# Investigating Repeatable Snow Distributions and Meteorological Conditions over Four Years in Finse, Norway

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A thesis

submitted in partial fulfillment of the

requirements for the degree of

Master of Science in Civil Engineering

University of Washington

2020

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Program Authorized to Offer Degree:

Civil and Environmental Engineering

University of Washington

**Abstract**


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Snow distribution is an important factor in earth processes and is predominantly influenced locally through fixed controls (topography and vegetation) and fluctuating controls (wind magnitude and direction, snowfall, and storm timing and frequency). Therefore, snow seasons with similar fluctuating controls are expected to have similar or "repeatable" snow distributions. While the processes responsible for snow distribution are well-established, the tendency of snow distributions to repeat yearly at fine spatial resolution (2m) in alpine terrains, such as Finse, Norway, is not well understood. Using four years (2015-2018) of differential Global Positioning System standardized snow depth values along ski tracks (orientated NNE, ESE, SSW, WNW) and meteorological conditions at the study site, we sought to establish which years had similar snow distributions, and what meteorological conditions (based on wind and snowfall) were responsible for these years having repeatable snow distributions. While no meteorological link was found for years with repeatable distributions when analyzing the meteorological conditions

from 1 October until the survey date, a common meteorological characteristic was found when analyzing the 2 months preceding the survey date. Based on this analysis, the meteorological conditions during the 2 months before the survey date are more indicative of which years have repeatable snow distributions. Therefore, the similarity of snow distributions at Finse from year to year is determined by whether snowy days with winds from the WNW (as in 2015 and 2017) or ESE (as in 2016 and 2018) contribute the most snowfall in the two months before the snow distribution survey date. While the study provides insight into the repeatability of snow distributions and the dominant meteorological conditions that impact this repeatability, future work could expand our understanding through more distributed snow observations, such as lidar, that provide more continuous coverage of the study area.

## 1. Introduction

Snow is widely known to be an important component of many earth processes, including ecological processes and the hydrologic cycle. Globally, snow reflects the sun's incoming radiation, affecting albedo and surface energy processes, in addition to slowing the dissipation of heat from the ground through insulation. Snow can also transform a landscape through smoothing rough surfaces or roughening smooth landscapes, thereby physically altering the landscape for a period of days or months (Filhol and Sturm, 2019). As snow depth distribution directly impacts snowmelt, runoff, and water supply, improving knowledge of redistribution drivers is vital information for water management groups, and predicting avalanches, mudslides, and floods (Dozier et al., 2016; Grayson et al., 2002; Lundquist et al., 2005; Winstral and Marks, 2002; Woodruff and Qualls, 2019). In addition, snow depth thickness and snowmelt timing is consequential for vegetation growth and species composition (Wipf et al., 2009), animal migratory patterns, and habitat suitability of both land and water organisms (Liston et al., 2016; van der Wal et al., 2000).

Snow depth distribution is influenced regionally by fixed controls (topography and vegetation) and fluctuating variables (weather dynamics, winds, avalanches) (Elder et al., 1991; Liston, 2004; Sturm and Wagner, 2010; Trujillo et al., 2007). In tundra environments, where vegetation is slow changing and has a low profile, weather is the main driver of snow depth distribution (Benson and Sturm, 1993; Sturm et al., 1995). Wind magnitude, prevailing seasonal wind directions, and the number of storms all impact the snowpack. Additionally, the timing and sequence of weather events affects snow metamorphism, intra-season time-stability of a snow depth pattern, and the repeatability of a pattern occurring from one year to the next (Elder et al., 1991; Homan and Kane, 2015; Winstral et al., 2002). Consequently, during the accumulation period of the snow season, wind is a driving factor for snow depth distribution, especially in non-forested, Arctic, or alpine sites (Homan and Kane, 2015; Li and Pomeroy, 1997a; Pomeroy et al., 1993; Sturm and Wagner, 2010; Winstral and Marks, 2002, 2014).

While there has been a lot of research on the processes responsible for snow drifting and snow distribution patterns, there are still unknowns regarding why distributions vary in time, both within and across years (Sturm and Wagner, 2010; Winstral and Marks, 2014). Grayson (2002) referred to the repeatability of a pattern to be similar from year to year as "time stable." A limited number of existing studies have looked at snow distribution across several years, but at coarser spatial resolution or areas with more gently sloping terrain (Homan and Kane, 2015; Pflug and Lundquist, 2020; Sturm and Wagner, 2010; Winstral and Marks, 2014).

This study seeks to build off existing research and help answer questions regarding the "time stability" of snow distributions by investigating the snow distribution of a 1km$^2$ alpine area in Finse, Norway with 2m spatial resolution over a four year time period. Specifically, we seek to answer the following:

1) How time stable are snow depth profiles for our study site across four years?
2) How do the meteorological conditions affecting snow distribution vary across 2015-2018?

3) Can a common meteorological characteristic be identified for years with similar snow distributions?

To investigate these questions, we will analyze the snow distributions and meteorological conditions of each year. The results of the meteorological analysis will be used to shed light on what meteorology is responsible for years having similar snow distributions. First, we will analyze standardized snow depth along three transects for 2015-2018 and quantify the similarity using mean squared error and correlation coefficients. Second, we will analyze the meteorological data, focusing on the frequency and amount of snowfall contributed during different event types (breakdown of the event types and their defining criteria is detailed in Table 1). Lastly, these two steps will be analyzed together to determine if years with similar snow distributions have similar meteorology.

Based on prior literature, we believe that years with similar weather will have repeatable snow distributions. Specifically, years with similar distributions will have the same weather condition (direction of wind with snowfall, or snowfall without wind) contributing more snowfall during those years. Since the frequency and timing of weather conditions also affects snow distributions, we additionally expect years with similar snow distributions to have similar frequency distributions of weather conditions.

## 2. Background

Wind, both speed and direction, plays an important role in the deposition and redistribution of snow (Dadic et al., 2010). High wind speeds lead to erosion of the snowpack, and snow moved by wind is preferentially deposited on the leeward-side of topographic features or among tall vegetation, where wind speed reduces and is insufficient to move snow further (Hiemstra et al., 2002; Homan and Kane, 2015). While different years can have seasonal variability, Winstral and Marks (2002) found that consistently high winds and consistent wind directions led to unvarying drift and scour regions. This led to persistent wind-affected snow distributions year-to-year. Deems et al. (2008) looked at the temporal consistency of snow depth scaling features and observed the scaling features in snow depth distributions were relatively insensitive to annual variations in snowfall. Schirmer et al. (2011) determined that the snow distribution at maximum snow depth was primarily the result of a few major storms, predominantly coming from one direction. Similarly, Sturm and Wagner, (2010) studied 30m spatial resolution snow distribution at an Alaskan tundra and concluded the development of a "typical pattern" was dependent on sufficient snow + wind transport + typical storms occurring during the snow season.

Once snowfall is deposited, it undergoes changes, most notably in density and structure due to various types of metamorphisms. Snow grains sinter, easily bond together, which hardens the snow, making it less likely to be eroded by future storms or winds (Schmidt, 1980). This is one of the reasons that the timing of storms and time between storms is an important factor in snow distribution. Sommer et al. (2018) demonstrated through wind tunnel experiments that snow hardened more when it was rapidly deposited, as opposed to slowly accumulating. Additionally, they found snow generally hardened more on the windward side of obstacles (Sommer et al., 2018). These processes impact the threshold wind velocity at which snow movement is initiated, one of the most important and complex parameters when modeling snow distribution (He and Ohara, 2017).

Numerous studies have shown that the threshold friction velocity required to redistribute snow is complex and dependent on several factors such as temperature, humidity, deposition time, snow density, hardness and particle size (Li and Pomeroy, 1997). However, snow redistribution by wind through drift, saltation, suspension, erosion, and sublimation can be highly significant but hard to measure and quantify. Creep, the method by which snow particles roll along the surface, can account for one quarter of snow transport at low wind speeds. These particles influence snow distribution since they are easily trapped in topographic features and vegetation (Tabler, 1994). Mott et al. (2010) found that in-slope snow depth depression patterns developed primarily due to saltation-driven redistribution from a specific wind orientation. Wind redistribution by suspension is typically due to smaller particle sizes and/or stronger winds and has been found to comprise up to 90% of the total flux when wind speeds exceeded 15 m $s^{-1}$ (Pomeroy, 1989; Tabler, 2003). Across the Northern Hemisphere, blowing snow has been found to redistribute and sublimate 23-52% of the precipitation (Yang et al., 2010). This can equate to a -40 to 100% difference in accumulated gauge-measured snowfall and observed measurements on the ground at an alpine ridge (Pomeroy et al., 1998). Additionally, sublimation alone can lead to snowpack differences of 37-85 mm in tundra sites (Li and Pomeroy, 1997).

All of the processes described above highlight that the transport of snow is mechanic, and therefore relative snow depth in an area is constrained in its accumulation. If the topography is constant, and snow accumulation is mechanically constrained, this decreases the variation of snow patterns that can develop, leading to a higher likelihood of repeatable snow distributions. Several studies have found that in some cases topography leads to similar distributions in different years despite inter-season weather variability. Lehning et al. (2011) observed that the distribution of snow depth at peak snow distribution for two small areas in the central Swiss Alps was governed by terrain roughness and latitude gradient. Schirmer and Lehning (2011) found a strong correlation at maximum accumulation, noting that despite differing storm patterns, the topography led to a converging snow depth pattern for the study period. Similarly, Parr et al. (2020) concluded that the high level of drift fidelity observed in the Arctic was due to drift formation being primarily controlled by the landscape.

It is therefore expected that snow depth distribution patterns repeat yearly in environments where fixed controls dominate, and winds throughout the snow accumulation are relatively similar from year to year. However, in some places, snow distributions are expected to repeat even with differing weather conditions due to the similarity of weather at seasonal scales, and tendency of topography to constrain and greatly influence snow distribution.

## 2.1 Study Site:

Finse, Norway is located in the upper part of a valley on the northern part of the Hardangervidda mountain plateau along the Bergen-Oslo railway in southern Norway (Berthling et al., 2001). Located above tree-line in an alpine zone, the area has a rolling and steep topography (Gisnås et al., 2014) surrounded by higher mountain peaks (1800 m.a.s.l) and the Hardangerjøkulen ice cap to the south. Our study site, a grid 1x1km, has an elevation range of 1262-1381m and is about 100m above the valley bottom and 3.5 km SE of the railway station. Finse is located between the maritime western coast and continental eastern region of southern Norway. It has short vegetation mostly consisting of mosses, lichen, alpine heaths, and occasionally exposed boulders and bedrock (Bryn & Ullerud, 2018; Landa, 2020).

