A model for the snow water equivalent derived from stratigraphy observations in northern Sweden

Cecilia Johansson and Susanne Ingvander

ABSTRACT

A new parameterization of snow water equivalent (SWE) based on snow depth (HS) has been developed from observations made in northern Sweden. When applying previous SWE parameterization from the Alps on observations from northern Sweden, the SWE values are systematically 20% lower. The new SWE parameterization is derived from a snow layer density regression model using snow layer hardness and snow particle size. The model was evaluated with a detailed field reference dataset, and then applied to the long-term Abisko Scientific Research Station stratigraphic snowpack dataset. The model enables a regional adjustment of snow layer density values for northern Swedish conditions. The snow layer density model provides an accurate estimation of snow bulk density used to derive the SWE parameterization based solely on HS. Snow depth observations are made on a daily basis; by applying our new parameterization, daily values of SWE can be obtained for northern Scandinavian conditions, which can be used, for example, for hydropower production planning and risk assessments.

Key words | snow density, snow hardness, snow particle size, snow water equivalent

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INTRODUCTION

The seasonal snow cover is usually described by its depth and density as well as spatial and temporal extent. The snow cover extent affects the albedo of the ground surface, the snow depth and density governs the insulation capacity, and the snow density determines the permeability of the snowpack (Gray & Male 1981). By combining snow depth and snow bulk density, snow water equivalent (SWE) can be estimated which gives information about the amount of water stored in the snowpack (Armstrong & Brun 2008). These three parameters (snow depth, snow density and SWE) show spatial variations depending on the synoptic scale weather patterns (air temperature gradients, wind and precipitation patterns), topography (Mellor 1965; Jaedicke *et al.* 2000; Geddes *et al.* 2005; Skaugen *et al.* 2012) and vegetation (Geddes *et al.* 2005). A clear example of the weather influence of snow depth and its temporal and spatial variations over 50 years is given in Dyrrdal *et al.* (2013). In addition, the snowpack is subjected to change due to metamorphic and sublimation processes (Armstrong & Brun 2008). The snow depth is altered by precipitation, compaction and redistribution of snow due to winds. The snow density of the layers within the snowpack changes over the season, mainly due to changes in temperature and moisture in the snowpack, which alter the size, shape and bonding of the snow particles and thereby the porosity of the snowpack. Snow density can also be altered by wind compaction and overburden pressure (Anderson & Benson 1963).

Being able to estimate the SWE is essential for the risk assessment of avalanche hazards and spring melt floods, for runoff monitoring and hydropower production planning. Observation of solid precipitation is known to be difficult (Wolff *et al.* 2013). Observations using common rain gauges (e.g. Geonor precipitation gauge) will miss parts of the precipitation, especially during cold and high wind speed conditions. Here, SWE can be seen as a cumulative value of precipitation and the influence from weather (e.g. redistribution due to wind). Furthermore, the structure of

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the snowpack (its hardness, depth, etc.) is important for grazing ability of animals. Many animals rely on scent to localize food under the snowpack. The transport of scents through the snowpack depends on the depth of the snowpack and its structure. The snowpack creates a sheltered environment from the harsh winter conditions above for plants and animals (Kausrud *et al.* 2008). As reported in Johansson *et al.* (2011), the structure of the snowpack has changed in northern Sweden since the mid-1990s, for example with increasing number of very hard snow layers. The snowpack with its depth and density insulates the ground and influences the permafrost melt rate (Zhang 2005) and phenology. Thus, a change in the snowpack will influence the permafrost beneath.

SWE gives an integrated value of the water content of the snowpack. Measurements of SWE in the field can be cumbersome and require great effort (Lundberg *et al.* 2009). We therefore investigate the possibility of using alternative measurements to capture variations of snow density within the snowpack. By parallel measurements of multiple parameters (snow particle size, snow layer hardness, snow density and snow depth), we can investigate their relationship by linear regression analysis.

Snow density measurements are commonly performed by weighing a known volume of snow. Detailed measurements can be obtained by using a snow cutter with a small volume (DeWalle & Rango 2008). By using this method, the stratigraphy of the snowpack can be quantified (assuming that the individual snow layers in the snowpack are thick enough for the snow cutter). Recently, a more sophisticated method of measuring snow stratigraphy has been developed that utilizes the co-variation of physical snow parameters. For example, a snow fork (LK1001, TOIKKA AS, Espoo, Finland) measures permeability which can be converted to snow density. For a more general observation, a snow corer can be used in order to determine the bulk snow density of the entire snowpack and SWE (DeWalle & Rango 2008). As a non-intrusive method, a ground penetrating radar system can be used to study snow stratigraphy (Ingvander & Brown 2013). The result can then be used for building empirical models of SWE (Sundström *et al.* 2012).

Geldsetzer & Jamieson (2000) investigated the possibility of measuring alternative parameters of the snowpack in order to determine the density of snow. They identified a significant correlation between snow layer hardness subdivided by snow particle size and snow density. In this study, we have further developed their work by using both snow hardness and snow particle size and their relation to snow density on a reference dataset sampled in Järämä, northern Sweden in 2009–2012 (Ingvander *et al.* 2012). The determined relations have then been applied to the bi-weekly snow stratigraphy observations made at Abisko Scientific Research Station (Abisko SRS) since 1961 (Johansson *et al.* 2011).

