Analysis and modelling of snow bulk density in the Tyrolean Alps
J. Schöber, S. Achleitner, J. Bellinger, R. Kirnbauer and F. Schöberl

ABSTRACT

An extensive collection of in-situ snow measurements is used to characterize snow conditions in the entire elevation range of the alpine area of Tyrol, Austria. Regularly observed snow station data are evaluated with respect to mean snow density – time curves of the period 1952–2010. Dependent on the observed snow depth (HS), the snow bulk density (ρ) is statistically modelled for different elevation zones and snow-climate regions. Model improvements allow daily estimates of ρ, and introducing an additional parameter accounting for the decrease of bulk density in relation to new snow data further improved the results. This paper describes the development of an additional model for the glacierized sub-region of the Tyrolean Alps, based on snow course data from the peak snow accumulation period in April/May. The resulting relative errors of the different models range from 13 to 25% for single stations distributed over the entire investigation area and from 5 to 20% for annual snow courses in glacierized catchments. Regression models are most accurate at high elevations and for deep snowpacks. The transferability of the presented models is shown between Austria, Switzerland and Italy.

Key words | alpine snow cover, glaciological winter mass balance, new snow, snow bulk density, snow water equivalent

INTRODUCTION

Quantitative knowledge of snowpack properties is important as critical snow loads on structures and buildings (Strasser 2008) as well as snow melt-related processes (e.g., Rößler et al. 2014) can be hazardous. For instance, many Austrian regions are affected by snow melt and rain-on-snow floods (Merz & Blöschl 2005) and, hence, flood forecasting systems are improved by the additional use of snow data (Schöber et al. 2010; Nester et al. 2012). For water management, accurate information on the amount of water stored in the snow cover is crucial, e.g., for the planning of hydropower operation (Barnett et al. 2005; Skaugen et al. 2012). Thus, the primary goal of hydrological studies is to provide information on the snow water equivalent (SWE), for which, unfortunately, far fewer measurements are available than for snow depth (HS), e.g., Sturm et al. (2010) and Figure 1. Manual measurements of SWE are laborious, and automated measurements of SWE are still rare. In Tyrol, Austria, considerable effort has been invested in manually measuring SWE since the 1950s; in the 1980s, the first snow pillow was installed additionally in the catchment of a hydropower reservoir (Kirnbauer & Blöschl 1990) making it possible to record continuous SWE data, but also to decrease the amount of manpower needed for measuring snow courses.

To further reduce measurement costs, efforts are being made to develop methods for the estimation of snow density (ρ), which is required to convert HS into SWE – which is more relevant in terms of hydrology. Densification is governed by snow metamorphism, with the major physical processes being the mechanical damage of snow crystals during precipitation, the transport of water vapour caused by surface energy differences and thermal gradients within the pack, melting and refreezing as well as pressure
consolidation (Sommerfeld & LaChapelle 1970; Schneebeli & Sokratov 2004). Physical snowpack models (e.g., Brun et al. 1989; Bartelt & Lehning 2002) express these processes explicitly but are demanding with regard to input data and computational resources. By contrast, several empirical methods (e.g., Rohrer & Braun 1994; Jonas et al. 2009; Sturm et al. 2010; López-Moreno et al. 2013) are far less data demanding, but still reliable. Hence, this type of model is especially suitable for practical applications.

Probably the first empirical snow density model was an outcome of a Greenland expedition in 1930–1931 (Sorge’s law; Bader 1954). Supposing constant accumulation rates over time on arctic glaciers without melting in summer, \( \rho \) at a given depth below the surface does not change with time but can be formulated as a function of snow depth:

\[
\rho = f(HS)
\]
A given small volume of snow will increase in density as time passes and additional snow accumulates (Bader 1954). The resulting depth–density relation was used to derive accumulation and densification rates for arctic conditions. However, for a seasonal snow cover which only lasts for several months, the assumption of constant accumulation rates is not suitable (Kojima 1966). For seasonal snow covers, time and temperature are major factors for an increase in density. Very cold snow will change rather slowly, but under isothermal conditions it can for an increase in density. Very cold snow will change very rapidly (Sommerfeld & LaChapelle 1970). Under cold conditions far below freezing point, a snow-pack reaches a density of approximately 250 kg m\(^{-3}\) after several weeks, whereas under melt conditions, density reaches values between 350 and 400 kg m\(^{-3}\) in the same time (Hermann & Kuhn 1996). Accordingly, densification rates increase during mid-late spring (Bormann et al. 2015).

The density of new snow is related to temperature and wind speed (Schmucki et al. 2014). A rich snow dataset from the Swiss Alps exhibited a mean new snow (HN) density of 100 kg m\(^{-3}\) (Rohrer et al. 1994). Settling curves of HN as a function of time were applied for each snowfall event to model SWE with consideration of daily records of HN and HS (Martinec & Rango1991; Rohrer & Braun 1994). Weather data were solely used for the statistical modelling of \(\rho\) and snow loads in Norway (Meløysund et al. 2007), but this application required input data comparable to physical snow models (e.g., relative humidity and wind). Bormann et al. (2013) showed that the most dominant climate metrics for annual snow densification rates and spring densities are the winter precipitation sum, followed by temperature and a parameter accounting for melt-refreezing events. In the same manner as precipitation sum SWE is highly correlated with HS. Therefore, in practical applications on regional to global scales (Jonas et al. 2009; Sturm et al. 2010) HS was the main input variable for modelling \(\rho\) and SWE. Both approaches consider the time/temperature dependency of densification. Jonas et al. (2009) pooled long-term depth–density data from the Swiss Alps in a monthly resolution and applied three different elevation zones for the characterization of \(\rho\). Sturm et al. (2010) introduced the day of the year to account for the proceeding densification over time within snow climate regions on a global scale. Simultaneously to the present study, the Jonas model was improved regarding the temporal resolution by applying automated SWE data in daily resolution (McCreight & Small 2014) and the Sturm model was improved by the use of additional weather data (Bruland et al. 2005).

Moreover, linear depth–density models were recently applied to convert spatially distributed measurements for basin- or regional-scale studies. Such studies benefit from the finding that the spatial and temporal variability of \(\rho\) is lower than the variability of HS and SWE (Elder et al. 1998; Mizukami & Perica 2008). Correlations between HS and \(\rho\) were found to be statistically significant but are typically quite low as antecedent meteorological conditions (e.g., large amounts of new snow) can lead to varying snow conditions in the catchment (López-Moreno et al. 2013). Nevertheless, the depth–density correlation was shown to be accurate for the estimation of mean catchment snow conditions (Lundberg et al. 2006) and for end-of-winter snow conditions on glaciers (Jansson 1999). Jörg-Hess et al. (2014) applied a statistical depth–density model for the development of a gridded SWE climatology of Switzerland. Schöber et al. (2014) used a linear depth–density model (derived from snow course data) for the conversion of spatial patterns of HS (obtained from Lidar measurements) into SWE patterns of a glacierized catchment in Tyrol. These snow course data from high alpine areas (2,000–3,400 m a.s.l.) are also used in the present study to complete a rich snow dataset consisting of manual measurements from the permanently settled areas of Tyrol (500–2,000 m a.s.l.). The entire dataset consists of 18,048 HS, SWE and \(\rho\) records (mainly observed at weekly intervals) distributed over the entire investigation area allowing a systematic analysis of bulk density and SWE in Tyrol.

