Author Response

This document provides a point-by-point response to the reviews followed by a marked-up version of the revised manuscript

Phillip Harder April 29, 2020

Response to Reviewer 1:

The Cryosphere
Manuscript tc-2019-284
Title: Advances in mapping sub-canopy snow depth with unmanned aerial vehicles using structure from motion and lidar techniques
Authors: Phillip Harder, John W. Pomeroy, and Warren D. Helgason
Paper Summary:
The authors show a comprehensive comparison between snow depth derived from UAV structure from motion and UAV lidar. They compare both datasets in forested areas, shrub areas, and in open/smoother terrain to manual snow depth measurements that are geolocated with GNSS systems. The authors show that UAV lidar can provide information beneath the canopy. This allows the user to look at snow depth variability and snow-vegetation processes with lidar. The authors clearly show issues with UAV SfM. The authors also nicely show a cost comparison stating that lidar is more accurate but costs ~15,000 dollars per additional cm of accuracy. The paper is well written and it discusses many caveats and issues that remain with lidar. The paper is a nice demonstration of the accuracy of UAV lidar, its utility, and remaining limitations.
The authors do not just evaluate the two techniques. The authors show how lidar can capture fine scale variability, such as tree wells, and detect fine scale processes with prairies. This shows originality and significance. I recommend the paper be published pending minor revisions.

General/Major Comments:
No major comments. Mostly, nit-picky comments. Enjoyed the paper, particularly Figure 7 and Figure 10 and their ability to capture tree wells and their changes throughout time.

Thank you for the detailed review. The edits you suggest will make this a much stronger contribution- see my specific responses in red below.

Specific Comments:
Title sounds like a review paper. Perhaps consider something like, UAV lidar improves observations of sub-canopy snow depth variability over UAV SfM.

Good point- this is definitely not supposed to be a review paper. Changed to "Improving sub-canopy snow depth mapping with unmanned aerial vehicles: lidar versus structure from motion techniques "

Line 7: I would disagree that techniques are lacking. You might say something related to that they don't always exist; satellite remote sensing is difficult. Airborne lidar captures this. So does TLS. This has been shown.

Agreed- changed to "Vegetation has a tremendous influence on snow processes and snowpack dynamics yet remote sensing techniques to resolve the spatial variability of sub-canopy snow depth are not always available and are difficult from space-based platforms"

Line 26: Traditional remote sensing methods is vague. What's traditional to you might to be traditional to someone else.
Traditional = satellite in my mind. Has been changed. "Unfortunately, satellite remote sensing methods…"

Line 35: I would just say test processes
Changed

Line 38: I don't think Painter et al. 2016 initialized or validated a model. Andrew Hedricks recent WRR paper (Hedrick et al., 2018) would be better suited, which uses ASO data to update iSnobal (reinitialize).
Agreed and have changed reference.

Line 66: Leading to variably, I think you mean variability
Corrected

Line 70: It would be great to reference (Currier et al., 2019) here. Table 1 in their paper reviews this and they provide their own evaluation metrics of ALS in a forest and open area. I would also reference (Mazzotti et al., 2019). They showed a comparison of lidar in Switzerland to snow depth transects in forested areas as well.
Have added these references.

Line 75: TLS was used in the forest in (Currier et al., 2019). Yes, the TLS did not go all the way into the entire forest but from an evaluation perspective of airbone lidar or SfM there's little difference from being 300 meters in a forest as long as there are consistent trees overhead that would inhibit returns from the laser. Also, their paper did not explicitly show that TLS couldn't be used further in the forest, it just gets more complicated.
We are seeking a tool that can measure snow-depth below forest canopies to further process understandings at the landscape scale rather than simply evaluating differences in observational technique. TLS will work on forest edges but will always be at a disadvantage

further into forests versus mobile airborne platforms due to rapid decrease in point cloud density with distance from sensor, analogous to the lambert cosine law, and attenuation of laser penetration though canopy not to mention with slope aspect/slope/curvature/viewshed constraints. Forest edges, including several 10s of m within the forest canopy from the edge have distinctive snow accumulation and ablation energetics (Pomeroy and Gray, 1995; Musselman et al., 2015; Musselman and Pomeroy, 2016). TLS success is always site context/geometry specific while UAV-lidar will not be. Changed to:
"However, TLS has important limitations to furthering landscape scale understanding of snow processes in forested areas as it is limited by the site specific viewshed and viewing geometry (Deems et al., 2013) and occlusion by forest canopies and low vegetation which decreases point cloud density away from forest edges (Currier et al., 2019). It remains an excellent technique for detailed examination of the forest edge snow environment."

Line 90: Could add that (Zheng et al., 2016) lidar to understand vegetation processes effect on snow. They particularly note bias that might occur due to tree wells. (Currier & Lundquist, 2018) used lidar to understand the snow-vegetation interactions in multiple climates. (Mazzotti et al., 2019) also used airborne lidar data to improve the understanding of snow depth related to the forest in Colorado and Switzerland.
Have added these references.

Line 190: I would mention here that the code is provided on your github page. Great job with providing this.
Have added a reference to github at start of data processing section.

Line 205: Trees typically are taller than 50 cm. Most people consider a tree to be at least 2 m tall. Why did you choose 50 cm? This is inconsistent with what the caption shows in Figure 4.
This was a typo and has been corrected. Classes for vegetation height bins are open <0.5m, shrub 0.5 – 2m, and tree >2m.

Line 230: What is estimated and what is observed? I'd say UAV-derived Snow Depth and Snow Depth Probe Manual Observations, or something more specific.
Caption text for Figure 5 has been update to be clearer on what is observed and what is estimated.

Line 235: Yes, the reported error metrics are inflated when moving into the forest. It'd be worthwhile mentioning that the sample size is much less.
Have added a sentence to express this.
"The sample size of snow depth probe observations is smaller for vegetation sites than open sites has implications for error metrics –outliers will have greater weight."

Some lidar points do great. In the methods the GNSS mentions a ±2.5 cm accuracy, how was that determined. Is it possible that this is inflated when in the forest? If not, mention that. Are

these errors from how the point cloud was processed and points were classified? Is ±2.5 cm true for both horizontal and vertical accuracy?
The accuracy is reported by the Leica GS16 for each point at time of observation. It is computed from signal quality on the controller as the 3D uncertainty between the base and rover. Only points in the forest that were able to resolve the RTK solution were collected – there is no decrease in accuracy for the forest/non forest data analyzed. Have added the following to section 2.2.3 in methods: ". The 3D uncertainty of the relative position between the base and rover was computed in real-time to be < ±2.5cm accounting for errors in signal strength, satellite coverage, and instrument precision. RTK signal quality can degrade in forests but only points with fixed RTK solutions were used in this analysis so all survey points are of equal quality irrespective of vegetation cover."

Line 238: I'd start a new paragraph when introducing the error metrics with SfM.
Separated

Line 245: The authors should be using Digital Terrain Models instead of Digital Surface Models throughout.
I agree that DSM may not be appropriate here as its definition implies that it is the top of the surface whether that be the soil surface in open areas or the top of the canopy in forested areas. A DEM is closer to our meaning in that it is a bare-surface raster grid, with trees and vegetation excluded, referenced to a vertical datum. A DTM on the other hand has various definitions, some of which are incompatible with what we are describing in this paper:

1) DEM can be synonymous with DTM in some countries https://gisgeography.com/dem-dsm-dtm-differences/
2) In the US and other countries, a DTM is not a DEM, but is a vector data set composed of regularly spaced points and natural features such as ridges and breaklines. A DTM augments a DEM by including linear features of the bare-earth terrain. https://gisgeography.com/dem-dsm-dtm-differences/
3) DTM: bare-earth representation with irregular spaces between points (non-raster). Behrendt, R. Introduction to LiDAR and forestry, part 1: a powerful new 3D tool for resource managers. The Forestry Source, p. 14-15, set. 2012.

DTM is an acronym with various definitions that may complicate its application here as we are considering both bare ground and snow surfaces beneath a forest canopy. We feel that it is more appropriate to call these "snow DEM" and "ground DEM" as I am filtering out vegetation points and focusing on the extracted "bare surface" points. Deems et al. 2013 uses DEM to describe snow and bare ground surfaces.

Figure 6: Cool analysis. I would consider adding a black dashed line for 2.5 cm. This plot supports the results of Currier et al. 2019, that the airborne lidar is more likely to penetrate the shrubs than the TLS observations. What's the scientific name for the shrubs found at these locations?

Horizontal black line added at 2.5 cm as a reference in Figure 6. There are many shrub or similar low vegetation species at these locations. The Prairie sites have a lot of tall prairie grasses and reeds in the wetland areas along with willow and dogwood shrubs and poplar trees. In the cropland around it will be crop residues/standing stubble of wheat or barley. In the Fortress mountain site, shrubs are primarily willow but there are others too. The site descriptions have been updated to reflect these vegetation details.

Figures: I would change the easting northing to the total number of meters within the domain, or start at 0 and show ticks from 0 m. I don't know the projection information, and if I did the numbers aren't that meaningful. If the location is important, please provide the UTM zone. But still it's a bit annoying to do the subtraction each time to get a sense of scale. I would just make it easier for the readers, if possible. Otherwise the figures are great.

Have changed all the figures to have 0,0 UTM origins consistent to each scene.

Line 317: This seems like an appropriate time to re-mention UAV lidars ability to capture tree wells.
Have re-mentioned this here.

Line 321: Confusing sentence. Deems reported errors in the forest larger than 14 cm? Why is 14 cm mentioned. Figure 5 reports RMSE of 0.15 and 0.16. Also, in the previous sentence. Studies have masked out the forest? Studies have looked at airborne lidar accuracy in the forest.
These results report error metrics for forest situation that are comparable to airborne lidar for open areas. Some lidar snow depth errors in the forest are comparable to metrics reported here but it's always hard to have apples- to apples comparisons as "forest" is not a uniform landscape class in terms of structure/density and species with respect to how lidar interacts with it. The advantage of UAV-lidar is that we can get a much broader range in scan angle so we can improve probability of reaching surface points below the tree crown from "oblique" angles. Have changed text to be:

"This RMSE is comparable to previous efforts with UAV or airborne-SfM and airborne-lidar that have been focussed on mapping the snow depth of open snow surfaces. Applications of airborne-lidar to forested areas report similar errors (Currier et al., 2019; Mazzotti et al., 2019) but the higher flight altitude of airborne platforms and their near nadir perspective limit point densities near tree centres that are necessary to capture tree wells."

Line 355: Really cool figure and analysis
Thanks!

Line 375: Green polygons look cyan when zoomed out, might choose a different color.

Furthermore, the near infrared data seemingly comes out of nowhere – maybe provide some more context within the section for it and why it needs to be mentioned. Provide a citation for NIR serving as a proxy for albedo.

I have removed the NIR figure and discussion of its data as it is beyond the scope of the paper and needlessly complicates the story.

Line 435: "The accuracy and resolution demands mean that bare surface classification techniques suitable for airborne platforms that efficiently resolve topography and hydrography at watershed scales from last returns will be unsuitable for resolving the snow depth around a particular shrub from a dense point cloud for example" The paper did not show that using the last returns was unsuitable. The classification technique used something similar to last returns. Previous studies have showed using the last returns resulted in a generally unbiased snow depth estimate, and provided a reasonable approximation of the variability. I am not sure what this sentence is attempting to say.

A long winded way to say that where there are dense shrubs the last returns will not necessarily be the snow or ground surface and therefore last-return methods will not be appropriate. This is clarified as "Where there are dense shrubs, the last returns will not necessarily be the snow or ground surface and therefore last-return methods common to airborne applications will not be appropriate"

Line 465: A discussion referencing the difficulties with modeling in Mark Raleigh's paper seems appropriate and a better citation then Tom Painters 2016 paper. Furthermore, when mentioning snow pack density variability, mentioning Karl Wetlaufer's paper seems appropriate (Raleigh & Small, 2017; Wetlaufer et al., 2016).

These are much more appropriate references- thanks.

Line 479: "The UAV-lidar metrics consistently exceed the UAV-SfM metrics and are better than previously reported results in the airborne-lidar and UAV-SfM literature."
This isn't true. Metrics are similar but not better than. Please note line 69.
Have rewritten this sentence. To be "The UAV-lidar performance consistently exceeded the UAV-SfM performance and was better than previously reported results in the airborne-lidar and UAV-SfM literature"

References Currier, W. R., & Lundquist, J. D. (2018). Snow Depth Variability at the Forest Edge in Multiple Climates in the Western United States. *Water Resources Research, 54,* 1–18. https://doi.org/10.1029/2018WR022553

Currier, W. R., Pflug, J., Mazzotti, G., Jonas, T., Deems, J. S., Bormann, K. J., et al. (2019). Comparing aerial lidar observations with terrestrial lidar and snow-probe transects from NASA's 2017 SnowEx campaign. *Water Resources Research,* 1–10.

https://doi.org/10.1029/2018wr024533
Hedrick, A. R., Marks, D., Havens, S., Robertson, M., Johnson, M., Sandusky, M., et al. (2018). Direct Insertion of NASA Airborne Snow Observatory-Derived Snow Depth Time Series Into the iSnobal Energy Balance Snow Model. *Water Resources Research, 54,* 8045–8063. https://doi.org/10.1029/2018WR023400 Mazzotti, G., Currier, W. R., Deems, J. S., Pflug, J. M., Lundquist, J. D., & Jonas, T. (2019). Revisiting Snow Cover Variability and Canopy Structure Within Forest Stands: Insights From Airborne Lidar Data. *Water Resources Research, 55(*7), 6198–6216. https://doi.org/10.1029/2019wr024898
Raleigh, M. S., & Small, E. E. (2017). Snowpack density modeling is the primary source of uncertainty when mapping basin-wide SWE with lidar. *Geophysical Research Letters, 44(*8), 3700–3709. https://doi.org/10.1002/2016GL071999
Wetlaufer, K., Hendrikx, J., & Marshall, L. (2016). Spatial heterogeneity of snow density and its influence on snow water equivalence estimates in a large mountainous basin. *Hydrology, 3(*1). https://doi.org/10.3390/hydrology3010003
Zheng, Z., Kirchner, P. B., & Bales, R. C. (2016). Topographic and vegetation effects on snow accumulation in the southern Sierra Nevada: A statistical summary from lidar data. *Cryosphere, 10(*1), 257–269. https://doi.org/10.5194/tc-10-257-2016

Response to Reviewer 2:

Paper Summary:

The authors compare two relatively new methodologies for using UAVs for mapping snow depths in forested and open prairie environments with in situ ground validation GNSS surveys. They present a very thorough analysis involving an impressive collection of data from 19 unique survey dates from two distinct environments over the course of a single winter season. The time and effort taken to plan, collect, and process such a comprehensive dataset cannot be overstated! The results of the comparison on the ability of both the UAV-lidar and UAV-SfM to estimate snow depths are not necessarily new, but to my knowledge, they have not been compared as extensively with both the successes and failures of both methodologies clearly presented. In open environments, the UAV-lidar and UAV-SfM snow depth mapping capabilities are similar, but in vegetated areas, the UAV-lidar methods excel by having the ability to penetrate through vegetation and measure sub-canopy snow depth. However, in densely vegetated, tight canopy environments, even the UAV-lidar mapping method cannot penetrate the canopy and therefore cannot produce reliable snow depth estimates. An added benefit of using the UAV-lidar over UAV-SfM for snow depth mapping is the insensitivity of the lidar to homogeneous surface conditions and variable/poor solar illumination, both of which contribute to substantial errors in UAV-SfM mapping. In-addition, the increased vertical accuracy of the UAV-lidar sensors can be used to better detect patterns in snow distribution and depth previously not obtainable over basin-wide study sites in complex landscapes. The authors do a nice job at presenting their findings in a well-written manner using suitable figures. As an added bonus, the authors also discuss the cost difference between the UAV measuring methodologies, and calculate a metric that assigns a dollar value to each centimeter of improved RMSE between methods. This cost analysis is of interest, but probably has less relevance for the future, as the price for the type of equipment used in this study continues to decrease dramatically year-by-year. I recommend the publication of this paper pending minor revisions addressing the suggested comments and technical edits.

A PDF supplement has also been uploaded that contains all the suggested edits/comments. In the technical edits section, this PDF supplement has all changes highlighted in **BOLD.**

An example of the suggested changes to Figure 7a has also been uploaded as Figure 1 – Slide 1.JPG. This example figure provides a visualization of the changes being suggested for Figures 7a, 8a, 9a (applies to General Comment at Line 270/295/300).

First, thank you for this detailed review and you will find our responses in red below the corresponding comment.

General Comments:

Line 59 – 'differencing snow-covered (hereafter snow) and snow-free (hereafter ground)…' Double check terminology throughout paper for consistency. The following different term are used: bare-ground, bare ground, ground, surface, bare surface. Personally – I like the use of the term bare-ground.

We refer to 'surfaces' which can be either snow or snow-free. "Bare' refers to points left after vegetation point removal for either a snow or snow-free surface. 'Ground' implies a snow-free surface. We have edited the paper to make the terminology more consistent, following these rules throughout.

Line 59 – 'Digital Surface Models (DSMs)' I think you are actually referring to the Digital Terrain Models (DTMs). Change this reference throughout the paper.

I agree that DSM may not be appropriate here as its definition implies that it is the top of the surface whether that be the soil surface in open areas or the top of the canopy in forested areas. A DEM is closer to our meaning in that it is a bare-surface raster grid, with trees and vegetation excluded, referenced to a vertical datum. A DTM on the other hand has various definitions, some of which are incompatible with what we are describing in this paper:

1) DEM can be synonymous with DTM in some countries https://gisgeography.com/dem-dsm-dtm-differences/
2) In the US and other countries, a DTM is not a DEM, but is a vector data set composed of regularly spaced points and natural features such as ridges and breaklines. A DTM augments a DEM by including linear features of the bare-earth terrain. https://gisgeography.com/dem-dsm-dtm-differences/
3) DTM: bare-earth representation with irregular spaces between points (non-raster). Behrendt, R. Introduction to LiDAR and forestry, part 1: a powerful new 3D tool for resource managers. The Forestry Source, p. 14-15, set. 2012.

DTM is an acronym with various definitions that may complicate its application here as we are considering both bare ground and snow surfaces beneath a forest canopy. We feel that it is more appropriate to call these “snow DEM” and “ground DEM” as I am filtering out vegetation points and focusing on the extracted “bare surface” points. Deems et al. 2013 uses DEM to describe snow and bare ground surfaces.

Line 134 – ‘flight parameters to maximise mapping efficiency were set to…’ What about limiting the scan angle? The Riegl lidar can scan 360 degrees, what level of off nadir scan angle did you limit the data collection/processing to and why?
The Riegl scanner does scan in a 360° configuration. While data can be limited to specific scan angles at collection it was not limited in our application, as there is no increase in performance/accuracy to do so – the mirror is rotating the full 360°. The scan angle was not limit in processing the data either. The laser is relatively low powered and we have found that returns at angles shallower than 70° from nadir are rare. Hence, we did not limit the available data to perform our analysis – any points available were used to optimize the surface feature extraction.

Line 135 – ‘100 m flight altitude above the surface…’ Did the mission planning software make use of terrain following mode to ensure consistent flight altitude above ground? If so, what source of terrain information did you use?

Yes used terrain following with respect to a SRTM DEM. Have added ”The UgCS flight control software was used to generate flight paths with these parameters and terrain following with respect to an underlying SRTM DEM”

Line 148 – I deleted the term differential: differential GNSS corrections (code-based) are significantly less, accurate than RTK/PPK/PPP (carrier phase methods) – I suspect even though the Leica GS16 unit is DGPS capable, you used the more accurate carrier phase correction methods.

Correct, we were using the carrier phase methods. ‘differential’ has been removed

Line 150 - suggest removing the term ‘random within the survey areas and’ if the transects were also selected to most efficiently survey the greatest variety of vegetation types.
Agreed – we have removed that text.

