Mapping snow depth at very high resolution with RPAS photogrammetry

Todd A. N. Redpath, Pascal Sirguey, Nicolas J. Cullen

Response to reviewer comments

We thank the referees for their careful review and helpful feedback, from which we have improved the manuscript.

Referee comments in italic font

Response In normal font.

1. Response to RC1 comments

Initial paragraph or section evaluating the overall quality of the discussion paper ("general comments")

This manuscript aims to present a methodology combining RPAS and photogrammetry to capture high-resolution snow depth estimates, to provide its accuracy and associated statistics. I believe the study itself has some strengths and interesting aspects; they cover a relatively large area catchment area using a fixed-wing UAS (compared to most studies using rotor based UAS), there is a considerable elevation change, it provides some distinct statistical investigations, and is done for 2 epochs.

However, in my opinion the authors have overlooked recent literature treating the same subject, and therefore have framed the study on a too general context, lacking some novelty and specific aims within the research of this methodology. Furthermore, there are also some other scientific comments, which I will try to inquire further.

Therefore, I recommend major revisions to provide the opportunity to re-orient the focus and frame of their study, highlighting the strengths and further clarify on some more specific aspects of the method noted in literature.

Technically, I think the manuscript embodies a well-presented and carried-on study. Some structural changes and clarifications are recommended.

Response We thank the reviewer for their comments and thorough review.

Section addressing individual scientific questions/issues ("specific comments")

<u>TITLE AND OVERALL AIMS OF THE STUDY:</u>

I think the title and aim are too general considering that there are already several studies investigating the same snow depth mapping method, looking at similar datasets (multiple DEMs + GCPs + snow probing validation). Furthermore, very similar validation methods have already been applied in other studies for multiple types of terrain/snow and providing almost the same results in terms of accuracy and resolution (although some for smaller areas). The manuscript here presented has referenced and discussed only four of them, but some additional studies on the method are missing:

Avanzi, F.; Bianchi, A.; Cina, A.; De Michele, C.; Maschio, P.; Pagliari, D.; Passoni, D.; Pinto, L.; Piras, M.; Rossi, L. Centimetric Accuracy in Snow Depth Using Unmanned Aerial System Photogrammetry and a MultiStation. Remote Sens. ***2018****,* 10*, 765.*

Yves Bühler, Marc S. Adams, Andreas Stoffel & Ruedi Boesch (2017) Photogrammetric reconstruction of homogenous snow surfaces in alpine terrain applying near-infrared UAS imagery, International Journal of Remote Sensing, 38:8-10, 3135-3158, DOI: 10.1080/01431161.2016.1275060

Cimoli, E.; Marcer, M.; Vandecrux, B.; Bøggild, C.E.; Williams, G.; Simonsen, S.B. Application of Low-Cost UASs and Digital Photogrammetry for High-Resolution Snow Depth Mapping in the Arctic. Remote Sens. ***2017***, 9, *1144.*

Avanzi, F., Bianchi, A., Cina, A., De Michele, C., Maschio, P., Pagliari, D., Passoni, D., Pinto, L., Piras, M., and Rossi, L.: Measuring the snowpack depth with Unmanned Aerial System photogrammetry: comparison with manual probing and a 3D laser scanning over a sample plot, The Cryosphere Discuss., https://doi.org/10.5194/tc2017-57, 2017.

Fernandes, R., Prevost, C., Canisius, F., Leblanc, S. G., Maloley, M., Oakes, S., Holman, K., and Knudby, A.:
Monitoring snow depth change across a range of landscapes with ephemeral snow packs using Structure from Motion applied to lightweight unmanned aerial vehicle videos, The Cryosphere Discuss., https://doi.org/10.5194/tc-2018-82, in review, 2018.

I believe it would be good to have a look at these, and better frame the motivation and title of the study to the suggested gaps in the research stated in literature. Snow depth mapping with RPAS as you present it is not so novel, and accuracy has already been assessed in multiple ways with similar (or higher) sample sizes. Nevertheless, this study can emphasize other really interesting aspects (e.g. larger area, fixed wing and focus on discussing other statistics as already partially done) but limitations needs to be discussed and literature accounted.

Response We thank the reviewer for this constructive and well-informed suggestion. We agree that the point of difference brought by our study, namely the use of fixed-wing over an entire alpine catchment, could be strengthened. We have substantially reworked and widened the scope of the introduction to include some of the recent work suggested by the reviewer, and have emphasised our focus on mapping snow depth over a larger area and substantially more complex terrain compared to what has been reported in previous studies. We identify the additional set of challenges associated with the larger area and increased relief to justify the need for methodological assessment. From the citations proposed by the reviewer, we note that Avanzi et al. (2018) is arguably identical to Avanzi et al. (2017) and thus cited only the version accepted in Remote Sensing rather that the discussion paper in The Cryosphere Discussion.

An example of a more specific title suggestion could be:

"Investigating snow depth retrieval of an alpine catchment area using photogrammetry and fixedwing RPAS"

Response We agree the focus of the paper could be better conveyed in the title and appreciate the suggestion of the reviewer. We amended the title to "Repeat mapping of snow depth across an alpine catchment with RPAS photogrammetry"

1. *INTRODUCTION:*

Paragraph starting at line 23: there might be too much information on satellites and SCA. I think snow depth mapping with RPAS is not directly comparable with satellite in terms of applications and uses, therefore I would personally not give too much weight on comparing both. In addition, I think you speak a lot about SCA in the introduction, but you do not mention its retrieval as part of your objectives and rarely speak about it again during your methods, results and so on. So maybe part of it is avoidable, I guess your focus is snow depth here and SCA is just intrinsically bounded to it.

Author response This section of the introduction has been substantially reduced. We maintain some reduced context around remote sensing of SCA and other snow metrics as there is motivation in assessing how insight from high resolution data such as RPAS photogrammetry may improve inferences made from coarser space-borne products.

2. *STUDY SITE:*

Here a lot has been said about the topography, but what about the snow?

Response At the time this study was planned, very little data was available regarding snow within the study basin and surrounding areas, with the exception of the work of Sims and Orwin (2011) – this is a widespread problem in New Zealand. As noted, visual inspection of available satellite imagery was undertaken to assess the viability of the field site from a snow cover point of view. Ultimately, the topography of this site also makes it of interest for the study of snow in New Zealand, with the morphology being somewhat different from the Southern Alps, but similar to many of the eastern high ranges of Otago, which are under-represented in snow observation and study.

It is important to add information about the daylight conditions of the surveys, and the snow textures/types encountered. It is recognized that these can affect SfM reconstructions on snow, and potentially the final DEM product. Maybe add to Table 1 and describe change in snow conditions over time.

Response Additional information has been added to Table 1 and Section 3.1.2 to further describe snow and sky/lighting conditions at the time of each flight. We agree that these are of interest in terms of the application of the methodology. We shall however stress that potential limitations are related more to the hardware used to capture imagery (in particular the dynamic range of the camera being used), rather than the photogrammetry modelling itself. We clarified this by reporting in Section 3.1.2 about the suitable contrast achieved by the camera.

In my opinion, an interesting aspect of your study area is the variable slope, and the different types of snow encountered over the epochs (if different), so highlighting these over time and space would be good (as you have already partially done).

Finally, It would be great to add to Figure 1 (or as you see fit) the orthophoto of the Autumn DEM, this is not present in the manuscript and its very important to better showcase your terrain DEM, vegetation areas and so on.

Response wW agree, and have added the orthophoto and hillshaded DEM from the Autumn flight to an additional panel in Figure 3.

3. DATA AND METHODS:

3.1.1 RPAS platform and payload

What is the cost of the unit? You mention is low-cost, but compared to what? It does not sound like a very low cost system within the realm of drones (particularly if you consider DIY solutions), but it is low-cost compared to manned aerial systems. Please specify. Please use SI units, e.g. meters and not feet. Also, I does not seem you have specified what was your average flying altitude for each flight.

Response Our reference to low cost in the introduction is not specific to the unit used in this study, but to the use of RPAS in general, particularly relative to manned platforms. We have clarified this in the introduction. We prefer to retain units of feet when referring to aircraft heights, as this is established practice by regulatory bodies and within the aviation sector, but have included conversions to metres. We have added the average flying altitude (which was the same for the three flights) to section 3.1.2.

3.1.2 RPAS flights

Maybe more information like frame rate, software used for mission planning, how the missing was planned in such scenario etc. would be good.

Response Agreed. we have specified the software used for flight mission planning (Trimble Aerial Imaging). The system we used does not rely on a fixed frame rate but rather on predetermined locations of exposure stations to achieve the desired forward overlap. GNSS navigation and infrared trigger on-board ensures images are captured at the appropriate location. We clarified this in section 3.1.2.

3.1.3 Ground control survey

Same here, some information on the software used for processing GNSS data, and a reference (if available) would be good (e.g. the manual).

Response The name of the software used for processing GNSS data (Trimble Business Center) has been added.

In addition, it is not clear from the text if you used some of the points for co-registration of the multiple DSMs (I understand you did not, why?). Particularly since you speak about co-registration later, in chapter 5.2.2. Please make this clear in the text and if yes, display these points on one of the figures.

Author response No control points were used as co-registration points. Although the location of GCPs between flights were similar, they were not identical. Variable snow cover obscuring surface features between different flights precluded co-registration of the DSMs. This has been clarified in the text.

3.1.4 In situ snow depth measurements

I would call this chapter "snow probing validation" or something else similar.

Response We have amended the heading to *Reference snow depth measurements*

Also, please specify the GNSS accuracy of your RTK snow depth samples, and how are they representative of your claimed spatial resolution (0.15 m) if they are averaged over and arm distance of a meter or so.

Response The probe locations were surveyed according to the same protocol as GCPs, and achieved the same level of accuracy; the text has been updated to reflect this. We have added a comment in section 4.2.2. to note the influence of spatial uncertainty on the comparison between RPAS and probed snow depths.

3. DATA PROCESSING

3.2.1 Photogrammetric processing

Is all the formulation needed? Since all the calculations are carried on by a black-box software, maybe only a couple of references on the general photogrammetric principle should suffice.

Response We believe that the main formulation of the photogrammetric model is desirable here as it provides context to discuss the sensitivity of the method to errors in the estimate of interior and/or exterior orientation parameters, which is addressed later in the paper. We also think that given the recent proliferation of RPAS applications, and in particular when relying on black/grey-box software solutions, it is important to stress the mathematical fundamentals of photogrammetric modelling. This is critical to understand potential pitfalls in the technique, yet may be unfamiliar to many readers. We have amended the text to emphasise the relevance of this.

In addition, many of the variables/parameters in the equations are not defined and need to be specifically declared in the text.

Response Agreed. We have defined the K and T terms which had been erroneously omitted previously. We also moved to this paragraph the definition of (X_0, Y_0, Z_0) which was provided latter in the manuscript.

This section could also be coupled and properly merged with the following one, "software". (I assume they are black-box/off the shelf software, but little to none information is provided in this manuscript, particularly as you heavily discuss it in the discussion section).

Response We believe that this section is best kept separate from the following, as it introduces the general principles of photogrammetry, while the following section relates specifically to the software used and workflow implemented.

3.2.2 Software

Since the software's employed are out of the commonly used by the UAS snow depth mapping community, maybe a small introduction on how they compare to Photoscan (or others) and some references on them would be beneficial. Particularly as they are heavily discussed further on.

Response We have added some more detail regarding the software here, as well as references to documentation. Note we have re-named this section "Software and workflow".

An example: how do you locate GCPs in the DEM for this software, manually or automatically? From personal experience, this can be a considerable source of error and is worth mentioning.

Response We agree that the process to collect GCPs is important to clarify. In our case the collection of signalled markers is manual and we have added relevant detail in the text.

The paragraphs following line 29, are somewhat confusing. Does the process of removing GCPs you mention refers only to the autumn mapping? Is it an analysis that was performed before you place the GCPs on the other epochs? I think I understood, but please clarify this on the text.

Response The text has been edited to clarify that this test was applied only to the autumn epoch.

In addition, you do not mention which specific GCPs you removed. CPs RMSE values would probably change if you select a different combination of points, of the same sample size (e.g. 14), among your *set. This is because overall total CP RMSE will be dependent not only on the number of GCPs you have used in your model, but also on their location, their accuracy in image identification and GPS precision. Is not clear if you tested this or not.*

An interesting statistical approach would be to do a CPs validation using a bootstrap or similar method. By this I mean selecting random samples out of your GCPs and using them as CPs, multiple times. This would actually be an interesting approach to take that no study snow mapping study with RPAS has undertaken before. This for example be an interesting addition to your statistical investigation that has not been undertaken by previous studies.

Response We agree that the relative arrangement of GCPs and CPs is important to the quality of the triangulation, and have added this information to Figure 2. The objective was always to ensure that the perimeter of the basin was constrained by GCPs. We also agree with the reviewer on the merit of the proposed method, and as a matter of fact are used to leave-one-out cross-validation protocols to leverage efficiently limited GCP networks in photogrammetric projects. In this context however, it is important to note that the sheer number of images and TP involves a significant processing time for each adjustment which makes numerous repeats impractical. During early trials to test the robustness of our photogrammetric modelling on the autumn flight, we did in fact carry out a leave-one-out cross-validation when evaluating the performance of the TBC software, and found consistent AT results. However, as explained in the manuscript, despite such assessment the surfaces produced subsequently by TBC remained compromised, with errors not captured by the AT only revealed when differencing surfaces subsequently. This stresses the limitation of relying solely on GCP/CP residual reports as this may not capture all errors of the photogrammetric modelling. When reconsidering processing with a more capable software solution (UASMaster), we decided to repeat only a limited number of scenarios which we believed captured well the information needed to inform the GCP network design for winter flight, with the cross-validation protocol finally adding marginally to this assessment. In this case, the overarching objective remained to inform the minimum number of GCPs that might be needed to provide a robust triangulation in the context of this specific field site and the complications associated with the terrain and winter operations. The fact that we have differing spatial arrangements of GCPs and CPs for each of the flights, with comparable triangulation residuals despite independent networks, goes some way to illustrating this, and demonstrates that consistent results can be achieved in lieu of permanent, common, control marks in the field. Although we appreciate the well-informed comment of the reviewer, we believe our protocols remain sufficient to document robustness of the modelling and decided not to make changes to the manuscript to evaluate the suggestion of the reviewer.

3.2.3 Deliverables

I think this section would be better moved to the beginning of results, to outline all the final output retrieved.

Response In terms of deriving snow depth, these products are really an intermediary step. We considered shifting this section to the results, but that would lead to an inconsistency with section 3.2.4. Instead, we re-named this section *Intermediate deliverables*.

3.3 Quality and accuracy assessment

Three methods for assessing the accuracy of the method are here employed; calculated error propagation, manual snow probing and snow free validation. I agree that combination of all of them *helps assessing the overall accuracy of your results. However, each of them carry some limitations in this case, which require to be mentioned.*

First, as RPAS photogrammetry provides very high spatial resolution measurements, I think the best way to obtain a strong accuracy estimate would be to compare it with other high spatial resolution estimates such as Lidar. Therefore, it is important to note that the validation applied in this study still lacks such estimate comparison.

Response We agree that Lidar would provide a useful reference measurement, however such data are not available for the study area, which we have noted in the text.

Regarding validation tests for snow free areas, you need to mention that this validation is mostly representative of snow free areas, and not much of the snow-covered areas. Particularly since you have not mentioned anything about the snow type and about the photogrammetric reconstruction performance. Snow free areas can help assessing if the DSMs used for subtraction are shifted horizontally, and partially support you DSM reconstruction, but they cannot be used as a rigorous estimate of accuracy of snow depth mapping. I think is just important to mention this caveat.

Response We agree that the validation is mostly representative of snow-free areas. We are confident, however, that these results are transferable to snow covered areas given that good contrast was obtained over snow surfaces where dense photogrammetric restitution was not impaired. We don't expect (and haven't observed) any noticeable degradation in photogrammetric performance over snow covered areas. DSMs are free of widespread noise, and spurious surface elevations are uncommon. We attribute this mostly to the characteristics of the camera used (Sony NEX 5R), which has an APS-C sized sensor (considerably larger than the cameras deployed in many other RPAS platforms used for mapping). With an effective resolution of 16 M pixels, the NEX 5R individual photodetectors are >3 times larger than those found on the Canon ELPH 110 (commonly carried by the Sensefly eBee), and the cameras fitted to DJI Phantom systems (1/2.3" 16.1 M pixel), and about 0.8 microns larger than that of the Sony NEX 7. A high sensitivity to light and careful selection of exposure settings before flight ensures contrast and good sharpness across images are maintained, with high dynamic range and minimal occurrence of under or over exposure. Indeed, our experience has been that where scenes are mixed between snow and snow-free areas, the snow-free areas tend to be relatively under-exposed relative to the snow, which is well resolved. For us, this is preferred, and flights over snow are always operated with a high shutter speed accordingly. We have included sample image frames here to demonstrate the surface contrast achieved under varying snow conditions. Note also that we flew with a NIR modified NEX 5R for the winter flight, but this did not provide any substantial improvement over the RGB for the triangulation. Comparative study between modelling restitution of NIR vs RGB acquisitions are however not in the scope of this paper. In view of this, we therefore maintain that testing repeatability on snow-free areas informs equally on the robustness, consistency and performance of modelling over snow when such contrast is obtained.

Figure 1: Image of a mixed snow-covered and snow-free scene from the spring 2016 flight. Image captured at 1/4000 s and ISO 100.

Figure 2: Image of a mixed snow-covered and snow-free scene from the spring 2016 flight. Image captured at 1/4000 s and ISO 100.

Figure 3: Image of a fully snow-covered scene from the winter 2016 flight. This flight occurred shortly after a snow fall event. Wind erosion and deposition features are well preserved in the surface of the winter snow pack, and well resolved by the camera. Image captured at 1/4000 s and ISO 400.

Finally, in line 3 of page 9, you highlight the calculation of error propagation as the most rigorous validation among them and a bonus of this study. In my opinion, is the actual snow probing that validates better and independently your dDSM, particularly because for your calculation you have only a sample of 6 CPs each as I understand, whereas you have 86 snow depth probing samples.

Response Good point, this section has been re-worded to clarify. The key here is not necessarily that error propagation is the most rigorous approach, but that it should provide a good indication of uncertainty when no other data are available, an assumption that has been applied in previous recommendations in the literature (e.g., James et al., 2012). Ultimately, when deploying this technology for such application, relying on probing for each mission is not practical and arguably not desirable as it would defeat offered by the technique to some extent the advantage. In most case when repeating flights operationally, the uncertainty of the modelling can only be derived from an assessment of the AT. It should also be noted that the triangulations that provided the orthophotos and DSMs that were used for further analysis were fully constrained with all surveyed points used as control. The triangulation was then re-run with some points set as CPs to provide a conservative accuracy estimate, relative to the fully constrained solution. This has been clarified in section 3.2.2.

3.3.1 Uncertainty associated with RPAS-derived snow depth

Please mention why did you assume that planimetric precision of each constituent DSM is negligible. In my experience, if you subtract two DSMs and there is just a slight misalignment, errors in the final dDSM (and bulk snow pack volume) can be considerable. That is why other studies have shown that co-georeferencing the DSMs using common GCPs can improve accuracy of the method.

Response We agree that the planimetric contribution may not be (and often is not) negligible – that is a major focus of our discussion - we have re-worded this in an attempt to clarify. Our point here is that this assumption is inherent in only considering the contributions of vertical uncertainty of constituent DSMs to vertical uncertainty of dDSMs, which is an approach reported and recommended in the literature. Although we can only agree with the reviewer that common GCP across missions would be desirable, we must also stress that in our case it was not an option due to the inability to set permanent elevated markers on this protected conservation area. This and the lack of consistently exposed features such as rocks across missions dictated that a new GCP network needed to be setup, in turn justifying such careful assessment of repeatability and consistency. We have clarified this constraint in section 3.1.3.

3.3.3 Repeatability of photogrammetric modelling

Please describe a little bit more what you have done in your classification algorithm.

Response We have provided further detail in the text.

What do you mean by $dDSM_3$? I can't find this DSM identifier anywhere else in the text/tables.

Response Thank you, and we agree that this was ambiguous and have re-phrased to spring dDSM

4. RESULTS

4.2.2 Assessment against reference probe data

It would be great if you can also display on map the difference between snow probed and RPAS estimated snow depth for each of the 86 sample points. That would give a spatial overview of the error, or across the slope for example. It could also open up for discussion of accuracy across slope and epochs or snow types.

Response We agree that this could be an interesting analysis, and it was investigated initially as part of this research, but no clear spatial or terrain dependency was found (see Figure 4). We suspect that this is symptomatic of the shortcomings of the snow probe data, particularly the influence of vegetation, and potentially also geographic uncertainty in comparing high resolution datasets. The impact of slope and aspect on error with respect to field observations of snow depth deserves more attention, but would benefit most from a targeted field experiment.

