

Snow depth mapping with unpiloted aerial system lidar observations: A case study in Durham, New Hampshire, United States

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Abstract. Terrestrial and airborne laser scanning and structure from motion techniques have emerged as viable methods to map snow depths. While these systems have advanced snow hydrology, these techniques have noted limitations in either horizontal or vertical resolution. Lidar on an unpiloted aerial vehicle (UAV) is another potential method to observe field and slope scale variations at the vertical resolutions needed to resolve local variations in snowpack depth and to quantify snow depth when snowpacks are shallow. This paper provides some of the earliest snow depth mapping results on the landscape scale that were measured using lidar on a UAV. The system, which uses modest cost, commercially available components, was assessed in a mixed deciduous and coniferous forest and open field for a thin snowpack (< 20 cm). The lidar classified point clouds had an average of 90 and 364 points/m² in the forest and field, respectively. In the field, in-situ and lidar mean snow depths, at 0.4 m resolution, had a mean absolute difference of 0.96 cm and a root mean squared error of 1.22 cm. At 1 m resolution, the field snow depth confidence intervals were consistently less than 1 cm. The forest and heavily vegetated areas had modestly reduced performance with typical confidence intervals within 4 cm. Although the mean snow depth was only 10.3 cm in the field and 6.0 cm in the forest, a pairwise Steel-Dwass test showed that snow depths were significantly different between the coniferous forest, the deciduous forest, and the field land covers ($p < 0.0001$). Snow depths were shallower and snow depth confidence intervals were higher in areas with steep slopes. Results of this study suggest that performance depends on both the point cloud density, which can be increased or decreased by modifying the flight plan over different vegetation types, and the within cell variability that depends on site surface conditions.

1 Introduction

30 Snowpacks are highly dynamic, accumulating and ablating throughout the winter with associated changes in snowpack density, grain size, and albedo (Adolph et al., 2017) as well as ice formation. Wind redistribution, sloughing of snow-off slopes, trapping of snow by vegetation, and forest canopy interception result in a range of spatial features at varying scales (Clark et al., 2011; Mott et al., 2011; Mott et al., 2018). Modest differences in snowpack depth can differentially impact many hydrologic, agricultural, and ecosystem processes. Differences in snowpack meltwaters can alter streamflow volumes (Gichamo and Tarboton, 2019), change the likelihood of spring floods (Tuttle et al., 2017) and intensify overland nutrient transport and soil erosion (Seyfried et al., 1990; Singh et al., 2009).

High-resolution snow depth measurements are also needed to discern processes that depend on the snow state. Insulation by seasonal snow in the Arctic and Antarctic slows sea ice growth (Sturm et al., 2002). High-resolution Arctic snow depths from ICE-Sat2 revealed seasonal snow on ice that would be missed when using coarser snow information (Kwok et al.

2020). Thin, ephemeral snowpacks have limited insulation and allow the underlying soils to freeze more readily in the winter (Groffman et al., 2001; Starkloff et al. 2017; Yi et al. 2019). Soil frost severity impacts soil respiration, carbon sequestration, nutrient retention, and microbial communities as well as a plant root health and tree growth (Aase and Siddoway, 1979; Isard and Schaetzel, 1998; Monson et al., 2006; Henry, 2008; Aanderud et al., 2013; Tucker et al., 2016; 45 Sorensen et al., 2018; Reinmann and Templer, 2018). Detection and mapping of rapid thinning of snowpacks followed by frigid cold during “winter whiplash” events (Casson et al. 2019) is therefore important for understanding ecosystem impacts of soil freezing events, which are otherwise not well quantified (Kraatz et al. 2018; Prince et al. 2019). High vertical resolution snow mapping would greatly improve our understanding of these unique habitats.

50 Distributed modeling and mapping of snowpacks can increasingly provide output at fine spatiotemporal scales but snow state change validation typically relies on in situ observations (Gichamo and Tarboton 2019; Starkloff et al., 2017). Despite importance, few spatially continuous high-resolution snowpacks datasets are available to support modelling, and mapping efforts. Because snowpacks have considerable spatiotemporal variability, a large number of snow depth measurements are often needed to characterize the snowpack (Dickinson and Whiteley, 1972). Using traditional, precise point measurements 55 with a limited sample size, the experimental design requires a balance between the sampling extent and sample spacing (Clark et al. 2011). However, the choice of sampling resolution may yield different measures of snow depth spatial variability when the snow exhibits multifractal behaviour (Deems et al. 2006).

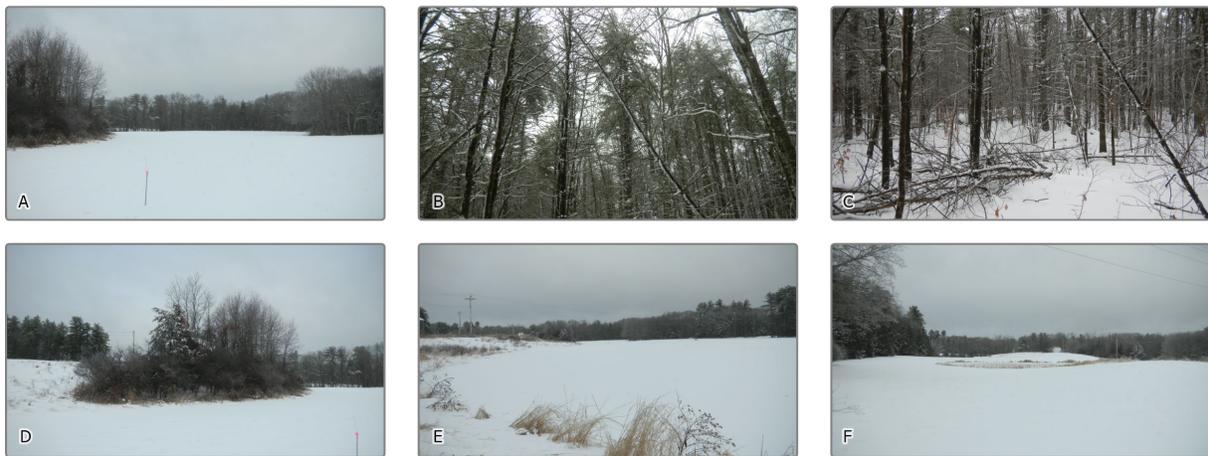
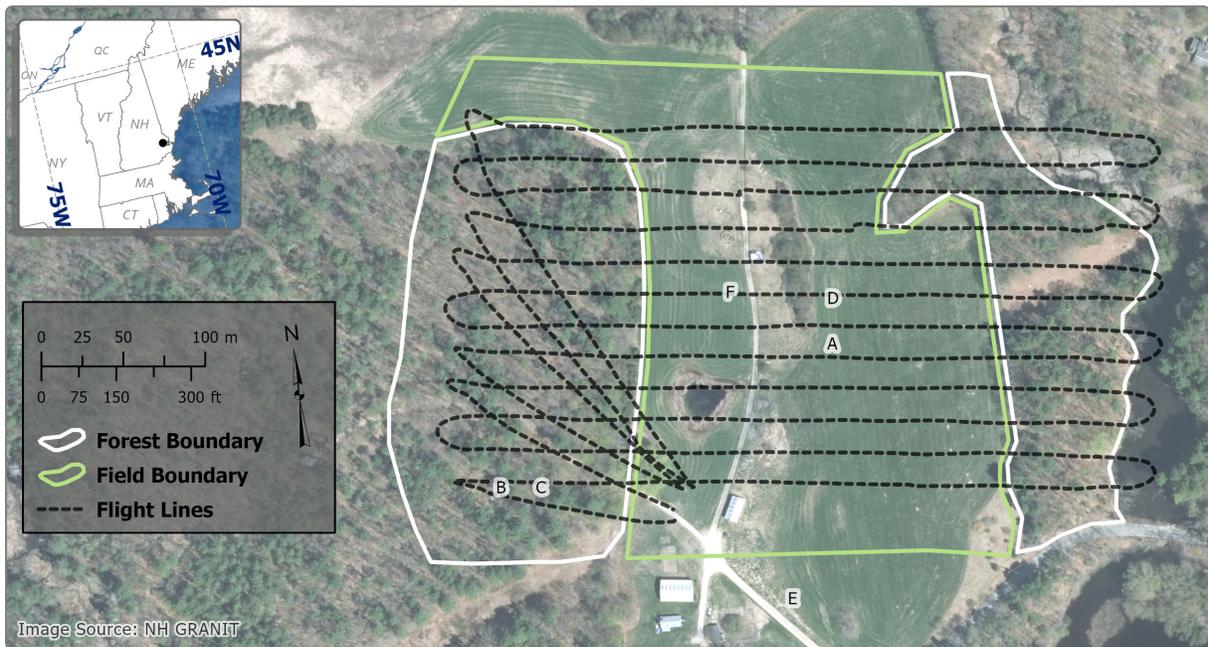
Over the past two decades, remote sensing methods, providing spatially continuous, high-resolution snow depth maps at 60 local and regional scales, have greatly advanced the ability to characterize the spatiotemporal variability of snow depth over earlier work using snow probes (see reviews in Deems et al., 2013; López-Moreno et al., 2017). Spaceborne photogrammetry (e.g. Marti et al. 2016, McGrath et al. 2019, Shaw et al. 2020), airborne laser scanning (ALS) (Deems et al., 2013; Harpold et al., 2014; Kirchner et al., 2014), terrestrial laser scanning (TLS) (Grünewald et al. 2010; Currier et al. 2019), and structure-from-motion photogrammetry (SfM) (Nolan et al., 2015; Bühler et al., 2016; Harder et al., 2016) have 65 emerged as viable methods to map surface elevations with snow-off and snow-on conditions in order to differentially map snow depths.

