Light and Shadow in Mapping Alpine Snowpack With Unmanned Aerial Vehicles in the Absence of Ground Control Points

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Abstract Recent developments in unmanned aerial vehicles (UAV) and structure from motion (SfM) algorithms have shown reliable results for retrieving snow depth distribution. However, their ability to obtain accurate results usually relies on deploying and measuring the exact position of ground control points (GCP) for georeferencing the information. Commercial UAVs can now provide real time kinematic (RTK) positioning of the images with centimetric accuracy. Nonetheless, their operational applicability for observing snow distribution in highly heterogeneous mountain areas has not been evaluated. This study presents a complete assessment of the reliability of snow depth observations from a fixed-wing UAV working in RTK mode with an RGB camera. During the 2018–2019 season, seven field campaigns (13 UAV flights) were undertaken covering 0.48 km² in complex alpine terrain in the Pyrenees. The UAV observations obtained under different light conditions and flight block configurations (altitude and image overlaps) in the same day were evaluated with terrestrial laser scanner acquisitions. Two SfM processing options of the UAV images were also compared. When the study area received direct solar light, the results were comparable to previous studies that had used GCPs, with an average root mean squared error of 0.19 m and an average absolute snow volume discrepancy lower than 4%. However, when large areas were under shadow from the terrain, or solar light was affected by clouds, the estimated error tripled. The quality of the snow depth maps was little affected by the snow covered area and the flight mission configurations.

1. Introduction

Snowpack evolution controls many mountain processes, including soil erosion (Meusburger et al., 2014), plant survival (Wipf et al., 2009), and glacier surface mass balance (López-Moreno, Revuelto, Rico, et al., 2016; Réveillet et al., 2017). Moreover, water accumulated as snow and ice in mountain areas has a determining role in the timing of streamflow. From this, it is estimated that about one-sixth of the Earth’s population directly depends on the water supply from snow and ice melt from mountain areas (Barnett et al., 2005). Since snowpack evolution is a determinant in glacier dynamics and it is also highly variable in space and time (Robinson & Frei, 2000), many scientific works have focused their attention on applying various remote sensing techniques to observe its evolution in remote mountain areas, including satellite acquisitions (Frei et al., 2012), manual observations (López-Moreno, Fassnacht, et al., 2011) and close range sensing techniques, such as LiDAR (Deems et al., 2013). In the last five years, the technical development of unmanned aerial vehicles (UAV), as well as advances in photogrammetric techniques, and particularly in one of its most popular approaches, structure from motion (SfM) algorithms (Snively et al., 2006), have returned compelling results for observing snow distribution with high spatial resolution (De Michele et al., 2016; Goetz & Brenning, 2017; Harder, Schirmer, et al., 2016). The 3-D reconstruction of homogeneous surfaces, such as fresh snow, or those under irregular lighting conditions (i.e., shadows cast from the terrain) may drastically affect the performance of SfM algorithms (Boesch et al., 2016; Cimolli et al., 2017; Gindraux et al., 2017). These points, together with the rapid changes in weather that characterizes mountain areas, show the need for an in-depth evaluation of the reliability of UAVs when mapping snow distribution under different weather and snowpack conditions, including dissimilar lighting conditions (De Michele et al., 2016; Harder, Schirmer, et al., 2016; Vander Jagt, Durand, et al., 2013).

The generation of accurate snow depth observations with UAVs in most previous studies relies on the availability of ground control points (GCP) within the study area (Gaffey & Bhardwaj, 2020) to geo-reference the
point cloud into a global coordinate system (Agüera-Vega Francisco et al., 2017). GCPs are important for camera self-calibration quality, and also impacts the accuracy of the 3D point clouds (Harwin et al., 2015). Nowadays, some commercial UAVs allow on-site geotagging of the acquired images using Global Satellite Navigation Systems (GNSS) with real-time kinematic (RTK) configurations (here after RTK-UAV). This development provides successful geo-location of the 3-D point cloud with an accuracy for horizontal coordinates within 1 cm of that obtained with GCP (Forlani et al., 2018), and sufficient for most applications. This innovative UAV configuration opens up fresh potential for extending surveys over larger and more remote mountain domains without depending on placing GCPs in the target area. RTK-UAVs will not only capture information more rapidly, but also lead to a major reduction of costs for filed campaigns and exposure of personnel to natural hazards in snow dominated areas (Bühler, von Rickenbach, et al., 2018; Miziński & Niedzielski, 2017).

The RTK configuration for accurately geolocating UAV images has recently motivated different works to test the possibility of conducting GCP-free photogrammetry (Benassi et al., 2017; Hugenholtz et al., 2016), including assessments to observe snow distribution (Eberhard et al., 2021; Gabrlik et al., 2019; Harder, Pomeroy, & Helgason, 2020). These studies either used manual snow depth measurements (<100 observations) to evaluate UAV observations (Eberhard et al., 2021); or were conducted in a very small and highly homogeneous study area (Gabrlik et al., 2019). To date, the reliability of UAVs in observing snow depth distribution with RTK configurations has not been assessed in detail with a well-established close range sensing technique under a wide variety of snow and lighting conditions in complex alpine terrain.

Readily available UAVs and SfM software nowadays allow a relatively simple application of these techniques which may broaden its applicability. Nevertheless, some acquisition options when planning UAV flights have an important impact on the quality of UAV observations. For instance, the spatial information captured by the sensor; named as ground sampling distance (GSD), largely depends on the height above ground level (AGL). AGL has a major weight on the precision of models generated with UAVs (Goetz et al., 2018). Another configuration option that has a major influence on the quality of the 3D point cloud is the image overlap. SfM algorithms require that the images acquired with UAVs have both sidelap and frontlap. Different authors have assessed the minimum overlap between images to observe snow depth distributions recommending high overlap values (>70%; Goetz & Brenning, 2017; Goetz et al., 2018; Harder, Schirmer, et al., 2016; Vander Jagt, Durand, et al., 2013). Nonetheless, the impact of higher overlaps has not been evaluated so far.

In this study, we aimed to assess the easiest, safest and fastest acquisition of snow depth distribution in remote mountain areas with a UAV without any further requirement to the experimental setup. Bearing in mind straightforward UAV acquisition and relatively fast post-processing of the information; we present and evaluate a simple methodology to generate snow depths maps with a RTK-UAV, as these devices allow a highly accurate positioning without additional requirements (GCP and or GPS base stations within the study area). We intend to open up this technique to a broad community of users who do not need specific skills in geomatics. The reliability of RTK-UAV snow depth observations from different flights in a single day and acquisitions during an entire snow season, has been evaluated using as benchmark terrestrial laser scanner (TLS) observations (Prokop, 2008; Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014). Moreover, the impact of the altitude on the UAV flight, image overlap, and the SfM processing speed/quality were tested in a specific target area. In total, we carried out 13 UAV flights with each conducting four different flight blocks (varying image overlap and flight altitudes) in six experimental campaigns in the 2018–2019 snow season.

