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Snow Depth Distribution in Canopy Gaps in Central Pyrenees

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ABSTRACT

This research analyses the snow depth distribution in canopy gaps across two plots in Central Pyrenees, to improve understanding of snow–forest and topography interactions. Snow depth maps, forest structure–canopy gap (FSCG) characteristics and topographic variables were generated by applying *Structure from Motion* algorithms (SfM) to images acquired from Unmanned Aerial Vehicles (UAVs). Six flights were conducted under different snowpack conditions in 2021, 2022 and 2023. Firstly, the snow depth database was analysed in terms of the ratio between the radius of the canopy gap and the maximum height of the surrounding trees (r/h), in order to classify the gaps as *small-size*, *medium-size*, *large-size*, or *open areas* at both sites independently. Then Kendall's correlation coefficients between the snow depth, FSCG and topographic variables were computed and a Random Forest (RF) model for each survey was implemented, to determine the influence of these variables in explaining snow depth patterns. The results demonstrate the consistency of the UAV SfM photogrammetry approach for measuring snowpack dynamics at fine scale in canopy gaps and open areas. At the northeast exposed Site 1, the larger the r/h observed, the greater was the snow depth obtained. This pattern was not evident at the southwest exposed Site 2, which presented high variability related to the survey dates and categories, highlighting the relevance of topography for determining optimum snow accumulation in forested areas. *Slope* systematically exhibited a negative and significant correlation with snow depth and was consistently the highest-ranked variable for explaining snow distribution at both sites according to the RF models. *Distance to the Canopy Edge* also presented high influence, especially at Site 1. The findings suggest differences in the main drivers throughout each site and surveys of the topographic and FSCG variables are needed to understand snow depth distribution over heterogeneous mountain forest domains.

1 | Introduction

Snow plays a key role in a large number of physical, ecological and socioeconomic processes and has a strong influence on Earth's climate and ecosystems (Thorn 1978; Pomeroy and Gray 1995; Huning and AghaKouchak 2020). Snow and ice melt govern river and lake downstream discharge, supplies fresh water for about 1.9 billion people and provides approximately 35% of the world's water used for crop irrigation in mountainous areas (Viviroli et al. 2020; Immerzeel et al. 2020).

In forested areas, the spatial and temporal evolution of the seasonal snow cover are determined by energy and mass fluxes that are more diverse than the fluxes in open areas (Varhola et al. 2010; Jonas and Essery 2011). The tree canopy in boreal forests can intercept up to 60% of snowfall in mid-winter, as much as 30%–40% of which can directly sublimate, while the rest falls or melts gradually, modifying the snowpack distribution on sub-canopy layers (Pomeroy and Schmidt 1993; Hedstrom and Pomeroy 1998; Barlett, MacKay, and Verseghy 2006). Trees also generate shading effects limiting incoming shortwave radiation to the snowpack, while subsequent tree trunk heating increases longwave radiation emission (Essery et al. 2003; Musselman et al. 2012; Mazzotti et al. 2020). During the ablation period, snowmelt rates can be up to 70% slower in forest compared to open areas due to the attenuation of incoming solar radiation (Varhola et al. 2010; Aygün et al. 2022). Additionally, the forest vegetation regulates snow cover accumulation over the forest-floor and surrounding areas through physical protection, affecting snow redistribution by wind and reshaping turbulent heat fluxes (Hardy et al. 2004; Hiemstra, Liston, and Reiners 2006; Varhola et al. 2010). The leaf litter beneath canopy also increases albedo, which adds complexity to the understanding of forest-snow energy fluxes (Melloh et al. 2001).

Forest structure is far from regular and canopy gaps in unmanaged forests exhibit high spatial heterogeneity in size and shape, making them complex spots for snow accumulation (Donager et al. 2021). Canopy gaps have commonly been assumed to be optimal sites for storing snow (Broxton et al. 2015), with longer-lasting snow accumulation, particularly in temperate climates (Zakrisson 1987; Lundquist et al. 2013). Snow retention by surrounded trees, influenced by interception, aerodynamic trapping, redistribution and other processes, has been related to the canopy gap size (Swanson 1998). Nevertheless, the impacts of these factors can vary considerably among sites, depending on climatic conditions (Lundquist et al. 2013), topographic properties (Ellis, Pomeroy, and Link 2013) and vegetation characteristics (Pomeroy and Gray 1995; Essery et al. 2003).

Several methods have been used to classify forest gaps according to their impact on snow distribution, including the ratio between the height of the surrounding trees and the radius of the canopy gaps (Golding and Swanson 1986; Musselman, Pomeroy, and Link 2015; Dickerson-Lange et al. 2023), the distance to the canopy edge (Mazzotti et al. 2019; Koutantou et al. 2022) or the size and extent of the canopy gaps (Tan et al. 2020; Hojatimalekshah et al. 2021).

Attempts have been made to manipulate forest structure to control canopy gap size and geometry in order to optimise snow and water management (Gary and Troendle. 1982; Pomeroy, Fang, and Ellis 2012; Piske, Harpold, and Advisor 2022). For instance, snow-hydrology experiments at Marmot Creek Watershed, Canada, have shown that small forest gaps (12.2–18.3 m in diameter) increase snow accumulation, but that forest management has low impact on streamflow volume and melt rates at the catchment scale. They also showed that those effects are strongly related to the clearing size, slope and aspect (Golding and Swanson 1986; Rothwell, Hillman, and Pomeroy 2016). Dickerson-Lange et al. (2023) estimated snow storage impacts of forest thinning and man-made canopy gaps across a west-to-east transect of the Eastern Cascade Range, USA. They concluded that snow accumulates more and lasts longer in north-facing gaps.

In the Central Pyrenees, Revuelto et al. (2016) found that pruning branches up to 3 m height of the tree trunk resulted in a 14% increase in snow accumulation. Belmonte et al. (2021) suggested for arid regions in Arizona that thinning trees over an area 1.5 times squared larger than the mean tree crown height impacted snowpack accumulation and its persistence due to tree shadow.

Snow cover patterns in both managed and unmanaged forests are also determined by climatic and geographic conditions (Lundquist et al. 2013). The snowpack is controlled by a wide variety of energy and mass fluxes with the atmosphere and the solar irradiance (Musselman et al. 2012; Seyednasrollah and Kumar 2014), as well as affected by topography (i.e., slope, aspect or elevation [Dharmadasa, Kinnard, and Baraër 2023; Murray and Buttle 2003; Lundquist, Cayan, and Dettinger 2004]). Hojatimalekshah et al. (2021) showed that windward slopes present a greater impact of topographic variables on snow accumulation than vegetation metrics according to multiple linear and decision-tree regression analyses across six plots in Grand Mesa, Colorado. Meanwhile in the Swiss Alps, Koutantou et al. (2022) showed that snow accumulation in forest gaps with opposite aspects is markedly impacted by solar radiation even at sites relatively close together and snow depletion was much faster on south-facing slopes.

In recent years, passive and active remote sensing techniques have frequently been used to investigate snowpack dynamics in forested areas. These have produced remarkable benefits and improvements, such as the possibility of monitoring several attributes and indexes of snow by coverage over large areas and improving acquisition speed, reducing cost and effort (Broxton & van Leeuwan, 2020; Avanzi et al. 2018; Belmonte et al. 2021).

Unmanned Aerial Vehicle (UAV) and airborne- Light Detection and Ranging (LiDAR), used at large scales, can provide a comprehensive view of multiple tracking variables further forest and sub-forest domains (Revuelto et al. 2016). LiDAR snowpack mapping has demonstrated widespread accuracy over both forest canopy and sub-canopy levels (Mazzotti et al. 2019; Harder et al. 2020; Safa et al. 2021). However, the technology setup cost is rather expensive, restricting its widespread application compared to other more accessible remote sensing techniques (Harder et al. 2020). UAVs together with Structure from Motion (SfM) photogrammetry have allowed three-dimensional (3D) reconstruction of snow and forest structure with high spatial resolution at an affordable price. Several studies have used UAV SfM to map snowpack dynamics in open forest stands at fine spatial resolution (< 50 cm/pixel) (Vander Jagt et al. 2015; Lendzioch, Langhammer, and Jenicek 2016; Meriö et al. 2023). Donager et al. (2021) indicated high accuracies (92%–97%) for mapping snow cover persistence in a sparsely forested ecosystem. Nonetheless, Schimer and Pomeroy (2020) cautioned that its application could only be made in areas covered by sparsely vegetated ground or forest gaps where major forest-snow interactions and solar illuminations issues could be avoided.

In the Spanish Pyrenees, UAV SfM techniques have been applied to monitor snow dynamics, especially in sub-alpine areas (Revuelto et al. 2021a, 2022; Revuelto, López-Moreno, and Alonso-González 2021b). Snow–forest interactions were studied using terrestrial laser scanning (TLS) (Revuelto et al. 2015, López Moreno et al. 2017). López-Moreno and Latron (2008), using manual measurements and hemispheric photos, estimated a 50% reduction in snow water equivalent (SWE) in forested areas compared to open areas in a mixed beech–fir stand. Sanmiguel-Vallelado et al. (2020) also found that snow duration beneath canopy was 10–17 days shorter than in open areas. Additionally, they observed a maximum decrease of 60% in annual peak SWE and a significant increase (190%) in spatial snowpack heterogeneity beneath the canopy compared to forest gaps.