ALS and TLS both rely on well-established lidar (light detection and ranging) technology. TLS, applied from a fixed ground position, is able to measure snow depth with high vertical accuracy (Fey et al., 2019), and has the advantage of being 70 relatively low-cost and portable, making repeat observations possible. However, TLS uncertainties are caused by large incident angles, occlusion from hills and trees that can cause data gaps in forested domains (Currier et al., 2019; Palace et al., 2016), and challenges to provide a stable scanner position for the tripod in snow-on conditions (Schweizer et al., 2003). ALS technology such as that deployed on the Airborne Snow Observatory (ASO) (Painter et al., 2016) has the advantage of being able to cover large areas, but it is extremely expensive and has limited availability and flexibility of deployment, which 75 impacts its use for most studies. ALS also has issues with observation gaps in forested regions (Broxton et al., 2015; Currier and Lundquist, 2018; Mazzotti et al., 2019) but possibly to a lesser extent than TLS (Currier et al., 2019). For some snowpack features, the typical vertical accuracies from these platforms, on the order of 10 cm (Kraus et al., 2011; Deems et al., 2013), as well as relatively low return density (~ 10 returns/m²) (Cook et al., 2013) may not be adequate to observe spatial variations at point scales (0 to 5 m) to hillslope and field scales (1-100 m) or to detect snow depth changes over short time 80 scales.

SfM can create a digital surface model (DSM) from photographs taken using a standard consumer-grade digital camera. When deployed on an unpiloted aerial system (UAS) platform, SfM is a low cost method that has the capacity for routine

snow depth monitoring (Adams et al., 2018; Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016; Vander Jagt et al., 2015). Reported accuracies range from 8 to 30 cm using UAS SfM (Adams et al., 2018; Bühler et al., 2016; Goetz and Brenning, 2019; Harder et al., 2016; Meyer and Skiles, 2019; Harder et al., 2020). The primary drawbacks of UAS SfM as compared to lidar for mapping snow depth are that the DSM needs to be georeferenced using ground control points (GCPs) with known coordinates and may require significant manual steps (Tonkin et al., 2016; Meyer and Skiles, 2019), although new techniques are emerging that may reduce field data collection time (Gabrlik et al., 2019; Meyer and Skiles, 2019). Dense canopy or vegetation can reduce performance when snow compresses the vegetation relative to the snow-off imagery or when above-canopy vegetation is falsely interpreted to be the snow surface (Bühler et al., 2017; Cimoli et al., 2017; De Michele et al., 2016; Fernandes et al., 2018; Harder et al., 2016; Nolan et al., 2015). Canopy effects impact SfM snow mapping capability in regions where snowpacks are masked by dense forest canopies. The inability to sense portions of the ground/snow surface beneath dense canopies results in fine scale variations in snow depth, such as tree wells, not being accurately represented in UAS SfM snow depth products (Harder et al., 2020).

UAS-based lidar has been widely used in forest-related research (e.g. canopy height and forest change detection) (Wallace et al., 2012; 2014) and appears to offer the advantages of both the UAS SfM and lidar for snow depth mapping. A UAS platform also eliminates many of the drawbacks that arise from ALS and TLS systems discussed earlier. However, to date there is only one previous study that estimates snow depth using UAS-based lidar (Harder et al., 2020). The purpose of this paper is to assess the ability of a UAS platform to provide snow depth using a modest cost UAS-based lidar. The pilot study described here serves as a proof-of-concept for providing a high vertical resolution snowpack dataset in open terrain and forests in the north-eastern United States. Snow depth magnitude and variability are mapped and analyzed for differences by land use and terrain. The study highlights results from the 2019 winter season that provide insights as to the potential for UAS lidar mapping of snow depth as well as details about the system, its deployment, and operational and validation challenges. We explore the capability of UAS through the comparison of contemporary field-based snow depth measurements collected in a landscape containing fields and forests.



110 **Figure 1.** 2015 imagery of Thompson Farm, Durham NH showing both forest and field region with lidar flight lines (top). Ground
 120 imagery (a to f), collected in December 2019, locations are noted on the top map and show the surface and leaf off forest conditions
 (bottom panels).

2 Site, Data, and Methods

2.1 Site

The test flights were conducted at the University of New Hampshire’s Thompson Farm Research Observatory in southeast
 115 New Hampshire, United States (N 43.10892°, W 70.94853°, 35 m above sea level, ASL), which was chosen for its mixed
 hardwood forest and open field land covers (Burakowski et al., 2015; Burakowski et al., 2018) that are characteristic of the
 region (Figure 1). Thompson Farm has an area of 0.83 km² and little topographic relief (Perron et al., 2004). The agricultural
 fields are actively managed for pasture grass. The mixed deciduous and coniferous forest is composed primarily of white
 120 pine (*Pinus strobus*), northern red oak (*Quercus rubra*), red maple (*Acer rubrum*), shagbark hickory (*Carya ovata*), and
 white oak (*Quercus alba*) (Perron et al., 2004). There are two “wood roads” that run north-south through the pasture and into
 the western forest section.

2.2 UAS Laser Scanning

A series of UAS lidar surveys were conducted over approximately a 0.1 km² (9.8 hectares) area (430 by 225 m) within the farm during the winter 2018/2019 (Figure 1). Here, we focus on the snow-on flight conducted on January 23, 2019 and the snow-off flight conducted on April 11, 2019. We selected the January 23 flight because it had snowed approximately 11.5 cm with 1.8 cm of snow water equivalent from January 19th to January 20th and the air temperature was persistently below freezing prior to the flight. For the April 11, 2019 snow-off flight, the deciduous component of the canopy and understory were both dormant.

130 We used an Eagle XF UAS manufactured by UAV America, which carried a small, light-weight lidar sensor (Velodyne VLP-16) suitable for UAS deployment (see Table S1 in supporting information). The VLP-16 is a 16-channel lidar sensor with a 30-degree vertical field of view with rotating lasers that are spaced evenly between -15 to +15 degrees. Each channel rotates to provide a horizontal field of view of 360-degrees. The VLP-16 collects up to 300,000 points per second with an accuracy of +/- 3 cm at a range of 100 m. The sensor was mounted with the vertical field of view parallel with the ground.

135 The payload is equipped with an Applanix APX-15 UAV inertial navigation system (INS), which has 2-5 cm positional, 0.025-degree roll and pitch, and 0.08-degree true heading uncertainties following post-processing. The INS has a measurement rate of 200 Hz, allowing for a timestamp to associate each lidar pulse with the closest data for latitude, longitude, altitude, and perspective information (roll/pitch/yaw), which is required for georeferencing returns.

