Uncertainties in estimating winter balance from direct measurements on glaciers

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ABSTRACT. Accurately estimating winter surface mass balance for a glacier is central to quantifying overall mass balance and melt runoff. However, measuring and modelling snow distribution and variability is inherently difficult in alpine terrain, resulting in high winter balance uncertainty. The goal of this paper is to examine methods and sources of error when converting snow measurements to estimates of winter balance and to gain a more comprehensive understanding of uncertainties inherent in this process. We extensively measure snow depth and density, at various spatial scales, on three glaciers in the St. Elias Mountains, Yukon. Elevation is found to be the dominant driver of accumulation variability but the relationship varies between glaciers. Our results also suggest that wind redistribution and preferential deposition affect snow distribution but that more complex parametrization is need to fully capture wind effects. By using a Monte Carlo method to quantify the effects of various sources of uncertainty, we find that interpolation of SWE measurements is the largest source of winter balance uncertainty. Snow distribution patterns differed considerably between glaciers, highlighting strong inter- and intra-basin variability. Accurately and precisely estimating winter balance therefore continues to be a difficult and elusive problem.

INTRODUCTION

Accurate estimation of winter surface mass balance is critical for correctly simulating the summer and overall mass balance of a glacier (Réveillet and others, 2016). Effectively representing spatial distribution of snow is also important for simulating snow and ice melt as well as energy and mass exchange between the land and atmosphere to better monitor surface runoff and its downstream effects (Clark and others, 2011). Snow distribution is sensitive to a number of complex process that partially depend on glacier location, topography, and orientation (Blöschl and others, 1991; Mott and others, 2008; Clark and others, 2011; Sold and others, 2013). Current models are not able to fully represent these processes so the distribution of snow in remote, mountainous locations is not well known. There is, therefore, a significant source of uncertainty that undermines the ability of models to represent current glacier conditions and make predictions of glacier response to a warming climate (Réveillet and others, 2016).

Winter surface mass balance is the net accumulation and ablation of snow over the winter season (Cogley and others, 2011), which constitutes glacier mass input. We refer to this quantity as winter balance throughout the paper. Accurate estimates of winter balance are critical for calculating glacier mass balance, not only because winter balance constitutes half of the glacier mass balance but also because the distribution of snow on a glacier initializes the summer balance and high snow albedo contributes to reduced summer melt (Hock, 2005; Réveillet and others, 2016).

Winter balance is notoriously difficult to estimate. Snow distribution in alpine regions is highly variable and influenced by dynamic interactions between the atmosphere and complex topography, operating on multiple spatial and temporal scales (Barry, 1992; Liston and Elder, 2006; Clark and others, 2011). Extensive, high resolution and accurate accumulation measurements on glaciers are almost impossible to achieve due to cost benefits of the various methods used to quantify snow water equivalent (Cogley and others, 2011; McGrath and others, 2015). For example, snow probes obtain accurate point observations but have negligible spatial coverage. Conversely, gravimetric methods obtain extensive measurements of mass change but cannot capture relevant spatial variability of snow (Cogley and others, 2011). Glacierized regions are also generally remote and challenging to access during the winter due to poor travelling conditions.

Most glacier mass balance programs estimate winter balance in a similar way to summer balance. Measurements of the amount of snow at the end of the winter season are taken at a few stake locations and then basic interpolation methods are used to estimate winter balance (e.g. Hock and Jensen, 1999; Thibert and others, 2008; MacDougall and Flowers, 2011; Cullen and others, 2017). However, equivalence between summer and winter balance estimation methods is likely inappropriate. Melt is strongly affected by air temperature and solar radiation (Hock, 2005), both of which are consistent across large spatial domains (Barry, 1992). Conversely, snow distribution is largely driven by precipitation (Lehning and others, 2008) and wind patterns (Bernhardt and others, 2009; Musselman and others, 2015), which are known to be highly heterogeneous in alpine environments (Barry, 1992). Snow distribution is therefore highly variable and has short correlation length scales (e.g. Anderton and others, 2004; Egli and others, 2011; Grunewald and others, 2010; Helbig and van Herwijnen, 2017; López-Moreno and others, 2011, 2013; Machguth and others, 2006; Marshall and others, 2006).

Detailed studies of winter balance are far less common than those of summer balance and uncertainty in winter mass balance currently overshadows differences between summer balance models (Réveillet and others, 2016). Studies that focus on estimating winter balance employ a wide range of snow measurement techniques (Sold and others, 2013), including direct measurement (e.g. Cullen and others, 2017), lidar/photogrammerty (e.g. Sold and others, 2013) and ground penetrating radar (e.g. Machguth and others, 2006; Gusmeroli and others, 2014; McGrath and others, 2015). Spatial coverage of measurements is often limited for winter balance studies and typically consists of an elevation transect along the glacier centreline (e.g. Kaser and others, 2003; Machguth and others, 2006). Interpolation of these measurements is primarily done by computing a linear regression that includes only a few topographic parameters (e.g. MacDougall and Flowers, 2011), with elevation being the most common. Other applied techniques include hand contouring (e.g. Tangborn and others, 1975), kriging (e.g. Hock and Jensen, 1999) and attributing measured accumulation values to elevation bands (e.g. Thibert and others, 2008). Physical snow models have been applied on a few glaciers (Mott and others, 2008; Dadic and others, 2010) but a lack of detailed meteorological data generally prohibits their widespread application. Error analysis is rarely considered and to our knowledge, no studies have investigated uncertainty in winter balance estimates.

There is a disparity in snow survey sophistication within glacier winter balance studies when compared to snow science studies. Winter mass balance surveys employ similar techniques and methods as snow science surveys (e.g. Elder and others, 1991; Deems and Painter, 2006; Nolan and others, 2015; Godio and Rege, 2016) but favour more simple approaches (Kaser and others, 2003; Sold and others, 2013). Snow science surveys are generally extensive and designed to measure snow throughout the basin and ensure that all terrain types are sampled. A wide array of measurement interpolation methods are used, including linear (e.g. López-Moreno and others, 2010) and non-linear regressions (e.g. Molotch and others, 2005) and geospatial interpolation (e.g.

Erxleben and others, 2002) such as kriging, and methods are often combined to yield improved fit (e.g. Balk and Elder, 2000). Physical snow models, such as Alpine3D (Lehning and others, 2006) and SnowDrift3D (Schneiderbauer and Prokop, 2011), are continuously being improved and tested within the snow science literature. Snow survey error has been considered from both a theoretical (Trujillo and Lehning, 2015) and applied perspective (Turcan and Loijens, 1975; Woo and Marsh, 1978; Deems and Painter, 2006).

The precision and accuracy of winter balance estimates can likely be improved by incorporating snow science tools and interpolation methodologies and by gaining a more comprehensive understanding of uncertainties inherent when estimating winter balance on glaciers. Ultimately, we need a thorough knowledge of the processes that affect spatial and temporal snow variability and an effective method to predict snow accumulation. The contribution of our work toward these goals is to (1) examine methods and uncertainties when moving from direct snow depth and density measurements to estimating winter balance and (2) show how snow variability, data error and our methodological choices interact to create uncertainty in our estimate of winter balance. We focus on commonly applied low-complexity methods of measuring and predicting winter balance with the hope of making our results broadly applicable to current and future winter mass balance programs.

STUDY SITE

Winter balance surveys were conducted on three glaciers in the Donjek Range of the St. Elias Mountains, located in the south western Yukon, Canada. The Donjek Range is approximately 30 × 30 km and Glacier 4, Glacier 2, and Glacier 13 (labelling adopted from Crompton and Flowers (2016)) are located along a SW-NE transect through the range. There is a local topographic divide in the Donjek Range that follows an "L" shape, with one glacier located in each of the south, north, and east regions (Figure 1). These mid-sized alpine glaciers are generally oriented SE-NW, with Glacier 4 dominantly south facing and Glaciers 2 and 13 generally north facing. The glaciers are low angled with steep head walls and steep valley walls. The St. Elias mountains boarder the Pacific Ocean and rise sharply, creating a significant climatic winter gradient between coastal maritime conditions, generated by Aleutian–Gulf of Alaska low-pressure systems, and interior continental conditions, determined by Yukon–Mackenzie high-pressure system (Taylor-Barge, 1969). The average dividing line between the two climatic zones shifts between Divide Station and the head of the Kaskawalsh Glacier based on synoptic conditions. The Donjek Range is located approximately 40 km to the east of the head of the Kaskawalsh Glacier. Research on snow distribution and glacier mass balance in the St. Elias is limited. A series of research programs were operational in the 1960s (Wood, 1948; Danby

Table 1. Physical details of study glaciers

	Location	Elevation (m a.s.l)		Slope (°)	Area
		Mean	*Range*	*Mean*	(km)
G4	595470 E 6740730 N	2344	1958–2809	12.8	3.8
G2	601160 E 6753785 N	2495	1899–3103	13.0	7.0
G13	604602 E 6763400 N	2428	1923–3067	13.4	12.6

and others, 2003) and long-term studies on a few alpine glaciers have arisen in the last 30 years (e.g. Clarke and others, 1984; Paoli and Flowers, 2009).

METHODS

Estimating winter balance involves transforming snow depth and density measurements to distributed estimates of snow water equivalent (SWE). We use four main processing steps. First, we obtain measurements of snow depth and density. Since density is measured more sparsely than depth, the second step is to interpolate density measurements to all depth measurement locations and to calculate the SWE at each measurement location. Third, we average all SWE values within one grid cell of a digital elevation model (DEM) with given spatial resolution to produce a single value of SWE for each grid cell. Fourth, we interpolate SWE values to obtain a distributed estimate of SWE across the surface of the glacier. We choose to use a linear regression between SWE and topographic parameters as well as simple kriging to interpolation grid cell SWE. To estimate the specific winter balance we then calculate aerially-averaged integrated SWE. For brevity, we refer to these four steps as (1) field measurements, (2) distributed snow density, (3) grid cell average SWE and (4) distributed SWE. Detailed methodology for each step is outlined below.