This rich dataset is further used to set up a new easy-to-use snow density model (1) for the whole region of Tyrol with consideration of the complete winter season, and (2) a specific model is developed for glacierized catchments with a focus on the peak snow accumulation period. Whereas Jonas et al. (2009) used a monthly clustering of data (bi-weekly resolution), the present study introduces a daily clustering of the data (weekly resolution) applying a moving window approach to overcome discontinuities and jumps at the end of months. Additional model improvements, e.g., the consideration of new snow, are tested for specific locations selected based on data availability. Furthermore, the question arose if it is possible to transfer such a model between different alpine regions. Therefore,
the model developed for Tyrol was compared to the model by Jonas et al. (2009) based on Swiss data, considering an application without parameter adjustment to the regional datasets. A second spatial validation was made using the model developed for glacierized catchments in Tyrol by applying it to snow data from Italian and Swiss glaciers.

DATA

Station data

In Tyrol, manual snow measurements are available from the hydrological year 1952/53. HS and SWE are sampled weekly by staff of the Tyrolean Hydrological Service in the close proximity of meteorological stations. These ‘station data’ are the basis for a regional-scale application accounting for an area of more than 12,000 km² (Figure 1). For measuring SWE, snow pits are dug to ensure that no snow is lost when the core is extracted from the pack. Additionally, data from a snow pillow at Kühtai (1,950 m a.s.l.) are used (Kirnbauer & Blöschl 1990) to densify the data pool at higher elevations. For consistency with the other station data, only one measured pair of HS and SWE from the snow pillow per week (randomly picked) in the period 1993–2010 is added to the calibration dataset. Overall, data from 35 stations were compiled for the period of 1952 to 2010. The mean observation length is 33 years and the data cover mainly the months from November to May. The stations are located at elevations between 528 and 2,036 m a.s.l., covering approximately 60% of the area of the province of Tyrol (Figure 1). Following Jonas et al. (2009), quality checks were carried out using ρ computed from HS and SWE, with data rejected where the computed ρ was outside the range of 50–600 kg m⁻³. Table 1 provides information about the snow data, the providers and the application of the data for calibration or validation.

For six of the Tyrolean stations with measurement periods longer than 30 years, series of daily new snow

<table>
<thead>
<tr>
<th>Spatial scale</th>
<th>Type</th>
<th>Parameter</th>
<th>Temporal scale</th>
<th>Period</th>
<th>Source</th>
<th>Usage</th>
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</thead>
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<tr>
<td>Regional scale</td>
<td>Tyrolean station data</td>
<td>HS SWE ρ</td>
<td>Weekly</td>
<td>1953–2010 (winter season)</td>
<td>HDT, BMLFUW</td>
<td>Calibration</td>
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<td>Snow pillow Kühtai</td>
<td>425</td>
<td>✓ ✓ ✓</td>
<td>Sampled: 15 min</td>
<td>1993–2010 (winter season)</td>
<td>TIWAG</td>
<td></td>
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<tr>
<td>Snow pillow Kühtai</td>
<td>3,362</td>
<td>✓ ✓ ✓</td>
<td>Sampled: 15 min used: daily mean</td>
<td>1993–2010 (winter season)</td>
<td>TIWAG</td>
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<tr>
<td>Snow course data</td>
<td>762</td>
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<td>Monthly–yearly</td>
<td>1966–2011 (January–May)</td>
<td>TIWAG, BMLFUW, BADW, alpS, IMGI</td>
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<tr>
<td>Watershed scale</td>
<td>Snow course data (WB) (HS soundings)</td>
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<td>Yearly</td>
<td>1977–2011 (end of April/beginning of May)</td>
<td>BADW, alpS, IMGI</td>
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<tr>
<td>Snow course data (WB)</td>
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<td>Yearly</td>
<td>1977–2011 (end of April/beginning of May)</td>
<td>TIWAG, BMLFUW, BADW</td>
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<tr>
<td>Snow course data (WB)</td>
<td>71</td>
<td>✓ ✓ ✓</td>
<td>Yearly</td>
<td>1960–2011 (end of April/beginning of May)</td>
<td>IMGI, alpS, BADW, HSB, UFR</td>
<td></td>
</tr>
</tbody>
</table>

Sources: TIWAG, Tyrolean Hydropower Company, Innsbruck, Austria; BMLFUW, Hydrographic Yearbooks of Austria, see BMLFUW (1953–2010); HDT, Hydrographic Service Tyrol, Innsbruck; BADW, Commission for Glaciology of the Bavarian Academy of Sciences and Humanities, Munich; alpS, Centre for Climate Change Adaptation, Innsbruck; IMGI, Institute of Meteorology and Geophysics, University of Innsbruck; UFR, Unit of Geography, University of Fribourg, Switzerland and Huss & Bauder (2009) and Huss et al. (2013); HSB, Hydrological Service Bolzano, South Tyrol/Italy (Glacier Report 2006–2010; http://www.provinz.bz.it/wetter/glacierreport.asp).
(HN) are also available (Hinterriss, Jochberg, Ginzling, Boden, Obertauern and Felbertauern – see Figure 1) and used for model refinements. Additional meteorological data from Kühtai, such as wind speed (1993–1999) and air temperature (1993–2010) are the basis for the analysis of bulk density during snowfall.

Snow course data

Additionally, snow data from different field surveys in Tyrol were collected. The majority (93%) were measured above 2,000 m a.s.l. (above sea level) and are referred to as ‘snow course data’. This dataset was obtained in different watersheds of the Ötztal, a partly glacierized sub-region of Tyrol (Figure 1). In total, the dataset consists of 762 snow pit measurements including records of HS, ρ and SWE. Although the measurements are provided by different institutions, no differences in the variability of the data are detectable. All measurements are obtained by the gravimetric method. Roughly two-thirds of the dataset (provided by the Tyrolean hydropower company – TIWAG) were sampled between the 1970s and 1990s in basins of hydropower facilities. What is remarkable about this dataset is that between 20 and 50 snow pits were dug within short periods (1–3 days) providing a temporal snapshot of the spatial distribution of the snow cover at the watershed scale. Unfortunately, the positions of the measurements are known only approximately and the only available topographic information is the elevation of the snow pits. For the glacierized zones (Figure 1), the data are extended by measurements from the following glaciers: Vernagtferner (V) (Escher-Vetter et al. 2009), Hintereisferner (H), Gepatschferner (G) and Kesselwandferner (K) (Helfricht et al. 2014). An additional 1,080 HS soundings from that region are used for analysing spatial snow cover characteristics on the watershed scale. The larger part of this dataset (measured from January to April) is used for validations of the regional-scale models derived from the station data.