All previous research motivated the use of UAV SfM photogrammetry to increase spatial coverage and be able to identify optimal conditions for snow accumulation and duration within a forest stand which is highly representative of many forests in the Spanish Pyrenees. The main goal is to determine the role of forest structure–canopy gap (FSCG) and topographic variables in local-scale snow variability over canopy gaps and open areas in three snow seasons and at two sites with the same climatic conditions. To achieve this general target, the following objectives were established:

1. Characterise basic forest properties, canopy gaps and snow depth distribution over complex mountain forest terrain applying UAV SfM photogrammetry.
2. Explore the link between snow depth accumulation and canopy gap size by a conventional classification approach based on the ratio of the canopy gap width (ratio of the gap, r) divided by the mean canopy height (h) of the surrounding trees (r/h).
3. Analyse the influence of FSCG and topographic variables on snowpack distribution across time and sites.

2 | Study Area and Meteorological Conditons

2.1 | Study Area

This study was performed over two forested slopes at the Baños de Panticosa in Tena valley, central Spanish Pyrenees (Figure 1). Data were collected at two experimental plots designated as *Site 1* (northeast exposed) and *Site 2* (southwest exposed). Both sites share similar elevation range (1910–2190 m a.s.l.) and area (0.21and 0.20 km^2, respectively). They are separated by 1.2 km horizontal distance and are located at mid-elevation of a Quaternary overdeepening glacial basin. The experimental area is dominated by heterogeneous forest structure that includes dense forest stands covered by *Pinus uncinata*, several canopy gaps of varying sizes and geometry and wide-open areas, generally at the contact of the tree line (Camarero, Gutiérrez, and Fortin 2000).

2.2 | Meteorological Conditions

Precipitation mostly falls from November to March, with a mean December to February (DJFM) 0°C isotherm around 1600 m a.s.l. (López-Moreno et al. 2011). The snowfall timing and intensity are strongly influenced by high inter-annual variability. The total accumulation and melt of the seasonal snowpacks oscillate depending on the dominant atmospheric circulation by advection from the Mediterranean Sea and the Atlantic Ocean (López-Moreno and Vicente-Serrano 2007). According to Morán-Tejeda, López-Moreno, and Sanmiguel-Vallelado (2017), López-Moreno et al. (2020) and Sanmiguel-Vallelado et al. (2022), seasonal snowpack has been affected by warmer temperatures in the last few decades, leading to earlier snowmelt onset and decreasing snow accumulation.

Strong inter-annual variability is visible during our study period (Figure 2). Snow cover duration in 2022/23 was much shorter than in 2020/21 and 2021/22, with no significant snowfalls after late January. Of the three analysed years, 2021/22 recorded the deepest snowpack, after substantial snowfalls in December and January. 2020/21 had the longest snow duration, with alternating periods of snowfall and settling, followed by the steady melting in the late-season.

3 | Methods

3.1 | UAV Acquisition and SfM Photogrammetry Processing

Five field surveys were made over the two sites between January 19, 2021 and March 01, 2023, with the aim of mapping snow depth distribution after relevant snowfall and melting events. We also overflew snow-free conditions to retrieve the bare ground surface and forest stand cover (June 8, 2021).

An *ebee X Sense Fly* UAV was used for the first four survey dates. It was equipped with a *3D S.O.D.A.* RGB camera (1-in. 20 Megapixels (3648 × 5472) CMOS sensor) that changes orientation during mission to capture three different orientation images (two oblique, one nadir). Flight missions were designed on Emotion 3 software. The last two field surveys (in 2022 and 2023) were done with a *DJI Matrice 300 RTK* multirotor UAV. The *DJI* aircraft payload was settled up with a *Zenmuse P1* camera (45-megapixel resolution (8192 × 5460) full frame sensor) and was controlled on *DJI* pilot software. The flight on May 5, 2022 also included acquisitions with a multispectral *MicaSense Altum* camera that allowed computation of the Normalized Difference Vegetation Index (NDVI) to support the identification of canopy cover (Pettorelli et al. 2005).

No Ground Control Points were arranged in terrain. In contrast, a virtual connection between the UAVs and the local geodetic network of Aragón ARAGEA (https://gnss.aragon.es) was allowed by Real Time Kinematic (RTK) positioning. Applying a well-designed methodology allows equivalent accuracies on the final snow depth maps to those derived with GCPs (Revuelto, López-Moreno, and Alonso-González 2021b). Both UAV devices acquired images with an accuracy below 3 cm in horizontal resolution (X and Y) and a vertical accuracy of 5 cm in altitude (Z) (Forlani et al. 2018).

Images of all the surveys overlapped a minimum of 60% transversally and 80% longitudinally. These images were obtained by high spatial resolution (5.3 cm/pixel average Ground sampling distance [GSD]), to ensure the quality of the 3D point cloud reconstruction, as summarised in Table 1. Factors such as the illumination and cloud cover during the flights were considered to

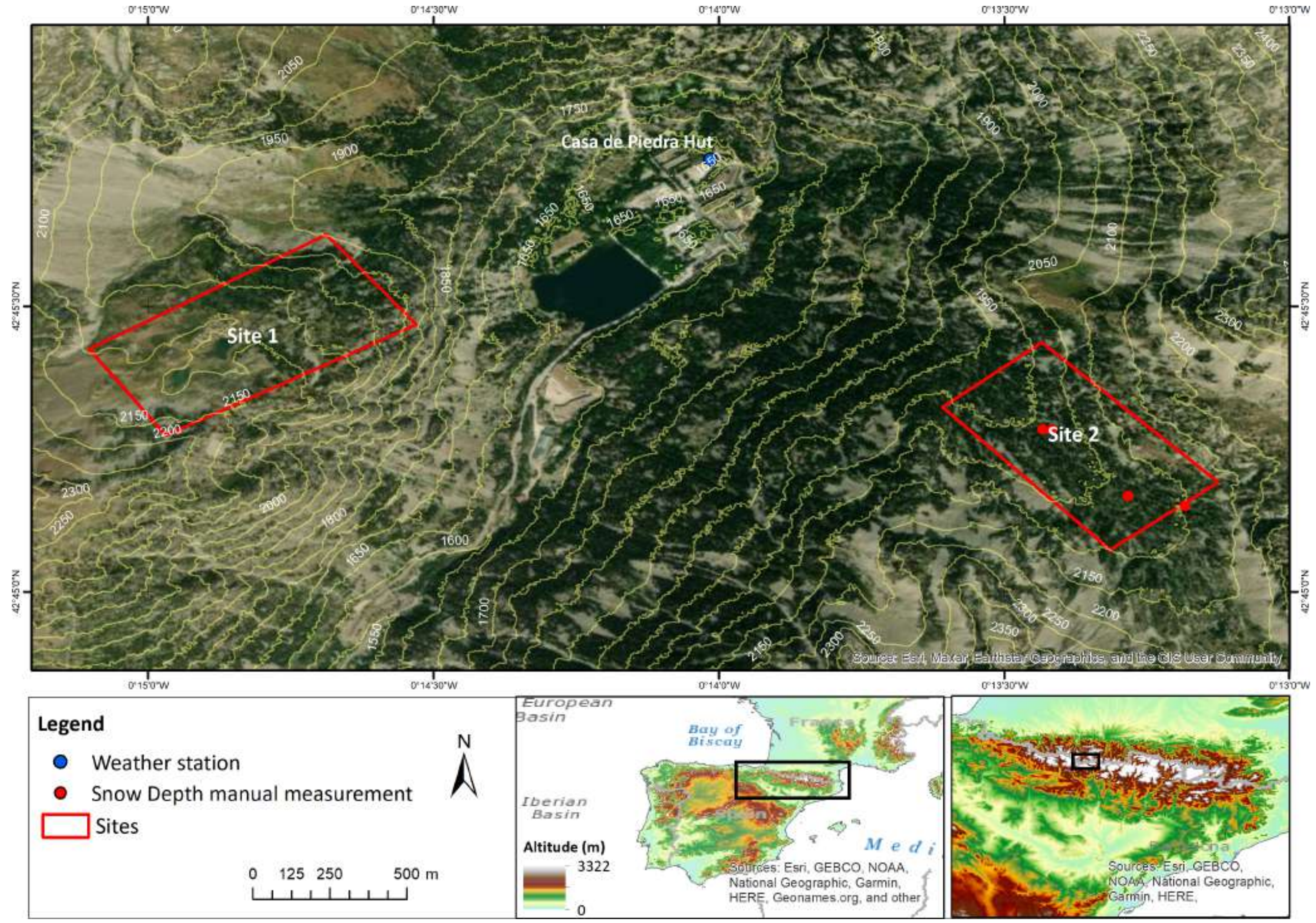

FIGURE 1 | Map showing the location of Site 1 and Site 2 (red rectangles), the weather station (blue dot) and snow depth manual measurements made on May 05, 2022 (red dots).

properly interpret the quality of the subsequent methodological steps (Revuelto, López-Moreno, and Alonso-González 2021b). All survey days were chosen to ensure adequate weather and lighting conditions (no changing cloudiness and low wind speed) to minimise uncertainties in snow map production (Revuelto et al. 2016). Flights over each plot were conducted at the most appropriate time of the day to take advantage of the best solar angles, reducing shadows projected by the canopy into the forest gaps (except for one flight acquisition with thin altostratus cloud cover on February 16, 2021).