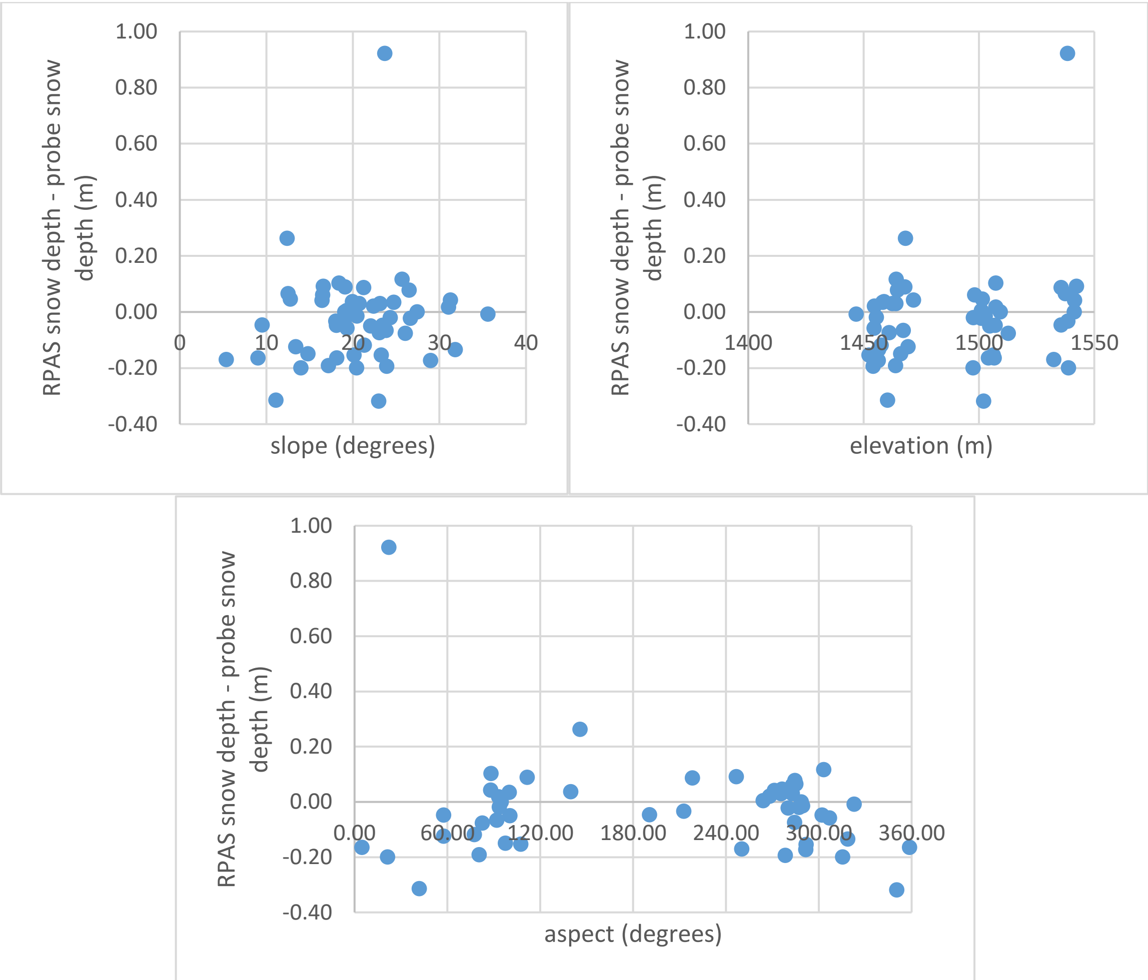


Figure 4: Scatter plots of residual between RPAS derived and probed snow depths and slope, elevation, and aspect.

<u>*4.2.3 Comparison of DSMs from independent RPAS flights*</u>

I would suggest merging Figure 6 and Figure 5 somehow. I think the manuscript has already too many Figures that can be reduced.

Response This is a good suggestion and we have merged these figures into a single Figure 5.

5. *DISCUSSION*

5.1 Performance of RPAS photogrammetry for resolving snow depth

I believe here you highlight well the main strength of your study; that is a relatively larger area and mapped at high resolution. This is interesting and perhaps your study should be more centered on this. However, you should highlight what are some of the limitations in your validations here.

Line 3, page 14: "Achievement of uncertainties <0.13 m": Please mention to which statistics you refer. I guess the propagation of error?.

Response The text in both sections has been re-written to clarify, and the number adjusted to 0.14 m to reflect more accurate rounding. The value of 0.13 m comes from the empirical 90th percentile shown in Figure 6 and discussed previously in 4.2.3. As per our reply to an earlier comment, we reworked substantially the introduction and the merit of this study to highlight the fact that it applied to a relatively large area compared to previous studies.

5.2.1 Vegetation

This has been highlighted by every study on snow depth mapping from RPAS, so should not be much of a novel finding discussion topic. I would however mention how it affected your dataset (as you already do), how it affected other studies and stress that solutions are really needed to solve this important caveat of the methodology.

Response We have made some edits here to reflect these suggestions, particularly to stress the impact of potentially unreliable probe measurements on the validation, and the need for future work to characterise sub-snow vegetation processes in order to improve the applicability and reliability of this method.

It would be interesting to know instead how did error varies with slope or with snow type spatially across your catchment area and across epochs (if any difference is noticeable).

Response As noted previously and illustrated by additional figures in our response, there was no relationship observed between error relative to probed snow depths and terrain parameters. This is possibly a product of shortcomings in the reference dataset, as our other results provide an expectation of terrain dependent uncertainty. As such, no changes have been made to the text.

5.2.2 Geo-location and co-registration

It would be good if the authors stress more clearly/directly/shortly what is the importance of all this and its relevance in a RPAS snow-mapping context. What I understand here is that the authors first want to point out that vertical dDSM uncertainties and errors increase when planimetric and horizontal geo-location errors are present, and particularly on steep slopes or presence of rock outcrops (not surprisingly). Then the aim to is to justify the found statistics in this study, particularly for the slope and this is interesting, but requires a more clearer explanation of the benefits and consequences.

Response Understanding the impact of planimetric uncertainty on the quality of measurements obtained by DSM differencing is fundamental to characterising the uncertainty associated with surface change analysis. The importance of this increases with the advent of very high resolution datasets, such as those obtained from RPAS photogrammetry, and in areas of complex terrain. These effects have been identified previously (e.g., Nolan et al., 2015), but not characterised in the context of snow depth mapping using RPAS photogrammetry. The characterisation we provide here should provide useful guidance on the potential limitations of the technique. We have amended the text to highlight the importance of this section.

The main issue here is that is claimed that utilizing independent aero triangulation is better that cogeoreferencing the DSMs. I personally disagree with this statemet, co –georeferencing saves considerable time when snow free areas are available. And if not available, it's always easier to leave artificial features like high poles (seen all over the year), which require only 1 measurement for the entire seasonal snow cycle over multiple years. Many studies have reported that co-georeferencing their terrain and snow DSMs using common GCPs considerably improved the snow depth maps accuracy performance (because of all the problems you mentioned). They mitigate considerably all the issues of planimetric misalignment.

Response We certainly agree that having permanent GCP markers installed in features to act as common GCPs throughout the year would provide desirable consistence with expected benefits on the accuracy of the dDSM. To us this process still leverages independent AT that should result in consistently co-registered DSMs "by design". However due to the status (Conservation Area) of our field site, this is simply not possible, a point that we did clarify in Section 3.1.3. Notwithstanding this, what we discuss here is the process of co-registering DSMs produced subsequently to AT, not processing AT that are inherently co-registered thanks to the use of common GCPs. This is an important difference and we invite the reviewer to reconsider his comment in view of this. To address this comment, we shall further describe and discuss below the four approaches that can be taken to producing well co-registered products. In view of this, we stand by our statements in Section 5.2.2:

1. The use of permanent, common GCP markers. A big advantage of this approach is in the time that can be saved in the field, although markers may still need to be cleared of snow and ice. Another advantage of this approach is that the contribution of GNSS uncertainty of GCP measurement to the total error budget will be constant for all triangulations. Drawbacks of this approach include the possibility that markers still need to be cleared of snow and/or ice prior to flights, negating time savings, and the potential for the introduction of a positive bias into surface elevations when markers are consistently elevated above ground level.
2. The use of GCPs placed in the field and surveyed for each measurement campaign, which is the approach we took. Where GCPs are surveyed in the appropriate coordinate system and related by a common benchmark (as in our study), the contribution to the total error budget of independently surveyed sets of GCPs will be minimised, and should be comparable to 1.
3. The use of "soft" GCPs, for which 3D coordinates are extracted for features from the triangulation of the first (reference) mission and then used as GCPs for subsequent missions. We evaluated this approach following our Autumn flight, but a combination of low contrast on exposed rock features, and snow obscuring features in later flights limited the utility of this approach. Furthermore, this approach will compound three sources of error for all subsequent DSMs, that of the initial GNSS GCP measurement, that of the reference triangulation, and that of the final triangulation.
4. Explicit co-registration of DSMs (e.g., Nolan et al., 2015) is what we discuss in the manuscript and represents an appealing solution because it can potentially minimise co-registration uncertainty substantially. While it may be appropriate for coarse models, where surface features are highly smoothed, we consider this method to be the least desirable, particularly for very high resolution products where spatial resolution and geo-location accuracy converge. The processes of applying a transformation between constituent DSM grids and resampling pixel values to the new grid will introduce a level of distortion and error to the co-registered product that may further degrade the snow depth signal that is being sought. Such degradation may in turn compromise the desired level of accuracy of the dDSM product.

In addition, I would see this discussion to be more focused on snow itself, and its changes in aspect, and elevation in accordance with underlying terrain and how this will affect statistics of other people employing the method, under different snow landscapes. This rather than focusing on a general DSM context.

Response We have modified this section to focus more directly on the relevance of measuring snow depth. The relationship between the magnitude of the residual between RPAS and probe derived snow depths and slope, aspect and elevation was assessed, but no clear dependency was revealed. This is possibly due to the quality of the probe measurements (e.g., impact of vegetation and sampling error) and in the case of elevation, the limited range of elevation sampled by probing (only along three elevation contours). We agree that the influence of terrain on uncertainty in derived snow depths is worthy of further investigation, but this would require a more targeted experiment.

Finally, you mention that high quality GCPs are important, but you don't discuss the future of systems with on-board RTK which will probably substitute GCPs in the near future and can account more directly and precisely the errors you mention in roll, pitch and yaw by integrating IMU components.

Response We agree that RTK equipped RPAS and "direct geo-referencing" are promising for improving the quality of output with reduced need of GCPs. With an absence of any GCPs, however, it becomes more difficult to confidently characterise triangulation quality, and the risk that gross errors may go un-detected is also increased. Additionally, RTK systems often suffer a weight and power consumption penalty that sees flight times reduced (e.g., an advertised 35 minute endurance of the Trimble UX5 HP, compared to the 50 minutes of the UX5 used here, https://www.trimble.com/agriculture/ux5). We have added these points to the manuscript.

5.3 Pitfalls and limitation of RPAS photogrammetry

This large sub-chapter and more than three figures are dedicated to comparing the performance of two different black-box photogrammetric software's. I guess this is not part of your initial aims, and while is partially interesting for some communities, I think your goal is to outline a snow depth mapping method and not the performance of the particular software's. Therefore, I would personally reduce considerably this section. Particularly since inferences are made based on two different black-box software's and you don't really comment/outline/reference on the particular workflow of these products.

Response We agree that there was scope to shorten this section, and have done so, including the removal of Figure 13, and merging of Figures 12 and 15. We however believe that this section has merit as it clearly demonstrates that commercially available and used software cannot always be relied upon for robust implementation and generation of high quality results, with the main metric used to assess AT being potentially misleading. The artefact detected is particularly problematic in the context of snow depth mapping, as when full snow cover exists over a study area, there is no straight-forward possibility to apply an empirical correction, and other approaches to remove such stripping (e.g., Fourier Transform) present a risk of loss of real signal. The mapping of snow depth is one of the few applications of RPAS photogrammetry where an entire surface may be transformed between measurements, making such issues particularly problematic to this application. We also believe that although this issue may affect only the one software we tested, the question it raises is significant and implications are far-reaching and relevant to others. We believe being able to document such issue and the process of its discovery, as well as our attempt to understand the source of the short-coming makes it relevant to the increasing community of RPAS users to inform about such limitations. We have clarified this important point in the text.

Another issue is that here you generalize as "limitations and pitfalls of RPAS photogrammetry" problems that were encountered within the particular software employed. Other studies have not reported these discussed issues with other software that I am aware (or they could not be verified?). Therefore, is difficult generalize such a discussion for snow depth mapping with RPAS.

Response We agree that in this the artefact was a product of specific software and have made changes to the text to clarify. That said, it was fortuitous that the subtle error was discovered in the first place, and it is possible that it may have gone un-detected had each flight not had a near-identical flight path. It is possible that such errors appear in other datasets, yet they will become less obvious when flight paths differ between flights, or as surface complexity increases (e.g., due to either terrain, or vegetation). The take home message here is that these techniques demand vigilance, and should not be treated as "black box" solutions. As noted, we have amended the text to ensure that this key point is clear to readers.

5.4 Spatial and temporal trends in snow cover

This section much better highlights the strengths of your study and more should be reflected in the introduction and aims. The same can be said about your conclusion. Nevertheless, more could be said about the high repeatability/change detection potential of your methodology, since your covered 2 distinct epochs.

Response We thank the reviewer for this positive comment. We made our best to address the reviewer's constructive comments which helped us refine our focus and the strength of our study in the introduction in particular, and throughout the paper.

Purely technical corrections at the very end ("technical corrections": typing errors, etc.).

Please make units consistent thorough the manuscript. Either cm or m (e.g. line 4 of page 6).

Response This is a good suggestion and we have updated all cm units to m.

In all tables and figures, please include full names and abbreviations. Often, only abbreviations are shown and the reader is forced to look for them in the text.

Response Captions have been updated with definitions for abbreviations where necessary.

Line 4 page 11: There is clearly a typographical error.

Response This has been corrected.

In figure 2 please add "points" to Ground Control…

Response This has been corrected.

2. Response to RC2 comments

Interactive comment on "Mapping snow depth at very high spatial resolution with RPAS photogrammetry" by Todd A. N. Redpath et al.

Anonymous Referee #2

Received and published: 1 July 2018

This study presents results for a small watershed in New Zealand where repeat unmanned aircraft flights were used to map surface elevations using photogrammetric methods, and then snow depth via digital surface model differencing. There was one snow free flight, and two snow on flights, one winter and one spring. Although the snow depth results are presented, the main focus of the paper is more technically focused on methods, uncertainty, and validation.

The use of unmanned aerial systems in earth science is growing in popularity for good reason; the units are small, relatively inexpensive, easy to deploy, and the software to carry out structure from motion photogrammetry is becoming more accessible and user friendly. This study is a relevant and useful contribution to the growing body of literature using UAS to map snow depth and cryospheric processes at high resolution, fits within the scope of The Cryosphere, and should be accepted for publication after revisions. Following are broad recommendations that would improve the manuscript, namely in terms of readability and accessibility by a broader audience, particularly one that may not be familiar with mapping surface elevations/snow depth with UAS.

Response We thank the reviewer for their positive comments. We have made a number of edits which we hope will improve the clarity and readability of the work, particularly for readers less familiar with the use of RPAS.

- *The acronym RPAS was new to me, likely a regional difference in terminology that I am unfamiliar with. In terms of search-ability I would suggest the switch to UAV or UAS (which is already used in the paper- so that would simplify things), or at minimum, mention the different terms use for unmanned aerial systems in the introduction and justify the use of RPAS rather than UAS.*

Response We prefer and have retained RPAS as this is the term used by relevant regulatory authorities, and is widely used within the surveying and geospatial community. RPAS also more accurately describes the operation of the UX5 (i.e., the flight is overseen by a human "pilot") and is a gender neutral term. We have, however, noted the use of synonymous terms unmanned aerial systems (UAS) and unmanned aerial vehicles (UAV) when the term RPAS is first introduced.

- *The manuscript reads as if the authors assume the reader has some understanding of photogrammetry, which is not necessarily a safe assumption. Something as simple as 'overlapping pictures are used to reconstruct a continuous 3 dimensional surface' very early on in the introduction would be helpful to provide context to the reader, and also making sure important terms are defined (like tie point). Also aerotriangulation is simply the georeferencing method by which ground control values are assigned to points, this could be defined once and then the term georeferencing could be used afterwards, which is a more accessible term. This paper dives into the technical very quick, but shouldn't forget to cover the basics, as well, since this is still a relatively new method for mapping snow depth.*

Response We agree that some of this material was potentially unclear to readers who are not familiar with photogrammetry and have amended the text to make it more accessible. In section 3.2.1., we now point out that the aero-triangulation is a means of georeferencing, but have retained the term aero-triangulation (AT) elsewhere in the text as it is an approach specific to photogrammetry.

- *This paper does a great job of covering uncertainty, but I think it is interesting and important to recognize the practical limitations of this method early on in the paper. It currently cannot scale up* *beyond small watersheds for practical reasons, namely flight times and flight restrictions, which vary widely from country to country. Also setting out ground control points can be just as time consuming and limiting as carrying out snow surveys, which is why the authors themselves wanted to reduce the numbers of GCPs used per flight. Also vegetation is a critical issue in watersheds that have thick brush, or trees for that matter, so it is only useful and accurate in alpine watersheds. Discussing how these issues might be be overcome in the future to make this method operationally useful would be very interesting (i.e. that use of RTK on the UAS). As it stands snow in medium to large scale, and/or vegetated, watersheds can only be mapped with lidar, and while it is notably missing in the paper, repeat high resolution lidar flights for snow depth and SWE are being done in the Western US by the Airborne Snow Observatory at operationally relevant scales (https://doi.org/10.1016/j.rse.2016.06.018).*

Response We agree that the limitations are important and have added comments addressing these and have emphasised the demand for characterisation of vegetation compaction and the uncertainty that this introduces. Regarding onboard RTK, it is noted that the addition of RTK hardware to the payload typically comes at the expense of increased power demand and reduced flying time. Even with RTK, it is desirable to have some form of surveyed control marks in the study area in order to confidently characterise uncertainty and reduce the risk of gross errors being undetected. In the New Zealand context we benefit from the fact that almost all seasonal snow occurs above the treeline.

-In the introduction the authors emphasize how valuable this method could be for understanding spatial variability in snow depth at high resolution, but then spend very little time actually presenting snow depth results for the two snow-on flights. I do think the uncertainty discussion is important and relevant, but so is the snow depth results, and more time should be spent on them. Also, snow water equivalent is only mentioned briefly at the end, this should be an entire results in the section and the measurement of densities should be covered in the methods. An estimate of SWE for the two flights would be really interesting.

Response We agree that SWE comparisons are of great interest, and that is the focus of ongoing work, hence only briefly presented here. We have added more detail around measurement of densities, and the SWE results to this discussion point, but have kept this brief to maintain emphasis on assessment of the performance of RPAS photogrammetry, and the resolution of spatial variability in snow depth, which is the primary motivation for this work.

(Minor note, on pg 9, line 29 the authors say the nominal accuracy for snow probes is +/- 1 cm, if this is from the literature it should have a citation, because I understand it to be much larger due mostly to user error, which they themselves recognize, in detail, later.)

Response We agree that accuracy was not the best term in this case and have replaced it with precision – that being defined by the interval of graduations on the probes used. We agree that user error, and sampling uncertainty (e.g., presence of vegetation below the snow pack) may substantially limit the accuracy of probe measurements.

-It is quite obvious that one of the authors has a thorough understanding of statistics. It gets tedious, and in these sections/figures most readers will just skip over. I would suggest for each relevant result adding 1 plain language summary before diving into the details to improve readability. 'Uncertainty is larger for more rapid changes in topography'.

Response We have amended the text to improve clarity and bring forward the emphasis on key findings.

-It is not clear to me why the authors spend so much space in terms of text and figures on georeferencing errors with older software when it could be covered in a few sentences, and more time could spent on more relevant results (i.e. the gist of this is that the old software had large errors, the new software performs better, so the old software should be avoided). This would also reduce the number of figures (there are so many).

Response We believe the discussion of the relative performance of software is an important one, especially in the case of a relatively new methodology, such as RPAS photogrammetry, where commercially available software packages are commonly implemented. We have edited this section to make it more concise, and have reduced the number of figures here by two. We have merged the original Figures 12 and 15, and deleted Figure 13. As the reviewer rightly notes, such software packages are becoming increasingly accessible and widely used, but given the non-trivial nature of photogrammetry, we believe the emphasis on the significant impact of a small error is warranted. The error detected highlights a fundamental problem in the implementation of the photogrammetric solution in commercial software, emphasising the need for vigilance when using such products. The specific error detected here has the potential to be particularly problematic in applications of this methodology to snow studies, as there will often be no means to determine and apply an empirical correction.