Field measurements

Sampling design

The sampling design attempted to capture depth variability at multiple spatial scales. We measured winter balance at three glaciers along the precipitation gradient in the St. Elias Mountains, Yukon (Taylor-Barge, 1969) in an attempt to account for range-scale variability (Clark and others, 2011). We measured winter balance on Glaciers 4, 2, and 13, which are located increasingly far from the head of the Kaskawalsh Glacier

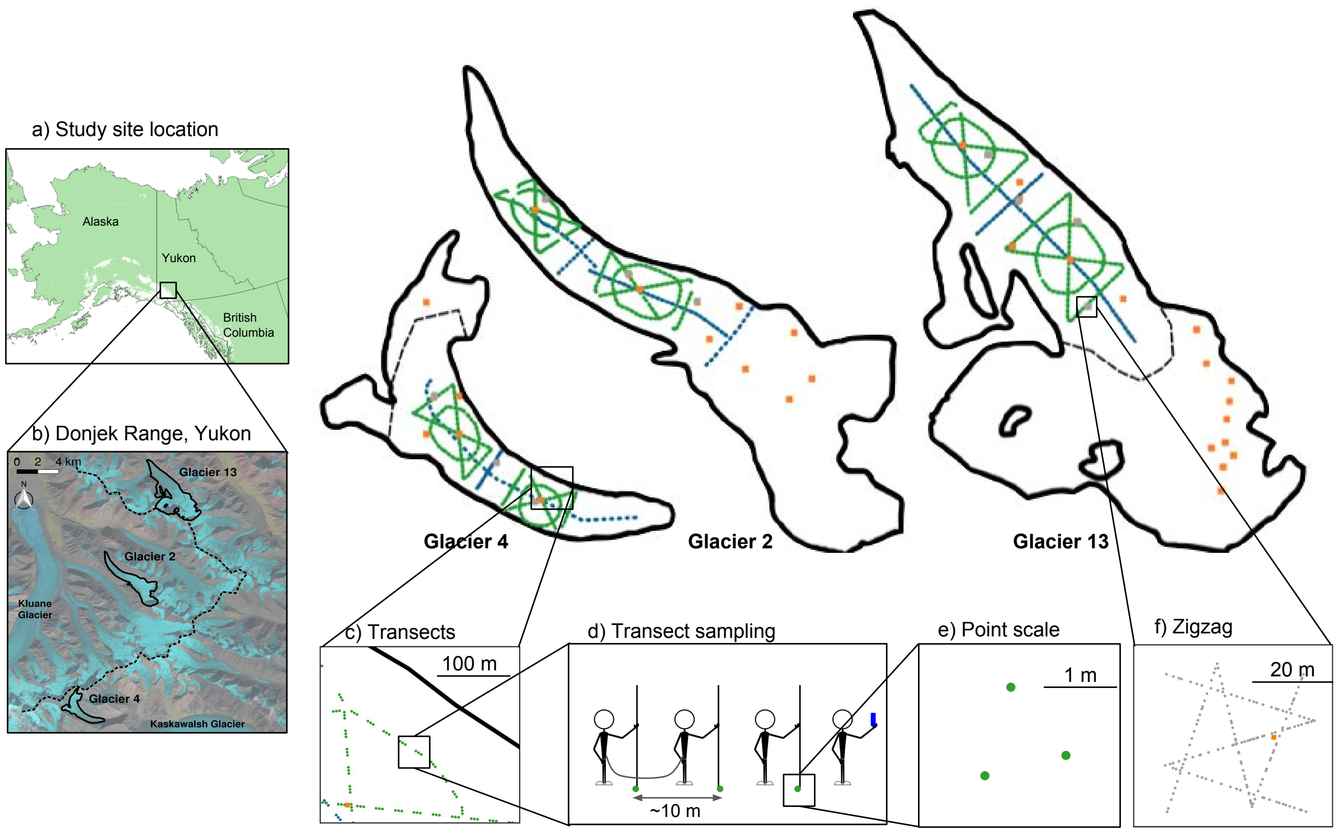

Fig. 1. Sampling design for Glaciers 4, 2 and 13, located in the Donjek Range, Yukon (a,b). Centreline and transverse transects are shown in blue dots, hourglass and circle design are shown in green dots. (c) Linear and curvilinear transects typically consist of sets of three measurement locations, spaced ∼10 m apart (d). (e) At each measurement location, three snow depth observation are made. (f) Linear-random snow depth measurements in 'zigzag' design are shown as grey dots. Orange squares are locations of snow density measurements.

(Figure 1b). Snow depth was measured along linear and curvilinear transects to account for basin-scale variability. At each measurement location, three values of snow depth were recorded to account for point-scale variability (Clark and others, 2011). We selected centreline and transverse transects with sample spacing

Table 2. Details of snow survey conducted in May 2016 at Glacier 4 (G4), Glacier 2 (G2), and Glacier 13 (G13). Values shown include number of snow depth measurement locations along transects (n_T), total length of transects (d_T [km]), number of combined SP and FS density measurement locations (n_ρ) and number of zigzag (n_{zz}).

	Date	n_T	d_T	n_ρ	n_{zz}
G4	May 4–7	649	13.1	7	3
G2	May 8–11	762	13.6	7	3
G13	May 12–15	941	18.1	19	4

of 10 – 60 m (Figure 1d) to capture previously established correlations between elevation and accumulation (e.g. Machguth and others, 2006; Walmsley, 2015) as well as accumulation differences between ice-marginal and centre accumulation. We also implemented an hourglass and circle design (Figure 1), which allows for sampling in all directions and easy travel (Parr, C., 2016 personal communication). At each measurement location, we took 3 – 4 depth measurements within ∼1 m of each other (Figure 1e), resulting in more than 9,000 snow depth measurements throughout the study area.

Snow depth

The estimated SWE is the product of the snow depth and depth-averaged density. Snow depth is generally accepted to be more variable than density (Elder and others, 1991; Clark and others, 2011; López-Moreno and others, 2013) so we chose a sampling design with relatively small measurement spacing along transects that resulted in a ratio of approximately 55:1 snow depth to snow density measurements. Our sampling campaign involved four people and occurred between May 5 and 15, 2015, which corresponds to the historical peak accumulation in the Yukon (Yukon Snow Survey Bulletin and Water Supply Forecast, May 1, 2016). While roped-up for glacier travel at fixed distances between observers, the lead person used a single frequency GPS (Garmin GPSMAP 64s) to navigate as close to the predefined transect measurement locations as possible (Figure 1). The remaining three people used 3.2 m aluminium avalanche probes to take snow depth measurements. The location of each set of depth measurements, taken by the second, third and fourth observers, was approximated based on the recorded location of the first person.

Snow depth sampling was primarily done in the ablation area to ensure that only snow from the current accumulation season was measured. Determining the boundary between snow and firn in the accumulation area, especially when using an avalanche probe, is difficult and often incorrect (Grunewald and others, 2010; Sold and others, 2013). We intended to use a firn corer to extract snow cores in the accumulation area but due to environmental conditions we were unable to obtain cohesive cores. Successful measurements within the accumulation area were done either in a snow pit or using a Federal Sampler with shovel validation so that we could identify the snow-firn transition based on a change in snow crystal size and density.

Zigzags

To capture variability at spatial scales smaller than a DEM grid cell, we implemented a linear-random sampling design, termed 'zigzag' (Shea and Jamieson, 2010). We measured depth at random intervals (0.3−3.0 m) along two 'Z'-shaped transects within three to four 40 × 40 m squares (Figure 1c) resulting in 135 – 191 measurement points for each zigzag. Zigzag locations were randomly chosen within the upper (∼2350 m a.s.l.), middle (∼2250 m a.s.l.), and lower portions (∼2150 m a.s.l.) of the ablation area of each glacier. We were able to measure a fourth zigzag on Glacier 13 that was located in the middle ablation area (∼2200 m a.s.l.).

Snow density

Snow density was measured using a wedge cutter in three snowpits on each glacier. We measured a vertical density profile by inserting a $5 \times 10 \times 10$ cm wedge-shaped cutter (250 cm^3) in 5 cm increments to extract snow samples and then weighed the samples with a spring scale (e.g. Gray and Male, 1981; Fierz and others, 2009). Uncertainty in estimating density from snow pits stems from measurement errors and incorrect assignment of density to layers that could not be sampled (i.e. ice lenses and 'hard' layers).

While snow pits provide the most accurate measure of snow density, digging and sampling a snow pit is time and labour intensive. Therefore, a Federal Snow Sampler (FS) (Clyde, 1932), which measures bulk SWE, was used to augment the spatial extent of density measurements. A minimum of three measurements were taken at each of $7 - 19$ locations on each glacier and an additional eight FS measurements were co-located with each snow pit profile. Measurements where the snow core length inside the FS was less than 90% of the snow depth were assumed to be an incorrect sample and were excluded. Density values were then averaged for each location.

During the field campaign there were two small accumulation events. The first, on May 6, also involved high winds so accumulation could not be determined. The second, on May 10, resulted in 0.01 m w.e accumulation at one location on Glacier 2. Warm temperatures and clear skies occurred between May 11 and 16, which we believed resulted in significant melt occurring on Glacier 13. The snow in the lower part of the ablation area was isothermal and showed clear signs of melt and snow metamorphosis. The total amount of accumulation and melt during the study period could not be estimated so no corrections were made.

Distributed snow density

Measured density is interpolated to estimate SWE at each depth sampling location. We chose four separate methods that are commonly applied to interpolate density: (1) mean density over an entire range (e.g. Cullen and others, 2017), (2) mean density for each glacier (e.g. Elder and others, 1991; McGrath and others, 2015), (3) linear regression of density with elevation (e.g. Elder and others, 1998; Molotch and others, 2005) and (4) inverse-distance weighted density (e.g. Molotch and others, 2005). SP and FS densities are treated separately, for reasons explained below, which results in eight density interpolation options (Table 3).

Table 3. Description of density interpolation methods used to calculate SWE used in the topographic regression. Abbreviations with 'S' used snowpit-derived densities and abbreviations with an 'F' used Federal Sampler-derived densities.

	Snow density source		**Estimation method**
	Snowpit	*Federal Sampler*	
S1	■		Mean of all glaciers
F1		■	
S2	■		Glacier mean
F2		■	
S3	■		Linear regression of elevation and density for each glacier
F3		■	
S4	■		Inverse distance weighted mean
F4		■	

Grid cell average SWE

We average SWE values within each DEM-aligned grid cell. The locations of measurements have considerable uncertainty both from the error of the GPS unit (2.7−4.6 m) and the estimation of observer location based on the GPS unit. These errors could easily result in the incorrect assignment of a SWE measurement to a certain grid cell but this source of variability was not further investigated because we assume that SWE variability is captured in the zigzag measurements described below. There are no significant differences between observers ($p>0.05$), with the exception of the first transect on Glacier 4. No corrections to the data based on observer differences are applied.

Distributed SWE

Linear regression

SWE are interpolated and extrapolated for each glacier using linear regression (LR) as well as simple kriging (SK). Linear regressions relate observed SWE to grid cell values of DEM-derived topographic parameters (Davis and Sampson, 1986). We choose to include elevation, distance from centreline, slope, aspect, curvature, "northness" and a wind redistribution parameter in the LR. Topographic parameters are weighted by a set of fitted regression coefficients (β_i). Regression coefficients are calculated by minimizing the sum of squares of the vertical deviations of each data point from the regression line (Davis and Sampson, 1986). The distributed estimate of SWE is found by using regression coefficients to estimate SWE at each grid cell. Specific winter balance is calculated as the aerially-averaged, integrated SWE for each glacier ([m w.e.]).