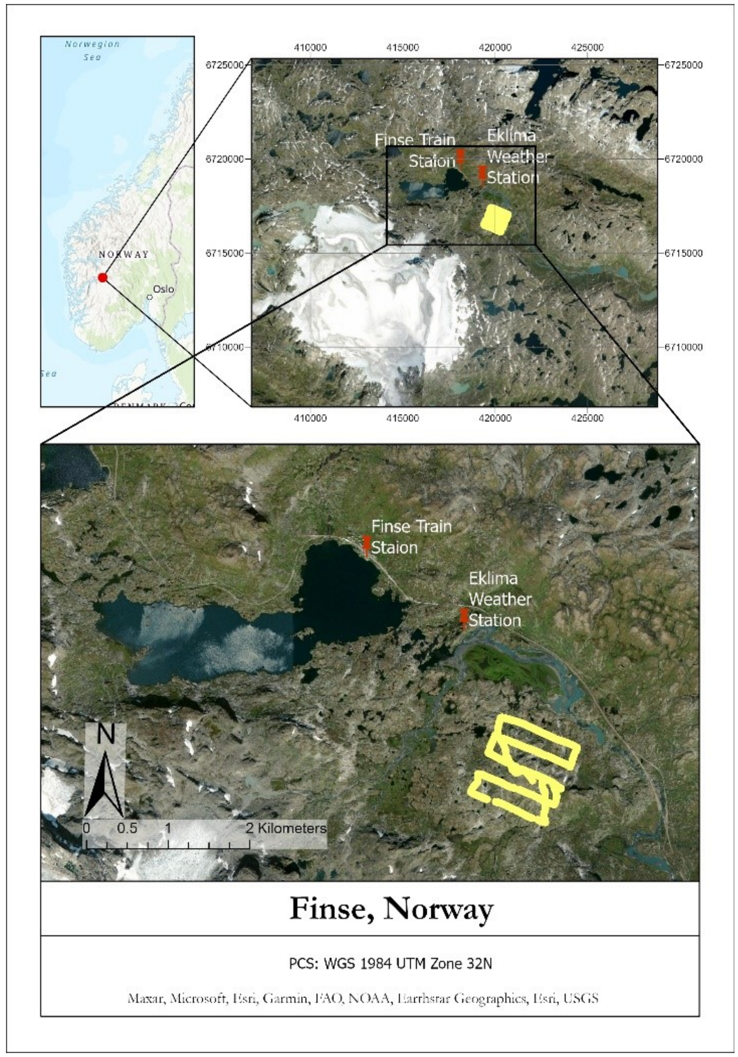


Figure 1: Map of Finse study site (yellow grid) in relation to the eKlima Finse Weather Station and Finse Train Station.

Snow typically begins in October and can last until June/July, accumulating an average peak snow depth of 1.5-2m (Data from eKlima, MET Norway*)*. Average snow density in February and March ranges from 350 to 450 kg $m^{-3}$. Measured mean annual air temperature at the Finse weather station, located 1.5 km from our study site, was -0.5°C for 2012-2019, and mean winter temperature (Oct 1-Apr 30) was -5°C. Due to the synoptic weather patterns and reinforced by the mountain topography surrounding the valley and study site, the prevailing wind direction is from the west (Suppl. Figure 2), with hourly mean and maximum wind speeds of 5.6 m $s^{-1}$ and 26.5 m $s^{-1}$, respectively. While avalanches, another fluctuating control of snow distributions, can be a problem in the region, they are unlikely to occur within our study area. Several other studies in this region have focused on ecology and vegetation (Landa, 2020; Litherland, 2013), and snow process and permafrost (Berthling et al., 2001; Etzelmüller et al., 2003; Gisnås et al., 2014).

## 3. Methods

This study has three main data sources: in-situ differential Global Positioning System (dGPS) tracks, Copernicus ERA5-Land hourly data (Muñoz, 2019), and Norwegian Meteorological Institute eKlima Finse station weather data (FINSEVATN station from eKlima.met.no, service provided by MET Norway).

### 3.1 Differential GPS Data

Differential GPS measurements of the snow surface elevation have been taken at Finse from 2015 until present. Measurements were taken a few times throughout each snow season. Due to weather constraints (low visibility, poor weather, or avalanche risk) and researcher schedule constraints, observations were not completed at the same date each year and at times were incomplete. Figure 2 shows the monthly availability of observations for our time period (water years 2015-2018). These observations were gathered by skiing along the 1x1km grid while pulling a sled with a dGPS unit attached. The corresponding base station was mounted on a large fixed granite rock near the Finse Weather Station. The receiver and antenna are Topcon GNSS (Global Navigation Satellite system) devices which utilize GPS and GLONASS signals. The dGPS antenna recorded snow surface elevation every second while the skier roughly followed the gridlines.

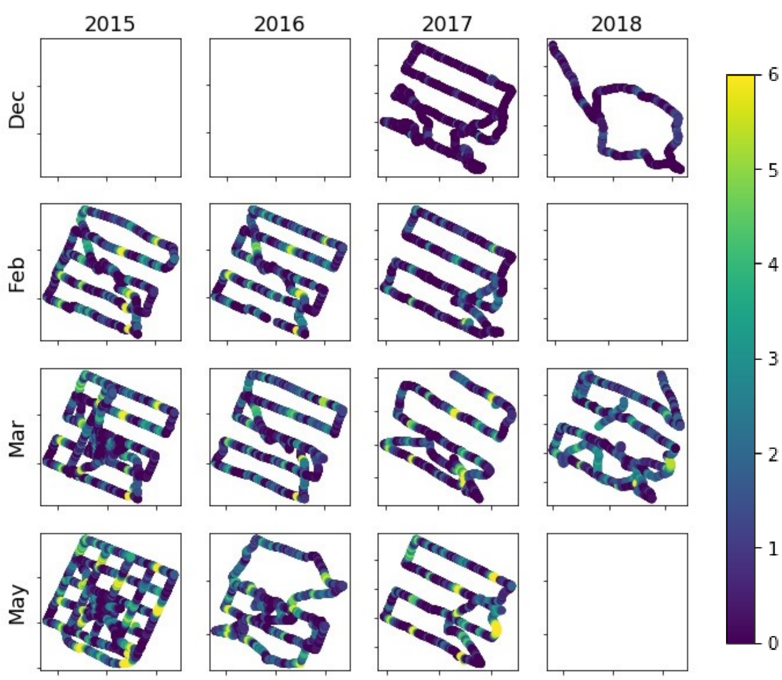


Figure 2: Differential GPS tracks for each water year symbolized with snow depth from 0-6 m. There were no observations during January or April. 2018 December is actually from November 20 of that year. For 2015, February and March ski tracks were completed over the course of 2-3 consecutive days. For these, the partial ski tracks were combined into one ski track and assigned the first survey date's date.

The dGPS data points were aggregated to a weighted mean value on a 2 m regular grid. Ground elevations, which are used to compute snow depth from the snow surface elevation, come from a 2015 airborne lidar survey (Høyde DTM 50 (UTM32) WMS, Norwegian Mapping Authority) that was converted to ellipsoid by adding the mean elevation difference in the study area. This point cloud was then rasterized to 2m resolution using PDAL (PDAL Contributors, 2018), and the mean elevation of each pixel was used to define the "ground elevation." From this, snow depth (snow elevation minus ground elevation) was computed at every dGPS data point.

Upon further investigation into the dGPS data, it was found that some snow depth points had negative values, with the snow surface elevation lower than the ground elevation. The individual dGPS elevation points are aggregated, which means their error is reduced as a function of the number of values averaged. Error from the airborne lidar Digital Elevation Model (DEM) is also propagated into the reference ground elevation. Since the snow depth is the difference between the snow surface elevation and ground elevation, errors from the dGPS and DEM are propagated in the snow depth. The aggregated March snow depth values were found to have a median error of +/- 25 cm as a result of error propagation from the DEM (+/- 27 cm) and dGPS measurements (+/- 2 cm). The largest source of error was from lidar DEM. Additionally, irregularities in the terrain, such as a large boulder, can skew the mean elevation of a pixel, resulting in a higher ground than snow elevation. This led to some negative snow depth values (0 to -0.99 m). To account for this, data points with snow elevations lower than their corresponding ground elevation were omitted from processing and analysis. As described in further detail in this section, this study focused on snow build up in depressions, where snow depth values are larger than the areal mean. Therefore, the inclusion or exclusion of these snow depth values is inconsequential since almost none of these values are in the specific transect sections analyzed.

It is important to note that while attempts were made to ski along the same grid tracks every time, some variation in location exists. The study area falls within a landscape preservation reserve, and is the site of non-motorized recreation. Therefore, it is not reserved for research, and to prevent from artificially altering the landscape, there are no stakes marking out the grid. Observation points from different surveys for a given transect were generally within 15m of each other, though in some places this increased to 30m. Looking at Figure 2, it is also evident that for some surveys a less complete grid was measured (2018 Dec), or transects were skied less precisely (May 2016), possibly due to weather, time, terrain, or skiing ability constraints. However, this study specifically focuses on data along transects that were closest in geographical location each year. While the exact snow depth at an observational point cannot be compared across different surveys due to the slight differences in location, this is not a hinderance to this study. Since we are interested in the general trend of snow distribution in our area, we can still compare the behavior of snow to fill (or not fill) depressions across specific transects of the different surveys.

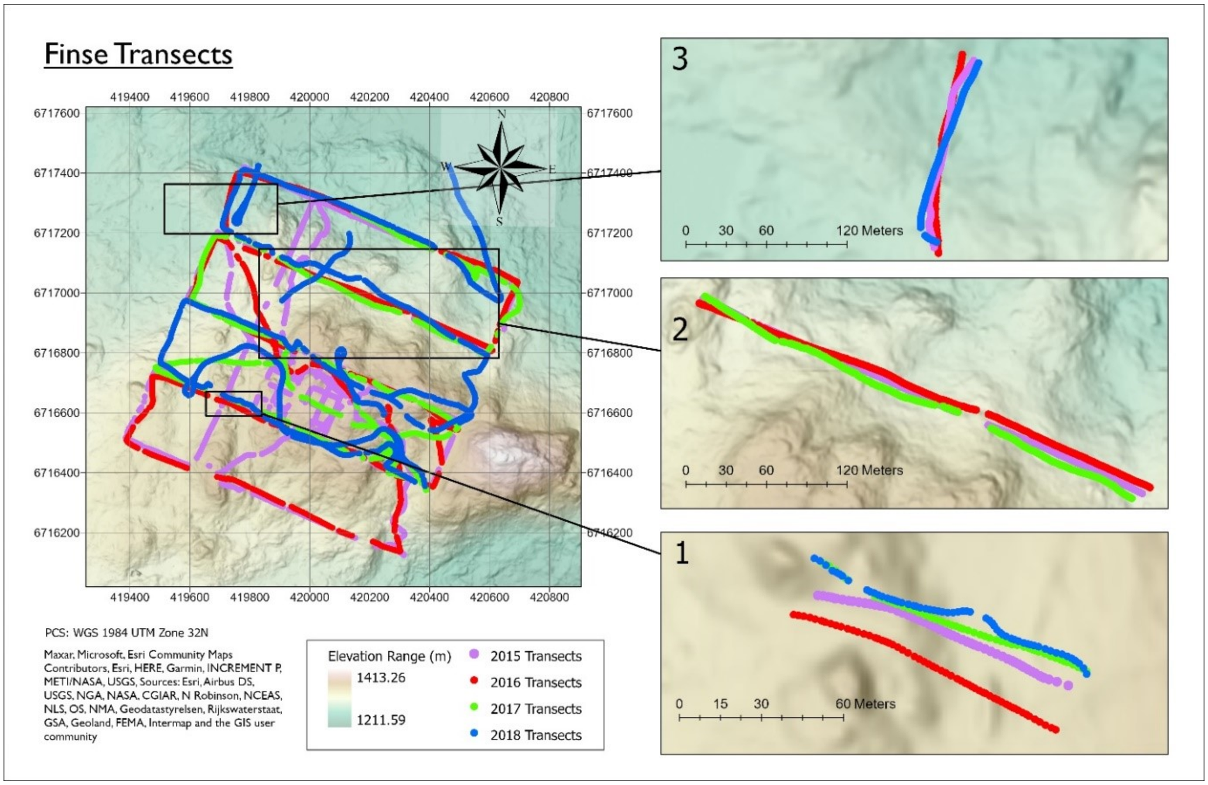


Figure 3: Left: Map of Finse study site and the March surveys for 2015-2018.
Right: Zoomed in on the three transects of interest for 2015-2018. Symbolized with elevation.