General editing comments: Writing structure and grammar need some attention, as they were notable enough to distract from the science being presented. The first paragraph of the Intro needs to be rewritten to read more consistently and should introduce the context and motivation for this study specifically. All paragraphs should be at least three sentences in length. There are many run on sentences that made reading and interpreting intent challenging. Watch out for the use of colloquial terms in a scientific context ('hamper' or 'impair' for something that is a challenge or difficult, the use of the word 'see' or 'saw' for things that don't have eyes). A small but related note, I associate the term epoch with geologic time scales (a division of time that is a subdivision of a period and is itself subdivided into ages, corresponding to a series in chronostratigraphy), I suggest not using this term and in most places through out the text it is unnecessary. For overall readability of the technical sections it might be useful to think about what content contributes to the overall purpose of the study given the audience (like equations 1-5, I don't find these critical to include, interested readers could be provided with a reference to follow up with). It maybe useful to have someone that is a physical scientist, but not involved in the study, read through the paper and give feedback.

Response Thank you for the important feedback. We have made substantial edits to the text to improve clarity and readability. We have reduced the usage of epoch throughout the manuscript. We have retained equations 1-5 as they underscore some of the later findings and discussion points and are fundamental to the application of photogrammetry. This is addressed in more detail in response to reviewer one.

References

James, L. A., Hodgson, M. E., Ghoshal, S. and Latiolais, M. M. (2012): 'Geomorphic change detection using historic maps and DEM differencing: The temporal dimension of geospatial analysis', Geomorphology, 137(1), pp. 181–198. doi: 10.1016/j.geomorph.2010.10.039.

Nolan, M., Larsen, C. and Sturm, M. (2015): 'Mapping snow depth from manned aircraft on landscape scales at centimeter resolution using structure-from-motion photogrammetry', The Cryosphere, 9(4), pp. 1445–1463. doi: 10.5194/tc-9-1445-2015.

Sims, C. and Orwin, J. F. (2011): 'Snowmelt generation on a hydrologically sensitive mountain range, Pisa Range, Central Otago, New Zealand', Journal of Hydrology (NZ), 50(2), pp. 383–405.

Repeat mapping of snow depth across an alpine catchment with RPAS photogrammetry~~Mapping snow at very high spatial resolution with RPAS photogrammetry~~

Todd A. N. Redpath[1,2], Pascal Sirguey[2], Nicolas J. Cullen[1]

[1]Department of Geography, University of Otago, Dunedin, 9016, New Zealand
[2]National School of Surveying, University of Otago, Dunedin, 9016, New Zealand

Correspondence to: Todd A. N. Redpath (todd.redpath@otago.ac.nz)

Abstract. Dynamic in time and space, seasonal snow represents a difficult target for ongoing *in situ* measurement and characterisation. Improved understanding and modelling of the seasonal snowpack requires mapping snow depth at fine spatial resolution. The potential of remotely piloted aircraft system (RPAS) photogrammetry to resolve spatial variability of snow depth is evaluated within an alpine catchment of the Pisa Range, New Zealand. Digital surface models (DSMs) at 0.15 m spatial resolution in autumn (snow-free reference) winter (02/08/2016) and spring (10/09/2016) allowed mapping of snow depth via DSM differencing. The consistency and accuracy of the RPAS-derived surface was assessed by the propagation of check point residuals from the aero-triangulation of constituent DSMs, and via comparison of snow-free regions of the spring and autumn DSMs. The accuracy of RPAS-derived snow depth was validated with *in situ* snow probe measurements. Results for snow free areas between DSMs acquired in autumn and spring demonstrate repeatability, yet also reveal that elevation errors follow a distribution that substantially ~~departing~~ departs from a normal distribution, symptomatic of the influence of DSM co-registration and terrain characteristics on vertical uncertainty. Error propagation saw snow depth mapped with an accuracy of ±0.08 m (90% c.l.). This is lower than the characterization of uncertainties on snow-free areas (±0.~~13~~ 14 m). Comparisons between RPAS and *in situ* snow depth measurements confirm this level of performance of RPAS photogrammetry, while also highlighting the influence of vegetation on snow depth uncertainty and bias. Semi-variogram analysis revealed that the RPAS outperformed systematic *in situ* measurements in resolving fine scale spatial variability. Despite limitations accompanying RPAS photogrammetry, which are relevant to similar applications of surface and volume change analysis, this study demonstrates a repeatable means of accurately mapping snow depth for an entire, yet relatively small, hydrological ~~basin~~catchment (~0.4 km^2), at very high resolution. Resolving snowpack features associated with re-distribution and preferential accumulation and ablation, snow depth maps provide geostatistically robust insights into seasonal snow processes, with unprecedented detail. Such data will enhance understanding of physical processes controlling spatial distribution of seasonal snow, and their relative importance at varying spatial and temporal scales.

1 Introduction

~~Water storage within a snowpack is a function of snow depth and density.~~ Seasonal snow provides a globally important water resource (Mankin et al., 2015; Sturm et al., 2017), which is highly variable in space and time (Clark et al., 2011). Difficulties associated with collecting field observations ~~hamper in characterising~~limit the characterisation and understanding of spatial variability in snow depth, and, in turn, our ability to improve ~~improving~~ spatially distributed modelling of seasonal snow. While insight can be gained via modelling at moderate to large scales (Winstral et al., 2013), resolving the fine-scale variability and its controlling processes remains limited by the ability to capture such variability in the field (Clark et al., 2011). Since water storage within a snowpack is a function of snow depth and density, and the former exhibits higher spatial variability than the latter, advances in measuring snow depth at high spatial resolution offer promise for improved estimates of snow water equivalent (SWE) (Harder et al., 2016).~~The labour intensive nature of collecting widespread *in situ* measurements of snow depth has resulted in a focus on quantifying snow distribution at, or near, to the time of peak accumulation (Kerr et al., 2013), which may limit inferences regarding controlling processes operating earlier in the accumulation season.~~

~~). Because snow depth exhibits higher spatial variability than snow density, advances in measuring snow depth at high spatial resolution offers promise for improved estimates of snow water equivalent (SWE) (Harder et al., 2016).~~

~~Difficulties associated with collecting field observations hamper in characterising and understanding spatial variability in snow depth, and in turn improving spatially distributed modelling of seasonal snow. While insight can be gained via modelling at moderate to large scales (Winstral et al., 2013), resolving the fine-scale variability and its controlling processes remains limited by the ability to capture such variability in the field (Clark et al., 2011). The labour intensive nature of collecting widespread *in situ* measurements of snow depth has resulted in a focus on quantifying snow distribution at, or near, to the time of peak accumulation (Kerr et al., 2013), which may limit inferences regarding controlling processes operating earlier in the accumulation season.~~

Historically, studies of seasonal snow processes have relied on *in situ* observations. With biweekly temporal resolution, Anderson et al. (2014) gained substantial insights into physical controls on seasonal snow processes, albeit with a dependence on statistical scaling to relate transect scale observations to basin scale processes. Alternatively, the nature of automated snow measurement instrumentation often precludes continuous *in situ* measurement across networks sufficiently dense to characterise fine scale spatial variability. Kinar and Pomeroy (2015) provide a comprehensive review of instrumentation and techniques for measuring snow depth and characterising snow packs. In summary, while instrumentation and methodologies exist for obtaining accurate, and temporally continuous, measurements of snow depth and related snowpack properties at point locations, adequately resolving the high spatial variability of snow depth remains a challenge. This is exacerbated by local field conditions, such as exposure to wind or the complexity of the topography and vegetation increasing further the spatial variability in snow depth (Clark et al., 2011; Kerr et al., 2013; Winstral and Marks, 2014).

Remote sensing has provided substantial advances in quantification of seasonal snow variability, with imaging sensors supporting spatial and temporal resolutions that allow a range of scales to be explored. Space-borne satellite imagers,

~~particularly optical sensors,~~ provide a synoptic view and accompanying step-change capability in capturing properties of snow covered areas, although trade-offs exist between competing spatial, spectral and temporal resolutions ~~(Dozier, 1989; Nolin and Dozier, 1993; Hall et al., 2002, 2015; Sirguey et al., 2009; Rittger et al., 2013)~~(Dozier, 1989; Nolin and Dozier, 1993; Hall et al., 2002, 2015; Sirguey et al., 2009; Malenovský et al., 2012; Rittger et al., 2013; Roy et al., 2014; Bessho et al., 2016). ~~For example, the MODerate resolution Imaging Spectroradiometer (MODIS) permits near-daily mapping of snow covered area (SCA) at continental to global spatial scales, although relatively coarse spatial resolution limits the inferences that can be made regarding fine scale spatial variability and leads to uncertainty in subsequent applications, such as assimilation into hydrological models. The advance of geostationary meteorological satellites such as Himawari 8 & 9 sees comparable spatial resolution to MODIS acquired in near real-time (Bessho et al., 2016). Contemporaneously, multispectral sensors such as Sentinel-2 and Landsat 8 continue to improve the temporal resolution of imagery suitable for mapping snow at resolutions of 10 – 30 m (Malenovský et al., 2012; Roy et al., 2014).~~ Passive and active microwave sensors offer the capacity to retrieve estimates of snow water equivalent directly from space-borne platforms, but also suffer substantial limitations, including coarse spatial resolution in the case of passive microwave sensors, and complexities in successfully processing snow signals and accounting for complex terrain in the case of both passive and active sensors (Lemmetyinen et al., 2018).

Despite the progress in ~~mapping SCA~~remotely mapping snow, reliable determination of snow depth, particularly in complex terrain, remains challenging. Modern, very high resolution stereo-capable imagers show promise for retrieving snow depth over large areas~~,~~ from space, although the influence of topography on uncertainties, and complications introduced by shadows in alpine terrain demand attention (Marti et al., 2016).

Advances in Light Detection and Ranging (LiDAR) technologies have become increasingly relevant for measurement of snow depth, firstly from air (Deems et al., 2013; Painter et al., 2016) and more recently from space-borne platforms (Treichler and Kääb, 2017). Of the three modes of LiDAR data capture, Terrestrial Laser Scanning (TLS) (e.g., Revuelto et al., 2016) offers the best performance in terms of precision and accuracy. TLS can resolve snow depth at a fine scale across relatively large areas, but remains ~~hampered~~ limited by view-obstruction and logistical challenges of placing equipment *in situ* in complex terrain~~,~~. ~~and logistical challenges of placing equipment *in situ* may limit deployment.~~ Airborne LiDAR provides a balance of spatial resolution and accurate surface elevation measurement and, combined with density estimates, can provide SWE estimates at the catchment scale across substantial areas of hundreds of square kilometres (Painter et al., 2016)~~,~~. ~~but h~~High financial costs and logistical challenges, however, ~~impair~~ preclude regular airborne LiDAR data capture in many regions globally. Treichler and Kääb (2017) assessed ICESat LiDAR data, which is designed primarily for measuring surface elevation~~s~~ over polar regions, ~~for measuring~~to characterise seasonal snow depth in sub-polar southern Norway. Despite reasonable estimates of snow depth, measurements were accompanied by relatively large errors for most temperate locations. ICESat measurements are ~~further~~ also limited by their punctual nature and footprint, yielding a relatively sparse and coarse spatial distribution, in turn complicating inferences about spatial variability.

~~Merit remains in characterising fine scale variability in snow depth distribution beyond the typical spatial scales of *in situ* measurements. Overcoming this challenge will enhance efforts to understand the processes controlling spatial variability of~~

~~snow distribution at the basin scale, and improve understanding of the relative importance of meteorological and topographic controls of seasonal snow distribution.~~

Recent technological advances, including the miniaturisation of imaging and positioning sensors, as well as improvements in battery power and autonomous navigation have significantly lowered the barriers associated with remotely piloted aircraft system (RPAS, also known as "unmanned aerial systems", UAS, and "unmanned aerial vehicles", UAV) operation (Watts et al., 2012). This, combined with ever-increasing computing power and significant improvements in machine-vision for dense photogrammetric reconstruction~~s~~ (Hirschmuller, 2008; Lindeberg, 2015) provides new opportunities to map small areas photogrammetrically at very high resolution in a temporally flexible, on-demand, fashion~~ using RPAS~~. Examples of RPAS use related to mapping snow depth are promising, but tend to apply to sub-~~basin~~catchment scales and to not fully characterise the uncertainty associated with ~~measurements~~ photogrammetric modelling (Vander Jagt et al., 2015; Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016, Cimoli et al., 2017; Avanzi et al., 2018). Furthermore, most RPAS studies of snow depth to date have mapped terrain of relatively low complexity (e.g., Avanzi et al., 2018; Fernandes et al., 2018). Additionally, with a few exceptions (e.g., Harder et al., 2016; Bühler et al., 2017; Marti et al., 2016), previous studies have often relied on multi-rotor platforms despite their relatively short endurance and reduced spatial coverage relative to fixed-wing alternatives. Merit remains in characterising fine scale variability in snow depth distribution across an entire catchment, a scale that fixed-wing RPAS can more easily capture. However, increased terrain complexity, and the magnitude of the image block, can, in turn, challenge photogrammetric modelling.

Determination of snow depth via RPAS photogrammetry relies first on the reconstruction of three-dimensional scenes from a set of overlapping images, and then on the principal of differencing between temporally subsequent surfaces, provided by point clouds or digital surface models (DSM) (Vander Jagt et al., 2015; Harder et al., 2016). A snow-free surface provides a reference dataset for absolute snow depth, while changes in snow distribution through winter can be assessed by comparing surfaces obtained while snow cover is present in the ~~basin~~catchment. Because changes in snow depth through time, either through processes of accumulation, ablation, or re-distribution may be subtle, the repeatability and vertical accuracy achieved by photogrammetric modelling is paramount.

The aim of this paper is to test a methodology for retrieving snow depth across an entire catchment via RPAS photogrammetry from a fixed-wing platform. ~~and~~ We seek to evaluate the performance, limitations and usefulness of this approach, and assess how well snow depth can be resolved at the catchment scale. Associated challenges include minimising spatial uncertainties sufficiently to reliably detect changes in snow depth over time, with a decimetre level of vertical accuracy targeted, while also reducing the need and complication of extensive *in situ* collection of ground control points (GCPs). ~~Achieving this will resolve spatial variability in snow depth with improved detail compared to traditional methods, supporting improved insights into snowpack evolution. To this end,~~This approach was assessed during a campaign of winter RPAS-based photogrammetric surveys of ~~a small~~an alpine ~~basin~~catchment in the Pisa Range, New Zealand, was undertaken.

The paper describes the field site, field and photogrammetric methods, as well as the ~~approach to~~ quality and accuracy assessment. Results are considered in terms of the validation and repeatability of the method, as well as considering the spatial distribution of snow within the catchment.~~ before presenting the results both in terms of the photogrammetric derivation of snow depth and the assessment of the quality and accuracy of derived snow depth maps.~~ The discussion addresses the performance of RPAS photogrammetry in this context, sources and nature of the associated uncertainty as well as pitfalls and limitations that were encountered, before demonstrating the insight that RPAS-derived data can provide for the study of seasonal snow. While primarily exploring and assessing the potential of RPAS photogrammetry for measuring seasonal snowpack, this study has broader implications for the wider field of modern close-range photogrammetry, as typically implemented from low cost (relative to manned systems), unmanned systems. ~~Through scrutinising the performance of the RPAS system and associated software, and investigating potential sources of uncertainty, beyond those inherent in the aero-triangulation itself, this paper demonstrates some of the limitations and pitfalls that may affect~~While considered here in terms of seasonal snow, the characterisation of RPAS photogrammetry performance presented also applies to~~, particularly in applications~~ other applications involving three-dimensional surface and/or volume change analysis.

2 Study site

The study ~~basin~~catchment (Figure 1), a tributary of the Leopold Burn located in the Pisa Range of the Southern Alps/Kā Tiritiri-o-te-Moana of New Zealand (44.882°S, 169.081°E), is 0.41 km^2 in size, ~~and,~~ and has been the subject of prior snow-hydrology investigations (Sims and Orwin, 2011). Elevation of the ~~basin~~catchment ranges between 1440 and 1580 m a.s.l. with a near-uniform area-elevation distribution (Figure 1**)**. Average slope is moderate, with 80% of the ~~basin~~catchment having a surface slope of 24° or less. The ~~basin~~catchment runs north to south, and is drained by a small stream. While east of the Main Divide of the Southern Alps, the Pisa Range is representative of several large fault-block mountain ranges that dominate the eastern portion of the Clutha Catchment within the Otago region. These ranges are bounded by moderately steep slopes, rising to broad continuous ridge and plateau systems, in turn dissected by relatively shallow gullies, basins and gorges. These ranges feature relatively large areas above the winter snowline, with complex micro-terrain features, which are of interest in the context of re-distribution, preferential accumulation, and ablation of seasonal snow. In combination with typically windy conditions, the topography is expected to produce complex, highly variable spatial distributions of seasonal snow, convolved with, and potentially overtaking the role of elevation in influencing variability in snow depth. The ~~basin~~catchment mapped in this study is larger than areas mapped for other similar studies published to date (Vander Jagt et al., 2015; Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016), and has a relatively complex topography, with several gullies dissecting the main slopes, separated by broad, steep sided ridges.

~~A visual~~ Visual assessment of Landsat, Sentinel-2, and MODIS imagery revealed that while the ~~basin~~catchment could be considered to be in the marginal snow zone, snow cover persists from June to late September most years, thus providing opportunities for repeated mapping and the capture of the snowpack in various states.

3 Data and methods

3.1 Field approach

3.1.1 RPAS platform and payload

We used the Trimble UX5 Unmanned Aircraft System, a fixed wing RPAS manufactured by Trimble Navigation for photogrammetric applications. A single two-blade propeller, driven by a 700 W electric motor, propels the platform. Power is supplied from a 14.8 V, 6000 mAh Lithium-polymer battery allowing a flight endurance of 50 minutes. Autonomous navigation is supported by a single channel GPS receiver, which also provides approximate coordinates for each photo centre, while an accelerometer logs orientation data.

Imagery is captured by a large-sensor (APS-C) Sony NEX 5R mirrorless reflex digital camera providing a maximum imaging resolution of 4912 pixels by 3264 pixels, or about 0.04 ~~c~~m GSD at 400 ft (122 m) a.g.l. The camera is fitted with a Voigtländer Super Wide-Heliar 15 mm f/4.5 Aspherical II lens, with focus fixed to infinity. Appropriate exposure to ensure suitable contrast on the range of imaged targets was achieved with maximum aperture, high shutter speeds between 1/~~2500~~1000-1/4000 sec to minimize forward motion blurring, and automatic ISO sensitivity. Camera settings were checked prior to each flight to accommodate varying light conditions and the relative share of ground cover (vegetation vs. snow).

3.1.2 RPAS flights

Three RPAS missions were undertaken with identical planning and differing states of snow cover in the ~~basin~~catchment (Table 1). Flight planning was carried out using the Trimble Aerial Imaging software. All flights imaged 15 strips, aligned along the major axis of the study ~~basin~~catchment (Figure 2). The study area was imaged with 90/80% forward/sideward overlap with respect to the lowest elevation to ensure that sufficient overlap was maintained when mapping rising ground. Exposure locations are determined automatically by the software to achieve the desired overlap, with the camera being triggered accordingly during flight using on board GNSS navigation. The duration of each flight was ~35 minutes, with about 900 images being captured per flight. Average flying altitude of the flights was 1650 m a.s.l., with a standard deviation less than 1.5 m during the mapping phase of the flight. For both the winter and spring flights, the snow surface had considerable texture, with a greater surface roughness overall for winter missions. Wind-affected recent fresh snow was present for the winter flight. It is recognised that homogeneous snow surfaces may represent particularly challenging targets for photogrammetry (Bühler et al., 2017). Nevertheless, the imaging quality and dynamic range of the camera used in this study provided sufficient contrast for all flights, across snow as well as when imaging mixed snow-bare ground conditions. Subsequently, full photogrammetric restitution could be completed without the need for image post-processing (e.g., Cimoli et al., 2017).