140 Flights were conducted to maximize spatial coverage while conserving batteries due to the limited flight time of the Eagle XF (approx. 9 minutes flight time to discharge to 3.6 V per cell). Because of the limited flight time, flights were conducted at an altitude of 81 m for greater spatial coverage and multiple return flight lines were necessary for battery exchanges (Figure 1). Automated flights were conducted using UgCS flight planning software. Flight speed was 7 m/s, with a total of 12 parallel flight lines with targeted overlap of 40 percent. Because of degrading accuracy at distances >100 m with the

145 VLP-16, returns acquired outside of +/- 30 degrees of nadir view angles in the horizontal field of view were filtered to limit target distance and improve overall accuracy.

Applanix APX-15 INS data were post-processed to a Smoothed Best-Estimate Trajectory (SBET) file using POSPac MMS UAV (v. 8.2.1), resulting in approximately 3 cm positional accuracy for both the snow-on and snow-off flights. Lidar returns were matched to post-processed INS data and georeferenced using Headwall Photonics, Inc.'s Lidar Tools software. Boresighting calibration was performed using returns from the first two flight lines that were collected in antiparallel directions. A roll offset was determined using 10 m cross sections along the flight lines over flat terrain, and a pitch offset was determined using 1 m cross sections across the flight lines over terrain with moderate relief (see Figure S2 in supporting information). Resulting LAS (LASer) point clouds were generated for the entire study area and projected in WGS84 UTM

155 Zone 19N (EPSG 32619). Flight and filtering parameters of the raw point cloud resulted in return densities of approximately 150 returns/m² for each of the two flights.

2.3 Lidar Classification and Gridding

Three-dimensional point clouds were processed using the progressive morphological filter algorithm (PMF), in the lidR package (<https://github.com/Jean-Romain/lidR>) of R (v. 3.4, Team, 2018) to identify ground returns. The PMF operates iteratively on sets of two parameters, window size and elevation thresholds to erode and dilate point cloud data sets to estimate surface topography as an approach to filter out non-ground returns (i.e. trees, shrubs, and noise) from point cloud data sets (Zhang et al., 2003). For ground classification, point clouds were chunked into 100 m square tiles with a 15 m buffer on all sides using catalog options in lidR to ensure returns near tile edges were classified. Processing was distributed

across 8 computing cores to improve efficiency. PMF was parameterized using a set of window sizes of 1, 3, 5, and 9 m, and elevation thresholds of 0.2, 1.5, 3, and 7 m, which were determined by varying value sets and assessing digital terrain models (DTMs) to determine the parameter sets that produced a visually smooth surface over a dense grid (*sensu* Muir et al., 2017). Following ground classification for each tile, returns within the 15 m tile buffers were removed, and all resulting 100 m square ground classified tiles were merged. The resulting point clouds for each data set included both the classified ground returns and the non-ground returns. Snow-on and snow-off ground point clouds were gridded at 0.1, 0.2, 0.4, 0.5, and 1.0 m spatial resolutions using the average of all grid points within each grid cell (Currier et al., 2019). Gridded products for each data set were forced to the same coordinate grid to generate DTMs as raster files.

2.4 Slope and Vegetation Cover Classification and Analysis

The snow-off DTM was used to develop a 1 m resolution map of slope (Horn, 1981). Vegetation cover type (field/forest) was determined from the known boundaries of field and forest. The forested area was further classified as coniferous or deciduous for the study region using the following methodology (Figure 1). Within the forested area (Figure 1), a Canopy Height Model (CHM) was used to distinguish the intact upper canopy from other forest cover using our snow-off survey, collected with leaf off in the spring (Sullivan et al., 2017). The CHM was generated by subtracting the DTM produced using ground-classified points from the DSM produced using all lidar points. This results in a digital model consisting solely of canopy heights with no terrain or topography. The CHM generation used raster images with a 1 m resolution. A 3 by 3 maximum convolve filter was used to enhance the edges of canopy crowns and expand smaller regions that might have just one pixel of an intact canopy or a hole in a larger canopy (Palace et al., 2008). A 15 m threshold was used to differentiate between the upper level intact coniferous canopy. CHM pixels that were below this threshold were deemed deciduous canopies (see Figure S3 in supporting information for intermediate figure). The 5.6 ha forested area has a forest type that is 65% deciduous and 35% coniferous.

Once the vegetation forest type was classified, the raster binary image was vectorized. Within the forest and field regions of our study, a subsample was created from the entire image of 5000 random points in the field and 5000 random points in each of the eastern and western forested areas (Palace et al., 2017). At each of these random points, slope, vegetation type (field, deciduous, coniferous), snow depth, and snow depth confidence interval values were extracted. Because of missing values in the raster images, not all random points extracted values. Slope was assigned to one of three categories: 0-10 degrees, 10-20 degrees, and greater than 20 degrees. Because the extracted datasets (i.e., snow depth, confidence interval, and slope) were not normally distributed, the non-parametric Steel-Dwass Method test was used to test for differences. This non-parametric method is useful when sample numbers are large and groups are small, because it allows type I errors to be controlled (Dolgun and Demirhan, 2017).

2.5 *In Situ* Observations

A magnaprobe (Sturm and Holmgren, 2018) was used to compare to the UAS lidar surveys (hereafter noted as ALS measurements) over two transects. The first transect consisted of 12 sample locations in the field and 5 locations in the eastern forest of our study site. The second transect consisted of 11 sample locations in the western forest. Sample locations were separated by approximately 10 m. The field transect follows the prevailing westerly wind direction with its west side at the foot of a modest depression (approximately 3-4 m below the land further to the west) and the east side transitioning into a wooded area. Following (Harder et al. 2016) and (Bühler et al. 2016), each sample location includes 5 samples in a cross pattern with the four ordinal directions sampled approximately 20 cm from the center sampling location in the cross. The five samples are used to provide a measure of snow depth central tendency and variation over a 0.4 x 0.4 m pixel. Because the magnaprobe GPS has an absolute accuracy of 8 m, a Trimble[®] Geo7X GNSS Positioning Unit with Zephr[™] antenna was

205 used to collect each sampling location's center point with an estimated horizontal uncertainty of 2.51cm (standard deviation
 σ 0.95 cm) and 4.17cm (σ 4.60 cm) for the field and forest, respectively after differential correction. Along the same forest
and field transects, a federal snow tube sampler was used to collect a single sample of snow depth and snow water equivalent
(SWE) at each magnaprobe sample location for a total of 12 field samples and 16 forest samples. SWE was measured by
inserting the aluminium tube vertically into the snowpack and a core was extracted and weighed using a spring scale.

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An independent study collected soil frost depth from three locations at the Thompson Farm Research Observatory using
Gandahl-Cold Regions Research and Engineering Laboratory (CRREL) style frost tubes. The frost tubes have flexible,
polyethylene inner tubing filled with methylene blue dye whose color change is easy to differentiate when extruded from ice
(Gandahl 1957). A nylon string housed inside the polyethylene tubing affixes ice during periods of thaw. The outer tubing
215 consists of PVC pipe installed between 0.4 to 0.5 m below soil surface (Ricard et al., 1976; Sharratt and McCool, 2005).
Prior to the January 19th and 20th, 2019 snowfall event, soil frost was 23.5 to 25.5 cm in the field and 5.5 to 8.5 cm in the
west forest.

2.6 Snow Depth Uncertainty Assessment

The snow depth accuracy was assessed by comparing the lidar snow depth measurements to the magnaprobe measurements.
220 Here, accuracy is the measure of the agreement of the lidar snow depth measurements relative to the in situ measurements
(Eberhard et al., 2020; Maune and Nayegandhi, 2018). Error statistics were calculated and the results were summarized by
forest and field locations. At each magnaprobe location, the average and standard deviation of the five magnaprobe samples
were calculated. The average lidar snow depth was determined for a 0.4 x 0.4 m cell centered on the center magnaprobe
location. The mean absolute difference (MAD) and root mean square deviation (RMSD) were used to characterize the
225 differences between the magnaprobe snow depths and the lidar snow depths.