The generation of orthomosaic, Digital Elevation Model (DEM), Digital Surface Model (DSM) and 3D point clouds was performed on *PIX4D mapper* (4.4.12 version). The process started with internal calibration of the camera parameters to identify common areas that can be linked across at least two images. Then the initial common layer allowed the calibration of the external camera parameters for a preliminary low-densified 3D point cloud. Finally, the densified 3D point cloud was block-adjusted by stereoscopic alignment (Revuelto et al. 2021a).

3.2 | Snow Depth Distribution Computation

The 3D point clouds derived from PIX4D were processed on *CloudCompare* v.2.2 software to extract snow-on and snow-off surface data (Westoby et al. 2012). We applied the *Cloth Simulation Filtering Algorithm* to obtain ground and off-ground surface classification and subsequently removed residual points of potential low vegetation less than 2 m above the ground surface by the *Statistical Outlier Removal* low-pass filter (Zhang et al. 2016).

To determine snow depth, we employed the *Multiscale Model to Model Cloud Comparison* (M3C2) algorithm. This calculates the difference in distance between two 3D point clouds (Lague, Brodu, and Leroux 2013), in our case, the ground and the snow surface. The search radius was dynamically adjusted by the Nearest Neighbour algorithm, ranging from 1.5 to 4 m, using a cylindric window between the point clouds. Finally, the snow depth was rasterized into a 0.5 × 0.5 m layer and masked with a canopy presence layer (characterised in the next subsection). The workflow that summarises snow depth distribution processing is presented in Figure 3a.

On May 5, 2022 at Site 2, four sets of manual snow depth validation data were established. Snow depth was acquired with a snow probe at specific locations by making equidistant replications in a 1 × 1 m grid along 3 × 3 m squares (9 manual snow depth acquisitions per each set location). These data were compared with the average snow depth of the corresponding pixels within a 3 × 3 m UAV snow depth acquisition's window. Due to time and logistical limitations, we were only able to obtain a limited validation dataset in a single survey day and site.

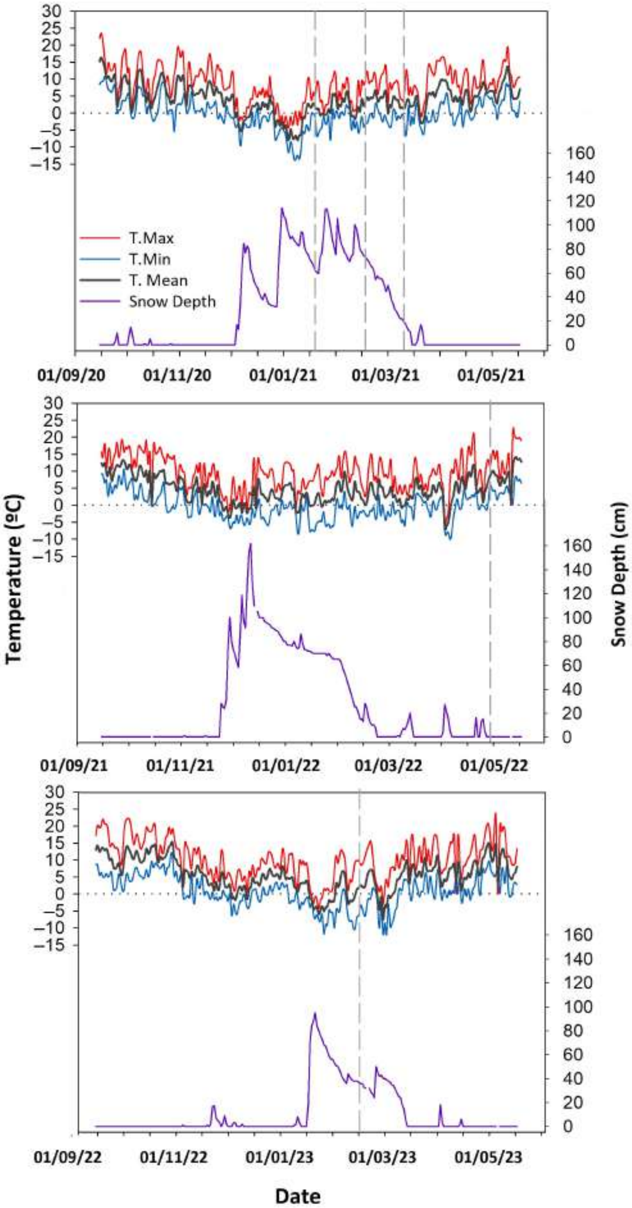

FIGURE 2 | Temperature and snow depth series were obtained from a weather station of Spain's State Meteorological Agency– AEMET, located at 1636 m a.s.l. beside Casa de Piedra hut. Mean (black), maximum (red) and minimum (blue) temperature and snow depth (purple) records were collected daily throughout extended-snowfall seasons from September 15 to May 15 (2020/21, 2021/22 and 2022/23). UAV date flights are represented by grey vertical dashed lines.

3.3 | Canopy Gap Outline

Tree canopy contour was initially determined from the 3D point clouds, using a disaggregated scalar field of the digital colours of every point in the cloud by (R + G + B)/3 composition. Subsequently the potential forest point clouds were classified according to the light conditions for each flight. This initial canopy cover was then exported as a raster layer and re-delimited with an NDVI layer mask on ArcGis 10.4.1.

Canopy height *H* values were derived as a *Normalized Digital Surface Model* (NDSM), representing relative elevations derived from ground elevations by subtracting DEM values from DSM values. A minimum 2 m height threshold was applied in order to avoid areas under the tree canopy such as shrubs and big boulders (Tennant et al. 2017; Mazzotti et al. 2019). A dissolve function (ArcGIS, data management tools) was employed to aggregate tree canopy clusters and individual tree canopies, resulting in canopy height model. These layers were then used to compute zonal statistics, specifically the maximum tree-height value for individual trees or tree clusters. Eventually, the canopy height was rasterized in a 0.5 × 0.5 m layer. The workflow summarising the forest canopy determination is presented in Figure 3b.

The outlines of the canopy gap were determined through geoprocessing analyses using a binary layer indicating the presence of forest canopy. We applied a 4 m circular moving window to calculate the sum for each cell neighbourhood and extracted up to 20% of these cells by focal statistic tool. We used a − 1.5 m buffer to the canopy gap outline to avoid potential noise from the canopy mask due to sharp branch shadows or error artefacts. Finally, the canopy gap contours were refined manually if needed.

3.4 | Forest Structure–Canopy Gap (FSCG) and Topographic Variables

We calculated a set of variables from snow-free layers to explore whether FSCG or topographic characteristics were the main influence on snow depth distribution at the study sites.

3.4.1 | Forest Structure and Canopy Gap Characteristics

We first calculated the FSCG variables as the total *Gap area* of each canopy gap and the *r*/*h* ratio as a relation of the canopy gap width (*r*) to the surrounding mean canopy height (*h*), which is the main canopy height within 4 m buffer distance of each gap edge. We opted to use width instead of gap length to identify more restrictive values, aiming to avoid as far as possible canopy gap shapes with elongated and markedly asymmetric features.

The *r*/*h* metric has been recognised as a forest gap criterion in many previous snow–forest interaction studies (Golding and Swanson 1978; Sun et al. 2018; Bouchard, Nadeau, and Domine 2022). The gap width was obtained by measuring the minimum bounding enclosing each gap with a convex hull threshold using the *Minimum Bounding Geometry* function (ArcGIS, data management) tool. This outline is defined as the smallest convex set that contains every gap vertex.

We also generated the *Opening* variable, which represents the ratio between *Gap area* and the mean canopy height *h*, after normalising the *area*/*h* ratios. The *Distance to Canopy Edge* (*DCE*), defined as the distance of each pixel to the nearest canopy edge (Mazzotti et al., 2019), was also computed for the study.

The spatial dimension of the different gridded variable dataset was maintained at the pixel scale, assigning the same value to each pixel within the gap for the FSCG variables, except for the DCE.

TABLE 1 | UAV survey dates, point cloud properties and lighting conditions during the flight surveys.

