of  
309 other topographic features can also introduce bias across sites. However, as data-collection time  
310 in this study only differed by a few days, *in situ* snow-depth sensor data suggest that the melting  
311 and densification effect was under 2 cm ([https://czo.ucmerced.edu/dataCatalog\\_sierra.html](https://czo.ucmerced.edu/dataCatalog_sierra.html)). As  
312 for other topographic variables, the observation of a slope effect, shown as the trend lines in  
313 Figure 7a and the negative regression coefficients of the two linear-regression models, could be  
314 explained by steeper slopes having higher avalanche potential, fewer trees and thus more wind;  
315 and thus some snow is more likely to be lost from these slopes. Snowpack located in south-  
316 facing slopes receives higher solar radiation, with the snowmelt being accelerated (Kirchner et  
317 al., 2014). This explains the trends observed in Figure 7b and the negative regression coefficients  
318 of the multivariate models. Although Lidar has measurement errors caused by slope and aspect  
319 (Baltsavias, 1999; Deems et al., 2013; Hodgson and Bresnahan, 2004), the error is not able to be  
320 quantitatively traced back to each variable; and we assumed that its influence on the trends could  
321 be neglected. As canopy interception results in reduced snow depth under canopy, the snow-  
322 depth residuals are found changing from negative to positive with penetration fraction and the  
323 regression coefficients are positive (Figure 7c). The multivariate linear-regression model built

324 from the Lidar data is a significant improvement, as the variability of the snow distribution could  
325 explain 15-25% more than the univariate linear-regression model with elevation as the only  
326 predictive variable (Table 4) and the estimation bias has a narrower distribution (Figure 10a,  
327 10b). Also, fitting an individual linear-regression model for each site is slightly better than using  
328 a general model with all data combined (Figure 10c, 10d). This may be because an individual  
329 model can capture regional micro-climate within a site better than a general model. The opposite  
330 trend of the relative importance of predictive variables observed in Shorthair is because it is a  
331 relatively flat site (Figure 1, Figure 8), which implies that topographic variables other than  
332 elevation need to be considered when studying areas with small elevation ranges.

### 333 **4.3 Vegetation effects on snow distribution along elevation**

334 Under-canopy snow distribution is governed by multiple factors that affect the energy  
335 environment, as observed by melting (Essery et al., 2008; Gelfan et al., 2004) and accumulation  
336 rates (Pomeroy et al., 1998; Schmidt and Gluns, 1991; Teti, 2003). Our results show different  
337 responses when comparing the snow-depth difference between open and canopy-covered areas  
338 between study sites (Figure 9a). In the rain-snow transition zone from 1500 to 2000 m at  
339 Providence we see a sharp linear increase between open and under-canopy snow depth that is  
340 likely governed by the under-canopy energy environment and the canopy-interception effect on  
341 precipitation, which accelerate snowmelt and prevent accumulation of under-canopy snow.  
342 Above 2000 m, the snow-depth difference observed at Bull and Shorthair stabilized around 40  
343 cm and 20 cm respectively, with fluctuations less than 10 cm along elevation. Breaking from this  
344 pattern, the large dip in snow-depth difference, down to 10 cm, observed at Wolverton at  
345 elevations of 2250-2750 m deviates from the 35-40 cm plateau. Also, the snow-depth difference  
346 at Shorthair stabilizes around 20 cm, which is 20 cm lower than the stabilized value at Bull.



347 Based on the scatterplots shown in Figures 6a and 6b that are color coded by northness, at an  
348 elevation range of 2300-2700 m, there are a lot more data points with both low snow depth and  
349 extremely negative northness in the open area than under the canopy, which implies that  
350 anisotropic distribution of other topographic variables is affecting the snow-depth difference.  
351 This is further shown by filtering out the data points not within a small certain range (-0.1 to 0.1)  
352 of northness, and then reproducing Figure 9a using the filtered data. As presented in Figure 11, it  
353 is apparent that the large dip at Wolverton is flattened out owing to a canopy effect of around 25-  
354 45 cm. Thus a sigmoidal function was used to characterize the snow-depth difference changes  
355 with elevation, excluding topographic interactions. The interactions between topographic  
356 variables and vegetation is most likely attributable to the under-canopy snowpack being less  
357 sensitive to solar radiation versus snowpack in the open area (Courbaud et al., 2003; Dubayah,  
358 1994; Essery et al., 2008; Musselman et al., 2008, 2012).