The study area was the Izas Experimental Catchment (Revuelto, Azorin-Molina, et al., 2017). The flights covered 0.48 km² which is, to our knowledge, one of the largest study areas with a highly heterogeneous topography where UAV snow products have been evaluated. Previous works on sites exceeding 0.5 km² had relatively simple topography (i.e., a prairie site or the bottom of a river valley) or only compared UAV observations to some manual measurements (Eberhard et al., 2021; Harder, Schirmer, et al., 2016). Other works have assessed the quality and uncertainty of the snow depth distribution from UAV observations in more complex study sites (Adams, Bühler, & Fromm, 2018; Avanzi, Michele, et al., 2016; Bühler, Adams, Bösch, & Stoffel, 2016; Gabrlik et al., 2019; Goetz & Brenning, 2017; Redpath et al., 2018), but in all cases with smaller extent. This reveals the need of determining the reliability of snow depth maps generated with UAVs in...
complex alpine terrain over extended areas with these platforms working in RTK, to find the strengths and weaknesses in operational application.

2. Methods and Experimental Setup

2.1. Study Area

The Izas Experimental Catchment is located in the central Spanish Pyrenees (42°44′N, 0°25′W), at the head waters of the Gallego river, close to the main water divide of the mountain range. Its elevation ranges from 2,000 to 2,300 m above sea level (a.s.l.), it has an extent of 0.48 km$^2$ and has a highly heterogeneous topography, with deep gullies and prominent ridges alternating with relatively flat areas and some steep slopes (Figure 1). The mean slope of the catchment is 16°, but several areas exceed 40°. The catchment is predominantly oriented to the east, with slopes facing in nearly all directions. This site is almost entirely covered by alpine grassland (Festuca eskia and Nardus stricta) with no trees and has rocky outcrops in the steeper areas.

A large data set of snow depth distribution maps retrieving snow and soil surface with a TLS has been generated in this study site since 2011 (Revuelto, Azorin-Molina, et al., 2017). The long range device used (RIEGL LPM-321) and experimental setup of this site generated snow depth distribution maps with deviations below 0.1 m when compared to manual measurements (Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014). The area covered by the TLS within the area surveyed by the UAV was 0.36 km$^2$ (76% of the area covered by UAV), due to topographic shadowing from the TLS acquisition positions.

An automatic weather station located at a lower elevation of the Izas Experimental Catchment captured a wide variety of meteorological and snow variables, comprising air temperature and humidity, wind speed and direction, total precipitation, downward and upward broadband radiation and snow depth, among others (Revuelto, Azorin-Molina, et al., 2017). The experimental setup of this site also contained a webcam (Campbell CC640 digital camera) fixed in the eastern corner, which photographed three time-lapse images per day of about 0.3 km$^2$ of the east-facing area (note that this extent is reduced to about 0.16 km$^2$ due to the topographic occlusion of certain areas in the webcam viewpoint). These images were projected into a 1 m spatial resolution digital elevation model. The routines for such a projection make first a viewing transformation for the optics of the camera and second a perspective projection (Corripio, 2004). Afterward the projected images were binarized to create snow presence/absence maps (Revuelto, Jonas, & López-Moreno, 2016). These images provided information nearly on a daily basis (about a 20% of all photographs from the camera had to be discarded because cloud or snow obscured the camera lens) of the snow covered area, which accounted for 33.5% of the UAV surveyed area.

2.2. Study Period

The 2018–2019 snow season had several snow accumulation and melting events (Figure 2), displaying high intra-annual snowpack variability, one of the most important characteristics of snow dynamics in the Pyrenees (López-Moreno, 2005). Previous studies carried out in the catchment also revealed a strong year-on-year variability in snow conditions, and complex spatial patterns, with some areas exhibiting limited snow accumulations, while at the same time, others accumulated a snowpack of 5–10 m (Revuelto, López-Moreno, Azorin-Molina, & Vicente-Serrano, 2014). This enabled UAV acquisitions to be evaluated for different extents of snow and snow surface conditions. Figure 2 shows the time series of snow depth observed at the meteorological station, and the time series of the percentage of snowcover from the area where webcam images were taken. This figure also depicts the proportion of snow cover from the area surveyed by UAV for the six snow-on experimental campaigns carried out on February 21, 2019 (2 days), March 26, 2019, and May 5, 9, 23, and 30 (2 days), 2019.

Table 2 gives information on the meteorological conditions during the UAV acquisitions observed at the weather station. It also includes the % of the area shadowed by terrain without direct solar radiation, that is, cast shadow. Details on the downward and upward broadband radiation observed at the meteorological station, including the acquisition time of each flight, are provided in Figure 3.
2.3. UAV Platform

The UAV platform we used in this study is the SenseFly eBee-Plus, a fixedwing UAV. This device has a maximum endurance of 59 min with a wind resistance of 45 km/h. The eBee-Plus weighs 1.1 kg and has a wing-span of 110 cm. For transport and storage, the main body is divided into three pieces enabling the UAV to be carried in a backpack, suitably protected, and taken to remote study sites in winter by cross-country skiers.

Figure 1. Study area location and topography. Bottom panels show the area surveyed by the terrestrial laser scanner (TLS), time-lapse webcam and the unmanned aerial vehicles (UAV) flight pattern.
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SenseFly eBee-Plus flights must be planned in the eMotion 3 controller software, followed by transmitting it to the UAV via a radio link. To control and visualize the flight, eMotion 3 must be installed on a computer (in our case a sturdy tablet) with a USB connection to the 2.4 GHz frequency radio modem. Once the UAV is launched manually, the on-board autopilot manages the flight independently.

This UAV is equipped with a GNSS for RTK correction of the images with three options: A physical RTK base station (this is a GNSS receiver working in the experimental site during the flight and connected to the UAV via radio communication), a post-processing engine PPK (from post-processing kinematic) using RINEX files from the geodesic network; or a virtual RTK base station calculated through a real time triangulation of the closest stations from the local geodesic network if it is accessible via internet. The latter option uses the radio link between the controller and the UAV, to correct GNSS coordinates of the images. Since the study site has a good quality internet connection, we chose the virtual RTK base station option. However, if an internet connection is not possible, PPK positioning with the local geodetic network allows achieving similar accuracies to those obtained with RTK positioning (Harder, Pomeroy, & Helgason, 2020). eMotion 3 through the connection to the local geodesic network (Aragua https://gnss.aragon.es), provided a simulation of a virtual RTK antenna within the study site, enabling centimetric accuracy on the positioning of images.