Jonas *et al.* (2009) derived relationships for snow bulk density and SWE (described below) based on snow depth by exploring an extensive dataset from the Alps. Here, we have applied the method from Jonas *et al.* (2009) on our snow depth measurements from Abisko SRS and compared the resulting snow layer density and SWE values. The results from Abisko SRS were then used to adjust the Jonas *et al.* (2009) equation for snow density and SWE in order to apply the method to a different geographical region. Abisko is considered a high latitude, low elevation and relatively dry site. The Alp site in Jonas *et al.* (2009) is located at lower latitude, has larger elevation and larger amount of precipitation compared with Abisko. The snow depth is up to three times as large as in Abisko.

We hypothesize that the snow density is mainly governed by the porosity of the snow (the ratio between snow particles size and cavities of air in the snowpack) and the snow layer hardness (the bonding strength between snow particles) (Bader *et al.* 1939; Pielmeier & Schneebeli 2003). By combining information on these parameters, it should be possible to estimate the snow density. Hence, snow density is determined by correlating information on snow particle size, which is affected by the level of metamorphism in the snowpack, and snow layer hardness, which mirrors the bonding strength of the snowpack.

Implementation of the method can be used where there is a lack of either observed snow density or SWE values. Our approach is based on the study by Geldsetzer & Jamieson (2000). In their study, they use a dataset of dry snow observations from two sites, Columbia and Canadian Rockies between 1993 and 2000. We will here test our hypothesis on field observations from Järämä (northern Sweden) and apply the model on the historical dataset from Abisko SRS in order to estimate snow layer density and SWE (which are not measured at Abisko SRS).

Finally, we will compare the estimated SWE values with a SWE estimation based solely on snow depth from Jonas *et al.* (2009).

METHODS

In this paper, we use three sets of field data: a reference dataset from three field campaigns in Järämä, northern Sweden, a historical dataset from Abisko SRS and one dataset from Abisko SRS including snow layer density observations. Abisko SRS is located in the Swedish mountain range (68°21′ N, 18°49′ E) and runs an extensive environmental monitoring programme (Jonasson *et al.* 2012). The snow stratigraphy dataset from Abisko SRS is described further in Johansson *et al.* (2011). The data used here consist of bi-weekly data of snow depth and snowpack properties and cover the winters 1961/62–2013/14. In total, the Abisko SRS dataset consists of 524 snow stratigraphy profiles and observations from 2,552 individual snow layers. As a complement to the regular observations, snow layer density observations were made at Abisko SRS during spring 2009 (observations from 14 snow layers). The reference dataset was sampled at Järämä (67°53′ N, 21°57′ E) in 2009, 2011 and 2012 and consists of 20 stratigraphy profiles with a corresponding 101 individual snow layers. The dataset and site are described in Ingvander *et al.* (2012) where the methodology of snow particle size analysis from Abisko SRS was compared with other existing methods (Fierz 2009; Ingvander *et al.* 2013).

In the Abisko SRS dataset, the snow hardness and snow particle size are registered. In Järämä, these two parameters are registered together with snow layer density. This allows us to study the relationship between the morphology parameters and the snow density. The snow hardness was sampled manually by pressing the wall of the snow pit using a pen (hard), finger, fingers and fist (soft) (Fierz 2009). In the Abisko SRS sampling protocol, there are six classes of snow layer hardness (large cavities (R0), very low (R1), low (R2), medium (R3), high (R4), very high + ice hard layer (R5)). A snow layer can also be classified as an ice layer. But, analyses have shown that what one observer classified as an ice layer another observer classified as a layer with very high snow layer hardness. For this reason, these two classes are grouped together (R5 thus consists of both very high and ice layer observations).

The snow particle size was determined using visual interpretation at Abisko SRS and in Järämä, by using digital image interpretation. The two methods are compared in Ingvander *et al.* (2012). Snow particle size is, in the Abisko SRS protocol, sampled in six classes (nuts (E_N), peas (E_p), rice (E_R), semolina (E_S), flour (E_F) and flakes (E_{Flake})). Intermediate classes sometimes occur in the Abisko SRS dataset: for example, E_{FS} size between flour and semolina and E_{SR} size between semolina and rice. Snow density was measured using a Toikka AS snow fork. An average value from three measurements in each layer has been used. The snow layer density observations at Abisko SRS during spring 2009 were obtained by weighing a fixed volume of snow. For both the Abisko SRS and Järämä datasets, the snow has been analysed by stratigraphic analysis where each layer in the snow is documented separately. The stratified analysis gives us detailed information on the snowpack and the different parameters measured.

The Abisko SRS snow stratigraphy dataset has the advantage of being made at one site and covers a time span of more than 50 years, but snow information on density is missing (except during spring 2009). The reference dataset is smaller, but contains measured snow layer density in addition to the stratigraphy observations. Modification of the method in Geldsetzer & Jamieson (2000), based on data from the reference dataset, will enable snow layer density estimations from the Abisko SRS data. From snow layer density, SWE values can be calculated given estimates of thickness of all individual layers (ΔHS) in the snowpack.

Snow layer density calculations

Geldsetzer & Jamieson (2000) presented a method to estimate snow density from observations of snow layer hardness and snow particle size. For observations in a given snow particle size class they determined how the snow density varied with snow layer hardness. Following the method suggested in Geldsetzer & Jamieson (2000), snow layer density for a given snow particle size class is estimated in Equation (1) from its snow layer hardness, using linear regressions.

$$\rho_{\text{snow}} = k_{\text{E}} \cdot R_{\text{i}} + m_{\text{E}} \tag{1}$$

where ρ_{snow} is the snow layer density. In the regression, the snow layer hardness classes have been given an index value R_{i} ($\text{R0} = 1$–$\text{R5} = 6$); k_{E} and m_{E} are regression coefficients for a given snow particle size class. Note that the regression model is based on the index values (quantitative values on hardness are not needed).