Three transects were chosen for analysis. March dGPS tracks (25-Mar-2015, 31-Mar-2016, 22-Mar-2017, 04-Mar-2018) were chosen due to their temporal proximity to peak snow depth and the availability of surveys from all four years. Other studies have found that pattern repeatability is highest near peak snow depth (Schirmer et al., 2011; Schirmer and Lehning, 2011; Vögeli et al., 2016). All transects chosen were picked based on the close spatial proximity of survey points, in addition to their location along topography that has relief and depressions. We expect snow along relief and depressions will be more sensitive to interannual differences in fluctuating controls than snow on gently sloping or flat terrain due to more complex wind redistribution. For each transect, the analysis was constrained to sections of interest directly bounding depressions and topography where we expect to better see similarities and differences. Due to inconsistencies in spatial location of the grid tracks from year to year, transect 1 has survey lines from all four years, but transects 2 and 3 each only have three years. The first two transects occur along a grid track from WNW to ESE, while the third is along a grid track from SSW to NNE. A more detailed view of these locations can be seen in Figure 3 where the four survey lines are shown with the 2m resolution DEM used to calculate the snow depth from the snow elevation. The topography between the different survey lines for each transect is sufficiently similar to allow us to compare the snow profiles of the different years despite the surveys not being in the exact same location.

To compare the dGPS snow depth across the four years while accounting for different snow depths and survey dates each year, the snow depth of each data point was standardized using the z-score (Equation 1):

$$1)\quad SD_{yi} = (d_{yi} - \mu_y)/\sigma_y$$

where $d_{yi}$ is the measured snow depth at point $i$ of year $y$, $\mu_y$ is the mean snow depth of year y and $\sigma_y$ is the standard deviation of year y. This was calculated using all the observation points for each year's respective March survey. Due to the different track locations, each year's survey has slightly different coverage of the study area, in addition due a different number of observation points. While some snow depth values were very small, the study area was snow-covered during the March surveys. Figure 4 displays the histogram of snow depth for all points in the March

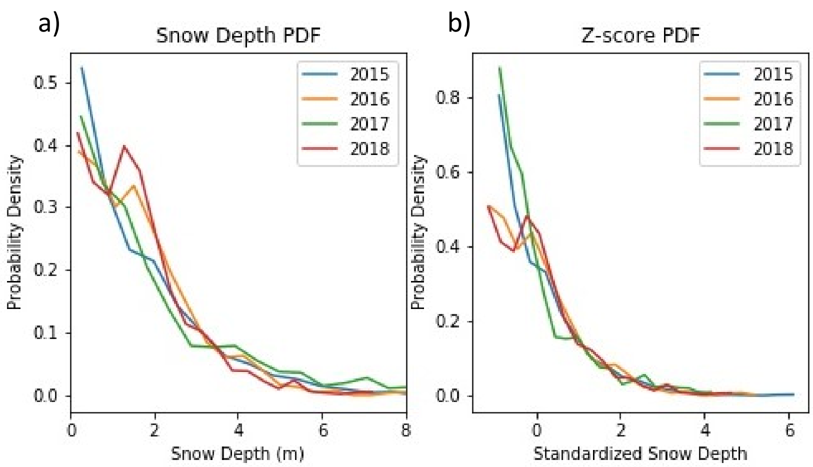


Figure 4: Probability density function (PDF) of Snow Depth for all points of March tracks, before (a) and after (b) standardization using z-score (equation 1).

surveys before and after standardization. Since we are primarily looking at snow drifts inside depressions, we are more concerned with standardization of the deeper snow depth values. The smaller snow depth values occur in high erosion areas that we will not be comparing. While the z-score failed to properly standardize the shallower snow depth values, Figure 4b shows the probability density functions of the different years closely agree for larger snow depths. The z-score is better suited for normal distributions. However, similarity in each year's ratio of mean/standard deviation (1.0-1.29) combined with the converging distributions near the tail-end, indicate our use of the z-score to analyze larger snow depths is reasonable. Additionally, this standardization method is commonly used in literature (Pflug and Lundquist, 2020; Sturm and Wagner, 2010) focusing on snow. Using this method in our study facilitates comparison between our study and previous work.

**3.2 Metrics:**

To analyze differences along a transect for different water years, we looked at the snow elevation profile, snow depth profile, and standardized snow depth of the 4 years. Using the data's UTM coordinates, the distance between each successive point along the transect was calculated using the Euclidean Distance Formula. Due to the nature of our dGPS data, each transect sample group had different sample sizes with points at slightly different cumulative distance (CDIST) locations along the transect. This was circumvented by rounding each point's CDIST to the nearest meter and interpolating snow depth points for each integer CDIST locations that was missing. Linear interpolation was accomplished with the function interpolate in the Python Library Pandas (McKinney, 2010). These interpolated points were then compared to the original dGPS survey points to ensure they matched the survey snow depth profile (Suppl. Fig 1).

To quantify similarities or differences between the standardized snow depth profiles, the mean squared error (MSE) and correlation coefficient (r) metric were calculated. The mean squared error takes the difference between two points (in this case the points along the two standardized snow depth profile lines) and squares it to find the error. The mean of squared errors is then used with a lower value indicating greater similarity. The correlation coefficient (range from –1 to 1) provides a measure of how strongly related 2 variables are, with values close to 1 indicating positive correlation. Since the survey lines did not follow identical trajectories, some variation is expected even in years that visually appear to have similar profiles. However, we do expect to be able to discern which years are more similar based on comparing the statistical values to each other.

### 3.3 Meteorological Data

The ERA5-Land dataset is a gridded hourly reanalysis dataset with a resolution of 0.1°x0.1° which we resampled to daily values from Oct 2014 to Sept 2018 (Muñoz, 2019). Variables used include: 2m air temperature, 10m wind speed, wind direction, snowfall, snow depth, and precipitation. The Finse weather station (data provided by MET Norway) is located approximately 1.8 km from the center of our study site, and the following variables were utilized: 2 m air temperature, 10 m wind speed, wind direction, and precipitation. However, this dataset is not continuous and contains gaps, therefore the ERA5-Land dataset was used for the study after it was bias corrected and re-scaled to statistically fit local conditions described by the eKlima dataset. The daily resampled data from both datasets were compared using only data falling between October and April, in order to ensure we were fitting to the time period of interest, since conditions vary between the winter and summer. The study site can have temperature inversions in wintertime at the valley bottom where the Finse weather station is located, therefore priority was placed on fitting the bulk of temperature values (-10 to +10°C), resulting in the median temperature bias of +1.95°C being added to the ERA5-Land timeseries (Suppl. Fig. 3a). As mentioned in section 2, wind speeds near 5 m $s^{-1}$ can have an important effect in determining if there is wind redistribution of snow. Therefore, we opted for ensuring a better fit for wind speeds less than 8 m $s^{-1}$ using a scaling factor of 2.8. This led to a slight under correction for larger wind speeds (Suppl. Fig 3b), but since our study used a wind speed threshold of 5 m $s^{-1}$ (sect. 3.2), this is inconsequential.

Wind direction and precipitation were not adjusted. While there are discrepancies between the two datasets regarding total precipitation, especially during the winter months (Nov-

Apr), the two temporal timeseries have precipitations with similar timing and intensity (Suppl. Fig ). Precipitation is widely known to be a difficult variable to measure in hydrology, with errors common in both gauge and satellite datasets. Gauge under catch, especially in windy areas, can lead to large differences in precipitation values (Kochendorfer et al., 2020; Wolff et al., 2015); meanwhile the ERA5-Land precipitation variable might not completely represent local conditions. However, the accuracy of precipitation model output has in many places outpaced the accuracy of gauge data (Lundquist et al., 2019). Since both precipitation datasets are likely representative of site conditions without either being completely accurate, the decision was made to use the ERA5-Land precipitation and snowfall datasets as is, and not correct based on the eKlima precipitation observation data.

### 3.4 Assigning Event Type Categories to Dataset

Using the variables mentioned above, each day was assigned an "event type" based on its daily meteorological variable values. This provided insight into the timing, sequence, and frequency of the different meteorological conditions that affect snow depth and distribution. We defined six different event type categories based on a combination of four thresholds (Table 1). Additionally, categories in which wind speed was above the threshold, were further divided by 90° wind sectors, (WNW, NNE, ESE, SSW), corresponding to the orientation of our dPGS tracks, leading wind directions to be either along or across our dGPS survey lines. For ease of naming convention, these will be referred to as (W, N, E, S). In the table, "other", refers to a day that is below 0.5°C and windless and snowless according to the defined criteria.

| **Event Types** | **Criteria** |
|---|---|
| Wind Only | wind ≥ 5 m/s & snow fall < 2 mm & temp < 0.5 C |
| Wind and Snow | wind ≥ 5 m/s & snowfall ≥ 2 mm & temp < 0.5 C |
| Snow Only | wind < 5 m/s & snowfall ≥ 2 mm & temp < 0.5 C |
| Rain on Snow | precip ≥ 2 mm & snowfall < 2 mm |
| Melt | precip < 2 mm & snowfall < 2mm & temp ≥ 0.5 C |
| Other | wind < 5 m/s & snowfall < 2 mm & precip < 2 mm & temp < 0.5 C |

Table 1: Event Type Categories and their corresponding criteria. "Wind" and "wind and snow" are further divided into 4 cardinal directions (WNW, NNE, ESE, SSW). These are abbreviated as (W, N, E, S) throughout the paper. Temperature is abbreviated "temp," and precipitation is abbreviated "precip."