Within the snow course dataset, 256 snow pits were measured between mid-April and mid-May; the aim of these measurements was to observe the peak snow accumulation and to determine the glaciological winter mass balance. This dataset, referred to as ‘snow course (WB) data’ is the basis for the development of a statistical density model. Spatial validation is performed with additional measurements (n = 55) from glaciers in Switzerland (Huss & Bauder 2009; Huss et al. 2015) and South Tyrol/Italy (Hydrological Service Bolzano 2006–2010). An overview of the different datasets is provided in Table 1.

METHODS

Depth–density models for Tyrol (regional scale)

The Tyrolean station data are the basis for inferring mean density–time curves using a moving window approach. The mean ρ at a given day in the winter period is calculated within a timeframe of ±16 days including all measurements from 1952 to 2010. Beforehand, the data are pooled with regard to the elevation of the station. In line with Jonas et al. (2009), an elevation threshold of 1,400 m a.s.l. is used to separate valley sites (low elevations) and alpine sites. Complementary mean depth–time curves are calculated in the same way. Daily densification rates are derived from the mean density–time curves. Linear regressions between observed HS (HSobs [m]) and the observed snow density (ρobs [kg m⁻³]) are made to simulate snow density ρsim:

\[ ρ_{sim} = k \cdot H_{Sobs} + d. \]  

The regression parameters \( k \) [kg m⁻⁴] and \( d \) [kg m⁻³] are derived as ordinary least square fits of the Tyrolean station data for any daily dataset following the moving window approach. In this paper, 1 November is considered as the start of the winter (snow) season. For 1 November, around 50 HS and ρ records are available. The end of the ablation period is defined using this number of records as a minimum threshold. Thus, starting from 1 November, the model was applied on 188 days in the zone below 1,400 m a.s.l. and on 206 days in the zone between 1,400 to 2,000 m a.s.l. This period corresponds to the typical snow cover duration. According to the Hydrological Atlas of Austria (BMLFUW 2007), a snow cover duration of approximately 60–90 days is found for the lowest elevation zone, increasing to a full 365 days in the highest elevation zone. During that winter period (November–May), a maximum of 1,068 records (in the 30-day window) is found above 1,400 m a.s.l. and up
to 2,618 records are found below 1,400 m a.s.l. In both elevation zones, most records are available between January and March.

Spatial model refinements were successfully applied in recent studies (Jonas et al. 2009; Sturm et al. 2010). This paper uses snow-climate regions from the Hydrological Atlas of Austria (BMLFUW 2007) to capture regional characteristics (e.g., precipitation regimes). These regions were derived from a regression analysis between elevation and snow-climate parameters such as mean annual sum of new snow, mean maximum snow depth or duration of snow cover. Within each of these regions, a region- and elevation-specific mean residual (OS_{reg}) between observed density (\rho_{obs}) and simulated density (\rho_{sim} in Equation (2)) is calculated. Thus, the full data set is split according to five snow-climate regions and two elevation zones. Note that in regions 1 and 2, measurements are available only from one elevation zone.

\[
OS_{reg} = \frac{\sum_{i=1}^{n} \rho_{obs}^i - \rho_{sim}^i}{n} \quad (3)
\]

The mean residual (OS_{reg}) is applied as an additional offset in the linear regression. In contrast to the offset d, which reflects season and elevation, this offset describes the regional characteristics (valid for the entire season) and extends Equation (2) to calculate the snow density \rho_{sim}:

\[
\rho_{sim} = k \cdot HS_{obs} + d + OS_{reg} \quad (4)
\]

Finally, the simulated SWE_{sim} [mm] is calculated as:

\[
SWE_{sim} = HS_{obs} \cdot \rho_{sim} \quad (5)
\]

This model is calibrated with the data indicated in Table 1. The remaining data from the Kühtai snow pillow and the entire snow course data are used for validation.

The influence of new snow on snow bulk density

Thus far, the density model is being kept simple using only HS as predictor. Additional meteorological data might not be available (radiation, precipitation or wind). However, a parameter which can be assessed in addition to HS is the new snow height (HN). Manual HN measurements are typically related to a 24 hour standard observation period (Fierz et al. 2009). \rho is known to decrease during snowfall since the new snow layer has a lower density than the already settled snow accumulation. Equation (4) is therefore extended to account for HN. Instead of adding an additional regression term accounting for HN, an offset \Delta \rho [kg m^{-3}] is introduced. It describes the density change due to new snow having recently fallen and not settled yet.

\[
\rho_{sim} = k \cdot HS_{obs} + d + OS_{reg} + \Delta \rho \quad (6)
\]

\Delta \rho refers to the 24 hour standard period and is calculated between two consecutive days of the continuous \rho data from from Kühtai. Due to the lack of representative HN observations at Kühtai, AHS is extracted in the same manner as \Delta \rho from the automated HS data measured above the snow pillow. Due to the settling of the snowpack during snowfall, automated determinations of the new snow height such as AHS underestimate the actual HN (Schmid et al. 2014). Under new snow conditions (\Delta HS > 0), \Delta \rho is negative. The dependency of \Delta \rho on \Delta HS is described with a linear regression. In addition, multiple linear regression models are tested including measurements of HS, air temperature and wind speed to quantify their effects. At the Kühtai station, data to apply these models to are available for the period 1993–1999.

Accuracy thresholds were defined regarding the uncertainties of the automatic sensors from the Kühtai station. For this evaluation, accuracies in the order of 5 cm (HS) and 10 mm (SWE) are used. If HS and SWE are low (≤ the measurement accuracy), calculated \rho values are often unrealistic and are discarded. Additionally, \Delta HS values lower than 1 cm are excluded from the analysis. From all records in the calibration period 1993–1999, 69% show SWE > 0 mm; from this ‘snow covered’ dataset, approximately 85% remain when the accuracy cut-off level of 10 mm is applied. However, only 17% of the corrected SWE dataset (i.e., 10% of all records) show \Delta HS > 1 cm.

Validations of \rho_{sim} are performed for seven stations for which long-term \rho and HN data are available. This dataset is used to describe the influence of the additional parameter \Delta \rho which is calculated applying either HN or \Delta HS. This allows quantifying possible model errors related to the uncertainties of \Delta HS. To quantify the approach’s transferability
within the Alps, the model of Jonas et al. (2009) is included in the modelling of these stations. For comparison with the Swiss model parameters, the daily-based model is evaluated a second time using only the 15th of each month, thus achieving a resolution equivalent to the Swiss model.

**Depth–density model for peak snow accumulation in glacierized catchments (watershed scale; Ötztal Alps)**

For the density model of glacierized catchments, again a linear regression approach comparable to Equation (2) is used with parameters $k$ and $d$ derived as ordinary least square fits. The snow course (WB) data cover a sub-area of snow region 3 (Figure 1) and focus on the peak snow accumulation. Thus, no separate OS$_{reg}$ calculation applies. Furthermore, most of the data originate from altitudes above 2,000 m and are treated primarily as being located in one high alpine elevation zone. This high alpine area can only be accessed in fair weather conditions and there is a high risk of avalanches when a large amount of new snow accumulates. Thus, no model refinements regarding new snow are applied since the dataset is not influenced by considerable accumulations of new snow. The snow courses of 2011, which contain an exceptional amount of records, are used for validation. Additionally, a spatial validation is made using glacier data from Switzerland and Italy (Table 1) for different years.