However, we hypothesize that snow layer density would be more accurately estimated if the variation of snow layer hardness with snow particle size were investigated (i.e. in reverse order compared with Equation (1)). This hypothesis is based on the fact that snow particle size is sensitive to the metamorphic processes altering the snowpack properties (Sommerfeld & LaChapelle 1970). Therefore, we have modified Equation (1) based on our hypothesis and propose Equation (2) where snow layer density for a given snow layer hardness class is estimated from its observed snow particle size class, using linear regressions.

$$\rho_{\text{snow}} = k_{\text{R}} \cdot E_{\text{i}} + m_{\text{R}} \tag{2}$$

where E_{i} is the snow particle size index (from $E_N = 1$ to $E_{\text{Flake}} = 6$) and k_{R} and m_{R} are regression coefficients for a given snow layer hardness class.

SWE calculations

SWE is defined as (DeWalle & Rango 2008)

$$\text{SWE} = \text{HS} \cdot \frac{\rho_{\text{snow}}}{\rho_{\text{water}}} \tag{3a}$$

where $\rho_{\text{water}} = 1{,}000\ \text{kg/m}^3$ and HS = snow depth in m. SWE values are here presented in units of mm and thus the results from Equation (3a) are multiplied by 1,000. Since the total snow depth is used in Equation (3a), the corresponding snow density is the bulk snow density.

If the snow density of each individual layer is known, SWE can be obtained by summarizing SWE values from individual snow layers

$$\text{SWE} = \sum_{i=1}^{n} \Delta\text{HS}_{\text{i}} \cdot \frac{(\rho_{\text{snow}\ \Delta\text{HS}})_{\text{i}}}{\rho_{\text{water}}} \tag{3b}$$

Here, i is a number from 1 to the maximum number of individual layers (*n)* in the snowpack. Equation (3b) specifically takes the internal variations of the snow density within the snowpack into account when estimating SWE.

Another common way to estimate SWE is to use bulk snow density, which, for example, can be approximated from total snow depth. The expression is then multiplied by snow depth to estimate SWE. An example of this can be found in Jonas *et al.* (2009).

$$\rho_{\text{snow bulk Jonas}} = 60.1 \cdot \text{HS}^{0.89} + 237 \tag{4a}$$

$$\text{SWE}_{\text{Jonas}} = \left(60.1 \cdot \text{HS}^{0.89} + 237\right) \cdot \text{HS} \tag{4b}$$

RESULTS

Snow layer density, reference dataset

Following Geldsetzer & Jamieson (2000), snow density can be estimated using Equation (1). The results from our reference dataset are shown in Figure 1(a) and the corresponding regression coefficients are listed in Table 1(a). As can be seen, all lines except one have a positive slope and are closely grouped to each other. Figure 1(b) and Table 1(b) show the corresponding results for snow density using Equation (2). As can be seen for snow layer hardness R4–R5 (hard snow layers), the snow density is increasing with increasing snow particle size index, and for snow layer hardness R0–R3 (softer snow layers), the snow density is decreasing with increasing snow particle size index.

The significance values (*p*-values) of the determined regression coefficients are listed in Table 1. For Equation (1), the regression coefficient k_{E} for classes of larger snow particle sizes (E_N – E_{SR}) are not as well determined ($p < 50\%$) as for the classes including smaller snow particle sizes (E_S – E_F) ($p \geq 95\%$). This result is most likely linked to the