	Site 1		Site 2		Observations	
Survey date	Total number of points	Density (pts/m^3)	Total number of points	Density (pts/m^3)	Snow cover	Lighting conditions
January 19, 2021	5 933 791	25.51	12 604 336	20.54	X	Sunny and high illumination/ shadows behind trees over Site 1 NW/Site 2 SE aspects
February 16, 2021	8 894 647	25.93	10 768 871	19.59	X	Cloudy and low illumination/no shadows
March 10, 2021	10 820 742	29.54	12 450 698	21.28	X	Sunny and high illumination/ shadows behind trees over Site 1 NW/Site 2 SE aspects
June 21, 2021	8 610 297	23.67	8 383 234	19.95	Bare ground	Sunny and good illumination/no shadows
May 05, 2022	16 492 133	103.17	56 866 594	121.85	X	Sunny and good illumination/ shadows behind trees over Site 1 and Site 2 NW aspects
March 01, 2023	43 422 292	269.56	85 613 877	140.59	X	Sunny and good illumination/ shadows behind trees over Site 1 NW/Site 2 SE aspects

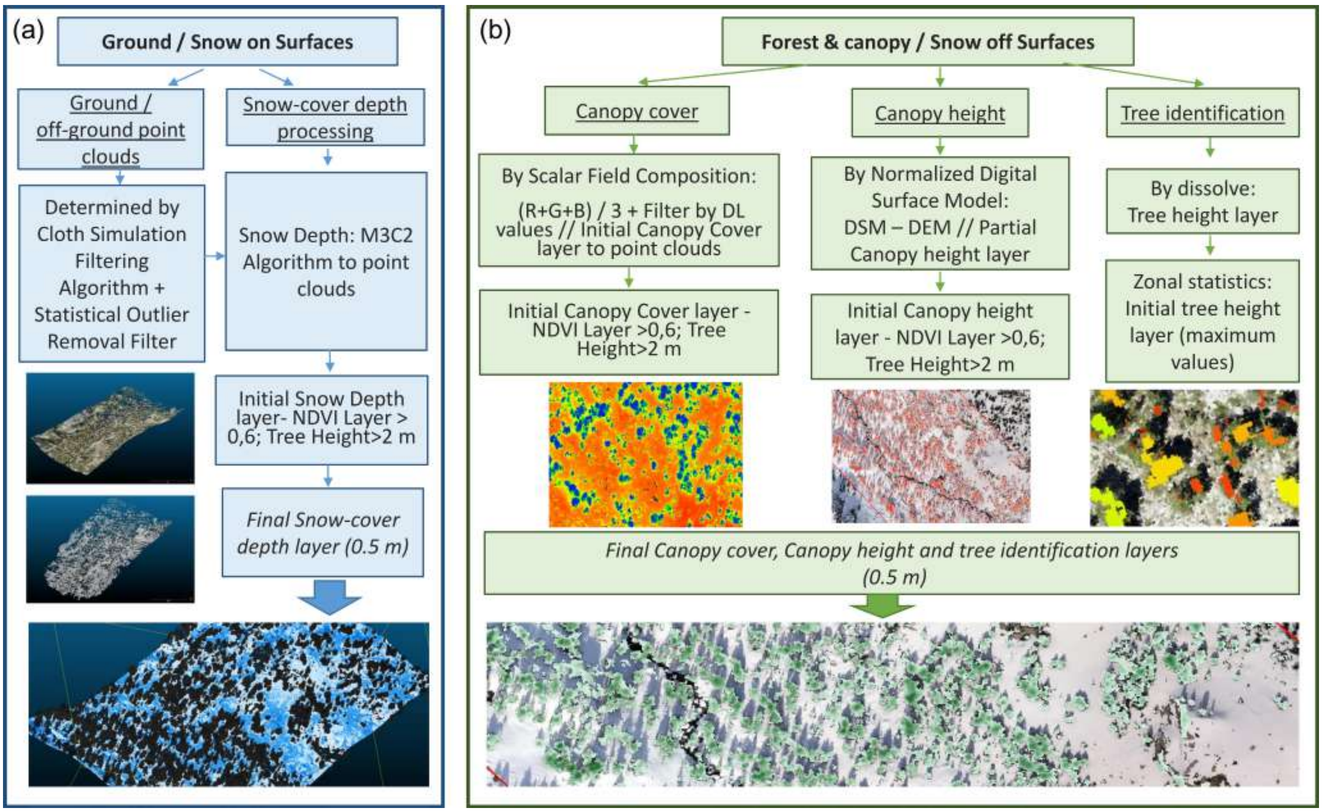

FIGURE 3 | Workflow of snow depth distribution and forest canopy assessment that was employed to generate snow-on and snow-off surfaces (3a), canopy cover distribution and canopy height layers (3b).

3.4.2 | Topographic Variables

Elevation and *Slope* were derived from the DEM. *Topographic Position Index* (*TPI*), as proposed by Weiss (2001), was also calculated from the DEM. *TPI* indicates the altitude difference between a specific pixel with respect to the average altitude of cells within a user-defined distance. We chose a circular window with a search distance of 20 m, as this is a commonly used distance for explaining snow distribution in the Pyrenees (Revuelto et al. 2014).

Potential Solar Radiation (*PSR*) under cloud-free conditions was calculated for a period of 15 days before each flight from the DSM. All of the above topographic variables were obtained from different tools available in ArcGIS.

The *Wind exposure parameter* or *Maximum upwind Slope parameter* (*Vx*) was calculated using the *maxus* software. This parameter renders the slope-exposure to wind from a given direction and search distance. It also allows wind exposition and sheltering zones to be described (Winstral, Elder, and Davis 2002). The *Vx* (Winstral, Marks, and Gurney 2009; Bilish et al. 2019) was calculated using a 20 m search distance with a 45° variance window in eight layers corresponding to different wind directions: North (0°), Northeast (45°), East (90°), Southeast (135°), South (180°), Southwest (225°), West (270°) and Northwest (315°). The calculation was based on the DSM layer considering trees, rocks and shrubs taller than 2 m.

3.5 | Data Analyses

3.5.1 | Canopy Gap Classification

The thresholds to divide canopy gaps into different size classes were obtained after applying multiple tree classification models and using different r/h combinations (Zhu et al. 2015; Sun et al. 2018). The canopy gaps were categorised according to the first split obtained from the tree regression relating gap size to accumulated snow. Subsequently the Kruskal-Wallis statistical tests were used to find the most significant differences among categories in the snow depth distribution. This ensures a regular distribution and occurrence of all canopy gap categories on both slope-sites.

3.5.2 | Explorative Correlation Analysis

The *Kendall's Tau* coefficient was calculated as an initial correlation measure of snow depth in canopy gaps with all potential independent variables, including the FSCG and topographic variables. This coefficient was chosen because the snow depth exhibited a log-normal snowpack distribution in the study area, consistent with observations at other mountain sites (Jonas et al. 2009). We only analysed correlations with a significance rate greater than 95%, equal to p values lower than 0.05. The correlations were calculated iteratively, extracting 100 random pixels in each of the layers and repeating the same calculation 1000 times, taking the mean value (Royston 1992). This analysis was applied for each UAV snow survey date and considered each site in the valley separately.

3.5.3 | Random Forest (RF) Classification

For our initial exploration, we built Random Forest (RF) models using a 20% random sample of data and treating both sites as independent categories, where the training and testing data was defined by default parameters. We aimed to assess the importance of predictor variables at each site separately. A substantial dependence of the local attributes, in both the topographic and FSCG variables, was observed for each site individually, emphasising the necessity of conducting simulations separately for each one.

That is how the dataset of each final model was split into 1000 random decision trees and the minimum number of observations in the terminal node was set to 20. A representative data sample from each survey was extracted in these simulations, where 63.2% of the total data was defined for training and the remainder as a testing source (36.8%). This last dataset is used to calculate the *Out Of Bag* hold-out test, which estimated the error of the generalisation by predicting the response of each particular observation (Ehrlinger 2015).

We considered a particular output of the package extensions, which determined the variable importance (vimp) of each explainer feature (the FSCG and Topographic variables) over the snow depth distribution. The analyses generate multiple random decision trees employing a separate bootstrap sample of the data and nodes, which are partitioned into the most effective predictor. These samples were chosen randomly from a subset at each node by the permutation method (Liaw and Wiener 2002). vimp yielded information about the rise in the predictions when each variable is deleted while other independent variables remain unchanged (Breiman 2001).

This method may exhibit bias in case of correlated predictor variables, attributed to collinearity (Meloche et al. 2022). Therefore, we first conducted matrix correlation tests using all predictive variables, from both the FSCF and the topographic dataset. Subsequently, we identified groups of variables that show high correlation and removed them in the final RFs. Thus, we performed 10 independent RFs, one for each UAV snow survey and site. We used the *RandomForestSRC* package in R studio version 2023.06.0.

The final variable predictors were assessed in terms of relative importance, ranging from 0 to 1. We used vimp ranking to quantify the role of each predictor variable to explain snow distribution independently at each site in the valley.

4 | Results

4.1 | Snow Depth Maps and Canopy Gap Classification

The methodology used provided snow maps with only a few and small no data gaps (Figure 4), these often affecting the same sectors within and around the canopy clusters along all data surveys (especially at Site 1). Data gaps are associated with illumination issues and steep areas that cast tough shadows. Despite the presence of shadows in some areas, the observed spatial snow depth variability was as expected for a highly heterogeneous mountainous terrain (Figure S1). Additionality, the comparison of manual measurements and UAV derived snow depth estimates, offered consistent values between the two sets of observations. The coefficient of determination (R^2) was 0.93 and some accuracy metrics remained below 0.25 m: mean absolute error (0.18 m), mean bias error (−0.10 m) and the root mean squared error (0.21 m). A location map of the validation dataset, including different areas of canopy shadow, is shown in Figure S2.