Snow depth data are highly variable so there is a possibility for the LR to fit to this data noise, a process known as overfitting. To prevent overfitting, cross-validation and model averaging are implemented. First, cross-validation is used to obtain a set of β_i values that have greater predictive ability. We select 1000 random subsets (2/3 values) of the data to fit the LR and the remaining data (1/3 values) are used to calculate a root mean squared error (RMSE) (Kohavi and others, 1995). Regression coefficients resulting in the lowest RMSE are selected. Second, we use model averaging to take into account uncertainty when selecting predictors and to also maximize predictive ability (Madigan and Raftery, 1994). Models are generated by calculating a set of β_i for all possible combinations of predictors. Following a Bayesian framework, model averaging involves weighting all models by their posterior model probabilities (Raftery and others, 1997). To obtain the final regression coefficients, the β_i values from each model are weighted according to the relative predictive success of the model, as assessed by the Bayesian Information Criterion (BIC) value (Burnham and Anderson, 2004). BIC penalizes more complex models, which further reduces the risk of overfitting.

Topographic parameters

Topographic parameters are easy to calculate proxies for physical processes, such as orographic precipitation, solar radiation effects, wind redistribution and preferential deposition. We derive all parameters (Table 8) for our study from a SPOT-5 DEM (40×40 m) (Korona and others, 2009). Two DEMs are stitched together to encompass the Donjek Range. An iterative 3D-coregistration algorithm (Berthier and others, 2007) is used to correct the horizontal ($\sim$2 m E, $\sim$4 m N) and vertical (5.4 m) discrepancy between the two DEMs before stitching.

Visual inspection of the curvature fields calculated using the full DEM shows a noisy spatial distribution that did not vary smoothly. To smooth the DEM, various smoothing algorithms and window sizes are applied and the combination that produces the highest correlation between topographic parameters and SWE is chosen. Inverse-distance weighted, Gaussian and grid cell averaging smoothing all with window sizes of 3×3, 5×5, 7×7 and 9×9 are used. Grid cell average smoothing with a 7×7 window resulted in the highest overall correlation between curvature (second derivative) and SWE as well as slope (first derivative) and SWE. We use the smoothed DEM to calculate curvature, slope, aspect and "northness".

Simple kriging

Simple kriging (SK) estimates SWE values at unsampled locations by using the isotropic spatial correlation (covariance) of measured SWE to find a set of optimal weights (Davis and Sampson, 1986; Li and Heap, 2008). SK assumes that if sampling points are distributed throughout a surface, the degree of spatial correlation of the observed surface can be determined and the surface can then be interpolated between sampling points. We used the `DiceKriging` R package (Roustant and others, 2012) to calculate the maximum likelihood covariance matrix, as well as range distance (θ) and nugget. The range distance is a measure of data correlation length and the nugget is the residual that encompasses sampling-error variance as well as the spatial variance at distances less than the minimum sample spacing (Li and Heap, 2008).

Uncertainty analysis

To quantify effects of uncertainty on the winter balance estimate, we conduct a Monte Carlo experiment, which uses repeated random sampling to calculate a numerical solution (Metropolis and Ulam, 1949). Three sources of uncertainty, which encompass error and uncertainty within each processing step, are considered: (1) density uncertainty, (2) SWE uncertainty and (3) interpolation uncertainty. Uncertainty from each source is propagated individually through the process of converting snow measurements to winter balance. We quantify the effects of each uncertainty source by calculating the standard deviation of the resulting distribution of winter balance estimates. Then, all three uncertainty sources are considered together and their combined effect on winter balance uncertainty is quantified.

Density uncertainty

We incorporate uncertainty in interpolating density measurements by carrying forward all eight density interpolation options when estimating winter balance. The density measurement and interpolation methods used in our study encompass a broad spectrum of possible density values. The winter balance uncertainty due to density uncertainty (σ_ρ) is calculated as the standard deviation of winter balance estimates calculated using each density interpolation option.

$_{SWE}$ When calculating a grid cell average SWE, uncertainty stems from a distribution of SWE values within each grid cell, which is assumed to be caused by random effects that are unbiased and unpredictable (Watson and others, 2006). We therefore choose to characterize SWE uncertainty by generating a normal distribution of SWE values for each measured grid cell. The normal distribution has a mean equal to the grid cell average SWE and a standard deviation equal to the mean standard deviation of all zigzags on each glacier.

σ_{INT} When obtaining interpolated SWE, the best fit interpolation itself has uncertainty based on the data that are used to fit the regression line or kriging surface. LR uncertainty is represented by obtaining a multivariate normal distribution of possible β_i values. The standard deviation of each distribution is calculated using the covariance of regression coefficients as outlined in Bagos and Adam (2015). SK uncertainty is calculated using the `DiceKriging` package and is returned as an upper and lower 95% confidence interval for SWE at each grid cell.

In our study, we randomly sample the distributions for SWE uncertainty and interpolation uncertainty and carry these values through the data processing steps to obtain a value of winter balance. First, random values from the distribution of SWE values for each grid cell are independently chosen. Then, LR or SK is used to interpolate these SWE values. With the LR, a set of β_i values and their distributions are calculated and the β_i distributions are randomly sampled. These new β_i values are used to calculate winter balance. With SK, a distribution of winter balance is calculated from the 95% confidence interval kriging surfaces. Winter balance standard deviation is then calculated from the average SWE variance. Density uncertainty is accounted for by repeating the process for each density interpolation method. This random sampling process is done 1000 times, which results in a distribution of possible winter balance values based on uncertainty within the data processing steps. The output of the Monte Carlo experiment is a normal distribution of winter balance estimates. We quantify the width of the distribution using one standard deviation.

RESULTS

Measurements

A wide range of snow depth is observed on all three study glaciers (Figure 2). Glacier 4 has the highest mean snow depth and a high proportion of outliers, indicating a more variable snow depth overall. Glacier 13 has the lowest mean snow depth and a narrower distribution of observed values. At each measurement location, the median range of measured depths ($3-4$ points) as a percent of the mean depth at that location is 2%, 11%, and 12%, for Glaciers 4, 2 and 13, respectively.

Mean SP and FS density values are within one standard deviation of each other for each glacier and over all three glaciers. The standard deviation of glacier-wide mean density is less than 10% of the mean density. However, FS densities have a larger range of values ($227-431$kg m^{-3}) when compared to SP densities ($299-381$kg m^{-3}). The mean SP densities are within one standard deviation between glaciers, whereas mean FS densities are not.

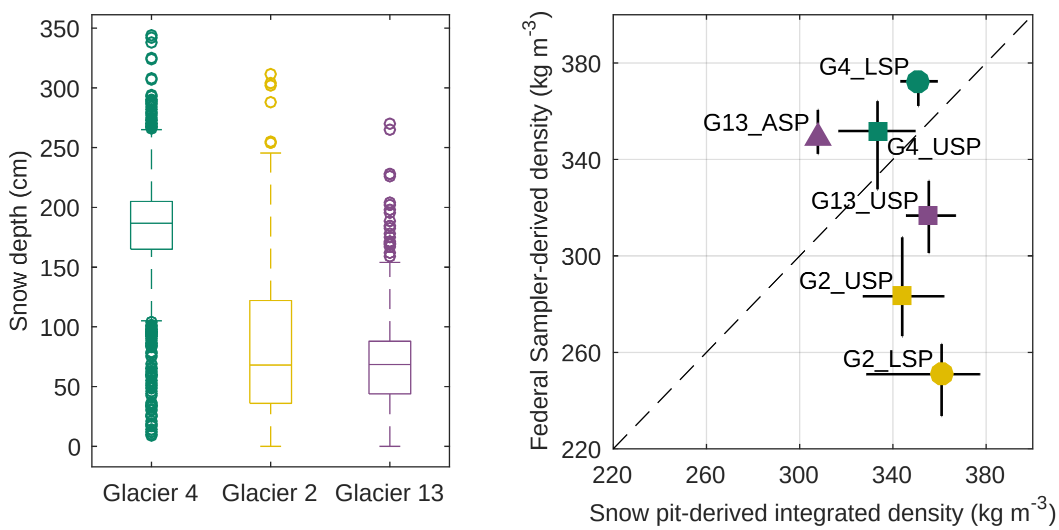

Fig. 2. (Left) Boxplot of measured snow depth on Glaciers 4, 2 and 13. The box shows first quartiles, the line within the box indicates data median, bars indicate minimum and maximum values (excluding outliers), and circles show outliers, which are defined as being outside of the range of 1.5 times the quartiles (approximately $\pm 2.7\sigma$). (Right) Comparison of integrated density estimated using wedge cutters in a snow pit and density estimated using Federal Sampler measurements for Glacier 4 (G04), Glacier 2 (G02) and Glacier 13 (G13). Snow pits were distributed in the accumulation area (ASP), upper ablation area (USP) and lower ablation area (LSP). Error bars are minimum and maximum values.

Uncertainty in SP density is largely due to sampling error of exceptionally dense snow layers. We quantify this uncertainty by varying three values. Ice layer density is varied between 700 and 900 kg m^{-3}, ice layer thickness is varied by ± 1 cm of the recorded thickness, and the density of layers identified as being too hard to sample (but not ice) is varied between 600 and 700 kg m^{-3}. The range of integrated density values is always less than 15% of the reference density, with the largest ranges present on Glacier 2. Density values for shallow pits that contain ice lenses are particularly sensitive to changes in density and ice lens thickness.

Distributed density

We find no correlation between co-located SP and FS densities (Figure 2) so each set of density values is used for all four density interpolation options. Regional and glacier mean densities are higher when SP densities are used (Table 4). The slope of a linear regression of density with elevation differs between SP and FS densities (Table 4). At Glaciers 2 and 13, SP density decreases with elevation, likely indicating melt and/or

Table 4. Snow density values used for interpolating density based on snow pit (SP) densities and Federal Sampler (FS) densities. Four interpolation methods are chosen: (1) using a mean snow density for all three glaciers (Range mean density), (2) using a mean density for each glacier (Glacier mean density), (3) using a regression between density and elevation (Elevation regression), and (4) inverse-distance weighted mean density (not shown).

		SP density ($\mathrm{kg\ m^{-3}}$)	**FS density ($\mathrm{kg\ m^{-3}}$)**
Range mean density		342	316
Glacier mean density	G4	348	327
	G2	333	326
	G13	349	307
Elevation regression	G4	$0.03z + 274$	$-0.16z + 714$
	G2	$-0.14z + 659$	$0.24z - 282$
	G13	$-0.20z + 802$	$0.12z + 33$

compaction at lower elevations. SP density is independent of elevation on Glacier 4. FS density increases with elevation on Glacier 2 and there is no relationship with elevation on Glaciers 4 and 13. There is a positive linear relation ($R^2 = 0.59$, $p<0.01$) between measured snow density and depth for all FS measurements. No correlation exists between SP density and elevation.

Grid cell average

SWE observations within a DEM grid cell are averaged. Between one and six measurement locations are in each measured grid cell. The distribution of grid-cell SWE values for each glacier is similar to that of Figure 2 but with fewer outliers. SWE measurements for each zigzag are not normally distributed about the mean SWE (Figure 3). The average standard deviation of all zigzags on Glacier 4 is $\sigma_{\mathrm{G4}} = 0.027$ m w.e., on Glacier 2 is $\sigma_{\mathrm{G2}} = 0.035$ m w.e. and on Glacier 13 is $\sigma_{\mathrm{G13}} = 0.040$ m w.e.