Line 152 – ‘provided a real-time-kinematic (RTK) survey solution …’ While conducting your manual surveys did you make use of the RTK capabilities – or did you post-process the rover data as indicated at line 153?

The difference between the rover and base was established during the surveys with RTK. Because the base position was not known in advance to the surveys the RTK observed rover positions needed to be adjusted to absolute locations in post processing once the base position was established through the PPP step – an offset needed to be calculated and applied to survey points. In post processing the only adjustment was made to the base position not the relative rover-base positioning. This is clarified as:
" Post-processing with Leica Infinity software (version 2.4.1.2955) established the absolute positions of the rover points by maintaining the RTK rover-base position but adjusting the base station absolute location to that established by the PPP tool."

Line 152 – 'accuracy of < ±2.5cm.' Can you provide a reference for this?
Not shown here but the uncertainty is computed in real-time as part of the RTK and PPP based solutions see below and was consistently less than of < ±2.5cm –not based on a reference.

Line 154 – '(https://webapp.geod.nrcan.gc.ca/geod/tools-outils/ppp.php)' Add this website to the references section
Have added this to the references.

Line 154 – 'absolute base station location.' How long did you collect your raw GNSS data for and what were the PPP computed standard deviations for the base station locations? Did you always use the same base station location for every flight?

Due to the logistics of conducting campaigns at multiple sites, raw GNSS data was only logged when we were on site with different tripod setups. Therefore logging varied in duration between 2.5 and 9 hours. The PPP computed standard deviations were consistently less than 2cm – often better. For simplicity the uncertainty of the survey solution was presented to be ± 2.5 cm. This value is based propagating a conservative uncertainty of the PPP based solution 2cm and the RTK solution off 1.5cm. sqrt (2^2+1.5^2)=2.5. We have updated section 2.2.3 to reflect this.

Line 174 – '<2.5 cm.' Do you mean +/- 2.5 cm as mentioned earlier in the text? Is this value based on the specs of the Leica GS16 GNSS survey equipment or was it based on the PPP online standard deviations? How did you obtain this value?
See comment above

Line 181 – '< ±2.5 cm' Same comment as above? Is this value based on the specs of the Leica GS16 GNSS survey equipment or was it based on the PPP online standard deviations? How did you obtain this value?
See comment above

Line 205 – 'vegetation height (open <0.1 m, shrub <0.5 m, and trees >0.5 m)…' These values differ from what is in the Figure 4 caption. Which vegetation height classes did you use, and how did you choose the class heights?

The caption for figure 4 and text were slightly incorrect due to relics of an earlier edit. Vegetation height classes were open <0.5 m, 0.5 m ≥ shrub ≤2 m, and trees >2 m. Vegetation classes were selected with a simple metric to differentiate vegetation based on the height data at hand. There will be variability in shrub heights, but for simplicity we used 0.5m and 2m thresholds as they were consistent with field observations at the various sites and thresholds previously reported in the snow hydrology literature which ranged from 0.5m to 3m in Marsh et al. (1997) and 0.3m to 2m in Rasouli et al. (2019).

Marsh, P., Pomeroy, J.W., Pietroniro, A., Neumann, N., Nelson, T., 1997. Mapping Regional Snow Distribution in Northern Basins Inuvik Area. Saskatoon, Saskatchewan. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.712.6847&rep=rep1&type=pdf

Rasouli K., Pomeroy J.W., and Whitfield P.H. (2019) Are the effects of vegetation and soil changes as important as climate change impacts on hydrological processes? Hydrology and Earth System Sciences: 23, pp. 4933-4954 DOI: 10.5194/hess-23-4933-2019

Line 223 – I deleted reference to RTK - In line 55 you indicate the rover survey points were post-processed, therefore I am assuming you used a PPK GNSS solution here?

RTK with a post processing of the base position to account for PPP. See comments above.

Line 230 – ‘points extracted from the point clouds or interpolated surfaces…’ This sentence is confusing. It is unclear whether you extracted the UAV snow depth values from the point clouds or the interpolated DSMs? Which one was it?
Caption was in error and is corrected as “Plots are segmented for vegetation class (rows), sites (columns) and observation method (colours).”

Line 256 – Figure 6 - Please add to the caption a description of which metrics are visualized by the whiskers of the boxplots.

Have added: “Median is indicated by the line inside the box, the upper bound is the 75th percentile and the lower bound is the 25th percentile and whiskers represent the range of values beyond the box.”

Line 266 – ‘The noisy UAV-SFM points in the middle of the slope challenge the snow surface extraction even without the presence of vegetation leading to an underestimation of the snow surface.' Do you have any idea on why the SfM product detected something in the open areas on the slope? Why does it lead to an underestimation of snow in this area? Based on the Figure 7a cross-section it looks like the UAV-SfM red points are equal to or above the green lidar points. Why did the interpolation go so low? Did the interpolation treat missing points as 0 or bare ground values?

Looking closer at the UAV-SfM noise in Figure 7a there was some vegetation mid slope near to the transect. The lidar was able to differentiate it well but the SfM-generated vegetation points occupied a larger space and intruded on the transect line. Therefore when vegetation was removed it led to a gap in the UAV-SfM point cloud at this point in the transect, which when interpolated through led to the underestimation in the snow surface. When gaps are present the interpolations are sensitive to edge points which tend to have poor quality and therefore challenge the validity of the resulting surface.

Have added: “These vegetation points occupied a larger space than the UAV-lidar and intruded on the transect line. Therefore, vegetation removal from this point in the transect led to a gap in the UAV-SfM point cloud, but not the UAV lidar point cloud. Interpolating through the gap in the UAV-SfM point cloud resulted in underestimation of the snow surface.”

Line 270/295/300 – Figure 7-8-9 - Suggest using shaded/transparent colour bars on plot a) to indicate the extent of the tree features. This will help highlight the tree well extent and how the UAV-SfM interpolation result in deeper snow values across these features (I have uploaded an example Figure of 7a. that illustrates what I am trying to describe – Slide 1.JPG). Suggest using a more obvious colour in Figure b) for highlighting the SfM only classes. Suggest trying to match the tone of colours in Figure c) to more closely match that used in Figure b). Making the open areas a little bluer, and again highlighting the SfM only points in a more obvious colour. Figure 7b It sort of looks like the SfM only class occur near the edges of the study area in a just a couple areas. Is this related to steeper scan angles at the edge of the study site, perhaps coupled with steep terrain?

Have modified the figures to have polygons outlining areas of interest in the cross sections and changed the colour scheme to more clearly show differences in point coverage. The SfM-only points occurred on the edges of the domain as this was nearing the edge of the lidar flight area (less overlapping scan areas reduces the point density and therefore reduces number of ground points)

Figure 9c) I suggest mentioning in the figure caption that the large dark areas of no lidar points represent the extent of the melt water ponds.
The figure caption is rather large already so prefer to leave this discussion in the text.

Line 288 – the negative UAV-SfM snow depth estimates discussed here are explained at lines 443-450. Perhaps also providing further explanation here might be helpful.
To simplify the results section would suggest that this explanation fits better into the discussion section as it is.

Line 316 – In the example of 7a, the interpolation resulted in erroneously deep snow depth estimates. This will not always be the case and in some instances can result in underestimations depending on the season, elevation, forest type, etc. Many studies have highlighted the differences in snow depths/characteristics between open/forested sites that will influence these interpolation errors. I think providing some further explanation on the type/magnitude of interpolation errors that may occur when using UAV-SfM techniques would help strengthen your findings/statement here.

Have added: "Open areas will have greater snow depths than forest areas (Troendle 1983; Swanson et al., 1986; Pomeroy et al., 2001; Mazzotti et al., 2019;) meaning UAV-SfM solutions, or any approach which requires interpolation of point cloud gaps beneath trees, will overestimate snow (Zheng et al., 2016)."

Line 318 – 'major improvement on previous attempts.' Can you provide some context on what is considered a major improvement, including references to previous studies/RMSEs?

Have removed "major" as that is an unquantifiable adjective. Have modified it to be "The ability of UAV-lidar to map snow-depths, with and without canopy cover, and capture tree wells with RMSE's ≤0.15 m is an improvement on previous attempts. This RMSE is comparable to previous efforts with UAV-SfM (Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016), airborne-SfM (Bühler et al., 2015; Nolan et al., 2015, Meyer and Skiles 2019) and airborne-lidar (Deems et al., 2013; Painter et al., 2016) that have been primarily focussed on mapping the snow depth of open snow surfaces. Applications of airborne-lidar to forested areas report similar errors (Zheng et al., 2016; Currier et al., 2019; Mazzotti et al., 2019) but the higher flight altitude of airborne platforms and their near nadir perspective limit point densities near tree centres that are necessary to capture tree wells."

Line 318 – 'previous efforts…' Can you provide some references?
Same as comment above.

Line 321 – '0.14 m RMSE (Deems et al., 2013).' Can you provide the actual magnitude of errors previously reported for comparison in the Deem et al., 2013? What is the significance of this 0.14 m RMSE?

Have removed this 0.14 m RMSE per comment from Reviewer 1

Line 342 – 'intermittent precipitation totaling approximately 100 mm' How was this determined/measured? What kind of uncertainties are associated with this reported precipitation value. I also want to confirm that you mean 10 cm of snow? This seems low for mountain snow.
There are a number of precipitation gauges (Geonor and Pluvio) within the Fortress mountain research basin. I say 'approximately' as this was an approximation of the raw storage gauges signals as the data QA/QC and undercatch corrections were beyond the scope of this project. And yes I do mean that this is approximately 10 cm of snow. It is low for a mountain situation but 2019 was a low snow year in this area and the February to April interval this is reflecting was a cold, dry period without any major snowfall events.
Have added; "measured at storage gauges at the study site"

Line 350 – 'and development of a tree well in the middle of the transect. The Figure 10b transect demonstrates the lack of wind redistribution in the canopies relative to the Figure 10c transect on the ridgeline.' It is unclear where the development of the tree well is highlighted/visible in Figure 10b. It also unclear how Figure 10b demonstrates the lack of wind re-distribution in the canopies. Please provide more detail here.
Have highlighted the tree wells with orange polygons in figure 10b. Have added the following to clarify the comment on demonstrating a lack of wind redistribution in the forest area. "The Figure 10b transect demonstrates the lack of wind redistribution in the forest; snow accumulation was consistently observed to be ≤ precipitation over the transect, versus the Figure 10c transect on the ridgeline, where the accumulation in the lee slope greatly exceeded the observed precipitation."

Line 366 – 'In contrast UAV-SfM struggled with sensing snow depths in the short shrubs on the edges of wetlands.' This sentence contradicts the results displayed in Figure 5, which illustrated that the UAV-SfM had lower RMSE in the shrub class compared to the UAV-lidar. It also does not support the discussion starting at Line 286 and expanded at Lines 443-450, which discusses the challenges that BOTH lidar and SfM face in trying to measure below the canopy in dense shrub vegetation.

This sentence needed to be a bit more nuanced. This is not a comment on the RMSE differences and should not have highlighted the shrubs in particular rather this was based on the fact that there is a higher point cloud density for the lidar versus SfM in wetland areas. This is clarified as "In contrast UAV-SfM struggles with sensing snow depth on the edges of wetlands as seen by the concentration of lidar only areas at the wetland in the Rosthern study area (wetland area highlighted by red polygon in Figure 8b).

Line 467 – 'Observational approaches are also a challenge as typical in situ measurements are destructive, limited in extent, and often too limited to develop robust relationships of depth versus density at the small scales needed (Kinar and Pomeroy, 2015a; Pomeroy and Gray, 1995).' The methods developed by Proksch et al., 2015 do provide a method for measuring snow density at a much smaller scale applicable for these process-scale studies. The Proksch et al., 2015 methods have been recently rigorously applied to a set of snow on sea ice measurements by King et al., 2020, highlighting the ability to document the local-scale variations in snow density relatively quickly over larger spatial extents.

Proksch, M., Löwe, H. and Schneebeli, M., 2015. Density, specific surface area, and correlation length of snow measured by high-resolution penetrometry. Journal of Geophysical Research: Earth Surface, 120(2), pp.346-362.

King, J., Howell, S., Brady, M., Toose, P., Derksen, C., Haas, C., and Beckers, J.: Local-scale variability of snow density on Arctic sea ice, The Cryosphere Discuss., https://doi.org/10.5194/tc-2019-305, in review, 2020.

These methods while very interesting and small scale are still destructive sample methods which means that their application to a UAV-based solution to SWE estimation, that captures local and landscape scale density spatial and temporal variability, will be limited. The small sample size and empirical calibration of the micro-penetrometer method results in uncertainty in its application.

This is communicated through a slight edit as " Observational approaches are also a challenge as typical in situ measurements are destructive, limited in extent, and often too limited to develop robust relationships of depth versus density at both the small local and large landscape scales needed (Kinar and Pomeroy, 2015a; Pomeroy and Gray, 1995). Opportunities may be available to pair UAV-lidar with other UAV-borne sensors such as passive gamma ray or snow acoustics (Kinar and Pomeroy, 2015b) to non-destructively develop high spatial and temporal resolution estimates of snow density and ultimately water equivalent.."

Line 474 – 'necessary spatial scales' – Please be more specific on what scales you are referring to.

Have removed this sentence as the scales are mentioned later in the conclusion section.

Technical Comments:

Line 13 – suggest changing to 'measure returns from a wide range of scan angles, **increasing the** likelihood of successfully…'

Changed

Line 51 – suggest changing to 'are valuable automated data sources, but **are spatially limited in extent and can often** suffer from location/elevation bias…'
Changed

Line 53 – suggest changing to 'and so **may** not **be** suitable for snow hydrology calculations or model validations **in forested regions** even though they are often…'
Changed

Line 60 – spelling correction: quality
Changed

Line 62 – suggest changing to 'pulse can be observed with **returns possible from within the canopy and from the sub-canopy ground surface.** In contrast UAV-SfM…'
Changed

Line 64 – spelling correction: variability
Changed

Line 80 – spelling correction: focused
This is correct Canadian English spelling.

Line 87 – punctuation: 'In dense forests, vegetation…'
Changed

Line 90 – suggest changing to 'increase in snow accumulation **over** aerodynamically rough surfaces or **in** sheltered areas **where the wind speeds decrease and snow is deposited** – this includes forest edges…'
Changed

Line 98 – suggest changing to 'varies across complex vegetated landscapes…'
Changed

Line 105 – suggest changing to 'ability of the UAV-lidar and UAV-SfM **techniques for measuring** snow depth in open
Changed

Line 106 - (50.833 N, 115.220 W)
Changed

Line 108 – spelling correction: focused

This is correct Canadian English spelling.

Line 109 – suggest changing to '(Figure 1a – background center)…'
It is already directly identified as the a) panel so will leave as is.

Line 111 – suggest changing to 'alpine ski resort in the 1960's, **but is** currently a limited-use…'
Changed

Line 114 – suggest changing to 'Canadian Prairies were **examined** in this study.'
Changed

Line 117 – correction: remove negative sign if using 'W' to indicate west (51.941 N, 106.379 W) & (52.694 N, 106.461 W)
Changed

Line 125 – Figure 1 caption: suggest changing to 'Figure 1: a) Fortress Mountain Snow Observatory in Kananaskis, Alberta Canada, b) **Rosthern** and c) **Clavet prairie** study locations in Saskatchewan Canada. Data collection was on Fortress Ridge (**background center)** an area of high topographic variability and **a mix of** dense forests and clearings. The Clavet **photo** highlights the **transition zone between the open upland terrain and the lower elevation vegetated** wetland. The Rosthern scene highlights the low vertical relief **of upland areas** and isolated
woodlands amongst cultivated fields.
Changed

Line 155 – suggest changing to 'GS16 rover points to **correct** for the PPP **updated** base station locations **were completed using** the Leica Infinity software…'
This section has been reworked and this edit no longer applies

Line 158 – 'suggest changing to 'To assess the accuracy of the **UAV snow depth measuring** methods, as well as provide insight into the **seasonally evolving** snow **depth/**distribution, **a total of** 19 **flight/manual** surveys were conducted **between all three study sites between** September 2018 to April 2019. These are summarised by date, **surveyed** surface, **UAV** data collected, and corresponding number of **manually surveyed** surface elevation points in Table 1.
Changed

Line 165 – suggest changing to 'difference between a bare ground DSM and a snow **surface** DSM.'
Changed but using DEM rather than DSM

Line 176 – suggest changing to 'Finally, overlapping scan data **from adjacent flight lines are** used to optimise the IMU trajectory, to align the scan lines and reduce the noise of the final point cloud within the RiPrecision tool. **This final step in noise reduction can improve the final product because the 1.5 cm laser data precision is greater than the post processed IMU trajectory accuracy.** (I used the 15mm stated precision of the Reigl sensor presented earlier in the text to get the 1.5cm value here)
Changed and absolutely correct on that last sentence to clarify matters.

Line 193 – suggest changing to 'For **the bare-**ground lidar scans, the height of vegetation…'
Changed

Line 207 – spelling correction: include
Changed

Line 214 – suggest changing to '2.3.6 **Point Cloud Density'**
Changed to 'Point Cloud Coverage' as density has a different meaning. Here I'm trying to quantify how gappy the bare point clouds are.

Line 221 – suggest changing to '3.1 **Accuracy of UAV-lidar versus UAV-SfM snow depth estimates**
Changed

Line 231 – suggest changing to 'Plots are segmented for points extracted from the point clouds or interpolated surfaces **within each vegetation class** (rows), sites (columns) and observation method (colours).' – See general comments above about clearing up the confusion concerning which product the points were extract from.
Changed

Line 232 – suggest changing to 'The influence of vegetation on **estimating** snow depths **from UAVs can be** directly assessed by…'
Changed

Line 234 – suggest changing to 'Open Prairie and **open** Fortress **RMSE values** are similar (0.09 m and 0.1 m RMSE respectively)…'
Changed

Line 235 – suggest changing to 'equally successful **at** penetrating the open leaf-off deciduous tree canopy at the prairie sites as the closed needleleaf canopy at the Fortress site **based on the similar RMSE values within each site's tree vegetation class.**'
Changed

Line 238 – suggest changing to ‘The Open vegetation has a large RMSE range **between sites** (0.1 m in Prairie and 0.3 m in Fortress respectively) while vegetation **class** RMSEs range from…’
Changed

Line 240 – suggest changing to ‘UAV-lidar in the prairie Shrub case, **the difference between these techniques is only 0.04 m, which is** within the **+/- 2.5 cm** observational **uncertainty** of **the GNSS** survey equipment **used in this project.**
Changed

Line 247 - suggest changing to ‘manual **GNSS** surveys **using boxplots** (Figure 6). **The boxplots in Figure 6 illustrate that** the UAV-SfM snow surface elevations…’
Changed

Line 257 – suggest changing to ‘3.2 **Point cloud density’**
Changed to “Point cloud coverage” per previous comment.

Line 263 – suggest changing to ‘could not reliably return surface points **with a density > 1 pt 0.25 m-2**whilst…’
Changed

Line 263 – punctuation: ‘At Fortress, UAV-lidar…’
Changed

Line 265 – suggest changing to ‘lack of UAV-SfM sub-canopy points identified within the treed vegetation class results in an interpolated snow surface that is erroneously deep under trees, completely missing the detection of the reduced snow depths which are clearly detected (green line) around the base of the trees by the UAV-lidar.’
Changed

Line 274 – suggest changing to ‘c) with **the same** overlain transparent point type classification **colour scheme as shown in b).’**
Changed

Line 276 – suggest changing to ‘The predominantly open nature of the Prairie sites demonstrates a minimal difference in **point density** between **UAV-lidar and UAV SfM measurement** techniques. The average **extent of the study domain covered with a point density of > 1 pt 0.25 m2 for** 5 coincident flights at the Prairie sites **was computed, resulting in the** mean coverage of 92% versus 83% **of the study area** for **the UAV-lidar and** UAV-SfM **respectively.**
Changed

Line 281 – suggest changing to 'These gaps in the **UAV-SfM** point clouds are interpolated and therefore will represent…'
Changed

Line 287 – suggest changing to 'both lidar pulses and SfM solutions interpret the vegetation surface as the **top of the bare-**ground **or snow** surface and therefore **little difference exists between these two DSMs during all measurement periods.** An additional challenge of **using the** UAV-SfM **techniques** is that large gaps **in points** appear beneath the tall wetland edge vegetation due to the inability to penetrate the sub-canopy, as visualized **in the cross-sections** of Figure 8a and 9a**,** where the estimated UAV-SfM snow surface is below the UAV-lidar ground surface.'
Changed

Line 316 – suggest changing to 'Sub-canopy snow depth mapping with UAV-SfM therefore becomes an exercise in **interpolating snow depth values observed in open** areas **without** vegetation **to areas with dense vegetation,** rather than sensing the actual snow depth under the canopy.'
Changed

Line 322 – suggest changing to '4.2 **Bare-ground point cloud density is critical'**
Ground in this case can be either 'ground' or snow so 'surface remains more appropriate.