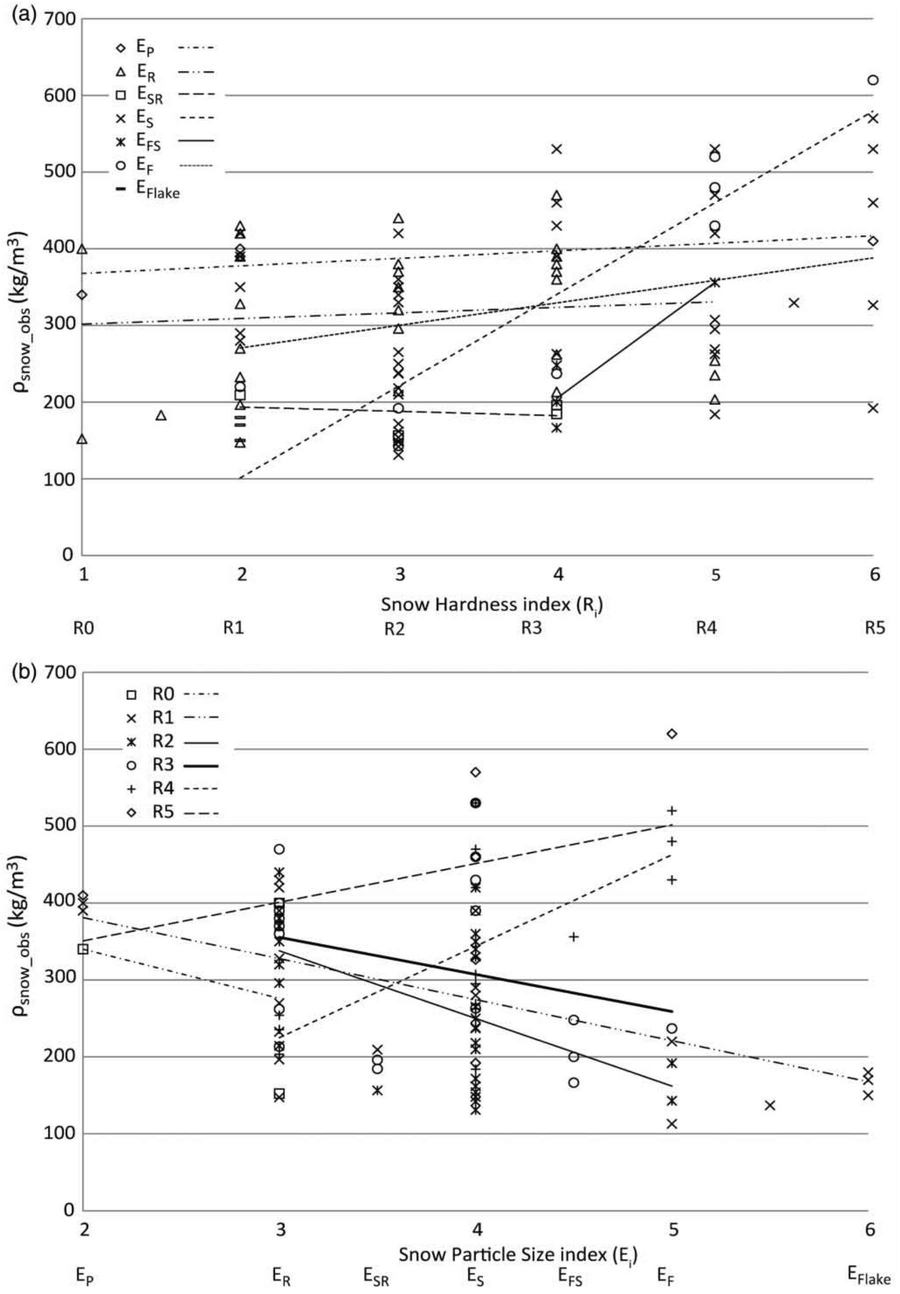

Figure 1 | Result from the reference dataset. (a) Snow layer density (ρ_{snow}) plotted against snow layer hardness index (R_i) for each snow particle size class (E) (see figure legend). Each line represents a linear regression for each E class. The regression coefficients for line E_P – E_{Flake} are listed in Table 1(a). (b) Snow layer density plotted against snow particle size index (E_i) for each snow layer hardness class (R) (see figure legend). Each line represents a linear regression for each R class. The regression coefficients for lines R0–R5 are listed in Table 1(b).

uneven distribution of the number of observations within each snow particle size class. Within the snow particle size class E_{Flake}, no regression line could be determined since observations were only available for one snow layer hardness class (R1). Instead, an average value m_{E} was determined. For Equation (2), the significance for the regression coefficient k_{R} are all above 50% (R1, R2 and R4 $p \geq 99\%$) except snow layer hardness class R0, i.e. the change in sign, slope of the regression lines from softer to harder snow layers are well determined. The slightly lower

Table 1 | Regression coefficient (k and m), correlation coefficient (R^2), standard deviation of regression coefficients (σ_k and $\sigma_{m'}$ (determined at the centre of the distribution)), significance level (p) of regression constants, and number observations for calculating snow density with (a) Equation (1) and (b) Equation (2); see Figure 1(a) and 1(b), respectively

Snow particle size (*E*)	k_E	m_E	R^2	σ_{k_E}	$\sigma_{m_{E'}}$	**p level of k_E (%)**	**p of $m_{E'}$ (%)**	**Number of observations**
(a)								
E_N	–	–	–	–				
E_P	0.0098	0.3580	0.49	0.0071	0.0136	80	99.9	4
E_R	0.0073	0.2944	0.01	0.0152	0.0168		99.9	31
E_{SR}	−0.0056	0.2047	0.06	0.0157	0.0131		99.9	4
E_S	0.0294	0.2119	0.11	0.0132	0.0169	95	99.9	44
E_{FS}	0.1512	−0.3998	0.01	0.0467	0.0202	99	99.9	4
E_F	0.1196	−0.1382	0.83	0.0180	0.0247	99.9	99.9	5
E_{Flake}	–	0.1700	–	–	0.0126		70	4

Snow layer hardness (*R*)	k_R	m_R	R^2	σ_{k_R}	$\sigma_{m_{R'}}$	**p level of k_R (%)**	**p level of $m_{R'}$ (%)**	**Number of observations**
(b)								
R0	−0.0639	0.4678	0.08	0.2165	0.1021		99.9	3
R1	−0.0533	0.4877	0.40	0.0136	0.0164	99.9	99.9	25
R2	−0.0879	0.6016	0.08	0.0283	0.0158	99	99.9	30
R3	−0.0482	0.5002	0.08	0.0389	0.0253	70	99.9	19
R4	0.1189	−0.1318	0.45	0.0363	0.0234	99	99.9	15
R5	0.0503	0.2502	0.09	0.0706	0.0588	50	99.9	7

When modelling snow layer density the regressions will be applied for all index values except for snow layer hardness class R4 in Equation (2). There, the regression line is not applied for snow particle size index 1 and 2 (corresponding to E_N and E_P).

significance level for k_R for snow layer hardness class R3 is not unexpected since the regression line changes sign from negative slope in R0–R3 and positive slopes for R4 and R5. However, the p-values for $m_{R'}$ (determined at the centre of each distribution) are high $p \geq 99\%$ (especially important for R3 since the slope of the regression line is weak) for all snow layer hardness classes. The low p-value for snow layer hardness class R0 is most likely due to the low number of observations.

By applying Equations (1) and (2) with coefficients from Table 1(a) and 1(b) on the reference dataset (101 data points), a modelled value of the snow density is obtained ($\rho_{\text{snow mod Equation1}}$ and $\rho_{\text{snow mod Equation2}}$), see Figure 2. The correlation coefficient and linear regression between observed and modelled snow layer density show very little difference using the two equations (Figure 2(a) and 2(b)). A comparison of the distributions of modelled and observed snow density indicates slightly too many values in the range 300–400 kg/m^3 using Equation (1) (see Figure 2(c)). Both equations seem to give a too low number of snow density values in the range of less than 200 kg/m^3. A comparison of the average values of snow layer density using Equations (1) and (2) calculated from the reference dataset show very little difference (306.2 kg/m^3 compared with 307.5 kg/m^3). That means that the distributions between the modelled results will be different but not the average value.