Interpolated SWE

The choice of interpolation method affects the specific winter balance (Table 5). SK produces the highest winter balance on Glacier 4 and the lowest winter balance on Glacier 13. winter balance estimated by SK is ~30% lower than winter balance estimated by LR on Glaciers 2 and 13. When using LR, the winter balance on Glaciers 4 and 2 are similar in magnitude.

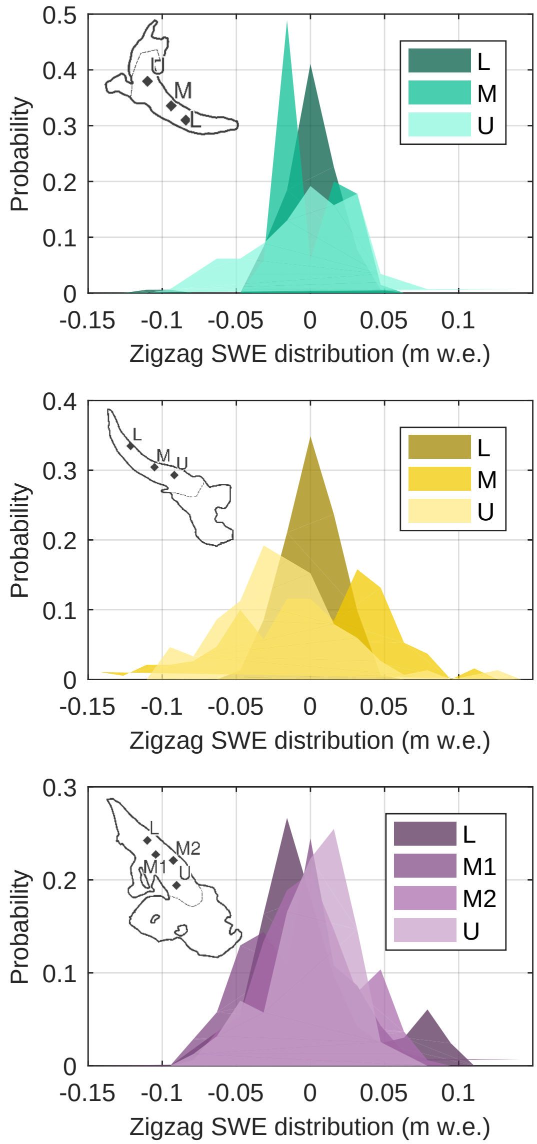

Fig. 3. Distribution of zigzag SWE values with the local mean subtracted on Glacier 4 (upper panel), Glacier 2 (middle panel) and Glacier 13 (lower panel). Zigzags are distributed throughout the ablation area of each glacier, with one located in the lower portion (L), one in the middle portion (M), and one in the upper portion (U). There were two zigzags in the middle ablation area of Glacier 13.

The predictive ability of SK and LR differ on the study glaciers. Generally, SK is better able to predict SWE at observed grid cells (Figure 4) and RMSE for all glaciers is lower for SK estimates (Table 5). Glacier 13 has

Table 5. Specific winter balance (WB [m w.e.]) estimated using linear regression and simple kriging interpolation for study glaciers. Average root mean squared error (RMSE [m w.e.]) between estimated and observed grid cells for all points, which were randomly selected and excluded from interpolation, is also shown. RMSE as a percent of the WB is shown in brackets.

	Linear Regression		**Simple Kriging**	
	WB	RMSE	WB	RMSE
G4	0.582	0.153 (26%)	0.616	0.134 (22%)
G2	0.577	0.102 (18%)	0.367	0.073 (20%)
G13	0.381	0.080 (21%)	0.271	0.068 (25%)

the lowest RMSE regardless of interpolation method, indicating lower SWE variability. The highest RMSE and the lowest correlation between estimated and observed SWE is seen on Glacier 4 (R^2 = 0.12), which emphasizes the highly variable snow distribution. The highest correlation between estimated and observed SWE is on Glacier 2 when SK is used for interpolation (R^2 =0.84) (Figure 4). Residuals using LR and SK for all glaciers are normally distributed.

The importance of topographic parameters in the LR differs for the three study glaciers (Figure 5). The most important topographic parameter for Glacier 4 is wind redistribution. However, the wind redistribution coefficient is negative, which indicates less snow in 'sheltered' areas. Curvature is also a significant predictor of accumulation and the positive correlation indicates that concave areas are more likely to have higher SWE. For Glacier 2, the most important topographic parameter is elevation, which is positively correlated with elevation. Wind redistribution is the second most important topographic parameter and has a positive correlation, which indicates that 'sheltered' areas are likely to have high accumulation. The most important topographic parameter for Glacier 13 is elevation. The coefficient is positive, which means that cells at higher elevation have higher SWE. Curvature is also a significant topographic parameter but the correlation is negative, indicating less accumulation in concave areas. Most of the topographic parameters are not significant predictors of accumulation on Glacier 13. Aspect and "northness" are not significant predictors of accumulation on all study glaciers.

Our sampling design ensured that the ranges of topographic parameters covered by the measurements represented more than 70% of the total area of each glacier (except for the elevation range on Glacier 2, which was 50%). However, we were not able to sample at locations with extreme parameter values and the distribution of the sampled parameters generally differed from the full distribution.

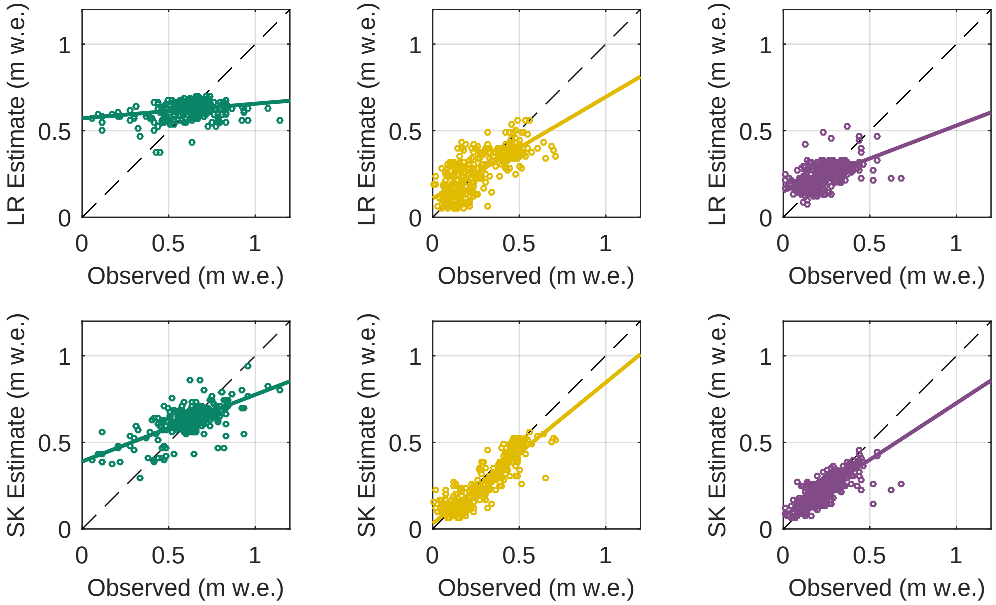

Fig. 4. Estimated grid cell SWE found using linear regression (LR) and simple kriging (SK) plotted against observed values of SWE on Glacier 4 (left), Glacier 2 (middle) and Glacier 13 (right). Line of best fit between estimated and observed SWE is also plotted.

Spatial patterns of SWE found using LR are similar between Glaciers 2 and 13 and differ considerably for Glacier 4 (Figure 6). Estimated SWE on Glacier 4 is relatively uniform, which results from the low predictive ability of the LR. Areas with high wind redistribution values (sheltered), especially in the accumulation area, have the lowest values of SWE. The map of modelled SWE on Glacier 2 closely matches that of elevation, which highlights the strong dependence of SWE on elevation. Glacier 2 has the largest range of estimated SWE ($0-1.92$ m w.e). The area of high estimated accumulation in the southwest region of the glacier results from the combination of high elevation and Sx values. The low SWE values at the terminus arise from low elevation and Sx values close to zero. The map of estimated SWE on Glacier 13 also closely follows elevation. However, the lower correlation between SWE and elevation results in a relatively small range of distributed SWE values.

There are large differences in spatial patterns of estimated winter balance for the three study glaciers found using SK (Figure 6). On Glacier 4, the isotropic correlation length is considerably shorter compared to Glacier 2 and Glacier 13 (Table 6), which results in a relatively uniform SWE distribution over the glacier with small deviations at measured grid cells. Nugget values for the study glaciers also differ, with the nugget

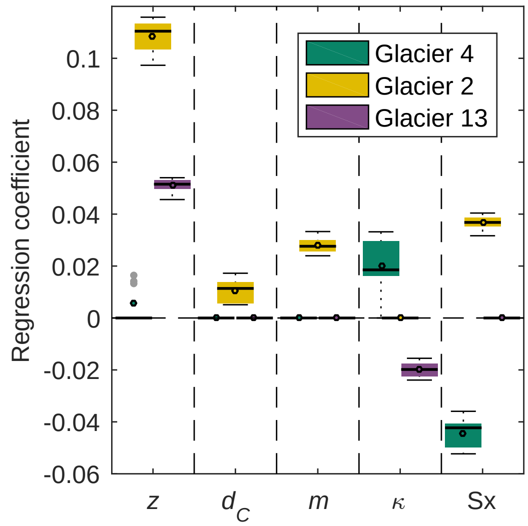

Fig. 5. Distribution of regression coefficients for linear regression of grid cell topographic parameters and SWE calculated using eight density options on study glaciers. Topographic parameters include elevation (z), distance from centreline (d_C), slope (m) , curvature (κ), and wind exposure (Sx). Regression coefficients that were not significant were assigned a value of zero. Aspect and "northeness" are not shown because coefficient values are zero for all glaciers. Outlier values are shown as gray dots.

of Glacier 4 more than twice as large as that of Glacier 2 and Glacier 13 (Table 6). Glacier 2 has two distinct and relatively uniform areas of estimated accumulation. The lower ablation area has low SWE (∼0.1 m w.e.) and the upper ablation and accumulation areas have higher SWE values (∼0.6 m w.e.). Glacier 13 does not appear to have any strong patterns and accumulation is generally low ($\sim 0.1 - 0.5$ m w.e.).