As all UAVs, the eBee-Plus has an inertial measurement unit (IMU) containing different sensors (gyroscope, accelerometers and magnetometer). The IMU provides real time information, of linear and angular accelerations and also orientation toward magnetic North. This allows determining changes in both, vertical and horizontal speed and the orientation in the three principal axes of the drone: roll (ϕ), pitch (ω), and yaw (κ). The UAV autopilot exploits the information of both the GNSS and the IMU to control the flight path of the device.

The UAV holds the senseFly S.O.D.A. (Sensor Optimized for Drone Applications) digital camera. This camera generates images with an RGB resolution of 5,472 × 3,648 pixels (~20Mpx). The focal length of its lens is 10.6 mm (F/2.8-11, 35 mm equivalent: 29 mm) and it has a 1” CMOS sensor. This camera has an automatic

Figure 2. Time series of the snow depth and snow covered area (SCA) retrieved with the experimental setup installed in the Izas Catchment. The area of snow cover observed with the UAV for the six experimental campaigns is also included.
white balance for capturing images under different lighting conditions and a GSD of 2.3 cm/px for a flight altitude of 100 m.

2.4. Flight Configurations

Each UAV flight was configured to run four different blocks, one covering the entire study area (ringed with a dark line in Figure 1) and the other three over a smaller test area of 0.043 km² (9% of total surface; ringed in red in Figure 1). The total time to fly these blocks was 30 min (Table 1), which enabled equivalent image acquisition conditions since lighting and meteorological conditions were almost unaltered during the flights. This enabled an evaluation of the impact that different image overlaps and GSD have on snow depth distribution maps under same ambient conditions. Despite the fact that the eBee-plus has a maximum endurance of 59 min (eBee Plus Drone User Manual), flights were planned for total times of about 37 min, including take-off and landing. This was a good safety margin for battery storage capacity under cold temperatures and any occurrence of strong winds. Information on the characteristics of each block (GSD, frontlap, and sidelap) is provided in Table 1. Note that first and last flights had the same overlap and GSD values with the objective of evaluating the reproducibility of the observations. The flight path (set as aerial grid) of the different flight blocks was almost the same for all flights. Aerial corridors of these grids were designed as perpendicular to main wind direction (270°; Revuelto, Azorin-Molina, et al., 2017) to avoid strong changes in the frontlap of images in case of strong tail wind. This flight strategy also aids maximizing battery endurance. For some acquisition dates the flight path was slightly rotated to guarantee perpendicularity to wind direction and thus to guarantee the overlap between images.

2.5. Generation of 3D Point Clouds From RTK Positioned Images

The SfM software used for processing images and creating the point cloud was Pix4Dmapper (version 4.4.12). This commercial photogrammetric software was specifically designed for processing UAV images, providing detailed information on the accuracy and quality of the process, and is optimized for working with eMotion 3 and SenseFly eBee-Plus, making the workflow easy and fast. The only final product we generated with Pix4Dmapper were point clouds in UTM 30°N with the European Terrestrial Reference System 1989 (ETRS 89). As most commercial software packages, Pix4Dmapper does not provide detailed insights on the different stages and the algorithms used for generating the point cloud because these software packages are protected by intellectual property rights (Benassi et al., 2017). The processing options selected in this work, were default settings from Pix4D processing templates (PIX4Dmapper manual).

The distortion, the focal length and other internal parameters of S.O.D.A. camera are already included in Pix4Dmapper database. The software automatically recognizes the camera when the images are imported for their later processing. However, internal parameters in small cameras (as S.O.D.A. camera) are highly sensitive to temperature and vibration. Therefore the optimizations of internal camera parameters is recommended (PIX4Dmapper manual). Similarly, Pix4Dmapper identifies the external camera parameters of each image. These external parameters are the X, Y, Z global coordinates (obtained from the UAV’s GNSS) and the orientation of the camera in the three axes (φ, ω, and κ) obtained from the IMU of the UAV.
Table 2

Mean Meteorological Variables Observed During UAV Flights

| Exp. Camp. | Date (2019) | Time (UTC) | Temp. (°C) | Altitude (°) | Azimuth (°) | Cast shadow area (%) | TLS obs. | TLS Mean | UAV Mean | TLS SD | UAV SD |
|-----------|-------------|------------|------------|--------------|-------------|----------------------|-----------|----------|----------|--------|--------|
| 1         | February 21 | 12:20      | 5.3        | 35           | 185         | 0                    | Yes       | 0.97     | 0.96     | 1.04   |        |
|           |             | 15:30      | 2.1        | 20           | 230         | 52                   |           | 0.89     |          |        |        |
|           |             | 16:40      | 1.6        | 15           | 240         | 100                  |           | 0.99     |          |        |        |
|           | February 22 | 6:40       | 4.3        | 5            | 110         | 15                   | 1.01      |          |          |        |        |
|           |             | 8:30       | 6.5        | 15           | 120         | 0                    |           | 0.99     |          |        |        |
| 2         | March 26    | 11:00      | 3.5        | 50           | 165         | 7                    | Yes       | 0.81     | 0.85     | 0.79   |        |
|           |             | 14:45      | 2.6        | 35           | 230         | 0                    |           | 0.79     |          |        |        |
| 3         | May 5       | 12:05      | −1.2       | 65           | 185         | 0                    | No        | Nan      | 1.14    |        |        |
| 4         | May 9       | 12:50      | 4.6        | 55           | 135         | 0                    | Yes       | 0.74     | 0.81     | 0.53   |        |
| 5         | May 23      | 9:30       | 10.8       | 50           | 115         | 0                    | No        | Nan      | 0.53    |        |        |
| 6         | May 30      | 16:30      | 10.5       | 55           | 254         | 70                   | Yes       | 0.40     | 0.33     |        |        |
|           | May 31      | 10:30      | 15.2       | 40           | 95          | 0                    | No        | NaN      | 0.37    |        |        |
| 7         | July 25     | 12:25      | 22.5       | 66.7         | 188         | 0                    | No        | NaN      | NaN     |        |        |

Note. Information on the solar position (https://www.suncalc.org) for the location of Izas Experimental Catchment at mid-time on each flight. The table includes the % of the study area with cast shadow from topography and clouds observed during the flights. It also provides mean snow depth values observed with the UAV and the TLS in the different acquisitions.

Figure 1. Time series of the upward and downward broadband radiation observed at the meteorological station. Vertical dashed lines denote UAV acquisition time for the different experimental campaigns.
Data processing of the UAV images starts with the calibration of internal and external camera parameters through an automatic aerial transformation (AAT) and a successive routine named bundle block adjustment (BBA). First the AAT computes the camera external parameters and their uncertainty, also generating the so called 2D Keypoints Observations (number of points that can be matched on at least two images). These outputs are used as inputs of the BBA, that calibrates the internal camera parameters and also optimizes the external parameters. BBA produces a sparse 3D points cloud (Gerke & Przybilla, 2016; Nocerino et al., 2013), which is finally utilized to generate a densified 3D point cloud via stereo matching (Hirschmüller, 2008). For a detailed account of SfM algorithms, the reader is referred to Forlani et al. (2018) or Westoby et al. (2012).