Snow layer density, Abisko SRS data

When applying Equations (1) and (2) on the Abisko SRS dataset (2,552 data points) in order to estimate snow layer density, the difference in performance between the two models is large (see Figure 3). The snow density values modelled by Equation (2) result in a distribution that is normally distributed (except for snow density >600 kg/m^3 which corresponds to snow layers with hardness classified as very high or as a layer of ice (R5)). The shape of the distribution compares well to previous snow density distributions determined from observed values (Jonas *et al.* 2009). The result on snow layer density modelled by Equation (1) is far from

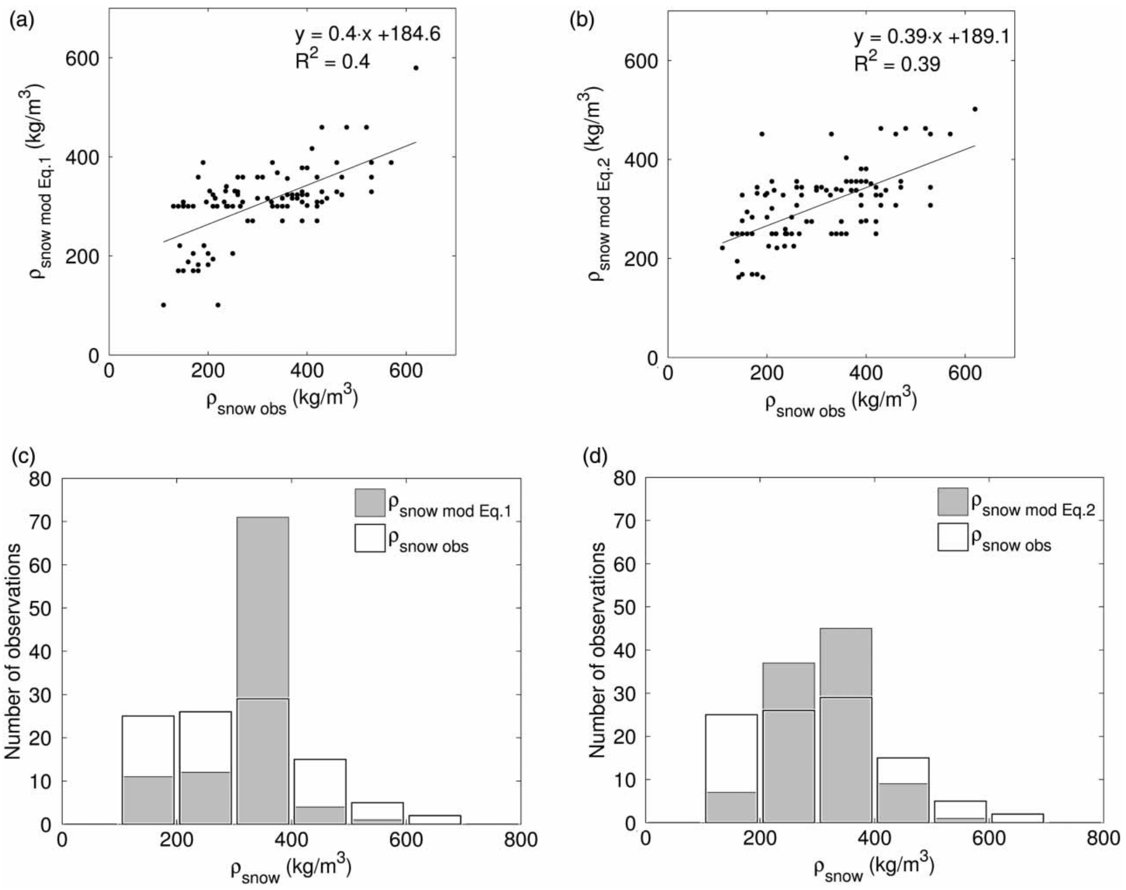

Figure 2 | Result from the reference dataset: (a) modelled snow density using Equation (1) with regression coefficients from Table 1(a), and (b) using Equation (2) with regression coefficients from Table 1(b) compared with the observed snow layer density. The solid lines show the linear regression lines. The regression constants are all determined with *p*-values $\geq$99.9%. (c) Distributions of modelled and measured snow layer density modelled using Equation (1) and (d) using Equation (2).

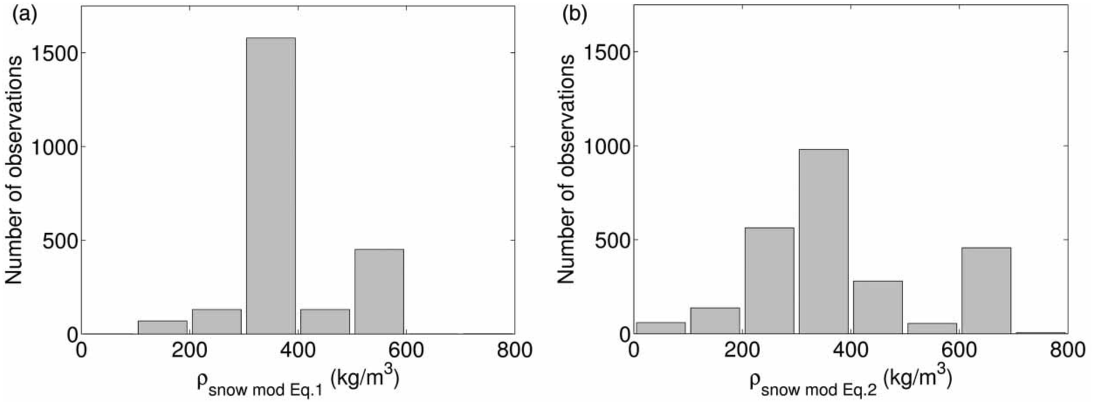

Figure 3 | Distribution of snow layer density calculated with data from Abisko SRS using (a) Equation (1) and (b) Equation (2) for each individual snow layer; (a) consists of 2,362 observations (190 missing data); (b) consists of 2,537 (15 missing data).