Table 6. Range and nugget values for simple kriging interpolation

	Range (m)	**Nugget ($\times10^3$m w.e.)**
G4	90	10.5
G2	404	3.6
G13	444	4.8

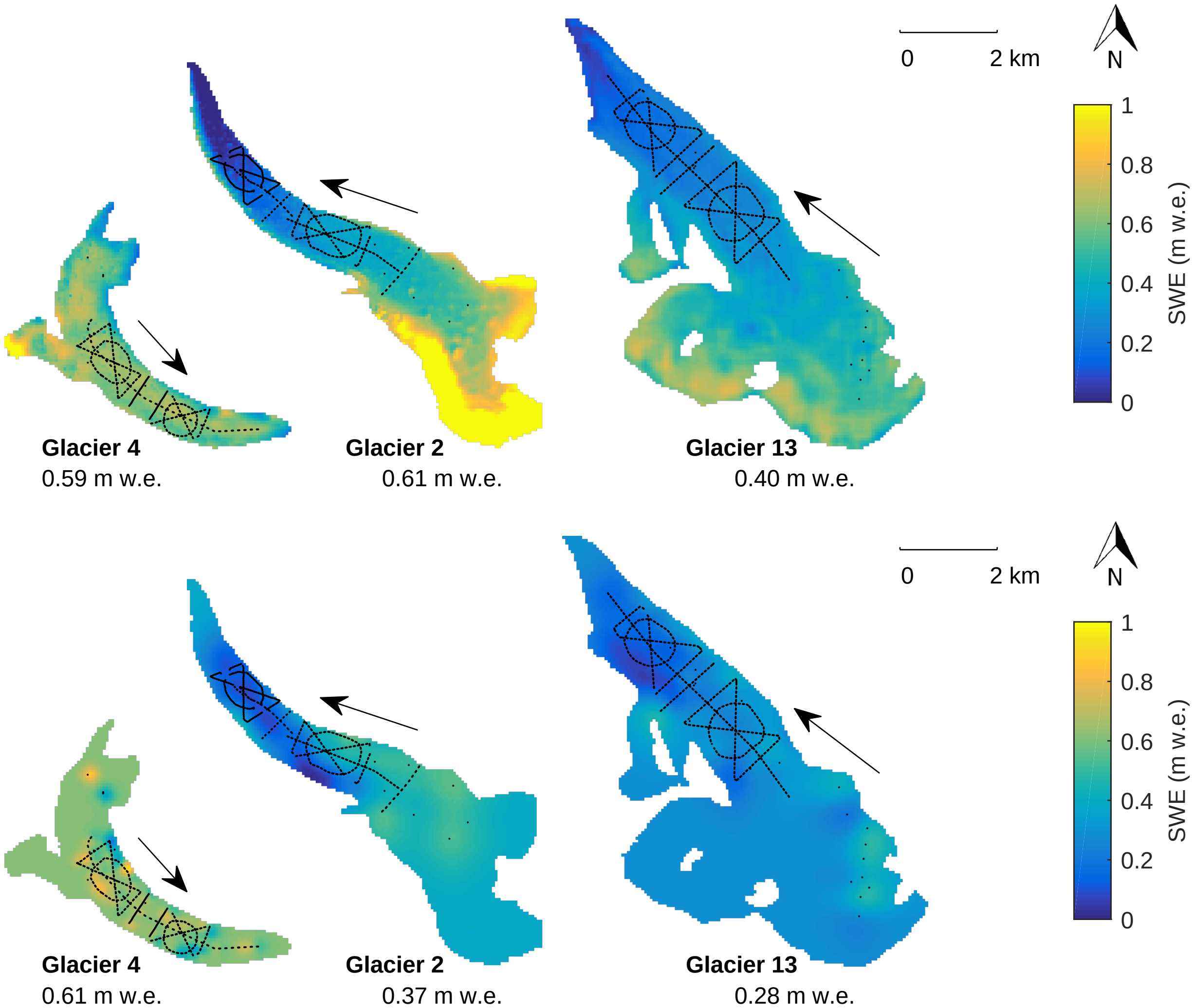

Fig. 6. Spatial distribution of SWE estimated using linear regression (upper) and simple kriging (lower). Grid-cell SWE observations are found using glacier wide mean snow pit density and are shown as black dots. Glacier flow directions are indicated by arrows. Specific winter balance values are also shown.

SWE estimated with LR and SK differ considerably in the upper accumulation areas of Glaciers 2 and 13. The significant influence of elevation in the LR results in substantially higher SWE values at high elevation, whereas the accumulation area of the SK estimates approximate the mean observed SWE.

Transferring LR coefficients between glaciers results in a high RMSE across the mountain range. The lowest overall RMSE (0.2051 m w.e.) results from calculating a LR using all available observations. Elevation is the only significant topographic predictor for a range-scale LR ($\beta_z = 0.0525$).

Table 7. Standard deviation ([$\times 10^{-2}$ m w.e.]) of specific winter balance estimated using linear regression (LR) and simple kriging (SK) when uncertainty is introduced. Density uncertainty (σ_ρ) is the standard deviation of winter balance estimated using SWE data with different density interpolation methods. SWE uncertainty (σ_{SWE}) is approximated by a normal distribution about the local SWE value with standard deviation equal to the glacier-wide mean zigzag standard deviation. LR interpolation uncertainty (σ_{INT}) is accounted for by varying the regression coefficients with a normal distribution with standard deviation calculated from regression covariance. SK interpolation uncertainty (σ_{INT}) is taken from the range of distributed SWE estimates calculated by the DiceKriging package. Result for Glacier 4 (G4), Glacier 2 (G2) and Glacier 13 (G13) are shown.

	Linear Regression			**Simple Kriging**		
	σ_ρ	σ_{SWE}	σ_{INT}	σ_ρ	σ_{SWE}	σ_{INT}
G4	1.90	0.86	2.13	2.15	0.85	14.05
G2	3.37	1.80	3.09	2.03	2.53	13.78
G13	1.68	1.12	2.80	1.27	1.15	9.65

Uncertainty analysis

Specific winter balance is affected by uncertainty introduced when interpolating density (density uncertainty), when calculating grid cell SWE values (SWE uncertainty), and when interpolating observations (interpolation uncertainty). We find that when using LR and SK, interpolation uncertainty has a larger effect on winter balance uncertainty than density uncertainty or SWE uncertainty. The probability density function (PDF) that arises from SWE uncertainty is much narrower than the PDF that arises from interpolation uncertainty (Figure 7 and Table 7).

The total winter balance uncertainty from SK interpolation is 3 to 5 times greater than uncertainty from LR interpolation. The PDFs overlap between the two interpolation methods although the PDF modes have lower winter balance values when SK is used for Glaciers 2 and 13 and higher for Glacier 4. SK results in winter balance distributions that overlap between glaciers and there is also a small probability of estimating a winter balance value of 0 m w.e. for Glaciers 2 and 13. LR results in overlapping winter balance distributions for Glaciers 2 and 4, with the PDF peak of Glacier 4 being slightly higher than that of Glacier 2.

Density, SWE, and interpolation uncertainty all contribute to spatial patterns of winter balance uncertainty (Figure 8). For both LR and SK, the greatest uncertainty in estimated SWE occurs in the accumulation area. When LR is used, estimated SWE is highly sensitive to the elevation regression parameter. In the case of SK, uncertainty is greatest in areas far from observed SWE, which consist of the upper accumulation area

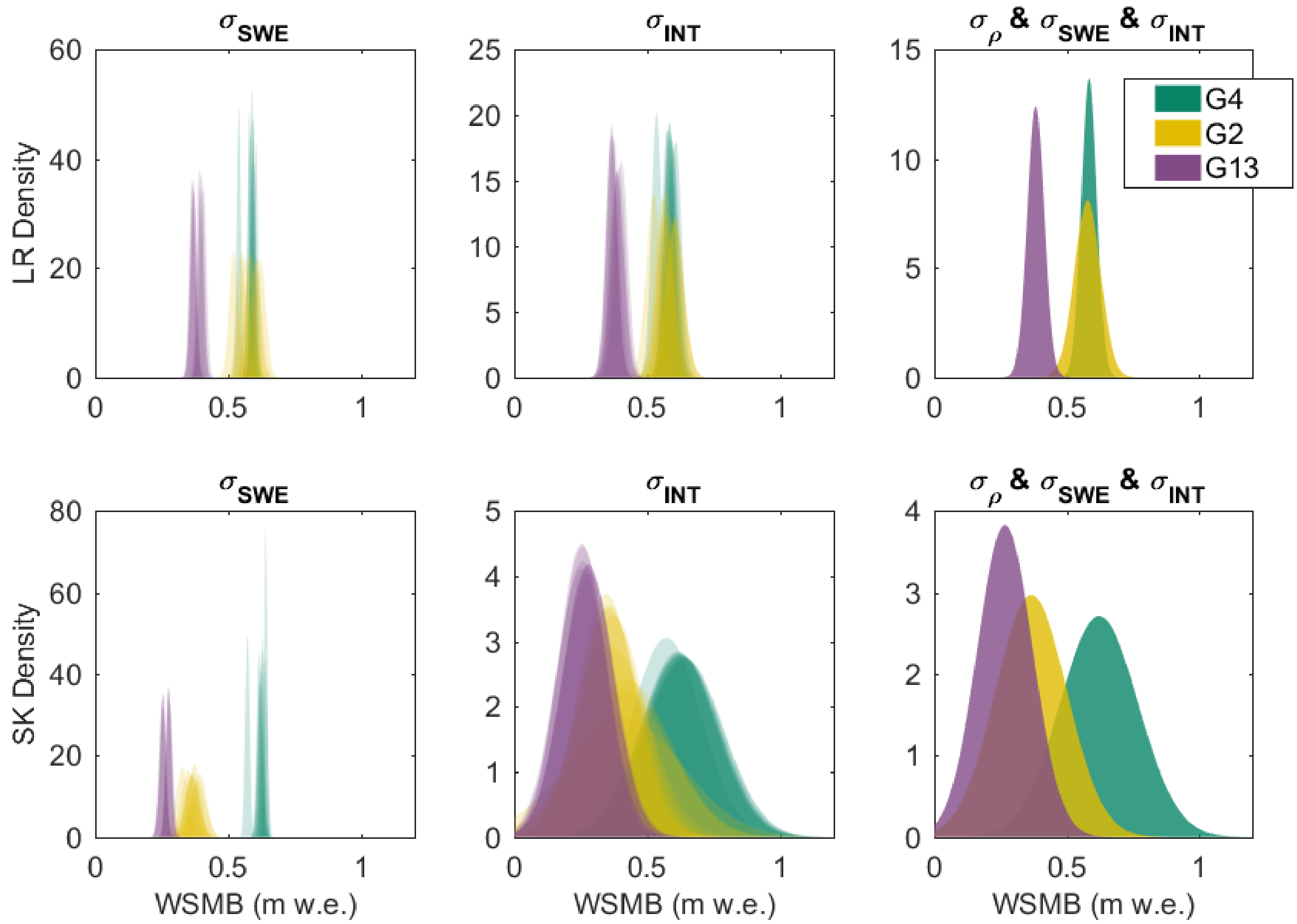

Fig. 7. Probability density functions (PDFs) fitted to distributions of specific winter balance values that arise from (left) SWE uncertainty (σ_{SWE}), (middle) interpolation uncertainty (σ_{INTERP}) and (right) all three sources of uncertainty. Results from a linear regression interpolation (top panels) and simple kriging (bottom panels) are shown. Each PDF is calculated using one of eight density interpolation methods for Glacier 4 (G4), Glacier 2 (G2) and Glacier 13 (G13).

on Glaciers 2 and 13. uncertainty is greatest on Glacier 4 when LR interpolation is used at the upper edges of the accumulation area, which correspond to the locations with extreme values of the wind redistribution parameter. When SK is used for interpolation on Glacier 4, uncertainty is greatest at the measured grid cells, which highlights the short correlation length and the large effect of density interpolation on the SK accumulation estimate.