359 In spite of filtering the topographic effect, there is still about a 20-cm magnitude of  
360 fluctuation in the snow-depth difference, which might be attributed to various clearing sizes of  
361 open area at different locations and various vegetation types in forests (Hedstrom and Pomeroy,  
362 1998; Pomeroy et al., 2002; Schmidt and Gluns, 1991); however, we were not able to explore  
363 these features of the sites from the current Lidar dataset.

## 364 **5. Conclusions**

365 The rasterized Lidar data show that the percentage of pixels with at least one ground  
366 return, and thus a snow-depth measurement, increases from 65-90% to 99% as the sampling  
367 resolution increases from 1 m to 5 m. However, this coarser resolution may mask undersampling  
368 of under-canopy snow relative to snow in open areas. With about 28% of the area in dense  
369 mixed-conifer forest having no returns, using snow depths in open areas as estimates of snow

370 depth under dense canopies would result in at least a 10-cm overestimation error in the average  
371 snow depth in the main snow-producing elevations of 2000-3000 m.

372         Using Lidar data gridded at 1-m resolution, average snow depth within each 1-m  
373 elevation band shows a strong correlation with elevation and consistent pattern across all sites.  
374 The linear-regression models show that elevation explains 43% of snow-depth variability; and  
375 that over 57% of the variability is explained when including all physiographic variables. This  
376 indicates that snow distribution in the southern Sierra Nevada is primarily influenced by an  
377 orographic-lift effect on precipitation. Snow-depth residuals calculated by de-trending the  
378 elevation dependency are correlated with slope, aspect and penetration fraction; and the  
379 regression coefficients of these variables in the multivariate linear-regression model show that  
380 they are statistically significant in explaining the snow-depth variability, all with p-values  
381 smaller than 0.01. Over the elevation range of 1500-3300 m, snow depth decreases 1 cm per 1°  
382 slope, and decreases 0.5 cm per 1° aspect in going from north to south. In open areas, snow  
383 depth increases 2 cm per 10% increase in penetration fraction, while under canopy the snow  
384 depth increases 10 cm per 10% penetration-fraction increase. Although the latter three variables  
385 were observed to be less important than elevation, the relative importance of all four variables  
386 varies with local elevation range and canopy.

387         The snow-depth difference between open and canopy-covered areas increased in the rain-  
388 snow transition elevation range and then stabilized around 25-45 cm at high elevation.  
389 Fluctuations in certain elevation ranges are attributed part to interactions from other topographic  
390 variables. Evidence of this is found by filtering northness into a narrow band, which results in  
391 these fluctuations flattening out.

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398 reviews of this work. Also thank R.D. Brown, Q. Guo, and N.P. Molotch for their helpful  
399 comments and J. Flanagan for providing canopy height model data.

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565 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 <sup>2</sup>	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, %	51	43	62	30

566

567 Table 2. Flight parameters and sensor settings

Flight parameters		Equipment settings	
Flight altitude	600 m	Wavelength	1047 nm
Flight speed	65 m s <sup>-1</sup>	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 m <sup>-2</sup>	Scan angle	±14°
Cross-track resolution	0.233 m	Scan cutoff	3°
Down-track resolution	0.418 m	Scan offset	0°