The basic gap classification to relate gap size and snow depth distribution was made up of three classes: (i) $0.6 < r/h$ as *small-size*,

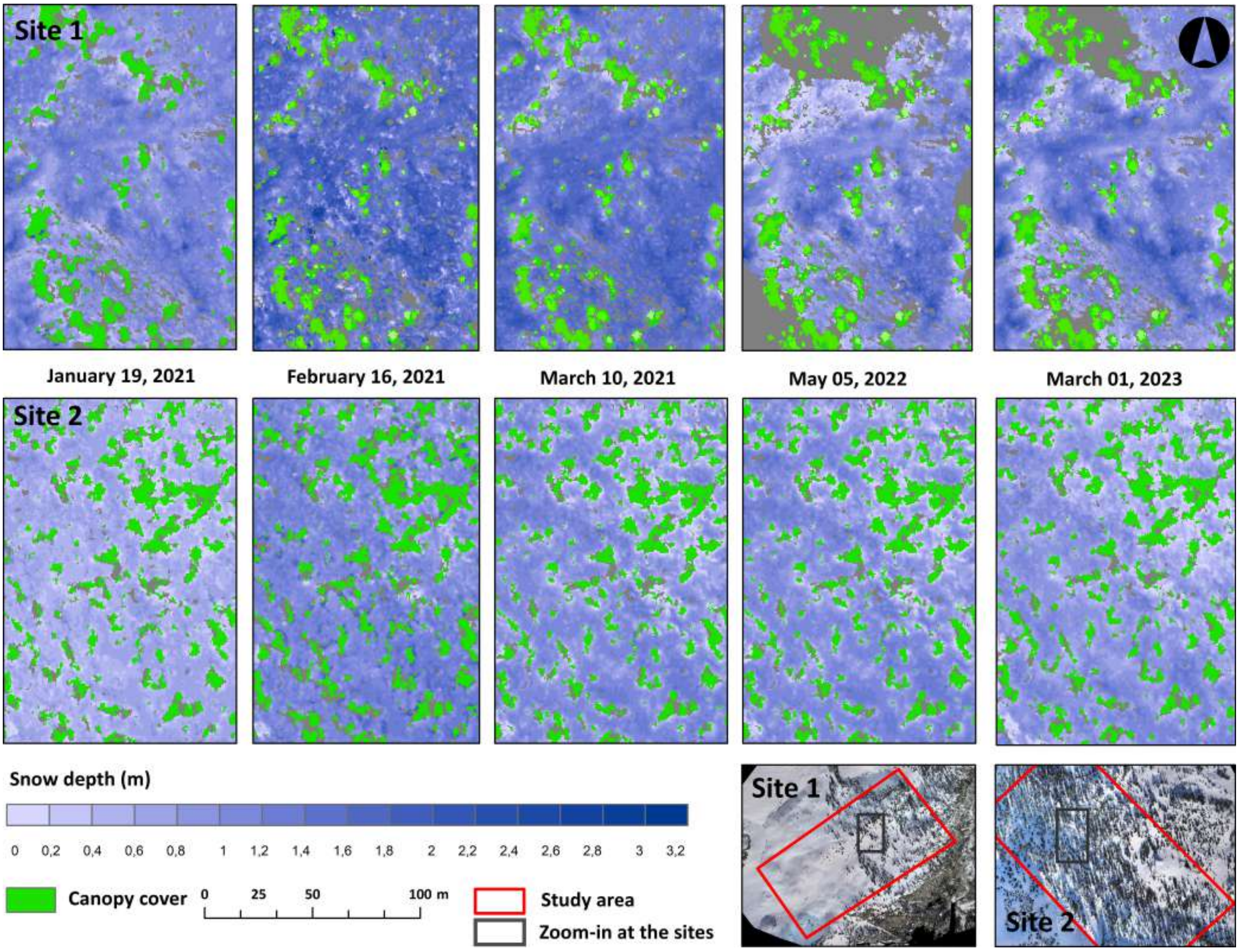

FIGURE 4 | Zoom-in maps of snow depth distribution over both sites. The variability of snow depth distribution along bare ground areas is shown by the colour intensity bar, no data by grey areas and canopy cover in solid green. The zoom-in zones, shown in the upper and middle snow depth maps, along all site areas (red rectangles), are characterised by grey rectangles in the legend.

(ii) $0.6 \leq r/h \leq 1.6$ as *medium-size* and (iii) $r/h > 1.6$ as *large-size*. In addition, an open-area category ($> 2000\,m^2$) was used for predominantly large extended areas where canopy trees influence may occur, but was not considered a canopy gap class itself, mainly due to the spatial pattern of its gap contours.

The classification generated a total of 434 gaps, 146 at Site 1 and 288 at Site 2 (Figure 5). Of these, 159 gaps were *small* (33 and 126 at Sites 1 and 2), 215 were *medium* (78 and 137 at Sites 1 and 2) and 48 were *large* (29 and 19 at Sites 1 and 2), while 12 were *open-area,* 6 over each Site.

Medium gaps were the most frequent category and *open-area* the least frequent, at both sites. The tree canopy present over the sites also meant that *small* and *medium* gaps represented 76.2% and 91.3% of the total gap categories (Sites 1 and 2 respectively). *Large* gaps were fewer, but more common at Site 1 (19.9%) than Site 2 (6.59%).

Site 1 had higher snow depths (Figure 6) than Site 2 in all acquisitions except for the survey on May 5, 2022. The survey on February 16, 2021 showed the highest average snow accumulation at both Sites and for all gap categories (except for Site 1 open areas which experienced a 5% greater snow depth on March 10, 2021).

Overall snow depth values at Site 1 increased in line with r/h, consistently along the survey dates. This pattern is slightly more obvious for the first two 2021 surveys than the others. The snow depth differences between categories were not as clear at Site 2 as at Site 1, especially across the 2021 surveys.

The *small* gap category exhibited the lowest snow depth accumulation at Site 1 and, in general, at Site 2 (except on May 5, 2022 and March 1, 2023 at Site 2). *Open-area* accumulated the deepest snowpack at Site 1 and together with *large* gaps registered the deepest snowpack, with 26% and 23% higher average snow depth values respectively than at Site 2. In contrast, the higher snow accumulation at Site 2 was observed mainly in *medium* gaps, except on January 19, 2021 over *open areas* and May 5, 2022 over *small* gaps. Even then, the average snow depth for those categories exceeded that for *medium* gaps by just ~2%. The snow depths for *small* and *medium* gaps at Site 2 were only 1% and 7% shallower respectively than at Site 1.

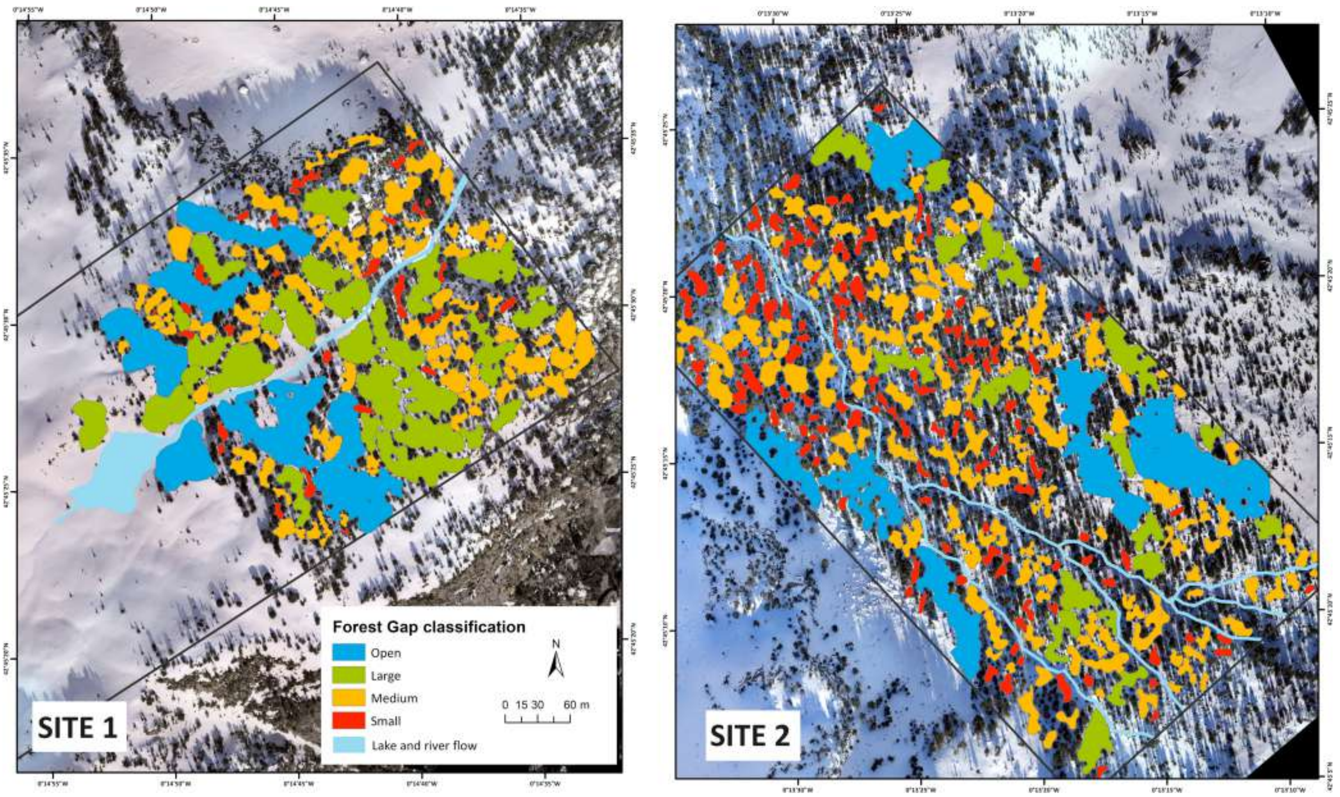

FIGURE 5 | Canopy gap classification maps of Sites 1 and 2. The different classes are separated by colours. Headwater flows and surrounding areas were masked and not taken into consideration in the canopy gap classification.