being normally distributed, and gives a peak in the range 300–400 kg/m^3. This tendency was indicated, but not as clear in the reference dataset (Figure 2(c)). One difference in the snow density distribution compared with Jonas *et al.* (2009) is that in the Abisko SRS dataset, layers with very high hardness/ice hard layers (R5) are included, which are needed for a full description of the snowpack stratigraphy. A full description will be needed for further calculation of SWE values (using Equation (3b)).

Another difference between the two equations, which can be hard to see from Figure 3, is the number of missing data points (i.e. conditions when snow density data cannot be calculated). Both equations need simultaneously observations of snow particle size and snow layer hardness. If either is missing, this automatically leads to missing data. Nevertheless, applying Equation (1) leads to missing data in 7% of the observations, whereas Equation (2) gives missing data in less than 1% of the observations. This can be attributed to the limited ranges of snow particle sizes in the reference dataset, which has larger impact on Equation (1). In the reference dataset there are no observations of the snow particle size nuts (E_N); hence, no regression estimation for this size class was possible. When using Equation (2), the regression lines have been extrapolated and the equation has been used for E_N for all classes except snow layer hardness R4 (Table 1).

A comparison of observed snow layer density made at Abisko SRS (spring 2009) with modelled snow density values with Equations (1) and (2) show that Equation (1) tends to give higher snow density values than Equation (2). The root mean square deviation from observed snow layer density using Equation (1) is 80.8 kg/m^3 and with Equation (2) 59.4 kg/m^3. The mean values are significantly different from each other on a 95% confidence level.

Our conclusion is that Equation (2) gives a better estimation of the snow density both concerning values and reliability. In the following calculations only results using Equation (2) will be shown.

SWE

SWE can now be estimated for the Abisko SRS dataset, using Equation (3b), in the following referred to as SWE$_{\text{Equation2}}$. Figure 4 shows the distribution of calculated SWE$_{\text{Equation2}}$ values. It is worth noting that a SWE $_{\text{Equation2}}$ value is obtained for 98% of the observed snow profiles in the Abisko SRS dataset, taking into account that snow density values are needed for all layers in the snowpack. The shape of the distribution is slightly skewed toward lower values, and again the shape is very similar to Jonas *et al.* (2009). The SWE range covered is however different which is due to the different snow depths (maximum 1.2 m at Abisko SRS, and 3 m in Jonas *et al.* (2009)).

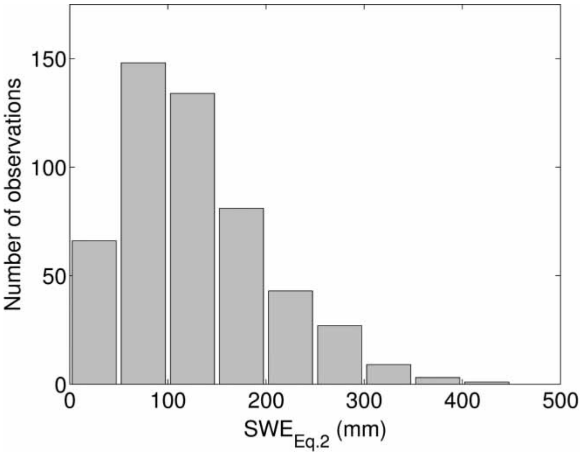

Figure 4 | Distribution of SWE for snow profiles from Abisko SRS stratigraphy data using Equation (3b) with snow density modelled by Equation (2), SWE$_{\text{Equation2}}$. In total 512 profiles (missing data for 12 profiles).

When comparing SWE$_{\text{Equation2}}$ values from Abisko SRS estimated from snow layer density and snow layer thickness (previously shown in Figure 4) with SWE values calculated from HS Equation (4b), it is clear that the SWE values are lower by the Jonas *et al.* (2009) method (Equation (4b); see Figure 5). The correlation coefficient between the two

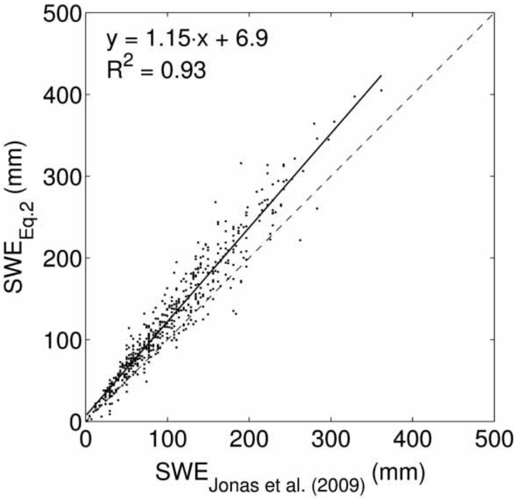

Figure 5 | Comparison of SWE$_{\text{Equation2}}$, and SWE calculated by the expression in Jonas *et al.* (2009) (Equation (4b)) based on corresponding Abisko SRS snow depth observations. The regression constants are determined with *p*-values ≥99.9%. The dashed line shows the 1:1 line.

methods to estimate SWE is high, $R^2 = 0.93$, but the SWE values determined from Equation (4b) are systematically 20% lower.