3.1.3 Ground control survey

Achieving a robust constraint of exterior orientation parameters during aero-triangulation (AT) depends on the availability of a set of high-quality ground control points (GCPs). This is particularly true where the imaging platform lacks precise point positioning (PPP) capability (e.g., it carries only single frequency GPS and is not capable of determining differentially corrected positions). Such code-only GPS navigation is accompanied by uncertainties two orders of magnitude greater than the expected accuracy of the models. Ground control networks were established for each RPAS flight mission using real time kinematic (RTK) Global Navigation Satellite System (GNSS) surveying with a Trimble R7 base station and R6 rover units. GCP locations were measured with accuracy on the order of ~0.02-0.03 ~~c~~m. GCPs were signalled with 0.6 × 0.6 m mats painted with a high contrast circular quadrant pattern for the autumn and winter flights. For the spring flight, chalk powder was used with a stencil to mark the target directly on the snow surface, using the same pattern as for previous flights. The use of chalk powder eliminated the need to retrieve GCP targets following RPAS flights. All survey work, as well as production of deliverables from photogrammetry, was carried out in terms of the New Zealand Transverse Mercator (NZTM) reference system. All RTK survey work utilised a base station established on a common benchmark, established for this project, the position of which was differentially corrected with respect to nearby continually operating reference stations (CORS). GNSS data were processed using Trimble Business Center (TBC) v3.40 software.

It is well established that photogrammetric control is best achieved within the bounds of the GCP network (Linder, 2016), while the uncertainty associated with the geo-location of resected points increases beyond the control network. To constrain the area within the study ~~basin~~catchment for photogrammetric processing, the GCP network was distributed around the ~~basin~~catchment perimeter, as well as through the central area of the ~~basin~~catchment. Additionally, placement of GCPs on the valley floor and at mid-elevation within the ~~basin~~catchment ensured that the network also sampled the elevation range of the ~~basin~~catchment. An extensive GCP network was established for the first flight with no snow on the ground, which permitted the robustness of AT to be tested under different GCP scenarios, as discussed further in Section 3.2.1. This allowed the network to be refined and reduced in size for subsequent missions, a matter of practical importance when working in alpine areas during the winter. Control point networks for each mission are illustrated in Figure 2. A new GCP network was established for each survey campaign due to the inability to establish permanent markers (e.g., on poles) due to the conservation status of the study area. Although the layout of the network was similar for each mission, there were no common GCPs shared between different flights, with the only common setting being the setup of the base station for each RTK survey.

3.1.4 ~~In situ~~ Reference snow depth measurements

To assess the quality of snow depth data derived from RPAS photogrammetry, independent measurements were collected by manual snow probing on 10/09/2016, the same day as the spring RPAS mission. This approach has been established as standard practice in similar studies (e.g., Nolan et al., 2015; De Michele et al., 2016). Aluminium avalanche probes with 0.01 m graduations, providing a nominal precision of 0.01 m, were used. The sampling strategy involved the measurement of snow depth every 50 m along three elevation contours within the study ~~basin~~catchment, namely 1460, 1500 and 1540 m (Figure 2). This strategy ensured that snow depth was measured across a representative sample of slope aspect and elevation, while optimizing navigation across the ~~basin~~catchment. Snow depths were measured at each location by probing five times within arm reach, and the location of the central measurement surveyed with RTK GNSS, under the same protocol and achieving the same level of accuracy as the GCP survey. This provided 430 measurements of snow depth, with the mean snow depth at each of the 86 locations providing a sample for comparisons with RPAS-derived snow depth.

3.2 Data processing

3.2.1 Photogrammetric processing

The goal of aero-triangulation (AT) in photogrammetry is to transform a set of images into a scene in which geometrically accurate measurements can be made in three dimensional, often geographic, space. This geo-referencing process requires a transformation from the inherent coordinate system of the device capturing imagery (a camera) to an appropriate geographic coordinate system (Vander Jagt et al., 2015; Linder, 2016). While traditional photogrammetry has long relied on metric (calibrated) cameras, the use of off-the-shelf non-metric cameras requires the simultaneous solving of both interior orientation (the camera model) and exterior orientation. This process, known as self-calibration, applies a bundle-block adjustment to solve the camera model describing the precise focal length (f), the offset between the principal point of autocollimation (PPA) and the centre of the imaging sensor plane (x_0, y_0), and the departure between the image point coordinate (x,y) and the idealized linear projection due to lens distortion. Camera calibration parameterises radial and decentering distortion with models such as that of Brown 1971:

$$\begin{aligned} \bar{x}' &= (1 + K_1 r^3 + K_2 r^5 + K_3 r^7)\bar{x} + 2T_1\overline{xy} + T_2(r^2 + 2\bar{x}^2) \\ \bar{y}' &= (1 + K_1 r^3 + K_2 r^5 + K_3 r^7)\bar{y} + 2T_2\overline{xy} + T_1(r^2 + 2\bar{y}^2)' \end{aligned} \quad (1)$$

in which K terms are the radial distortion coefficients, T terms are the tangential distortion coefficients, and

$$\bar{x} = x - x_0, \quad (2)$$

$$\bar{y} = y - y_0, \quad (3)$$

$$r = \sqrt{\bar{x}^2 + y^2}. \quad (4)$$

Image coordinates corrected for lens distortion are then used in the set of collinearity equations relating object point coordinates (X_A, Y_A, Z_A) to the corresponding image point coordinates ($\bar{x}_A{}'$, $\bar{y}_A{}'$) to solve for the exterior orientation (Vander Jagt et al., 2015; Linder, 2016):

$$\begin{pmatrix} \bar{x}_A{}' \\ \bar{y}_A{}' \end{pmatrix} = \begin{pmatrix} f\dfrac{r_{11}(X_A-X_0)+r_{12}(Y_A-Y_0)+r_{13}(Z_A-Z_0)}{r_{31}(X_A-X_0)+r_{32}(Y_A-Y_0)+r_{33}(Z_A-Z_0)} \\ f\dfrac{r_{21}(X_A-X_0)+r_{22}(Y_A-Y_0)+r_{23}(Z_A-Z_0)}{r_{31}(X_A-X_0)+r_{32}(Y_A-Y_0)+r_{33}(Z_A-Z_0)} \end{pmatrix}. \quad (5)$$

(X_0, Y_0, Z_0) are the coordinates of the perspective centre of the image frame in the ground coordinate system. The r_{ij} terms represent the 3×3 rotation matrix relating the sensor coordinate system orientation to the ground coordinate system. Since the UX5 camera is fixed with respect to the platform, the latter combines the roll, pitch and yaw (ω, φ, κ) of the platform at the time of exposure. The nature of bundle block adjustment with camera self-calibration dictates that the quality of the final photogrammetric model is highly sensitive to errors in both sensor position and orientation, as well as inaccurate refinements of the interior orientation parameters (Ebner and Fritz, 1980)

3.2.2 Software and workflow

Initially, ~~aero-triangulation~~AT was carried out using the photogrammetry module of Trimble Business Center, v3.40 (TBC), which relies on a~~n~~ simplified implementation of the adjustment process from Inpho UAS Master. Deliverables produced using TBC, however, suffered from severe elevation artefacts which limited their usefulness for further analysis. ~~These pitfalls are~~This is discussed further in Section 5.3.

~~Subsequent to~~Following the identification of shortfalls in TBC, ~~aero-triangulation~~AT was carried out using Trimble Inpho UAS Master® v8.0 (UAS Master). UAS Master is a feature rich photogrammetry package that is targeted to RPAS applications (Trimble, 2015~~,~~; 2016), and is a comprehensive alternative to software often used in similar studies such as Pix4D or Agisoft Photoscan. The AT solution is initialised by the positional parameters (X_0, Y_0, Z_0) for each photo centre, as provided by the on-board GPS receiver. Relative adjustment is achieved after automatic tie point (TP) collection ~~of tie points (TPs)~~. TPs are common targets recognised in multiple overlapping images, which allow the relative position and orientation of images within the block to be determined. Subsequent measurement of GCP~~s~~ positions in images ~~allows~~ enables the absolute adjustment. GCPs may be collected manually or automatically via feature recognition. In this case, targets marking GCPs were identified, and selected manually. The ~~that~~ absolute bundle block adjustment then concurrently refines the exterior and interior orientation~~, as well as solves for the~~ interior orientation parameters.

The robustness of photogrammetric modelling was assessed ~~via evaluation of~~by testing several alternate control scenarios, based on the autumn~~first~~ mission when 23 GCPs were placed and measured in the field. ~~This assessment aided the determination of an optimal number of GCPs to minimise the time required to place and survey control points when snow is present in the basin.~~ The following scenarios were evaluated:

1. All 23 control points as horizontal and vertical GCPs
2. 14 control points as horizontal and vertical GCPs
3. 6 control points as horizontal and vertical GCPs

In each scenario, the balance of the control points was provided as check points (CP). In retaining GCPs, we ensured that the perimeter of the study catchment remained fully constrained within the network.~~, and a~~ As the number of GCPs decreased, ~~the magnitude of~~ the Root Mean Square Error (RMSE) for CPs ~~was used to assess triangulation~~provided an indication of AT robustness. It was found that as few as 14 GCPs provided an acceptable triangulation across the study area, with some degradation apparent when only ~~6~~six GCPs were used, primarily in terms of z (Table 2). No spatial structure was evident in the distribution of GCP or CP error. This assessment aided the determination of an optimal number of GCPs to minimise the time required to place and survey control points when snow is present in the ~~basin~~catchment. On this basis, 14 control points were placed and measured in the field for each of the winter and spring missions. ~~, with eight of those set as horizontal and vertical GCPs, and the remaining six as CPs.~~For all missions, the AT from which deliverables were produced utilised all surveyed points as GCPs. A second AT was carried out using a subset of control points as CPs, as shown in Table 3. Thus, the

RMSE provided by CPs is expected to be conservative compared to the quality of the deliverables obtained from the fully constrained AT.

3.2.3 Intermediate ~~D~~deliverables

Standard deliverables from the photogrammetric modelling included a dense point cloud; a digital surface model, interpolated to 0.15 m spatial resolution; and an ortho-mosaic, resampled to 0.05 m spatial resolution. The digital surface model (DSM) and the ortho-mosaic are the principal products for further analysis. The DSM for each epoch provides the basis for determining snow depth, while the ortho-mosaics allow for assessment of the snow-covered area, and for snow-free areas to be identified when assessing the quality and repeatability of DSMs between flight missions. ~~Deliverables were generated from photogrammetric models utilising all surveyed points as GCPs in the aero-triangulation. A second aero-triangulation was then run using a subset of control points as CPs based on scenario 2 from Table 2. Thus, the RMSE provided from CPs is expected to be conservative compared to the quality of the deliverables obtained from the fully constrained AT.~~

3.2.4 Derivation of snow depth

Snow depth was derived by differencing DSM of flights 2 and 3 from the baseline obtained during flight 1 (*ref*) as:

$$dDSM_n = DSM_n - DSM_{ref}. \qquad (6)$$

Equation 6 provides a map of difference between the two DSMs, henceforth referred to as the dDSM (after Nolan et al., 2015). Values of the dDSM are considered to represent snow depth, with associated uncertainty considered in Section 3.3.

3.3 Quality and accuracy assessment

Summary statistics, typically based on the RMS error of GCPs and CPs from the ~~aero-triangulation~~AT, indicate the expected accuracy of deliverables. Since snow depth is determined by differencing two DSMs, error propagation can provide an assessment of uncertainty associated ~~uncertainty~~with the dDSM ~~should be determined via error propagation~~. The overall accuracy of the DSM differencing approach~~,~~ should also be validated against independent reference data (e.g., snow depth measured *in situ*), temporally coincident with RPAS measurements. Areas of snow-free terrain during Flight 3 further supplement snow depth observations by providing an extensive source of samples to assess the repeatability of the photogrammetric modelling process.

Previous studies have considered the accuracy of RPAS-derived snow depth by comparison with reference data from *in situ* snow depth alone (Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016), while ignoring the uncertainty inherent to each photogrammetric model and their propagation into the dDSM. Here, the accuracy of photogrammetrically derived snow depth is assessed by exploring both approaches. Relating photogrammetric model quality, as inferred from GCPs/CPs, to observed uncertainties in the determination of snow depth provides the basis for realistically informing uncertainties in snow depth from ongoing RPAS measurements. This in turn allows rigorous inferences about the evolution of snow depth to be made, without the need for further campaigns of *in situ* validation. While high resolution reference elevation data, such as Lidar derived elevation or surface models would provide a useful benchmark for assessing RPAS DSM quality, no such data were available for the study area.

3.3.1 Uncertainty associated with RPAS-derived snow depth

Since snow depth is determined via DSM differencing as a linear combination of two independently measured variables (Equation 6), the uncertainty associated with snow depth (SD), measured in the vertical dimension, for each epoch (n) can be obtained via Gaussian error propagation (James et al., 2012) as:

$$\varepsilon_{dDSM} = \sqrt{\varepsilon_n^2 + \varepsilon_{ref}^2}, \qquad (7)$$

where ε for each DSM is the elevation error determined from the ~~aero-triangulation~~AT as the $RMSE_Z$ value for the set of CPs. Inherent in this ~~This~~ simple approach ~~assumes~~ is the assumption that the planimetric ~~precision~~ accuracy of each constituent DSM has negligible contribution to ε_{dDSM}. Calculating ε_{dDSM} provides a single estimate of uncertainty assumed to apply equally throughout the map of RPAS-derived snow depth for each epoch. Under the assumption that errors are normally distributed and bias-free, the $RMSE_z$ derived from CPs identifies to standard deviation σ_z, allowing the 90% confidence level of z to be determined as $1.65\times\sigma_Z$. In turn, inferences associated with uncertainties for elevation differences, ε_{dDSM}, also depend on the Gaussian assumption to provide the 90% confidence level.

In reality, perfect co-registration between constituent DSMs, and the Gaussian assumption, are unwarranted. Subsequently, inferences associated with the evolution of snow depth may be compromised due to confidence intervals being conservative or immoderate. Therefore, we use dDSM for snow-free areas to characterise the experimental distribution of errors and assess the validity of the Gaussian assumption in this context.

3.3.2 Validation against reference ~~*in situ*~~ snow depth measurements

The approach above provides a means to determine the expected accuracy of snow depth derived from RPAS photogrammetric surveys. In order to validate this estimate, a reference dataset of *in situ* observations was sampled in the field using snow probes, with a nominal ~~accuracy~~ precision of ± 0.01 ~~c~~m, as described in Section 3.1.4. De Michele et al (2016) assessed the accuracy of RPAS-derived snow depths against snow depth surfaces interpolated from 12 point measurements. This approach, however, may be limited by an inability to accurately resolve the spatial variability of snow depth, as well as the compounding effects of uncertainty associated with the interpolation scheme, particularly beyond the domain defined by the measured points.

Here, 430 measurements of snow depth provided 86 mean reference values, with the standard deviation of each set of five measurements providing 95% confidence intervals. The aim of this sampling strategy was to assess and account for co-location uncertainty and spatial variability between the RPAS and reference snow depth datasets. Reference snow depths were compared with those from the spatially coincident pixels from the map of RPAS-derived snow depth. RPAS-derived snow depth quality was assessed in terms of residuals and weighted linear regression between reference and RPAS-derived snow depths.

3.3.3 Repeatability of photogrammetric modelling

Emergence of snow-free areas at the time of the spring flight facilitated comparison between autumn and spring DSMs on those areas. As the same terrain surface mapped from two independent flights should yield identical DSMs, the residual between them provides a means to characterise the distribution of errors in the photogrammetric processing, which can be readily compared to the assessment made from CPs. ~~Ultimately, this residual represents a measure of the repeatability of the technique for measuring surface height change.~~

Snow-covered and snow-free areas were segmented using an unsupervised classification of the spring ortho-image using the *Iso Cluster* classification tool in ArcGIS v10.3~~,~~. With five output classes, this approach enabled ~~to~~ discriminat~~e~~ion between illuminated snow pixels, shaded snow pixels, and vegetation and soil dominated snow-free pixels. Snow-free pixel classes were then grouped to provide a mask within which the distribution of spring dDSM~~3~~ values could be characterized. While this approach relies on characterisation of repeatability for snow areas, good image contrast and the high overall density of TPs generated across the image block, regardless of the presence or absence of snow, indicates that photogrammetric reconstruction performance should be comparable for both snow-free and snow-covered areas. This is a product of the camera properties, which maintain high dynamic range across scenes of mixed land cover and extensive snow cover. ~~Ultimately~~Therefore, this residual represents a measure of the repeatability of the technique for measuring surface height change, including derivation of snow depth.

3.3.4 Resolution of fine scale spatial variability

A primary motivation for exploring the use of RPAS photogrammetry for mapping a snow pack is the ability to resolve fine scale spatial variability in snow depth. This capability was assessed by computing and comparing the semi-variograms of reference and RPAS-derived snow depths from the autumn flight. While the sample size for reference snow depths remained fixed (n=86), the semi-variogram of RPAS-derived snow depths could be calculated from many more samples. Two random samples were extracted from the spring dDSM~~3~~ map (n = 1000 and n = 5000), each yielding a semi-variogram capturing the spatial variability of snow depth with increasing detail, which were compared to that of the *in situ* observations.

4 Results

4.1 Photogrammetric processing

4.1.1 Quality of the triangulation

~~RMSE for GCPs for all flights was at the centimetre to sub-centimetre level (~~

~~RMSE for GCPs for all flights was at the centimetre to sub-centimetre level (Table 3).~~ Since GCPs are used to solve the photogrammetric model, they do not provide an independent assessment of accuracy. Such an assessment is provided by the CPs, the RMSE of which was on the order of centimetres for all flights (Table 3). Planimetric RMSE (i.e., x and y) was always substantially less than the GSD. Vertical RMSE (z) tended to be about double that achieved planimetrically, but never exceeded 0.05 ~~c~~m. The final models were produced from a second and more constrained AT with all surveyed points used as GCPs, thus making the assessment conservative relative to the final products.

While the RMSE of CPs increased for the winter and spring ~~epochs~~flights, possibly due to a less constrained model, the level of accuracy achieved is compatible with expectations for the determination of snow depth. Additionally, the more tightly constrained first ~~epoch~~ AT reduced the error for the baseline model, in turn contributing a reduced uncertainty in derived snow depths, despite the reduced control for subsequent ~~epochs~~ATs. For all flight missions, the photogrammetric processing performed well in the correlation of images and the construction of the image block, as indicated in Table 3. Tie point (TP) generation relies on the successful match of unique targets across multiple images, which was achieved despite the complicated contrast over snow. For all flights >80,000 TPs were generated across the imaged area.

4.1.2 Determination of snow depth

Snow depth was found to be highly variable across the study ~~basin~~catchment for both ~~epochs two and three~~winter and spring (Figure 3). The mid-winter ~~epoch exhibited~~flight mapped near complete snow cover across the study ~~basin~~catchment, while large snow-free areas developed ~~in~~ by the spring ~~epoch~~flight, where snow covered area was reduced by about one third (Figure 3 A & B). Where snow was present, depths ranged from ~~a few centimetres~~less than 0.10 m, typically on exposed ridgelines and broad elevated slopes, to two metres or more where cornices formed along ridgelines, as well as in gullies. Average snow depth was greater ~~at the winter epoch~~for winter, although maximum depths were comparable between ~~both epochs~~winter and spring. Between winter and spring, considerable ablation was observed. Areas of deepest snow were spatially coincident between winter and spring, with the greatest retention of snow in cornices and gullies. Where shallow snow was present on ridgelines in winter, it was largely lost by spring.

4.2 Accuracy assessment and validation of snow depth

4.2.1 Propagation of aero-triangulation error

Propagation of errors under the Gaussian assumption, based on the RMSE from each ~~aero-triangulation~~AT, yielded vertical uncertainties for snow depths at the 90% confidence level of ±0.077 m for the winter flight and ±0.084 m for the spring flight. This one-dimensional approach to error propagation assumes that the planimetric geolocation of individual surfaces, and subsequently the co-registration of surface pairs does not contribute significantly to the vertical uncertainty.

4.2.2 Assessment against reference probe data

Comparison of RPAS-derived and reference snow depth yielded a mean residual of -0.06~~.~~9 ~~c~~m, indicating that, on average, reference depths were greater than RPAS-derived depths. Filtering the reference dataset to exclude reference measurements that were made in areas occupied by tussock (*Chionochloa rigida*) vegetation, however, improved the mean residual to -0.01 ~~c~~m (Figure 4A). The small residual is indicative of good agreement between the two datasets, while also indicating that overall, snow depths measured by probing may be overestimated. Limitations of probing and uncertainty introduced due to the presence of vegetation is discussed further in Section 5.2.1.

Good agreement between both datasets is further demonstrated in Figure 4B. Relatively large horizontal error bars accompanying the reference measurements (Figure 4B) reflect the substantial spatial variability in snow depth measured by probing, even within arm's reach. Substantial departure occurs for reference snow depths between 0.20 and 0.60 ~~c~~m which tend to exceed RPAS measurements. Negative depths in the RPAS-derived dataset is a product of co-registration uncertainty, particularly in areas where the surface model represents large vegetation, or is influenced by rock outcrops, as well as spurious values from the constituent DSMs. Agreement between reference and RPAS-derived datasets improved with the removal of reference measurements made above ~~of~~ tussocks. This filtering saw the R^2 value improve by 22%, while RMSE decreased by 23% (Table 4). The 1:1 ratio line was contained within the 95% confidence interval of the weighted (bisquare) regression between RPAS-derived and filtered reference snow depths. Some disagreement between RPAS derived and probed snow depths is likely due to the varying areas over which snow depth was sampled by the two techniques, and resulting spatial uncertainty in comparing the two datasets.