Line 323 – suggest changing to 'The **increased** point **density** of UAV-lidar…'
Not so much density as lack of gaps aka coverage. Changed to "The increased continuous point coverage of UAV-lidar"

Line 325 – suggest changing to 'The point cloud cross-sections **illustrated** in Figure 7 emphasize **these findings, highlighting the** wider gaps in the UAV-SfM point cloud beneath individual trees that require interpolation **over longer distances resulting in greater potential for error.**' (The lidar data also requires interpolation)
Changed

Line 332 – suggest changing to 'In contrast, **mountainous regions** have much more complex topography…'
Changed

Line 337 – suggest changing to 'continuous bare-**ground** point cloud coverage.'
Ground in this case can be either 'ground' or snow so 'surface remains more appropriate.

Line 338 – suggest difference word choice for: foreshadow
Changed to 'Two examples are presented here to exemplify analyses the possible with UAV-lidar'

Line 340 – suggest changing to ‘Differences between open and forest snow cover processes can be **explored** by **examining** the difference in snow depth…’
Changed
Line 342 – suggesting changing to ‘UAV-**lidar measured** change in snow depth visualizes…’
Changed

Line 343 – suggest deleting line: ‘The upper, open terrain clearly demonstrates the influence of blowing snow redistribution’ because this sentence is ambiguous.
Line deleted

Line 343 – suggest changing to ‘In the Figure 10c transect **cross-section** there was accumulation of up to 2 m over the **September-April time** period on lee slopes, whilst the upper windswept portions of the ridge demonstrate snow erosion **between February and April.**”
Changed

Line 346 – suggest changing to ‘The dynamics and extents of blowing snow sources **(grey/red)** and sinks **(blue)** are clearly visualized in **10a, which closely match the findings of** Schirmer and Pomeroy (2019) using SfM **for this same study region.**
Changed

Line 347 – suggest deleting line: ‘Considering the forest slope brings out features that UAV-SfM cannot observe.’ Because this sentence appears as a fragment
Deleted sentence

Line 349 – suggest changing to ‘there is a general decline in snow depth **from February to April** (due to melt on the south facing slope).’
Changed

Line 360 – suggest changing to ‘wind-blown snow from **open** upwind sources and are typically associated with…’
Changed

Line 366 – suggest changing to ‘Areas that the UAV-lidar was able **to** measure correspond to areas…’
Changed

Line 390 – suggest changing to ‘This gradient in dust and albedo **is likely associated with** the increases in snowmelt rates **observed** downwind of the grid road.’
Section has been reworked.

Line 405 – suggest changing to ‘UAV-lidar, relative to UAV-SfM, provides **the ability to measure** snow depth below vegetation…’
Changed

Line 408 – suggest changing to ‘and cheaper **equipment,** subscriptions to virtual reference station networks if available in the study area **(requires only a rover and not a base station),** or equipment rentals are all viable alternatives to lower costs.’
Changed

Line 410 – suggest changing to ‘The main cost difference **between UAV-lidar and UAV-SfM platforms** is therefore in terms of the **UAV** sensor **payload.**’
Changed

Line 412 – suggest changing to ‘like consumer grade UAVs (DJI Phantom 3 < $2,000 CAD), **to** more expensive options like…’
Changed

Line 413 – suggest changing to ‘Current integrated lidar systems suited to **UAV** snow mapping’
Changed

Line 423 – suggest changing to ‘In contrast, **most current** UAV-lidar **configurations** need larger platforms that require more cycles of large battery sets to cover similar areas, which represents a **logistical** challenge in **keeping the batteries warm and charged in** cold and remote areas.’
Changed

Line 428 – suggest changing to ‘Despite the lower **initial purchase** cost and **longer flight endurance,** the errors and artefacts that UAV-SfM **measuring techniques** introduce in sub-canopy **snow depth measurements,** as detailed in sections 4.3.1 and 4.3.2, **suggest that UAV-SfM is not able to directly measure snow depth** in **densely vegetated environments.**’
Changed

Line 434 – suggest changing to ‘Precise classification of surface points from snow and ground scans **are** needed to resolve…’
Changed

Line 435 – suggest changing to ‘The accuracy and resolution demands **are such** that bare-**ground** surface classification techniques **developed** for airborne platforms to resolve topography and hydrography at watershed scales from **lidar** last returns **may** be unsuitable for resolving snow depths.’
Have changed this sentence with respect to Reviewer 1 comments

Line 438 – suggest changing to ‘filtering tools and associated parameters to **be able to reliably detect the sub-canopy bare-ground surface and** achieve desired quality…’
Changed

Line 441 – spelling correction: ‘large-scale’
Changed

Line 448 – suggest changing to ‘the areas of negative snow are limited to areas where snow depth is **relatively** shallow **in comparison to the** deep snow in the wetland edges.’
Changed

Line 452 – suggest changing to ‘snow depth estimation in **these** hydrologically significant snow accumulation areas.’
Changed

Line 453 – suggest changing to ‘ground surface, but **current** sensors **with these characteristics** may exceed **the payload capacities** of most UAV platforms. Advances in bare surface classification/**filtering** software…’
Changed

Manuscript with Tracked Changes:

~~Advances in mapping~~Improving sub-canopy snow depth mapping with unmanned aerial vehicles: ~~- using~~lidar versus ~~-~~structure from motion ~~and lidar~~ techniques

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Abstract. Vegetation has a tremendous influence on snow processes and snowpack dynamics yet remote sensing techniques to resolve the spatial variability of sub-canopy snow depth are ~~lacking~~not always available and are difficult from space-based platforms. Unmanned Aerial Vehicles (UAV) have had recent widespread application to capture high resolution information on snow processes and are herein applied to the sub-canopy snow depth challenge. Previous demonstrations of snow depth mapping with UAV Structure from Motion (SfM) and airborne-lidar have focussed on non-vegetated surfaces or reported large errors in the presence of vegetation. In contrast, UAV-lidar systems have high-density point clouds, measure returns from a wide range of scan angles, ~~and so have a greater~~increasing the likelihood of successfully sensing the sub-canopy snow depth. The effectiveness of UAV-lidar and UAV-SfM in mapping snow depth in both open and forested terrain was tested in a 2019 field campaign in the Canadian Rockies Hydrological Observatory, Alberta and at Canadian Prairie sites near Saskatoon, Saskatchewan, Canada. Only UAV-lidar could successfully measure the sub-canopy snow surface with reliable sub-canopy point coverage, and consistent error metrics (RMSE <0.1~~7~~7m and bias -0.03m to -0.13m). Relative to UAV-lidar, UAV-SfM did not consistently sense the sub-canopy snow surface, the interpolation needed to account for point cloud gaps introduced interpolation artefacts, and error metrics demonstrate relatively large variability (RMSE <0.33m and bias 0.08 m to -0.14m). With the demonstration of sub-canopy snow depth mapping capabilities a number of early applications are presented to showcase the ability of UAV-lidar to effectively quantify the many multiscale snow processes defining snowpack dynamics in mountain and prairie environments.

1 Introduction

Snow accumulation and melt are critical parts of the hydrological cycle in cold regions (King et al., 2008). To understand these processes there needs to be robust and accurate observation methodologies to measure the depth and density of a snowpack, and its change, across all aspects of the landscape. Unfortunately, ~~traditional~~satellite remote sensing methods struggle to quantify the spatial distribution of snow at a high enough resolution and accuracy to account for the fine scale interactions between snow and vegetation (Nolin, 2010). Remote sensing conceptually promises the capability to gather this type of data at the spatial scales and extents needed, but the main challenge for snow observations across a heterogeneous landscape is that exposed vegetation and forests obscure the underlying snow surface (Bhardwaj et al., 2016; Nolin, 2010; Tinkham et al., 2014). This paper seeks to illuminate some of the challenges posed to UAV-based remote sensing of snow depth observations and how UAV-based lidar represents a promising opportunity to overcome this limitation at the small catchment scale (<5 km^2).

Capturing the spatial distribution of snowpacks and snowcover at a particular instance provides information about the integrated accumulation and ablation processes up to that point in time. Accurate quantification of snow accumulation and ablation is needed to improve the understanding of snow hydrology, test processes~~ understandings~~, examine spatial scaling of process interactions (Clark et al., 2011; Deems et al., 2006; Trujillo et al., 2007), and to initialise and/or validate model predictions (~~Painter~~Hedrick et al., 201~~6~~8). Snow depth, the focus of this paper, is not the variable of ultimate interest for hydrology. Rather, snow water equivalent (SWE) is used for snow hydrology applications (Pomeroy and Gray, 1995). Fully cognisant of this, the focus here is on snow depth, as it is well documented that snow depth varies much more than density (Pomeroy and Gray, 1995; Shook and Gray, 1996; Jonas et al., 2009; López-Moreno et al., 2013); therefore, improving the accuracy of snow depth observations in a drainage basin is critical to improving the estimation of SWE at and within basin scales.

Snow depth and SWE observations are traditionally collected though *in situ* observations (Goodison et al., 1987; Helms et al., 2008; Kinar and Pomeroy, 2015a; Sturm, 2015). *In situ* approaches, such as snow surveying, rely on manual sampling of snow depths and densities to get SWE. When conducted along landscape-stratified transects the lansdcape-scale SWE can be estimated (Pomeroy and Gray, 1995; Steppuhn and Dyck, 1974). The challenge for snow survey observations is that they are prone to observer bias, are labour intensive and time consuming, and are often unable to sample all aspects of a landscape such as avalanche zones (Kinar and Pomeroy, 2015a). Nonetheless, snow surveying is a proven approach to quantify SWE and has been operationalised across many regions. The practice has historical precedence and has created many long-term records which are a valuable data source (Goodison et al., 1987; Helms et al., 2008). Other point observations, such as snow pillows (Coles et al., 1985), acoustic sensors (Kinar and Pomeroy, 2009; 2015b), and passive gamma sensors (Smith et al., 2017) are valuable automated data sources, but are spatially limited in extent and can often suffer from location/elevation bias -- as demonstrated by the SNOTEL network in the western United States (Molotch and Bales, 2006).~~–~~ In particular, measurements of snow in forest clearings will ~~provide a much greater snowpack than would be found~~have relatively more snow than under the adjacent canopy (Pomeroy and Gray, 1995) and so may~~are~~ not be suitable for snow hydrology calculations or model validations in forested regions even though they are often used for just such purposes.~~–~~ Other techniques need to be developed to capture the small-scale spatial variability of snow-vegetation interactions to advance our process understandings and validate the next generation of distributed snow models.

Remote sensing approaches have shown promise to evaluate snow depth in open areas. Airborne-lidar and UAV Structure from Motion (UAV-SfM) approaches have been proven to provide snow depth mapping abilities when differencing snow-covered (hereafter snow) and snow-free (hereafter ground) Digital ~~Surface~~ Elevation Models (DE~~S~~M). Lidar, an active sensor, emits a pulse of light and detection of the reflected pulse results in a point cloud of a scene with a consistent qua~~i~~lity point cloud regardless of flight characteristics, wind conditions, or solar illumination. A clear benefit of lidar is that multiple returns per pulse can be observed with ~~points~~returns possible from within the canopy and from the sub-canopy ground or snow surface ~~within the canopy and at the underlying surface~~. In contrast UAV-SfM uses a passive RGB sensor where data quality is not actively controlled. This results in variable image quality because: inconsistent solar illumination influences image exposure; wind gusts influence platform stability leading to blurry images and inconsistent overlap; and surface heterogeneity means that some areas of the domain will have more key points--points automatically detected and matched in multiple images (Westoby et al., 2012)--leading to variability in the quality of the SfM solution (Bühler et al., 2016; Harder et al., 2016; Meyer and Skiles, 2019).~~–~~ So while SfM can provide similar quality error metrics in open areas the quality will vary between flights as conditions change, whereas lidar will be more consistent.~~–~~ Reported snow depth accuracy in open environments, expressed as root mean square errors (RMSE), varies from 0.08 m to 0.60 m for airborne-lidar (Currier et al., 2019; DeBeer and Pomeroy, 2010; Harpold et al., 2014; Mazzotti et al., 2019; Painter et al., 2016; Tinkham et al., 2014), 0.17 to 0.30 m for airborne-SfM (Bühler et al., 2015; Meyer and Skiles, 2019; Nolan et al., 2015), and 0.02 to 0.30 m for UAV-SfM (Harder et al., 2016; Vander Jagt et al., 2015; De Michele et al., 2016). A notable challenge is that the presence of exposed vegetation, especially dense forest, confounds SfM solutions and obscures airborne-lidar bare ~~ground~~ surface extractions which are needed for fine scale differencing of DE~~S~~Ms to evaluate snow depths or snow depth changes (Bhardwaj et al., 2016; Deems et al., 2013; Harpold et al., 2014). Terrestrial laser scanning (TLS) is another approach for observing high-resolution snow depth data which has been used to develop an understanding of snow depth distributions and for validating other snow depth observation methods (Currier et al., 2019; Egli et al., 2012; Grünewald et al., 2010; Mott et al., 2011). However, TLS has ~~had limited contributions~~important limitations ~~to furthering~~that restrict further landscape scale understanding of snow processes in forested areas as ~~they are restricted to~~it is limited by the site specific viewshed and viewing geometry (Deems et al., 2013) and occlusion by forest canopies and low vegetation which decreases point cloud density away from ~~visible open terrain and~~ forest edges (Currier et al., 2019). It remains an excellent technique for detailed examination of the forest edge snow environment.

Most applications of remote sensing for observing snow processes have focussed on open environments. However, vegetated portions of those same environments can play a large role in landscape-scale snow hydrology. For example, wetland vegetation accumulates deep snowdrifts and so has an exaggerated influence on snow accumulation processes in prairie environments (Fang and Pomeroy, 2009). Similarly, forests constitute large fractions of the mountain domain (Callaghan et al., 2011; Troendle, 1983) and have very different snow processes than found in open environments (Pomeroy et al., 2002). Snow-vegetation interactions are complex (Currier and Lundquist, 2018; Gelfan et al., 2004; Hedstrom and Pomeroy, 1998; Harder et al., 2018; Mazzotti et al., 2019; Musselman et al., 2008; Parviainen and Pomeroy, 2000; Pomeroy et al., 2001; Zheng et al., 2016) and involve both snow interception by the canopy and wind redistribution to forest edges. In dense forests, vegetation leads to interception and subsequent sublimation of snow resulting in an overall decrease in accumulation (Hedstrom and Pomeroy, 1998; Parviainen and Pomeroy, 2000; Reba et al., 2012; Swanson et al., 1986). In open environments, such as the prairies, tundra and alpine, wind redistribution of snow leads to a decrease in snow depth in exposed erodible areas and an increase in snow accumulation over ~~in~~ aerodynamically rough surfaces or in sheltered areas where wind speeds decrease and snow is deposited~~that act as snow sinks –~~ this includes forest edges (Busseau et al., 2017; Essery et al., 1999; Fang and Pomeroy, 2009; Liston and Hiemstra, 2011; Pomeroy et al., 1993; Schmidt, 1982). Much of the understanding of snow-vegetation interactions is based on snow surveys, which are limited in scale and extent. Thus approaches to systematically and efficiently quantify these dynamics across a drainage basin accounting for topographic and vegetation heterogeneity are needed to further develop and test our process understandings.

1.1 Research Questions and Objectives

The overall motivation of this work is to understand how snow depth, as well as the processes driving its accumulation and ablation, varies across ~~the~~ complex vegetated landscapes. Better tools are needed to measure snow at scales that resolve snow-vegetation interactions, which can involve individual trees and small forest gaps. So the specific objectives in this manuscript are to: 1) evaluate the ability of UAV-lidar versus UAV-SfM ~~to quantify~~techniques for measuring snow depth in open and vegetated areas, and 2) articulate challenges and opportunities for UAV's to map sub-canopy snow depth.

2 Data and Methods

2.1 Sites

Several sites from western Canada, which represent a range of surface condition and snow climates, were selected to test the ability of the UAV-lidar and UAV-SfM to ~~sample~~ measure snow depth in open and vegetated areas.

Fortress Mountain Snow Laboratory (hereafter Fortress), in Kananaskis AB (50.833 N, ~~-~~115.220 W), is a research basin operated by the University of Saskatchewan's Centre for Hydrology in support of mountain hydrology research. The 5 km^2 catchment's elevation ranges from 2000 m to 2900 metres above sea level (m.a.s.l.). Field observations for this paper focussed on the Fortress Ridge (Figure 1a) which spans an open alpine environment, a larch treeline zone near 2200 m.a.s.l., and a mixed lodgepole pine and subalpine fir forested slope to the valley bottom at 2000 m.a.s.l. (Schirmer and Pomeroy, 2019). Shrubs are primarily willows. The area was developed as an alpine ski resort in the 1960's, but is currently a limited-use ski operation without snowmaking, and some open ski runs remain through some of the slopes of interest.~~–~~ Strong winds result in substantial redistribution of snow by blowing snow in this environment (Aksamit and Pomeroy, 2018)

Two study areas in the Canadian Prairies were ~~tested~~ examined in this study. Both sites provide examples of cropland with hummocky terrain subject to significant blowing snow redistribution (Figure 1bc). Windblown snow from upland areas of short vegetation, wheat and barley stubble, is often transported to lower elevation wetland depressions where it is effectively trapped by wetland vegetation, shrub vegetation types include willows, dogwoods, tall grasses and reeds while the trees are primarily poplar. One site was located southeast of Saskatoon, SK (51.941 N, ~~-~~106.379 W), hereafter Clavet, with the other site north of Saskatoon, SK (52.694 N, ~~-~~106.461 W), hereafter Rosthern. The main difference between prairie sites was that

Rosthern received more snowfall and developed a deeper snowpack than Clavet in winter 2019. Where results from both sites are aggregated, they are collectively referred to as Prairie hereafter.

Figure 1: a) Fortress Mountain Snow Observatory in Kananaskis, Alberta, Canada, b) ~~Clavet~~ Rosthern and c) ~~Rosthern~~ Clavet pr~~Pr~~airie study locations in Saskatchewan, Canada. Data collection was centred on Fortress Ridge (ridgeline in background centre~~eline in middle of photograph~~) an area of high topographic variability and ~~variability between~~a mix of dense forests and clearings. The Clavet ~~scene~~ photo highlights the ~~tall dense grass and wetland~~transition zone between the open upland agricultural terrain and the lower elevation vegetated wetland ~~vegetation of a wetland and agricultural land transitions~~. The Rosthern ~~scene~~ photo highlights the low vertical relief of upland areas and isolated woodlands amongst cultivated fields.

2.2 Data Collection

2.2.1 Lidar System

The UAV-lidar system was comprised of a Riegl miniVUX-1UAV lidar sensor, integrated with an Applanix APX-20 Inertial Measurement Unit (IMU), and mounted on a DJI M600 Pro UAV platform (Figure 2a). The miniVUX1-UAV utilises a rotating mirror to provide a 360-degree line scan with a measurement rate of 100 KHz and up to 5 returns per shot with a 15 mm precision. The APX-20 provides positional accuracy of <0.05m in horizontal and <0.1m in vertical dimensions with a 200Hz sampling rate and 0.015 degree and 0.035 degree accuracy in roll/pitch and heading, respectively. The payload, 5 kg, approaches the maximum capacity of the M600 Pro platform so flight parameters to maximise mapping efficiency were set to 7 m/s ground speed, 100 m flight altitude above the surface, with ~~with~~ parallel flight lines 80 m apart. The UgCS flight control software (SPH Engineering, 2020) was used to generate flight paths with these parameters and terrain following with respect to an underlying SRTM DEM. Flight times are conservatively limited to 15 minutes. The generated UAV-lidar point clouds have densities of approximately 75 points per square metre (pt m^{-2}).