Using the Abisko SRS dataset, it is possible to calculate a best estimate of bulk snow density ($\rho_{\text{snow bulk}}$) based on the stratigraphy observations resulting in SWE $_{\text{Equation2}}$. Figure 6(a) shows the bulk snow density at Abisko SRS obtained from the calculated SWE $_{\text{Equation2}}$ and corresponding HS observations. Also, shown is a linear regression fit Equation (5a) to the data and the bulk snow density calculated with Equation (4a) from Jonas *et al.* (2009). The scatter of snow density in the Abisko SRS data is of the same order as in Jonas *et al.* (2009), but the average value is consequently higher. Equation (5b) shows the regression line for $\rho_{\text{snow bulk Abisko SRS}}$ expressed in a power curve as in Jonas *et al.* (2009)

$$\rho_{\text{snow bulk Abisko SRS}} = 41.2 \cdot \text{HS} + 306.9 \tag{5a}$$

$$\rho_{\text{snow bulk Abisko SRS}} = 60.1 \cdot \text{HS}^{0.89} + 292 \tag{5b}$$

Based on snow layer density of the individual snow layers, Figure 6(b) shows the estimate of snowpack SWE for the Abisko SRS dataset, and its variation with snow depth. The dashed line shows $\text{SWE}_{\text{Jonas}}$ (Equation (4b)), the solid line a linear regression to the data (Equation (6a)), and the thick line is an adjustment of the Jonas *et al.* (2009) expression to the data (Equation (6b)).

$$\text{SWE}_{\text{Abisko SRS linear}} = 338 \cdot \text{HS} - 4.1 \tag{6a}$$

$$\begin{aligned}\text{SWE}_{\text{Abisko SRS}} &= \rho_{\text{snow bulk Abisko SRS}} \cdot \text{HS} \\ &= \left(60.1 \cdot \text{HS}^{0.89} + 292\right) \cdot \text{HS}\end{aligned} \tag{6b}$$

As a consequence of the lower snow bulk density values obtained by Equation (4a), the SWE values from Equation (4b) are also lower. The root mean square error for Equation (4b) compared with SWE $_{\text{Equation2}}$ is 31.7 mm and by using Equation (6b) reduces to 21.0 mm.

DISCUSSION

By modifying and combining the methods developed by Geldsetzer & Jamieson (2000) and Jonas *et al.* (2009), an expression for SWE at Abisko SRS has been derived (Equation (6)), which in turn is based on Equation (2) for modelling snow layer density.

From a statistical point of view, Equation (2) and its regression coefficients are determined with a higher accuracy compared with Equation (1). Starting with the reference dataset (used to calibrate the regression models), the results on snow layer density are very similar comparing

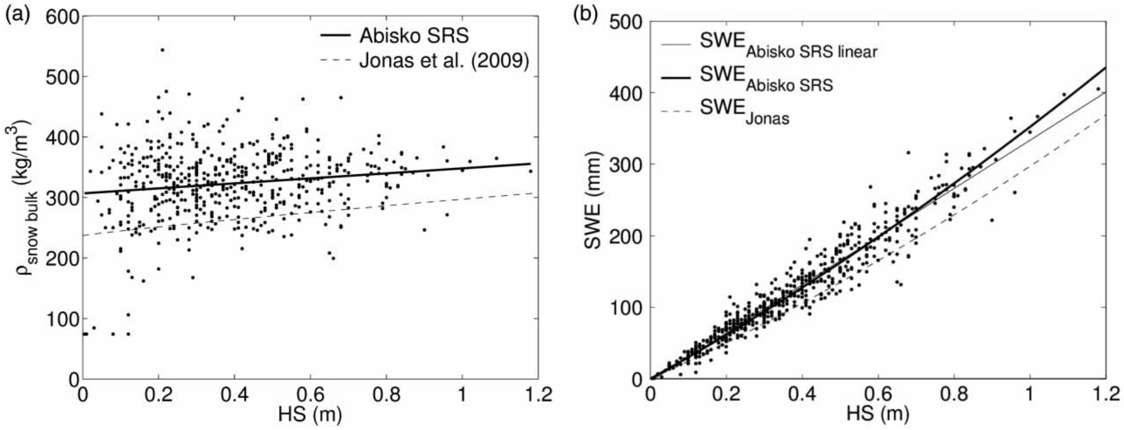

Figure 6 | (a) Dots show bulk snow density derived from $\text{SWE}_{\text{Equation2}}$ and corresponding total snow depth (HS) plotted against snow depth. The solid thick line is a linear fit to the data, Equation (5a), determined with p-values ≥99.9%. The dashed line is the bulk snow density from Jonas *et al.* (2009), Equation (4a). (b) Dots show SWE $_{\text{Equation2}}$ plotted against HS and the solid thin line is a linear regression fit to the data, Equation (6a), determined with p-values ≥99.9%. The dashed line shows SWE calculated according to Jonas *et al.* (2009), Equation (4b). The thick line is an adjustment of the Jonas expression to best fit the Abisko SRS SWE data (Equation (6b)).

Equations (1) and (2) (see Figure 2). Both equations result in fewer numbers of observations than observed in densities below 200 kg/m^3. Hence from this point it is difficult to say which equation gives the best results. A formal validation of the model is currently only possible for a limited dataset. The root mean square deviation is reduced by 20 kg/m^3 by using Equation (2) compared with using Equation (1). Even though the dataset is small it gives an indication that Equation (2) gives a better result.

