# Relationships between snowpack depth and primary LiDAR point cloud derivatives in a mountainous environment

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**Abstract** Two LiDAR data sets were acquired over the Marmot Creek headwaters of the Bow River, Alberta, Canada; the first during dry snow-free conditions in August 2007, and the second during snow covered conditions in March 2008. A LiDAR snow depth model (SDM) was derived by subtracting the snow-free digital elevation model (DEM) from the digital snow surface model (SSM). Field crews were deployed coincident with the 2008 LiDAR survey to collect snow depth transects in: (a) low elevation valley locations of shallow and discontinuous snow cover; (b) alpine locations of deep but discontinuous snowpack; and (c) forested locations at intermediate elevations displaying variable depth but more continuous cover. The SDM was validated using the field measurements and then stratified by the three LiDAR point cloud derivatives: elevation, intensity and canopy fractional cover. The SDM performed favourably over the alpine transect areas with no significant bias ($r^2$ = 0.94, n = 137), with the valley transects demonstrating a slight overestimation of 7 cm ($r^2$ = 0.48, n = 310) and the forest transects demonstrating the weakest correlation ($r^2$ = 0.20, n = 402) and a mean over-estimation of 13 cm. Canopy cover creates a challenge for mapping shallow snow depth with LiDAR in mountainous environments, but canopy also reduces the spatial accuracy of GPS field data so a weaker correlation is to be expected. The SDM illustrated increasing snow depth up to tree line at approximately 2250 m a.g.l. with reducing depth and cover in the alpine zone. Overall, high LiDAR intensity values were not well correlated with snowcover at the basin scale with only 44% spatial correspondence. However, above tree line this increased to 76%, suggesting that LiDAR intensity has some value for snow covered area (SCA) mapping as long as there is no forest canopy to attenuate or split the laser pulse returns.

**Key words** LiDAR; intensity; coniferous canopy; mountain snowpack; change detection

## INTRODUCTION

Within mountainous watersheds, snow depth varies with terrain and land cover (e.g. Elder *et al*., 1998). A demonstrated method for remotely mapping landscape-level snow depth at high resolutions is repeat airborne LiDAR, whereby a LiDAR ground surface digital elevation model (DEM) is subtracted from a LiDAR snow surface model (SSM) to derive a snow depth model (SDM) (Hopkinson *et al*., 2004). Hopkinson *et al*. (2004) found that whilst snow depth could be mapped accurately in open areas, low-level vegetation or understory could lead to systematic bias of a few cm. A further property of LiDAR data offering potential for snowpack mapping is the "intensity" or peak amplitude of the returning infrared laser pulse. An interpolated laser intensity image looks similar to a black and white photograph, and given many commercial airborne sensors operate in the near-infrared (1064 nm), snow appears bright relative to other surfaces. For example, in Hopkinson & Demuth (2006), a LiDAR intensity image was used to classify glacier snow and ice facies. The application of LiDAR to snowpack distribution assessments in mountainous environments has been studied by Fassnacht & Deems (2006), Deems *et al*. (2006) and Trujjillo *et al.* (2007).

To date, a thorough evaluation of LiDAR SDM accuracy over a range of mountainous surfaces has not been presented. However, some challenges associated with LiDAR surface comparison in alpine environments have been explored previously. For example, it is known that horizontal DEM uncertainty can propagate vertical errors (e.g. Hodgson *et al*., 2005), and when alpine DEMs are compared in areas of steep slope, errors of <100 m have been documented (Hopkinson & Demuth, 2006). Another characteristic that leads to potential bias in alpine landscapes is LiDAR point-based sampling either side of ridge or cliff edges, which typically