The snow course (WB) data are investigated further with respect to their correlation with elevation, which is the only topographical information available for all measurements. Site elevation $Z_m$ [m a.s.l.] is therefore used besides $HS_{obs}$ [m] as explanatory variable of $\rho_{sim}$ (WB) [kg m$^{-3}$] in a multiple linear regression approach in the form of

$$\rho_{sim}(WB) = k \cdot HS_{obs} + h \cdot Z_m + d.$$  

(7)

Again, the model parameters $k$, $d$ and $h$ are derived from the calibration data and are validated using the dataset described above.

**Data and model evaluation**

The coefficient of variation ($CV$; standard deviation ($\sigma$) divided by the data’s mean) is used as a measure for the spatial and temporal variability of the data. The correlation between different data are evaluated by means of Pearson’s correlation coefficient $r$, for which a significance test ($p < 0.05$) is applied. Mean absolute errors (MAE) for $\rho$ and SWE are calculated in order to check the quality of the model results. Additionally, relative mean absolute errors (MAE$_{rel}$) are calculated according to the standardized mean absolute error presented by López- Moreno et al. (2015), which is computed as the MAE divided by the mean of all respective measurements.

**RESULTS**

**Depth–density models for Tyrol (regional scale)**

The Tyrolean station data show that $\rho$ is almost normally distributed while both SWE and HS data tend to a log-normal distribution (Figures 2(a)–2(c)) as also shown by Jonas et al. (2009) and Sturm et al. (2010). The mean HS is 0.51 m (standard deviation $\sigma = 0.37$ m), the mean SWE is 140 mm ($\sigma = 131$ mm), and $\rho$ has a mean value of 264 kg m$^{-3}$ ($\sigma = 97$ kg m$^{-3}$). As described above, $\rho$ ranges between 50 and 600 kg m$^{-3}$. HS ranges between 0.01 and 4.18 m and SWE varies between 2 and 1,855 mm (for displaying reasons, extreme values of HS and SWE are not plotted). A pairwise correlation between HS and $\rho$ (Figure 2(d)) shows an increase of mean $\rho$ with increasing HS, which is in agreement with Equation (1) and the literature.

In Figure 3, time series of mean HS, SWE and $\rho$ for the winter seasons 1952/53 to 2009/10 are shown. The cumulative relative number of records indicates that only 20% of the records were accumulated until the end of the 1970s. In the complete series, the yearly mean station elevation ranges from 1,080 to 1,490 m a.s.l. As shown in Figure 3, the plotted CV values indicate the high intra-annual (i.e., within one winter season) variability of HS and SWE. For the latter, CV values are around 80% on average with extremes up to 160%. In contrast, intra-annual CV values of $\rho$ range only between 31 and 47%. The low year-to-year or inter-annual variability of $\rho$ is indicated by the low variation of the bars in Figure 3(c). Expressed by the CV, the inter-annual variability of $\rho$ amounts to approximately 7% due to the low $\sigma = 18.7$ kg m$^{-3}$ with a mean annual $\rho = 262$ kg m$^{-3}$. In
contrast, the year-to-year variability of HS (31%) and SWE (38%) is higher.

Figure 4 shows the spatial and temporal variability of long-term (1952–2010) mean values of HS, ρ and SWE over elevation and season. The data are grouped into monthly subsets and 200 m elevation zones. Note that the highest number of records is available for the calculation of mean values of the elevation zone 1,200–1,600 m a.s.l. for the months January to March (up to \( n = 914 \)). In contrast, only few records are available below 1,200 m a.s.l. in May, including unfortunately a minimum of \( n = 1 \) at 1,000 m a.s.l. Hence, the resulting patterns of HS, SWE and ρ are uncertain in that area as typically all snow has melted at that time. However, mean values of ρ show a gradual increase over the season with a comparably low spatial variability. The highest ρ values occur in the second half of the season in locations above 1,400 m a.s.l. The highest values of HS and SWE are typically observed between February and May above 1,400 to 1,600 m a.s.l. Compared to ρ, elevation gradients are more pronounced for HS and SWE. The transition between seasonally marked changes of HS, ρ and SWE is located around 1,200 to 1,600 m a.s.l. To allow for easier comparison with the model of Jonas et al. (2009), the elevation threshold separating measurements from valley sites (low elevations) and alpine sites is set at 1,400 m a.s.l for Tyrol. Figures 4(d)–4(f) also show the CV values of month/elevation subsets. The distribution of CV values of ρ shows a decreasing variability over the course of the season with increasing elevation. Lowest CV values are the case from February to May above 1,400 m a.s.l. CVs of ρ are clearly lower than those of HS and SWE, which appear randomly distributed without a clear spatial and temporal pattern.

The mean depth–time curves and the mean density–time curves are given in Figure 5 (below 1,400 m a.s.l.) and Figure 6 (1,400–2,000 m a.s.l.). Mean and σ of ρ are calculated using the moving window averaging technique (±16 days) including all data from the respective elevation zone. When the number of records drops below 50 in May (see Figures 5(b) and 6(b)) no mean HS and ρ values are given after 7 May (below 1,400 m a.s.l.) and after 25 May (1,400–2,000 m a.s.l.). In the lower elevation zone, mean HS starts with 0.23 m and the peak of the mean HS curve (0.5 m) is reached at the end of February. Mean ρ starts with 160 kg m\(^{-3}\) and rises up to 350 kg m\(^{-3}\) in mid-April. After that, mean ρ decreases due to late season records with ephemeral snow covers (Figure 5). In contrast, data from above 1,400 m a.s.l. result in a rising ρ until mid-May. While ρ below 1,400 m a.s.l. rises in an almost linear manner throughout the season, densification shifts to a
higher rate in the upper elevation zone in March. The shift of the densification rate goes hand in hand with a flattening of the mean HS curve at approximately 0.9 m (Figure 6). Simultaneously, the range of mean HS ±1σ becomes largest. Daily densification rates show a large noise and, therefore, monthly mean values are calculated (Table 2). Below 1,400 m a.s.l., densification rates have a low variability, with monthly values ranging from 0.9 kg m⁻³ d⁻¹ in January.

Figure 3 | Tyrolean station data: seasonal mean values, ±1 standard deviation (σ) and CV [%] of HS [cm] (a), SWE [mm] (b) and ρ [kg m⁻³] (c) plotted against the year of observation.
to 1.35 kg m\(^{-3}\) d\(^{-1}\) in March. Above 1,400 m a.s.l., densification rates are around 0.6 kg m\(^{-3}\) d\(^{-1}\) from November to January. After a transition phase in February, densification reaches its maximum rates in March and April (1.8–1.89 kg m\(^{-3}\) d\(^{-1}\)).