4.2 | Relation of Snow Depth Variability to Forest Structure–Canopy Gap and Topographic Variables

The FSCG variables exhibited weak correlation with snow depth, as demonstrated by Figure 7. Nevertheless, at Site 1, *DCE* exhibited a statistically significant positive correlation for all surveyed dates. For different aspects *Vx* also presented significant correlation having in most cases negative correlations. *Vx* values suggest that south/southeast exposures were more shielded and promoted more snow accumulation. Correlations with *Slope*, *PSR* and *Elevation* were significant for 3 (negative), 2 (positive) and 1 (positive) survey dates respectively.

At Site 2 the FSCG variables did not exhibit statistically significant correlation, showing lower relevance of the forest gap variables for explaining the snow distribution. *Slope* has negative statistically significant correlations for all dates and *Vx* also has significant correlation, indicating, as for Site 1, preferential deposition in south and southeast aspects. Correlations with *PSR* and *Elevation* were significant for 3 (negative) and 1 (negative) survey dates in each case.

The matrix correlation tests also showed some potential variables that may have exhibited strong correlations, such as *area* versus *r/h* and *Elevation* versus *PSR* (values above 0.5 and below −0.5 respectively). When choosing the final set of explanatory variables, we excluded *Area* and *Elevation* from further analyses. Neither had presented significant statistical correlation with snow depth in previous exploratory inspection and their inclusion could potentially introduce bias into the vimp evaluation.

The RF models exhibited a high capability to predict snow depth distribution. They provided R^2 values ranging between 0.68 and 0.7 (Table 2). The Mean Absolute Errors were also small at both sites, with an overall average of 0.11 m.

For Site 1, the variables with the highest explanatory importance in the RF models were *Slope* and *DCE* (Figure 8). The highest importance of *DCE* is observed during the late-winter season (the last three field surveys), despite *Slope* being highlighted in early winter surveys in 2022 and 2023. *PSR* and *TPI* ranked third and fourth respectively. The other FSCG variables ranked as the least important. *Vx* has generally low importance in the RF models at both sites, although it exhibited statistically significant correlations and relative variable importance in the survey on May 5, 2022. This observation occurred a few days after a snowfall under strong wind conditions.

At Site 2, *Slope* is the most influential variable according to vimp values. *PSR* and *DCE* were second and third respectively. At Site 2, *Opening* and *Vx* were slightly higher placed (fourth and fifth) than at Site 1. Site 2 also showed a high relative importance of *Vx* on May 5, 2022 due to the previous strong wind conditions. However, it should be noted that the *Vx* considered for Site 1 and Site 2 had different angles (315° for Site 1 and 45° for Site 2) as potential wind direction had higher correlations (see Figure 7), due to local topographic characteristics affecting wind redistribution. *TPI* and *r/h* are the least influential variables at this site.

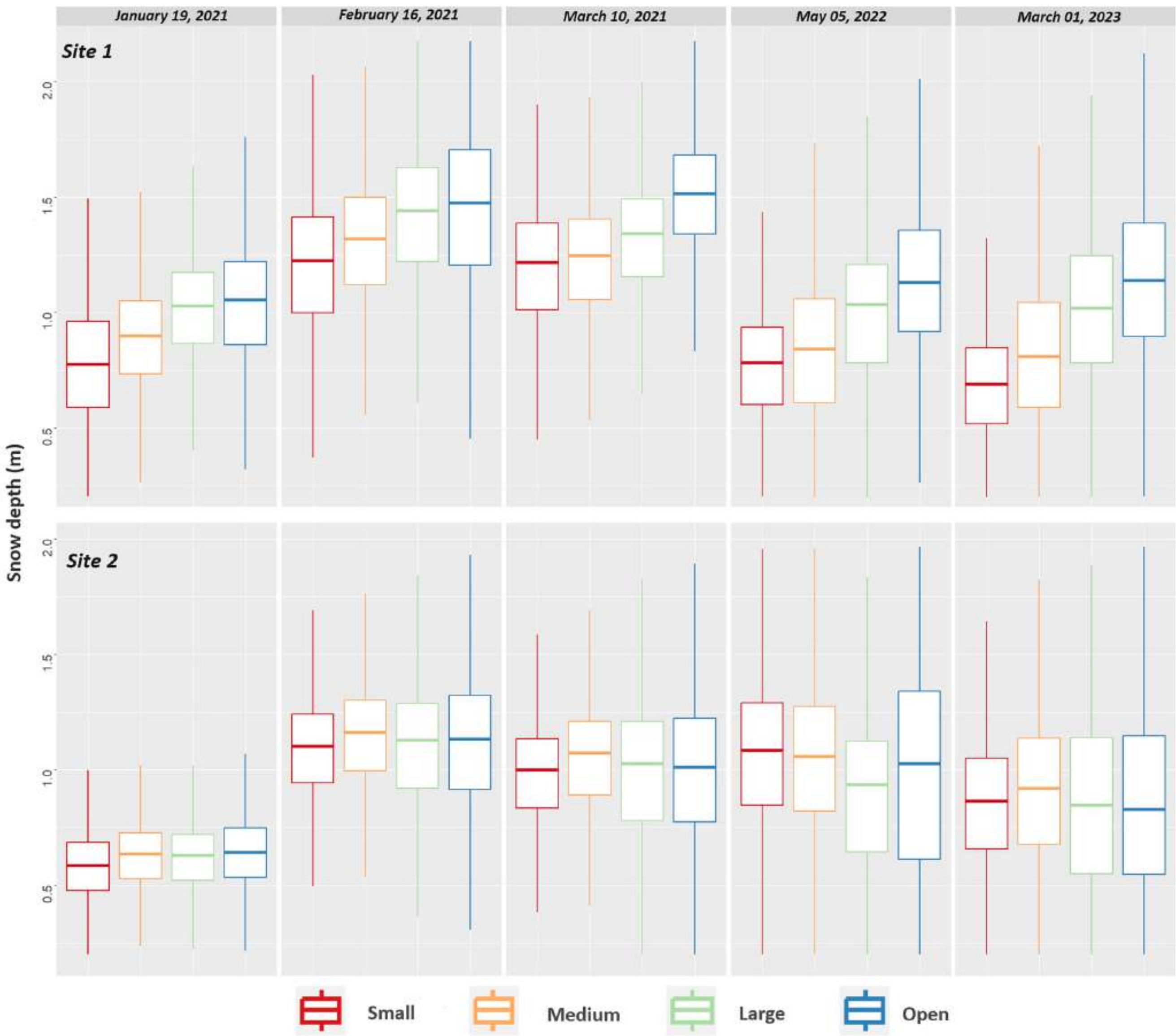

FIGURE 6 | Box plots of snow depth by category at each site. Horizontal lines indicate mean snow depth values. Boxes contain the interquartile range, from the 25th to 75th percentiles of the data distribution, while whiskers extend to the minimum and maximum values within 1.5 times the interquartile range.

5 | Discussion

5.1 | UAV SfM Photogrammetry Performance in Forest Mountain Stands

This work supports the capacity of UAV SfM photogrammetry for mapping snow depth distribution in canopy gaps and open areas within mountain sparse forest domains. Previous research considered this a challenging approach due to the low contrast of the snow surface, especially over fresh snowpacks (Buhler et al. 2016). However, the increased reliability of the technique, owing to recent enhancements in camera sensors and matching point processing techniques in SfM software, now allows its application to research on snow–forest interactions within a well-established framework. As Belmonte et al. (2021) demonstrated, the comparison of SfM point cloud-derived to field-measured and TLS data in semi-arid forest stand shows that it is possible to acquire reliable information on snow cover classification and forest structure metrics. Similarly, Donager et al. (2021) obtained high accuracies for snow cover classification in a sparse pine forest stand.