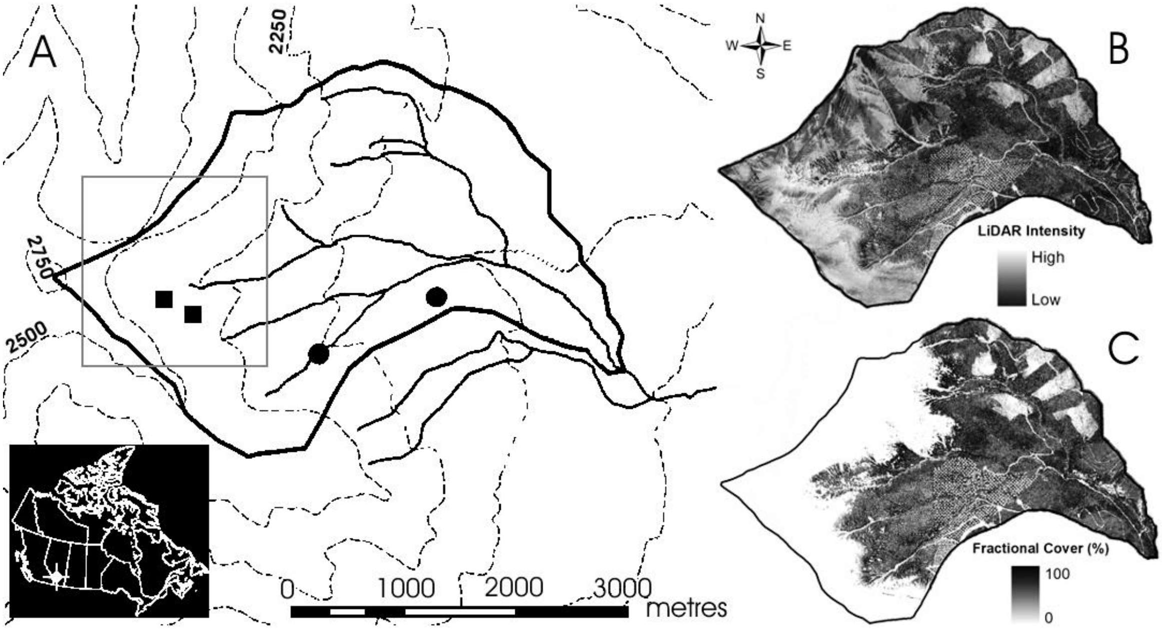


**Fig. 1** Study area. (a) Marmot Creek Research Basin, stream network and elevation distribution (grey box illustrates area in Fig. 3(a)). Circles represent forested sample sites and squares represent alpine sample sites (valley sites not shown); (b) LiDAR intensity image; (c) LiDAR canopy fractional cover. The alpine zone is the area with no canopy on the western side of the basin.

results in some rounding of these features in raster DEMs (Hopkinson *et al.*, 2009). Both of these potential error sources are associated with steep terrain, however, and can be mitigated with dense sampling and extreme care with data calibration procedures. This paper presents the results of a LiDAR-based SDM validation exercise in and around the Marmot Creek research basin (9.7 $km^2$) in the Canadian Rockies (Fig. 1). Relationships between the SDM and LiDAR terrain elevation, intensity and canopy cover (ratio of canopy returns to all returns) are presented to further explore the inter-related properties of the LiDAR point cloud and the snowpack we are attempting to model.

## METHODS

The first LiDAR data set was collected during dry summer conditions in August 2007 while the second was collected during winter in late March 2008. Both surveys were configured and flown identically at an altitude of ~3500 m a.g,l. using an Airborne Laser Terrain Mapper (ALTM) 3100 (Optech, Toronto, Ontario). Swath overlap was optimized to 50% at the 75th percentile terrain elevation, leading to a point spacing at ground level of between 1 and 2 m, with actual point density increasing and swath width decreasing with terrain elevation. Sensor calibration and validation was performed before and after each mission at an airport runway providing a vertical RMSE < 0.15 m. Before the SDM was generated, the two data sets underwent extensive calibration and georegistration to ensure accurate alignment, as even a slight horizontal shift in one data set could result in large SDM errors or a spatial autocorrelation with terrain features. The SDM was generated in a GIS by subtracting the DEM from the DSM.

SDM validation was conducted in three distinct areas: (i) four valley locations adjacent to the highway east of Marmot Creek; (ii) two mid-elevation mainly canopy covered locations on the montane slopes of the watershed; (iii) two alpine sites on the western side of the watershed (Fig. 1). Depth measurements (894 in total) were made at recorded distances along transects using a graduated aluminium rod. For registration of the field and LiDAR data, the end points of the transects were differentially GPS surveyed to the same base location used for the LiDAR missions, approx. 20-km northeast of Marmot Creek. Following calculation of all field sampling coordinates, the spatially coincident SDM values were extracted and compared. Relationships between LiDAR primary derivatives, the SDM and snow-covered area (SCA) (defined as SDM

>0 cm) were evaluated by stratifying the SDM into: (i) 100 m elevation bins from the DEM; (ii) high *vs* low intensity (defined as above or below the median intensity value); iii) (high (>30%) *vs* low (<30%) canopy fractional cover (30% being the approximate median value).