Regressions are fitted to daily datasets of \(HS\) and \(\rho\) which were pooled using the ±16 day moving window. The resulting daily parameters \(k\) and \(d\) are plotted in Figure 7 (elevation zone >1,400 m a.s.l.) and in Figure 8 (elevation zone <1,400 m a.s.l.) Residuals of \(\rho\) (not shown) are almost normally distributed and conform to the assumptions of the linear regression model. In both elevation zones, 95% confidence intervals are largest in November and in April/May as well as for 29 February where fewer records are available (Figures 5(b) and 6(b)). Parameter \(d\) follows approximately the course of the mean density–time curves. In November and December, the sign of \(k\) is negative in both elevation zones and in January, February and March in the lower elevation zone. However, correlations between \(HS_{\text{obs}}\) and \(\rho_{\text{obs}}\) are in most cases significant \((p < 0.05)\). Correlations with \(p > 0.05\) occur in the lower elevation zone in March and April when the confidence intervals of \(k\) also increase. In the upper elevation zone, correlations are not significant when the number of records is especially low at the beginning and the end of the season and in January when \(k\) is close to zero. The abrupt increase of \(k\) on 15th January denotes the availability of data from two stations where \(SWE\) is only observed from January to April/May. These stations are located in region 1 where \(HS\) is typically large. Correlation coefficients (not shown) are either negative or positive (same as \(k\)) and generally low ranging from 0.3 to 0.3.

Daily regression parameters \(k\) and \(d\) can be taken from Figures 7 and 8 to compute \(\rho_{\text{sim}}\) using the \(HS\) data of a certain day as input. As a first model test, all \(HS\) records of the station data are used to simulate \(\rho_{\text{sim}}\) (Equation (4)). Values of the regional offset parameter \(OS_{\text{reg}}\) are shown in Table 3. \(OS_{\text{reg}}\) is highest in regions where deep snow covers are commonly observed (e.g., region 1). In both elevation zones, absolute errors \((AE)\) of \(SWE\) are lower than absolute
errors of $\rho$ since this approach benefits from observed $HS$ as input (Figure 9). The curves of the relative mean absolute errors ($MAE_{rel}$) of $SWE$ are also calculated using the $\pm 16$ day window. $MAE_{rel}$ is constantly higher in the lower elevation zone and both error curves decrease over the course of the season (except April/May $< 1,400$ m a.s.l.).

The regression models (fitted to the Tyrolean station data) are validated using the remaining $SWE$ data from the Kühtai snow pillow (1,950 m a.s.l.), which is not used for calibration. The snow course data are used as a completely independent validation set (Table 1). For the $SWE$ of the Kühtai snow pillow, a $MAE$ of 27.6 kg m$^{-2}$ and a $MAE_{rel}$ of 13.25% is calculated. For the snow course data of the Ötztal Alps, a $MAE$ of 66.5 kg m$^{-2}$ and a $MAE_{rel}$ of 13.9% is calculated. Coefficients of determination ($SWE_{obs}$ vs. $SWE_{sim}$) are considerable for both validation datasets: $R^2$ is 0.95

Figure 5 | Long-term mean (1952–2010) of (a) snow depth–time curves and (c) density–time curves of Tyrolean station data of the elevation zone below 1,400 m a.s.l. The number of records available for calculating the mean values is given in (b).
for the snow pillow and 0.88 for the snow course data (data not shown). However, all of these records were measured in region 3 above 1,400 m a.s.l. Thus, validation of the regression models with more than 4,000 snow datasets, which are not included in the model fitting yields comparable or even better results than for the ‘calibration’ data of the upper elevation zone of the largest snow climate region 3.

The influence of new snow on snow bulk density

The influence of new snow on bulk density is illustrated in Figure 10, which shows time series of $HS$ and $\rho$ of the Kühtai snow pillow in the year 1999. In this example, $HS$ and $\rho$ are negatively correlated, as $HS$ increases and $\rho$ decreases during snowfall. The decrease of bulk density ($\Delta \rho$) is explained by means of a regression analysis between
automatically derived new snow height $\Delta HS$ and $\Delta \rho$, using data from the period of 1993–1999 (Figure 10(c)). The correlation between $\Delta HS$ and $\Delta \rho$ is significant and the regression is made without an offset (forced through zero) resulting in an $R^2$ of 0.5. The regression is denoted as:

$$\Delta \rho = -146.85 \cdot \Delta HS,$$

with $\Delta \rho$ expressed in [kg m$^{-3}$] and $\Delta HS$ in [m]. Furthermore, the decrease of bulk density ($\Delta \rho$) is influenced by other parameters such as $HS$, $\rho$ and $\rho_N$ (new snow density). As $\rho_N$ depends on wind speed ($w$) and air temperature ($T$), these two parameters (measured next to the Kühtai snow pillow) are included additionally in a multiple linear regression. The additional predictors $HS$, $T$ and $w$ are introduced successively. This leads to an increasing model performance (adjusted $R^2$) with $R^2 = 0.58$ for $\Delta \rho = f(\Delta HS, HS)$ and $R^2 = 0.60$ for $\Delta \rho = f(\Delta HS, HS, T)$. Including $w$ does not lead to any further improvement. Considering the use of $\Delta \rho$ as part of Equation (6), the small improvement when using air temperature as an additional predictor in explaining $\Delta \rho$ does not justify the additional data demand, which is why air temperature was

### Table 2 | Monthly mean values of daily densification rates of the Tyrolean station data

<table>
<thead>
<tr>
<th></th>
<th>&lt; 1,400 m a.s.l.</th>
<th>&gt; 1,400 m a.s.l.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nov</td>
<td>0.96</td>
<td>0.61</td>
</tr>
<tr>
<td>Dec</td>
<td>1.06</td>
<td>0.59</td>
</tr>
<tr>
<td>Jan</td>
<td>0.93</td>
<td>0.62</td>
</tr>
<tr>
<td>Feb</td>
<td>1.12</td>
<td>1.20</td>
</tr>
<tr>
<td>Mar</td>
<td>1.35</td>
<td>1.89</td>
</tr>
<tr>
<td>Apr</td>
<td>0.84           /</td>
<td>1.80</td>
</tr>
<tr>
<td>May</td>
<td>–</td>
<td>1.34</td>
</tr>
</tbody>
</table>

*Mean value for daily densification rates between 1 April and 20 April as density decreases afterwards.

**Figure 7** | Daily regression parameters $k$ and $d$ for simulating snow density $\rho_{sim}$ for the elevation zone $>1,400$ m a.s.l. and significance values of the correlation between $HS_{obs}$ and $\rho_{obs}$. 

Downloaded from https://iwaponline.com/hr/article-pdf/47/2/419/369062/nh0470419.pdf by guest
not taken into consideration. Finally, the original form shown in Equation (8) is used, since the predictor $H_S$ is already included in Equation (6).