The four variables used for the thresholds are: air temperature, wind speed, snowfall, and precipitation. For temperature, a threshold of 0.5°C was used as the rain-snow cutoff. This is in line with studies that have found the mean air temperature value differentiating rain from snow across the Northern Hemisphere to be 1.0°C and range from -0.4°C to 2.4°C, while maritime areas typically have a colder threshold as the boundary between rain and snow within the stated range (Jennings et al., 2018). For wind speed, a threshold of 5 m $s^{-1}$ was specified as the threshold wind speed needed for drifting snow and wind redistribution to occur. Liston (2007) showed that for new and slightly aged snow below 2°C, the wind speed threshold at 10 m height was generally between 4-5 m $s^{-1}$. This threshold was used to differentiate a windy day from one without sufficient wind to affect snow distribution. For snowfall, a daily threshold of 2 mm of Snow Water Equivalent (SWE) was specified to differentiate a day with sufficient snowfall to affect snow distribution from one that did not. This was largely based on the temporal data for our time period, excluding days with minimal snowfall, while keeping the bulk of snowfall that accumulated during the season (Suppl. Fig ). Similarly, the precipitation threshold was also assigned 2 mm. Rain on snow, was defined as a day with more than 2mm of precipitation but less than 2 mm of snowfall, to classify days where rainfall might impact snow properties and subsequent snow distribution.

**4. Results**

**4.1 dGPS Transects**

**4.1.1 Transect 1**

Transect 1, location shown in Figure 3, is oriented from WNW to ESE across a depression roughly 6-8m deep and 60m long at an elevation of 1340m. The depression is located partway up a western facing slope. Figure 5 shows the snow and ground elevation for this transect for all four years (a, b), along with the snow depth (c) and standardized snow depth (d). We were primarily interested in the behavior of snow depth in the depression and therefore focused on the area bounded by the dashed gray lines, 30 to 95 m along the transect. The ground elevation for 2016 had two bumps in its transect, likely from boulders, which subsequently skewed its snow depth. These values were removed and interpolated to

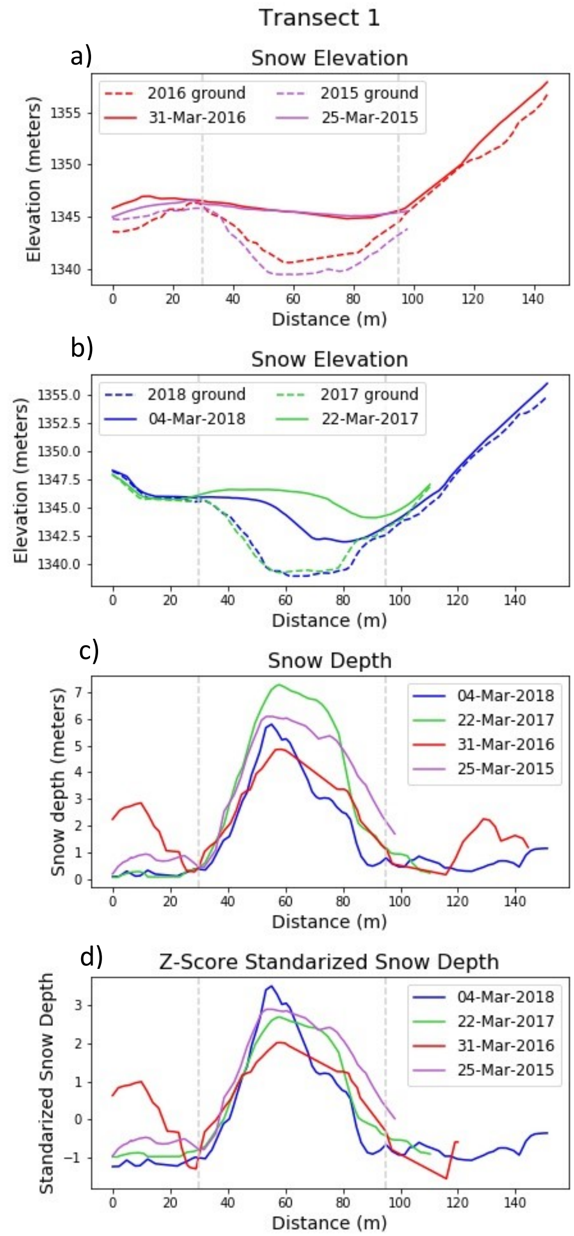


Figure 5: Transect 1 for 2015-2018, dashed gray lines bound the section of interest (30-95m). 2016 is corrected to remove boulders in ground elevation and snow depth; a) Snow and ground elevations for 2015 and 2016; b) Snow and ground elevation for 2017 and 2018
c) Snow depth for all four years
d) Standardized snow depth for all four years.

enable better comparison among the four years. Figure 5 depicts 2016's ground profile and snow depth profiles post-interpolation.

| Transect 1 | | | | |
|---|---|---|---|---|
| **MSE** | | | | |
| 2015 | | | | |
| 2016 | 0.20 | | | |
| 2017 | 0.19 | **0.02** | | |
| 2018 | 0.67 | 0.24 | 0.25 | |
| | 2015 | 2016 | 2017 | 2018 |
| | | | | |
| **Correlation Coef. (r)** | | | | |
| 2015 | | | | |
| 2016 | 0.94 | | | |
| 2017 | 0.94 | **0.98** | | |
| 2018 | 0.86 | 0.96 | 0.95 | |
| | 2015 | 2016 | 2017 | 2018 |

Table 2: Mean squared error (MSE) and correlation coefficient (r) of 2015-2018 for the 30-95 m section along transect 1. The lowest MSE and highest r have been bolded for ease of identification.

The MSE and correlation coefficient were calculated using the z-score standardized snow depth for the 30-95m section for all four years (Table 2). 2016&2017 had the lowest MSE (0.02) and one of the highest correlation coefficients (0.98). Meanwhile, 2015&2018 had the worst MSE (0.67) and correlation coefficient (0.86). The rest of the pairs of years had similar values to each other ($0.19 \leq$ MSE $\leq 0.25$; $0.94 \leq r \leq 0.95$). Some degree of error was expected based on the slightly different locations of the survey lines. We are therefore comparing the magnitude of the values against each other, to identify pairings with the lowest and highest values. This indicates that, for this transect, 2016&2017 had the highest similarity, while there was also some degree of similarity between 2015&2016, 2015&2017, and 2016&2018.

For all three transects, we did not calculate the p-value since we believe some degree of autocorrelation exists in the data set.

In this and future sections, the & symbol is used to denote pairs of years.

### 4.1.2 Transect 2

Transect 2, location shown in Figure 3, is orientated WNW to ESE north of the grid's peak. It is perpendicular to the northern slope of the peak and undulating terrain. The 2018 survey line in this location was slightly further away, and its elevation profile was too different from the other years for comparison. Figure 6 shows the snow and ground elevation (a, b) for the three years, along with the snow depth (c) and standardized snow depth (d). Three sections are bounded between colored dashed lines (blue: section 1, pink: section2, green: section 3) which highlight the areas of interest. Comparison metrics were calculated independently for each of these three sections.

2015&2017 had the smallest MSE (0.04 and 0.25) for the first and third sections, while 2016&2017 had the smallest MSE (0.28) for the second section (Table 3). However, 2015&2017 had the highest correlation coefficient for all three sections (r: 0.98, 0.96, 0.91). For section 2, this pair had a high MSE (1.10) and high r (0.96), indicating they had similar standardized snow depth profiles for this section but large differences in value. This is partly attributed to the 2015's snow depth curve upslope and downslope being spread further apart. This leads to large differences in value when the MSE compares two values at the same distance for 2015&2017. This could be due to slightly different topography or snow depth accumulation near the edges of the depression. All year pairings had relatively high correlation coefficient values for the second section

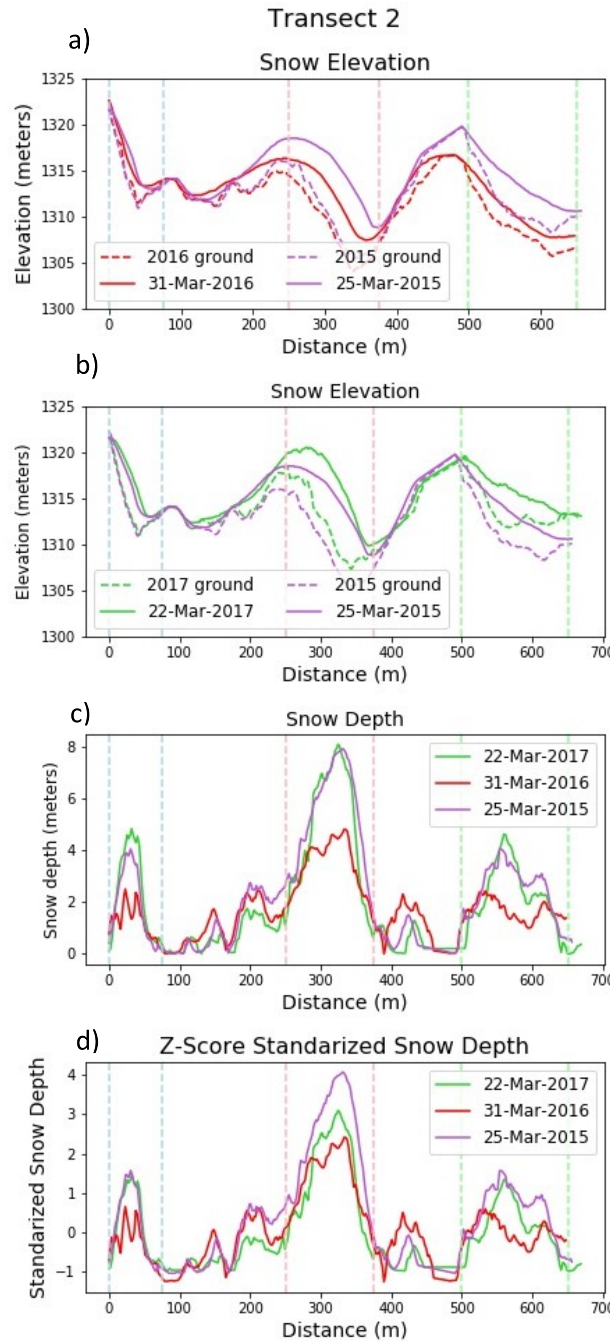


Figure 6: Transect 2 for 2015-2017, dashed sets of lines bound the sections of interest (blue: section 1, pink: section2, green: section 3);
a) Snow and ground elevations for 2015 and 2016; b) Snow and ground elevation for 2015 and 2017 c) Snow depth for three years
d) Standardized snow depth for three years.

(r >0.90), indicating overall similar profiles for this section despite different values. This is not true for the other sections. For the first section, 2015&2016 had a correlation coefficient of 0.84, while 2016&2017 was 0.8. For section three, the correlation coefficient for these two pairings was substantially lower (r < 0.25). This indicates that along transect 2, 2016 had a different snow depth profile from the other two years, leading to the variation in MSE and r values among the three sections. Meanwhile 2015&2017's correlation coefficients remained relatively high (r > 0.9) for all three sections.

| **Transect 2** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **MSE** | | | | | | | | | | | |
| Sect. | First (0-75m) | | | Second (250-375m) | | | | Third (500-650m) | | | |
| 2015 | | | | 2015 | | | | 2015 | | | |
| 2016 | 0.55 | | | 2016 | 1.48 | | | 2016 | 0.69 | | |
| 2017 | **0.04** | 0.54 | | 2017 | 1.10 | **0.28** | | 2017 | **0.25** | 0.43 | |
| | 2015 | 2016 | 2017 | | 2015 | 2016 | 2017 | | 2015 | 2016 | 2017 |
| | | | | | | | | | | | |
| **Correlation Coef. (r)** | | | | | | | | | | | |
| | First | | | Second | | | | Third | | | |
| 2015 | | | | 2015 | | | | 2015 | | | |
| 2016 | 0.84 | | | 2016 | 0.93 | | | 2016 | 0.21 | | |
| 2017 | **0.98** | 0.8 | | 2017 | **0.96** | 0.94 | | 2017 | **0.91** | 0.14 | |
| | 2015 | 2016 | 2017 | | 2015 | 2016 | 2017 | | 2015 | 2016 | 2017 |

Table 3: Mean squared error (MSE) and correlation coefficient (r) calculated for three different sections along the transect. The distance position of each section in specified in the Sect. row of the MSE. The lowest MSE and highest r for each section are bolded for identification.