Different 3D point cloud densities can be achieved, depending on the quality of the processing selected in the densification process. In this study, we tested two different processing options, high quality (HQ) and low quality (LQ), respectively rising to average point clouds of 50.9 pts/m$^3$ and 6 pts/m$^3$. Processing time for the whole catchment was about 15 h for HQ processing and less than 1 h for LQ with a regular CPU (processor Intel (R) Core (TM) i5-6200 CPU @2.3GhZ, 12 GB RAM memory and Intel (R) HD Graphics 520 graphic card).

When available, Pix4Dmapper exploits GCP coordinates to constrain camera self-calibration. During midday of the first acquisition campaign (February 21, 2019), five GCP were installed within the small test area (Figure 1). Thus, Pix4Dmapper self-calibration capability was assessed by comparing results obtained with images having an RTK positioning and a combined RTK images positioning with a GCP geolocation for this UAV flight. Finally, the performance of RTK solution to georeference the point cloud was assessed through a comparison of the root mean squared error (RMSE) obtained when the five GCPs are used as check points (instead using the GCPs to solve the photogrammetric model these points are used to evaluate the accuracy of the geolocation). An intermediate geolocation procedure was also evaluated, three out of the two GCPs were used in the SfM workflow and the other two were exploited as check points.

### 2.6. Snow Depth Distribution Maps

The first step for obtaining the snow depth distribution maps is the subtraction of the snow-on from snow-free point clouds. The snow-free flight took place around noon on July 25, 2019, with clear sky conditions, with the same flight configuration for the entire catchment for snow-on acquisitions (Table 1). The snow-on and snow-free point clouds were subtracted in CloudCompare software, using the Multiscale Model to Model Cloud Comparison tool (James et al., 2017; Lague et al., 2013). The differences in point clouds were rasterized into the same empty raster with 1 m grid cell size covering the entire study area. This grid cell size allowed both, to overcome computational constrains due to the large size of HQ point clouds and to ensure a direct evaluation, with a suitable resolution for observing snow depth distribution (López-Moreno, Revuelto, Fassnacht, et al., 2015). The TLS snow depth maps were generated in the same coordinate system (Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014), with same subtraction procedure (subtraction of snow-on from snow-free TLS observations).

The extent of cast shadow on each flight was retrieved from the RGB (Red Green Blue) colored point cloud. For each point cloud, a threshold in the blue channel was chosen, depending on the average lighting during the flight (note the 8-bit information which gives 256 discrete values). Threshold values ranged from 80 to 120 in the various flights. This information was exploited by an expert human operator for manually delimiting the polygons characterizing cast shadows on each UAV flight in GIS software.

### 2.7. Quantifying the Performance of the UAV on Retrieving Snow Depth Distribution

UAV accuracy on retrieving snow depth distribution was assessed through the mean absolute error (MAE) and the RMSE, the latter being variable the most commonly employed error measure in related studies of UAV snow observations (Avanzi, Michele, et al., 2016; Bühler, Adams, Bösch, & Stoffel, 2016; Eberhard et al., 2021; Harder, Pomeroy, & Helgason, 2020; Harder, Schirmer, et al., 2016). As a measure of precision we computed the normalized median absolute deviation (NMAD; Höhle & Höhle, 2009). NMAD is more resilient to outliers than the standard deviation, providing a more robust measure of precision (Eberhard et al., 2021). Similarly the signal-to-noise ratio (SNR) was computed, which contrast the mean snow depth
value with the measurement error (Harder, Schirmer, et al., 2016). If SNR is above four; the Rose criterion (Rose, 1974) signifies that the observation returns meaningful information (the observed signal is large enough to differentiate it from noise). Finally, we computed the average snow depth with both, the UAV and the TLS, and the total volume difference between the TLS and the UAV (as a % of TLS volume) for the common areas measured by both sensors in the four experimental campaigns with TLS acquisition (February 21, 2019, March 26, 2019, May 9 and 30, 2019). Other authors working on this topic have performed accuracy and precision evaluations of the 3-D snow surfaces obtained with the UAV, by directly comparing the digital surface model obtained with the UAV and the reference (Adams, Bühler, & Fromm, 2018) or when possible, evaluating differences between snow-on and snow-off UAV acquisitions over the snow free areas (Redpath et al., 2018). We preferred to evaluate the reliability of the final product, taking into account all the steps for generating snow depth distribution maps, from data acquisitions to the final post-processing. This means that the UAV snow depth maps have been directly evaluated with the TLS snow depth maps. Therefore, we were able to present an assessment of UAV snow depth observations when compared to a well-established technique for high density and resolution surveying (Wilson, 2012) by quantifying the deviations that could be expected under the circumstances (light, snow distribution, etc.) from the point of view of the end user.

The snow-free observations of both techniques are respectively used as ground reference for the snow distributions maps of the TLS and the UAV. In order to assess the error in snow depth maps coming from the snow-free flight, we computed different error estimators (NMAD, MAE, and RMSE) between both, the TLS and the UAV snow free models.

### 2.8. Impact of Block Configurations and Quality Processing on Snow Depth Maps

The evaluation of the snow depths maps obtained from the flight blocks (Table 1) was assessed by comparing them in the small test area (Figure 1). In addition, we tested the impact of different SfM processing options, providing high quality (HQ; denser point clouds) with longer processing times compared to low density point clouds generated with rapid, low quality (LQ) options in Pix4D mapper. Including the four blocks acquired on each UAV flight (Table 1), this double calculation of the snow depth maps (HQ/LQ) provided eight distinct snow depth observations within the small test area for each flight.

### 3. Results

#### 3.1. Impact of Including GCPs Under Good Lighting Conditions

The self-calibration of both internal and external camera parameters led to almost same uncertainties with and without GCPs. This result was obtained for two SfM reconstructions with the images acquired in the first flight of the February 21, the only flight in which GCPs were available. The uncertainty of the focal length of the camera lenses obtained when GCPs coordinates were included in the SfM algorithm was 0.21 pixel. This uncertainty increased to 0.25 pixel when GCPs were not included in the routine. Similarly, including GCPs coordinates in the software, the central point of the image had an uncertainty of 0.20 pixel and 0.15 pixel (respectively in x and y). If GCPs were not included for processing this UAV acquisition, these uncertainties were 0.23 pixel and 0.17 pixel (respectively in x and y). The image geolocation errors (RMSE between initial and final camera position and orientation; Table 3) show that the self-calibration of camera external parameters achieves equivalent results with and without GCPs.