2.2.2 Structure from Motion systems

Coincident surface mapping with SfM used imagery collected by EbeeX or Ebee+ fixed wing UAV platforms with SODA RGB cameras from Sensefly (Figure 2b). The longer flight times, up to 70 minutes, associated with a lightweight payload on a fixed wing platform allowed for efficient mapping of large areas. Overlap parameters were generally 80% for the longitudinal and 65% in the lateral axes. Flight altitudes of 120 m above the surface provided a ground sample distance of 2.8 cm with the SODA camera, which was used on both EbeeX and Ebee+ platforms. The generated UAV-SfM point clouds have densities of ~ 110 pt m^{-2}.

Figure 2: UAV-lidar platform: Riegl miniVUX1-UAV mounted on DJI M600 Pro (a) and UAV-SfM platform: Sensefly EbeeX (b).

2.2.3 Ground Validation Surveys

The assessment of snow depth accuracy used coincident surveys of surface elevation points with ~~differential~~ Global Navigation Satellite System (GNSS) surveys and manual measurement of snow depths with a ruler. The intention of the surveys was to validate the spatially distributed snow depth retrievals and ~~therefore~~ transects were ~~random within the survey areas and~~ selected in a manner for the surveyor(s) to efficiently sample the greatest variety of vegetation types and gradients. A Leica GS16 base/rover kit provided a real-time-kinematic (RTK) survey solution ~~that~~ to ~~allows~~ survey~~ing of~~ points. ~~to a~~The 3D ~~n accuracy of~~uncertainty of the relative position between the base and rover was computed in real-time to be < ±1.5 cm which accounts for errors in signal strength, satellite coverage, and instrument precision ~~< ±2.5cm~~. RTK signal quality can degrade in forests but only points with carrier-phase RTK solutions were used in this analysis so all survey points are of consistent quality irrespective of vegetation cover. Post-processing of the GNSS data used the Canadian Geodetic Survey of Natural Resources Canada Precise Point Positioning (PPP) online tool (Natural Resources Canada, 2020~~(https://webapp.geod.nrcan.gc.ca/geod/tools-outils/ppp.php~~) to define an absolute base station location. Due to multi-site logistics the base station location varied between flights and collection periods ranged between 2.5 and 9 hours and PPP computed standard deviations were consistently < 2 cm. Post-processing with Leica Infinity software (version 2.4.1.2955) ~~adjustment of the~~established the absolute positions of the ~~GS16~~ rover points ~~to account for~~by maintaining the RTK rover-base position but adjusting the ~~the PPP~~ base station absolute location to that established by the PPP tool. Propagating the uncertainty of the RTK solution (± 1.5 cm) and PPP derived absolute base location (± 2 cm) gives an uncertainty of ± 2.5 cm for the survey points. ~~used the Leica Infinity software (version 2.4.1.2955).~~

2.2.4 Campaigns

To assess the accuracy of ~~these~~the UAV snow depth measurement methods as well as provide insight into the seasonally evolving snow depth distribution a total of ~~evolution over periods of time~~ 19 flight/manual surveys were conducted ~~over the~~at all three study sites between ~~course of~~ September 2018 and~~to~~ April 2019. These are summarised by date, surveyed surface~~surface~~ condition, UAV data collected, and corresponding number of manually surveyed surface elevation points in Table 1.

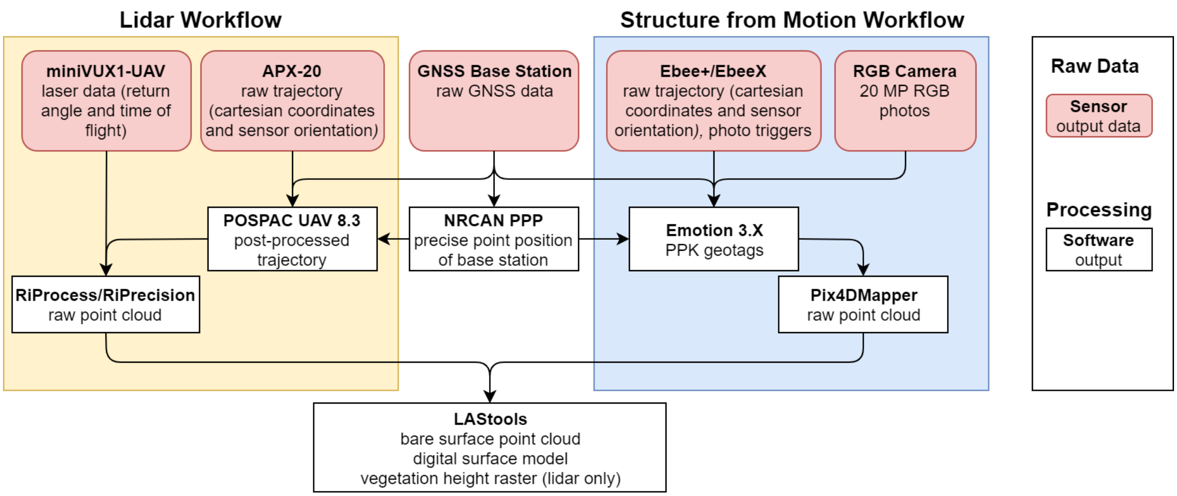
Table 1: Summary of data collection campaign, Sept 2018 to April 2019

Date (mm-dd)	Surface	Data Collected	Site	Number of Manual Observations
09-07	ground	lidar	Rosthern	0
09-19	ground	lidar	Fortress	0
10-10	ground	lidar	Clavet	0
12-13	snow	lidar	Clavet	0
01-31	snow	lidar,SfM	Clavet	51
02-13	snow	lidar,SfM	Fortress	81
03-11	snow	lidar	Clavet	30
03-13	snow	lidar,SfM	Rosthern	111
03-15	snow	lidar	Clavet	35
03-18	snow	lidar,SfM	Rosthern	81
03-20	snow	lidar,SfM	Clavet	69
03-22	snow	lidar,SfM	Rosthern	72
03-24	snow	SfM	Rosthern	0
03-26	snow	lidar,SfM	Rosthern	73
03-29	snow	lidar	Rosthern	77
04-03	snow	lidar	Clavet	0
04-04	snow	lidar	Rosthern	0

04-09	snow	lidar	Rosthern	0
04-25	snow	lidar	Fortress	39

2.3 Data Processing

Snow depth was quantified as the vertical difference between a bare ~~bare~~ ground DE~~S~~M and a bare ~~bare~~ snow surface DE~~S~~M. This approach was taken regardless of whether ~~point clouds or surface model~~DEMs come from lidar scanning or SfM processing. The workflows implemented to produce ~~point clouds and~~ DE~~S~~Ms vary between lidar and SfM approaches (Figure 3) and code is available at ~~.~~https://github.com/phillip-harder/UAV-snowdepth.



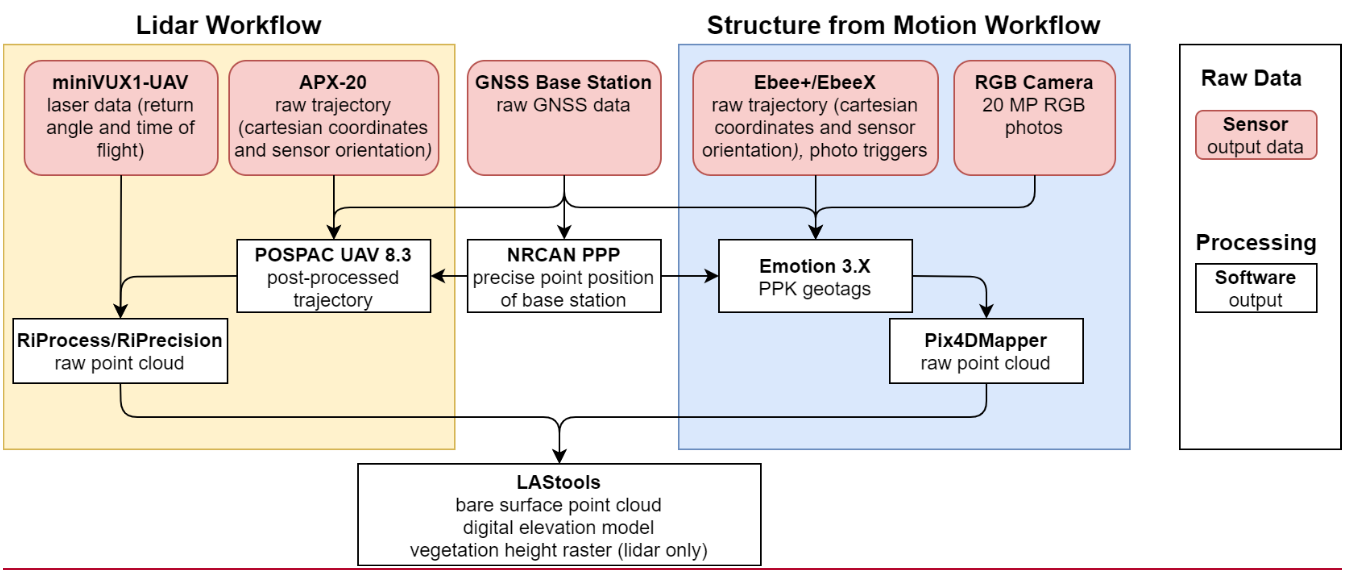


Figure 3: Data processing workflows for lidar and SfM point cloud generation.

2.3.1 Lidar processing workflow

To generate a georeferenced lidar point cloud several data streams need to be integrated in post processing. The raw high frequency trajectory (x, y, z, pitch, roll, and yaw) information from the APX-20 IMU was post processed with POSPAC UAV software, which includes a post processing kinematic (PPK) correction by integrating base GNSS data from a known point < 2 km from flight area, to provide an absolute sensor position uncertainty~~accuracy~~ of < 2.5 cm. The post-processed IMU data is merged with the scanner data within the proprietary RiProcess software package to translate the time of flight laser returns to an x, y, and z point. Finally, alignment of scan lines with overlapping scan data from adjacent flight lines is used to optimise the IMU trajectory with the RiPrecision tool~~, laser data accuracy is greater than the post processed IMU trajectory data, to align the scan lines and reduce the noise of the final point cloud within the RiPrecision tool. ~~. This final step in noise reduction improves the final product because the 1.5 cm laser data precision is greater than the post processed IMU trajectory accuracy.

2.3.2 SfM processing workflow

The UAV-SfM processing workflow begins with associating a high accuracy x, y, and z positon to the images taken. Within the Emotion 3.X software from SenseFly a PPK correction, with raw GNSS data collected at the known point base station, is applied to the photo locations to give geotag accuracies of < ±2.5 cm. The Pix4D Mapper (v 4.3.33) SfM software, with the "3D Maps" default options template, processed the collected imagery and post processed geotags to produce a densified point cloud. Within the study sites a minimum of 5 ground control points (GCP), blue 2 m x 2 m tarps with a white cross, were surveyed with the Leica GS16 rover and integrated into the Pix4D SfM workflow. For further details on how Pix4D implements SfM techniques and more generally the approach to use SfM to map snow depth refer to Harder et al. (2016) and Meyer and Skiles (2019).

2.3.3 Point Cloud Processing

The points representing the 'bare' surface, whether that is the snow or ground surface, are of interest for snow mapping. Lidar point clouds comprise of returns from vegetation *and* the snow/ground surface, while UAV-SfM point clouds comprise returns from vegetation *or* the snow/ground surface and exhibit substantial noise around snow patch edges (Harder et al., 2016). To remove noise and vegetation points a noise removal and bare surface point classification was applied to the point clouds with the LAStools software (Isenburg, 2019). The lidar workflow performed a noise removal followed by a bare surface point classification. For the bare-ground~~ surface~~ lidar scans, the height of vegetation (non-ground) points was also calculated. For the UAV-SfM point clouds, the noise removal and bare surface classification follows the workflow of Isenburg (2018).

2.3.4 Surface interpolation

A DE~~S~~M was generated in order to reduce the overall volume of data and to allow for simple surface differencing. The 'blast2dem' tool within the LAStools package generates a seamless triangulated irregular network (TIN) that conforms to the point cloud which is then resampled to a raster (Isenburg, 2019). A spatial resolution of 0.1 m was applied to all DE~~S~~Ms generated.

2.3.5 Error Assessment

To assess the accuracy of UAV-lidar and UAV-SfM with respect to observations, a ~~surface~~ DEM based comparison was undertaken. Snow and ground surface values were extracted from the DE~~S~~M raster cells for locations where a point was manually surveyed and snow depth measured. The snow depth was calculated from the vertical difference between the ~~DSM values for the~~ snow DEM and ground DE~~S~~M~~'s~~. The influence of vegetation height on snow depth errors was also considered by segmenting the error metrics with respect to vegetation height (open <0.5~~1~~ m, 0.5 m ≥ shrub ≤~~<0.5~~2 m,~~,~~ and trees >2~~0.5~~ m) derived from the snow-free ~~(ground)~~ UAV-lidar scan. The classified vegetation maps and location of all survey points are visualised in Figure 4. The error metrics employed to assess the differences between observations and estimates include~~d~~ the root mean square error (RMSE), and the mean bias (mb) (Harder et al., 2016).

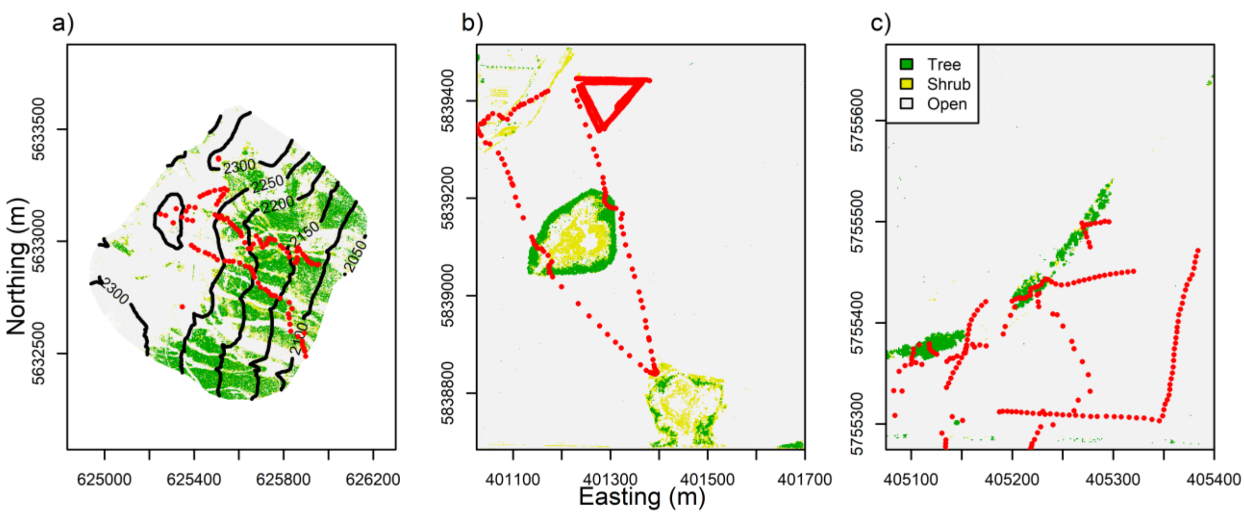


Figure 4: Fortress a), Rosthern b), and Clavet c) study sites classified by vegetation height derived from snow-free (ground) UAV-lidar into open (<0.5 m), shrub (>0.5 m and <2 m) and tree (>2 m) domains. Red points identify locations of manual snow depth survey observations sampled over the course of the data collection campaign. Black lines in Fortress map are 50 m elevation contours.

2.3.6 Point cloud c~~C~~overage

The continuity of bare surface point density between UAV-lidar and UAV-SfM methods was quantified in order to interpret how well the respective tools can sense sub-canopy surfaces. All surveys with coincident UAV-lidar and UAV-SfM flights were assessed with the LAStools (Isenburg, 2019) grid_metrics function to classify area with > 1 pt 0.25 m^{-2} and thereafter were summarised as percentage areas of each study site with >1 pt 0.25 m^{-2} with respect to technique.~~–~~ This is a rough metric of DE~~S~~M quality as it quantifies the relative amount of interpolation needed to translate a point cloud to a continuous surface.

3 Results

3.1 Accuracy of UAV-lidar versus UAV-SfM snow depth estimates

An accuracy assessment comparing the snow depth from UAV-lidar and UAV-SfM techniques to ~~that~~ the manually sampled through ~~the RTK~~ ground surveys is shown in Figure 5. UAV-lidar has consistently lower error than UAV-SfM in open environments and mountain vegetation. The exception is prairie shrub vegetation where the UAV-lidar RMSE is slightly larger than UAV-SfM RMSE. The significance of the different relative RMSE values for Prairie shrub vegetation is negligible relative to the much larger differences noted in the other domains. UAV-lidar bias is consistently negative (-0.03 m to -0.13 m), while the UAV-SfM bias is more variable and both positive and negative (0.08 m to -0.14 m).