4.2.3 Comparison of DSMs from independent RPAS flights

The emergence of snow-free areas for the September flight permitted a comparison of height derived on snow-free surfaces between the pre-winter and spring flights (Figure 5). The small magnitude of the residuals, compatible with errors consistent with the uncertainty of the triangulation CPs, demonstrates the repeatability in the derivation of snow-free surfaces. Furthermore, the absence of any spatially structured trend in the distribution of the residual indicates robust photogrammetric modelling from the RPAS platform. At 0.15 m resolution, the snow-free pixels from the spring mission provided a large sample (n = 5936428). The mean residual (bias) detected with respect to the pre-winter DSM was 0.024 m (σ = 0.239 m) (Figure 6~~Figure 6~~).

The set of residuals departed substantially from the Gaussian distribution, and was better represented by the Student's t location-scale distribution (Figure 6~~Figure 6~~):

$$f(x) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sigma\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)}\left(\frac{v+\left(\frac{x-\mu}{\sigma}\right)}{v}\right)^{-\left(\frac{v+1}{2}\right)}, \quad (9)$$

where μ, σ and v are the location, scale and shape parameters, respectively. Large kurtosis (calculated k = 1956) associated with the histogram of residuals in Figure 6~~Figure 6~~ shows significant departure from a Gaussian law (for which k = 3) of equal standard deviation, σ. The leptokurtic experimental distribution results in a narrower 90% confidence interval than that estimated under the Gaussian assumption with σ = 0.24 ~~c~~m, while the probability of large residuals is larger than predicted by a Gaussian distribution. Overall, the mean residual (μ = 0.02 ~~c~~m) and the precision of ±~~13~~ 0.14 ~~c~~m (90% confidence level, calculated from the distribution 90th percentile, (Figure 6) exceeds the uncertainties estimated from error propagation alone (±0.08 ~~c~~m at 90% confidence level, see Section 4.1.1), yet support the suitable repeatability of the photogrammetric modelling. Importantly, the significant departure from a normal distribution shows that assessing the variability from a Gaussian fit on stable targets (±0.39 ~~c~~m at the 90% level) would significantly overestimate the confidence interval. On the other hand, the 90% confidence interval calculated from the fitted Student's t location-scale is ±0.10 ~~c~~m (Table 5). The significance of this result with respect to statistical inferences is discussed further in Section 5.2.2.

The non-Gaussian nature of the residual distribution deserves further scrutiny. Similar distributions have been identified for comparable repeatability assessments of photogrammetric dDSMs used for mapping snow depth (Nolan et al., 2015), but have not been explored in detail. Analysing the variability of the mean and standard deviation of the residual, as well as the kurtosis of the residual distribution, for discrete classes of slope, provided insight into the role of terrain. For classes of slope up to 65° the mean residual remains within the standard error, before becoming increasingly negative for the remaining classes (Figure 6~~Figure 7~~). Standard deviation exhibits a similar trend, remaining largely within the overall standard error for slope classes up to 45°, beyond which variability increases.

The observed pattern in the mean and standard deviation of the residual indicates that larger and more variable errors are associated with steeper slopes. Reduced kurtosis accompanying the error distribution on larger slopes (Figure 6~~Figure 7~~) reveals a tendency towards a Gaussian distribution of residuals as mean slope increases. Here, for slopes >50°, kurtosis was reduced below 100, and for slopes >85°, kurtosis was less than 10, approaching that of the normal distribution. Therefore, the statistical distribution of error, whilst non-normal, also varies significantly with terrain characteristics, as highlighted by comparison of the residual histogram for discrete classes of slope (Figure 7~~Figure 8~~). Subsequently, the overall distribution of residuals ((Figure 5B~~Figure 6~~) is the result of a convolution between non-normal distributions and the hypsometry of the area (i.e., area-elevation distribution).

4.2.4 Characterising the spatial variability of snow depth

The semi-variograms for RPAS-derived snow depth, compared to that from the reference measurements, are shown in Figure 8~~Figure 9~~. They exemplify the new insight that high-resolution mapping provides into the spatial variability of snow depth. Both the 1000 and 5000 random point samples captured a comparable structure of spatial auto-correlation with a range of ca. 40 m. The 5000-point sample improved the resolution of the semi-variogram, with an improved signal to noise ratio. In contrast, the reference data, despite being demanding in fieldwork, performed poorly at capturing the spatial variability, as most measurements were separated by a minimum distance of 50 m. A lack of spatial auto-correlation in the reference data confirms a-posteriori that probing samples could be assumed to be independent of each other, which is desirable for the accuracy assessment. Additionally, it also reveals that probing failed to capture most of the spatial structure of the snow depth field, thus stressing a limitation of this classical method to characterise the snowpack.

5 Discussion

5.1 Performance of RPAS photogrammetry for resolving snow depth

Overall, RPAS photogrammetry ~~has been~~is found to be suitable for determining snow depth via DSM differencing. Primarily, the achievement of uncertainties <0.~~13~~ 14 m at the 90% confidence level for derived snow depth, demonstrated empirically by the repeatability analysis (Figure 5), ~~for derived snow depth~~ provides a basis for useful data capture, and robust inferences and interpretations. The reported magnitude ~~-~~of uncertainties account for the sources discussed further below, and compare favourably with other similar studies (Vander Jagt et al., 2015; Bühler et al., 2016; De Michele et al., 2016; Harder et al., 2016). Decimetre levels of uncertainty appear to be an emerging benchmark for snow depths measured by RPAS photogrammetry, and also considered as standard for airborne LiDAR (Deems et al., 2013). In terms of comparisons with *in situ* data, Figure 4 shows good agreement between RPAS and reference snow depth, and that RPAS photogrammetry performance improves as snow depth increases. At the same time, use of probed snow depths as references for validating such data can be compromised by the nature of the underlying vegetation.

Mapping snow depth continuously at 0.15 m resolution, across an entire hydrological ~~basin~~catchment, represents a new contribution to the quantification and characterisation of spatial variability in snow depth at this scale, which is up to two orders of magnitude greater than many similar studies to date. Before considering the broader implications of this in terms of snow processes, uncertainty, limitations, and pitfalls of the approach are considered.

5.2 Sources and nature of uncertainty

5.2.1 Vegetation

Vegetation contributes to uncertainty, particularly when validating RPAS-derived snow depths against reference snow depths. As described in Section 4.2.2, the agreement between RPAS-derived and probed snow depths improved substantially when ~~considered only away from~~areas of large tussock vegetation were excluded. It is likely that the presence of tussock introduces a bias into the snow depth measurement, whereby a probe may penetrate the tussock foliage, and possibly also a sub-vegetation void, before striking the ground surface. This is similar to the cavity effect highlighted for airborne LiDAR measurement of snow (Painter et al., 2016), and ~~S~~similar challenges have been documented by Vander Jagt et al. (2015). High resolution dDSMs, on the other hand, resolve the vegetation surface, and so vegetation height is inherently better accounted for.

As identified by Nolan et al. (2015), photogrammetrically-derived snow depths may also be affected by the compaction of vegetation below the snowpack, which may introduce an anomalous signal of surface height change, to the point of returning false negative snow depths. Correcting observed surface height change would not be straightforward, and is not possible with the data acquired within this study. The effects of vegetation compaction are likely to be greatest in the early winter. As grass typically does not rebound until after the complete removal of the winter snowpack, ongoing subsidence of vegetation below the snowpack through mid-winter and spring is expected to be minimal. Ongoing future measurement of snow depth via surface differencing (regardless of the source of DSMs) will benefit from the development and incorporation of vegetation compaction and cavity models.

Ultimately, this study suggests that for areas dominated by tussock vegetation, RPAS photogrammetry may provide a more reliable means of measurement than probing. A lack of knowledge regarding the specific location of sub-snow vegetation when making measurements by probing is likely to provide a systematic over-estimation of snow depth (Figure 4). In the New Zealand context, almost all seasonal snow occurs above the treeline, so the inability of photogrammetry to penetrate forest canopy is a lesser concern than for the Northern Hemisphere.

5.2.2 Geo-location and co-registration

In mapping snow depth across a catchment with relatively complex terrain, we have been able to characterise the influence of terrain on dDSM uncertainty. The assumption that error ~~distribution~~ associated with physical measurements is normally distributed ~~normal~~ often underpins subsequent statistical inferences. As demonstrated in Section 4.2.3, the error associated with the bias between independently acquired DSMs significantly departed from normal, and was better approximated by the Students *t* location-scale distribution. This extremely leptokurtic distribution of residuals reflects the influence of relatively low frequency, but high magnitude residuals beyond the probability of the normal law, despite an overall dominance of residuals about and close to the mean. A possible source of large residuals between two DSMs is their relative planimetric accuracy, and subsequent co-registration quality (Kääb, 2005). For steep terrain in particular, a horizontal displacement between DSMs could add a component to dDSM uncertainty beyond the vertical accuracy of constituent DSMs. The residual (Δh) between two surface profiles, which are identical but horizontally displaced by 0.5 m, is shown in Figure 9~~Figure 10~~A. The error introduced to DSM differencing resulting from co-registration uncertainty increases with steepening slope. Maximum residuals coincide with the steepest terrain (near vertical areas associated with rock outcrops), and exceed two metres. The sign of the error is aspect dependent, assuming a uniform horizontal displacement.

Consistent with Kääb (2005), the vertical error introduced by a uniform, one-dimensional (e.g., horizontal) offset, is given by:

$$\Delta h = dx \tan\theta, \tag{9}$$

where dx is the offset between transects (i.e., 0.5 m in this case), and θ is the surface slope in degrees, as seen in Figure 9~~Figure 10~~B. It is clear from Figure 9~~Figure 10~~B that where the average slope of target surfaces is low and co-registration quality is good, the error introduced to a dDSM as a product of co-registration will be minimal. Increasing slope and/or co-registration uncertainty is accompanied by increased vertical uncertainty in the dDSM. This relationship is consistent with the findings of Section 4.2.3 resulting in the distribution of residuals departing substantially from the Gaussian distribution when the proportion of steep slopes is low. These findings provide context for the effect noted by Nolan et al. (2015), whereby a non-normal distribution of residuals associated with photogrammetric mapping of snow depth was found to narrow further when the area considered was restricted to a frozen lake (i.e., near planar) surface.

Complicating this effect is the fact that co-registration uncertainty exists in two dimensions. Subsequently, it will become dependent on aspect as well as slope (Nuth and Kääb, 2011), with neither possessing a uniform spatial distribution. This effect is expected to be more pronounced with very high resolution (i.e., sub-metre) surface models due to a greater frequency and magnitude of breaks in surface slope being resolved compared to coarser models. The modification of surface slope for constituent DSMs (e.g., through the addition of snow) further convolves the propagation of vertical uncertainty. Despite this, the leptokurtic observed error distribution indicates that the reliance on statistics that assume a Gaussian distribution of errors will provide an over-estimated characterisation of the expected accuracy. Over-estimation of uncertainties may in turn affect statistical inferences and the computation of uncertainties on derived parameters.

~~Despite this, the leptokurtic observed error distribution indicates that the reliance on statistics that assume a Gaussian distribution of errors will provide an over-estimated characterisation of the expected accuracy. Over-estimation of uncertainties may in turn affect statistical inferences and the computation of uncertainties on derived parameters.~~

The convolution of vertical and planimetric accuracy stresses the importance of ensuring a robust ~~aero-triangulation~~ATs and the benefits of utilising high quality ground control. With new photogrammetric platforms leveraging non-metric cameras and resulting image blocks prone to sub-optimal photogrammetric modelling (Sirguey et al., 2016), there is a need to be wary of systematic bias, or spatial structure, in the distribution of errors, which may not be revealed readily by residuals from the ~~aero-triangulation~~AT alone. These considerations are especially important where a relatively high level of precision is required, and the signal to noise ratio may be low, when assessing relatively subtle surface height and/or volume changes from dDSMs. Utilising independent ~~aero-triangulation~~ATs as the control of co-registration quality, rather than explicitly co-registering DSMs, has the further advantage~~s~~ of simplifying the processing chain from data acquisition to change detection, mitigating against the risk of introducing gross error when co-registering DSMs and avoiding the need for snow-free (or stable) reference areas within the analysis region.

5.3 Pitfalls and limitations of RPAS photogrammetry

Initial processing, using the photogrammetry module of Trimble Business Center (v3.40) produced strong striping artefacts in the dDSM. Striping involved a periodic bias in surface height change, aligned with the 15 image strips. This was readily revealed ~~due to~~because identical flight plans between successive ~~epochs~~ surveys ~~making~~ made constructive errors obvious, rather than convoluted with terrain variability. This systematic error was severe and problematic, particularly when considering the surface change resulting from the addition of snow cover to the ground. ~~Changing surface height~~Extensive snow cover concealed stable references, precluding characterisation of the error and its empirical removal from the real signal of surface height change (e.g., Albani and Klinkenberg, 2003; Berthier et al., 2007). Products derived using UAS Master (v8.0) did not exhibit such artefacts, allowing the potential source ~~of the systematic error to be explored~~of error associated with AT from TBC to be investigated~~, and highlighting potential pitfalls in RPAS photogrammetry.~~.

The ~~lack~~ absence of systematic bias in dDSMs derived ~~from processing in~~using UAS Master indicates ~~that the latter provides~~ a more reliable ~~aero-triangulation~~AT. Thus, the UAS Master triangulation provided a reference surface for further exploration of the nature of the bias propagated in the TBC triangulation. Comparisons ~~are provided~~ from the winter flight are presented here. Given the nature of the photogrammetric problem, small errors in either or both interior orientation, as described by the camera calibration, or the rotational components of the exterior orientation (i.e., roll, pitch, yaw; ω, φ, κ, respectively), can result in large errors in the adjusted image block with a spatially structured pattern (Sirguey et al., 2016).

~~Firstly, interior orientation was assessed by comparing~~ Cimoli *et al.*, (2017) reported an improved performance in mapping snow depth with the application of a radial lens distortion correction. In our case, no significant difference was detected between the distortion models provided for each of the two software calibrations of the same camera, for the same flight. ~~No significant difference was detected~~ (Figure 11A).~~,~~ ~~with only a~~Minimal ~~small~~ divergence in lens distortion ~~occurring at~~was observed beyond ~~>~~10 mm radius, reaching 1% at 14.5 mm. ~~The observed a~~Agreement between lens distortion models indicated that ~~a difference in the~~differing interior orientation solutions between TBC and UAS Master was not the source of the artefacts seen in products of the TBC triangulation.

Since the observed artefact was propagated along the flight lines, the ~~nature of the~~ roll parameter (ω) was considered. Bias in the estimation of this parameter could lead to a systematic elevation offset of resected points between flight lines, either raising or lowering the terrain alternatively, as documented in the case of stereo-satellite imagery by Berthier et al. (2007). Occurrence of this for multiple flights with near identical flight lines would exacerbate ~~the~~ constructive biases, resulting in the striping in the dDSM. Alternatively, pitch and yaw parameters are unlikely to produce such an artefact along the flight direction (Ebner and Fritz, 1980). The residual of ω for individual photo centres between each of the two software packages confirmed a positive bias existed in the ω value as estimated by TBC v3.40 relative to that provided by UAS Master~~(Figure 13)~~. The mean residual ($\overline{r\theta}$) was found to be 0.014°.

The impact of bias in ω on the resected height h for a target with respect to a photo centre can be estimated simply as a right-angle triangle, since values of ω are small compared to the baseline length, l, which is equal to half the distance between adjacent flight lines (see Figure 12):

$$\tan\theta = \frac{h}{l}, \tag{10}$$

$$\tan(\theta - \overline{r\theta}) = \frac{h-\Delta h}{l}, \tag{11}$$

$$\Delta h = h - l\tan(\overline{r\theta}), \tag{12}$$

$$\Delta h = h - l\tan\left(\arctan\frac{h}{l}\ \overline{r\theta}\right). \tag{13}$$

Using the observed value of 0.014° for $\overline{r\theta}$, Δh was calculated for a range of typical values of h, yielding the relationship between h and Δh as shown in ~~Figure 15~~Figure 11B. Bias in the estimation of the ω parameter during the ~~aero-triangulation~~AT ~~has the potential to~~can introduce a significant vertical error, dependent (non-linearly) on flying height (h), propagating an error of ±0.12 m at a flying height of 110 m. The increase in error with flying height above ground level was consistent with the observed propagation of striping artefacts in DSM products, whereby the magnitude of the observed bias decreased as terrain height increased (Figure 10), while absolute flying height remained approximately constant.

The observed propagation reinforces the need for vigilance when working with such datasets, particularly those delivered from “off the shelf” photogrammetry packages, which are becoming increasingly popular. Artefacts such as the striping identified here, and evidence of non-optimal ~~aero-triangulation~~AT, are likely to be less obvious as the complexity of the mapped terrain increases. As RTK GPS equipped RPAS become more common, increased precision of initial AT parameters may mitigate the risk of error introduced by spurious solutions for refined parameters. Currently, however, RTK systems have an increased power demand, which can substantially reduce flight time. Overall,

5.4 Spatial and temporal trends in snow cover

Figure 8~~Figure 9~~ demonstrates the new insight that RPAS photogrammetry can provide over probing for resolving spatial variability in snow depth, particularly at fine scales. Therefore, RPAS photogrammetry can provide a basis for improving spatially distributed snowpack models. In turn, this contribution will further improve understanding of seasonal snow processes, where there has been a dependency on point-based observations over glaciers to characterise atmospheric controls on seasonal snow (e.g., Cullen and Conway, 2015). While knowledge of the atmospheric controls on ablation processes has improved (Conway and Cullen, 2016), our understanding of the redistribution of snow and preferential accumulation have not kept pace.~~ including redistribution, preferential accumulation and ablation~~ RPAS photogrammetry represents a valuable avenue for determining how these processes are represented in existing and new snow and glacier models, which will enable short-term hydrological forecasts and climate projections in snow-covered areas to be improved. Such data can also facilitate the use of geostatistical approaches for examining controls on spatial distribution of snow, such as that applied to the Brewster Glacier, New Zealand (Cullen et al., 2017). In this case, the density of measurements provides insights into spatial variability at scales that would allow consideration of terrain and meteorological controls on snow distribution at micro-scales, extending understanding beyond the spatial co-variance between snow depth and elevation.

The ability to resolve fine scale variability reliably from continuous raster snow maps lessens the dependence on interpolation through areas of sparse data for interpreting controls on spatial distribution of snow. While previous studies have been able to correlate between snow and terrain properties (e.g., Anderson et al., 2014), such studies rely on the inference of ~~basin~~catchment scale processes from transect scale observations. The ability to produce spatially continuous maps of snow depth, across an entire ~~basin~~catchment, at a resolution of 0.15 m bridges this gap and reduces the reliance on inferences when scaling up from point- or transect-based *in situ* observations to ~~basin~~catchment scale processes. Such datasets provide an opportunity to build on previous work in understanding the relationships between snow re-distribution, preferential accumulation and ablation, terrain and meteorology (Winstral et al., 2002, 2013; Webster et al., 2015; Revuelto et al., 2016). While RPAS photogrammetry is severely limited in spatial scale compared to airborne LiDAR~~Furthermore~~, resolving snow depth in this way across an entire ~~basin~~catchment facilitates robust integration into hydrological models, enhanced by validation against catchment discharge (e.g., from stream flow data).

The mapping of snow depth effectively provides a volumetric view of the snow pack across the ~~basin~~catchment (i.e., depth × area), the snow pack mass balance in terms of SWE can be calculated based on *in situ* measurements of snow density. While snow depth was only determined for two epochs in this case, emergent trends within the data can be explored. Between the winter and spring flights, the ~~basin~~catchment snow covered area (SCA) decreased from 100%, to 67%. Bulk snowpack densities, measured gravimetrically at a single snow pit for the winter flight (314 kg $m^{3\ -1}$), and two snow pits for the spring flight (391 kg $m^{3\ -1}$), allow catchment SWE to be ~~Simultaneously, SWE~~ calculated ~~using density measured from snow pits at both epochs, decreased by~~, revealing a 20% reduction in SWE between flights. This highlights the importance of effective concentration of snow in preferred areas, and the complex spatial distribution that results. The ability to detect this, even with a temporally limited dataset, indicates the potential for RPAS photogrammetry as a measurement approach for improving resolution and understanding of snow hydrology. In particular, such datasets may offer a unique opportunity to assess the performance of models forced by remotely sensed data of coarser resolution in estimating SWE from estimates of sub-pixel fractional SCA (Bair et al., 2016).