The effect of including $\Delta \rho$ in the bulk density model ($\rho_{sim}$) is illustrated in Figure 10(b). Due to the exceptionally large snow accumulation in January/February 1999 $\rho_{sim}$ (without $\Delta \rho = \text{diamond}$) overestimates the observed $\rho$. In contrast, when $H_N$ is included to model $\rho_{sim}$ (stars) the bias decreases on 29 January and 6 February. Note that $\rho_{sim}$ is not improved on days without new snow accumulation as the offset $\Delta \rho = 0$. Still on 2 February 1999 (Figure 10(b)), the bias between $\rho$ and $\rho_{sim}$ is particularly large as a result of the above average $H_S$ during that period (see also Figure 6(a)). The extended bulk density model is used to compute $\rho_{sim}$ and $SWE_{sim}$ of the stations where long-term records of $H_N$ are available (Table 4). The available time series of $SWE$ at the seven stations are reduced to times where daily $H_N$ measurements are available. At the different locations, 31–43% of the available $SWE$ data ($n$) was recorded during or shortly after snowfall (Table 4). In this table, $nH_N$ denotes the number of new snow events occurring in combination with manual $SWE$ measurements. Whether $H_N$ or $\Delta H_S$ is used to calculate $\Delta \rho$, almost no differences in the results for $\rho_{sim}$ and $SWE_{sim}$ are detected. At the stations Jochberg, Ginzling and

---

**Table 3** | Regional offset parameters [kg m$^{-3}$] of Equation (4) (locations of the snow regions are given in Figure 1)

<table>
<thead>
<tr>
<th>Snow region</th>
<th>$&lt; 1,400$ m</th>
<th>$&gt; 1,400$ m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>34.9</td>
</tr>
<tr>
<td>2</td>
<td>7.3</td>
<td>–</td>
</tr>
<tr>
<td>3</td>
<td>−5.7</td>
<td>−13</td>
</tr>
<tr>
<td>4</td>
<td>−12.3</td>
<td>34.3</td>
</tr>
<tr>
<td>5</td>
<td>1.4</td>
<td>−18.1</td>
</tr>
</tbody>
</table>
Felbertauern, the application of $HN$ leads to slightly better results but at Hinteriss, Boden and Obernberg the application of $\Delta HS$ results in slightly lower model errors. In Figure 11, the MAE$_{rel}$ of the seven stations are evaluated applying the different modelling approaches. Starting with the approach used by Jonas et al. (2009) (Figure 11(a)), an adapted version of the Tyrol model with daily resolution (Figure 11(c)) is introduced using a quasi-monthly resolution.

<p>| Table 4 | Metadata of seven stations providing long-term new snow data |</p>
<table>
<thead>
<tr>
<th>Station</th>
<th>Elevation [m]</th>
<th>Region</th>
<th>Years</th>
<th>n</th>
<th>nHN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hinteriiss</td>
<td>930</td>
<td>2</td>
<td>1977–2009</td>
<td>473</td>
<td>172</td>
</tr>
<tr>
<td>Jochberg</td>
<td>950</td>
<td>4</td>
<td>1971–2009</td>
<td>530</td>
<td>206</td>
</tr>
<tr>
<td>Ginzling</td>
<td>1060</td>
<td>3</td>
<td>1977–2009</td>
<td>431</td>
<td>133</td>
</tr>
<tr>
<td>Boden</td>
<td>1355</td>
<td>2</td>
<td>1977–2009</td>
<td>538</td>
<td>210</td>
</tr>
<tr>
<td>Obernberg</td>
<td>1360</td>
<td>3</td>
<td>1977–2009</td>
<td>515</td>
<td>203</td>
</tr>
<tr>
<td>Felbertauern</td>
<td>1650</td>
<td>4</td>
<td>1979–2009</td>
<td>517</td>
<td>217</td>
</tr>
<tr>
<td>Kühltai</td>
<td>1930</td>
<td>3</td>
<td>1993–2009</td>
<td>373</td>
<td>162</td>
</tr>
</tbody>
</table>

$n$, the number of records; $nHN$, the number of SWE measurements which are influenced by new snow.
(k and d of the 15th of a month (Figure 11(b)). Furthermore, the Tyrolean model with daily resolution is applied using an additional regional offset (Figure 11(d)) and the regional offset plus $\Delta \rho$ (Figure 11(e)).

Overall improved or equal predictive skills are observed when the model is calibrated with regional data. Comparing the models ‘Figure 11(a) Jonas et al. (2009)’ and ‘Figure 11(b) Tyrol monthly’ shows improvements at three stations (Jochberg, Ginzling and Küthai) and an increase of MAE$_{rel}$ at the stations Boden and Hinterriß. When changing to a daily resolution, the predictions at the stations Jochberg und Ginzling are again improved. An exception is the station Küthai, which exhibits an increase of the MAE$_{rel}$. Further adaptations (OS$_{reg}$ and $\Delta \rho$) show slightly improved or equal skills for the majority of the stations. Results of the transferred model ‘Figure 11(a) Jonas et al. (2009)’ are equally good or slightly better for the stations Obernberg, Boden and Hinterriß than the Tyrolean models, supporting the transferability of the approach.

**Depth–density model for peak snow accumulation in glacierized catchments (watershed scale; Ötztal Alps)**

The winter mass balance subset of the snow course data are used to characterize peak snow accumulation conditions (mid-April to mid-May) in glacierized regions of the Ötztal, Tyrol. In this area, no regularly observed SWE and $\rho$ data are available. The mean HS of the snow course (WB) data is 2 m ($\sigma = 0.75$ m), the mean SWE value is 620 mm ($\sigma = 320$ mm) with a mean bulk density of $\rho = 370$ kg m$^{-3}$ ($\sigma = 62$ kg m$^{-3}$). The HS records of this dataset range between 0.23 and 3.7 m with SWE ranging from 101 to 1,485 mm. Bulk densities vary between 232 and 538 kg m$^{-3}$.

Distributions of mean HS, SWE and $\rho$ over elevation and different years are shown for the Ötztal Alps in Figure 12. The variation within one subset is indicated by $\sigma$ and CV. Additionally, the relative number of measurements ($n\%$) per elevation band or per year is shown. Obviously, the mean HS increases with increasing elevation until 3,200 m a.s.l. (0.13 m/100 m) but above 3,200 m a.s.l. HS drops (−0.19 m/100 m; Figure 12(a)). The correlation coefficient $r$ between elevation and HS of the snow pits is 0.56 but drops to 0.32 when the additional 1,080 HS soundings (Table 1) of the snow course (WB) data are included. However, both correlations are significant. Consistent with the distribution of HS, mean SWE increases with elevation (Figure 12(c)). The drop at 2,900 m a.s.l. may be attributed to the lower number of available records at this elevation. From 2,000 to 3,200 m a.s.l., SWE increases by 52.5 mm per 100 m. The available SWE data are significantly correlated ($r = 0.45$) with elevation. In contrast, $\rho$ and elevation are not correlated (Figure 12(e)). CV values of $\rho$ of the different elevation zones (5–25%) are
considerably lower than for HS (35–55%) and SWE (20–60%). The CV of ρ and SWE drop slightly above 2,800 m a.s.l. but the corresponding measurements originate exclusively from glaciers. Figure 12(f) demonstrates the low inter- and intra-annual variation of ρ at the end of the accumulation season with, e.g., intra-annual CV values of ρ between 5 and 25%. In contrast, CV values of HS (20–45%) and SWE (15–50%) are higher (Figures 12(b) and 12(d)).