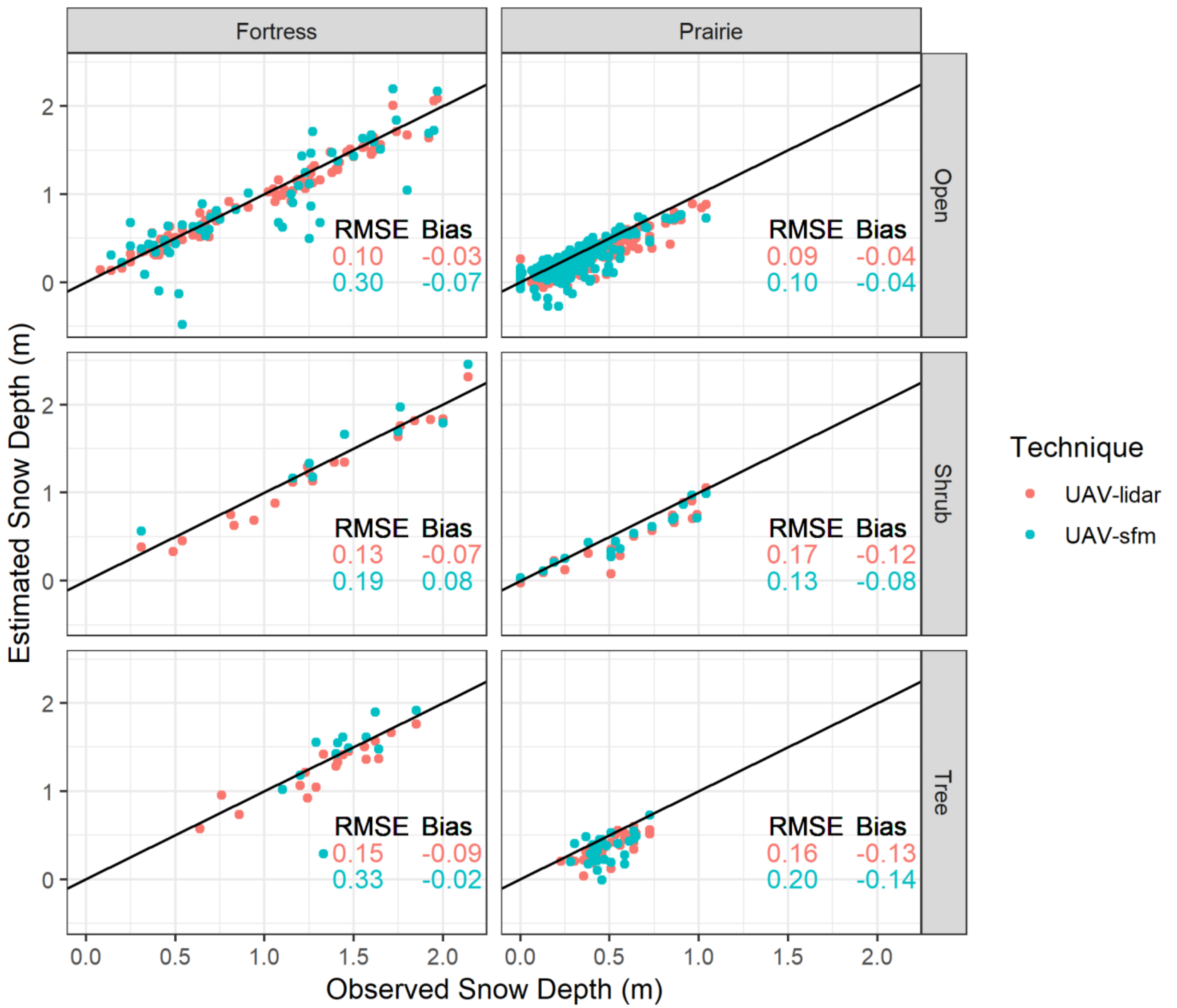
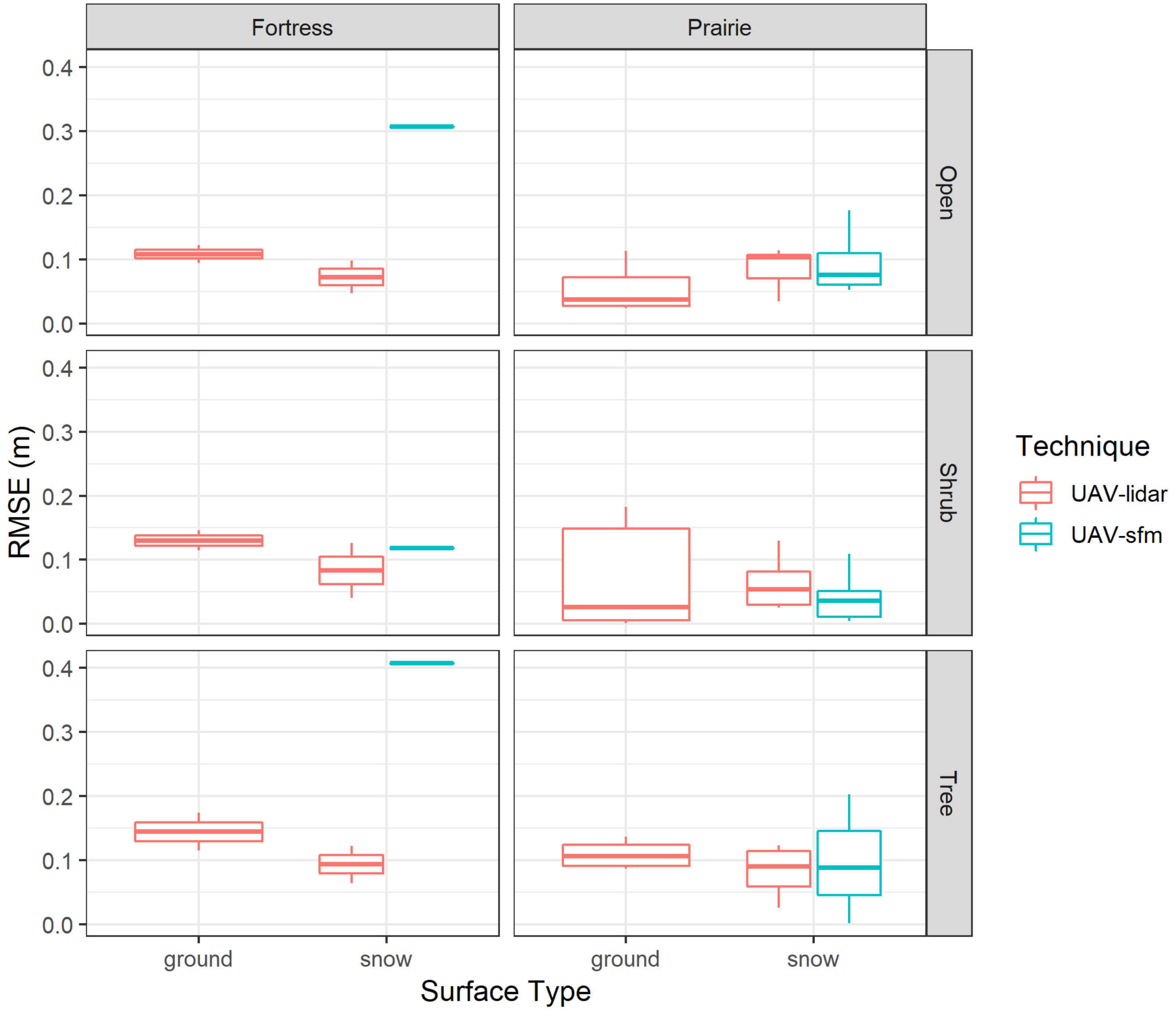


Figure 5: Comparison of snow depth observations from snow probes and ~~UAV-based~~ snow depth estimates from UAV techniques. Plots are segmented within each~~for~~ ~~points extracted from the point clouds or interpolated surfaces~~vegetation class (rows), sites (columns) and observation method (colours).

The influence of vegetation on estimating -snow depth~~-measurement~~ from UAV's can be~~-is~~ -directly assessed by considering the errors associated with different vegetation classes (Figure 5). When considering UAV-lidar, the errors are worse in the presence of vegetation. Open Prairie and open Fortress ~~samples~~ RMSE values are similar (0.09 m and 0.1 m RMSE respectively), whilst vegetated sites have larger error (0.13 m to 0.17 m RMSE) with no observed dependency upon vegetation class or type. The sample size of snow depth probe observations is smaller for vegetation sites than open sites has implications for error metrics –outliers will have greater weight. The UAV-lidar is equally successful at penetrating the open leaf-off deciduous tree canopy at the prairie sites as the closed needleleaf canopy at the Fortress site based on the similar RMSE values within each site's tree vegetation class. The UAV-lidar RMSE for Shrub and Tree vegetation classes at Fortress and Prairie sites are within 0.04 m. For UAV-SfM the errors differ widely for various vegetation covers. The Open vegetation has a large RMSE range between sites (0.1 m in Prairie and 0.3 m in Fortress respectively) while vegetation class RMSEs range from 0.13 m to 0.33 m. ~~While~~

The UAV-SfM reports slightly better metrics than UAV-lidar in the prairie Shrub case, the difference between these techniques is only 0.04 m which is within the ~~-it is within the~~± 0.025 m observational ~~error of RTK~~uncertainty of the GNSS survey equipment ~~and reasons will be examined in the discussion.~~used in this project. The influence of vegetation type is apparent in the UAV-SFM ~~T~~Tree class ~~errors~~ where the dense needleleaf forest at Fortress has a higher RMSE (0.33 m) than the leaf-off deciduous trees in the prairies (0.2 m). Overall UAV-lidar tends to consistently have lower RMSE's than UAV-SfM which provides confidence in this technique for mapping snow depth sub-canopy.

Snow depth is estimated from differencing the snow and ground ~~DSM~~DEMs. Therefore, the uncertainty of the snow depth is a propagation of the error of both the snow and ground ~~DSMs~~DEMs. To distinguish which ~~DSM~~ DEM may contribute more to the snow depth error, the remotely sensed surface elevations were compared to the surface elevations from ~~the RTK~~manual GNSS surveys using boxplots (Figure 6). The boxplots in Figure 6 illustrate that the UAV-SfM snow surface elevations have errors consistently greater than the corresponding UAV-lidar surfaces at Fortress. In the Prairie snow-surface case, the median RMSE is consistently lower for UAV-SfM than UAV-lidar, but the UAV-SfM does have more variability in its errors. The ground surface was only available from UAV-lidar for this study so no corresponding UAV-SfM ground surface analysis is available. The snow-free UAV-lidar survey has a consistently higher or more variable RMSE than the snow surfaces (with the exception of the Open Prairie and Open and Tree Fortress UAV-SfM).



Fortress
Prairie
Open
Shrub
Tree
RMSE (m)
0.4
0.3
0.2
0.1
0.0
ground
snow
Surface Type
Technique
UAV-lidar
UAV-sfm

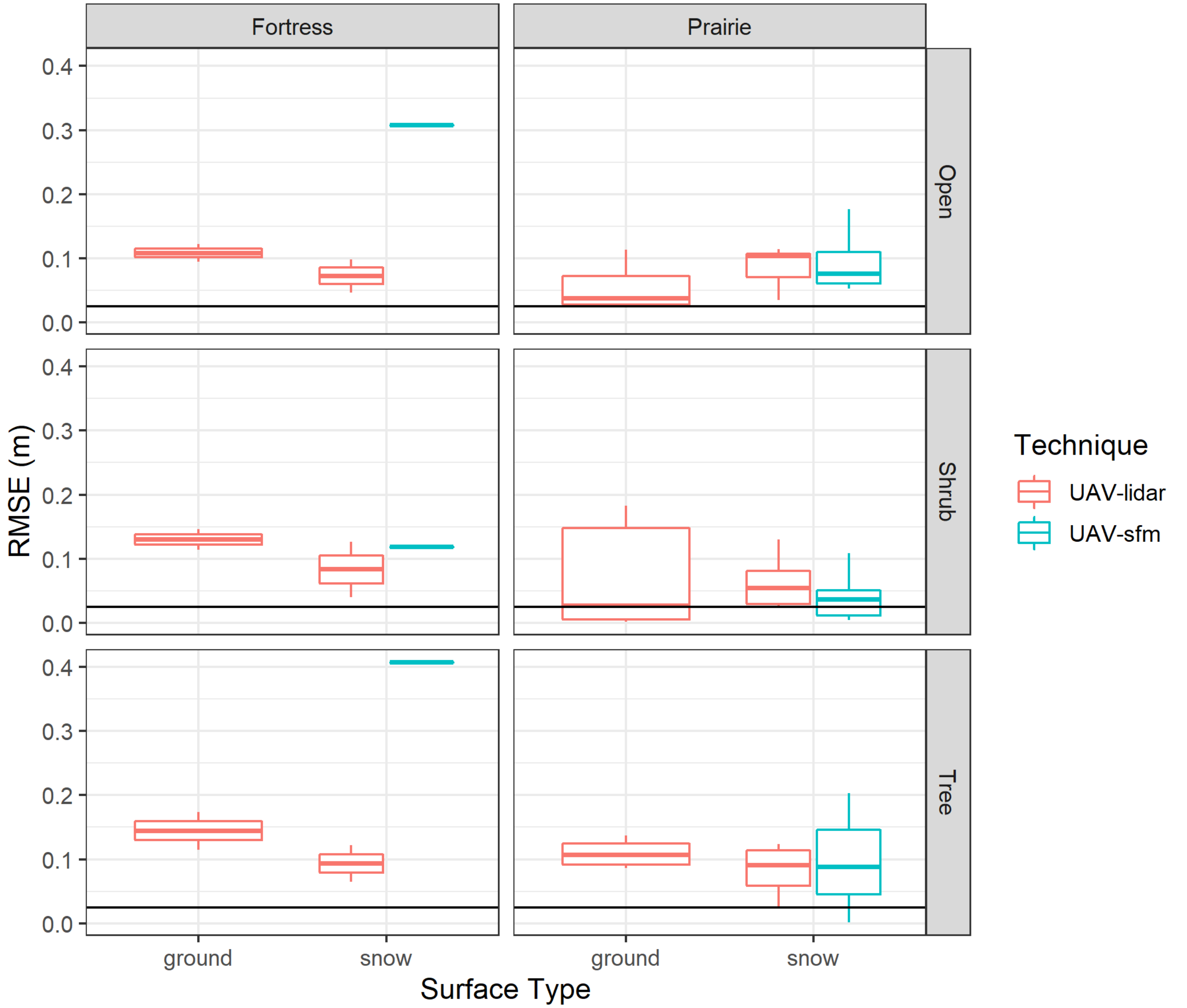
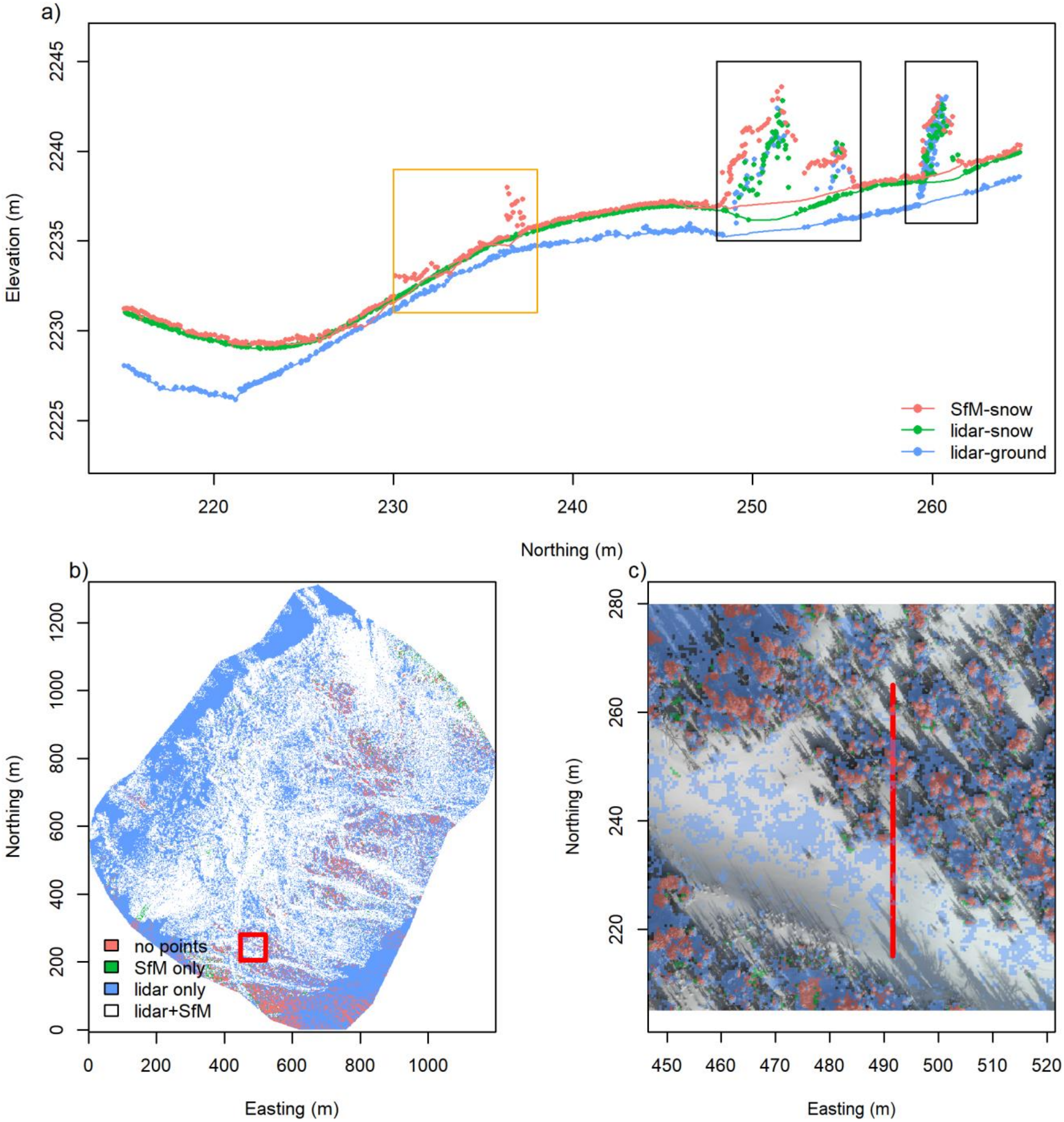


Figure 6: Boxplots of RMSE of UAV estimated and RTK survey surface elevations segmented by surface condition, technique, site, and vegetation classification. The error metrics approach the ± 2.5 cm uncertainty of the RTK survey data ~~+/- 2.5 cm data~~(black line). Median is indicated by the line within the box, the upper bound is the 75th percentile and the lower bound is the 25th percentile and whiskers represent the range of values beyond the box.

3.2 Point cloud coverage

The quality of a remotely sensed snow depth estimate is directly tied to how much interpolation is required to fill gaps in a point cloud. The point clouds were classified into areas where >1 pt 0.25 m^{-2} existed for each technique. Examples of this approach are visualized for the Fortress, Rosthern and Clavet sites on Feb 14, March 18 and March 20, 2019 survey dates in Figures 7-9 respectively. At the Fortress site (Figure 7b) the large areas of lidar only points (~~orange~~blue) correspond to areas of forest cover as the UAV-SfM technique could not reliably return surface points with a density > 1 pt 0.25 m^{-2} ~~-~~whilst the UAV-lidar could. At Fortress, UAV-lidar had > 1 pt 0.25 m^{-2} for 93% of the area of interest versus 54% for UAV-SfM. Considering the black polygons in the Figure 7a transect, the lack of sub-canopy points identified within the Tree vegetation class results in an interpolated snow surface that is erroneously deep under trees, completely missing the detection of the reduced snow depths which are clearly detected (green line) around the base of the trees by the UAV-lidar.~~lack of UAV-SfM points near trees means that the interpolated snow surface does not capture the tree wells, which are sharp decreases in snow depth around the base of trees, and evident from the UAV-lidar data.~~ The noisy UAV-SFM points in the middle of the slope, orange polygon, come from vegetation adjacent to the transect. These vegetation points occupied a larger space than the UAV-lidar and intruded on the transect line. Therefore when vegetation removal from this point in the transect led to a gap in the UAV-SfM point cloud, but not the UAV lidar point cloud. Interpolating through the gap in the UAV-SfM point cloud at this point led to an underestimation of the snow surface. ~~challenge the snow surface extraction even without the presence of vegetation leading to an underestimation of the snow surface.~~ An additional challenge for UAV-SfM is open areas with low surface contrast and surface homogeneity which resulted in ~~L~~large areas without ~~UAV-SfM point~~point coverage ~~occurred northwest~~on the northwest portion of the Fortress ~~of the ridge in open areas due to low surface contrast and surface homogeneity.~~study area.


a)
Elevation (m)
2225
2230
2235
2240
2245
Northing (m)
220
230
240
250
260
SfM-snow
lidar-snow
lidar-ground
b)
Northing (m)
0
200
400
600
800
1000
1200
Easting (m)
0
200
400
600
800
1000
no points
SfM only
lidar only
lidar+SfM
c)
Northing (m)
220
240
260
280
Easting (m)
450
460
470
480
490
500
510
520