The one-sided width of the 95% confidence limits for each cell's snow depth is a measure of the lidar snow depth variability.
Confidence intervals were calculated using a cell's pooled standard deviation, the number of lidar returns, and the pooled
degrees of freedom (Helsel and Hirsh, 1992) to calculate. A cell's snow depth pooled standard deviation σ_d of the snow-on
230 and snow-off elevations was calculated as

$$\sigma_d = \sqrt{\sigma_{on}^2 + \sigma_{off}^2} \quad (1)$$

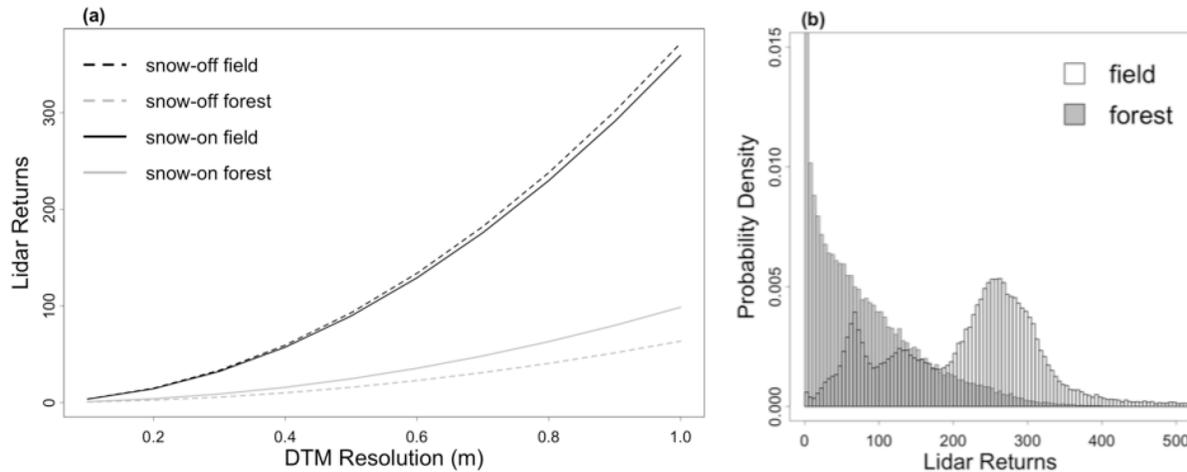
where σ_{on} and σ_{off} are the standard deviation of the snow-on and snow-off lidar return elevations, respectively. This pooled
standard deviation is a measure of the variability of the snow-on and snow-off lidar returns within a grid cell. This variability
depends on the lidar instrument's relative accuracy (Maune and Nayegandhi, 2018), which includes intra-swath accuracy
235 (i.e., precision or repeatability of measurements) and inter-swath accuracy (i.e., differences in elevations between
overlapping swaths), as well as surface elevation variations. The contribution from the individual sources of variability was
not assessed.

3 Results and discussion

240 3.1 Snow Depth Survey

The snow-on and snow-off lidar ground returns yielded an average point cloud density of 90 and 364 points/m² in the forest
and field, respectively, with 6.7% of the 1 m² forest cells and 0.03% of the 1 m² field cells having less than 5 point/m²
(Figure 2). There is a wide range of the point cloud densities (Figure 2b). The highest point cloud density occurred for those
cells sampled by both the regular flight lines and the multiple return flight lines conducted for the three battery exchanges.

245 The vast majority of field cells (82%) have more than 100 points/m². Only 1% of the field cells had less than 25 points/m² and most of those cells were in shrubbery or dense vegetation surrounding the small pond in the center of the study site (Figure 1). In contrast, 41% of the forest cells had more than 100 points/m² and nearly 20% of the forest cells had less than 25 points/m² with 8% having fewer than 10 points/m² (Figure 2b). Only 0.086% and 0.95% of the 1 m resolution field and forest cells, respectively, had no ground returns. The number of points per cell decreases with decreasing cell size (Figure 250 2a). In the field, reducing the gridded resolution from 1 m to 0.5 m lowers the mean cell return count to 91 points per cell on average. Thus a 0.5 m field cell has approximately the same number of returns as a 1 m forest cell. At a 0.2 m spatial resolution, the mean number of ground returns is 14.6 and 3.6 in the field and forest, respectively.



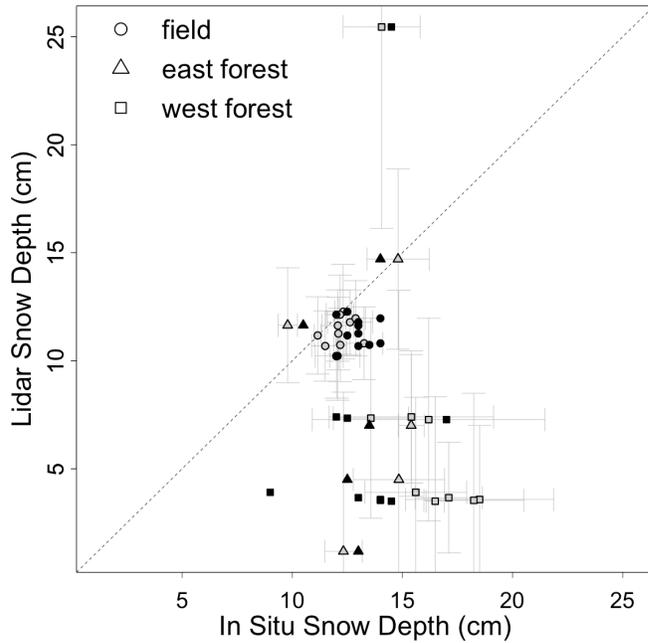
255 **Figure 2.** (a) Average lidar point cloud density of the ground returns versus cell size by land cover, and snow-on and snow-off state (top). (b) Probability density function for the number of lidar ground returns by square meter for the forest (gray) and the field (white) (bottom).

3.2 Lidar and *In Situ* Snow Depth Comparison

Based on the magnaprobe snow depth and UAS-mapped snow depth measurements, the accuracy of lidar snow depth measurements differed between field and forest cells (Figure 3). In the field, the mean snow depth from the magnaprobe (12.2 cm ± 0.56 cm) was only slightly greater than that from the lidar (11.2 cm ± 0.72 cm) and the MAD and RMSD values were 0.96 cm and 1.22 cm, respectively. In the forest, the mean snow depth from the magnaprobe (15.2 cm ± 2.3 cm) was twice as large as the lidar snow depths (7.8 cm ± 6.3 cm) and the MAD and RMSD were 9.6 cm and 10.5 cm, respectively. The mean snow depth from the Federal snow tube was (12.9 cm ± 0.71 cm) and (13.1 cm ± 1.9 cm) in the field and forest, respectively. There is a notable low bias in the lidar forest snow depth relative to the magnaprobe and snow tube for west forest in particular with exception of one site. 265

To provide insight to differences between the forest and field observations, mean height profiles were calculated for a 25 m² square region centered on forest and field study plots from lidar data (Figure 4). To do this, all lidar returns were extracted from the bounding box of each plot, then the mean elevation of ground returns was calculated within each plot. Return height profiles for each plot were determined by subtracting the mean ground elevation of the plot from each return, then the normalized return elevations were binned in 0.1 m height increments. Within the forests, an average of 2142 and 2889 returns were classified as ground and non-ground in snow-free conditions for each 25 m² plot, respectively. Snow-on conditions had a comparable number of ground returns (2218), but fewer non-ground returns (1721). In field plots, an average of 5666 ground returns and 154 non-ground returns in snow-free conditions were obtained for each 25 m² plot, with 275 7567 ground returns and 25 non-ground returns in snow-on conditions. Figure 4 also shows that there is a greater range of

ground return elevations in the forest as compared to the field. In forest plots, ground return elevations had an average standard deviation of 0.157 m and 0.154 m in snow-free and snow-on conditions, respectively, while in field plots, ground return elevations had standard deviations of 0.058 m and 0.050 m in snow-free and snow-on conditions, respectively.



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Figure 3. Comparison between the magnaprobe (gray fill) and snow tube (black fill) versus the lidar snow depth measurements by location. The mean and 95% confidence intervals were calculated using the five magnaprobe snow depths and the lidar snow depths averaged over a 0.4 x 0.4 m grid cell. Single snow tube snow depth measurements are shown without confidence intervals.