568 Table 3. Linear-regression results, averaged snow depth vs. elevation in four sites

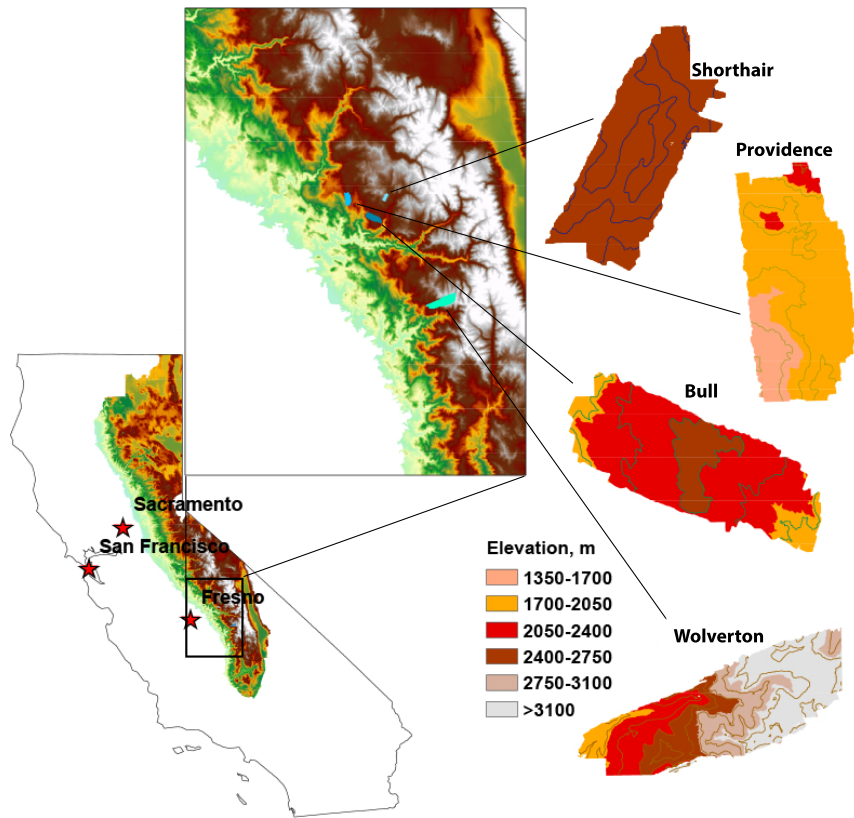
	Bull	Shorthair	Providence	Wolverton
$R^2$ , open	0.968	0.797	0.931	0.914
$R^2$ , vegetated	0.978	0.737	0.921	0.972
Slope, open, cm per 100 m	21.6	16.1	37.8	15.3
Slope, vegetated, cm per 100 m	19.9	13.1	26.0	13.4

569

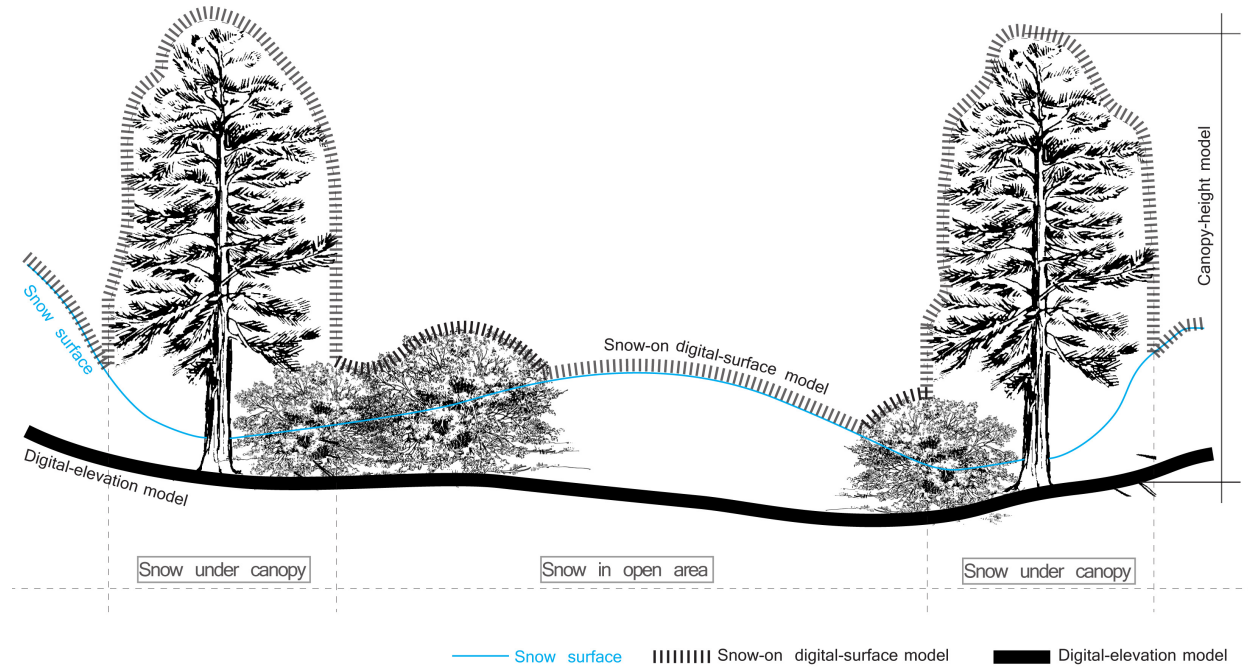
570 Table 4. Coefficients of determination of univariate and multivariate linear-regression models