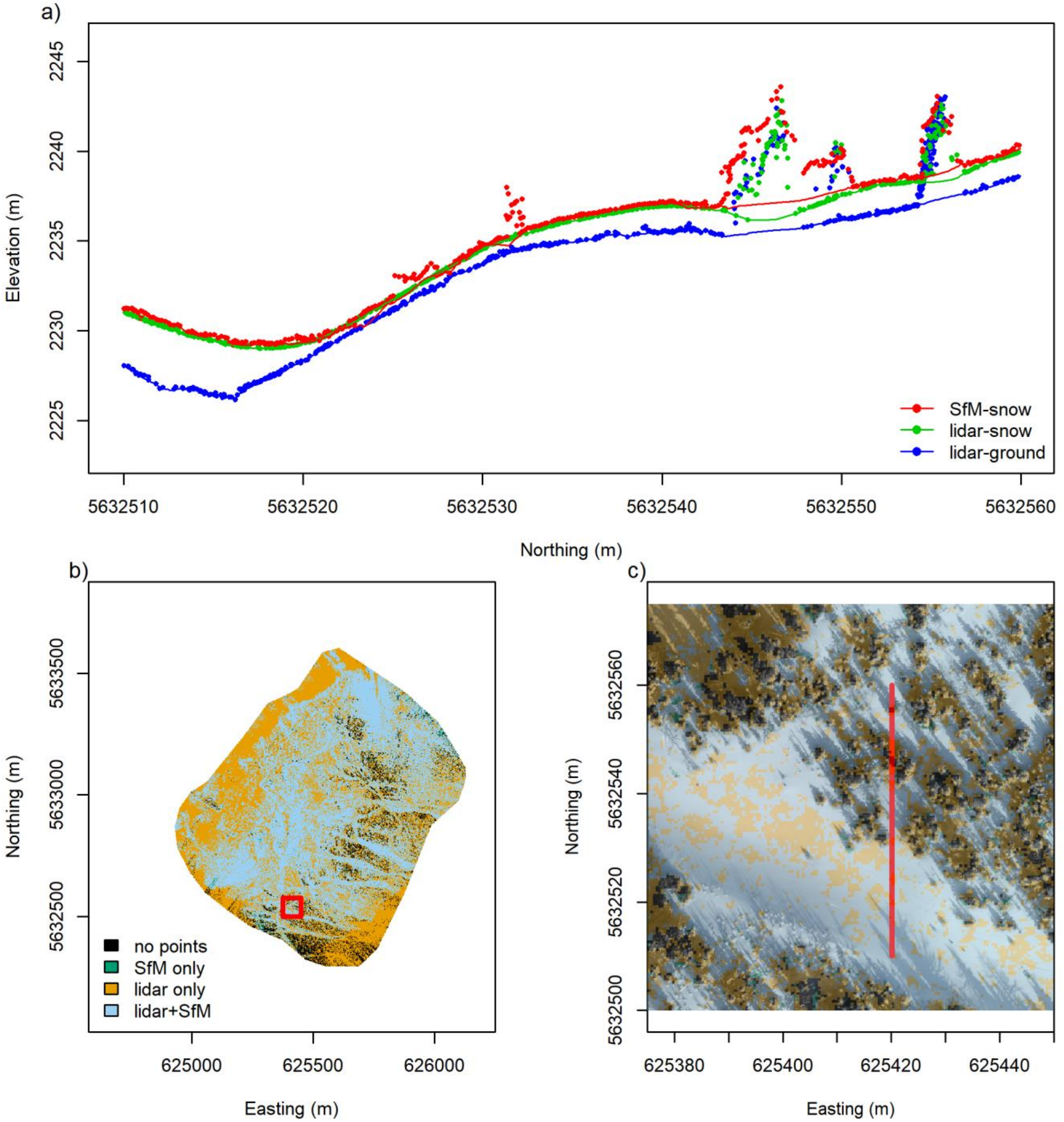
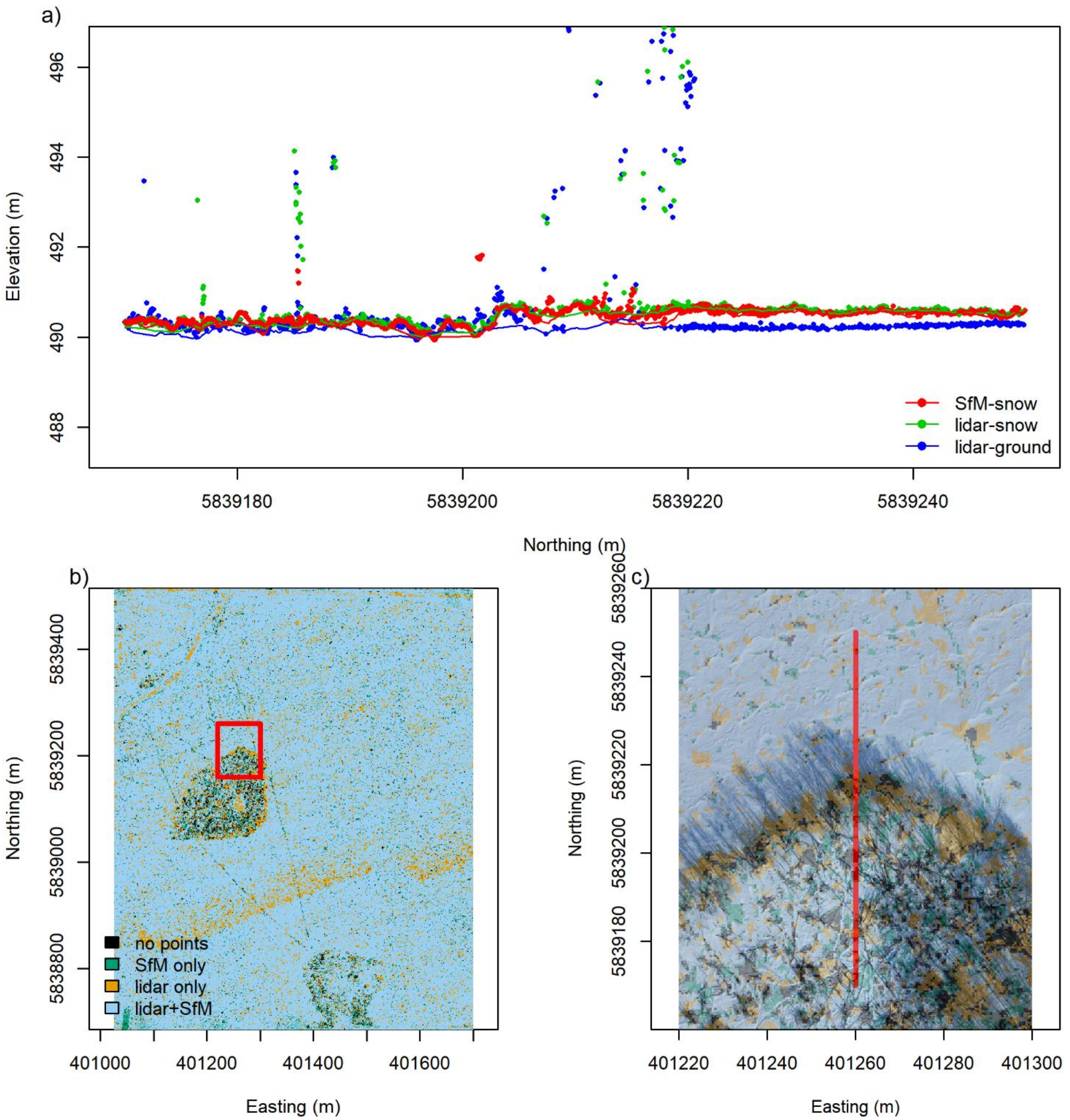


Figure 7: Fortress Ridge (February 14, 2019) study site with an example a) cross section with all points and interpolated vegetation-free surface (lines) for SfM-snow (red), lidar-snow (green) and lidar-ground (blue) surveys. The study area is classified by areas with greater than 1 pt per 0.25 m^{-2} in b) with respect to point clouds obtained from UAV-lidar and UAV-SfM techniques. In a) black polygons highlight areas of tree wells while the orange polygon highlights an area of UAV-SfM noise on a slope. The red inset polygon in b) identifies the area of the orthomosaics displayed in c) with ~~an~~ the same overlain transparent point type classification colour scheme as shown in b).~~.~~ Red line in c) corresponds to the cross section plotted in a).

The predominantly open nature of the Prairie sites demonstrates a minimal difference in point coverage between ~~techniques~~the UAV-lidar and UAV-SfM techniques~~.~~. The average extent of the study domain covered with a point density of > 1 pt 0.25 m^{-2} for 5 ~~of 5~~ coincident flights at Prairie sites was computed, resulting in the ~~gave UAV-lidar a~~ mean coverage of 92% versus 83% of the study area for the UAV-lidar and UAV-SfM respectively. As seen in Figure 8 at the Rosthern site, the areas without UAV-lidar points include some wetland shrubs (green areas in Figure 8 b and c), but predominantly are randomly distributed points. In contrast, UAV-SfM is missing points from areas where the snow surface is very uniform, in vegetated rings around wetlands, and in areas of dense vegetation (~~orange~~ blue areas in Figure 8 b and c). These gaps in the UAV-SfM point clouds are interpolated ~~during DSM interpolation~~ and therefore will represent areas of greater uncertainty. ~~—~~ There was ponded meltwater on the surface of the frozen ground and frozen wetland water surface at the Clavet Site on March 20, 2019, which is responsible for the many areas missing lidar points (green areas) in Figure 9b. ~~–~~ Water is a specular reflector therefore unless the lidar has a nadir perspective water areas will appear as a gap in the point cloud. Fortunately, since water surfaces are flat, minimal interpolation artefacts remain when generating DE~~S~~Ms from the point clouds if the pond edges are sufficiently captured. ~~–~~ The challenge in the prairies, as seen in black polygons in Figure 8a and 9a, is in areas of thick but short vegetation (S~~s~~hrub class) where both lidar pulses and SfM solutions interpret the vegetation surface as the ~~ground~~ top of the bare-ground or snow surface and therefore little difference exists between DEMs during all measurement periods. ~~the remotely sensed ground surface, and UAV-SfM and UAV-lidar snow surface are very similar.~~ An additional challenge of using the UAV-SfM technique ~~due~~ is that ~~to challenges in vegetation removal in bare surface generation is that~~ large gaps in points appear beneath the tall wetland edge vegetation leading to points, as visualised in ~~visualized by transects in~~orange polygons in Figure 8a and 9a cross-sections, where the estimated UAV-SfM snow surface is below the UAV-lidar ground surface.


a)
Elevation (m)
496
494
492
490
488
5839180
5839200
5839220
5839240
Northing (m)
SfM-snow
lidar-snow
lidar-ground
b)
Northing (m)
5839400
5839200
5839000
5838800
401000
401200
401400
401600
Easting (m)
no points
SfM only
lidar only
lidar+SfM
c)
Northing (m)
5839260
5839240
5839220
5839200
5839180
401220
401240
401260
401280
401300
Easting (m)

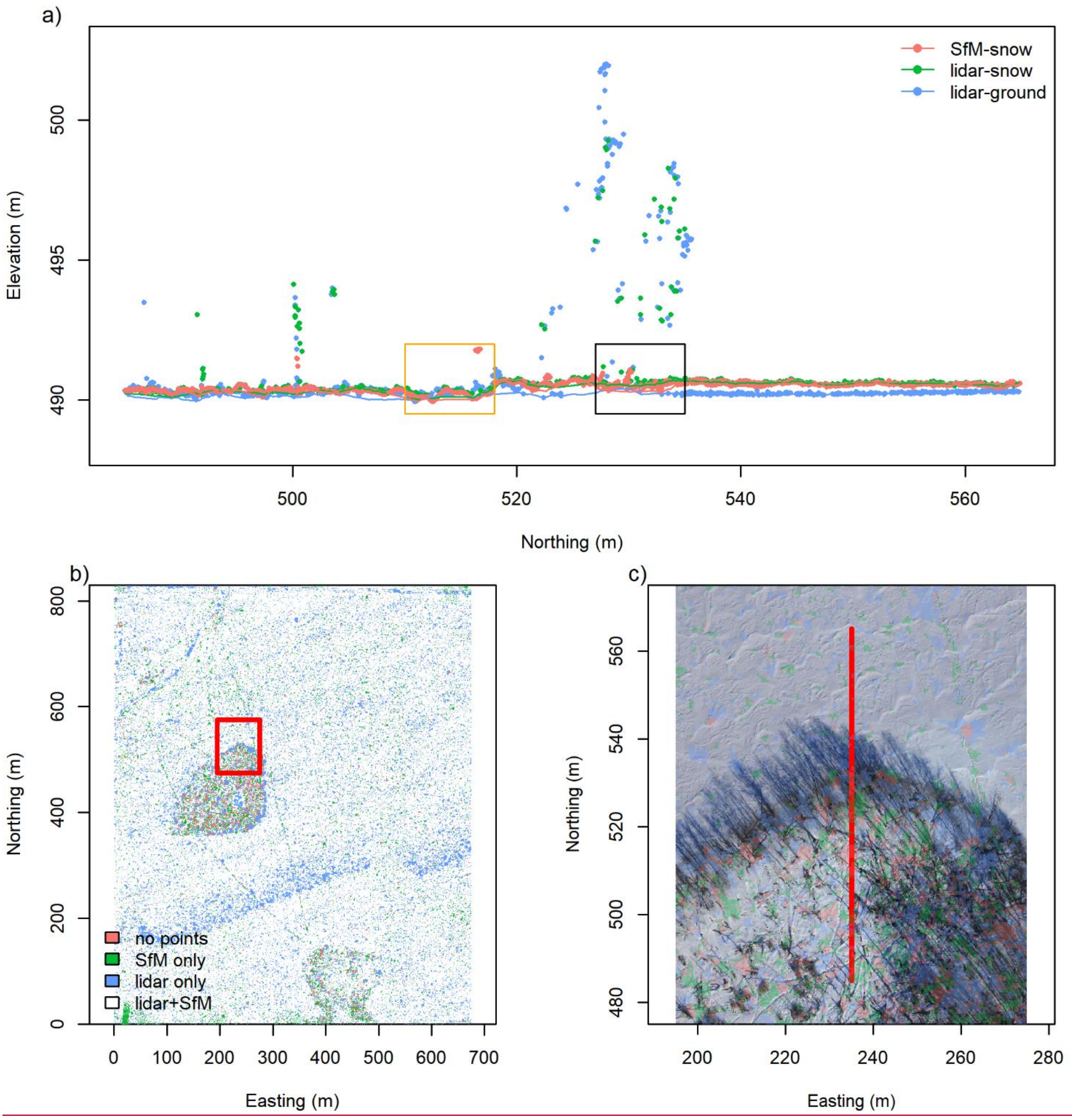
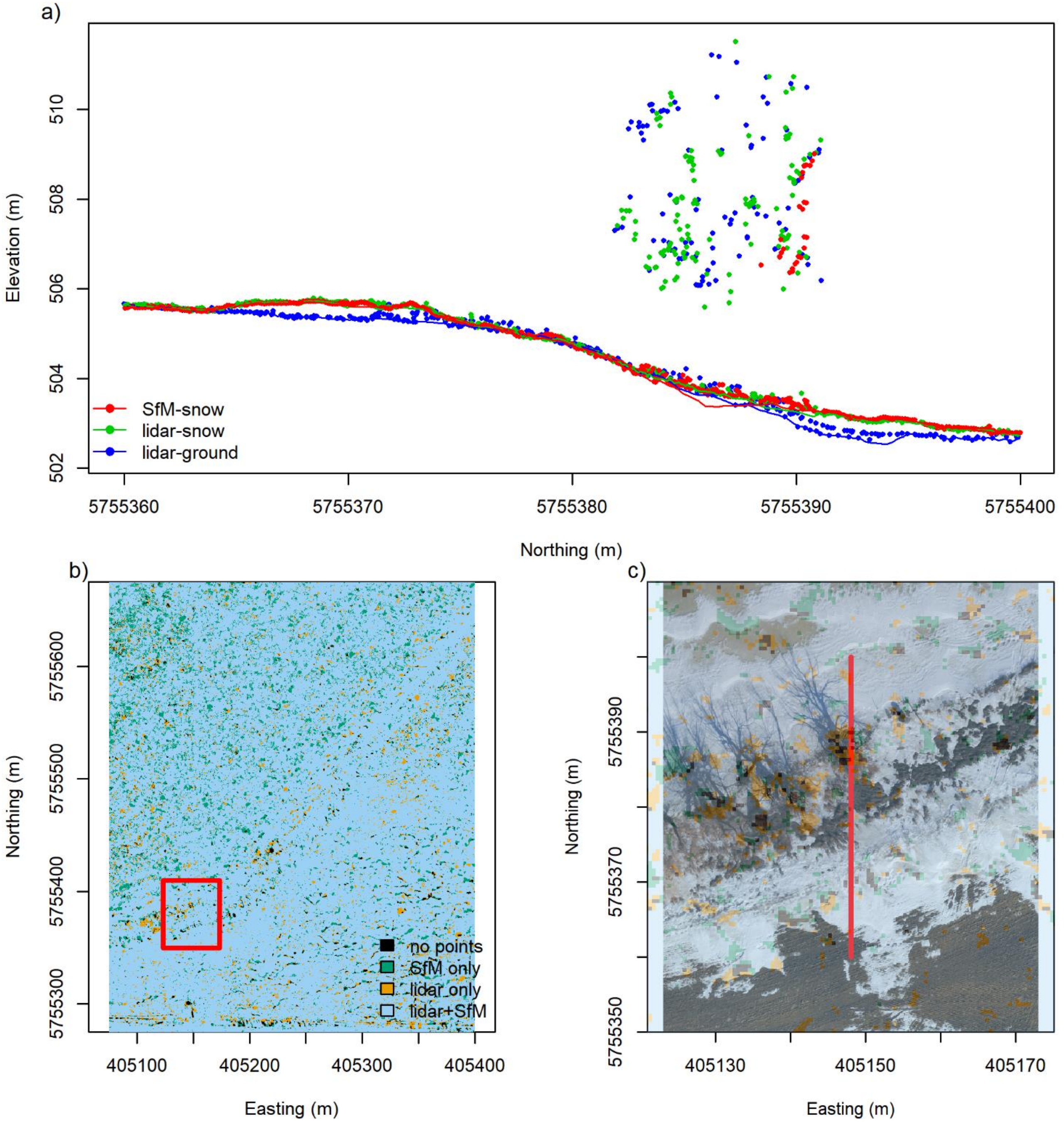


Figure 8: Rosthern (March 18, 2019) study site with an example a) cross section with all points and interpolated vegetation-free surface (lines) for SfM-snow (red), lidar-snow (green) and lidar-ground (blue) surveys. The study area is classified by areas with greater than 1 pt per 0.25 m^{-2} in b) with respect to point clouds obtained from UAV-lidar and UAV-SfM techniques. In a) the black polygon highlights areas of dense shrubs while the orange polygon highlights interpolation artefacts of the UAV-SfM. The red inset polygon in b) identifies the area of the orthomosaics displayed in c) the same overlain transparent point type classification colour scheme as shown in b)~~with an overlain transparent point type classification~~. Red line in c) corresponds to the cross section plotted in a).


a)
Elevation (m)
510
508
506
504
502
SfM-snow
lidar-snow
lidar-ground
5755360
5755370
5755380
5755390
5755400
Northing (m)
b)
Northing (m)
5755600
5755500
5755400
5755300
no points
SfM only
lidar only
lidar+SfM
405100
405200
405300
405400
Easting (m)
c)
Northing (m)
5755390
5755370
5755350
405130
405150
405170
Easting (m)

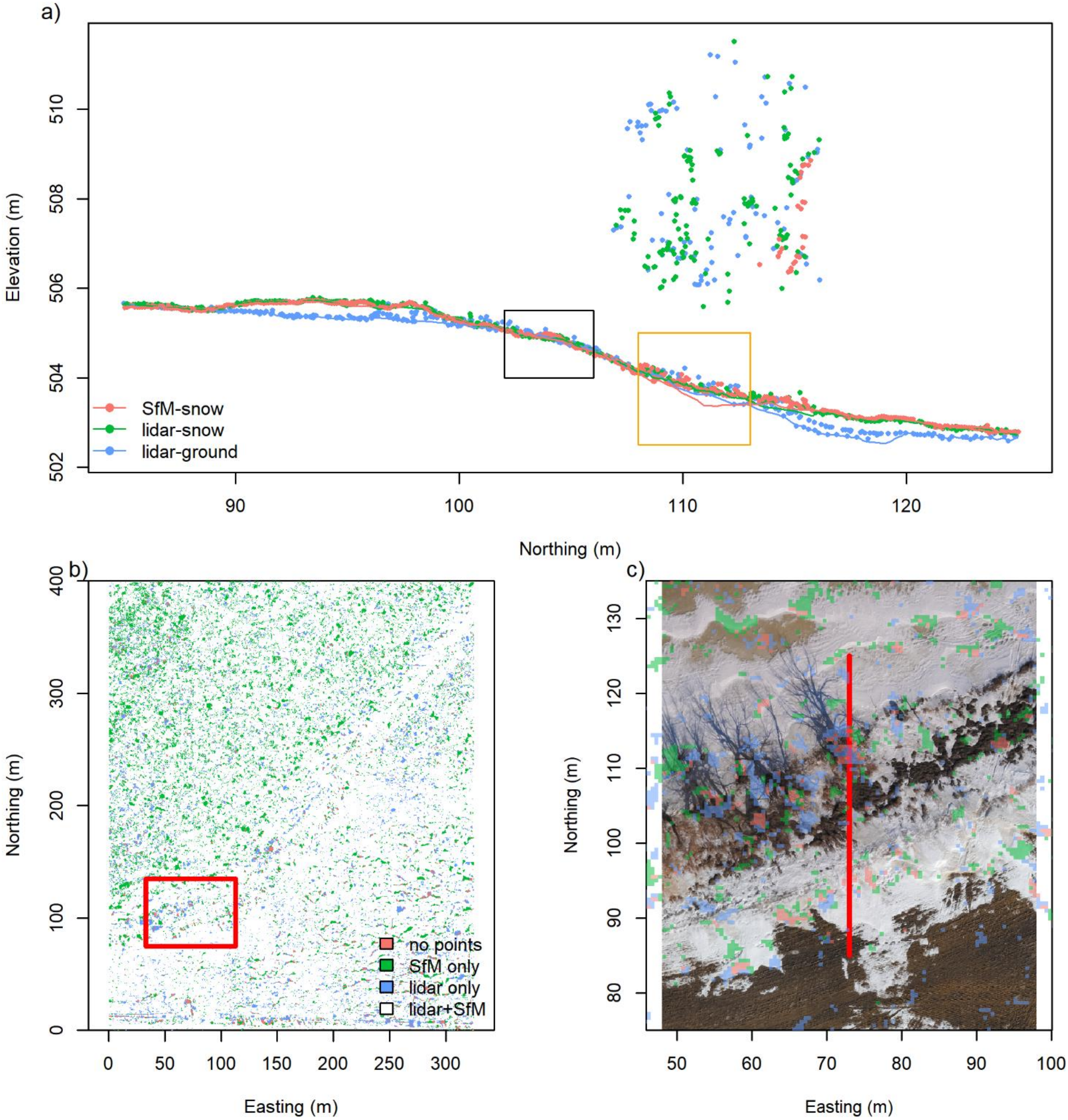


Figure 9: Clavet (March 20, 2019) study site with an example a) cross section with all points and interpolated vegetation-free surface (lines) for SfM-snow (red), lidar-snow (green) and lidar-ground (blue) surveys. The study area is classified by areas with greater than 1 pt per 0.25 m^{-2} in b) with respect to point clouds obtained from UAV-lidar and UAV-SfM techniques. In a) the black polygon highlights areas of dense shrubs while the orange polygon highlights interpolation artefacts of the UAV-SfM. The red inset polygon in b) identifies the area of the orthomosaics displayed in c) with the same overlain transparent point type classification colour scheme as shown in b)~~an overlain transparent point type classification~~. Red line in c) corresponds to the cross section plotted in a).