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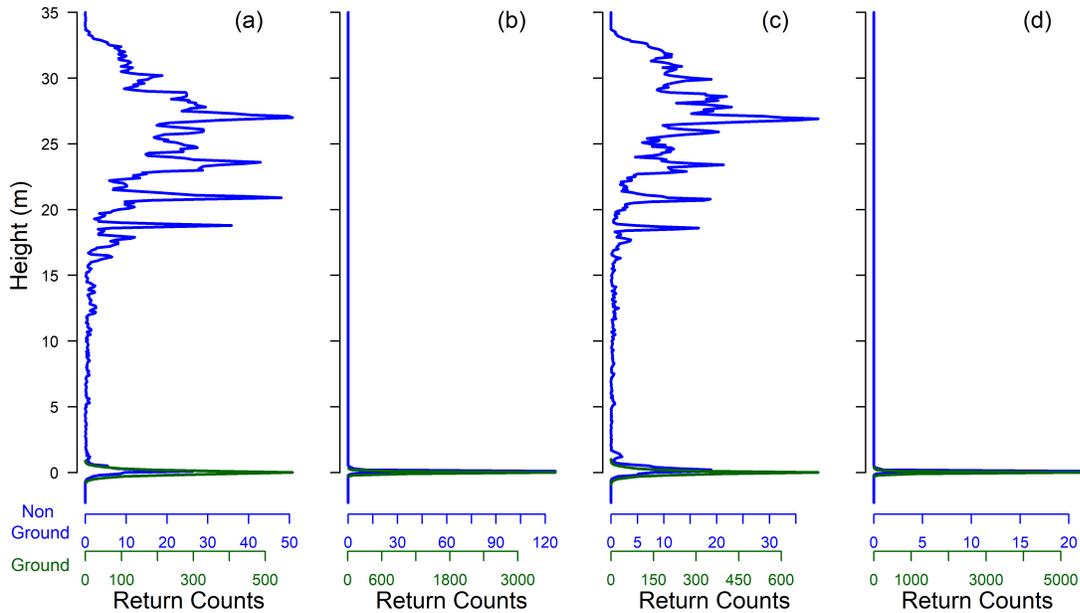


Figure 4. Mean height profiles for all ground (green) and non-ground (blue) returns within a 5 m x 5 m region centered on each transect plot in snow-free conditions (a, b) and snow-on conditions (c, d) in forest (a, c) and field (b, d) study plots.

290 3.3 Snow Depth Maps from UAS Lidar

The UAS-mapped snow depth, mapped by subtracting snow-off DTMs from snow-on DTMs, reveals a shallow snowpack whose depth ranges from less than 2 cm to over 18 cm (Figure 5). The mean lidar snow depth was 10.3 cm in the field and 6.0 cm in the forest. Despite the shallow conditions, spatially coherent patterns are readily discernible. The field snowpack depth has higher spatial variability than the west forest snowpack and more spatial organization. In the field, the deepest snow is in the low-lying northeast areas that are sheltered from westerly winds. A relatively moderate and consistent snowpack occurs in southern part of the east field and west of the small pond. The shallowest snowpack is found in the center portion of the field, which is slightly elevated and, unlike most of the field, was not mowed. Lower snow depth at the forest edge distinguishes the field to forest transition. A non-parametric Steel-Dwass test found significant variation for the mean snow depth among the two forest types and field ($p < 0.0001$) (Figure 6a). A pairwise Steel-Dwass test showed that snow depths were significantly different between the three pairs of field and forest types ($p < 0.0001$). When comparing just field and forest as categories, the test also found significant differences for snow depth ($p < 0.0001$). Snow depth was also determined to be significantly different among the three slope group categories using the Steel-Dwass test where regions with a limited slope (Group 1) had more decidedly different snow than steeper regions ($p < 0.0001$) (Figure 6b).

305 The one-sided confidence interval values of the mean snow depth estimate are remarkably consistent in the field and typically are between 0.5 to 1 cm regardless of snow depth (Figure 5b). Modestly larger confidence intervals occur adjacent to the north-south road where the fields were not mowed prior to winter as well as the northern and southern extents of the flight lines likely due to the reduced sampling density. The forest had an average one-sided confidence interval of 3.5 cm, which is considerably higher than the field. Where the forest is predominantly comprised of deciduous trees, the typical one-sided confidence intervals of the mean snow depth were as low as 1 to 2 cm. The largest one-sided confidence interval values occur in the middle of the field where there is dense shrubbery, at the edge of the fields, and in clusters within the forest where the forest sections are dominated by coniferous trees. The nexus of flight lines in the take-off and landing area resulted in a local area with very high confidence. A non-parametric Steel-Dwass test found significant variation for confidence intervals of the mean snow depth among the two forest types and field ($p < 0.0001$) (Figure 6c). A pairwise Steel-Dwass test showed that confidence intervals were significantly different between the three pairs of field and forest types and ($p < 0.0001$). Confidence intervals were also significantly different among the three slope categories as determined using a Steel-Dwass test ($p < 0.0001$) (Figure 6d).

3.4 Point Cloud Density, Spatial Resolution, and Canopy Profiles

320 Confidence intervals for the mean snow depths by grid cell were examined in light of the point cloud density and the spatial resolution at which lidar returns were aggregated. The confidence interval width for a mean snow depth of a 1 m^2 area increases dramatically as the lidar point cloud density increases (Figure 7a). Except for the cells with fewer than 10 point/m^2 , forest cells have larger confidence intervals for the mean depths than field cells for a given sample size. When the density exceeds 25 point/m^2 in the field and 50 point/m^2 in the forest, confidence intervals are typically 2 cm. The cells with the highest point cloud densities have one-sided confidence intervals of about 1 and 1.5 cm for the field and forest cells, respectively. The field cells with more than 50 point/m^2 did not have noticeably smaller confidence intervals, but the increased density did reduce the number of cells with anomalously small confidence intervals. Given the high lidar point cloud density for the field cells, it is possible that reasonable estimates of snow depth can be made at scales finer than 1 m (Figure 7b).