	Univariate model R <sup>2</sup>	Multivariate model R <sup>2</sup>
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

571

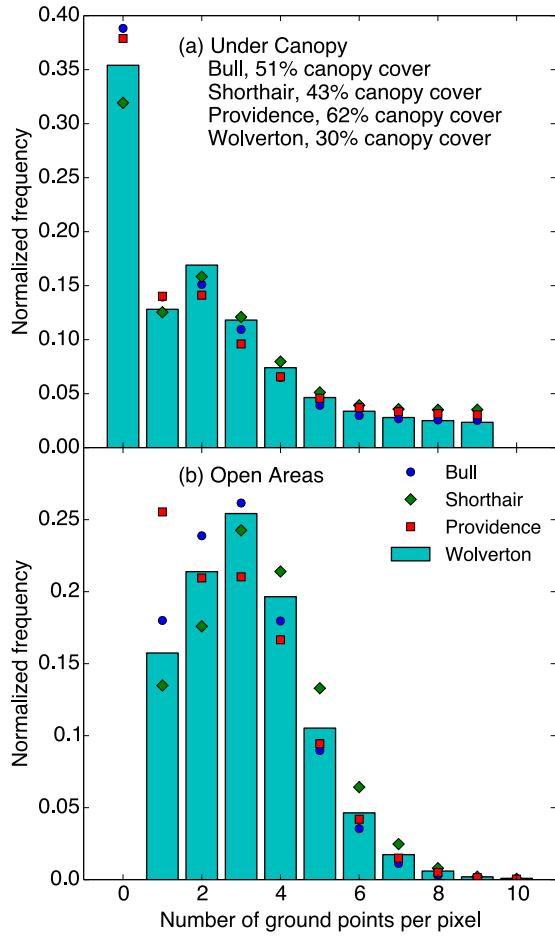


572  
 573 Figure 1. Study area and Lidar footprints. (Left) California with Sierra Nevada. (Center) Zoomed view to  
 574 show the locations of Lidar footprints. (Right) Elevation and 200-m contour map (100-m for Bull) of  
 575 Lidar footprints



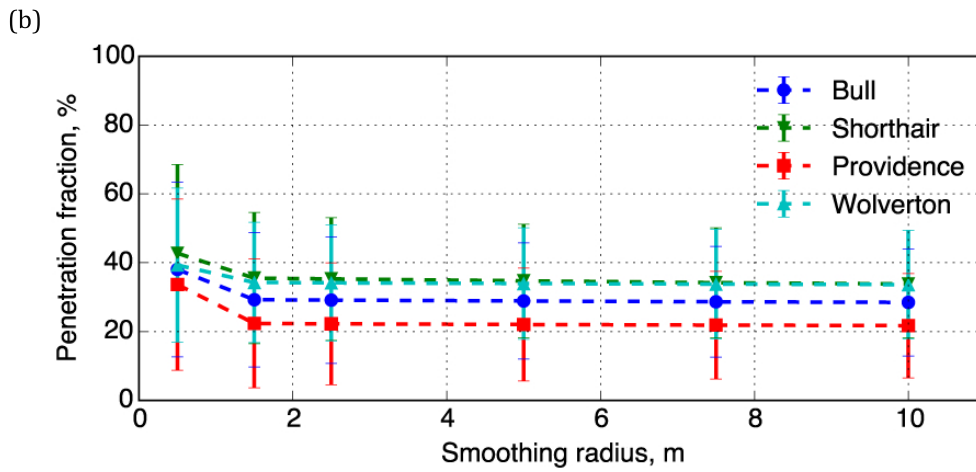
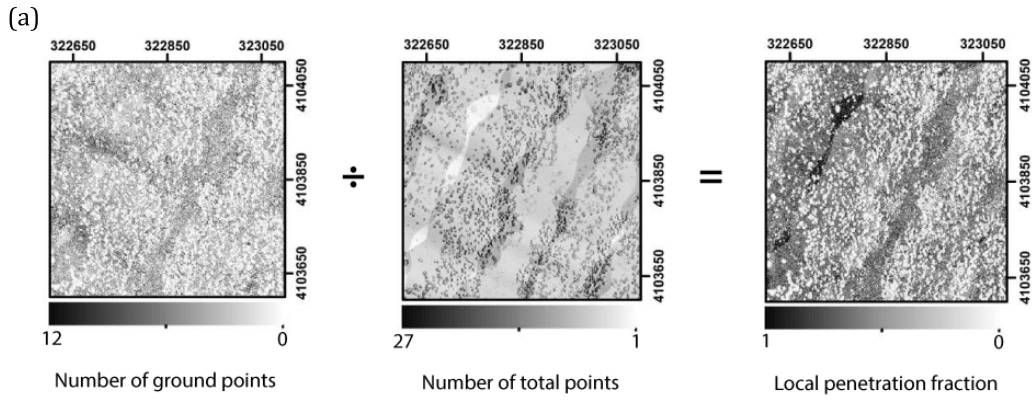
576