4 Discussion

4.1 UAV-lidar is more accurate and consistent than UAV-SfM

Snow depth mapping with UAVs has had widespread application in recent years (Bühler et al., 2016; Harder et al., 2016; Vander Jagt et al., 2015; De Michele et al., 2016). The emphasis has been on using SfM techniques to difference DE~~S~~Ms. One of the objectives of this work was to consider the snow depth accuracies possible with the current state of the art of UAV-SfM versus UAV-lidar platforms. What has been demonstrated here is that while there are still errors in UAV-lidar (as with any measurement), they are smaller and more consistent relative to UAV-SfM. An unavoidable problem for all SfM implementations, which is reflected in this work, is that SfM can only sense the surface -- whether that it is the ground/snow surface or the top of a vegetation canopy (Westoby et al., 2012). This makes it fundamentally inappropriate for sub-canopy mapping of snow. Sub-canopy snow depth mapping with UAV-SfM therefore becomes an exercise in interpolating snow depth values observed in open areas without vegetation to areas with dense vegetation, rather than sensing the actual snow depth under the canopy. Open areas will have greater snow depths than forest areas (Troendle 1983; Swanson et al., 1986; Pomeroy et al., 2001; Mazzotti et al., 2019;) meaning UAV-SfM solutions, or any approach which requires interpolation of point cloud gaps beneath trees, will overestimate snow (Zheng et al., 2016). ~~. Sub-canopy snow depth mapping with UAV-SfM therefore becomes an exercise in interpolation between areas of open vegetation rather than sensing the actual snow depth under the canopy.~~ The ability of UAV-lidar to map snow-depths, with and without canopy cover, and capture tree wells with RMSE's ≤~~<~~0.17~~7~~ m is an ~~major~~ improvement on previous attempts. ~~–~~ This RMSE is comparable to previous efforts with UAV-SfM (Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016), ~~or~~ airborne-SfM (Bühler et al., 2015; Nolan et al., 2015, Meyer and Skiles 2019) and airborne-lidar (Deems et al., 2013; Painter et al., 2016) that have been primarily focussed on mapping the snow depth of open snow surfaces~~by masking out forested domains~~. ~~In a~~Applications of airborne-lidar to forested areas ~~much larger errors have been reported than 0.14 m RMSE (Deems et al., 2013).~~ report similar errors (Zheng et al., 2016; Currier et al., 2019; Mazzotti et al., 2019) but the higher flight altitude of airborne platforms and their near nadir perspective limit point densities near tree centres that are necessary to capture tree wells.

4.2 Bare surface point cloud coverage is critical

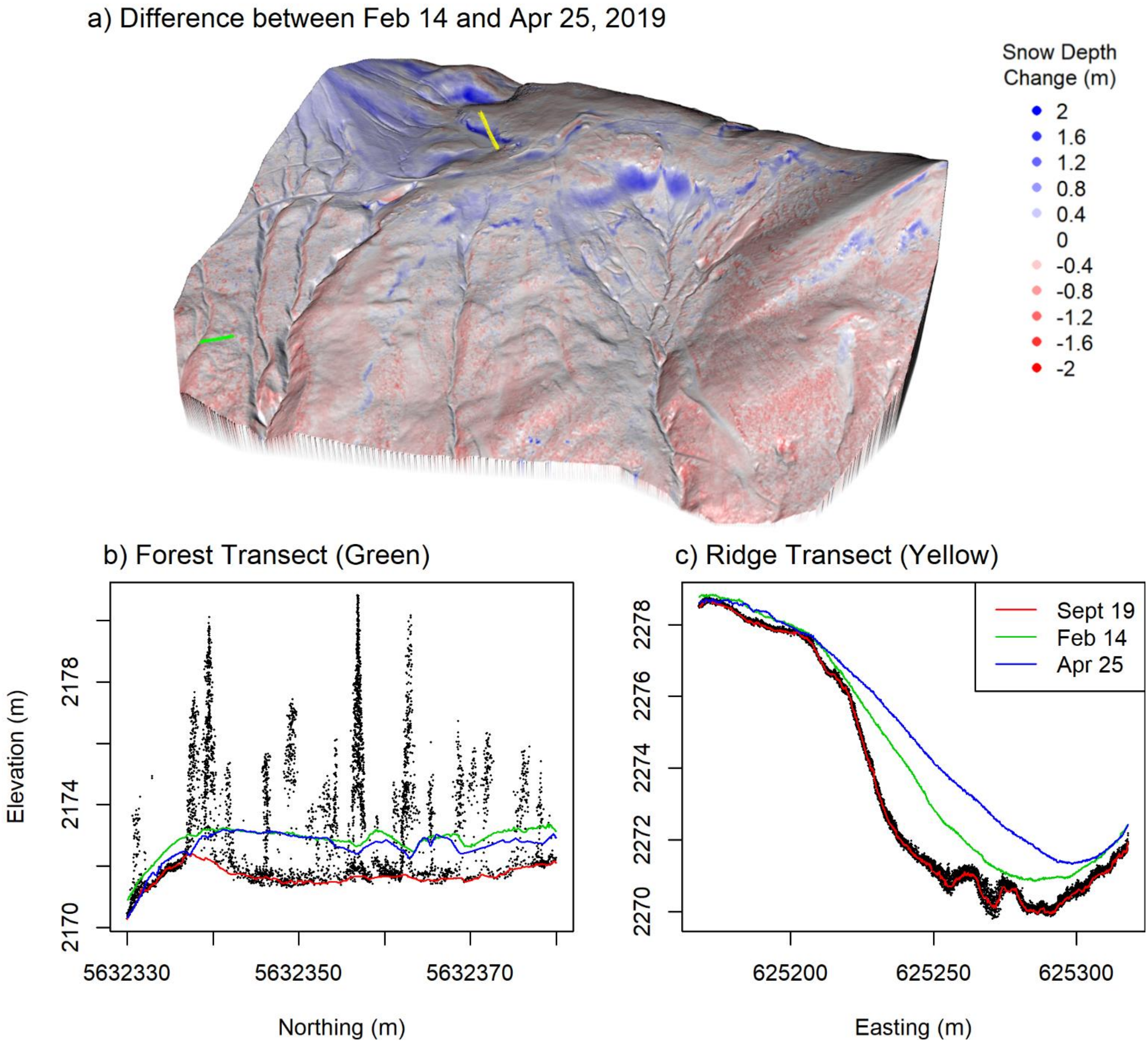
The increased continuous point coverage of UAV-lidar is the main advantage over UAV-SfM when trying to map sub-canopy snow depth. While snow depth accuracy at times can be similar between techniques, the ability of UAV-lidar to sense a surface below vegetation is critical to develop a coherent snow surface DE~~S~~M. ~~An example of a~~The point cloud cross-section ~~of~~ illustrated~~a~~ ~~UAV-SfM and UAV-lidar~~ in Figure 7 emphasizes ~~this point~~these findings, highlighting ~~. T~~the wider gaps in the UAV-SfM point cloud~~data will have wider gaps in the point cloud~~ beneath individual trees that require interpolation over longer distances resulting in greater potential for error.~~.~~ Features such as tree wells, where the snow depth decreases with proximity to a tree due to interception/sublimation losses and radiative melting (Pomeroy and Gray, 1995; Musselman and Pomeroy, 2017), will be missed. An interesting dynamic of the RMSE errors is that while lidar is comparable across all the sites and vegetation categories, the UAV-SfM RMSE values are much greater in the mountain domain. This is attributed to interpolation artifacts. In the Prairies where topography is fairly flat, interpolation of the few gaps can give a reasonable approximation of the actual surfaces. In contrast, mountainous regions~~s~~ have much more complex topography and the interpolation of large gaps misses much of the small scale topography and snow-vegetation interaction features. Interpolation works better between two points that are on the same plane (prairies) rather than on a complex non-linear slope (mountains) and where gaps in the point cloud are smaller.

4.3 Lidar snow depth maps and quantifying snow-vegetation interactions

The ability of UAV-lidar to map sub-canopy snow depth is established by the consistent error metrics reported as well as the continuous bare surface point cloud coverage. The dynamics of snow depth at snow-vegetation process-resolving scales can therefore be examined. Two examples are presented here to exemplify~~foreshadow some of the~~ analyses~~ available~~ the possible with UAV-lidar.

4.3.1 Fortress ~~S~~snow d~~D~~epth c~~C~~hange~~.~~

The differences between open and forest snow cover processes can be ~~resolved~~ explored by examining~~considering~~ the difference in snow depth between UAV-lidar scans that took place February 13 and April 25, 2019 at Fortress. Over this interval there was intermittent precipitation totaling approximately 100 mm measured at storage gauges within the study area. UAV-lidar ~~M~~measured change in snow depth visualizes how snow-vegetation interactions translated this snowfall into a snow depth distribution change over a two month interval (Figure 10). ~~The upper, open terrain clearly demonstrates the influence of blowing snow redistribution.~~ In the Figure 10c cross-section~~transect~~ there was accumulation of up to 2 m over the September-April time period on lee slopes, whilst the upper windswept portions of the ridge demonstrate snow erosion between February and-April. The dynamics and extents of blowing snow sources (grey/red) and sinks (blue) are clearly visualized in Figure 10a, which closely match the findings ~~as similarly noted by~~of Schirmer and Pomeroy (2019) using SfM for the same study region. ~~Considering~~ In the forest ~~slopes brings out features that UAV-SfM cannot observe. T~~the UAV-lidar ~~can o~~observes the increasing snow drifts in the tree line (in the krummholz and tree islands – blue areas on top of facing slope in Figure 10a). Within the forested (Figure 10b) transect, there is a general decline in snow depth from February to April ~~with variability~~ due to melt on a south facing slope (on left of figure), and development of a tree wells in the middle of the transect (orange polygons). The Figure 10b transect demonstrates the lack of wind redistribution in the forest; snow accumulation was consistently observed to be ≤ precipitation over the transect, ~~in the canopies relative to~~versus the Figure 10c transect on the ridgeline which demonstrates significant wind redistribution, snow accumulation on the lee slope greatly exceeded the observed precipitation.~~.~~


a) Difference between Feb 14 and Apr 25, 2019
Snow Depth Change (m)
2
1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
-1.6
-2
b) Forest Transect (Green)
Elevation (m)
2170
2174
2178
5632330
5632350
5632370
Northing (m)
c) Ridge Transect (Yellow)
2270
2272
2274
2276
2278
625200
625250
625300
Easting (m)
Sept 19
Feb 14
Apr 25

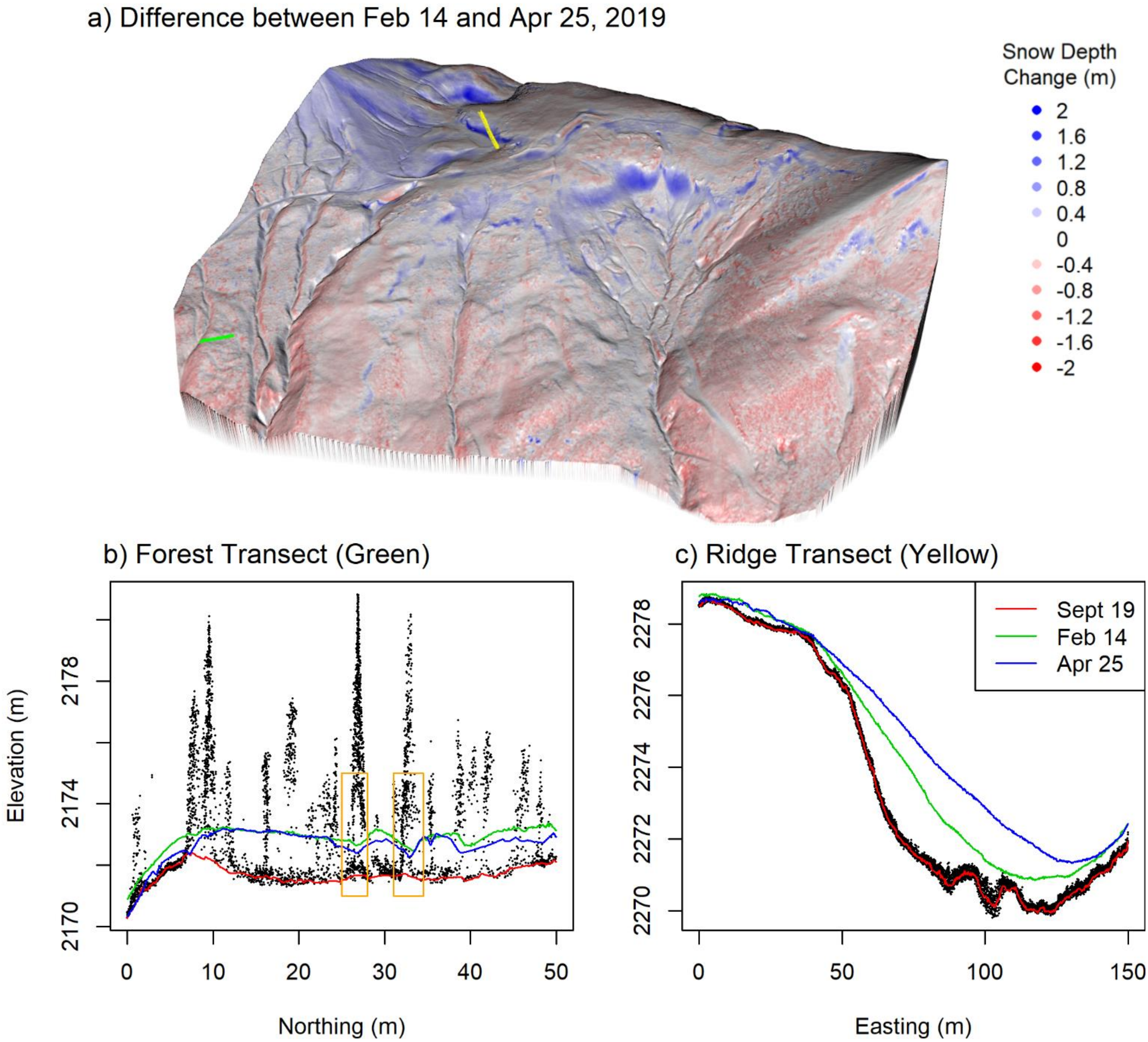
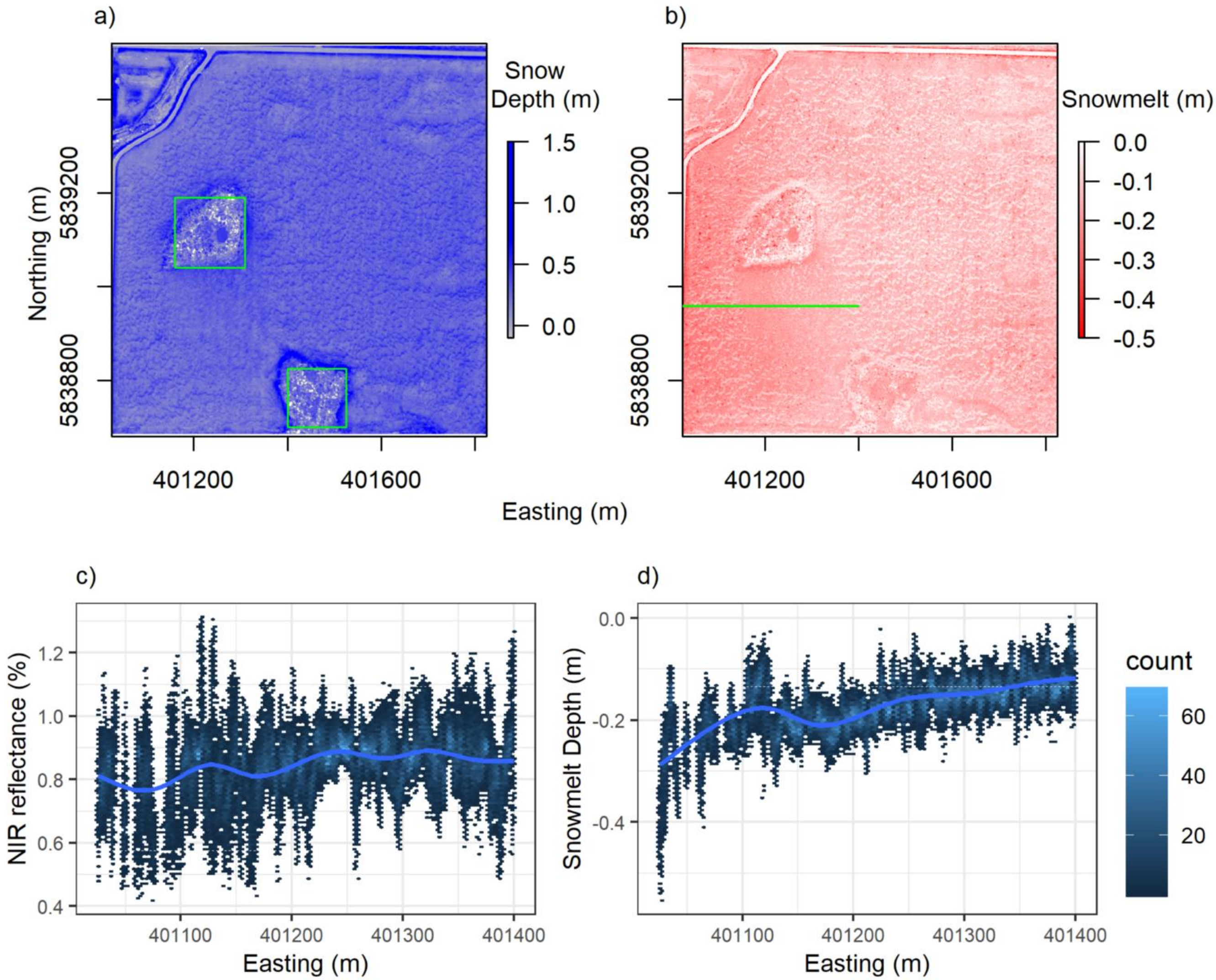


Figure 10: a) UAV-lidar derived snow depth difference between Feb 13 and Apr 25, 2019. Green and yellow lines in a) correspond to the forest and ridge line transect locations for cross-sections in b) and c) respectively.~~–~~ Cross-section figures plot the 0.5m wide point cloud cross section from the September 19, 2018 snow-free scan (black points) to show the point cloud and the processed surfaces of the bare ground from September 19, 2018 (red), and snow surface from February 14, 2019 (green) and April 25, 2019 (blue) UAV-lidar scans. Orange polygons in b) highlight locations of tree wells.