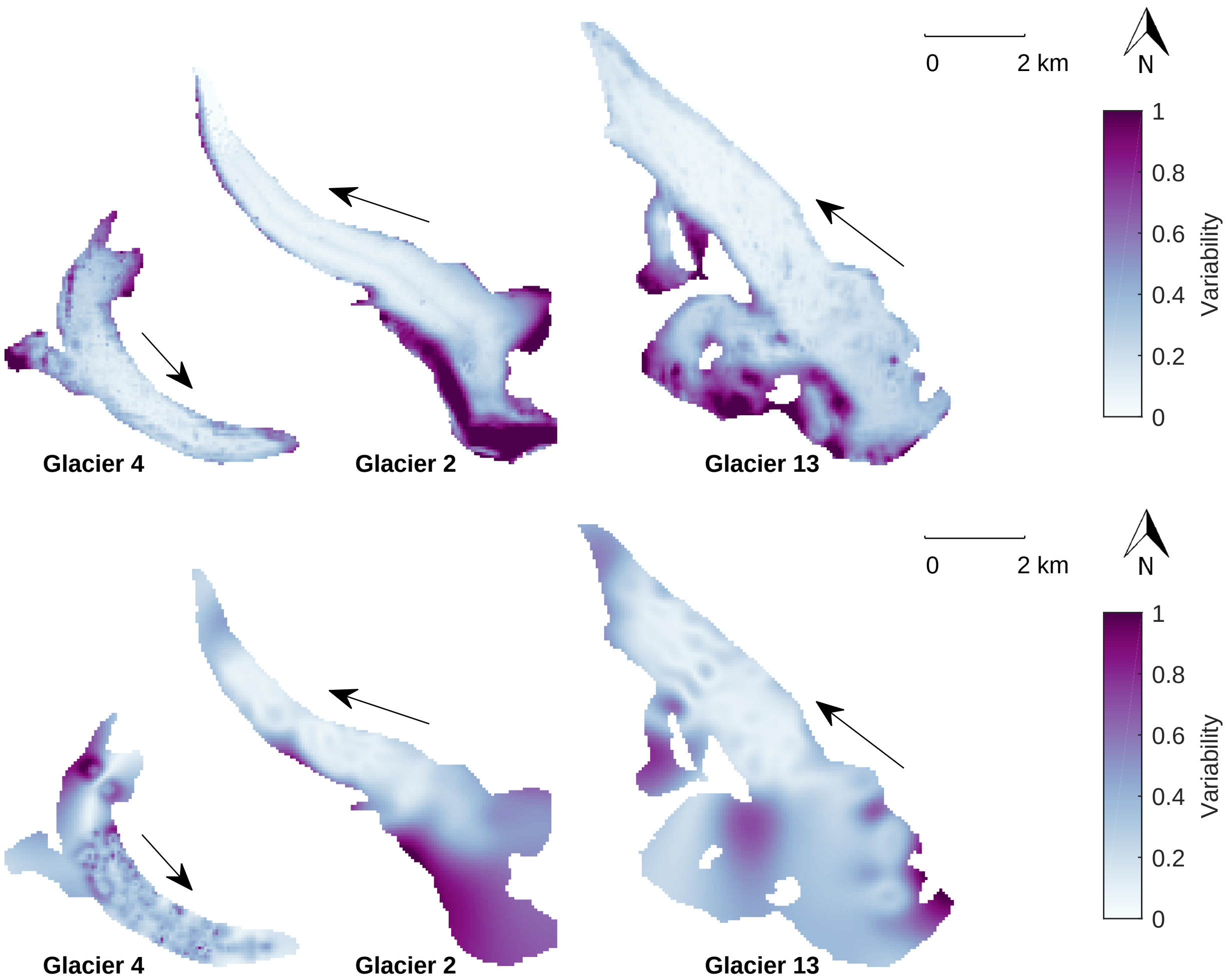

Fig. 8. Uncertainty of SWE estimated using linear regression (top) and simple kriging (bottom). Uncertainty is a relative quantity measured by taking the sum of differences between one hundred estimates of distributed winter balance that include SWE uncertainty and, in the case of linear regression, regression uncertainty. The sum is then normalized for each glacier. Glacier flow directions are indicated by arrows.

DISCUSSION

Measurements

Our study suffers from lack of data in the accumulation area, especially along steep head walls. Snow probing cannot be used reliably in the accumulation area because the snow-firn transition is often difficult to determine. Sold and others (2013) noted that a systematic bias can result from incorrect values of winter balance, particularly because inaccessible areas such as cliffs and ridges have relatively shallow accumulations (due to wind erosion), while heavily crevassed areas can accumulate deep snow packs. Measuring SWE in the accumulation area is difficult and subject to large errors regardless of the data collection method.

We measured snow density by sampling a snow pit (SP) and by using a Federal Sampler (FS). We found that FS and SP measurements are not correlated and that FS density values are positively correlated with snow depth. This positive relationship could be a result of physical processes, such as compaction, but is more likely a result of measurement artefacts for a number of reasons. First, the range of densities measured by the Federal sampler is large (225–410 kg m^{-3}) and the extreme values seem unlikely to exist in our study region, which experiences a continental snow pack with minimal mid-winter melt events. Second, compaction effects would likely be small at these study glaciers because of the relatively shallow snow pack (deepest measurement was 340 cm). Third, no linear relationship exists between depth and SP density ($R^2 = 0.05$). Together, these reasons lead us to conclude that the Federal Sampler measurements are biased but in a way that cannot be easily corrected.

The FS appears to oversample in deep snow and undersample in shallow snow. Oversampling by small diameter (area of 10–12 cm^2) sampling tubes has been observed in previous studies, with a percent error between +6.8% and 11.8% (Work and others, 1965; Fames and others, 1982; Conger and McClung, 2009). Studies that use Federal Samplers often apply a 10% correction to all measurements (e.g. Molotch and others, 2005). Dixon and Boon (2012) attributed oversampling to slots “shaving” snow into the tube as it is rotated, as well as cutter design forcing snow into the tube. Beauont and Work (1963) found that FS oversampled due to snow falling into the greater area of slots only when snow samples had densities greater than 400 kg m^{-3} and snow depth greater than 1 m. Undersampling is likely to occur due to snow falling out of the bottom of the sampler (Turcan and Loijens, 1975). It is likely that this occurred during our study since a large portion of the lower elevation snow on both Glaciers 2 and 13 was melt affected and thin, allowing for easier lateral displacement of the snow as the sampler was extracted. For example, on Glacier 13 the snow surface had been affected by radiation melt (especially at lower elevations where the snow was shallower) and the surface would collapse when the sampler was inserted into the snow. It is also difficult to measure the weight of the sampler and snow with the spring scale when there was little snow because the weight was at the lower limit of what could be detected by the scale. Therefore, FS appears to oversample in deep snow due to compaction and/or shaving snow and to undersample in shallow snow due to snow falling out of the sampling tube.

Distributed density

We choose four different density interpolation methods and separate SP and FS measurements for a total of eight density interpolation options. Despite the wide range of measured density values and different types of density interpolation, density does not appear to strongly affect winter balance estimates and is usually not the dominant source of winter balance uncertainty. Our preferred density interpolation is to use a glacier-wide mean of SP densities. Many winter balance studies assume uniform density (e.g. Elder and others, 1991; McGrath and others, 2015; Cullen and others, 2017) and it is realistic for future studies to measure snow density profiles at a few locations in the study basin. SP measurements are chosen over FS measurements because of the bias observed in FS densities. However, using a glacier-wide mean snow density omits known spatial variability in snow density (Wetlaufer and others, 2016).

Grid cell average

The zigzag sampling scheme offers a relatively easy way to take a large number of probe measurements in order to capture spatial variability of SWE in a grid cell. While the distribution of SWE values at each zigzag is qualitatively consistent in our study, future studies would benefit from increasing the number of zigzags and focusing on areas with both high variability (e.g. debris covered ice) and low variability (e.g. accumulation area) to determine how variability differs across the glacier.

Since such a large number of points are needed to characterize the variability in a grid cell there is little advantage to measuring and then averaging snow depth at multiple measurement locations. Rather, time should be spent extensively characterizing grid-cell variability in a few locations and to then decrease the spacing of transect measurements to extend their spatial coverage over the glacier. In our study, the grid cell variability appeared to be captured with dense sampling in select grid cells but the basin-scale variability was not captured because sampling was limited to the ablation area. By decreasing transect spacing, grid cells would only have one or two measurements but more grid cells could be measured.

Interpolated SWE

Linear regression

Elevation is the only topographic parameter that offered insight into topographic controls on accumulation. Even so, elevation had little predictive ability for Glacier 4 and the correlation was moderate on Glacier 13. It is possible that the elevation correlation was accentuated, especially on Glacier 13, during the field campaign due to warmer than normal temperatures and an early ($1-2$ weeks) start to the melt season

(Yukon Snow Survey Bulletin and Water Supply Forecast, May 1, 2016). The southwestern Yukon winter snow pack in 2015 was also well below average, possibly emphasizing effects of early melt onset.

Our mixed insights into dominant predictors of accumulation are consistent with the conflicting results present in the literature. Many winter balance studies have found elevation to be the most significant predictor of SWE (e.g. Machguth and others, 2006; McGrath and others, 2015). However, accumulation-elevation gradients vary considerably between glaciers (Winther and others, 1998) and other factors, such as orientation relative to dominant wind direction and glacier shape, have been noted to affect accumulation distribution (Machguth and others, 2006; Grabiec and others, 2011). Machguth and others (2006), Grünewald and others (2014) and Kirchner and others (2014) observed elevation trends in snow accumulation for the lower parts of their study basins but no correlation or even a decrease in SWE with elevation for the upper portion of their basins. Helbig and van Herwijnen (2017) suggest that an increase in accumulation with elevation can better be approximated by a power law (of the form $y = ax^k$ with k 1). There are also a number of accumulation studies on glaciers that found no significant correlation between accumulation and topographic parameters and the highly variable snow distribution was attributed to complex local conditions (e.g. Grabiec and others, 2011; López-Moreno and others, 2011).