### 4.1.3 Transect 3

Transect 3, located in the NW corner of the grid, is oriented from SSW to NNE (downhill), contrarily to the other two transects oriented WNW to ESE. The transect crosses a slight depression 55m long over an elevation range of 10 m (Figure 7). 2017 did not have a survey line in this location and was omitted.

For this transect, 2016&2018 had the lowest MSE (0.09) and the highest correlation coefficient (0.92) (Table 4). The two other pairs had lower correlation coefficients (2015&2018: r=0.83; 2015&2016: r=0.85) and higher MSE values of 0.25 and 0.43, respectively. However, despite very similar ground elevation profiles for all three years in the analyzed section, 2015's profile had a different shape, increasing in height in the second half of the section. The standardized snow depth profile of 2015 also had greater values than the other two years leading to larger MSE values for these two pairs containing 2015.

| Transect 3 | | | |
|---|---|---|---|
| **MSE** | | | |
| 2015 | | | |
| 2016 | 0.43 | | |
| 2018 | 0.25 | **0.09** | |
| | 2015 | 2016 | 2018 |
| | | | |
| **Correlation Coef. (r)** | | | |
| 2015 | | | |
| 2016 | 0.85 | | |
| 2018 | 0.83 | **0.92** | |
| | 2015 | 2016 | 2018 |

Table 4: Mean squared error (MSE) and correlation coefficient (r) of 2015, 2016, 2018 for the 55-110 m section along transect 3. The lowest MSE and highest r have been bolded for identification.

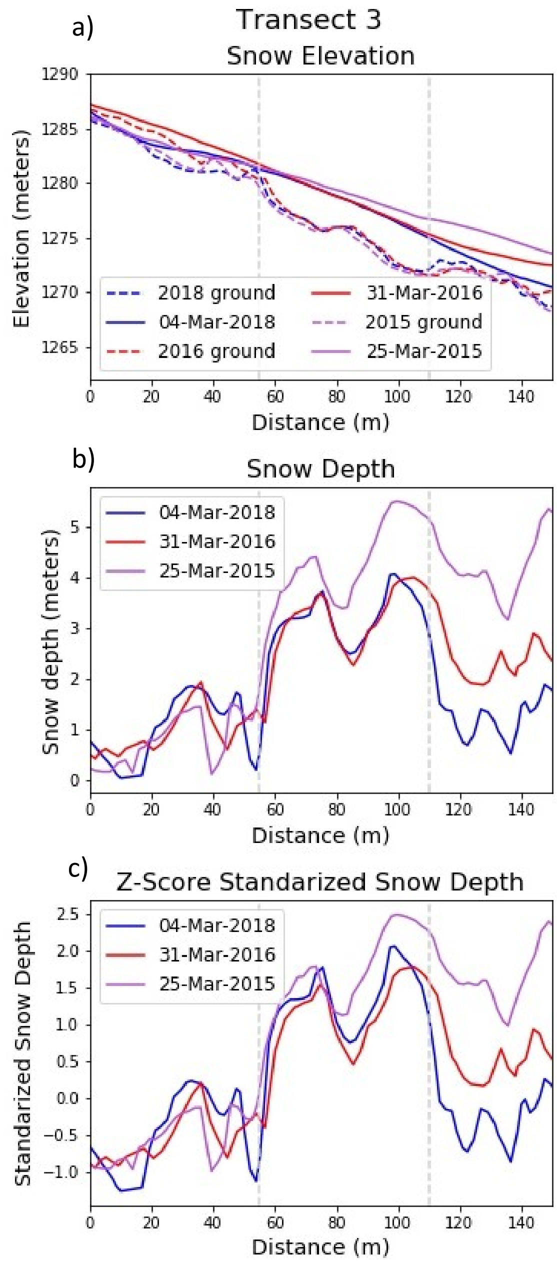


Figure 7: Transect3 for 2015, 2016, 2018, dashed lines bound the section of interest; a) Snow and ground elevations for 2015, 2016,2018, b) Snow depth for three years, c) Standardized snow depth for three years.

**4.2 Meteorological Conditions**

To accurately compare weather conditions leading up to each year's survey date and impacting the snow distribution at the time of survey, meteorological analysis was constrained from 1 October until the survey date. Table 5 outlines the survey date along with the snow depth and cumulative snowfall of each year on its survey date. Given an average snow density of 350-450 kg $m^{-3}$ at our study site, cumulative snowfall is expected to average 40% of the snow depth.

| Water Year | Survey Date | Snow Depth (meters) | Cumulative Snowfall (m of SWE) |
|---|---|---|---|
| 2015 | March 25 | 1.72 | 0.76 |
| 2016 | March 31 | 1.61 | 0.67 |
| 2017 | March 22 | 1.67 | 0.66 |
| 2018 | March 4 | 1.65 | 0.64 |
| mean | | 1.66 | 0.67 |

Table 5: Snow depth (meters) and cumulative snowfall (meters of Snow Water Equivalent) on the survey date of each year. The survey date is also provided as reference, along with the mean snow depth and cumulative snowfall.

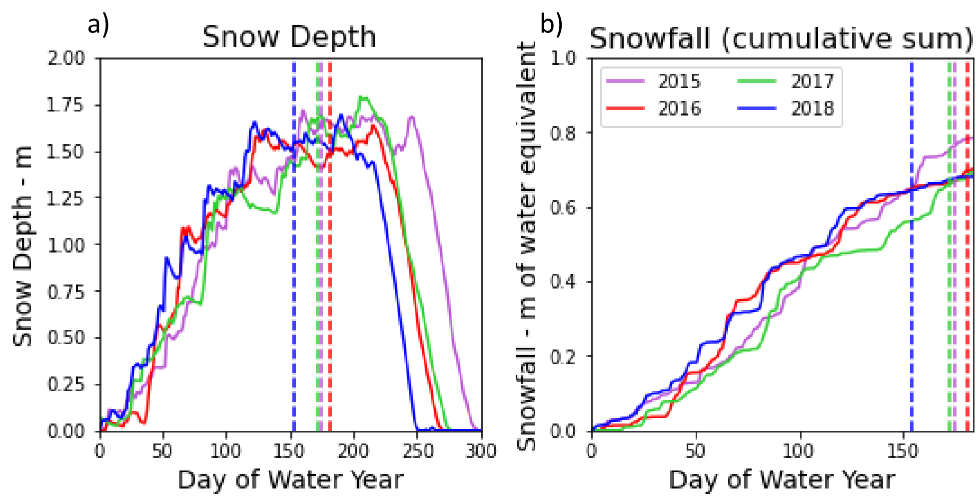


Figure 8: a) Snow depth (meters) and b) cumulative snowfall (meter of snow water equivalent) for each year. Each year's survey date is represented by a dashed line of that year's color.

Water year 2018 had the earliest survey date by 18 days while the other years were within 9 days of each other. However, all years had comparable snow depth (range 0.107 m, 6% of the mean snow depth) and small differences in cumulative snowfall (range 0.118 m, 18% of the mean cumulative snowfall). This similarity can further be seen in Figure 8. Further analysis focused on the frequency and quantitative contribution of cumulative snowfall of each event type.

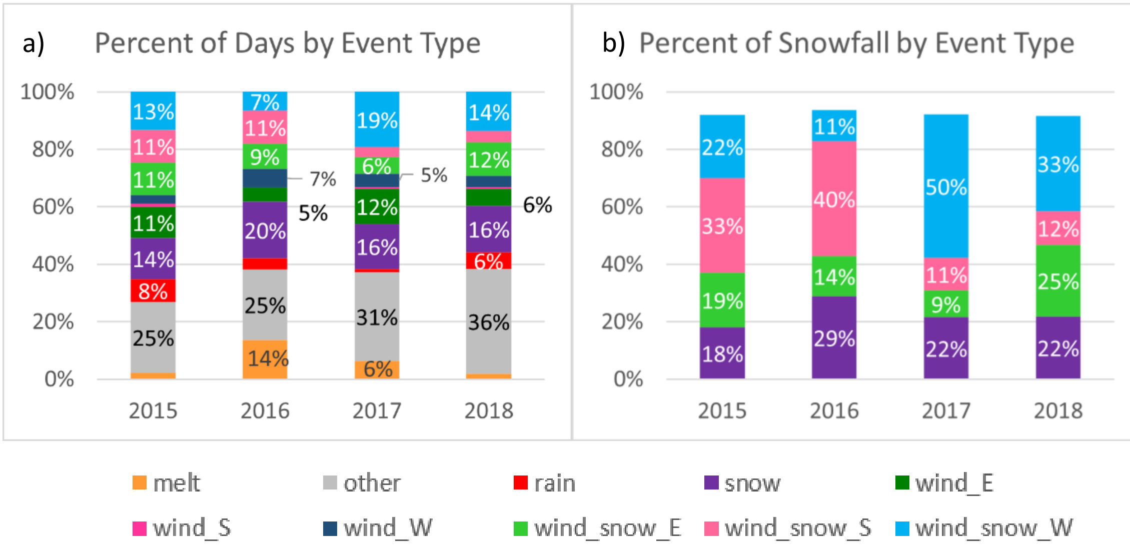


Figure 9: a) Percent of days (Frequency) (1 Oct to survey date) of each event type. Labeled with percent. b) Percent of total snowfall (from Oct 1 to survey date) that was contributed by each event type, labeled with percent. Percent labels are only shown for 5% or more.

Since the dGPS analysis indicated 2015&2017, and 2016&2018, had similar snow distributions, according to our hypothesis these pairs are expected to have similar weather conditions contributing more snowfall, in addition to a similar frequency distribution of event types, To investigate this, the frequency (percent of days) of each event type and the percent of snowfall contributed by each event type was calculated (Figure 9). For 2015, by its survey date, snowfall from "W wind snow" (22%), "E wind snow" (19%), and "snow" (18%) contributed almost equally to its snowpack, with "S wind snow" contributing slightly more (33%). The frequency of each event type contributing snowfall was comparable: "S wind snow" and "E wind snow" accounted for 11% of the days each, and "W wind snow" and "snow" had slightly more days at 13% and 14%, respectively. Contrarily, for 2017 "W wind snow" was 19% of total days and snowfall from this event type accounted for 50% of its total snowfall. This is the largest percentage of snowfall coming from a single event type for all four years. Additionally, "snow" contributed the second most snowfall (22%) for 2017, while "S wind snow" was just 11%.