When the five GCPs were used to solve the photogrammetric model, the mean RMSE for their ground coordinates was 0.024 m (Table 4). Nonetheless this evaluation was biased since these points were used to both, obtain and evaluate the model. Two further solutions of the 3D point cloud were also evaluated for this flight, one including three GCPs to solve the

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**Table 3**

|                      | x RMSE (m) | y RMSE (m) | z RMSE (m) | φ RMSE (°) | ω RMSE (°) | κ RMSE (°) |
|----------------------|------------|------------|------------|------------|------------|------------|
| GCPs                 | 0.0020     | 0.0125     | 0.0159     | 2.29       | 4.81       | 5.85       |
| No GCP               | 0.0019     | 0.0083     | 0.0086     | 2.38       | 4.86       | 8.83       |

**Table 4**

|                      | X RMSE (m) | Y RMSE (m) | Z RMSE (m) | Mean RMSE (m) |
|----------------------|------------|------------|------------|---------------|
| 5 GCP as GCP         | 0.0098     | 0.0079     | 0.0574     | 0.024         |
| 3 GCP as GCP         | 0.018      | 0.0113     | 0.081      | 0.037         |
| 2 GCP as checkpoints | 0.014      | 0.012      | 0.065      | 0.030         |
| 5 GCP as checkpoints | 0.014      | 0.012      | 0.065      | 0.030         |

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photogrammetric model and considering the other two GCPs as check points; and the other using the five GCPs as check points to evaluate the RTK based positioning. Despite none of these solutions improved the results obtained when the five GCPs are used by the SfM algorithm, differences were small, which shows that RTK positioning of the images allows to generate a point cloud with an accurate geolocation.

The GCP-supported snow depth observations bias estimates, computed from the TLS evaluation: RMSE = 0.23 m, MAE = 0.12 and volume difference of 1.6%, NMAD = 0.13 m and SNR = 7.2. The snow depth distribution observed with same images (similarly with virtual RTK positioning) but without including GCPs in the SfM processing led to equivalent deviations, with an RMSE of 0.21 m, MAE of 0.13 m, a volume difference of a 1.2% a NMAD of 0.14 m and a SNR of 6.9, when compared to TLS observation.

### 3.2. TLS–UAV Snow Depth Comparison

Figure 4 shows two snow depth maps, one generated with the UAV and the other with the TLS for February 21, 2019. The shadowing effect of terrain from the TLS acquisition locations causes some data gaps (dark areas). Despite the fact that the UAV has not this limitation, same TLS data gaps have been included in the UAV map to make easier the visual examination of both maps. The general spatial pattern of snow depth is highly coincident. In the two maps the areas with the highest accumulation of snow have good agreement. Overall, small differences in the spatial distribution of the differences between the TLS and the UAV snow depth maps are observed. Nonetheless, in some areas, noisy snow depth values in the UAV observations are
retrieved, as observed in the top right area of the TLS-UAV difference map, where the biggest deviations are obtained. These deviations reach in some cases 0.5 m.

An example of the impact that lighting conditions have on the snow depth distribution maps is presented in Figure 5. Areas of cast shadow (solar radiation shadow) on the left side map, show large data gaps (in black) and irregular snow depth values, with extreme snow depth values not observed in the map on the right (acquired with direct solar radiation in the whole catchment).

Mean snow depth values from the UAV acquisition are closer to the mean values observed with the TLS (Table 2) when the surface of the catchment affected by topographic cast shadow is smaller. Similarly, RMSE, MAE, NMAD, and volume differences are smaller when the percentage of area under shadow is reduced (Figure 6). This behavior is exemplified in the February 21–22 experimental campaigns, with major deviations in the third acquisition (RMSE = 0.77 m, MAE = 0.44 m, NMAD = 0.31 m), when the UAV flew directly after the sun went down behind the surrounding topography (no direct lighting in the study area).

Conversely, the first flight at midday and thus with no cast shadow in the study area, showed better scores of accuracy (RMSE = 0.21 m, MAE = 0.13 m) and precision (NMAD = 0.14 m) when compared to the TLS. Snow depth maps obtained from UAV flights with cast shadow present data gaps (see left-hand map in Figure 5).

The average RMSE of all flights is 0.37 m. When flights with bad lighting conditions (area with cast shadow >50% or no direct solar radiation illuminating the study area due to cloud cover; Figure 3) are not included,
the RMSE decreases to 0.19 m. Similarly, excluding these flights, the average MAE is 0.12 m (0.19 m including all flights) and the absolute volume difference is less than 4% (8.6% when all flights are included). Computing all flights the average NMAD is 0.17 m, decreasing to 0.13 m when bad lighting conditions flights are not considered. The Rose criterion shows that UAV acquisitions obtained under bad lighting conditions are not reliable, since the SNR are quite low under these circumstances.

The NMAD between the TLS and the UAV snow-free models was 0.07 m and the RMSE was 0.08 m. These values show that under good lighting conditions, the contribution to the error budget of the snow depth
map coming from the snow-free model is not negligible but in all cases represents less than half of the error estimate of the snow depth (Figure 6).

When a larger extent of the study area is affected by cast shadow, error estimates increased (Figure 7). Additionally, when flights with SCA under 70% are considered (right panel in Figure 7), a linear increase of error estimates as cast shadows increase is observed, independently of the broadband radiation impacting the study area (see Figure 3). This tendency in the accuracy (RMSE) and precision (NMAD), despite it is obtained for few points, shows the remarkable impact of projected shadows in UAV snow observation. The increase referred above may be related to the decrease of point cloud density obtained under these lighting conditions obtained with both high quality and low quality processing options (Figure 8). In sparse point clouds, the point density decrease is originated in poorly illuminated areas which show a marked scarcity of points (i.e., shadowed area in Figure 5).

3.3. Comparison of Snow Depth Maps With Different Flight Configurations and Processing Quality

The image overlap, and GSD (mainly controlled through the height AGL) tested here had a minor impact on the quality of the snow depth maps, with little differences in mean RMSE and MAE (Figure 9). However, high dispersion in these error estimators is observed when all flights are plotted together (left side graphs in Figure 9). When flights with poor lighting conditions (shadow >50% or overcast sky) are not included in the boxplots (right side panels in Figure 9), the largest bias among block configurations is removed and thus boxplot dispersion is reduced. This demonstrates the major impact of lighting conditions when observing snow depth distribution with UAVs, compared to that of different block configurations (changing image overlap and flight altitude AGL) on final snow depth maps.

It was observed that blocks with identical configurations acquired in the same flight (first vs. last block with high AGL/low overlap) have almost the same dispersion and mean error values. It confirms that potential small changes in lighting or snow conditions during the flight do not have a significant impact on the results. The quality of the SfM processing (HQ/LQ) has also minor impact on the scores.