Wind redistribution and preferential deposition of snow is known to have a large influence on accumulation at sub-basin scales(Dadic and others, 2010; Winstral and others, 2013). The wind redistribution parameter used in our study is found to be a small but significant predictor of accumulation on Glacier 4 (negative correlation) and Glacier 2 (positive correlation). This result indicates that wind likely has an impact on snow distribution but that the wind redistribution parameter is perhaps not the most appropriate way to characterize the effect of wind on our study glaciers. For example, Glacier 4 is located in a curved valley with steep side walls so having a single cardinal direction for wind may be inappropriate. Examining wind redistribution parameter values that assume wind moving up or down glacier and changing direction to follow the valley could allow the wind redistribution parameter to explain more of the variance in SWE. Further, the scale of deposition may be smaller than the resolution of the Sx parameter in the relatively large DEM grid cells in our study. An investigation of the wind redistribution parameter with finer DEM resolution is also needed. Our results corroborate McGrath and others (2015), who completed a winter balance study on six Alaskan glaciers (DEM resolutions of 5m) and found that Sx was the only other significant parameter, besides elevation, for all glaciers. Regression coefficients were small (< 0.3) and in some cases, negative. Sublimation from blowing snow has also been shown to be an important mass loss from ridges (Musselman and others, 2015). Incorporating snow loss as well as redistribution and preferential deposition may be needed for accurate representations of seasonal accumulation.

Since we are unable to measure SWE in grid cells that have high topographic parameter values, we must extrapolate relationships linearly. The accumulation area, where there are few observations, is most susceptible to extrapolation errors. This area typically also has the highest SWE values, affecting the specific winter balance estimated for the glacier. In our study, the dependence of SWE on elevation, especially on Glacier 2, means that LR extrapolation results in almost 2 m w.e. estimated in the parts of the accumulation area. This exceptionally large estimate of SWE is unlikely for a continental snow pack. Extrapolating a LR that is fitted to predominantly ablation area SWE values is likely erroneous.

While a LR can be used to predict distributed SWE in other basins, we found that transfer of LR coefficients between glaciers results in large estimation error. Applying LR coefficients to unmeasured basins therefore results in high winter balance uncertainty. The LR fitted to all observed data produced the best overall predictor of SWE in the Donjek Range. Our results are consistent with Grünewald and others (2013), who found that local statistical models are able to perform well but they cannot be transferred to different regions and that regional-scale models are not able to explain the majority of variance. The inter-basin variability in our study range is greater than the intra-basin variability.

Simple kriging

For all study glaciers, simple kriging (SK) is a better predictor of observed SWE than LR. However, the winter balance uncertainty that arises from using SK is large, and unrealistic values of 0 m w.e. winter balance can be estimated. Our observations are generally limited to the ablation area so SK estimates an almost uniform distribution of SWE in the accumulation areas of the study glaciers, which is inconsistent with observations described in the literature (e.g. Machguth and others, 2006; Grabiec and others, 2011). Extrapolation using SK leads to large uncertainty in estimating winter balance, which further emphasis the need for SWE observations in the accumulation area.

SK cannot be used to understand physical processes that may be controlling snow distribution and cannot be used to estimate accumulation beyond the study area. However, fitted kriging parameters, including the nugget and spatial correlation length, can provide insight into important scales of variability. Glaciers 2 and 13 have long correlation lengths and small nuggets indicating variability at large scales. Conversely, Glacier 4 has a short correlation length and large nugget, indicating that accumulation variability occurs at small scales. Using a higher resolution sampling design and DEM may allow us to capture more of the variability on Glacier 4 and to perhaps improve the predictive ability of both LR and SK interpolation.

A number of studies that relate SWE to topographic parameters have found success when using a regression tree interpolation model, which is a non-linear regression method (e.g. Elder and others, 1998; Erickson and others, 2005; López-Moreno and others, 2010). Many relationships between accumulation and topographic parameters have been observed to be non-linear so regression tree are valuable in snow modelling and may yield improved results (Erxleben and others, 2002; Molotch and others, 2005).

Uncertainty analysis

Interpolation uncertainty is the greatest contributor to winter balance uncertainty for both SK and LR. A large contributor to uncertainty arises from extrapolation beyond the sampled region, which results in high uncertainty in estimated SWE in the accumulation area. The winter balance distributions obtained using LR and SK overlap for each glacier but the distribution modes differ, with SK generally estimating lower winter balance in the accumulation area, which lowers the overall winter balance estimate. It is important to note that although the distributions from LR are narrower than those from SK, that does not necessitate that LR is a more accurate method of estimating winter balance. Based on the sources of uncertainty chosen, LR appears to be more precise than SK but the methods of calculating interpolation uncertainty are different so the distributions should not be directly compared.

SWE uncertainty is the smallest contributor to winter balance uncertainty. Therefore, obtaining the most accurate value of SWE to represent a grid cell, even a relatively large grid cell, does not need to be a priority when designing a snow survey. Many parts of a glacier are characterized by a relatively smooth surface, with roughness lengths on the order of centimeters (Hock, 2005) resulting in low snow depth uncertainty. However, we assume that the sampled grid cells are representative of the uncertainty across the entire glacier, which is likely not true for areas with debris cover, crevasses and steep slopes.

Using a Monte Carlo experiment to propagate uncertainty allowed us to quantify effects of uncertainty on estimates of winter balance. However, our analysis did not include uncertainty arising from a number of data sources, which we assumed to contribute negligibly to the uncertainty in winter balance or to be encompassed by investigated sources of uncertainty. These sources of uncertainty include error associated with SP and FS density measurement, DEM vertical and horizontal error and error associated with estimating measurement locations.

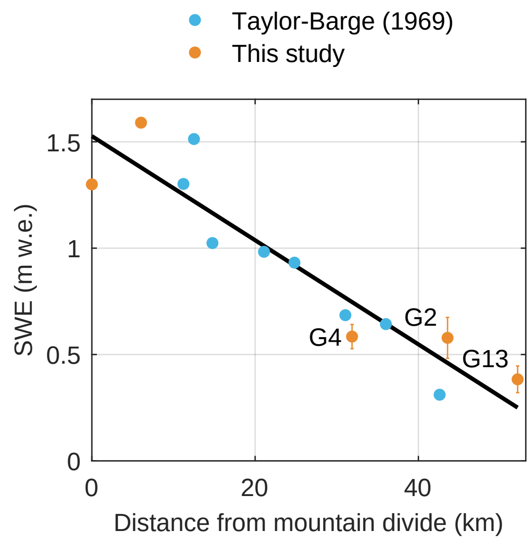

Fig. 9. Relation between SWE and linear distance from St. Elias mountain divide, located at the head of the Kaskawalsh Glacier. Blue dots are snow pit derived SWE values from Taylor-Barge (1969). Orange dots furthest from the divide are mean winter balance from Glaciers 4, 2 and 13, with 95% confidence interval using a linear regression interpolation. Orange dots close to the divide are snow pit derived SWE value at two locations in the accumulation area of the Kaskawalsh Glacier collect in May 2016. Black line indicates line of best fit ($R^2 = 0.85$).

Mountain range accumulation gradient

An accumulation gradient is observed for the continental side of the St. Elias Mountains (Figure 9). Accumulation data are compiled from Taylor-Barge (1969), the three glaciers presented in this paper, as well as two snow pits we dug near the head of the Kaskawalsh Glacier in May 2016. The data show a linear decrease in observed SWE as distance from the main mountain divide (identified by Taylor-Barge (1969)) increases, with a gradient of -0.024 m w.e. km^{-1}. While the three study glaciers fit the regional relationship, the same relationship would not apply when just the Donjek Range is considered. Therefore, glacier location within a mountain range also affects glacier-wide winter balance. Interaction between meso-scale weather patterns and mountain topography is a major driver of glacier-wide accumulation. Further insight into mountain-scale accumulation trends can be achieved by investigating moisture source trajectories and orographic precipitation contribution to accumulation.

Limitations and future work

Extensions to this work could include an investigation of experimental design, examining the effects of DEM grid size on winter balance and resolving temporal variability. Our sampling design was chosen to extensively sample the ablation area and is likely too finely resolved for many future mass balance surveys to replicate. Determining a sampling design that minimizes error and reduces the number of measurements, known as data efficiency thresholds, would contribute to optimizing snow surveys in mountainous regions. For example, López-Moreno and others (2010) concluded that $200 - 400$ observations are needed to obtain accurate and robust snow distribution models.

DEM grid cell size is known to significantly affect computed topographic parameters and the ability for a DEM to resolve important hydrological features (i.e. drainage pathways) in the landscape (Zhang and Montgomery, 1994; Garbrecht and Martz, 1994; Guo-an and others, 2001; López-Moreno and others, 2010), which can have implications for calculating a LR that uses topographic parameters. Zhang and Montgomery (1994) found that a 10 m grid cell size is an optimal compromise between increasing resolution and large data volumes. Further, the importance of topographic parameters in predicting SWE is correlated with DEM grid size (e.g. Kienzle, 2004; López-Moreno and others, 2010). A decrease in spatial resolution of the DEM results in a decrease in the importance of curvature and an increase in the importance of elevation. A detailed and ground controlled DEM is therefore needed to identify the features that drive accumulation variability. Even with a high resolution DEM, microtopography that creates small scale snow variability cannot be resolved. For example, the lower part of Glacier 2 has an undulating ice surface (on the order of 5 m horizontal and 0.5 m vertical) that results in large variability in snow depth. Future studies could also evaluate the effects of DEM uncertainty on elevation and derived topographic parameters (e.g. Guo-an and others, 2001; Wechsler and Kroll, 2006).

Temporal variability in accumulation is not considered in our study. While this limits the extent of our conclusions, a number of studies have found temporal stability in spatial patterns of snow accumulation and that terrain-based model could be applied reliable between years (e.g. Grünewald and others, 2013). For example, Walmsley (2015) analyzed more than 40 years of accumulation recorded on two Norwegian glaciers and found that snow accumulation is spatially heterogeneous yet exhibits robust time stability in its distribution.

CONCLUSION

We estimate spatial accumulation patterns and specific winter balance for three glaciers in the St. Elias mountains from extensive snow depth and density sampling. Our objectives are to (1) examine methods and uncertainties when moving from snow measurements to estimating winter balance and (2) show how snow variability, data error and our methodological choices interact to create uncertainty in our estimate of winter balance.

Overall, elevation is the dominant driver of SWE distribution but results vary between glaciers. Accumulation spatial patterns and scales of variability are considerably different on Glacier 4 when compared to Glaciers 2 and 13. Glaciers 2 and 13 have a dominant elevation-accumulation trend and long spatial correlation lengths. No topographic parameters are able to explain snow distribution on Glacier 4 and a short correlation length and large nugget indicate variability at shorter length scales. Our results also suggest that wind redistribution and preferential distribution are significant drivers of SWE distribution but these effects are not captured by the wind redistribution parameter used. Improved modelling of wind effects on accumulation through modification of the wind redistribution parameter as well as increased physical modelling are needed. A LR applied to our study glaciers resulted in little insight into dominant physical processes indicating that accumulation is controlled by complex interactions between topography and the atmosphere and that a finer resolution DEM is needed to resolve SWE distribution and potentially relevant topographic parameters, such as curvature and wind redistribution.