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



580

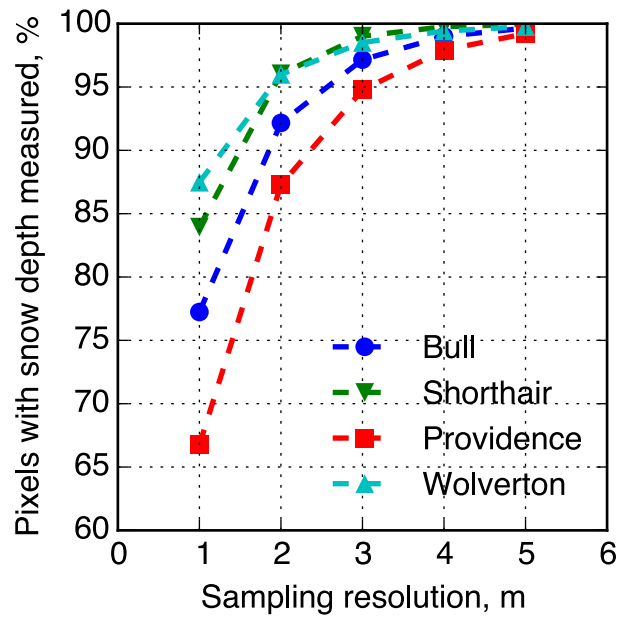
581 Figure 3. Normalized histogram of the number of ground points for (a) under-canopy and (b) open 1-m  
 582 pixels.



583

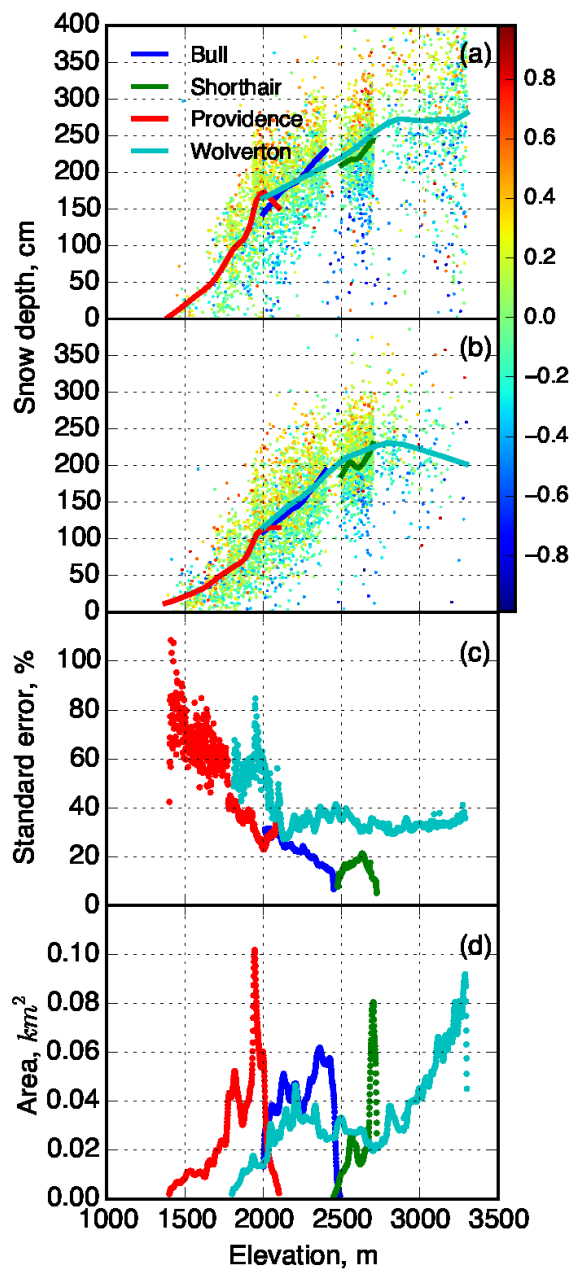
584 Figure 4. (a) Dividing the number of ground points of each 1-m pixel by the total number of points in the  
 585 pixel gives the penetration fraction of the local pixel. (b) Sensitivity of the smoothed penetration fraction  
 586 to the smoothing radius.