6 Conclusions and outlook

This study has demonstrated that RPAS photogrammetry provides a suitable, repeatable means of reliably determining snow depth in an alpine ~~basin~~catchment of low relief, but possessing some terrain complexity. Achieving decimetre level accuracy for measuring snow depth provides a basis for monitoring ~~of a~~ seasonal snowpacks and associated processes, especially considering the capacity to provide very high resolution, spatially continuous measurements across an entire hydrological ~~basin~~catchment. Such ability to characterise the seasonal snowpack will provide an important stepping-stone for improved modelling of seasonal snow and associated processes, especially through accurate mapping of an entire hydrological ~~basin~~catchment.

Challenges encountered through this deployment provide important points for consideration in this and other applications of close-range photogrammetry, especially from RPAS platforms, for surface and volume change analysis. Specifically, small but persistent bias in photogrammetric solutions for the roll parameter exemplify the possibility of sub-optimal solutions in processing software. Such bias can introduce substantial systematic errors which may be difficult to ~~correct, and~~correct and can compromise further analysis.

We show that uncertainty analysis from the ~~aero-triangulation~~AT only, and based on a limited number of check points, may underestimate the uncertainty. Alternatively, an assessment of repeatability of photogrammetric modelling on stable ground can support a more detailed uncertainty analysis. It reveals, however, that the statistical distribution of the error of differentiated surface models is more complex than normal and governed by terrain parameters. The leptokurtic residual distribution demonstrates that an assumption of Gaussian law can substantially overestimate confidence intervals, in turn compromising inferences. This result has important practical applications to the computation of uncertainties in studies that characterise volume change from repeated surface modelling.

Finally, there is scope to further refine the characterisation of uncertainty associated with RPAS photogrammetry in order to ensure that all potential sources of error are captured, and that statistical analysis is appropriate to the distributions within underlying data. Existing methods for mitigating the impact of co-registration uncertainty of coarser products may permit modelling and correction of such errors in the very ~~high resolution~~high-resolution products that are now available.

Acknowledgments

The authors are grateful to those who provided assistance in the field: Julien Boeuf, Kelly Gragg, Mike Denham, Craig MacDonell, Aubrey Miller, Sam West, Thomas Ibbotson and Alia Khan. Sean Fitzsimons provided helpful feedback on the draft manuscript. This research was carried out under Department of Conservation Research & Collection Authorisation 53609-GEO. This research was funded by a University of Otago Doctoral Scholarship with support from the Department of Geography and an internal grant of the National School of Surveying, as well as a Fieldwork Grant from the New Zealand Hydrological Society.

Author contributions

TR and PS designed the study and collected the data. TR processed and analysed the data and wrote the manuscript with input from PS and NC. PS and NC supervised the research.

References

Albani, M. and Klinkenberg, B. (2003): ‘A spatial filter for the removal of striping artifacts in digital elevation models’, Photogramm. Eng. Rem. S., 69(7), pp. 755–765. doi: 10.14358/PERS.69.7.755.

Anderson, B. T., McNamara, J. P., Marshall, H.-P. and Flores, A. N. (2014): ‘Insights into the physical processes controlling correlations between snow distribution and terrain properties’, Water. Resour. Res., 50(6), pp. 4545–4563. doi: 10.1002/2013WR013714.

Avanzi, F., Bianchi, A., Cina, A., De Michele, C., Maschio, P., Pagliari, D., Passoni, D., Pinto, L., Piras, M. and Rossi, L. (2018): ‘Centimetric accuracy in snow depth using unmanned aerial system photogrammetry and a multistation’, Remote Sensing, 10(5), pp. 1–16. doi: 10.3390/rs10050765.

Bair, E. H., Rittger, K., Davis, R. E., Painter, T. H. and Dozier, J. (2016): ‘Validating reconstruction of snow water equivalent in California’s Sierra Nevada using measurements from the NASA Airborne Snow Observatory’, Water. Resour. Res., 52(11). doi: 10.1002/2016WR018704.

Berthier, E., Arnaud, Y., Kumar, R., Ahmad, S., Wagnon, P. and Chevallier, P. (2007): ‘Remote sensing estimates of glacier mass balances in the Himachal Pradesh (Western Himalaya, India)’, Remote Sens. Environ., 108(3), pp. 327–338. doi: 10.1016/j.rse.2006.11.017.

Bessho, K., Date, K., Hayashi, M., Ikeda, A., Imai, T., Inoue, H., Kumagai, Y., Miyakawa, T., Murata, H., Ohno, T., Okuyama, A., Oyama, R., Sasaki, Y., Shimazu, Y., Shimoji, K., Sumida, Y., Suzuki, M., Taniguchi, H., Tsuchiyama, H., Uesawa, D., Yokota, H., Yoshida, R. (2016): 'An Introduction to Himawari-8/9 - Japan's New-Generation Geostationary Meteorological Satellites', J. Meteorol. Soc. Jpn. Ser. II, 94(2), pp. 151–183. doi: 10.2151/jmsj.2016-009.

Brown, D. C. (1971): 'Close-range camera calibration', Photogramm. Eng., 37(8), pp. 855–866. doi: 10.1.1.14.6358.

Bühler, Y., Adams, M. S., Bosch, R. and Stoffel, A. (2016): 'Mapping snow depth in alpine terrain with unmanned aerial systems (UASs): Potential and limitations', The Cryosphere, 10(3), pp. 1075–1088. doi: 10.5194/tc-10-1075-2016.

Bühler, Y., Adams, M. S., Stoffel, A. and Boesch, R. (2017): 'Photogrammetric reconstruction of homogenous snow surfaces in alpine terrain applying near-infrared UAS imagery', International Journal of Remote Sensing. Taylor & Francis, 38(8–10), pp. 3135–3158. doi: 10.1080/01431161.2016.1275060.

Clark, M. P., Hendrikx, J., Slater, A. G., Kavetski, D., Anderson, B., Cullen, N. J., Kerr, T., Hreinsson, E. Ö. and Woods, R. A. (2011): 'Representing spatial variability of snow water equivalent in hydrologic and land-surface models : A review', Water. Resour. Res., 47. doi: 10.1029/2011WR010745.

Conway, J. P. and Cullen, N. J. (2016), 'Cloud effects on surface energy and mass balance in the ablation area of Brewster Glacier, New Zealand', The Cryosphere, 10, pp. 313–328. doi:10.5194/tc-10-313-2016,

Cullen, N. J. and Conway, J. P. (2015): 'A 22 month record of surface meteorology and energy balance from the ablation zone of Brewster Glacier, New Zealand', J. Glaciol., pp. 61, 931–946. doi:10.3189/2015JoG15J004.

Cullen, N. J., Anderson, B., Sirguey, P., Stumm, D., Mackintosh, A., Conway, J. P., Horgan, H. J., Dadic, R., Fitzsimons, S. J. and Lorrey, A. (2017): 'An 11-year record of mass balance of Brewster Glacier, New Zealand, determined using a geostatistical approach', J. Glaciol., 63(238), pp. 199–217. doi: 10.1017/jog.2016.128.

Deems, J. S., Painter, T. H. and Finnegan, D. C. (2013): 'Lidar measurement of snow depth: A review', J. Glaciol., 59(215), pp. 467–479. doi: 10.3189/2013JoG12J154.

Dozier, J. (1989): 'Spectral signature of alpine snow cover from the Landsat Thematic Mapper', Remote Sens. Environ., 22, pp. 9–22.

Ebner, H. and Fritz, L. (1980): 'Aerotriangulation', in Slama, C. C. (ed.) Manual of Photogrammetry. 4th edn. Falls Church, Va.: American Society of Photogrammetry, pp. 453–518.

Fernandes, R., Prevost, C., Canisius, F., Leblanc, S. G., Maloley, M., Oakes, S., Holman, K. and Knudby, A.: 'Monitoring snow depth change across a range of landscapes with ephemeral snow packs using Structure from Motion applied to lightweight unmanned aerial vehicle videos', The Cryosphere Discuss, https://doi.org/10.5194/tc-2018-82, in review, 2018.

Hall, D. K., Crawford, C. J., Di Girolamo, N. E., Riggs, G. A. and Foster, J. L. (2015): 'Detection of earlier snowmelt in the Wind River Range, Wyoming, using Landsat imagery, 1972 - 2013', Remote Sens. Environ.. Elsevier B.V., 162, pp. 45–54. doi: http://dx.doi.org/10.1016/j.rse.2015.01.032.

Hall, D. K., Riggs, G. A., Salomonson, V. V, Di Girolamo, N. E. and Bayr, K. J. (2002): 'MODIS snow-cover products', Remote Sens. Environ., 83, pp. 181–194. doi: http://dx.doi.org/10.1016/S0034-4257(02)00095-0.

Harder, P., Schirmer, M., Pomeroy, J. and Helgason, W. (2016): 'Accuracy of snow depth estimation in mountain and prairie environments by an unmanned aerial vehicle', The Cryosphere, 10(6), pp. 2559–2571. doi: 10.5194/tc-10-2559-2016.

Hirschmuller, H. (2008): 'Accurate and efficient stereo processing by semi-global matching and mutual information', IEEE. T. Pattern Anal., 2(2), pp. 807–814. doi: 10.1109/CVPR.2005.56.

Vander Jagt, B., Lucieer, A., Wallace, L., Turner, D. and Durand, M. (2015): 'Snow depth retrieval with UAS using photogrammetric techniques', Geosciences, 5, pp. 264–285. doi: 10.3390/geosciences5030264.

James, L. A., Hodgson, M. E., Ghoshal, S. and Latiolais, M. M. (2012): 'Geomorphic change detection using historic maps and DEM differencing: The temporal dimension of geospatial analysis', Geomorphology, 137(1), pp. 181–198. doi: 10.1016/j.geomorph.2010.10.039.

Kääb, A. (2005): Remote Sensing of Mountain Glaciers and Permafrost Creep. Zürich: Geographisches Institut der Universiturich, Zürich.

Kerr, T., Clark, M., Hendrikx, J. and Anderson, B. (2013): 'Snow distribution in a steep mid-latitude alpine catchment', Adv. Water Resour., 55, pp. 17–24. doi: 10.1016/j.advwatres.2012.12.010.

Kinar, N. J. and Pomeroy, J. W. (2015): 'Measurement of the physical properties of the snowpack', Rev. Geophys., 53, pp. 481–544. doi: 10.1002/2015RG000481.

Lemmetyinen, J., Derksen, C., Rott, H., Macelloni, G., King, J., Schneebeli, M., Wiesmann, A., Leppänen, L., Kontu, A. and Pulliainen, J. (2018): 'Retrieval of Effective Correlation Length and Snow Water Equivalent from Radar and Passive Microwave Measurements', Remote Sens-Basel, 10(2), p. 170. doi: 10.3390/rs10020170.

Lindeberg, T. (2015): 'Image Matching Using Generalized Scale-Space Interest Points', J. Math. Imaging Vis., 52(1), pp. 3–36. doi: 10.1007/s10851-014-0541-0.

Linder, W. (2016): Digital Photogrammetry: A Practical Course. 4th edn. Heidelberg: Springer.

Malenovský, Z., Rott, H., Cihlar, J., Schaepman, M. E., García-Santos, G., Fernandes, R. and Berger, M. (2012): 'Sentinels for science: Potential of Sentinel-1, -2, and -3 missions for scientific observations of ocean, cryosphere, and land', Remote Sens. Environ., 120, pp. 91–101. doi: 10.1016/j.rse.2011.09.026.

Mankin, J. S., Viviroli, D., Singh, D., Hoekstra, A. Y. and Diffenbaugh, N. S. (2015): 'The potential for snow to supply human water demand in the present and future', Environ. Res. Lett., 10(11). doi: 10.1088/1748-9326/10/11/114016.

Marti, R., Gascoin, S., Berthier, E., De Pinel, M., Houet, T. and Laffly, D. (2016): 'Mapping snow depth in open alpine terrain from stereo satellite imagery', The Cryosphere, 10(4), pp. 1361–1380. doi: 10.5194/tc-10-1361-2016.

De Michele, C., Avanzi, F., Passoni, D., Barzaghi, R., Pinto, L., Dosso, P., Ghezzi, A., Gianatti, R. and Vedova, G. Della (2016): 'Using a fixed-wing UAS to map snow depth distribution: An evaluation at peak accumulation', The Cryosphere, 10(2), pp. 511–522. doi: 10.5194/tc-10-511-2016.

Nolan, M., Larsen, C. and Sturm, M. (2015): 'Mapping snow depth from manned aircraft on landscape scales at centimeter resolution using structure-from-motion photogrammetry', The Cryosphere, 9(4), pp. 1445–1463. doi: 10.5194/tc-9-1445-2015.

Nolin, A. W. and Dozier, J. (1993): 'Estimating snow grain size using AVIRIS data', Remote Sens. Environ., 44, pp. 231–238. doi: http://dx.doi.org/10.1016/0034-4257(93)90018-S.

Nuth, C. and Kääb, A. (2011): 'Co-registration and bias corrections of satellite elevation data sets for quantifying glacier thickness change', The Cryosphere, 5, pp. 271–290. doi: 10.5194/tc-5-271-2011.

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P., Richardson, M., Skiles, S. M. K., Seidel, F. C. and Winstral, A. (2016): 'The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo', Remote Sensing of Environment, 184. doi: 10.1016/j.rse.2016.06.018.

Revuelto, J., Vionnet, V., López-Moreno, J. I., Lafaysse, M. and Morin, S. (2016): 'Combining snowpack modeling and terrestrial laser scanner observations improves the simulation of small scale snow dynamics', J. Hydrol, 533, pp 291-307. doi: 10.1016/j.jhydrol.2015.12.015.

Rittger, K., Painter, T. H. and Dozier, J. (2013): 'Assessment of methods for mapping snow cover from MODIS', Adv. Water Resour., 51, pp. 367–380. doi: http://dx.doi.org/10.1016/j.advwatres.2012.03.002.

Roy, D. P., Wulder, M. A., Loveland, T. R., C.E., W., Allen, R. G., Anderson, M. C., Helder, D., Irons, J. R., Johnson, D. M., Kennedy, R., Scambos, T. A., Schaaf, C. B., Schott, J. R., Sheng, Y., Vermote, E. F., Belward, A. S., Bindschadler, R., Cohen,

W. B., Gao, F., et al. (2014): 'Landsat-8: Science and product vision for terrestrial global change research', Remote Sens. Environ., 145, pp. 154–172. doi: 10.1016/j.rse.2014.02.001.

Sims, C. and Orwin, J. F. (2011): 'Snowmelt generation on a hydrologically sensitive mountain range, Pisa Range, Central Otago, New Zealand', Journal of Hydrology (NZ), 50(2), pp. 383–405.

Sirguey, P., Boeuf, J., Cambridge, R. and Mills, S. (2016): 'Evidence of sub-optimal photogrammetric modelling in RPAS-based aerial surveys', in Moore, A. and Drecki, I. (eds) Proceedings of the GeoCart'2016 and ICA Symposium on Cartography, pp. 91–98.

Sirguey, P., Mathieu, R. and Arnaud, Y. (2009): 'Subpixel monitoring of the seasonal snow cover with MODIS at 250 m spatial resolution in the Southern Alps of New Zealand: Methodology and accuracy assessment', Remote Sens. Environ., 113, pp. 160–181. doi: http://dx.doi.org/10.1016/j.rse.2008.09.008.

Sturm, M., Goldstein, M. A. and Parr, C. (2017): 'Water and life from snow: A trillion dollar science question', Water. Resour. Res., 53(5). doi: 10.1002/2017WR020840.

Treichler, D. and Kääb, A. (2017): 'Snow depth from ICESat laser altimetry — A test study in southern Norway', Remote Sens. Environ., 191, pp. 389–401. doi: 10.1016/j.rse.2017.01.022.

Trimble (2015): 'UAS Master 7.0: Tutorial'. Trimble Germany.

Trimble (2016): 'Release Notes for UASMaster 8.0.0'. Trimble Navigation Limited.

Watts, A. C., Ambrosia, V. G. and Hinkley, E. A. (2012): 'Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use', Remote Sens-Basel, 4(6), pp. 1671–1692. doi: 10.3390/rs4061671.

Webster, C. S., Kingston, D. G. and Kerr, T. (2015): 'Inter-annual variation in the topographic controls on catchment-scale snow distribution in a maritime alpine catchment, New Zealand', Hydrol. Process., 29(6), pp. 1096–1109. doi: 10.1002/hyp.10224.

Winstral, A., Elder, K. and Davis, R. E. (2002): 'Spatial Snow Modeling of Wind-Redistributed Snow Using Terrain-Based Parameters', J. Hydrometeorol., 3(5), pp. 524–538. doi: 10.1175/1525-7541(2002)003<0524:SSMOWR>2.0.CO;2.

Winstral, A. and Marks, D. (2014): 'Long-term snow distribution observations in a mountain catchment: Assessing variability, time stability, and the representativeness of an index site', Water. Resour. Res.. doi: 10.1002/2012WR013038.

Winstral, A., Marks, D. and Gurney, R. (2013): 'Simulating wind-affected snow accumulations at catchment to basin scales', Adv. Water Resour., 55, pp. 64–79. doi: 10.1016/j.advwatres.2012.08.011.

Table 1: Timing details for RPAS flights during 2016. All flights were completed between noon and early afternoon.

Mission/flight	Date	Season	Epoch	Snow cover	Sky conditions
M001f01	17/05/2016	Autumn	1	Minimal – remaining traces of early snowfall	Clear sky, light winds
M002f01	02/08/2016	Mid-winter	2	Extensive – winter snowpack, high surface roughness	Thin high cloud, light winds

M003f01	10/09/2016	Spring	3	Spring melt underway, extensive snow-free areas. Reduced snow surface roughness	Clear sky, light winds

Table 2: Summary results of alternative ground control point (GCP) and check point (CP) scenarios tested for aero-triangulation within UAS Master.

Scenario	GCP RMSE (m)				CP RMSE (m)			
	n	*x*	*y*	*z*	*n*	*x*	*y*	*z*
1	23	0.0069	0.0076	0.0055	0	N/A	N/A	N/A
2	14	0.0017	0.0010	0.0004	9	0.0119	0.0184	0.0320
3	6	0.0033	0.0039	0.0009	17	0.0263	0.0207	0.0575

Table 3: Summary statistics for each of the triangulations used to produce DSMs and ortho-mosaics from each of the three flight missions for ground control points (GCP) and check points (CP).

Flight	*n* images captured	*n* images used	*n* TP	GCP RMSE (m)				CP RMSE (m)			
				n	*x*	*y*	*z*	*n*	*x*	*y*	*z*
1	885	885	100,390	14	0.0083	0.0073	0.0034	9	0.0134	0.0163	0.0220
2	920	917	98,730	8	0.0067	0.0085	0.0018	6	0.0368	0.0293	0.0409
3	891	889	88,791	8	0.0105	0.0108	0.0028	6	0.0246	0.0247	0.0457

Table 4: Parameters of weighted regression between reference and RPAS-derived snow depths.

	n	β_0	β_1	RMSE	R^2	p-value
All points	86	0.92	0.80	14.7	0.67	0.000
Non-tussock	52	1.69	0.86	11.3	0.82	0.000

Table 5: Observed (calculated under Gaussian assumption) and fitted normal and t location-scale (t l-s) parameters for the residual distributions shown in Figure ~~6~~5B.

Parameter	Distribution	Value
	Observed	0.024
μ	Normal fit	0.036
	t l-s fit	0.019
	Observed	0.239
σ	Normal fit	0.236
	t l-s fit	0.056
ν	t l-s fit	2.579

Table 6: Observed (calculated under Gaussian assumption) and fitted normal and t location-scale (t l-s) parameters for the residual distributions shown in Figure ~~8~~7.