Glacier accumulation is strongly affected by interactions between topography and atmospheric processes at the basin- and range-scale. Although we could not conclusively identify processes at the basin scale due to low predictive ability of the LRs, there is a dominant trend in accumulation at the regional scale. We identify a clear linear decrease in SWE with increased distance from the main topographic divide along the continental side of the St. Elias Mountains. This trend indicates that glacier location within a mountain range has a large influence on winter balance. Further investigation of meso-scale weather patterns could provide insight into relevant processes that affect accumulation at the range scale.

We also quantify the effects of variability from density interpolation, grid cell SWE calculation as well as interpolation method on uncertainty in estimating winter balance. We conduct a Monte Carlo experiment to propagate variability through the process of estimating accumulation from snow measurements. The largest source of uncertainty in our study stems from variability in interpolation method, both within and between methods. We find that SK results in high uncertainty and the distribution of winter balance estimates encompasses unrealistic values. Spatial distribution of interpolation variability indicates that the accumulation area is the greatest area of uncertainty. This large variability is a result of the accumulation area being poorly sampled, sensitive to estimates of dominant regression coefficients, and having the largest values of estimated SWE within the glacier. Density and SWE variability are found to be small contributors to winter balance uncertainty. We conclude that the choice of interpolation method in combination with sampling design, especially in the accumulation area, has a major impact on the uncertainty in winter balance estimates.

Our thorough analysis of linear regression to estimate winter balance and rigorous approach to quantifying uncertainty has resulted in no significant insights into the controls on alpine glacier snow accumulation. Snow distribution patterns differed considerably between glaciers, highlighting strong inter- and intra-basin variability. Our results indicate that SWE interpolation uncertainty overshadows both measurement and density interpolation uncertainty for all glaciers. A universal predictor of distributed SWE continues to elude researchers and accumulation variability due to complex interactions between topography and the atmosphere needs to be further investigated at finer resolutions to better estimate winter balance.

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SUPPLEMENTARY MATERIAL

Table 8. Description of topographic parameters used in the linear regression.

Topographic parameter	Definition	Calculation method	Notes	Source
Elevation (z)		Values taken directly from DEM		
Distance from centreline (d_C)		Minimum distance between the Easting and Northing of the northwest corner of each grid cell and a manually defined centreline		
Slope (m)	Angle between a plane tangential to the surface (gradient) and the horizontal	`r.slope.aspect` module in GRASS GIS software run through QGIS		Mitášová and Hofierka (1993); Hofierka and others (2009); Olaya (2009)
Aspect (α)	Dip direction of the slope	`r.slope.aspect` module in GRASS GIS software run through QGIS	$\sin(\alpha)$, a linear quantity describing a slope as north/south facing, is used in the regression	Mitášová and Hofierka (1993); Hofierka and others (2009); Olaya (2009)
Mean curvature (κ)	Average of profile (direction of the surface gradient) and tangential curvature (direction of the contour tangent)	`r.slope.aspect` module in GRASS GIS software run through QGIS	mean-concave (positive values) terrain with relative accumulation and mean-convex (negative values) terrain with relative scouring	Mitášová and Hofierka (1993); Hofierka and others (2009); Olaya (2009)
"Northness" (N)	-1 represents a vertical, south facing slope, a value of $+1$ represents a vertical, north facing slope, and a flat surface yields 0	Product of the cosine of aspect and sine of slope		Molotch and others (2005)
			Calculation based on	

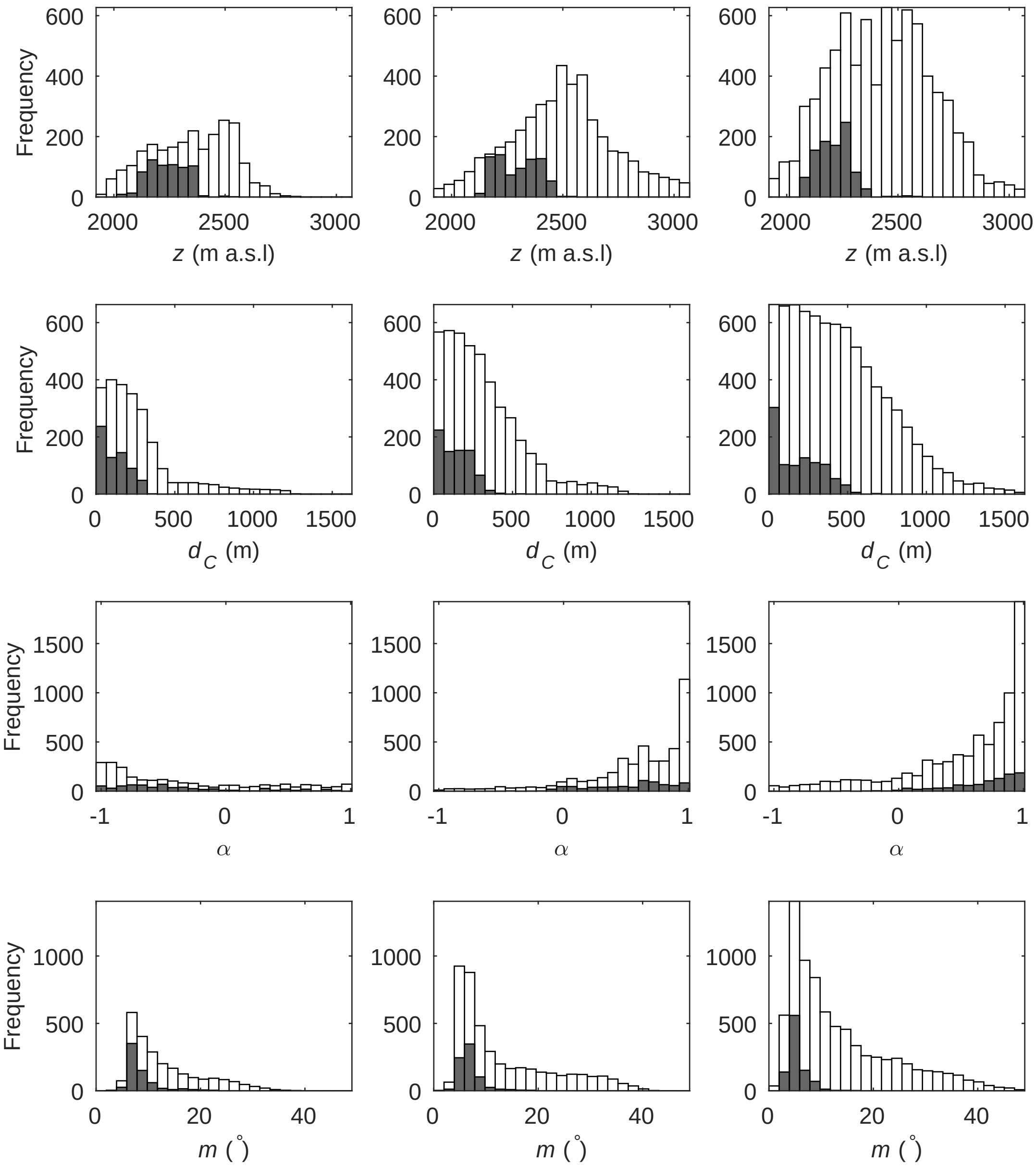

Fig. 10. Distribution of topographic parameters over Glacier 4 (left), Glacier 2 (middle) and Glacier 13 (right) are shown in white. Distribution of topographic parameter values from sampled grid cells in shown in gray. Topographic parameters include elevation (z), distance from centreline (d_C), aspect (α), slope (m), northness (N), mean curvature (κ), and winter redistribution (Sx).

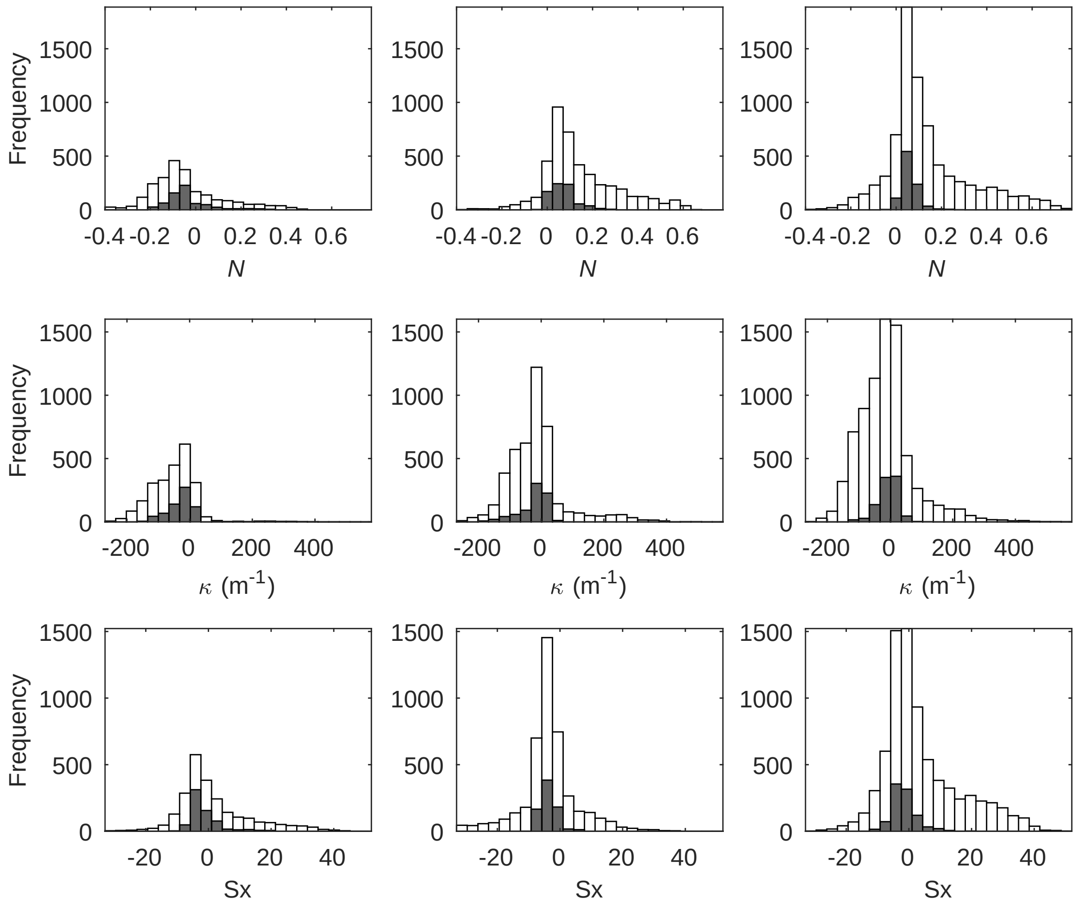

Fig. 11. See Figure 10