Figure 7. Error estimates (RMSE and NMAD) versus cast shadow area for all flights (left panel) and for flights having a snow covered area above 70% (right panel). The lines included in the right panel show the linear adjustment between the error estimates and the cast shadow area.
Figure 10 illustrates the low impact of flight configurations tested in our experiments. The frequency distribution of the UAV derived snow depths in the small test area under good lighting conditions (February 21, 2019 at 12:20 UTC) show good agreement with the frequency distribution observed with the TLS (Figure 10 top right panel histograms). The qualitative comparison of the snow depth maps, demonstrates that the spatial pattern of the three UAV configurations and the TLS is quite similar. A more quantitative evaluation through the frequency distribution shows that for small snow depths (below 0.3 m) some differences are obtained and this is relevant since the frequency of low snow depths is high. However, for medium and high snow accumulations, the frequency distribution is almost the same for the four snow depth maps. In this example, the UAV flight configuration with a better agreement with the TLS frequency distribution is the high AGL/low overlap. The similarity of snow depth observations in the three blocks configurations is also displayed in the error estimators of all flights in this later experimental campaign. For the three block configurations tested, similar accuracy and precision estimates were obtained along each UAV flight on February 21 (Table 5). The failure of flights under bad lighting conditions is evident if error estimates of the two flights with cast shadows >50% (acquired at 15:30 and 16:40 UTC on February 21, 2019) are contrasted with those acquired with a negligible presence of cast shadows (12:20, 6:40, and 8:30). For flights performed while cast shadows had a remarkable extent, all error estimates increased (SNR decrease), without a clear impact of block configuration. These results exemplify that the image overlap and GSD tested for observing snow distribution with 1 m grid cell size, was mostly insignificant when compared to errors caused by lighting conditions. SNR of these blocks under good lighting conditions demonstrate that under good lighting conditions the three blocks obtain meaningful snow observations.

4. Discussion
4.1. RTK-UAV Snow Observation Errors

The need to deploy and measure GCP is one of the major drawbacks in UAV applicability, which highlights the need for further research on the use of UAVs with real time RTK positioning (Bühler, Adams, Bösch, & Stoffel, 2016; Harder, Schirmer, et al., 2016). The comparison of RTK-UAV snow distribution maps with those obtained with the TLS has shown reliable agreement under good lighting conditions (no cast shadow.
In the literature, only three authors (Adams, Bühler, & Fromm, 2018; Bühler, Adams, Stoffel, & Boesch, 2017; Harder, Pomeroy, & Helgason, 2020) have compared UAV snow depth observations with LiDAR derived acquisitions (including TLS). Except Harder, Pomeroy, and Helgason (2020), these works used GCPs for accurate georeferencing the observations retrieved with the UAVs. Adams, Bühler, and Fromm (2018) reported an average RMSE < 0.31 m for good lighting conditions and >0.39 m under poor light. In the same study site, different UAV flights conducted by Bühler, Adams, Stoffel, and Boesch (2017) obtained an RMSE ranging from 0.18 to 0.77 m.

Other works evaluated UAV snow depth observations with different observation techniques. For instance, Avanzi, Bianchi, et al. (2018) acquired the snow depth distribution with a UAV, a total-station (working on scanning mode) and they also carried out a few manual snow depth observations. The comparison of the UAV with these two techniques returned an RMSE ranging from 0.20 to 0.45 m depending on the acquisition date. However, they reported a substantial reduction in RMSE (ranging from 0.06 and 0.17 m) when

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**Figure 9.** Box plots with the scores of the UAV-TLS comparison in the test area for all flights. Panels on the left include values (RMSE (top) and AME (bottom)) for blocks from all flights in which the TLS comparison was possible. Panels on the right show the same scores but with flights with shadow area above 50% removed. Each block configuration (Table 1) has two boxplots, one for high quality (HQ) processing and another for low quality (LQ) processing.
excluding areas of potential outliers. Other UAV evaluation datasets as snow depth maps from Pleiades satellites (Marti et al., 2016) or manual observations (Adams, Bühler, Boesch, et al., 2016; Goetz & Brenning, 2017; Lendzioch et al., 2016; Miziński & Niedzielski, 2017; Vander Jagt, Lucieer, et al., 2015), obtained RMSE ranging from 0.07 to 0.58 m in a wide variety of study sites. The average performance in reproducing snow depth distribution that we obtained with a RTK-UAV returned an RMSE of 0.19 m for flights accomplished under good lighting conditions, which rose to 0.37 m when all flights were included. As shown, the estimated errors show similar values to previous studies even though we did not exploit GCPs to georeference the information retrieved with the UAV. This demonstrates that, following a detailed acquisition and processing protocol, RTK-UAVs allows retrieving snow distribution under good lighting conditions over extended mountain areas with complex topography and under a wide variety of snow surface conditions happening along the snow season. This is particularly relevant since to the date, no research had recursively evaluated so many RTK-UAVs snow observations (13 UAV flights) with a well-established and spatially distributed snow observation technique (TLS).

The error estimates we computed were also similar to these obtained in the only two works, as far we know, in which UAV observations were not supported with GCPs (RTK/PPK positioning of the UAV; Eberhard et al., 2021; Harder, Pomeroy, & Helgason, 2020). Harder, Pomeroy, and Helgason (2020) obtained a RMSE of 0.1 m when comparing snow depth observations of two UAVs, one based on SfM and the other on LiDAR technology in an alpine study area. Eberhard et al. (2021) used some manual and snow pole observations to
perform their evaluation of the RTK-UAV snow observations. They obtained a RMSE of 0.16 m and a NMAD of 0.12 m, which are comparable to our mean RMSE (0.19 m) and mean NMAD (0.13 m) under favorable conditions. Nonetheless, these last two references, only analyzed one UAV acquisition date avoiding further assessments on the impact of different snow surface or lighting conditions on their results.

4.2. Impact of Lighting Conditions on UAV Snow Observations

Further evaluations under distinct lighting conditions are required to confirm the high similarities we found in camera self-calibration and in the snow depth mapping when including GCPs in SfM routines (first UAV flight on February 21). Several authors mention in their works, that lighting conditions strongly affected the accuracy and the quality of UAV snow observations with SfM algorithms without a quantitative evaluation of the error introduced under unfavorable conditions (Bühler, Adams, Bösch, & Stoffel, 2016; Cimoli et al., 2017; Harder, Schirmer, et al., 2016). Other studies have shown an increase of error estimates when the study area is partially or entirely affected by shadows (Adams, Bühler, & Fromm, 2018; Bühler, Adams, Stoffel, & Boesch, 2017). Our results have also shown a marked increase of error measures under unfavorable lighting conditions. As far we know, none of previous researches have detailed shadows extent or broadband radiation for poor lighting conditions what prevents further comparison with our findings.