A comparison of results from Equations (1) and (2) applied to the large Abisko SRS dataset shows a large difference in snow density distribution (see Figure 3). Equation (1) results in a large number of values in the range 300–400 kg/m^3 (Figure 3(a)) giving a distribution with a distinct peak, whereas Equation (2) gives a distribution (Figure 3(b)) that is normally distributed up to densities 600 kg/m^3, comparable to the shape of snow density distribution presented in Jonas *et al.* (2009).

With Equation (1), the resulting regression model (see lines in Figure 1(a)) is similar to Geldsetzer & Jamieson (2000), but our snow density values are higher (as also seen compared with Jonas *et al.* 2009). Whether this is due to the location of the observations (Geldzetser and Jamieson's observations are made in Purcell, Selkirk, Monashee, and Rocky Mountain Ranges in western Canada) resulting in different snow density values compared with those at Abisko SRS, or the fact that they use average values in their model, is difficult to say.

For Equation (1) our reference dataset has a limitation. When using Equation (1), where snow density is correlated to snow hardness, subdivided by snow particle size, there is no separation in the size class E_{Flake}. All observations have the same hardness, very low (R1). The result of this is more missing data from Equation (1) compared with Equation (2).

In general, Equation (1) gives increasing snow layer density with increasing snow layer hardness index, with some slight modifications depending on snow particle size (Figure 1(a)). Equation (2) on the other hand shows that snow density of a soft snow layer is decreasing with increasing particle size index (corresponding to decreasing snow particle size up to E_{F}) and that snow density of a hard snow is increasing with increasing particle size index (see Figure 1(b)).

Equation (2) agrees well with the system established by Bader *et al.* (1939), linking 12 types of snow with different metamorphic and transformation states, to particle size and snow layer hardness. According to Colbeck (1982), the numbers of bonds between snow particles influence the hardness of the snow layer. The snow particle size on the other hand, for a given hardness, influences the pore space in the snow layer, and thus the snow density. That is, we argue that Equation (2) takes the physical processes within the snowpack into account in a better way than Equation (1). A general weakness in regression models can be that temporal development is not taken into account. By developing a model based on six different classes, temporal changes in the snowpack will be captured. For example, if rain falls on snow and refreezing occurs, hard layers may form inside the snowpack. As long as the change in snow layer property is observed (for example that a layer has become harder) modelled snow layer density will also change. Since the models are based on the behaviour of a given class of either snow particle size (Equation (1)) or snow layer hardness (Equation (2)), temporal changes within the snowpack properties and hence the change in snow layer density will be captured by the models.

Our best estimate of SWE from Abisko SRS is given by first modelling the individual snow layer density by Equation (2), and then calculating SWE by Equation (3b). The shape of the distribution of $SWE_{\mathrm{Equation2}}$ looks similar to the SWE distributions in Jonas *et al.* (2009) (their Figure 2(a)).

A less detailed way to estimate SWE is to use a bulk snow density value. When applying Equation (2) to the Abisko SRS dataset we obtain consequently larger bulk densities than when using Equation (4a) from Jonas *et al.* (2009) (see Figures 5 and 6(a)). A comparison of average snow layer values from Equations (1) and (2) does not indicate that Equation (2) on average gives larger values than Equation (1) (seen from both the reference and Abisko SRS dataset). That means that the higher values are not likely to be caused by the choice of regression model. Rather these systematically larger values are probably due to the different geographic settings between Abisko and the Alps. Abisko is located at low elevation (388 m above sea level (a.s.l.)) and high latitude (67 degrees north). The snow depth is generally lower in Abisko because it is situated in a rain-shadowed region behind the Scandinavian mountain range (Kohler *et al.* 2006). Our best estimation of SWE is based on individual layers, and both the reference and historical Abisko SRS datasets are from the same region (100 km between the field sites) and we thereby have a solid dataset for locally adjusting the

Jonas *et al.* (2009) equation. The Jonas *et al.* (2009) equation, Equation (4b), has thereby been adjusted into an Abisko-corrected SWE equation ($\mathrm{SWE}_{\mathrm{Abisko\ SRS}}$), Equation (6b).

CONCLUSIONS

A regression model for snow layer density based on snow layer hardness and snow particle size has been developed. The snow layer density values have been used to develop a SWE expression from snow depth. Our method shows the ability to use alternative parameters for estimating snow density and SWE. This information can be used to homogenize datasets or analyse datasets that lack information on either snow density or SWE; for example, in estimating SWE from operational snow depth measurement or field campaigns. The results can also be compared with existing SWE models such as the data provided by the Globe Snow project or other products that model SWE on a spatial or temporal scale. A recommended improvement of the $\mathrm{SWE}_{\mathrm{Abisko\ SRS}}$ model is, in addition to collecting more data for the snow density regression model, to apply a temporal (seasonal) adjustment to it such as shown by McCreight & Small (2014), in order to capture seasonal changes of the snowpack caused by metamorphism. Furthermore, Equation (6b) is not yet applicable to really deep snow depths such as glacier accumulation areas or similar. This is because the equation is near to linear.

We have found that snow density in northern Sweden is higher than previous results from the Alps (Jonas *et al.* 2009) and western Canada (Geldsetzer & Jamieson 2000), and the models from these areas are thus not directly applicable to northern Sweden. We therefore recommend using Equation (6b) instead in which the coefficients have been scaled to northern Scandinavian conditions.

To conclude, by applying Equation (6b) to daily snow depth observations, daily values of SWE can be obtained for northern Sweden.

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