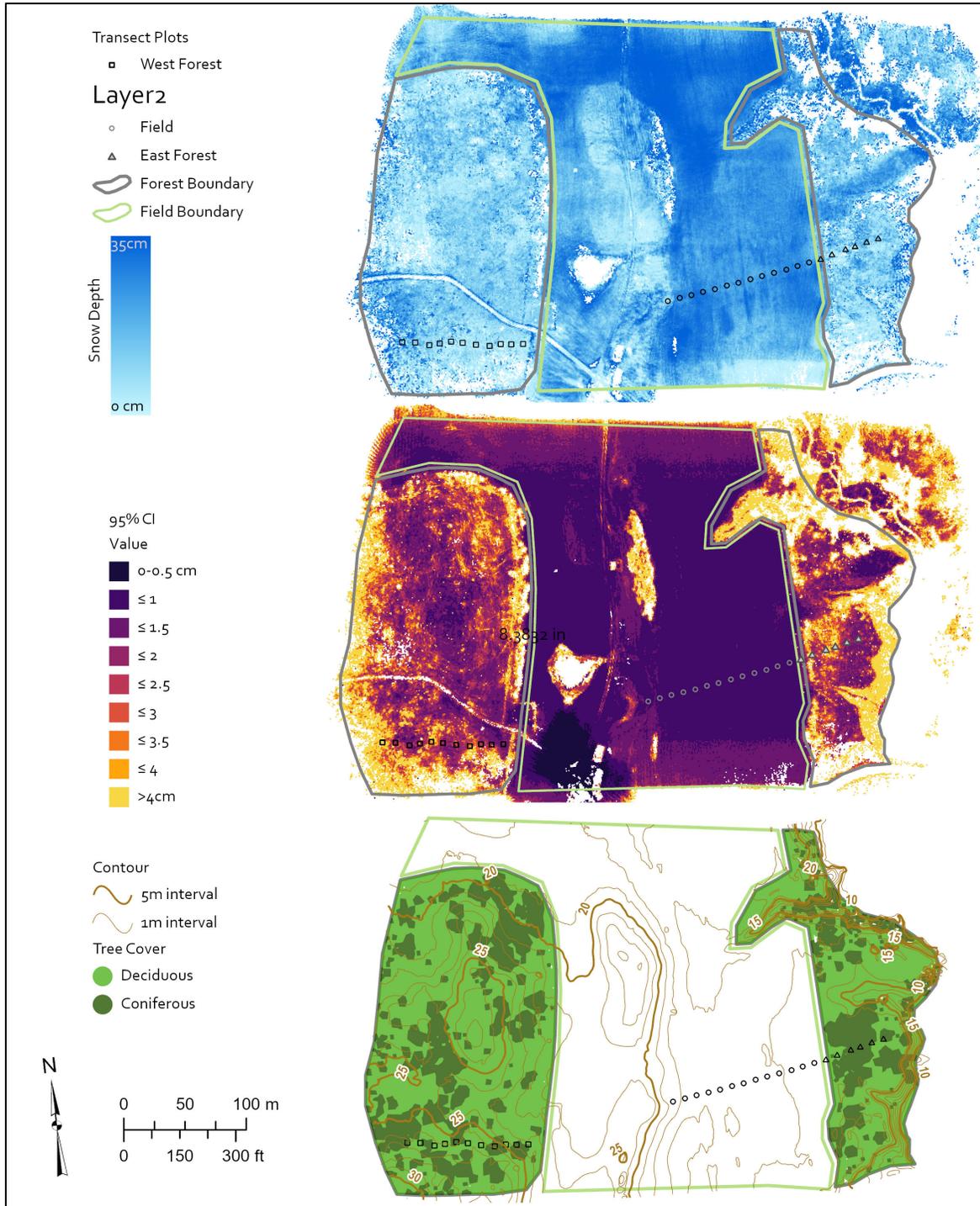


Figure 5. Average (top) snow depth values, (middle) one sided confidence intervals, and (bottom) topography and forest cover type. Snow depth and confidence intervals calculated from the snow-on and snow-off lidar point clouds for 1 m² cells at Thompson Farm, Durham, NH. Topography and forest cover type determined from snow-off lidar point clouds on snow-off flight for 1 m² cells conducted on April 11, 2019.

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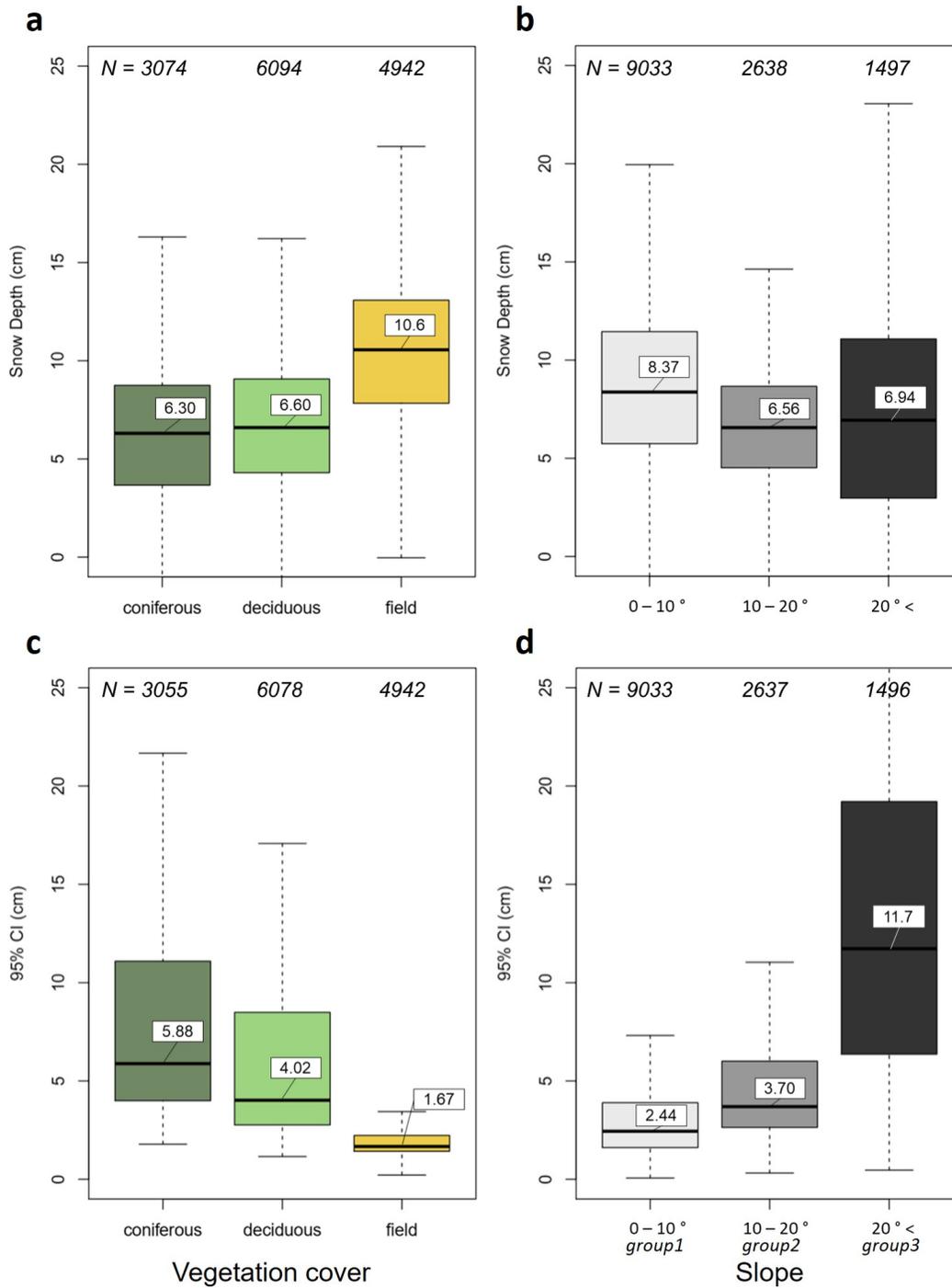


Figure 6. Snow depths (a,b) and their one sided confidence intervals (c,d) from the random sample points of the field and forest at Thompson Farm, Durham, NH on January 23, 2019 from the individual cells for 1 m² cells by vegetation cover (a,c) and slope group (b,d). Boxplots show the lower quartile, median, upper quartile, and whiskers with the median value noted. Because of missing values in the raster images, not all random points extracted values and resulted in different numbers of sample points for vegetation cover classes.

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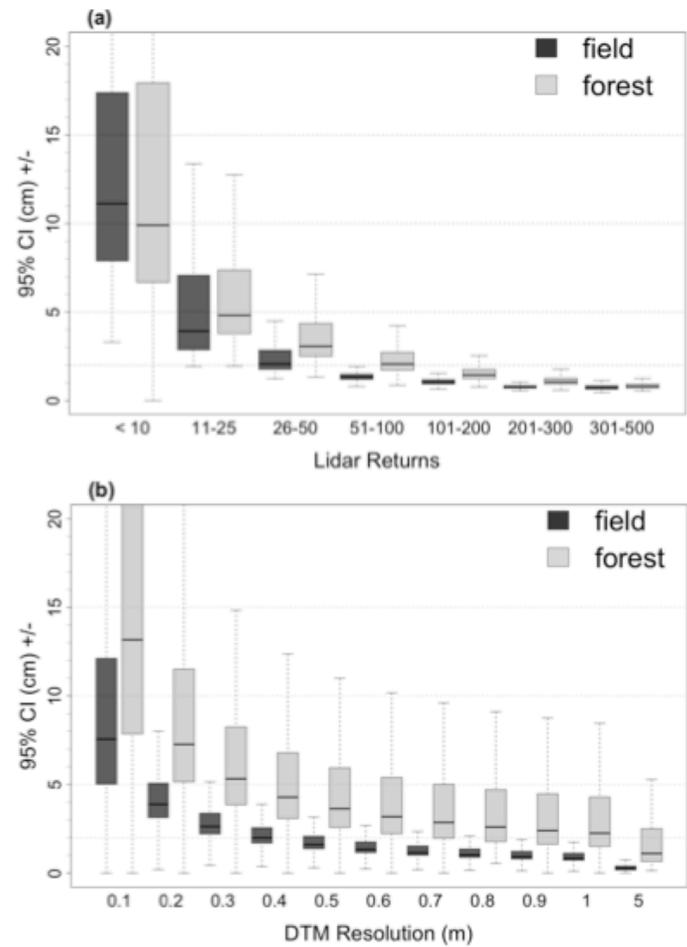
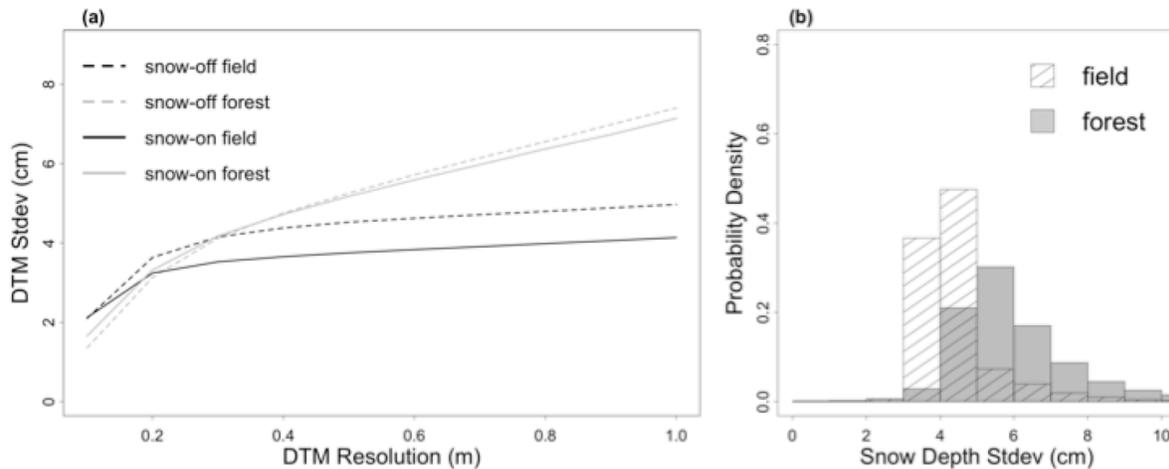