However, Harder et al. (2016) showed that complex topography in mountain regions can impact UAV SfM photogrammetry techniques, resulting in missing values and artefacts that underestimate snow depth interactions compared to flat areas. There have only been a few similar studies on snow–forest interactions in complex mountain terrain, which mainly used UAV-borne LiDAR approaches (Harder et al. 2020; Jacobs et al. 2021, Staines and Pomeroy, 2023). Some of these studies report that snow depth measurements on sub-canopy and beneath tree areas by UAV SfM photogrammetric techniques have restricted accuracy because optical sensors are unable to acquire data below trees in densely vegetated areas. This is why we did not retrieve snow depth under canopy areas.

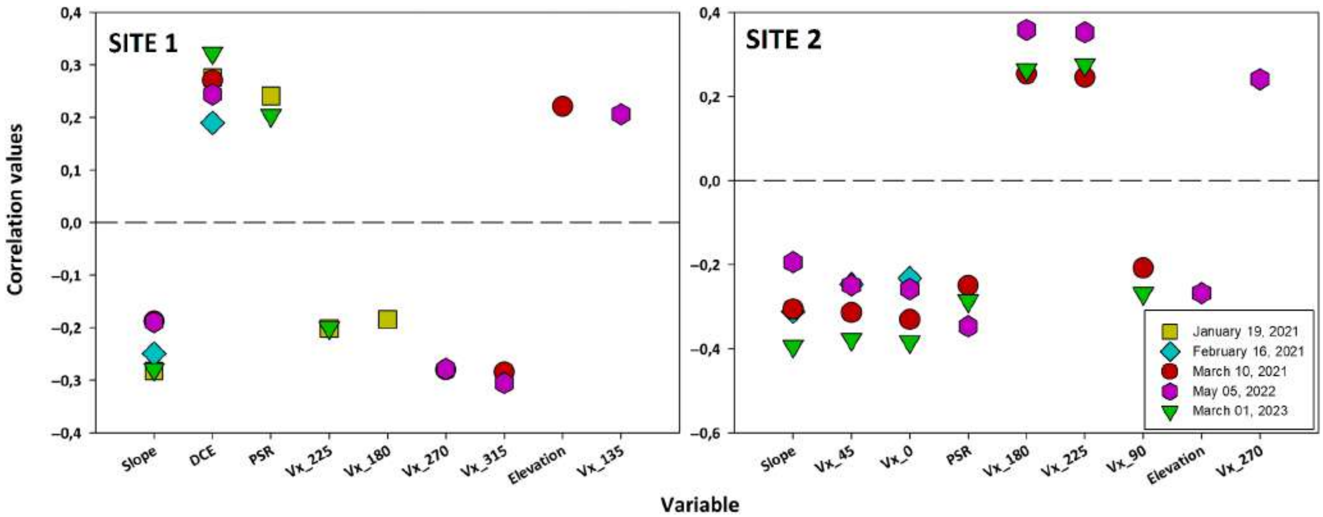

FIGURE 7 | Kendall´s correlations of the FSCG and topographic variables with snow depth. Only variables with statistically significant correlation greater than 95% confidence (equal to p values lower than 0.05) were considered and are shown here.

TABLE 2 | Error estimators obtained from the RF models.

	Survey date	Sample model	Mean absolute error	Out of bag R^2
Site 1	January 19, 2021	207.046	0.1	0.68
	February 16, 2021	177.768	0.1603	0.52
	March 10, 2021	169.036	0.1016	0.72
	May 05, 2022	132.041	0.1157	0.72
	March 01, 2023	109.944	0.1152	0.76
Site 2	January 19, 2021	293.611	0.0730	0.58
	February 16, 2021	271.999	0.1082	0.62
	March 10, 2021	264.791	0.0897	0.77
	May 05, 2022	232.308	0.1136	0.79
	March 01, 2023	44.189	0.1112	0.72

Our results show that following specific flight criteria, such as acquiring images with high overlap, low flight altitudes and multiple shoot angles (Revuelto, López-Moreno, and Alonso-González 2021b; Donager et al. 2021) and seeking optimal sun angles to minimise the presence of shadows in the gaps, UAV SfM photogrammetry over canopy gaps and open areas in medium to large mountain forest domains is a cost-effective monitoring technique when UAV-borne LiDAR is not feasible. Although the study sites represent only a small portion of the total forest in the sector, this technique has the potential to be replicated or expanded on a larger scale across different forest domains. Particularly, in areas with limited access to manual measurement methods.

5.2 | Snow Depth Between Valley Sites and Canopy Gap Classes With Different r/h

Without reference to canopy gap size categories, Site 1 accumulated more snow than Site 2. This behaviour has also been observed in recent studies comparing various slope orientations (Koutantou et al. 2022; Dickerson-Lange et al. 2023). This fact is explained by the effect that slope, aspect and exposure to main wind direction have on snow distribution (Berndt 1965; Golding and Swanson 1986; Zheng et al. 2019).

Defined thresholds from tree regression models and statistical comparison of populations provide analogous values to use in other analysis performed in coniferous forests (Zhu et al. 2015; Sun et al. 2018; Zhu et al. 2019). That is how we arrived at a canopy gap classification composed of four groups and based primarily on r/h thresholds ($0.6 < r/h$ for *small*, $0.6 \leq r/h \leq 1.6$ for *medium*, $r/h > 1.6$ for *large* and *an area larger than* $2000\,\mathrm{m}^2$ for *Open areas*). The snow depth values observed in each canopy gap showed that there is no ideal gap size for higher snow depth accumulation at either site. Despite this, *small* gaps systematically stored less snow at Site 1 and for early winter at Site 2. The snow depth distribution on this gap class can be explained by the higher canopy density of the surrounding canopy compared to the other classes. This enclosure geometry increases

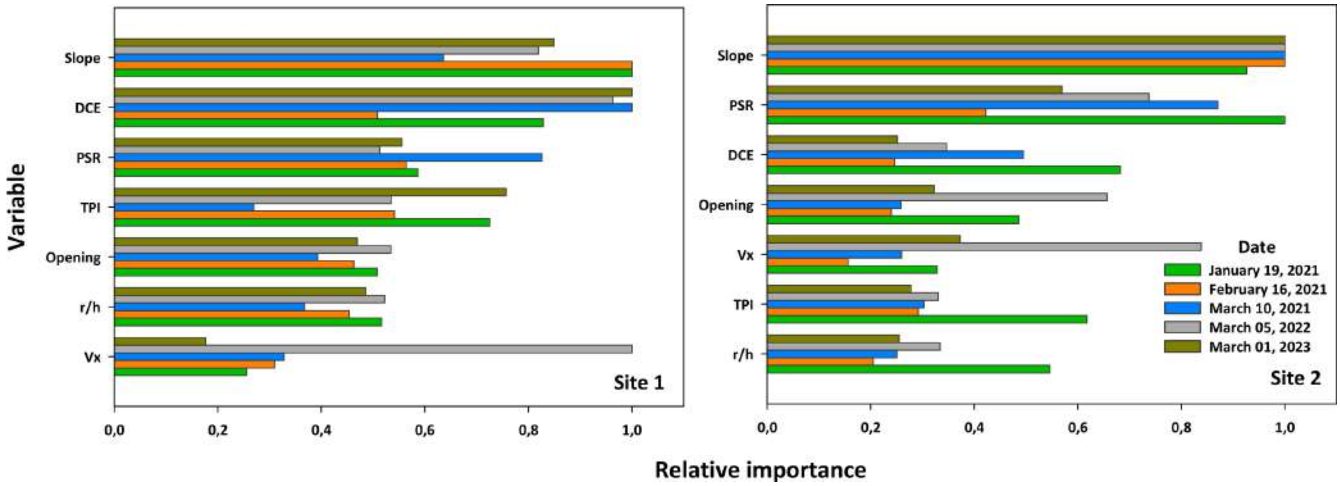

FIGURE 8 | Relative variable importance for predicting snow depth distribution with the RF analysis for each site and survey date. They are ranked by the sum of the total amount of vimp values, from most important at the top to least at the bottom, independently at each site.

the interception of snow and causes less accumulation in subcanopy areas (Varhola et al. 2010). Moreover, *radiative paradox*, defined as the increase in longwave radiation from warmer trees and resulting in greater snowmelt rates, instead of the shadow effect maintaining the snowpack, could have increased the loss rates particularly in early winter (Sicart et al. 2004; Lawler and Link 2011).

The increase in snow depth corresponding to larger *r*/*h* canopy gap classes at Site 1 agrees with the findings of Tan et al. (2020) by manual observation of coniferous forest in southwest China. In addition, other studies have found greater snow depth over *large* gaps and *open* areas compared to smaller classes (Mazzotti, et al., 2019; Hojatimalekshah et al. 2023; Dharmadasa, Kinnard, and Baraër 2023).