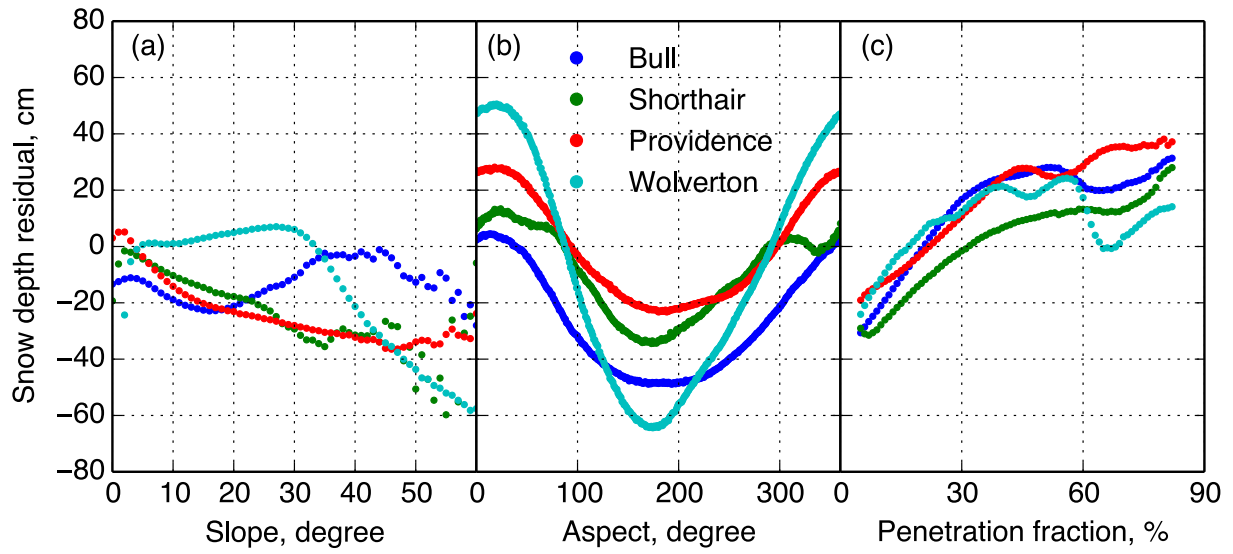
587

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



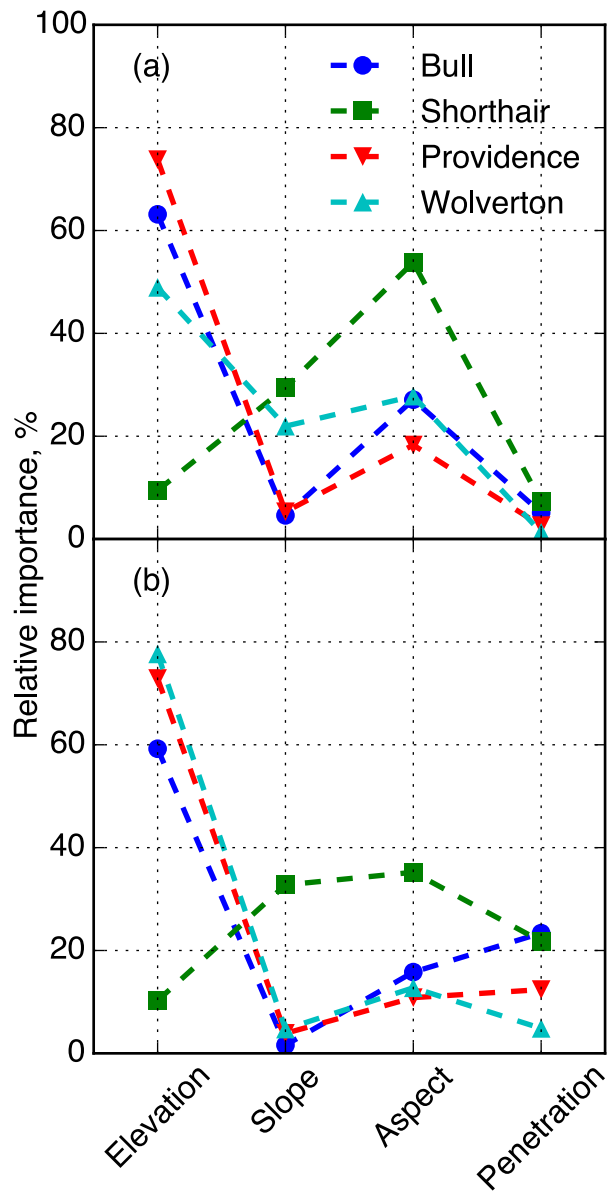
590

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



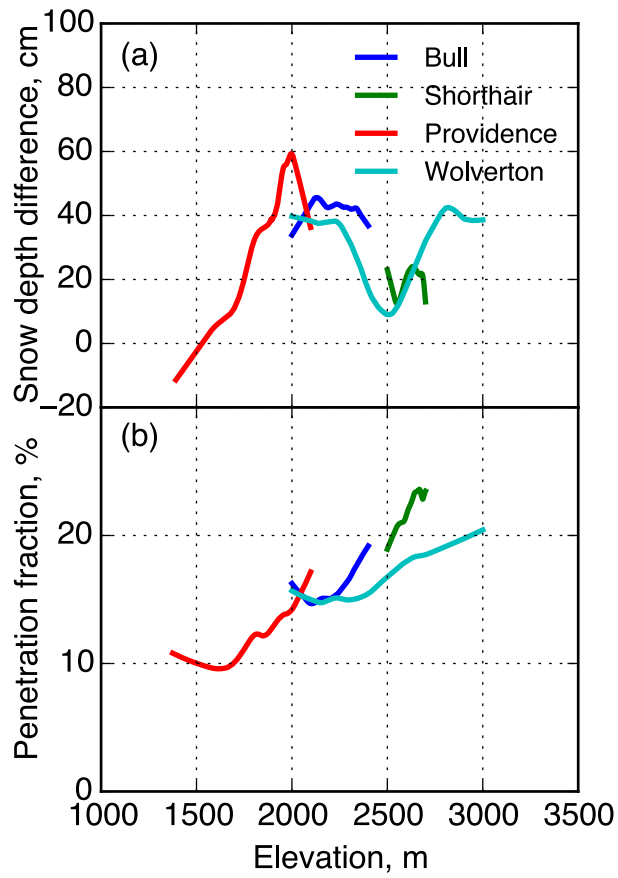
595

596 Figure 7. Average snow-depth residual, calculated as difference between Lidar-measured snow depth and  
 597 snow depth from the linear-regression models (open areas) versus: (a) slope, aspect, and (c) penetration  
 598 fraction.