Figure 7. One sided confidence intervals of the mean snow depth values in the field and forest at Thompson Farm, Durham, NH on January 23, 2019 from the individual cells for 1 m² cells by land cover and point cloud density (a) and for grid resolutions ranging 0.1 to 5 m (b). Boxplots show the lower quartile, median, upper quartile, and whiskers.

In addition to the lidar point cloud density, the ability to capture the mean snow depth also depends on the ground surface variability within a cell as well as the lidar performance. For this site and its shallow snowpack, the local scale variability of the ground surface elevation was estimated by calculating the standard deviation of the lidar elevation values and found to depend primarily on the cell size and, to a more limited extent, on land cover and snow cover (Figure 8a). Snow cover reduces the within cell variability in field by about 1 cm, but has a limited effect in the forest. It is possible that the modest snowpack was able to flatten the higher grass in the field, while the forest's vegetation and terrain features that dominate the within cell variability are only minimally compacted by the snow. Within the 1 m grid cells, snow depth variability was much lower in the field than the forest (Figure 8b). Both distributions had a positive skew. Typical standard deviations of the lidar surface elevation values within a 10 cm cell are on the order of 1.5 and 2 cm for the field and forest, respectively. That variability doubles for a 20 cm cell. The within cell variability increases gradually to about 3 to 4 cm in the field, and to about 6 cm in the forest.

Thus, confidence intervals largely depend on the point per cell in the lidar cloud because the standard deviation of a cell's surface elevation is relatively constant for spatial scales from 0.5 to 1 m (Figure 8a). In the field, reducing the cell size from 1 m to 0.5 m still yields about 100 points/m² and provides snow depth estimates within +/- 1.5 cm. Because the forest cells require a higher ground return density to capture these snow depths within a 1 cm, any reduction in cell size below 1 m greatly increase the cell mean snow depth's confidence intervals.



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Figure 8. Lidar surface elevation standard deviations by (a) cell size and land cover. (b) Probability density function of the pooled snow depth standard deviation for each 1 m² cell in the forest (gray) and field (hashed).

4. Challenges and Recommended Improvements to UAS Lidar Snow Depth Mapping

Despite UAS-based lidar’s increasing use in the natural sciences and capacity to make high-resolution snow maps, there are many operational and technical challenges that require consideration prior to successfully conducting UAS-based lidar surveys that produce research grade, high-resolution snow depth data. Even though the UAVs are modest in size (i.e., weighing less than 25 kg), the hardware and supporting software analysis tools can be expensive and require trained pilots and lidar data analysis specialists. In this section, we present some general considerations regarding validation of the lidar snow depth maps, selection and deployment of a lidar sensor on a UAV for snow depth mapping as well as specific insights that we experienced when using our system.

4.1 *In Situ* and UAS Sampling

While UAS-based lidar surveys can measure snow depth to within a centimeter at high spatial resolutions, validation of those observations is challenging. A time consuming collection of high accuracy GNSS survey points was required to collocate magnaprobe and lidar observations. Surveying in sample locations prior to the winter season might reduce this effort. It is also challenging to make *in situ* snow depth measurements that provide centimeter accuracy. In this study, the magnaprobe *in situ* snow depth observations made in the forest were considerably higher than the lidar observations as compared to the open field where the magnaprobe and lidar measurements were within 1 cm. Previous studies also found that snow depth observations from ALS measurements are biased lower than those from snow-probe observations in the forest (Hopkinson et al., 2004, Currier et al., 2019; Harder et al., 2020). In past studies, the causes of these differences have been partially attributed to the snow probe’s ability to penetrate the soil and vegetation, human observers tending to make snow depth measurements in locations with relatively high snow (Sturm and Holmgren, 2018) and the reduced accuracy of the GNSS. Our study suggests additional issues in forest sampling including enhanced terrain variability in forested areas relative to adjacent field areas and reduced lidar returns in forested areas as compared to field areas combine with sampling issues to contribute to the higher uncertainty in the forest snow depths observed in our study.

In this study, the cold temperatures and snow-free conditions prior to the January 19th and 20th snowfall event resulted in deeper frozen soils (23.5 to 25.5 cm) in the field and shallower soil frost depth (5.5 to 8.5 cm) in the west forest, which

would have limited the probe penetration into soils at both sites. However, the forest has a 1-4 cm thick organic leaf litter layer that may have been penetrated by the magnaprobe. The average Federal snow sampler tube depths (13.1 cm) were not as deep as the magna probe (15.2 cm) and thus more closely match the lidar snow depth (7.8 cm; see Figure 3), though a considerable low bias (~5.3 cm) similar to that found by Harder et al. (2020) persists in the lidar snow depth relative to the federal snow sampler snow depths. Additional factors such as downed logs, thick understory, and fine-scale topographic features (ie: small boulders and hummocky terrain) as well as reduced ground return density may contribute to the lidar snow depth errors in a forest, whereas these factors are absent in the field.

An improved understanding of forest canopies impacts on lidar returns is also warranted. Recent work has demonstrated that lidar pulses are “lost” at a much higher rate in forest canopies than open ground terrain due to interception, absorption, and scattering through canopy transmission, with the loss ratio largely influenced by the range of the target from the sensor (Liu et al., 2020). The data that we presented in this paper were acquired using constant flight speed and at consistent altitude above target areas. Because of this, it is feasible that forest canopy conditions and variable understory vegetation density may have resulted in lost pulses and increased uncertainty in our data set. Indeed, we did observe lower return densities for both ground and all returns in forested areas in our data set (Figure 4).

One possible outcome of these lidar sampling issues in forests was a significant difference in snow depth confidence intervals between field and forest types and among slope groups. Confidence intervals were highest in conifer stands and on steep slopes and lowest in the field. While this result is not entirely surprising, it is likely partially the result of lower ground return density in forests due to the combined effects of lost pulses and canopy occlusion in forested areas. Additionally, this observation may be driven by increased variability in snow depth due to pockets of duff and woody debris, and due to higher variability in subnivean terrain in the forested areas of the study site. Areas of high terrain relief are expected to have more variability in ground return elevations over shorter distances, which would partially drive higher confidence intervals of ground surface elevation for pixels located in high relief areas. High relief areas of the study site were more common in forested areas of the study site, and the uncertainty resulting around high slopes also carries through snow depth estimation. Snow depth was significantly different between field and forested areas, as well as between conifer and deciduous forest types, despite the relatively high uncertainty. This indicates the possible influence of tree canopies on snow accumulation due to enhanced snow interception in forests, and particularly in conifer stands, but also could be the result of an under-sampled ground surface in forested areas relative to field areas. Snow depth also was significantly different among the three slope groups, possibly due to wind-driven snow displacement and sloughing on slopes during accumulation.