Looking at 2016 and 2018 in Figure 9, they had different event types contributing most of the snowfall. For 2016, most of its snowfall was from "S wind snow" (40%) and "snow" (29%). Compared to the other years, it had a relatively small amount of snowfall from "W wind snow" (11%), in addition to a small number of days classified as this event type (7%). However, 2018's snowfall mostly came from "W wind snow" (33%) followed by "E wind snow" (25%) and "snow" (22%). Additionally, it had the highest percentage of "other" days (36%), compared to 25% for 2016.

According to both the frequency of days, and which event type contributed the most snowfall each year, 2015&2016 and 2017&2018 have more similar meteorology, which should result in more similar snow distributions. However, these year pairings were observed to have less similar dGPS transects (Sect. 4.1).

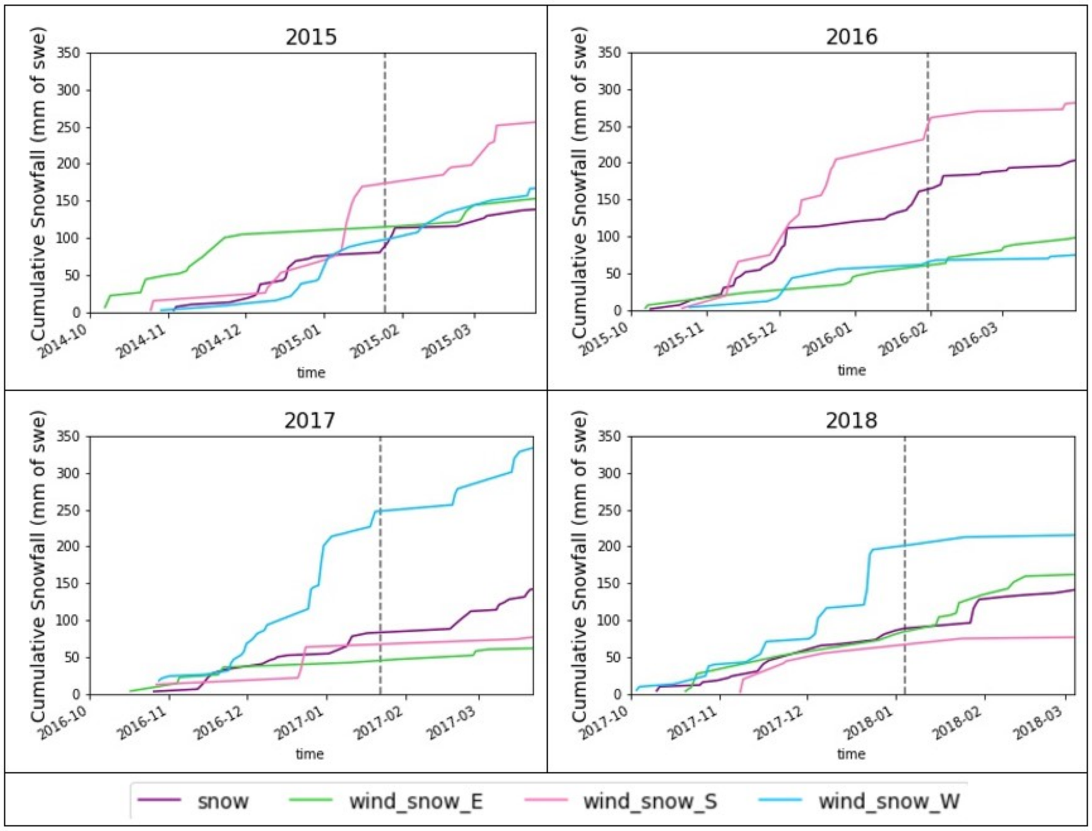


Figure 10: Cumulative snowfall (mm of snow water equivalent) by event type for all four years from 1 October until their survey date, plotted on the same y axis (0-350 mm). The gray vertical dashed line in each graph is located 2 months before that year's survey data.

Since the timing and sequence of event types also affects snow distribution, the cumulative snowfall of the four event types predominantly expected to affect snow distribution was plotted (Figure 10) to gain insight into their timing and temporal distribution. Figure 10 highlights that some years had temporal variability regarding what event types were contributing snowfall throughout the season. While 2015 had 33% of its snowfall from "S wind snow," 40% of it came from a single event at the beginning of January. In addition, almost all its "E wind snow" snowfall fell before 1 December. The same is true for 2017 and its "S wind snow" falling almost entirely before 1 January. Similarly, in 2018, while "W wind snow" contributed the most snowfall (33%), almost all of it fell before 1 January.

The timing of event types is an important factor to consider. Depending on weather conditions, wind will have time to erode or redistribute early season snowfall, and subsequent event types can potentially drastically alter the landscape and snow distribution. Taking this and our findings in Figure 10 into account, the meteorological analysis was further constrained to two months before the survey date (ie., 2015: survey date was March 25, analysis from January 25 until March 24). Two months before each survey date is identified with a gray dashed line in Figure 10.

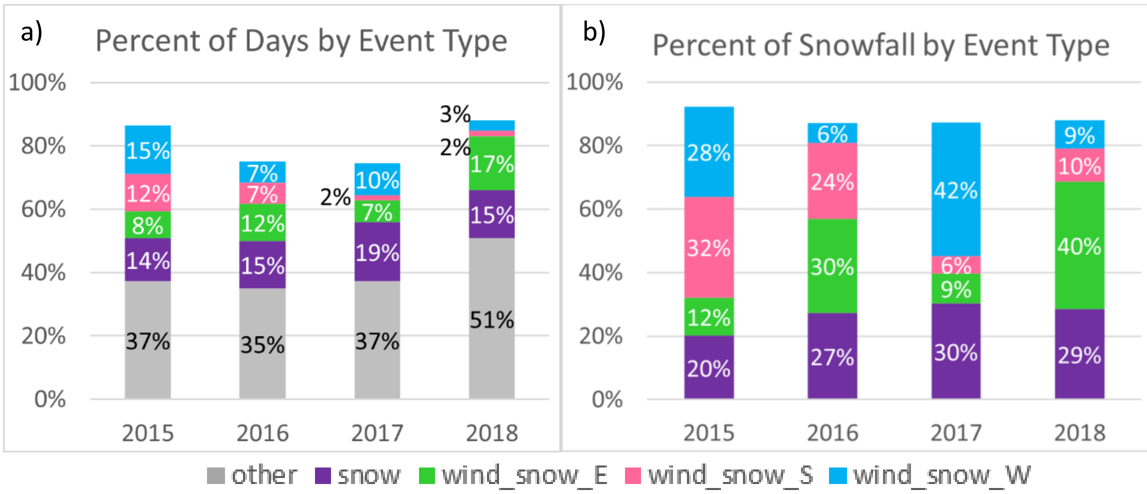


Figure 11: Percent of days of each event type for 2 months before each year's survey date. b) Percent of snowfall from each even type for 2 months before each year's survey date.

Figure 11 above shows the frequency of each event type (a) and the percent of snowfall (b) it contributed during the shortened 2-month time period. Only the four events contributing snowfall, along with "other" are included in the bar graphs. Since our daily snowfall threshold was 2 mm for a day to be considered snowy, a nominal amount of snow fell during all the event types not shown (wind only, other, melt) which cumulatively added up to the ~10% of snowfall missing from each column. "Other" was included in Figure 11a, since this event type provides insight into the number of cold days without snowfall or wind. The total snowfall that fell in the 2 months preceding each year's survey can be seen in Table 6.

| Total snowfall during 2 months preceding survey (m of swe) | |
|---|---|
| 2015 | 0.26 |
| 2016 | 0.15 |
| 2017 | 0.19 |
| 2018 | 0.19 |

Table 6: Total snowfall in mm of snow water equivalent (m of swe) that fell in the 1 month and 2 month time period preceding each year's snow distribution survey date.

As expected, Figure 11 tells a different story than Figure 10. Looking first at Figure 11b, the most noticeable difference is that 2015&2017 and 2016&2018 share similarities regarding which event types contributed more snowfall. 2015&2017 both received the most "W wind snow" (28%, 42% respectively) out of all 4 years, more than 3x the percentage of snowfall 2016&2018 received from this event type (6% and 9%). Contrarily, 2016&2018 had the most "E wind snow" (30% and 40%, respectively) out of the four years and this event type also contributed the most snow for these two years. Broadening to all four years, 2016-2018 had similar snowfall contributions from "snow" (27%, 30%, 29%), while 2015 had slightly less

(20%). Similar to Figure 9b, in Figure 11b 2015&2016 also had more snowfall from "S wind snow" than 2017 or 2018. The similarities observed regarding percent of snowfall, are also seen in the frequency of event types. One additional point in Figure 11a is the similarity in "other" between 2015-2017 (35-37%) which contrasts with 2018 (51%).

In Table 6 we see that for the two months preceding each year's survey date, the total snowfall during this time-period was comparable for 2017 and 2018, almost 0.20 m of swe, while 2015 had more snowfall (0.26 m of swe) and 2016 had less (0.15 m of swe). In Table 5, the mean snowfall from Oct 1 until the survey date for our years was 0.67 m of swe, indicating almost a third of the total pre-survey snowfall fell during the 2 month time-period.

Overall, when analyzing the entire snow season up until each year's survey date, 2015&2016 and 2017&2018 had consistent meteorology impacting snow distribution. However, when we constrain the analysis to the 2 months prior to the survey date, 2015&2017 ("W wind snow") and 2016&2018 ("E wind snow") had similar event types contributing more snowfall. Some similarity is also seen for 2015&2016 regarding "S wind snow".

## 5. Discussion

In this section we will briefly individually expand on the results of the dGPS (sect. 5.1) and the meteorological conditions (sect 5.2), and then we will investigate whether years with similar dPGS transects had a common meteorological condition (sect 5.3). In section 5.4, shortcomings of this study along with possible further research will be addressed.

### 5.1 How "time stable" are snow depth profiles for our study site and time period?

According to our differential GPS analysis of standardized snow depth along ski tracks, certain years had more similar snow distributions than others. 2015&2017 had consistently high correlation coefficients ($r > 0.90$), and while their MSE values varied (0.04-1.10), they were generally lower than the MSE of the other year pairs. Given that each year's survey line was not in the exact same location (typically all years were laterally within 30m), some variation in value was expected based on their location. However, we used MSE and r to evaluate which pairs of years were most consistently similar and had r values above 0.9. Based on this, 2015&2017 had similar snow distributions according to 2 transects. The high correlation coefficients and variable MSE values indicate that their standardized snow depth profiles were generally the same shape even if the values themselves differed. Since 2017 could not be included in transect 3, we can only conclude similarity along the WNW to ESE transects.