Interestingly, Site 2 exhibited a very different pattern. The only result shared with Site 1 is that the smaller gap class exhibited the shallowest snowpack in early winter 2021. The higher snow distribution variability and complexity in Site 2, may be associated to the predominate southwest exposure that is affected by solar radiation early in winter (Mazzotti et al. 2023). Differences in forest structure between sites may also affect snow retention separately. *Small* and *medium* gaps were more common along Site 2 than Site 1 and retained constantly more snow depth than larger gap classification and open areas during late-winter flight surveys as descripted before. This effect may be related to that mentioned by Broxon et al. (Broxton, van Leeuwen, and Biederman 2020), where shallow snow only persists in areas that are shaded by trees in late-winter along high-elevation site in Arizona. In general, vegetation density plays a significant role in snow retention. Conversely, *open* areas extensively observed in Site 1, exhibit higher snow depth values through the flight surveys. The lack of this process in Site 2 could be related once more to radiative forcing, where increased vegetation density influences by enhancing the longwave radiation emitted by warmer trees, leading to reduced snowpacks (Safa et al. 2021).

However, such indistinct patters prove the difficulty of determining ideal size-gaps for the longest duration of snowpack, as well as identifying peak snow storage places in temperate and highly heterogeneous mountains, with different snow accumulation rates than those found in more homogeneous topography and colder areas (Golding and Swanson 1978; Bernier and Swanson 1993; Sun et al. 2018). Thus, other factors such as forest structure and local topography are key to explaining the snow depth variability even in relatively similar areas and geographic conditions (Varhola et al. 2010; Hojatimalekshah et al. 2021; Mazzotti et al. 2023), as also demonstrated in this study.

5.3 | Forest Structure–Canopy Gap and Topography Variables Control Over Snow Distribution

Our results indicate that the snow depth distribution in canopy gaps is influenced more by topographic variables than FSCG variables. Nevertheless, this trend displays several local particularities across the study sites and field survey campaigns. *Slope* was identified as the main driver according to our analyses. The importance of this topographic variable for snow depth rates has also been observed in other forested environments (Harder et al. 2020; Dharmadasa, Kinnard, and Baraër 2023). Snow depth was thinner on steep slopes, likely linked to creeping snow moving downhill and major exposure to wind redistribution (Golding and Swanson 1986). The two analysed sites have a steep average slope (22°), but there are particular differences within the contour-form of each site and gap classification setting. Site 1 presented irregular terrain over the low-altitude portion (north-northeast orientations) of the study area, but flat terrain in the uppermost part. Site 2 displayed a different pattern, with a concave terrain shape and with most of the *large* gaps and *open areas* located on the sidelines (Figure 5). Higher slope values were observed in *large* gaps and in *open areas* across Site 2 than at Site 1 (62° vs. 58° and 63° vs. 51° respectively). This may also have influenced the differences in snow depth distribution between the sites within these same *r*/*h* classes, showing the relevance of combining FSCG and topographic variables to understand snow accumulation in heterogeneous forested areas.

This gap arrangement might have exposed more areas to the wind, creating a better linkage between *Vx* for both sites during the survey on 5 May 2022. According to the correlation analyses on this date, the wind potentially came from the north, affecting the sites slightly differently (stronger at 315° at Site 1 and 45° at Site 2). The variable split by directions showed that the snow depth distribution for this day was heavily affected by previous wind-induced snow redistribution. The wind could create favourable conditions for preferential deposition of blowing snow, when the wind velocity decreases at windward forest edges (Essery, Li, and Pomeroy 1999) and tree shapes serve as shelters for snow redistribution, increasing the snow accumulation on leeward aspects (Schmidt 1982; Pomeroy and Essery 1999; Winstral, Marks, and Gurney 2013). The better position that *Vx* held at this survey date also emphasises its significance in relation to tree presence, particularly with more *medium* gaps than *open areas*.

PSR had a significant influence on snow depth distribution at both sites, as shown in previous statistical models. This variable had a major effect on the energy budget of the snowpack accumulation (Musselman et al. 2012; Lundquist et al. 2013; Musselman, Pomeroy, and Link 2015), hence its high degree of relevance in the models.

Compared to the topographic variables, the FSCG variables made a low overall contribution to RFs. A clear exception is the high contribution of *DCE*, showing that snow depth tends to increase with *DCE*, especially at Site 1 which presented a higher prevalence of *large* gaps. Overall, results show the highly complex ways in which forest characteristics control snow distribution (Mazzotti et al. 2019; Belmonte et al. 2021; Aji et al. 2022). In addition, some variables that exhibited statistically significant correlation with snow depth show very little influence in the snow depth RF models. The opposite happens with *TPI*, which exhibited no statistically significant correlation coefficients but had greater relative influence on RFs along Site 1. This can only be explained by interactions and non-linear processes that RFs can identify, but they can behave differently within very short distances or after a short time between survey dates (López-Moreno et al. 2017). Besides, preliminary linear correlations also exploited the mean snow depth values versus the FSCG and topographic variables mean values for 422 gaps (open area outlines were not included). These analyses were inconclusive a tended to be scattered, even among topographic variables, as represented in Figure S3 for some FSCG and different Snow depth data surveys. This variability could influence the results depending on the statistical analysis used. Therefore, we took advantage of the use of RF, which, despite aggregating spatial data for some FSCG variables, can handle both distributed and aggregated values without compromising performance or ability to assess variable importance (Breiman 2001; Chavent et al. 2019; Fouedjio 2021).

5.4 | Insights and Limitations

Our results can be transferable to other forest areas lying in mountainous complex topography with variable forest structures, including differences in canopy density, tree heights and irregular forest gap shapes. Nonetheless, this study demonstrates the intricate interplay of processes that affect snowpack patters in mountain forested areas.

Lundquist et al. (2013) have shown that the balance between snow intercepted by canopy, sublimated snow and water that drips or is deposited on the ground depends on forest structure and slight differences in climatic conditions at each mountain forest location and season. Furthermore, the surrounding topography and forest structure, which influence exposure to winds and incoming solar radiation, are also significant drivers of snow cover dynamics in forested areas (Mazzotti et al. 2023). This could be less variable under homogeneous forest structure conditions, such as canopy gaps with similar size and geometry (often man-made) and smooth topography, where snow depth distribution responds consistently to changes in gap size or other vegetation structure management practices (Gary and Troendle. 1982; Swanson 1988; Rothwell, Hillman, and Pomeroy 2016).

To better quantify the drivers of the observed complexity, increased flight frequency and improved monitoring of weather and SWE conditions at each site should be considered for further research. Additionally, a quantification of snow interception on the forest canopy and a proper distinction of the fraction that are subsequently sublimated, downloaded and dripped in liquid form is needed. This information would facilitate a better linkage between individual accumulation and melting events and the evolution of the snowpack in forest gaps. Consequently, it would enable a more detailed link between snow dynamics in forest gaps and fundamental hydrological processes that govern snow accumulation and retention, such as the varying impacts of topography on the components of the energy balance and the role of wind in accumulation and erosion (Pomeroy and Essery 1999; Musselman et al. 2012; Hojatimalekshah et al. (2021)).

5.5 | Forest Management Perspectives for Snow Retention

Forest thinning, pruning or gap creation practices that reduce forest density could help to optimise snowpack accumulation and the subsequent snowmelt timing (Lundquist et al. 2013; Sun et al. 2018; Dickerson-Lange et al. 2023; Revuelto et al. 2016). Previous work on the study area also revealed increasing snow accumulation and longer duration in canopy gaps compared to sub-canopy areas (Sanmiguel-Vallelado et al. 2020). Lastly and only focusing on canopy gap classes, the results suggest that increasing the size of the smallest canopy gaps may lead to higher snow depth values, particularly at Site 1. However, these forest management activities must take careful account of topographic and FSCG arrangements, as well as the geographic context and climatic zone (Broxton, van Leeuwen, and Biederman 2020; Dickerson-Lange et al. 2023).

6 | Conclusions

Based on the results and discussion presented in this work, the following main conclusions can be drawn:

1. This work demonstrates that Unmanned Aerial Vehicles combined with Structure from Motion photogrammetry is not able to map sub-canopy snowpack, but it provides realistic mapping of snow depth within canopy gaps and open

areas measurements in heterogeneous forested mountain stand, extracting several characteristics related to their shape and forest structure attributes.

2. Classification of canopy gaps by r/h ratio revelled that there is no ideal gap size for maximum snow depth accumulation on differently oriented slope-sites. However, small gaps ($r/h < 0.6$) systematically stored less snow at Site 1 and on three survey dates at Site 2. Radiative forcing by incoming solar shortwave radiation, tree emitted longwave radiation and wind exposure, is likely modulated by slight differences in the forest structure and slope-exposure conditions of each site and period of the year.
3. Topographic variables are more important than FSCG variables for explaining snow depth variability in the study area. Slope exhibited negative and statistically significant correlations with snow depth throughout the survey period and across both sites. DCE was the only FSGC that presented high importance over the study sites.
4. Our findings suggest variation in the significance of different drivers, strong non-linear responses and complex interactions among predictors in explaining snow distribution at each site. This highlights the very complex processes that affects snowpack in forested areas with complex topography, where forest structure and canopy gap variables, topographic characteristics and weather are all important drivers in explaining snow cover dynamics.

All these complexities must be considered when the goal is to optimise snow storage in mountain forests as part of forest management strategies and interventions.

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Data Availability Statement

The data supporting the findings of this study are available upon request from the corresponding author.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.