RESEARCH ARTICLE

10.1002/2016WR019872

Key Points:

- Mean snow depth is parameterized using elevation, sky view factors, and flat field snow depth as input
- Power law describes elevation trend of domain-averaged snow depth better than a linear lapse rate
- Seven high-resolution snow depth data sets were normalized, pooled, and detrended to derive the parameterizations

Correspondence to:

N. Helbig,
norahelbig@gmail.com

Citation:

Helbig, N. and A. van Herwijnen (2017), Subgrid parameterization for snow depth over mountainous terrain from flat field snow depth, *Water Resour. Res.*, 53, 1444–1456, doi:10.1002/2016WR019872.

Received 30 SEP 2016

Accepted 15 JAN 2017

Accepted article online 24 JAN 2017

Published online 12 FEB 2017

Subgrid parameterization for snow depth over mountainous terrain from flat field snow depth

N. Helbig¹ and A. van Herwijnen¹
¹WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland

Abstract Snow depth is an important variable for a variety of models including land-surface, meteorological, and climate models. Various measurement networks were therefore developed to measure snow depth on the ground. Measurement stations are generally located in gentle terrain (flat field measurements) most often at lower or mid elevation. While these sites have provided a wealth of information, various studies have questioned the representativity of such flat field measurements for the surrounding topography, especially in alpine regions. Using highly resolved snow depth maps at the peak of winter from two distinct climatic regions in Switzerland and in the Spanish Pyrenees, we developed two parameterizations to estimate domain-averaged snow depth in coarse-scale model applications over complex topography using easy to derive topographic parameters. The first parameterization uses a commonly applied linear lapse rate. Removing the dominant elevation gradient in mean snow depth revealed remaining underlying correlations with other topographic parameters, in particular the sky view factor. The second parameterization combines a power law elevation trend scaled with the subgrid parameterized sky view factor. Using a variety of statistic measures showed that the more complex parameterization performs better when using mean high-resolution flat field snow depth. The performances slightly decreased when formulating the parameterizations for a single flat field snow depth measurement. Nevertheless, the more complex parameterization still outperformed the linear lapse rate model. As the parameterization was developed independently of a specific geographic region, we suggest it could be used to assimilate flat field snow depth or snowfall into coarse-scale snow model frameworks.

1. Introduction

Information on the current state of the snow cover as well as future changes is of great relevance for various model applications such as hydrological, hydroglaciological, avalanche, weather, and climate forecasts. For instance, when a large rain event is forecasted, for snow hydrologists it is crucial to know if it will fall on bare ground or on an existing snow cover. Similarly, for avalanche forecasting, it is important to know if a forecasted large snowfall will deposit on a well-consolidated thick snow cover or on a thin weak snow cover, i.e., a snow cover containing instabilities consisting of a buried layer of kinetic growth crystals [Schweizer *et al.*, 2003]. Furthermore, there is an increasing need to account for snow in climate forecasts. Fractional snow covered area, for instance, is used to derive surface albedos, an essential component of the surface radiation balance in climate models [e.g., Roesch *et al.*, 2001]. Fractional snow covered area of a coarse grid cell requires knowledge of mean snow depth [Helbig *et al.*, 2015]. Also, in glacierized regions, data on snow depth are of great importance to compute mass balance changes driven by climate change impacts [e.g., Farinotti *et al.*, 2015]. Clearly, estimating the amount of snow currently lying in the mountains is relevant for many applications.

Various measurement networks exist throughout the world to measure snow depth at so-called index stations and measurement stations are generally located in gentle terrain (flat field measurements) and most often at lower or mid elevation. While for some applications data on snow depth is sufficient, snow water equivalent (SWE, the amount of water in the snow pack) is typically the more relevant parameter. However, SWE measurement networks are less common and snow depth measurements are therefore often converted to SWE using parameterized snow densities [Martinez and Rango, 1991; Jonas *et al.*, 2009]. Thus, point measurements of snow depth are of great relevance.

Assimilating snow depth in models is mostly done by extrapolating single flat field measurements to relatively large geographic regions either qualitatively or by using linear elevation trend corrections. However, many studies have found that snow depth measurements at index stations only poorly represent snow depth in the surrounding terrain, especially in mountainous regions (for a literature review see *Grünwald and Lehning* [2015]). Using high-resolution spatial snow depth data, *Grünwald and Lehning* [2015] showed that measured snow depth at index stations is only marginally representative for snow depth means of the surrounding terrain at distances of up to 400 m as well as for their catchment mean values. They also found large differences between snow depth at index stations and average snow depth of the corresponding 100 m elevation band in the entire region. However, by analyzing high-resolution spatial snow depth data in domain sizes ranging from 50 to 3000 m, *Helbig et al.* [2015] found that domain-averaged snow depth can roughly be approximated with means of flat field snow depth values within the same domain, especially for domain sizes larger than 1500 m. These results suggest that depending on the scale and the topography in a domain, flat field snow depth measurements could be representative for the surrounding terrain. A thorough analysis to investigate the influence of topography on the relationship between domain-averaged and flat field snow depth is thus required.

In general, flat field snow depth is representative for a larger region, i.e., larger than a few kilometers, as it is inherently related to the larger-scale precipitation patterns [see e.g., *Goovaerts*, 2000]. On the other hand, fine-scale interactions between terrain and various meteorological drivers can induce large snow depth variations [see e.g., *Kirchner et al.*, 2014; *Mott et al.*, 2014]. Indeed, wind will lead to spatially different deposition and drift patterns, terrain shading will lead to spatially different snow melt, and settling rates and gravitational forces lead to snow relocation due to avalanches. Identifying the relevant topographic parameters that link flat field snow depth to domain-averaged snow depth will thus depend on the horizontal length scale of the domain.