Another year pairing that had similarity is 2016&2018. For both transect 1 and 3, the correlation coefficient was relatively high ($r > 0.90$), and their MSEs were 0.25 and 0.09, respectively. Since 2018 could not be included in transect 2, we only have two transects and therefore two data points for comparison. However, transect 1 and 3 were orientated in different directions (WNW to ESE and SSW to NNE), indicating that these two years might have a repeatable snow distribution in both directions. An additional year pair that showed some similarity is 2016&2017. These years had relatively low MSEs for transect 1 and section 2 of transect 2, but not for the other two sections of transect 2. Since a small section of 2016's ground elevation was interpolated in transect 1, it is possible that the metric values for this transect are artificially more similar. Due to the metrics showing inconsistency in similarity between 2016&2017 across the four sections analyzed ($0.14 \leq r \leq 0.98$), this pairing of years was deemed not similar. However, this could be investigated in further studies encompassing more of the study area.

### 5.2 How do the meteorological conditions thought to affect snow distribution vary across our time period?

Our initial analysis investigated the event types expected to predominantly impact snow distribution ("wind and snow" from 3 different wind directions, "snow", and "other") from 1 October until each year's survey date. We found for two years (2015,2016) "S wind snow" contributed the most snowfall, while for the other two years (2017,2018) "W wind snow" contributed the most. Additionally, the frequency of all event types was most similar between 2015 and 2016. Similarly, "other" accounted for 31% and 36% for 2017 and 2018, respectively, but only 25% for 2015 and 2016. This event type is important to consider since a lot of cold windless, snowless days allows time for snow metamorphism processes which cause the current snow distribution to "harden" and become harder to erode and be redistributed by future storms or wind events.

Afterwards, we focused our analysis on the 2 months before each year's survey date since early season events likely had less impact on the snow distribution. This altered during which years each event type contributed the most snowfall. 2016&2018 had the highest percentage of snowfall from "E wind snow" and very little from "W wind snow." Meanwhile, compared to the other two years, 2015&2017 had a large percent of snowfall from "W wind snow" by roughly 3 times. Similarity between 2016&2018 and 2015&2017 was also seen in the distribution of frequency of days among the different event types. Additionally, 2015&2016 had the highest percentages of "S wind snow" compared to the other years. All four years had similar frequency of "snow" days, and "snow" contributed 20-30% of the snowfall for each year. The deposition of snow without wind distribution is important to consider, as this can alter and smooth out snow distributions that have already formed. Lastly, while 2015-2017 had similar frequency of "other" days, 2018 had significantly more. While the effects of "snow" and "other" on the dGPS transects may be harder to observe, these likely still had an important role in shaping the snow distribution.

### 5.3 Can a common meteorological characteristic be identified for years with similar dGPS tracks?

Our dGPS analysis revealed that the two pairs, 2015&2017 and 2016&2018, had similar snow distribution patterns along the transects. Based on our hypothesis, we expected that years with similar dGPS profiles have a common meteorological characteristic. While this was not the case when analyzing the entire snow season until the survey date, it was true when focusing on the last 2 months before the survey date. During the 2 months preceding each year's survey date, each year received 22-32% of the total pre-survey snowfall (from 1 October until the survey date), with 2015 on the higher end of the range and 2016 on the lower end of the range.

The 2 month meteorological analysis showed that 2015 and 2017 were most similar in terms of frequency of event type, and "W wind snow" contributed more snowfall during these two years. Meanwhile, 2016 and 2018 both had "E wind snow" contributing the most snowfall. While "S wind snow" contributed significant snowfall during both 2015 and 2016, based on the dGPS analysis, these two years were not found to have similar snow distributions.

Based on this analysis, the meteorological conditions during the 2 months before the survey date are more indicative of which years have repeatable snow distributions. Therefore, the similarity of snow distribution at Finse from year to year is determined by if "E wind snow" or "W wind snow" contributes the most snowfall in the two months prior to the March survey date.

### 5.4 Study Assumptions and Future Work

A major assumption of this study was that the three transects were representative of the larger study area. Emphasis was placed on picking three transects in different sections of the study site and including both grid orientations. However, transect data might be insufficient to accurately determine which years had repeatable snow distributions. Isolated transects do not consider the surrounding topography which also influences the snow distribution, since snow redistribution is not isolated and happens over the entire area as a whole. For example, transect 2 was located perpendicular to the northern slope of the peak in our study area. While we would expect 2015 and 2016 to be similar here compared to 2017 due to their larger snowfall percentages from "S wind snow," we did not see this. In fact, across all 3 transects, 2015&2016 only showed similarity in 1 of the 5 transect sections. Observations covering a larger area might have told a different story.

Additionally, the transects were specifically in more rugged terrain since this was expected to better show differences and similarities between years. While these locations had survey lines relatively close together (within 30m for transect 1 and 2, within 15m for transect 3), small spatial variations in complex terrain can disproportionately affect the snow depth at the observation point. This terrain also has more complex snow processes and turbulent winds, meaning these areas may be too complex to analyze with transect profiles, and results may not extrapolate to the less "rugged" areas of the study site. Ideally, time stability of snow distribution would be investigated using three dimensional, continuous observations of snow depth. Future work could look into using lidar surveys, airborne structure-from-motion photogrammetry (Nolan et al., 2015), or snow redistribution models to investigate snow depth at the study site, using the dGPS surveys to verify accuracy. While modeling snow distribution has its own complications arising from the alpine terrain and difficulty in accurately modeling wind redistribution of snow, any of the three listed methods would enable better spatial comparison of snow depth between years, since the entire study site could be compared and years would have data points at the exact same spatial location, unlike the dGPS transects. It would also be interesting to repeat the snow distribution analysis, using the dGPS surveys or another method, to investigate earlier and later dates in the snow season. This could shed light on the intra-season time stability of snow distribution at this study site. This would in turn provide guidance on the which pre-snow distribution time-period the meteorological analysis should focus on.

Regarding the meteorological analysis there are two points that could be explored in future work. Due to the orientation of our dGPS tracks, four wind direction sectors were picked to be aligned with the dGPS grid (WNW, NNE, ESE, SSW). Having a complete grid of snow depth values, would enable flexibility to divide the wind direction into eight sectors, providing greater accuracy in analyzing the direction of wind in relation to snowfall. The second point is that the meteorological analysis focused on all conditions between 1 October till the survey date and 2 months until survey date. A meteorological link for years with similar snow distributions was only found in the 2 month analysis. Future work could re-do the analysis with time periods of different lengths before the survey date to observe how the snowfall percent of each event type varies throughout the snow season. While the quantity of snowfall that occurred during the 2 month period was not a common characteristic between 2015&2017 and 2016&2018, in the graphs of cumulative snowfall (Figure 10), 2015 and 2017 appear to have had more snowfall closer (<1 month) to the survey date. This could be explored with the repeated meteorological analysis of different lengths of time. It is possible the presence of more recent new snowfall, regardless of the event types, is a common meteorological characteristic between years with similar snow distributions. This might be especially true for years with similar weather conditions. Lastly, a system of "weights" could be implemented where more recent days or days with larger amounts of snowfall are assigned more importance during the analysis.

One last hinderance of this study that could be addressed with future work, is the small sample size of years used in the study. Our sample size was constrained to years which had dGPS tracks sufficiently close spatially and temporally to compare, which is why 2019 and 2020 were excluded. As the dGPS measurements continue in the coming years, these can be added, increasing sample size. Additionally, if a dGPS-verified model output or lidar can successfully be used to analyze snow distribution, all years with dGPS observations (2015-present) could be utilized, since overlap between the tracks will no longer be a constraint. A larger sample size would help in defining a specific comparison metric threshold to specify how similar years need to be, to be considered repeatable. This could also lead to establishing how often each different snow distribution occurs and what is considered a "typical snow distribution pattern" for Finse. Since prevailing winds at the study site are from the west, and 2015&2017 both received more snowfall from this wind direction, we expect that these years might be typical snow distributions. This could be confirmed in future work by looking at the dominant snow distribution across a large sample size of years.

## 6. Conclusion

Snow distributions are strongly controlled by topography and influenced by fluctuating variables (snowfall, wind speed and direction, and storm timing and frequency). Repeatable snow distributions are therefore expected to occur when years have similar fluctuating controls. Knowledge of an area's snow distribution is vital information for many groups. If the snow distribution can be predicted based on a meteorological characteristic, such as which "wind and snow" wind direction contributed more snowfall, this can be used to identify the areas that will have larger snow drifts and therefore snow later into the melt season. This is useful for ecologists and wildlife biologists that track and research species that are affected by snow distribution and snowmelt. Also, daily meteorological data is more widely available than snow depth data. While this study focused on a small study area, if the results can be extrapolated to a larger spatial area or if the study can be repeated over a larger area, being able to predict a snow distribution according to a meteorological characteristic can be extremely valuable information for water managers. This could provide insight into which areas might have avalanches or flooding due to where deeper snow drifts are expected to occur according to the predicted snow distribution. Subsequently, this would also provide insight regarding which rivers might have greater or less snowmelt runoff in a particular year, which is consequential for hydropower and water supply.

Based on prior literature, we expected years with similar standardized snow depth profiles along our ski track transects to have the same weather condition(s) (direction of wind above a threshold + snowfall, or wind below a threshold + snowfall) contributing more snowfall. This was not observed when analyzing the entire snow season preceding each year's survey date; however, our hypothesis was correct when focusing only on the 2 months before each year's survey date. Based on our dGPS transects and meteorological analysis, it was concluded that the repeatability of snow distribution at Finse from year to year was determined by if: snowy days with ESE winds (2016 and 2018) or snowy days with WSW winds (2015 and 2017) contributed the most snowfall in the two months prior to that year's snow distribution observations. While 2015 and 2016 both had the most snowfall from snowy days with SSW winds, based on our dGPS transects, they had different snow distributions.

While there are limitations in using isolated transects to represent a larger study area, the study was successful in providing insight into what meteorological conditions led some years to have similar snow distributions. A large assumption of this study was that the three transects were representative of the larger study area. In the future, expanding the work by using methods that provide for continuous snow depth values over the entire study site, such as lidar, or models, could greatly help extrapolate this study's conclusions to the greater study area. Additionally, future work could further expand on the meteorological analysis by analyzing different lengths of time prior to the survey date to investigate how conditions change throughout the snow season. Additionally, snow distributions with survey dates later in the season could be analyzed to see if the years with repeatable distributions stay consistent. Lastly, another downside of this study is the small sample size of years used. Continuing the field observations in the future will enable a larger sample size and better comparison for how similar repeatable years are and how often they occur.

**Acknowledgements**

The author would like to thank the Valle Scholarship & Scandinavian Exchange Program for providing the funding and opportunity to conduct research in Norway during the past year. The author also gratefully thanks advisors and colleagues at the University of Oslo for the support while in Norway and for welcoming them as a guest researcher. Lastly, the author gives sincere thanks to their committee, for their time, advice, and guidance throughout graduate school.