		Slope class	
Parameter	**Distribution**	**5 - 10°**	**70 - 75°**
	Observed	0.026	-0.022
μ	Normal fit	0.0257	-0.0217
	t l-s fit	0.0211	-0.118
	Observed	0.186	0.892
σ	Normal fit	0.186	0.8922
	t l-s fit	0.0463	0.3758
ν	t l-s fit	4.1037	2.0927

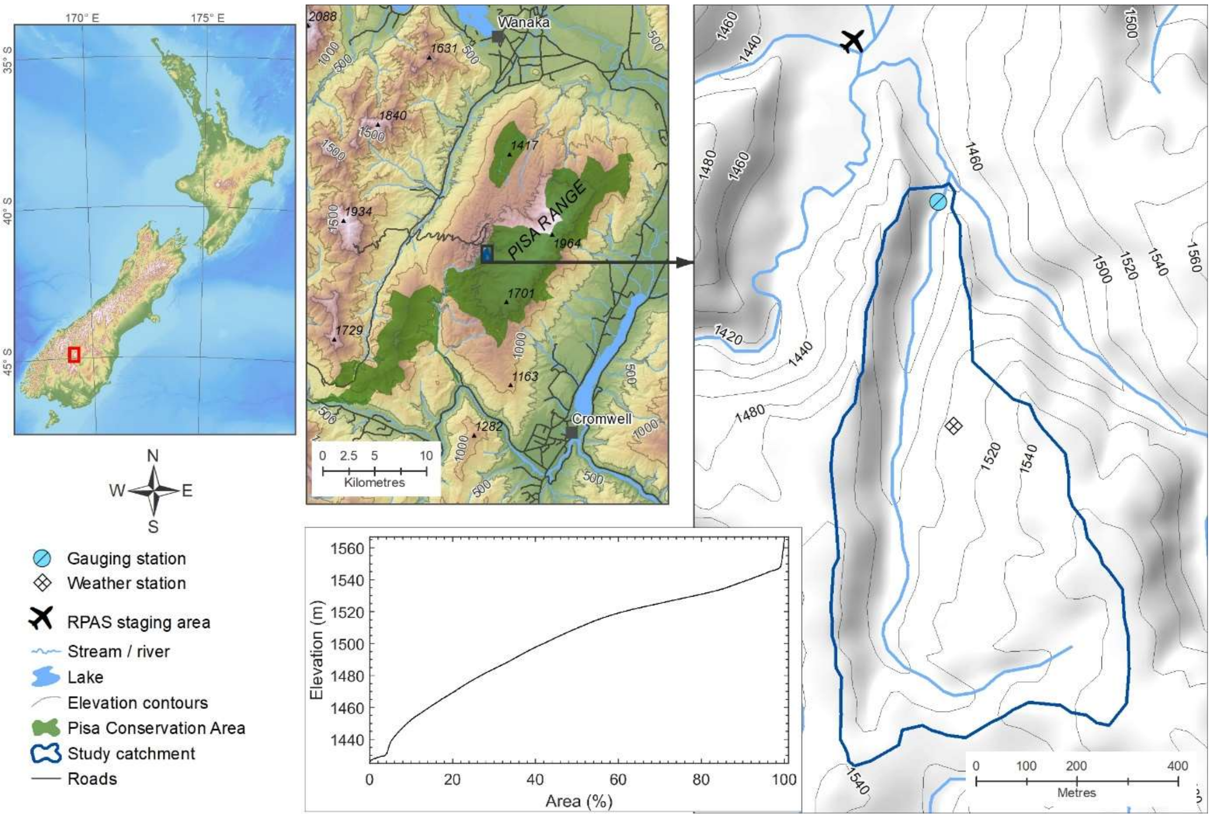


Figure 1: Location and hypsometry of the study ~~basin~~catchment within the Pisa Range, New Zealand.

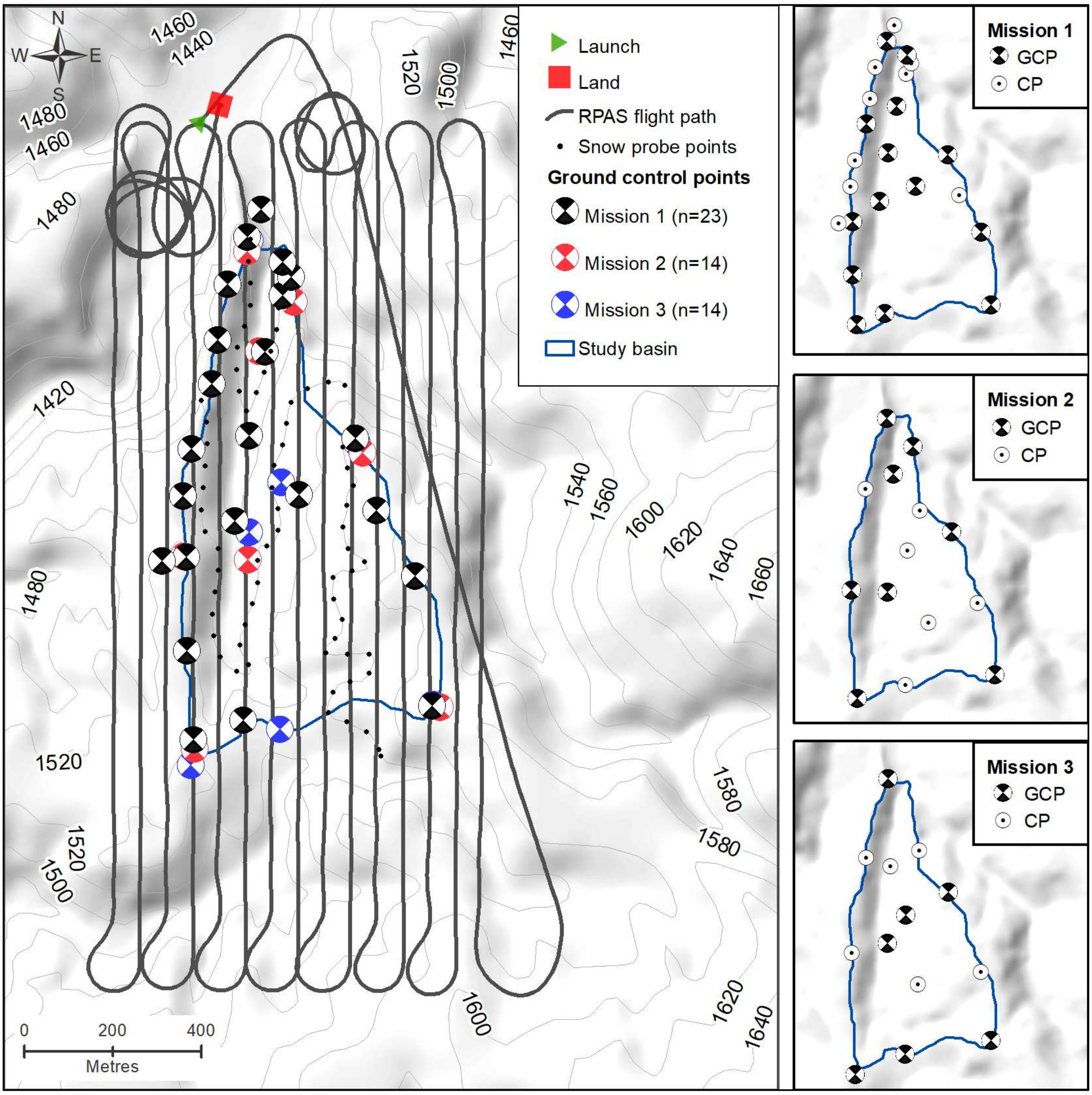


Figure 2: Typical flight path for the mapping of the study ~~basin~~catchment using the Trimble UX5, GCP network established for each flight mission, and reference snow depth locations. Flight log is from the spring flight mission. The configuration of the ground control point (GCP) and check point (CP) assignment for the triangulation of each flight is shown in the panels on the right hand side.

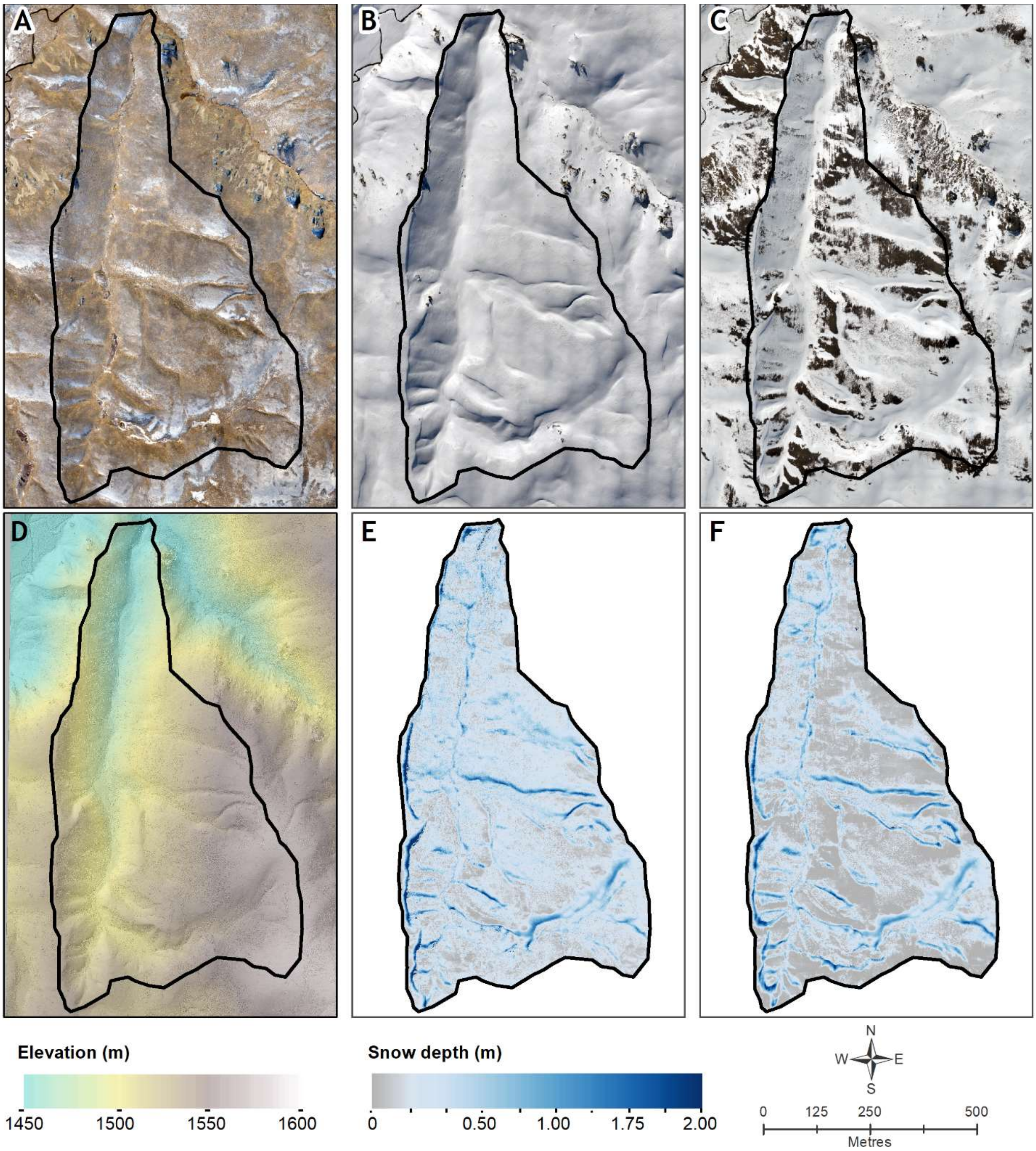


Figure 3: Processed ortho-mosaics for autumn (A) winter (~~A~~B) and spring (~~B~~C) flights, with corresponding autumn hill-shaded DSM (D) and maps of snow depth derived for winter (~~C~~E) and spring (~~D~~F).

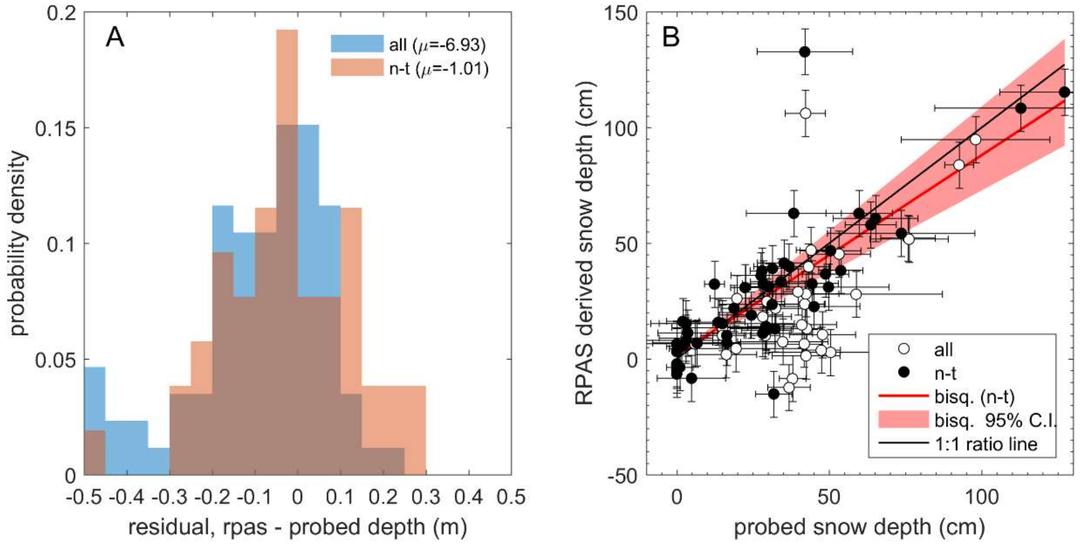


Figure 4: Residuals between snow depths measured by RPAS photogrammetry and probing for all probe locations ("all", blue) and non-tussock probe locations ("n-t", red) (A), and bisquare (bisq.) weighted regression between snow depth derived from a 0.15 m RPAS grid and probed snow depths (B). Vertical error bars are determined from the error propagation associated with DSM differencing and have magnitude of ±0.094 m, while horizontal error bars are calculated from the standard deviation of probe measurements made at each reference sampling location.

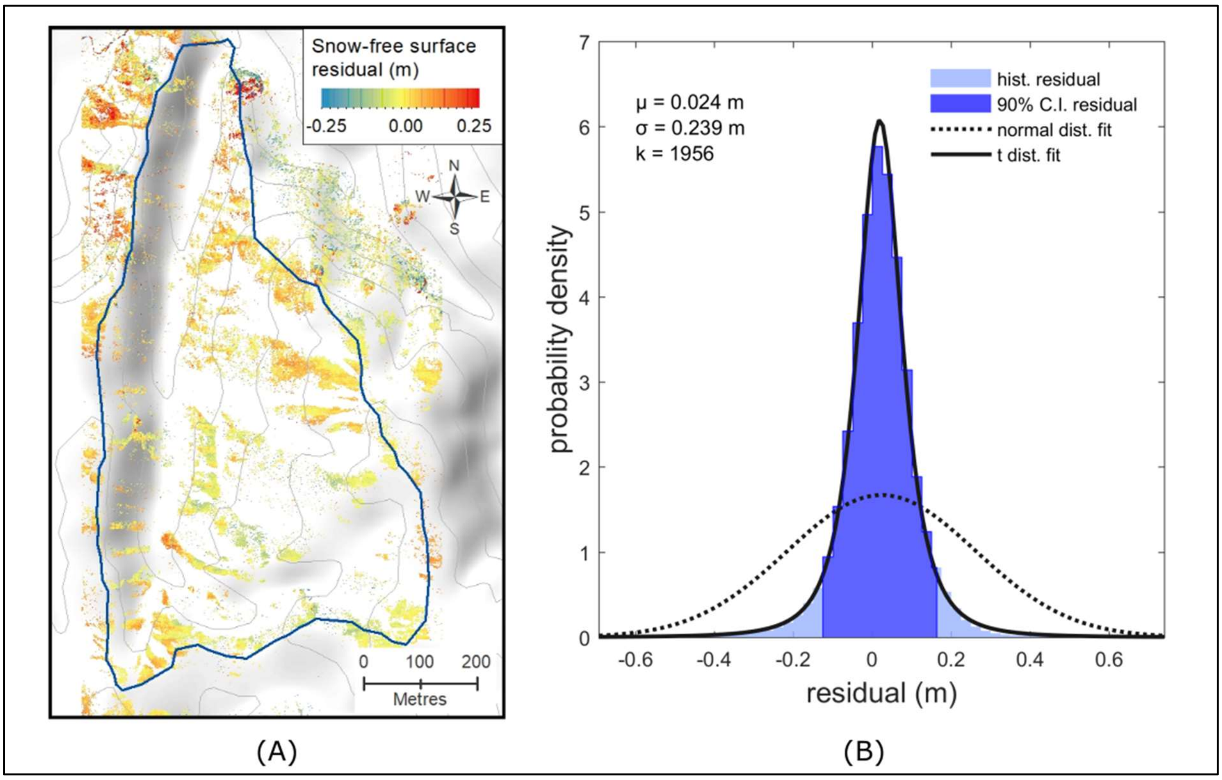
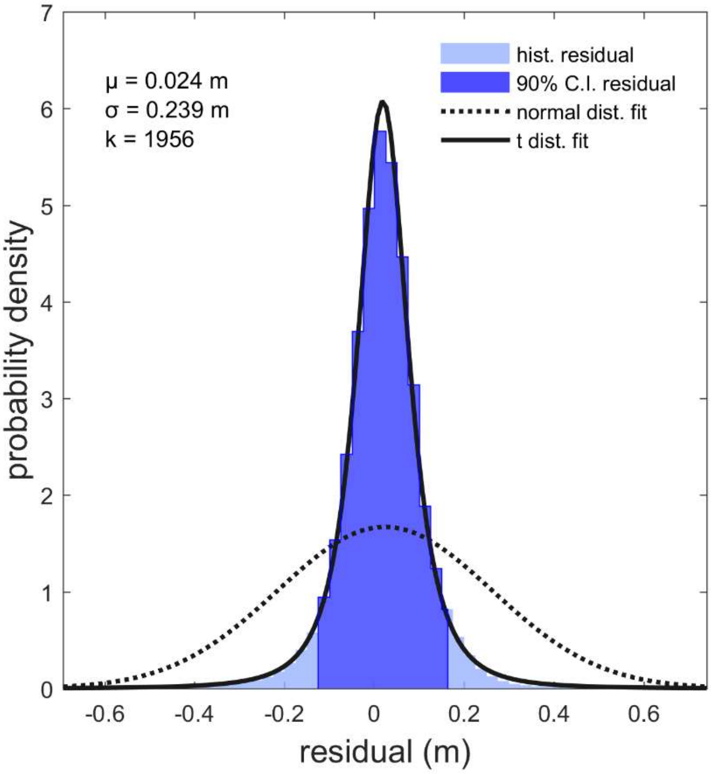


Figure 5: Map (A) and histogram (B) of the vertical residual for snow-free areas for surface models derived from the autumn and spring flights. The histogram includes fitted normal and t location-scale (t) distributions.



~~Figure 6: Histogram of residuals for snow-free areas following differencing of autumn and spring DSMs, including fitted normal and t distributions.~~

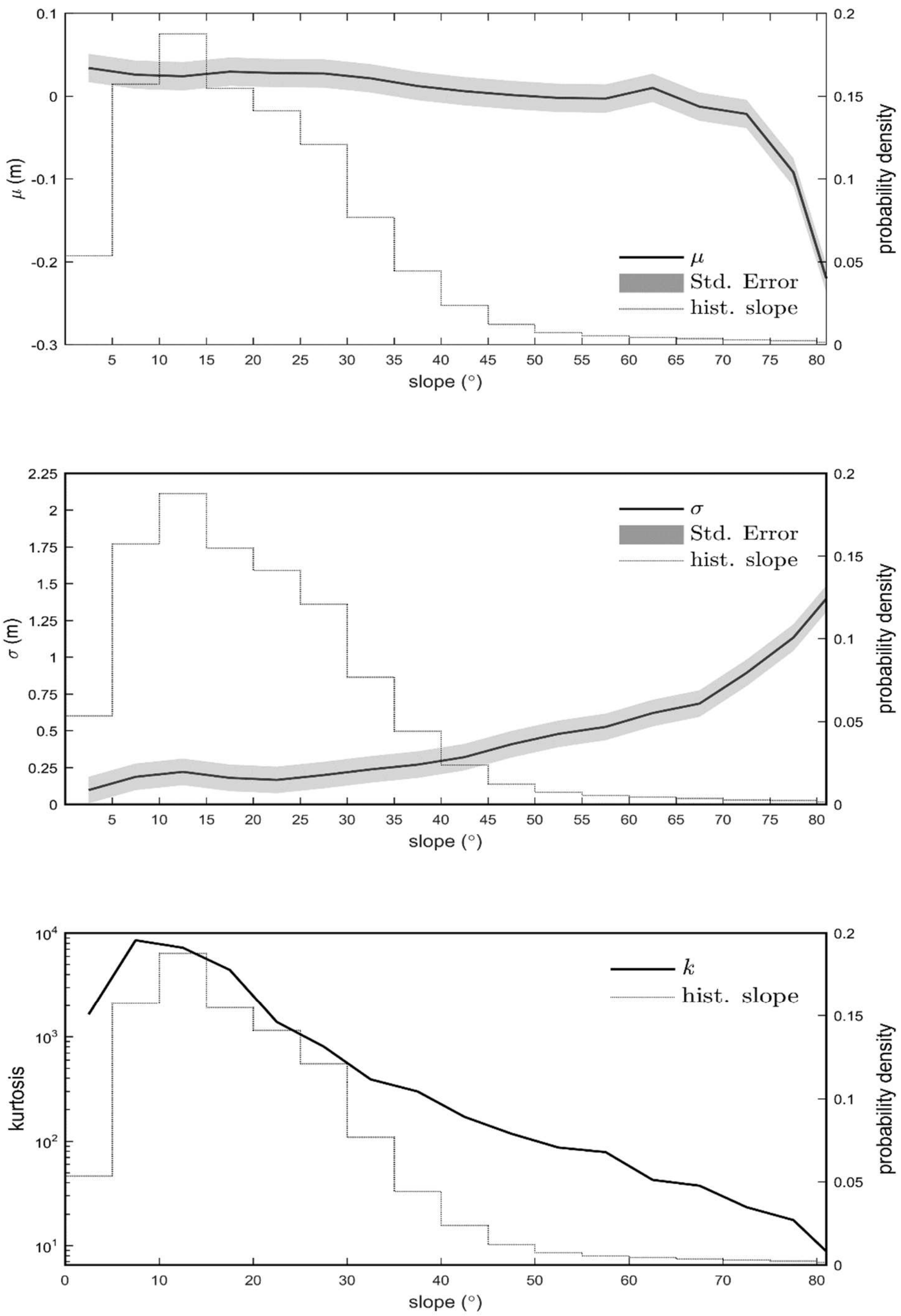


Figure 6: Mean (μ), standard deviation (σ) and distribution kurtosis for the residual, in terms of discrete classes of slope (5° width), up to the 90th percentile of slope. Kurtosis is plotted on a log scale, and is accompanied by a standard error of 606. The slope histogram has been clipped to the 90th percentile.