4.2 Flight Planning

Because larger UAVs that can carry heavier payloads have challenges that may differ from small UAVs, a well-formulated flight plan that addresses weather conditions, logistics of flying at proposed site, flight lines, UAS equipment, and personnel is clearly needed. Weather impacts operations. UAS surveys cannot be conducted when there is any type of precipitation or in dense fog/clouds because moisture can cause electronic components to malfunction and moisture build-up on the propellers can also adversely affect lift production. Depending on the UAV, wind speeds exceeding 7 to 10 m/s may make flights more difficult. This project’s Eagle XF high lift capacity UAS cannot be flown comfortably in winds greater than 8 m/s. At the study site, wind speeds often exceeded this threshold in the days immediately following snowfall except early in the morning. High wind speeds can also significantly reduce battery life as well as impact the accuracy of sensor observations. Low air temperatures can cause batteries to rapidly discharge. For winter UAS surveys, all flight and operational batteries were kept warm in a building, vehicle, or insulated cooler prior to the UAS survey. This also applies to the computer used to upload flight lines and relay telemetry information. A MIL-STD-810 certified Panasonic Toughbook

was used in this study to handle the anticipated cold temperatures. Additionally, cold temperatures can severely limit the dexterity of the person manipulating the flight controls.

440 High lift UAVs capable of carrying a lidar sensor package have the potential to cause significant damage to person and property. The selection of a survey site not only needs to meet the scientific objectives of the UAV survey, but also must have the proper attributes for safe and legal UAV operation including permission to operate the UAV at the site. Visual line of sight (VLOS) of the UAV needs to be maintained throughout the flight. When it is difficult to maintain VLOS (e.g., flying over forested or mountainous sites), spotters can be used if there is constant two-way communication between the spotters
445 and the person operating the flight controls. For this study, an on-site, walk up tower with a spotter was necessary while the UAV was flown over the forest.

The deployment of a UAV lidar system requires additional flight patterns designed for boresighting to ensure that point clouds are aligned (Painter et al., 2016). Provided that GNSS data are accurate, the most common reason for misalignment of
450 point clouds is boresight angle errors (Li et al., 2019). Boresighting is the process of calculating the differences between lidar sensor and IMU roll, pitch, and yaw angle measurements to correct those errors in point clouds. Due to battery flight time limitations, we were unable to complete the flight pattern that is commonly used for boresighting alignment. Because of this, we leveraged our first two antiparallel flight lines for boresighting calibration. Additional details on boresighting calibration, our technique due to the flight time limitations, and examples of roll and pitch alignment errors observed during
455 this field campaign appear in the supplemental materials.

4.3 UAS Sampling Strategies

While lidar calibration and data post-processing requirements are quite similar for UAS and airborne surveys, the UAS lidar surveys presented in this study have key differences from previous ALS surveys. As noted above, UAS flight durations are
460 considerably shorter, resulting in limited spatial coverage as compared to previous ALS snow depth surveys. An advantage of UAS over ALS surveys is that the average point cloud density is much higher and has fewer missing pixels in the forest. This study's sampling densities and the proportion of areas with no ground returns are quite different from previous airborne lidar SD studies. This study had ground returns of 90 and 364 points/m² in the forest and field, respectively, and had no ground returns in only 0.086% and 0.95% of the 1 m resolution field and forest cells, respectively. In contrast, ALS surveys
465 typically report surface model densities between 8 to 16 points/m² (Broxton et al., 2015; 2019; Currier et al., 2019; Kirchner et al., 2014) and ground returns between 3 and 6 points/m² (Broxton et al., 2019; Kirchner et al., 2014). ALS derived snow depth maps have a much greater proportion of areas that are masked due to no ground returns, particularly under trees, with masking areas ranging from less to 10% to more than 23% (Harpold et al., 2014; Mazzotti et al., 2019). While gap filling is possible, interpolation using measured snow depth values to fill under tree can overestimate snow depth (Zheng et al., 2016).
470 Based on our work comparing field and forest lidar collections from a UAS, we suggest testing alternative flight plans, including reduced flight speed over forest canopies to account for lost pulses and canopy returns to produce ground return density that is comparable to field ground return density and to further reduce the number of missing pixels in an acquisition area.

475 A well understood challenge exists when developing a spatial sampling strategy in which, for given resources, there is a trade-off between spatial extent and sampling density (Clark et al. 2011). Increasing flight altitude can expand the spatial extent of an aerial survey. However, flying at higher altitudes results in a decreased point density. In theory, a higher point density could be achieved by slower speeds and increased swath overlap. The targeted spatial extent of an aerial survey dictates whether a manned aircraft or a UAV platform should be used. If the targeted area has a limited domain then using a

480 manned airborne platform is probably overkill and inefficient for many studies and the use of a UAV would be more cost effective. However, as the domain increases in size, additional batteries would be required, much of the battery power would be used to reach the outer limits of the domain, and the ability to maintain the required line of sight could be difficult. Thus, there are end-members for survey site or regions where it is self-evident as to whether a UAV or an airborne platform should be used, but that leaves considerable gray areas where an appropriate choice of UAV platform with a well designed mission
485 could stretch the domain. Future research and technological advances are needed to offer insights for snow science observation platforms and trade-offs.

5. Conclusions

This paper describes and demonstrates a UAV lidar system for snow depth mapping using commercially available components. The UAS was assessed in a mixed deciduous and coniferous forest and open field with little relief over a thin
490 snowpack. The UAS includes an Eagle XF UAV manufactured by UAV America, a small, light-weight VLP-16 lidar (Velodyne, Inc.), and an Applanix APX-15 UAV INS. The INS has a measurement rate of 200 Hz, allowing returns to be georeferenced without ground control points. Data, post-processed to a SBET) file, resulted in approximately 3 cm positional accuracy. Flights were conducted at an altitude of 81 m and flight speed of 7 m/s, with a total of 12 parallel flight lines with targeted overlap of 40 percent. Once the point clouds were classified as ground and non-ground points, the flights yielded an
495 average of 90 and 364 ground points/m² in the forest canopy and field, respectively, with 6.7% of the forest and 0.03% of the field cells having less than 5 point/m².

The snow depth map, generated by subtracting snow-off from snow-on DTMs derived from the resultant point clouds, reveals a snowpack whose depth ranges from less than 2 cm to over 18 cm. For both snow depth and confidence intervals,
500 differences were found between vegetation cover types and slope, indicating complex snow-vegetation interaction that can be observed by UAV lidar return numbers. For 0.4 x 0.4 m cells, the *in situ* and lidar mean snow depths in the field were nearly identical with the MAD and RMSD values of approximately 1 cm. In the forest, the *in situ* mean snow depths from a magnaprobe were twice as large as the lidar snow depths with a correspondingly high RMSD. These forest differences have numerous possible explanations; 1) the snow probe's ability to penetrate the soil and vegetation resulting in random errors,
505 2) higher uncertainty in areas with canopy cover and areas of high terrain relief that occur more commonly in forested areas, 3) reduced total and ground return density in forests due to occlusion and lost pulses. Nevertheless, the results support previous findings indicating that there are limits to lidar snow depth validation at high horizontal and vertical spatial resolutions in some land covers and conditions. Mapped at 1 m² cells, a 0.5 to 1 cm snow depth confidence interval was achieved consistently in the field with confidence intervals increasing to median values of 4.0 cm in the deciduous forest and
510 5.9 cm in the coniferous forest. In the field, snow depth can be mapped at finer spatial resolutions with limited reduction in performance when reducing the cell size to 0.5 x 0.5 m and still achieving snow depth confidence intervals of less than 5 cm for a 0.2 x 0.2 m. Performance depends on both the point cloud density, which can be increased or decreased by changing the flight plan, and the within cell variability that depends on site surface conditions.

Acknowledgements

515 This material is based upon work supported by the Broad Agency Announcement Program and the Cold Regions Research and Engineering Laboratory (ERDC-CRREL) under contract number W913E5-18-C-005. Any opinions, findings and conclusions or recommendations in this material are those of the author(s) and do not necessarily reflect the views of the Broad Agency Announcement Program and the Cold Regions Research and Engineering Laboratory.

520 The authors are grateful to Lee Friess for providing a technical review of the draft manuscript, Mahsa Moradi Khaneghahi for supporting manuscript preparation, and Ronny Schroeder contributing to the field data collection.

Data Availability

The UAS-based lidar point clouds and in-situ snow observations are available from the corresponding author upon reasonable request.

525 Author Contributions

JJ, AH, FS, and MP designed research and performed analysis. JJ, AH, FS, MP, EB, and EC conducted field work to obtain lidar and/or in-situ snow observations. AH, FS, CH, and EC produced figures. JJ wrote the initial draft. All authors contributed to manuscript review and editing.

Competing Interests

530 The authors declare that they have no conflict of interest.

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