## RESULTS AND DISCUSSION

Mean field-measured snow depths at the valley, forested, and alpine sites were, respectively: 28 cm (n = 310, σ = 21 cm); 50 cm (n = 447, σ = 20 cm); and 72 cm (n = 137, σ = 67 cm). While for the corresponding LiDAR SDM grid values, the depths were: 35 cm (σ = 33 cm); 63 cm (σ = 28 cm); and 68 cm (σ = 65 cm). Therefore, the LiDAR SDM deviated from the field measurements by, respectively: +7 cm (σ + 12 cm), +13 cm (σ + 8 cm) and –4 cm (σ – 2 cm). While the means and standard deviations are all within 13 cm, the variable level of bias and noise at each site (Fig. 2) requires investigation. The alpine comparison was most favourable and this is likely due to the terrain being the closest to the sensor platform (i.e. reduced propagation of sensor calibration and platform error) and minimal ground vegetation cover. The valley transects were predominantly in open canopy over variable relief terrain. However, due to nearby forest cover and steep surrounding terrain, the GPS data associated with the validation transects were of variable quality. Consequently, the increased noise and slightly elevated bias was likely due to a combination of: (i) calibration- and platform positioning-related error propagation (Goulden & Hopkinson, 2010); (ii) mismatch between the DEM and SSM; and (iii) mismatch between the SDM and field data due to GPS errors. The correlation between SDM and field data is lowest at the intermediate elevation forested sites. While the canopy and understory likely play a significant role in introducing noise into the SDM (Hopkinson *et al.*, 2004) it must be noted that the field GPS data collected in the forested and small clearing hillslope locations were the lowest quality of all, with many points having a float solution. Consequently, there is little confidence in the registration of the field and SDM data, resulting in a weak correlation. When the field and SDM data at the forest sites are grouped into localized spatial clusters we find an offset in standard deviation of ~9 cm but there is a clear correlation (Fig. 2(d)). This shows that even in the forested areas, localized SDM variability could be used as an index for actual snow depth variability and therefore, offers potential for SCA depletion simulations (e.g. DeBeer & Pomeroy, 2010).