In this study the reliability of UAVs did not depend on the snow depth distribution or characteristics of the snow surface. Nevertheless, it must be highlighted that flights with optimum lighting conditions provided a mean RMSE of 0.19 m showing that UAVs are not suitable for monitoring shallow snowpacks. In the past, fresh snow was considered to hamper the application of photogrammetry on snow-covered terrain. Technical developments in the last years have overcome most limitation and now observing fresh snow with photogrammetry is feasible and accurate enough for most applications (Bühler, Adams, Bösch, & Stoffel, 2016; Cimoli et al., 2017) under good lighting conditions (Gindraux et al., 2017). Oppositely, our results have identified cast shadows as one of the major drawbacks for observing snow distribution with UAVs in heterogeneous mountain areas, independently of the radiation impacting the study area or the snow surface characteristics. Cast shadows areas have shown an important decrease of point cloud density and a significant increase of noisy values (resulting on not reliable UAV snow observations. Lighting derived limitations when observing snow distribution; require further attention of the developing community of SfM routines.

### Table 5

| Time       | Block configuration | RMSE (m) | MAE (m) | NMAD (m) | Vol dif (%) | SNR  |
|------------|---------------------|----------|---------|----------|-------------|------|
| 12:20 (Flight 1) | High elev.-Low overlap | 0.18     | 0.13    | 0.12     | 3.5         | 6.21 |
|            | High elev.- High overlap | 0.23     | 0.16    | 0.15     | 4           | 5.75 |
|            | Low elev.-Low overlap  | 0.17     | 0.12    | 0.14     | −3          | 5.83 |
| 15:30 (Flight 2) | High elev.-Low overlap | 0.39     | 0.24    | 0.18     | −19         | 1.9  |
|            | High elev.- High overlap | 0.37     | 0.23    | 0.17     | −19         | 2.4  |
|            | Low elev.-Low overlap  | 0.42     | 0.24    | 0.19     | −21         | 2.6  |
| 16:40 (Flight 3) | High elev.-Low overlap | 0.65     | 0.41    | 0.32     | −26         | 1.2  |
|            | High elev.- High overlap | 0.78     | 0.46    | 0.36     | −39         | 0.9  |
|            | Low elev.-Low overlap  | 0.72     | 0.50    | 0.41     | −38         | 1.4  |
| 6:40 (Flight 4) | High elev.-Low overlap | 0.26     | 0.25    | 0.14     | −8.3        | 5.1  |
|            | High elev.- High overlap | 0.24     | 0.26    | 0.12     | −6.8        | 5.5  |
|            | Low elev.-Low overlap  | 0.25     | 0.23    | 0.14     | −8.2        | 5.2  |
| 8:30 (Flight 5) | High elev.-Low overlap | 0.21     | 0.17    | 0.15     | 4.3         | 5.9  |
|            | High elev.- High overlap | 0.26     | 0.18    | 0.14     | 4           | 5.8  |
|            | Low elev.-Low overlap  | 0.19     | 0.15    | 0.13     | 3.7         | 6.1  |

Note. These error estimates were computed for the observations obtained in the small test area (see Figure 1 delimitation) within Izas Experimental Catchment.
as these routines have difficulties in reconstructing 3D surfaces in shadowed areas. This issue is particularly relevant when extending snow observations with UAV over larger domains since steep mountain areas are frequently impacted by cast shadow, particularly in winter when the sun has lower incidence angles.

4.3. Influence of UAV Flight Configurations on Snow Depth Maps

Previous studies have recommended a high image overlap (>85% for frontlap and >70% for sidelap) to observe low contrast surfaces such as snow (Harder, Schirmer, et al., 2016; Vander Jagt, Lucieer, et al., 2015). Thus, we compared previously reported thresholds (low overlap) and a more restrictive one (90% frontlap and 85% sidelap overlaps high overlap). Furthermore, we have evaluated the worth of conducting low altitude flights, with longer acquisition times and smaller GSD, or higher altitude flights, with a faster acquisition time and larger GSD. Results did not show a significant influence of flight configuration on the snow depth maps, highlighting that lighting is the critical parameter in obtaining accurate observations of the snowpack. Since these results were obtained within a small test area, dissimilar results may be found when covering larger domains as the entire Izas Experimental Catchment. The premise of a safe UAV flight, together with the requirement of equivalent lighting conditions during the flight, both detailed in methods section, did not allow attempting this evaluation in a larger area. Nonetheless the occurrence of ridges, gullies, flat areas and different aspects within the small test area, might allow extending conclusions to areas having similar characteristics.

From our experience higher flight altitudes are recommended, since the UAV devices are less exposed to potential crashes over complex terrain and faster acquisitions are achieved (note that the area surveyed on each image is larger from higher altitudes). Nonetheless we only tested two flight altitudes which lead to 4.8 and 2.8 cm/pixel and did not have a major impact on the snow products we evaluated. Alternatively, flying too low can lead to a reduction in overlap over high points of undulating terrain to the point that overlap may become insufficient to support photogrammetry (Goetz et al., 2018). This can be a major shortcoming in alpine areas usually characterized by a sufficient relief, and oppositely it does not matter on flat areas. Thus, a compromise between high flight altitudes and the expected GSD is required, bearing in mind the final spatial resolution of the snow depth maps to be generated. Main findings of Goetz et al. (2018), show that the spatial variation of precision in distinct UAV acquisitions is highly impacted by images height AGL and overlap. The overall median precision of 0.03 m they estimated, with an interquartile range of 0.05 m, may have little impact on our UAV snow depth observations, since mean snow depths were for all acquisition dates higher than 0.4 m (mean snow depths ranged from 0.4 to 1 m).

Regarding images overlap, our results show that higher overlaps to those recommended by other authors (Harder, Schirmer, et al., 2016) are not required since they increase the acquisition time and do not reduce deviations obtained when observing snow depth distribution. In view of maintaining these minimum overlaps when strong winds affect the UAV during the flight, we want to highlight the unfeasibility of respecting the images overlap if tail winds occur because the high ground speed of the device in these cases. From our field experience, we can avoid this issue if the flight path is designed perpendicular to main wind direction. This allows the UAV to correct the wind drift and acquire images respecting the overlap.

Poor contrast over snow surfaces has been already pointed out as one of the shortcoming having the greatest influence on the UAV snow depth maps (Boesch et al., 2016). This issue may be behind the negligible improvement on the final snow depth maps obtained with full processing options of the images (we named HQ). The long processing times and the large size of the point clouds generated (about 1 Gb making processing challenging), together with the minor improvement of HQ processing options to generate snow depths maps at 1 m spatial resolution, justify using moderate/low SfM processing routines in study areas surpassing Izas Experimental Catchment extent (0.48 km²).