4.3.2 Prairie peak snow peak depth and ablation patterns

In the prairies, wind redistribution is the main driver of snow depth spatial variability. Areas of tall vegetation accumulate wind-blown snow from ~~large~~ open upwind sources ~~areas~~ and ~~so~~ are typically associated with the deepest snowpacks. In the winter of 2019, the chronology of snow, temperature, and wind events defined the final snow depth distribution (Figure 11a). The UAV-lidar flown on March 13 captures all of these interactions. Deep snow drifts are found in the roadside ditches (linear features of 1.5m snow depth on the north and north west corners Figure 11a), in the edges of wetland vegetation (>1m snow depths on edges of wetlands identified by ~~green~~red polygons in Figure 11a), and the development of a sastrugi dune complex in open areas (parabolic dune shapes and small scale snow depth variability in middle of Figure 11a). Areas that the UAV-lidar was able to measure correspond to areas where snow depth are the deepest and have important snow-vegetation interactions. ~~-~~ In contrast UAV-SfM struggles with sensing snow depth ~~in the short shrubs~~ on the edges of wetlands as seen by the concentration of lidar only (blue) areas on the wetland edge in the Rosthern study area (wetland area highlighted by red polygon in Figure 8b). In the prairies, mapping of the areas with deep snow is critical as the deepest snow areas are the ones that dominate runoff generation and runoff contributing area, are critical for ephemeral wetland ecology, and have the longest snowcover duration with the related runoff timing implications (Fang and Pomeroy, 2009; Pomeroy et al., 2014).



a)
Snow
Depth (m)
1.5
1.0
0.5
0.0
Northing (m)
5839200
5838800
401200
401600
b)
Snowmelt (m)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
5839200
5838800
401200
401600
Easting (m)
c)
NIR reflectance (%)
1.2
1.0
0.8
0.6
0.4
401100
401200
401300
401400
Easting (m)
d)
Snowmelt Depth (m)
0.0
-0.2
-0.4
401100
401200
401300
401400
Easting (m)
count
60
40
20

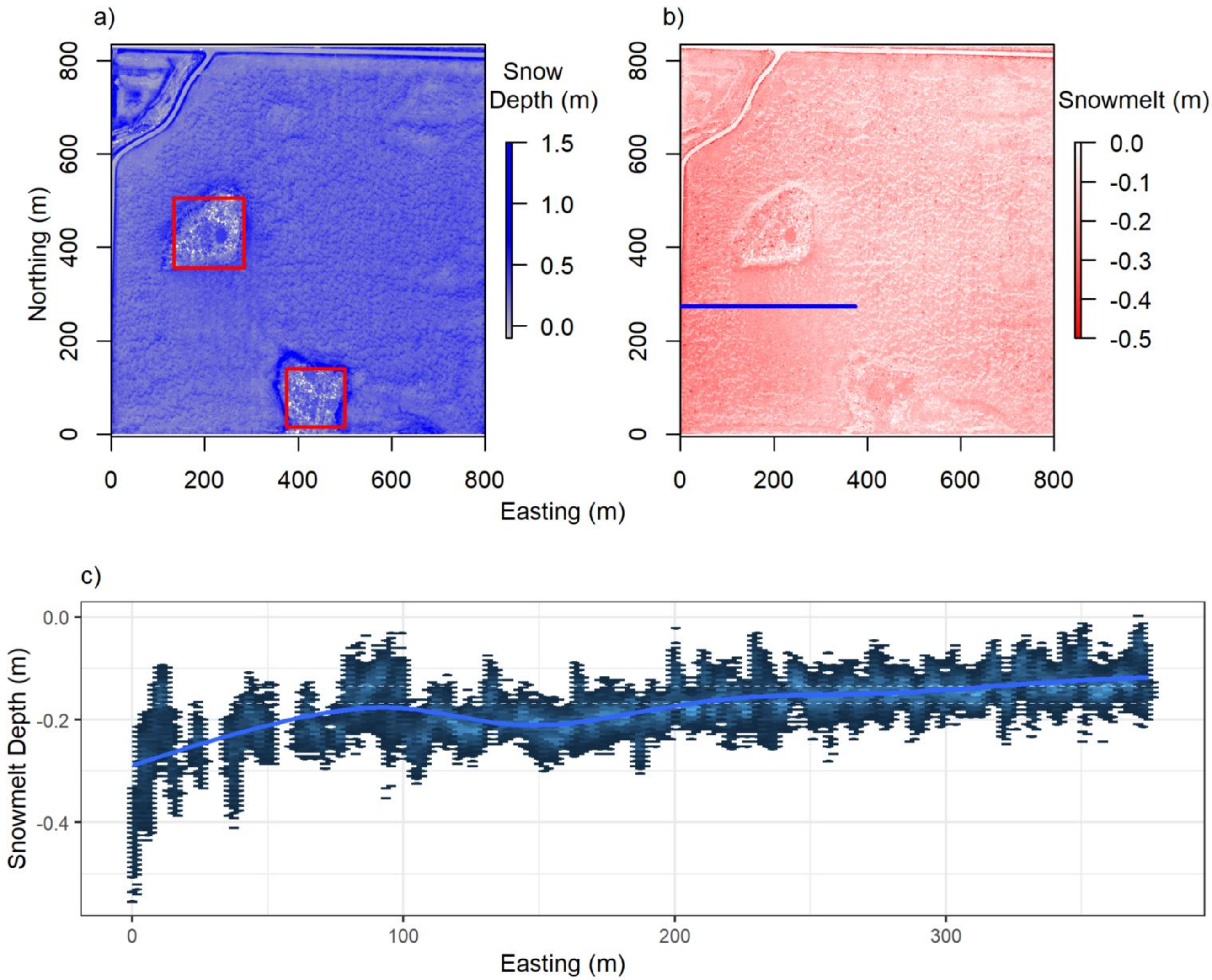


Figure 11: Peak snow depth at the Rosthern site from UAV-lidar scan on March 13, 2019 a) and snow melt depth difference from UAV-lidar scans on March 18 and March 22, 2019 b). ~~Snow surface near infrared (NIR) reflectance c) and s~~Snow depth change c~~d~~) over a transect (~~green~~blue line in b) are plotted with a hex plot (to show variability) and smoothed line (to show mean change). ~~Green~~Red polygons in a) highlight wetland areas.

Prairie snowpacks are shallow, leading Harder et al. (2016) to conclude that UAV-SfM was unable to capture snow ablation patterns as the signal to noise ratio in the open domain was too large and vegetated area errors were not considered. With the demonstrated ability of UAV-lidar to consistently map shallow snow in open areas and deep snows in the vegetated areas this can be reattempted. Consider the difference in snow depth between March 18 and 23 (Figure 11b) which represents the earliest part of the active melt period in this particular snowmelt season. Two examples of the spatial variability of process interactions can now be visualized at the appropriate resolutions. First, the spatial variability of albedo is a major driver of snowmelt. The greatest melt occurs alongside the gravel-covered "grid" roads in the ditches where road dust significantly lowers the albedo thereby accelerating melt of the deep snowpacks. Moving eastward from the road ditches into the open fields there is a decrease in snowmelt depth in the overall scene, visualized in the Figure 11c~~d~~ transect. This pattern is likely due to the redistribution of dust from the grid roads to the open field snow surface by the prevailing westerly winds. A snow surface dust concentration gradient develops over the winter with higher concentrations of dust, and therefore lower albedo (Woo and Dubreuil, 1985), in the west than the east.~~ Near-infrared (NIR) reflectance data, a proxy for snow surface albedo from a coincident multispectral UAV flight part of a separate study and not discussed further, demonstrates an increase in albedo (Figure 11c).~~ This increase in albedo, and therefore decrease in solar radiation available to melt snow, corresponds to a decrease in snowmelt rate (Figure 11~~d~~c), moving easterly away from the grid road. ~~The gradient in dust and albedo describes the increases in snowmelt rates downwind of the grid road.~~ Second, the spatial variability of snowpack cold content influences melt rates in the early part of the melt season. Within the agricultural field, the sastrugi drifts are not melting – due to the larger cold content of the deep cold snowdrifts relative to the smaller cold content of the shallower surrounding snowpacks. This is also prevalent in the non-melting deep snowdrifts at the vegetated wetland edges. With UAV-lidar, a complete picture of the early and asynchronous snowmelt processes is possible. If reliant on UAV-SfM the interpolation needed to fill gaps in the point cloud, near vegetation and tops of the sastrugi, will obscure the full spatial pattern of snow depth change that conveys the heterogeneity of ablation processes. The high spatial resolution and vertical accuracy of UAV-lidar is required to capture these spatial patterns as the length scales of the snow surfaces features of interest are small, i.e. sastrugi drifts are on metre scales, and their changes at daily timesteps are at the centimetre scale.

The processes visualized in the Fortress and Rosthern examples are not new, but the value of UAV-lidar is that spatial patterns and changes can be observed across complex landscapes and vegetation gradients with a consistent resolution and accuracy. UAV-lidar will therefore be a powerful tool to understand the landscape scale snow-vegetation interactions as well as make a core contribution to the validation and improvement of distributed snow process modelling~~ of snow processes~~.

4.4 Are the costs and logistics of UAV-lidar worth it?

UAV-lidar, relative to UAV-SfM, provides the ability to ~~a superior observation of~~measure snow depth below vegetation canopies but it does come at a higher cost and logistical complexity. There are many similarities between approaches and one commonality is that both UAV-lidar and UAV-SfM require access to a GNSS solution to geolocate point clouds in absolute space.~~—~~ The Leica GS16 package used here is on the expensive side of the spectrum ($70,000 CAD) and cheaper ~~products~~equipment, subscription to virtual reference station networks if available in the study area (requires only a rover and not a base station), or equipment rentals are all viable alternatives to lower costs.~~–~~ The main cost difference between UAV-lidar and UAV-SfM platforms is therefore in terms of the UAV ~~the~~ sensor ~~type~~payload.~~–~~ A plethora of UAV-SfM options with and without RTK or PPK photo geotagging are available and can range from small inexpensive systems like a consumer grade UAVs (DJI Phantom 3 < $2,000 CAD) ~~or~~ to more expensive options like the Sensefly EbeeX PPK system ($30,000 CAD) used here. Current integrated lidar systems suited to UAV snow mapping (laser wavelengths < 1000 nm, small size, weight, and power requirements, and absolute errors < 5 cm) remain an order of magnitude more expensive than UAV-SfM. The cost of the complete UAV-lidar system (lidar, IMU, software suite, and UAV) used here approached $300,000 CAD. New and cheaper UAV-lidar sensor options are coming to market all the time, largely driven by the sensing advances coming from development of autonomous vehicles, but these need testing and still require high grade IMU/GNSS solutions to allow for absolute geolocation of point clouds. An underappreciated aspect of UAV-lidar is that the IMU/GNSS solutions can often be more expensive than lidar sensor itself. The additional cost of UAV-lidar to increase sub-canopy snow depth accuracy in dense forest situations in this application can be simplified to $15,000 CAD per cm reduction in RMSE (difference in equipment costs/difference in Fortress~~-~~ Tree RMSE).~~–~~ Logistical differences between UAV-lidar and UAV-SfM are more subtle than the stark cost difference. UAV-SfM simply requires a UAV platform and camera in its basic configuration and therefore high endurance, small platforms, with small batteries can be easily deployed to map large areas.~~–~~ In contrast, most current UAV-lidar configurations need~~s~~ larger platforms that require more cycles of large battery sets to cover similar areas which represents a logistical~~cal~~ challenge in keeping batteries warm and charged in cold and remote areas. Previous UAV-SfM experience (Harder et al., 2017) demonstrated the need to utilise GCPs even with PPK/RTK photo geotagging to minimise the bias error metric.~~–~~ The low bias of UAV-lidar errors, without assimilating GCPs, removes the need to deploy GCPs for UAV-lidar applications which can be a large time sink. Data processing software suites and workflows are distinct but ultimately the same level of geomatics expertise is needed to generate useable information. Despite the lower initial purchase costs and longer flight endurance the~~simpler logistics the~~ errors and artefacts that UAV-SfM techniques introduce in the sub-canopy ~~domain~~snow depth measurements, as detailed in sections 4.3.1 and 4.3.2, suggest that UAV-SfM is not able to directly measure snow depth in densely vegetated environments~~results in the noise obscuring the signal (Harder et al., 2017) particularly in dense forest situations~~. If accurate sub-canopy snow depth is required UAV-lidar is the superior option and therefore worth the added logistics and costs.

4.5 Ongoing Challenges and Future Research Needs

The ability of UAV-lidar to resolve sub-canopy snow depths is not without challenges. Precise classification of surface points from snow and ground scans are~~is~~ needed to resolve the snow depth at the resolutions needed to confidently capture snow-vegetation interactions. Where there are dense shrubs, the last returns will not necessarily be the snow or ground surface and therefore last-return methods common to airborne applications will not be appropriate~~The accuracy and resolution demands mean that bare surface classification techniques suitable for airborne platforms that efficiently resolve topography and hydrography at watershed scales from last returns will be unsuitable for resolving the snow depth around a particular shrub from a dense point cloud for example~~. Sub-canopy snow depth mapping requires careful selection of the appropriate point cloud classification and filtering tools and associated parameters to be able to reliably detect the sub-canopy bare-surface and achieve desired quality and precision in a final point cloud. To preserve the small-scale surface variability point cloud processing will be less efficient as all points need consideration and the focus on small-scale features will at times lead to erroneous inclusion of points representing large~~-~~-scale non-surface objects. The algorithm and parameters decisions also have to be adjusted for each flight and site/environment for UAV-SFM due to the variable quality and noise of the generated point cloud.

An especially challenging feature in resolving a ground surface is the presence of low and dense vegetation such as shrubs and wetland reeds. This is evident in looking in the centre of the wetland zones (~~green~~ red polygons) of Figure 11a where there are negative snow depths calculated. In this case, the lidar pulses cannot penetrate the dense vegetation to the underlying ground surface and the classified bare ground ~~surface~~ points have a positive bias. As snow accumulates, the reeds compress and shrubs bend over to the extent that the corresponding snow surface is below the biased bare ground surface. In the examples presented above, the areas of negative snow are limited to areas where snow depth is relatively shallow in comparison to ~~and are not as critical to capture as~~ the deep snow in the wetland edges. This challenge might also be apparent in other regions, such as the Arctic tundra, where shrub bending and burial by snow has been extensively documented (Pomeroy et al., 2006; Sturm et al., 2005). While shrubs are much sparser than wetland reeds their dynamic change in height and potential to bias positively the ground surface extraction will increase uncertainty of snow depth estimation in these hydrologically significant snow accumulation areas. More powerful lasers and higher scan rates may be possible to increase point cloud density and penetration to the ground surface but ~~leads to~~current sensors with these characteristics ~~that~~ may exceed the payload ~~capabilities~~capacities of most UAV platforms. Advances in bare surface classification/filtering software tools to address the large noise associated with low and dense vegetation is an obvious avenue of improvement. This avenue is inherently limited, as even a perfect bare surface extraction algorithm will not identify points at the ground surface if pulses cannot penetrate dense vegetation to the ground surface. The time of year chosen for the ground surface scan, ideally right after snowmelt when vegetation is at its lowest and not growing yet, may minimize errors. Unfortunately, this may not be feasible if the critical wetland areas are inundated as is often the case in the Canadian Prairies in spring.

Mapping sub-canopy snow depth is important but the ultimate variable of interest is SWE. The challenge is that at snow-vegetation interaction scales there may be significant variability from snow pack densification being driven by different processes across a landscape (Faria et al., 2000). Densification from wind packing is prevalent in open areas versus metamorphic densification due to temperature gradients in sheltered sub canopy areas (López-Moreno et al., 2013). Current methods of modelling or measuring snow density are not without problems at these small scales. Modelling snow density will impose conceptual understandings of these processes (Raleigh and Small, 2017; Wetlaufer et al., 2016~~(Painter et al., 2016~~) which may be inappropriate for the small scale features that need to be represented – these may miss mechanical densification from snow clumps unloading or dripping from the canopy for example. Observational approaches are also a challenge as typical *in situ* measurements are destructive, limited in extent, and often too limited to develop robust relationships of depth versus density at both the small ~~scales~~ local and large landscape scales needed (Kinar and Pomeroy, 2015a; Pomeroy and Gray, 1995). Opportunities may be available to pair UAV-lidar with other UAV-borne sensors such as passive gamma ray or snow acoustics (Kinar and Pomeroy, 2015b) to non-destructively develop high~~er~~ spatial and temporal resolution estimates of snow density and ultimately water equivalent.

5 Conclusions

Remote sensing techniques to determine snow~~ depth~~ -vegetation interactions have consistently been challenged by the presence of vegetation. ~~This has complicated efforts to observe and understand snow-vegetation interactions at the necessary spatial scales.~~ This work directly considers emerging UAV-lidar and UAV-SfM techniques to address this gap in observational capacity. Based upon extensive data collection at a variety of sites and snow conditions with varying snow-vegetation processes, the ability of UAV-lidar to measure sub-canopy snow depth is demonstrated. UAV-lidar provides snow depth estimates with RMSE's <0.1 m in open areas and <0.17 m in vegetated areas. The UAV-lidar ~~metrics~~ performance consistently exceeded the UAV-SfM ~~metrics~~ performance and ~~are~~was better than previously reported results in the airborne-lidar and UAV-SfM literature. The ability of UAV-SfM to measure snow depth in open areas is validated with respect to the growing body of literature and reconfirms that UAV-SfM is fundamentally inappropriate to sense sub-canopy surfaces. The clear advantage of UAV-lidar is that, as an active sensor, it provides a high point cloud density that is unaffected by surface homogeneity and allows for reliable bare surface detection. With UAV-lidar we can now confidently observe sub-canopy snow depth at centimetre scales needed to examine snow-vegetation interactions at research catchment extents (ie <5 km^2). UAV-lidar is an emerging tool that will contribute to improving basin-scale snow accumulation estimates, validation and parametrisation of distributed snow models, and enhancing snow vegetation interaction process understanding over the landscape scale.

Code/Data Availability

The data underlying this analysis and its documentation is available at https://dx.doi.org/10.20383/101.0193 under a Creative Commons CC-BY-4.0 license. The LAStools workflows and R code used to complete the analysis are available from https://github.com/phillip-harder/UAV-snowdepth under a GNU General Public License v3.0.

Author contribution

PH designed the field campaigns, performed the data collection, and completed/managed the data processing and analysis. PH prepared the manuscript with contributions from all authors.

Competing interests

The authors declare that they have no conflict of interest.

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