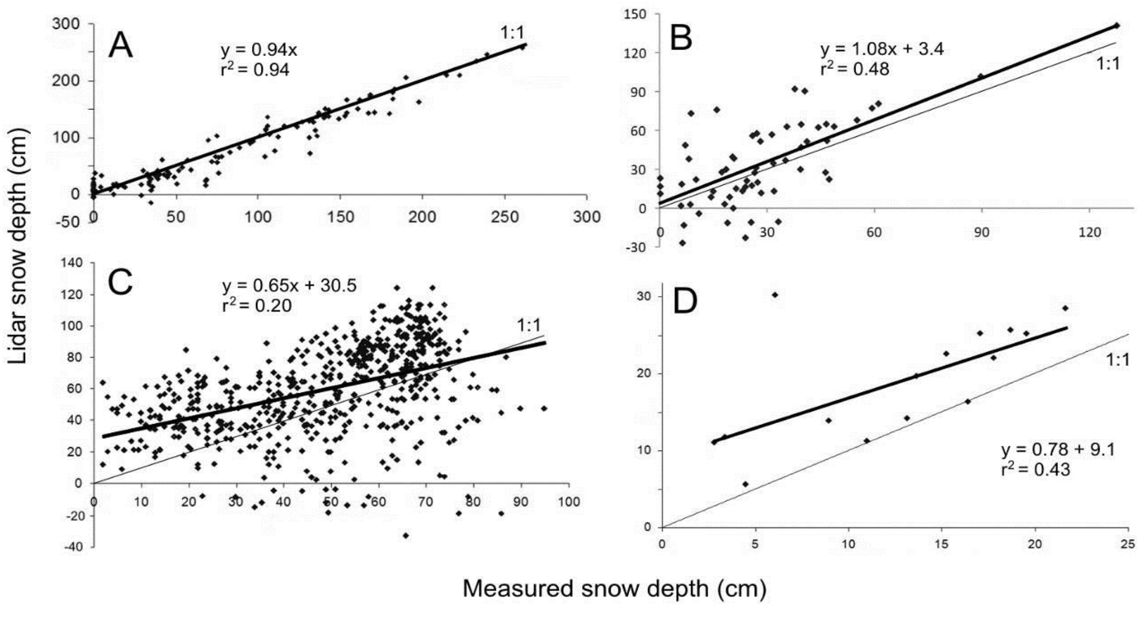


**Fig. 2** Regression plots of LiDAR snow depth against field measurements for: a) alpine sites; b) valley sites near the highway; c) intermediate elevation forested sites; d) Grouped snow depth standard deviations for the forested sites.

The SDM illustrated a peak in snow depth (by elevation-band and SCA) at treeline (Fig. 3(a)), with a systematic increase in depth and cover up to this zone, and decrease above (Fig. 3(b)). Snowpack above treeline is ablated by blowing snow and at lower elevations by canopy interception in evergreens (Pomeroy & Gray, 1995). However, the treeline is dominated by deciduous larch trees that trap blowing snow and do not have significant interception losses (Fisera, 1977). Overall, LiDAR intensity values had no better than a random association with SCA at the basin scale with only 44% spatial correspondence. It was found that canopy cover exerted a stronger control on intensity than snowcover, with 84% of low intensity returns corresponding with canopy covered areas, and 68% of high intensity returns corresponding with open areas. Above treeline, high intensities had a 76% spatial correspondence with SCA, suggesting LiDAR intensity imagery does have potential for mountain SCA mapping as long as there is no forest canopy to attenuate or split the laser pulse signal. This needs to be further examined, as it is possible that intensity is actually a better indicator of true SCA than SDM > 0 cm, given: (i) the SDM is known to contain some bias and noise (Fig. 2); and (ii) a thin dusting of snow can raise the surface albedo sufficiently to produce a high intensity while not changing the surface elevation appreciably.

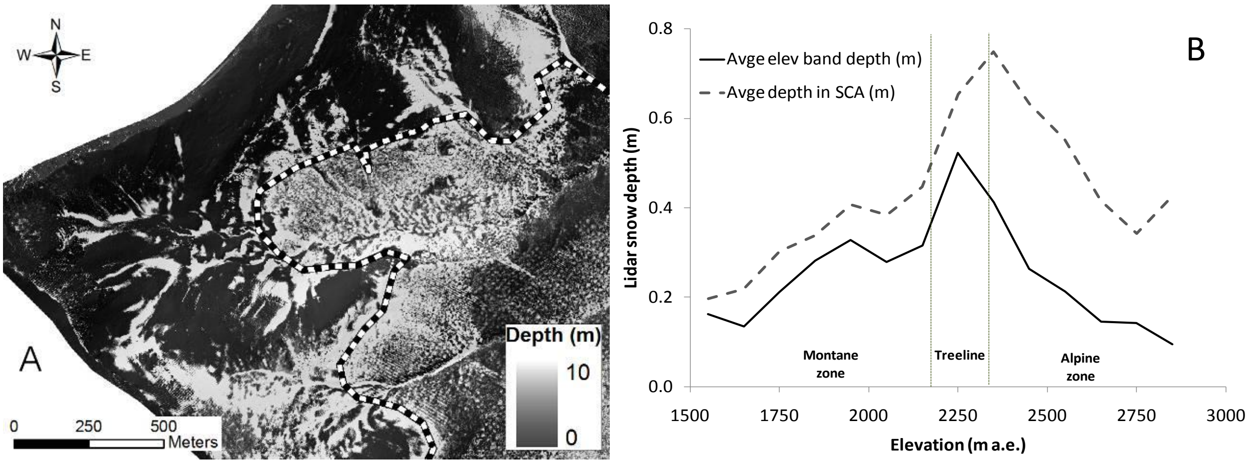


**Fig. 3** (a) LiDAR SDM near treeline (dashed line) and on high elevation alpine slopes at the western extremity of Marmot Creek Research Basin (see Fig. 1). SDM is visibly greatest in gulleys, foot of slopes, along corniced ridges and at treeline. (b) Distribution of LiDAR snow depth with elevation both as an average for the elevation band and only within SCA.

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