4.4. UAV Observations, Improvements, and Constraints

Snow distributions maps with a 1 × 1 m grid cell size have proved to be a good estimator of the spatial distribution of snow in highly heterogeneous mountain areas (López-Moreno, Revuelto, Fassnacht, et al., 2015). The mean value, the standard deviations, the coefficient of variation and the minimum and maximum values obtained when mapping snow distribution for spatial resolutions higher than 1 m are the same to
those captured at 1 m. Oppositely coarser resolutions show a marked change on those metrics (De Michele et al., 2016). This way, a grid cell size of 1 m in snow depth maps is known to provide reliable spatial patterns in small to medium sized domains (Grünewald & Lehning, 2015; Revuelto, López-Moreno, Azorin-Molina, & Vicente-Serrano, 2014; Schön et al., 2018). On the other hand, the spatial resolution of the TLS point cloud used here (Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014), did not allow generating snow depth maps at higher spatial resolution. Thus, an evaluation of UAV snow depth maps, eventually generated at higher spatial resolution, with the TLS; would require increasing grid cell size of UAV products.

TLS data is often used as ground truth when validating other techniques. However, as any other observations, it has associated a measurement error (Morin et al., 2020). TLS have been validated for different acquisition distances from 500 m to nearly 1,000 m with an accuracy of 0.1 m (Deems et al., 2013; Prokop, 2008; Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014). In our study area this validation was assessed in three plots of 400 m², where TLS observations were evaluated with manual observations. Differences between both datasets were no statistically significant as Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al. (2014) showed, and had a MAE of 0.07 m calculated for six TLS acquisition dates. Nonetheless, some outliers were found, revealing that; despite here we accepted TLS as ground truth; it may include a very small percentage of wrong snow observations (Höhle & Höhle, 2009).

Taking advantage of the fast data acquisition of fixed-wing UAVs, in a single RTK-UAV flight of about 20 min (first block flight duration), the snow surface of more than 0.45 km² was obtained with few data gap areas. On the contrary, TLS observations have much longer acquisition times; in the Izas Experimental Catchment it took about 6 h (Revuelto, López-Moreno, Azorin-Molina, Zabalza, et al., 2014) to cover approximately 76% of the UAV surveyed area (depending on the conditions, this percentage may change slightly) However, current long-range TLS (e.g., RIEGL VZ-6000) have much higher measurements rates, largely reducing acquisition times but are still limited by line of sight limitations and terrain occlusions, issue that UAVs overcome. The first UAV flight on February 21, 2019 had good lighting conditions returning an RMSE of 0.22 m and a volume difference of 1.2% in the overlapping area (snow volumes of 314,028 m³ (TLS) and 310,234 m³ (UAV)). This shows that for this acquisition date both techniques are in good agreement. However, the total snow volume from this flight, also including shadow areas from the TLS viewpoint, was 408,189 m³. This implies an underestimation of a 31% of snow volume if only the TLS–UAV common area is considered (which is 24% smaller than the total UAV area surveyed). In this context, the UAV is clearly an improvement for assessing snow stored in the catchment compared to TLS.

The meteorological constraints (precipitation absence, relatively low wind speeds, clear sky or at least absence of strong cloud shadow effects) needed to operate UAVs require a precise interpretation of the weather forecast together with ready prepared equipment and easily available technical staff. The fixed-wing UAV used has a wind limit of 12 m/s according to the manufacturer, thus all flights respected that limit when launched. For some flights, peak wind speeds reached 10 m/s (measured by the UAV platform); however, this did not affect the quality of the snow depth maps. This agrees with Harder, Schirmer, et al. (2016), who obtained the most consistent performance for UAV flights with wind speeds <10 m/s under good lighting conditions (clear sky and the sun at high angles).

Once this ready-to-use technique has been validated, and its main shortcomings identified, our results provide an opportunity to map snow distribution in remote mountain areas covering several square kilometers in a single day. In 20-min flights, commercial RTK-UAVs (fixed-wing) with an RGB camera can cover almost 0.5 km². The direct geotagging of the information and both the GSD and the overlap of the images we tested here are accurate enough to retrieve the snow depth distribution. Therefore, proper organization of various UAV flights aimed at optimizing battery life, and good reception of the radio signal between the drone and the base (clear radio signal between the drone and the base precludes this setup for many rugged alpine areas), could allow extensive areas to be covered in the same experimental campaign if several charged batteries are available (less than 300gr each, and thus easily transported in the backpack). This represents a big step forward in close range sensing techniques, which not only enables large areas to be covered, but also reduces data gaps to the minimum due to the zenithal viewpoint of UAVs. The relatively simple and direct acquisition protocol and fast and easy post-processing of the information; open new insights into observing snow accumulation and melting processes at scales only available to, usually, much more expensive techniques (airborne LiDAR and satellite observations). Nonetheless when increasing area size,
UAVs may also run into the issue of losing sight to the UAV (lose of radio connection), as well to potentially run into more varying weather conditions, additionally increasing challenges for flight path design due to the terrain. These constrains must be considered when planning future UAV observations over extended mountain areas.

5. Conclusions

This paper showed the reliability of UAV derived snow depth distribution maps without using GCPs. This is possible thanks to recent technical developments of UAVs enabling direct, automatic RTK positioning of the images acquired during the flights. Our results obtained in 13 UAV flights along one snow season, also showed the major role of lighting conditions in obtaining reliable snow depth distribution information from RGB images. If poor lighting is avoided during the UAV flights, that is, cloudy skies hiding direct solar radiation, or images with large shadow cast by the topography, the MAE and RMSE was reduced to almost half, giving an average RMSE of 0.19 m. Under these acquisition conditions the average absolute snow volume discrepancy lower than 4% when compared to TLS snow depth observations, which is in line with previously reported accuracy using GCPs. This way, in order to generate high quality snow depth observations from UAV images, a nearly uniform illumination of the study area under clear sky conditions is highly recommended.

Other potential constraints that could affect the quality of snow maps, such as snow surface conditions, wind speed during the flight (always under the 10 m/s recommended by manufacturer), overlap of the UAV images (always exceeding the 70/80% frontlap/sidelap), and flight altitude AGL (images overlap and flight altitude evaluated here in a small test area within the study site); seemed to play a minor role on the error estimators reported in this study under good lighting conditions.

The high spatial resolution of the snow depth maps presented here demonstrate that this ready-to-use technique can be applied for observing snowpack evolution in remote mountain areas at medium scales, respecting lighting and weather constraints. Moreover, the bird’s-eye point of view of UAVs ensures observation with negligible data gaps, enabling full monitoring of the snow depth distribution with enhanced capabilities to the previously used TLS. Commercial UAVs with RTK positioning provide a safe, fast and user-friendly snow depth observations in remote mountain areas.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The database of UAV and TLS acquisition obtained in Izas Experimental Catchment is available in this repository with https://doi.org/10.5281/zenodo.4066637.

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