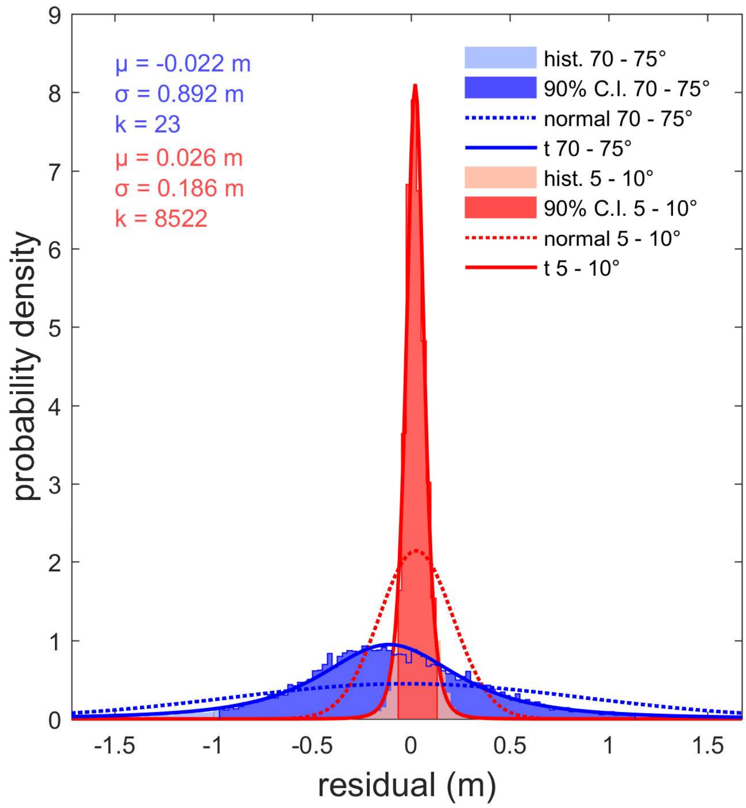


Figure 7: Comparison of histograms and accompanying descriptive statistics for the residual between DSMs for slopes between 5 and 10° and slopes between 70 and 75°. Flatter slopes are found to exhibit extreme kurtosis relative to steeper slopes. Normal and t location-scale (t) distributions are shown.

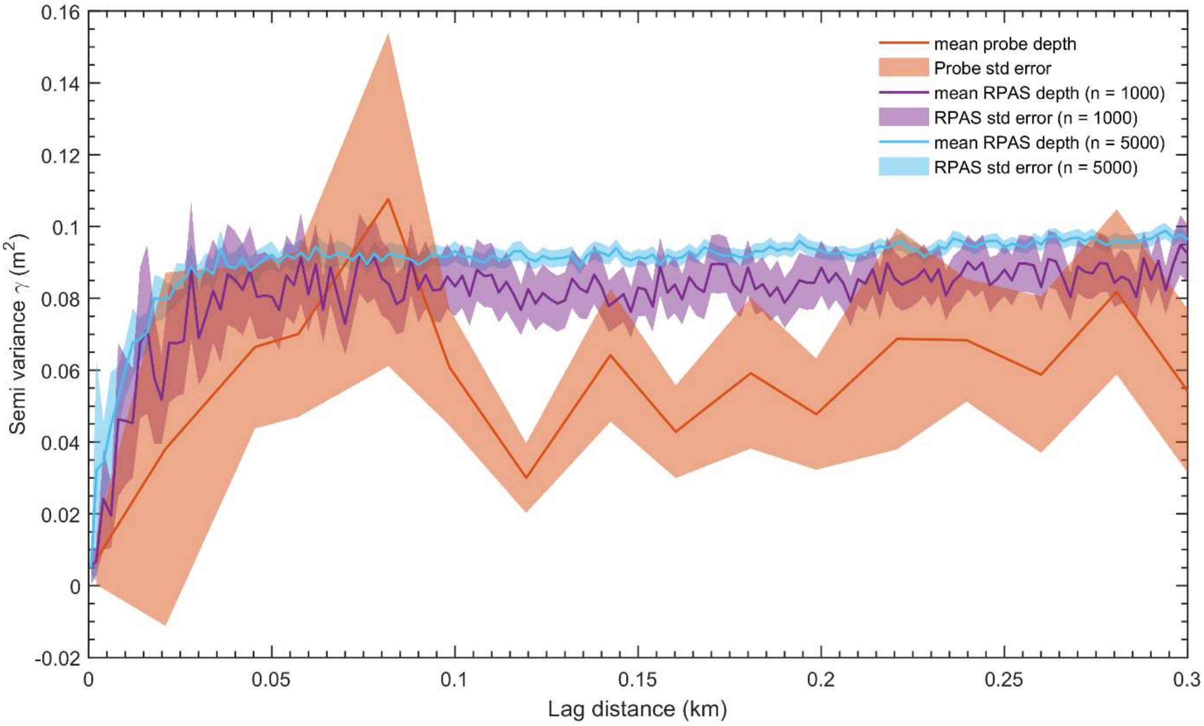


Figure 8: Semi-variograms for snow depth, based on measurements provided by probing (86 samples), and two random samples drawn from RPAS-derived snow depth of 1000 and 5000 observations.

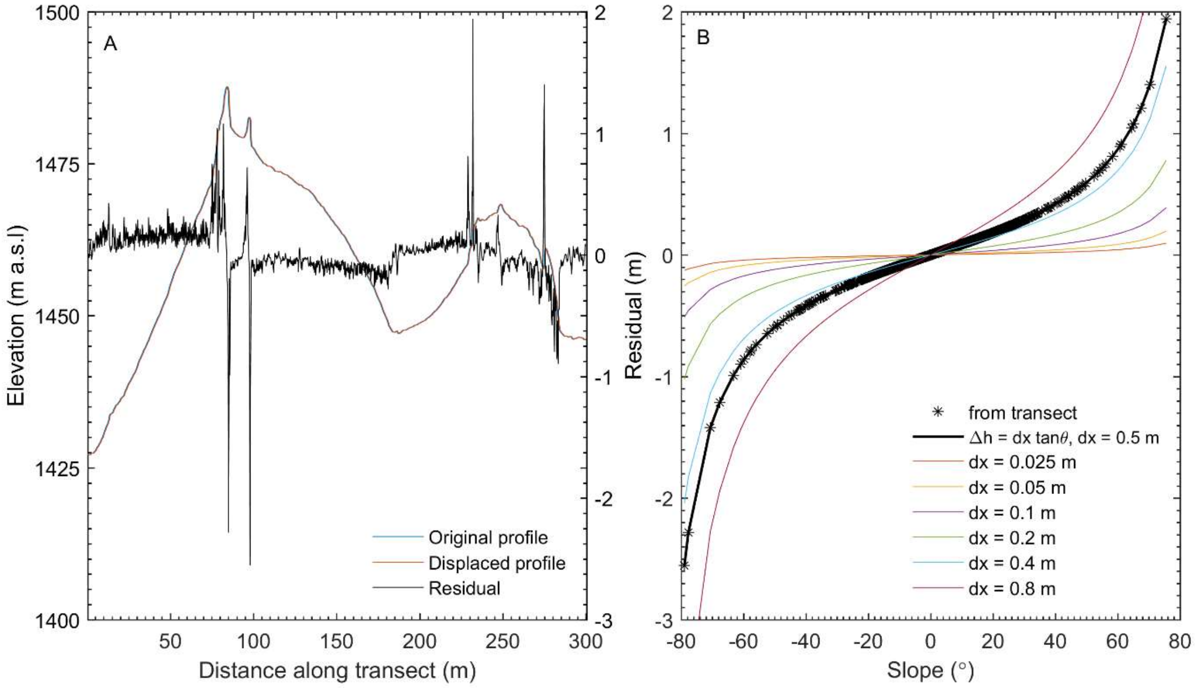


Figure 9: The vertical residual between two elevation profiles, extracted from the same DSM, along a common transect, and offset horizontally by 0.5 m (A), and the resulting residuals plotted as a function of terrain surface slope, for the applied offset of 0.5 m, and a range of other offsets (dx) (B).

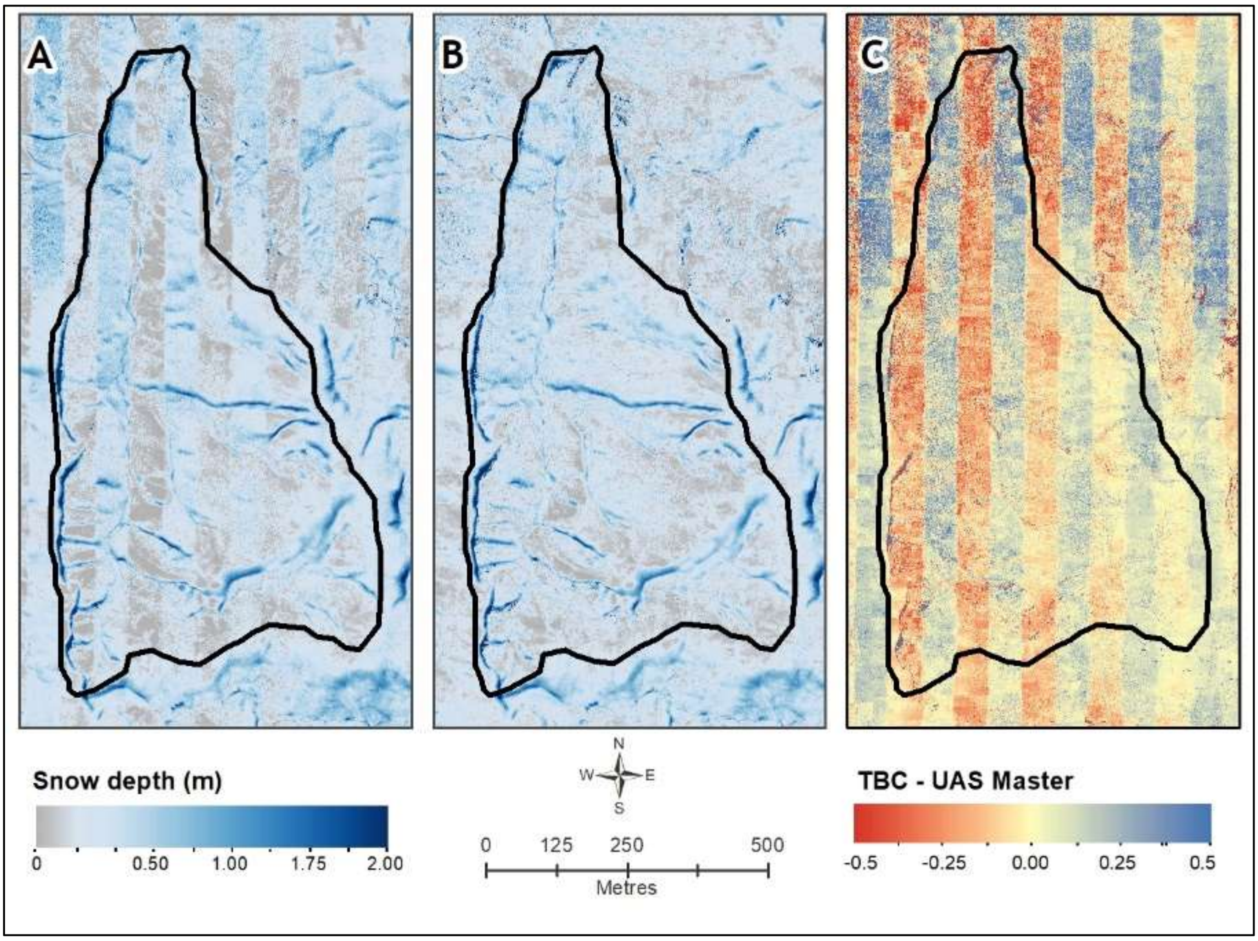


Figure 10: Map of the systematic artefacts in surface height change (dh) (expected to represent snow depth), propagated when differencing digital surface models (DSMs) resulting from aerial-triangulation in TBC v3.40 (A) compared with the dDSM from UAS Master (B). Vertical (north – south aligned) striping is highlighted in (C), the residual between dDSMs derived from TBC and UAS Master.

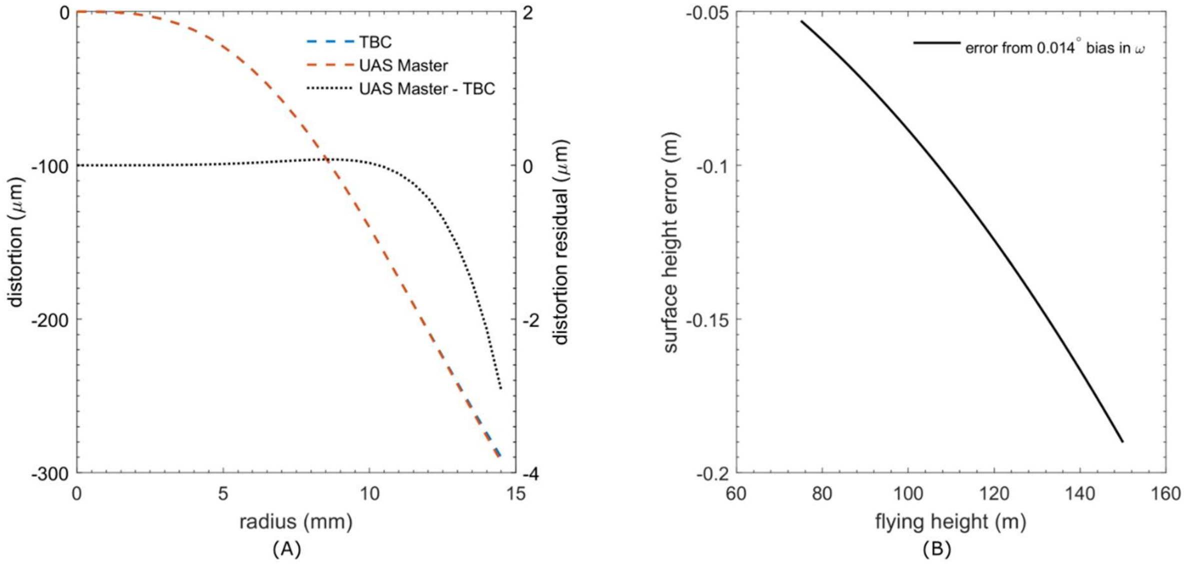
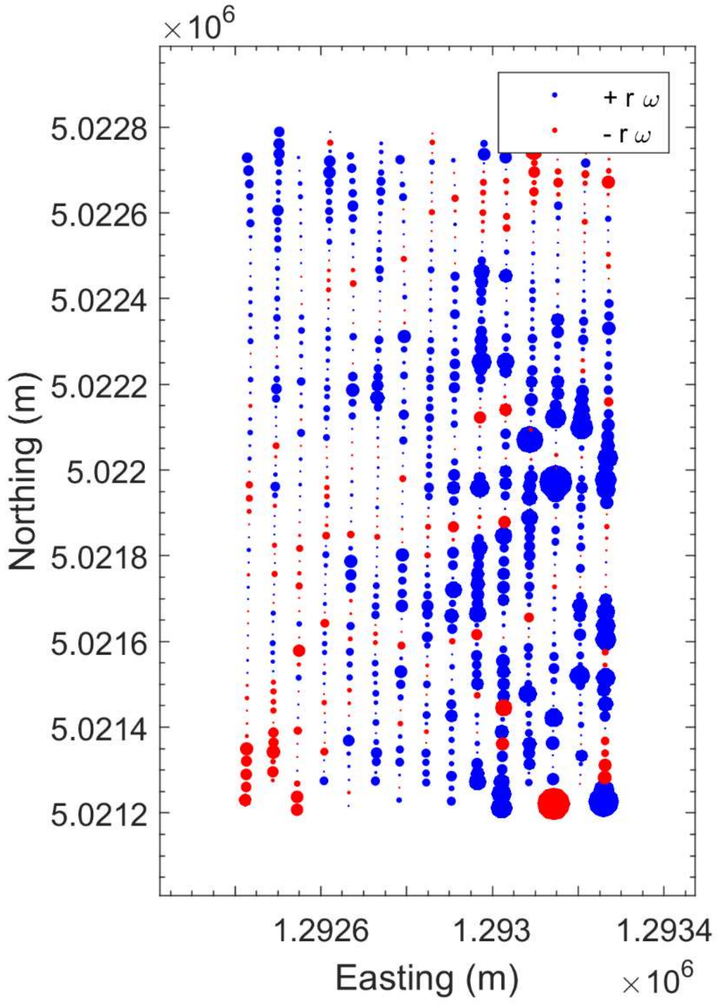


Figure 11: Comparison of lens distortion characterised by individual triangulations of data from the same flight carried out in two different software packages, TBC and UAS Master (A), and the error in surface height propagated by a bias in the roll parameter, ω, in relation to flying height (B).~~.~~ A shows that ~~T~~the residual was only apparent at radial distances >12 mm, while B demonstrates that the observed mean bias in ω that was propagated by TBC results in substantial errors in surface height~~.~~



~~**Figure 13: Spatial distribution of residual in ω between TBC and UAS Master.**~~

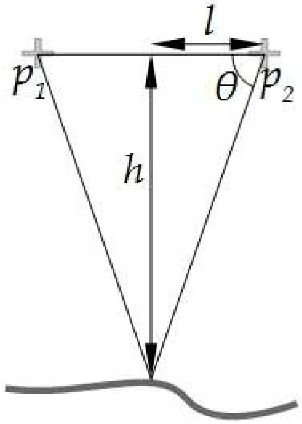
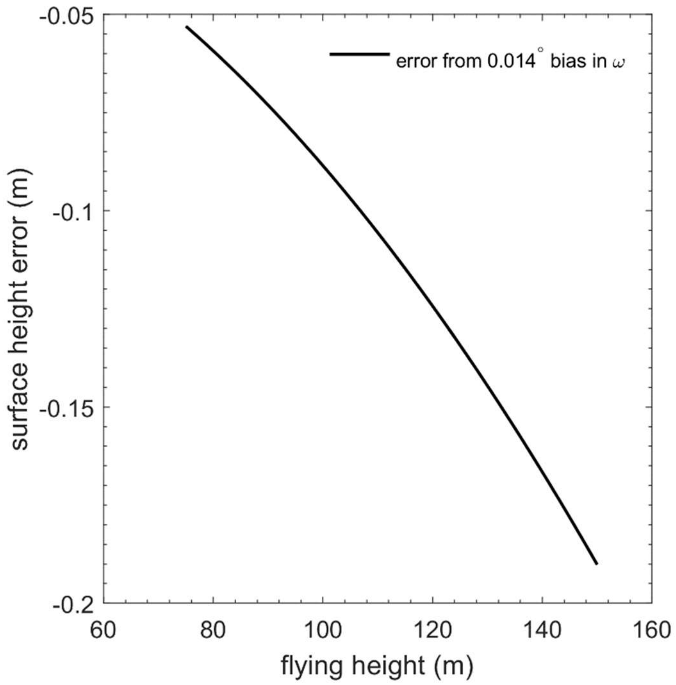


Figure 12: Schematic of the relationship between height (*h*), baseline length (*l*), and and the interior angle (*θ*) that may be affected by a bias ($r\theta$) for a terrain point position resected from images centred at p1 and p2, when the mean bias ($\overline{r\theta}$) is small (e.g., 0.014° in this case).



~~**Figure 15: Error in surface height propagated by a bias in ω, in relation to flying height.**~~