In Figure 13(a), ρ_{obs} and HS_{obs} of the snow course (WB) are plotted in a pairwise correlation plot. The correlation coefficient r = 0.16 of ρ against HS is significant. The resulting regression line in Figure 13(a), hereinafter referred to as WB model, is expressed by a parameter k = 14.8 and a parameter d = 346. The application of the WB model results in a MAE = 73.8 mm and a MAE_{rel} = 12.7% for SWE. The calculated SWE_{sim} (WB) matches the observed SWE_{obs} (WB) (Figure 13(b)) and explains a large part of the observed variance (R² = 0.87). Snow course data collected in 2009 and 2011 at the Hintereisferner, Gepatschferner, Kesselwandferner and Vernagtferner glaciers (16 snow pits) are used for validation of the WB model. Overall, a MAE = 40.1 mm and a MAE_{rel} = 4.8% is calculated for SWE (Figure 14(c)).

In addition, the WB model is spatially validated using measurements obtained at the Langenferner and Weißbrunnferner glaciers in South Tyrol, Italy (Hydrological Service Bolzano 2006–2010), and the following Swiss glaciers: Findelen (years 2012–2013), Plainemorte (2011–2013), Tsanfleuron (2013), Claridenfirn (nine measurements between 1993 and 2008) and Silvretta (6 years between 1960 and 1980).
Missing years in the long-term snow stake series on the Claridenfirn and Silvretta glaciers were measured outside the defined temporal range of the WB model (mid-April to mid-May). Based on the entire validation data from Italy and Switzerland, a MAE = 86.7 mm and a MAE$_{rel}$ = 7% are calculated for SWE. As an
example for the Swiss validation data, the snow courses on Fin-
delen glacier for the years 2012 and 2013 are plotted in
Figures 14(b) and 14(d). The satisfying results of the Tyrolean
WB model regarding $\text{SWE}_{\text{rel}}$ (8.3% in 2012 and 7.3%
in 2013) show that the model is suitable to be transferred for
estimations of $\rho$ and $\text{SWE}$ at the end of the accumulation.

The WB model is extended by the elevation ($Z_m$) being the
only available topographical parameter for the snow course
(WB) data. Equation (9) shows the resulting regression:

$$\rho_{\text{sim}}(\text{WB}) = 29.9 \cdot \text{HS}_{\text{obs}}(\text{WB}) - 0.05 \cdot Z_m + 449 \quad (9)$$

In this equation, $Z_m$ is the site elevation [m a.s.l.] of a snow
pit. When comparing $\text{SWE}_{\text{sim}}$ of the individual years, the use
of elevation as an additional predictor improves the result in 8
out of 15 available years (Figure 15). When using Equation (9)
to model $\rho$ of the entire snow course (WB) data, the $\text{MAE}_{\text{rel}}$
decreases slightly to 12.1% (instead of 12.7%, see above). Main improvements are found in the years 1999, 2005,
2006, 2008 and 2009. However, a reduced performance is

**DISCUSSION**

**Depth–density models for Tyrol (regional scale)**

The presented mean density–time curves of the Tyrolean
region cover data from the period 1952–2010. With regard
to the temporal distribution of the number of records ($n$),
80% of the data have been collected since the late 1970s,
with an almost constant number of records per year collected
until 2010. With a mean station observation length of 33
years, the results may be interpreted in terms of climatological
mean values of $\text{SWE}$ and $\rho$. The observed higher values of
$\text{SWE}$ and $\text{HS}$ in the mid-1960s might correlate to the higher
mean station elevation at that time. Mean daily densification
rates ($0.6$–$1.9 \text{ kg m}^{-3} \text{ d}^{-1}$) extracted from the long-term mean
density curves of the Tyrolean station data are in the range of
the alpine snow class of a density dataset with an almost
global spatial coverage \cite{Bormann2013a}. However, a
shift to an increased densification rate, as found by Bormann
et al. \cite{Bormann2013a} or Mizukami & Perica \cite{Mizukami2008}, is visible in Tyrol
only in the elevation zone between 1,400 and 2,000 m a.s.l.

In contrast to the Swiss model by Jonas et al. \cite{Jonas2013}, the
regression gradient $k$ is occasionally negative in the Tyro-
lean model. Below 1,400 m a.s.l., almost the complete
season faces negative gradients $k$. Negative correlations
may be caused by a large amount of new snow in the Tyro-
lean data (Table 4) and differences in the sign of $k$ between
Tyrol and Switzerland may be attributable to the different
sampling scheme (Tyrol = weekly, Switzerland = bi-
weekly). At timescales of a few days, $\text{HS}$ and $\rho$ are negatively
correlated due to new snow which decreases the bulk den-
sity. Afterwards, when $\text{HS}$ decreases due to settling, $\rho$
increases, which leads to negative correlations as well.
This is illustrated in Figure 10. Melt implies a negative corre-
lation between $\text{HS}$ and $\rho$ at several days to several weeks. A

![Figure 15](https://iwaponline.com/hr/article-pdf/47/2/419/369062/nh0470419.pdf)

**Figure 15** | Relative errors of SWE (i.e., $\text{MAE}_{\text{rel}}$) for a single year’s snow courses at the end of the accumulation period (WB model [Figure 13]; WB model $+ Z_m$ [Equation (9)].
positive correlation between $HS$ and $\rho$ is the case at a monthly scale during the accumulation period (McCreight & Small 2014). In the long-term mean values of Tyrol, mean $HS$ typically increases from November to March along with a slight increase of $\rho$ (i.e., positive correlation). However, the gradient $k$ is mostly negative during that time. As shown in Figure 8, the negative correlations are significant from November to March. The plateau of the mean $HS$ (0.9 m) from March to May (above 1,400 m a.s.l.) indicates a weak correlation with an ongoing increase of $\rho$ (Figure 6). Still, with only a few exceptions, the correlation is significant and during that time the approach involves the lowest uncertainties (Figure 9). The high resolution data used by McCreight & Small (2014) enabled the predictor to be derived separately for individual years in a temporal window of several days. Differences may occur due to the lower resolution of the Tyrolean data. In contrast, in the same temporal window the predictors represent mean values, aggregating data from all available years. According to McCreight & Small (2014), a 30 day timescale faces mainly negative correlations between $HS$ and $\rho$. This is only partly the case in the present study which may be due to the different data resolution and the way of deriving the predictors as multi-year mean values.

The daily representation of the depth/density–time relation in the present study is an improvement compared to the original model of Jonas et al. (2009), overcoming data jumps when changing parameters between months. However, the comparison between the Tyrolean models in daily versus monthly resolution reveals only a slight improvement on average. For two stations, it improves the results distinctly (Figure 11). At the Kühtai snow pillow station, however, the shift to the daily resolution decreases the performance measures. The analysis of this behaviour revealed that the data of this station (randomly picked data in weekly resolution) include an especially large number of November and May records where the confidence intervals of the parameters $k$ and $d$ indicate uncertain daily values. Hence, the daily model resolution may include a performance reduction in periods where the confidence interval of parameters becomes too large.