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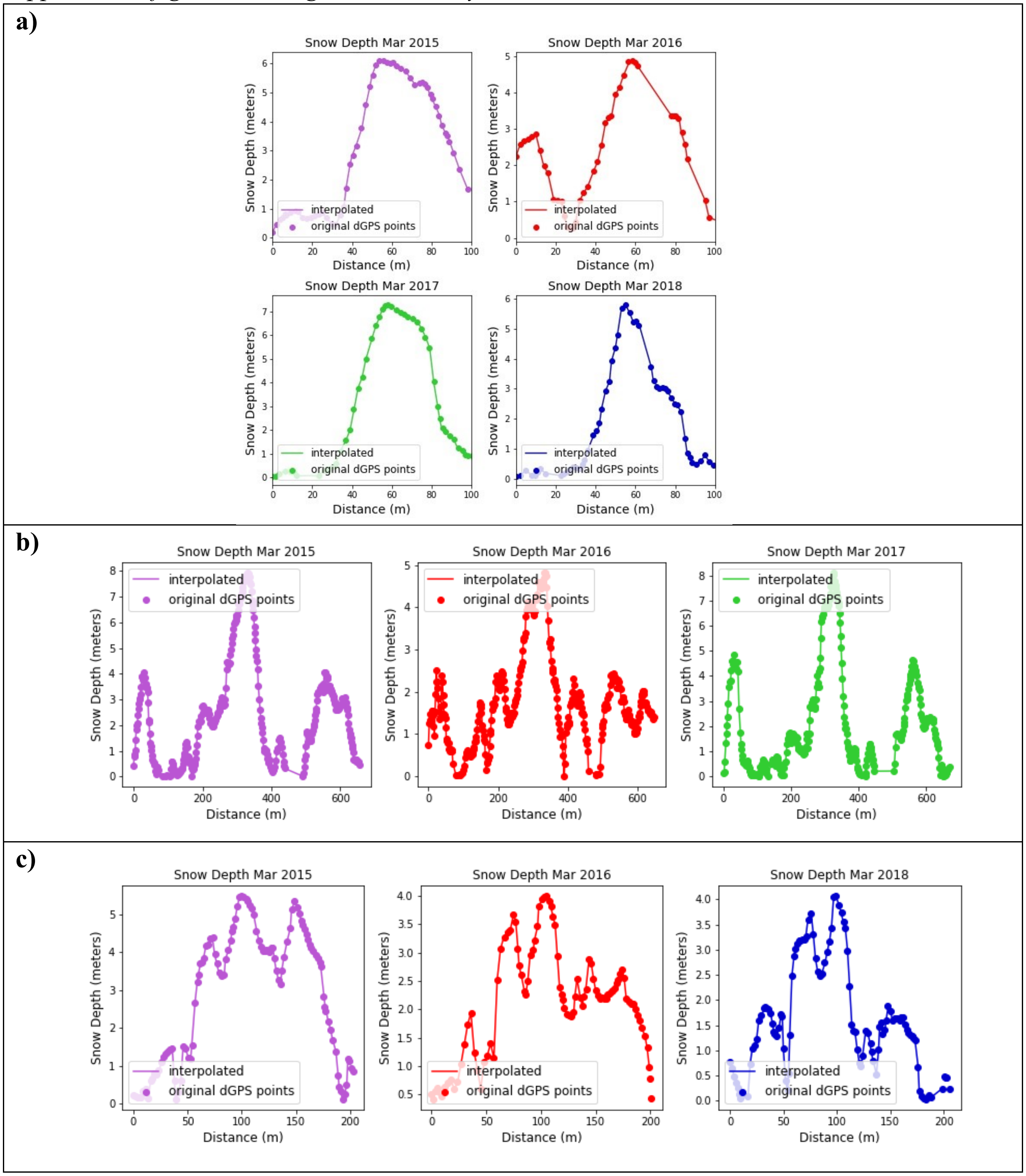
## Supplemental Figures

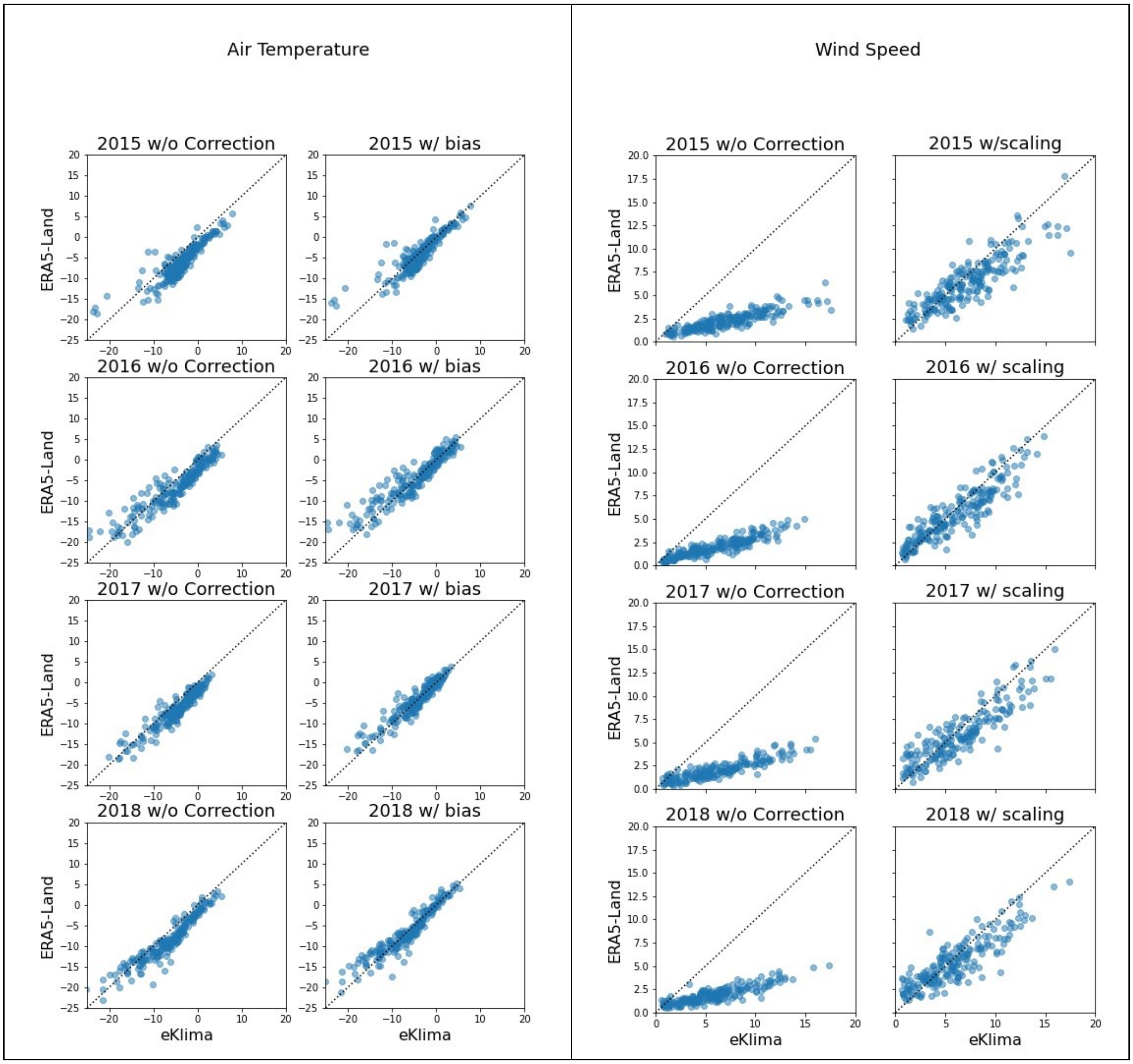
*Supplemental figures relating to dGPS analysis:*



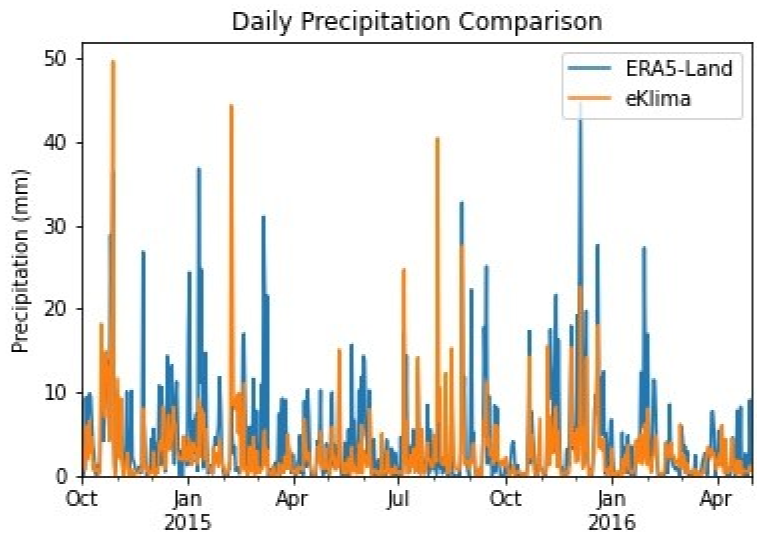

Suppl. Fig 1: Comparison of interpolated snow depth points (solid line) with original dGPS snow depth observations to ensure the interpolated points are representative of the true snow depth profile. a) Transect 1, b) transect 2, c) transect 3

*Supplemental figures regarding meteorological variables used for ERA5-Land and eKlima*

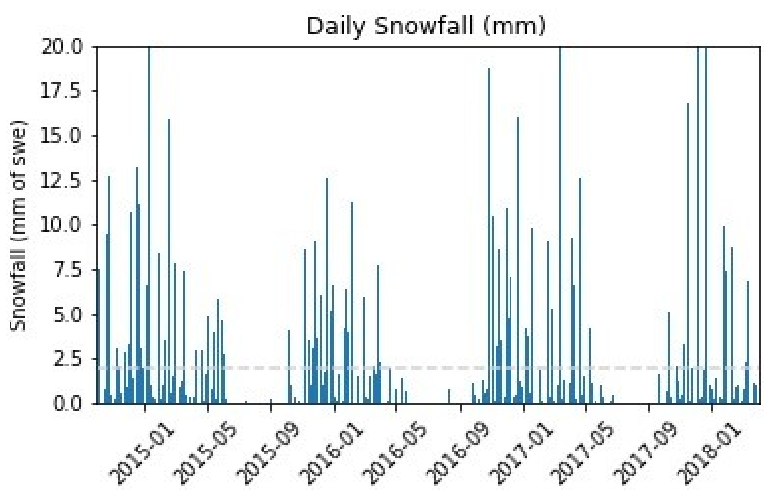

Suppl. Fig 2: Wind rose, based on daily wind speed and wind direction, for each year (2015 - 2018) from 1 October until that year's survey date. The last windrose, in the bottom left, is from 1 October to 31 March for 2015 to 2018. The value on the different rings of the windrose is the percent of time the wind blew from that direction during the time-period.




Suppl. Fig 3: a) Comparison of air temperature between ERA5-Land (y-axis) and eKlima (x-axis) before and after a bias of +1.9 degrees C was added b) Comparison of wind speed before and after a mean scaling factor of 2.8 was applied.




Suppl. Fig 4: Temporal comparison of precipitation (mm) between ERA5-Land and eKlima for Oct 2015 to May 2016




Suppl. Fig 5: Daily snowfall (mm of Snow Water Equivalent) for 2015-2018, with a horizontal line drawn at 2mm, indicating the snowfall threshold used in the study.