599

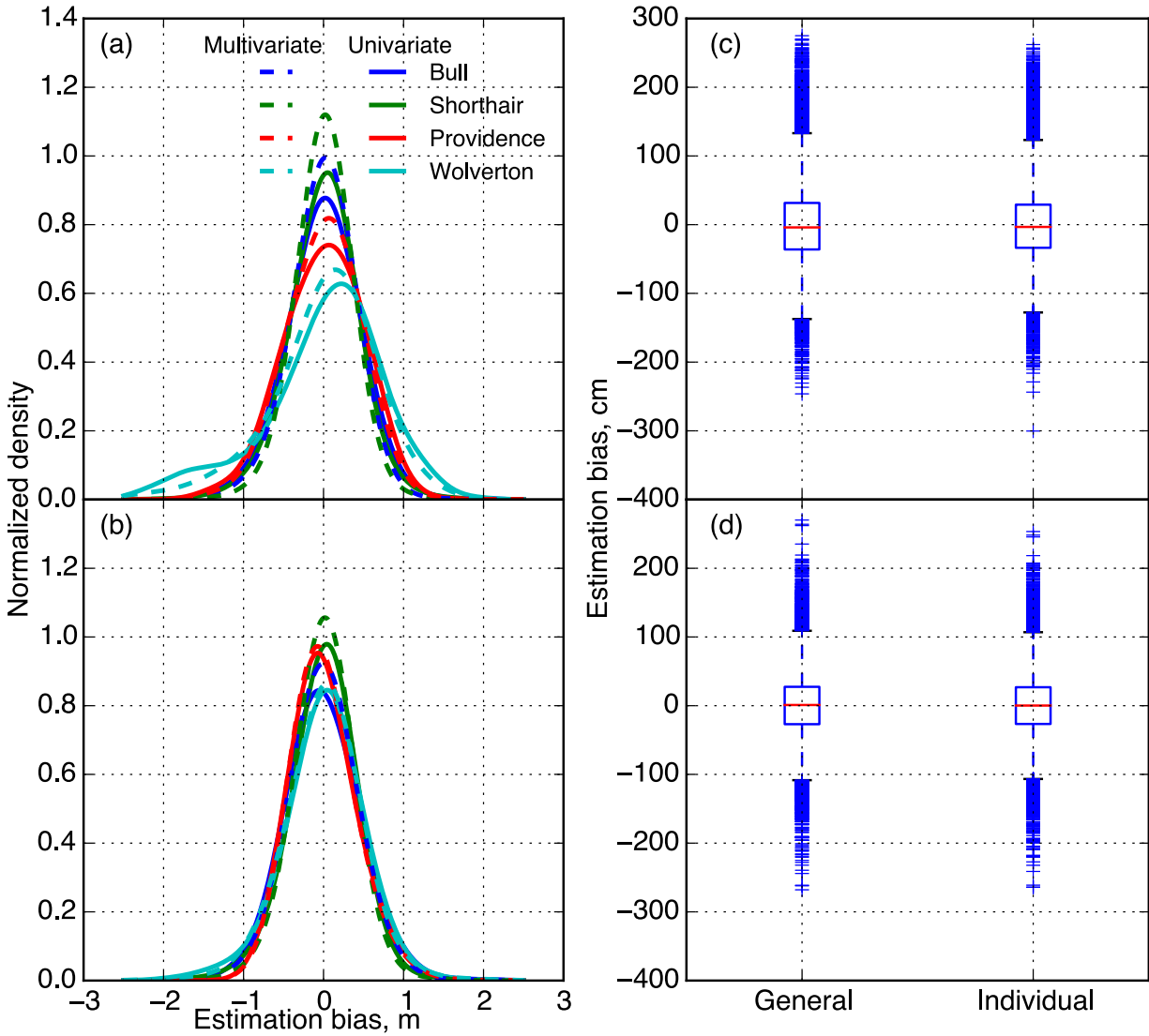
600 Figure 8. Relative importance of each physiographic variable in predicting the snow depth from each site  
 601 for (a) open area (b) under-canopy area



602

603 Figure 9. (a) Snow-depth difference along elevation for each site calculated from the LOESS smoothed

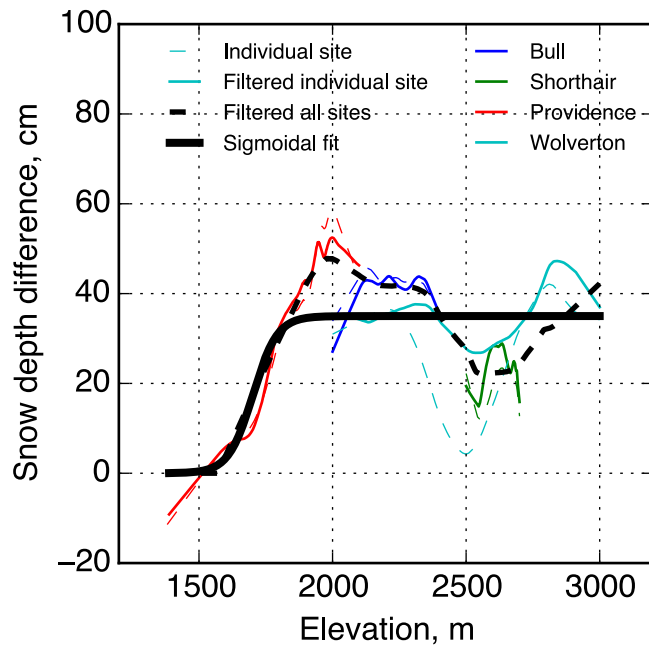
604 snow depth. (b) Average penetration fraction versus elevation for each site.



605

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

609



610

611 Figure 11. Snow-depth difference between open and under-canopy areas versus elevation, calculated as  
 612 difference between raw 1-m pixel snow depth and northness-filtered 1-m pixel snow depth, together with  
 613 the sigmoidal fit of the snow-depth difference.

614