The present study also applies a regional offset parameter ($OS_{reg}$; comparable to Jonas et al. 2009) to account for regional characteristics such as a horizontal precipitation gradient. However, the overall model performance is only partly improved by that. The change in the predictive performance appears site specific (Figure 11).

The influence of new snow on snow bulk density

Regarding the possible negative correlation on a daily timescale (Figure 10), a simple parameterization of the decrease of $\rho$ during snowfall is introduced. The bulk density model is extended by an additional offset $\Delta \rho$ as a function of the new snow height. The applied regression is based on data from the Kühtai snow pillow. The advanced method shows improvements at most stations with $HN$ records available (Figure 11). However, a limited transferability of this parameterization might be the case as the largest improvement was found for the Kühtai station itself. $\Delta \rho$ was not sensitive to the different new snow data inputs and led to almost similar results when using either manually observed $HN$ or $\Delta HS$ (extracted from automated $HS$). Thus, the approach could be improved in the future by using other automatic sensor sites to derive a regional mean relation for $\Delta \rho$.

Depth–density model for peak snow accumulation in glacierized catchments (watershed scale; Ötztal Alps)

At elevations above 2,000 m a.s.l., mean values of $SWE$ and $\rho$ were evaluated for the peak snow accumulation period at the end of winter, with 15 years of data available during the period 1977–2011. That dataset alone does not make it clear whether the data cover the full range of possible snow accumulation (minimum and maximum $SWE$) during the observation period. An additional data source is available in the form of three cumulative precipitation gauges in the area which were analysed by Helfricht et al. (2014). A comparison of the winter precipitation statistics with the peak snow accumulation data of the Ötztal Alps collected here reveals that the extremes of winter precipitation within the period 1983–2012 are included in the $SWE$ measurement series (minimum in 1996 and maximum in 2009; Figure 12). Moreover, the mean $SWE$ of 620 mm corresponds well to the long-term mean winter precipitation (1983–2012) of 632 mm.

In the glacierized areas of Tyrol, site elevation ($Z_m$) as an additional predictor in addition to $HS$ did not improve the $SWE$ estimates considerably. Correlations between $\rho$
and elevation are typically not significant in Tyrol. This finding is similar to results of other studies, e.g., Braun (1984) or López-Moreno et al. (2013). However, in years with large accumulations of SWE (1999, 2005, 2006, 2008 and 2009), the use of $Z_m$ seems to increase the model performance (compare Figure 12 and Figure 15). In contrast, in the winters of 2007 and 2011, which were characterized by large positive deviations from the long-term mean temperature (ZAMG 2014), the model without $Z_m$ is significantly better. Thus, in the current model set-up it is not possible to recommend the use of $Z_m$ for estimating density in the glacierized catchments. In terms of a simpler model the glacierized catchments are seen as a third elevation zone (>2,000 m a.s.l) in the Tyrolean region. However, site-specific $Z_m$ may be useful in combination with additional weather data as predictors of $\rho$ (Bruland et al. 2015).

Model uncertainties

The accuracy of SWE measurement generally depends on snowpack characteristics, the ground surface, measurement tools and techniques and the human factor. Manual SWE measurements are expected to have an accuracy in the order of ±10% (Stuefer et al. 2015). The within-site variability of $\rho$ was found to be in the order of 10–20% in Switzerland (Jonas et al. 2009).

With respect to these findings, the results of the density model for glacierized regions are encouraging; a mean relative error of 12.7% with more than half of the annual data having relative errors below 10% (Figure 15) is close to the measurement accuracy of SWE and clearly at the lower bound of the within-site variability. The model benefits from the especially low spatial variability of snow accumulations on glaciers (Schöber et al. 2014) and the low year-to-year variability of $\rho$ at the end of the accumulation season (Figure 12(f)). López-Moreno et al. (2013) found a decreased uncertainty of $\rho$ and SWE estimates (simple function of HS) at the basin scale for ripened snow conditions in April with relative errors in the order of 15%. A more complex model (including additional weather data) which was used to simulate $\rho$ of numerous snow courses resulted in an average error of 9.4% (Bruland et al. 2015).

At the regional scale of Tyrol, model uncertainties are larger. Model errors are about 10% higher for the lower elevation zone (Figure 9) where mean HS is generally lower. Especially in November, a high $MAE_{rel}$ is found, attributable to the large variability of $\rho$ for shallow snow covers (Jonas et al. 2009; Sturm et al. 2010). This is emphasized by the increased confidence intervals of $k$ and $d$ in November and April/May (Figures 7 and 8). Still, the model performance of the regional scale model is encouraging in the context of the literature. For instance, Rohrer & Braun (1994) applied a model which is forced by daily time series of $HN$ at seven SWE stations in Switzerland. Mean absolute errors of SWE ranged from 25 to 91.2 mm. For the full model of the present study (Figure 11(e), Tyrol daily + $OS_{REG} + \Delta \rho$), $MAEs$ range from 16.3 to 35.7 mm at different stations. Egli et al. (2009) used the Jonas et al. (2009) approach to model bi-weekly SWE measurements of a Swiss snow research site with a root mean squared error (RMSE) of 48 mm. Results of the model in Figure 11(e) are equivalent to a RMSE range of 22.1 mm at the Ginzling station and up to 48.9 mm at the Felbertauern station. The model of McCreight & Small (2014) – involving time series in daily resolution – resulted in RMSE for SWE being approximately 63 mm.

Transferability of the models

The transfer of regression models calibrated for Swiss snow data to simulate SWE at Tyrolean stations led to almost similar $MAE$ values as achieved by the regionally fitted Tyrolean model in monthly resolution. As discussed above, the taking into account of locally fitted model extensions ($OS_{reg}, \Delta \rho$) leads to only minor improvements. The transferability of the WB model from glacierized sites in Austria to Switzerland and Italy is found to be reliable without any model extension. This emphasizes the applicability of the presented bulk density models for applications where SWE data are more advantageous than HS, such as the calculation of the glaciological winter mass balance or the calibration of a snow-hydrological model (Schöber et al. 2014).

CONCLUSIONS

Long-term mean density–time curves are calculated for Tyrol based on data of the period 1952–2010. Using this comprehensive dataset, an easy-to-use method for estimating snow
bulk density and SWE is developed. Daily regression parameters for elevations below and above 1,400 m a.s.l. are compiled (see Figures 7 and 8) and can be used to simulate snow bulk density based on observed snow depth. The presented approach denotes an improvement regarding the temporal resolution especially in the middle of the winter season when confidence intervals of the daily regression parameters are narrow. Model extensions taking into account regional snow characteristics or the impact of new snow improve the model performance locally. Considering new snow is especially important for a model operating on short timescales. However, most reliable model results occur for peak snow accumulation characteristics in spring in glacierized regions in the Alps. Overall, the developed models are beneficial for (1) decreasing manpower for field work and (2) providing SWE for hydrological and glaciological studies where only HS data are available.

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