Overall, it is well known that precipitation and thus snow depth increases with elevation. This is attributed to vertical lifting of air over mountainous terrain triggering adiabatic cooling and thus condensation [*Whiteman*, 2000]. However, based on high-resolution spatial snow depth data sets at peak of winter, *Grünwald et al.* [2014] and *Kirchner et al.* [2014] showed that mean snow depth in 100 m elevation bands only increases up to a certain altitude with a distinct decrease for higher elevations. They attributed this to redistribution of snow by wind or snow relocation by avalanches. Similarly, *Turcan* [1975] explained observed decreases of snow depth above tree line in the vicinity of mountain ridges by wind-drifting. Recently, *Voegeli et al.* [2016] successfully scaled single point precipitation measurements using measured high-resolution snow depth maps to obtain spatial precipitation input for fine-scale grid cells. While their approach seems promising, it does not explicitly account for the processes affecting the spatial snow distribution and requires highly resolved spatial snow depth maps. Describing these processes is complicated by the fact that in alpine regions the meteorological parameters which influence the snow depth distribution, such as wind speed or radiation, are also elevation-dependent. As a result, the various processes affecting snow distribution in complex terrain might balance, attenuate, or reinforce the well-known elevation dependencies of precipitation. Clearly, to account for all these processes is far from straightforward.

Some of the spatial complexities between snow depth and terrain characteristics can be removed by averaging snow depth over larger domain sizes. A scale analysis for aggregated snow depth in varying domain sizes can reveal a lower limit above which domain-averaged snow depth can reliably be described. This means that for domain sizes above this lower limit the scatter in snow depth, originating from local topographical effects at meters scales which cannot be parameterized, averages out. *Grünwald et al.* [2013] found a lower limit of 400 m but only investigated domain sizes up to 800 m. *Melvold and Skaugen* [2013] and *Helbig et al.* [2015] also included larger domain sizes in their analysis and found a lower limit of about 1 km for which local variability is mainly averaged out. Consequently, the domain size of a model using a mean snow depth as proxy for the grid cell has to be selected carefully.

In this article, we propose a method to correct flat field snow depth to describe domain-averaged snow depth (i.e., gridded snow depth) over complex, nonforested topography. To derive such a parameterization, we used several spatial snow depth data sets from two large regions in the Eastern Swiss Alps and from one region in the Eastern Spanish Pyrenees [*Moreno Banos et al.*, 2009; *Grünwald et al.*, 2013; *Bühler et al.*, 2015]. The highly resolved snow depth data from consecutive years were all acquired close to the peak of winter. A large number of snow depth subsets were obtained by randomly selecting domains of different sizes

Figure 1. (a) Measured snow depth on 20 March 2012 at Wannengrat and Dischma area in the eastern Swiss Alps. The underlying pixel map (1:200'000) stems from swisstopo [copyright] 2008. (b) Measured snow depth map on 9 March 2009 at Val de Núria in the eastern part of the Spanish Pyrenees. The black squares illustrate examples of randomly selected domains of varying size. The red stars show locations of automatic weather stations.

120 km² (Dischma) (Figure 1a). Wannengrat and Dischma span elevations from 1517 to 2781 m and from 1516 to 3227 m, respectively. Wannengrat has a mean regional elevation z_{reg} of 2236 m. The perimeter of the Dischma area changed slightly between the three gathering years leading to slightly different mean elevations z_{reg} of 2393 m for 2012 and 2013 and of 2383 m for 2015. The third alpine region, Val de Núria, is located in the Eastern Spanish Pyrenees and covers about 28 km² (Figure 1b). Val de Núria has a z_{reg} of 2535 m and elevations ranging from 1910 to 2910 m. More details on the study regions can be found in Helbig et al. [2015].

Spatial snow depth data for the Swiss regions were obtained from summer and winter stereo images using an optoelectronic line scanner (Sensor ADS80 and ADS100 from Leica Geosystems) [Bühler et al., 2012, 2015]. The snow depth maps have a horizontal resolution of 2 m and a Root-Mean-Square error (RMSE) of approximately 0.3 m compared to simultaneously conducted terrestrial laser scanning (TLS) measurements [Bühler et al., 2015]. The accuracy of the summer DSM was assessed using a digital terrain model acquired with airborne laser scanning (ALS). A similar RMSE of approximately 0.3 m was obtained. For the two Swiss

within each region, as was done by Helbig et al. [2015] to derive a parameterization for fractional snow covered area. In this manner, we were able to systematically analyze a variety of terrain characteristics in typically encountered domain sizes. We related subgrid terrain parameters, i.e., unresolved summer terrain parameters, of these subsets to domain-averaged snow depth using regional means of flat field snow depth measurements. Based on this, we were able to scale single flat field snow depth measurements to obtain domain-averaged snow depth by only using terrain parameters that describe subgrid topographic impacts, i.e., the unresolved spatial variability. In the conclusions, we discuss a potential application for coarse-scale winter precipitation once transformed into snow depth values [Martinec and Rango, 1991; Jonas et al., 2009].

2. Data

2.1. Spatial Snow Depth Data

Seven spatially continuous snow depth data sets from three alpine, mostly nonforested regions in two distant geographic locations were used to analyze snow depth as a function of terrain parameters. Two locations, called Wannengrat and Dischma, are located near Davos in the Eastern Swiss Alps covering about 30 km² (Wannengrat) and

regions, we used snow depth maps around the peak of winter from 3 years (20 March 2012, 15 April 2013, and 15 April 2015). Spatial snow depth data at a horizontal resolution of 1 m for the region in Spain were gathered by ALS [Moreno Banos *et al.*, 2009; Grünewald *et al.*, 2013]. The mean accuracy of this data set is also around 0.3 m. One data set was acquired around the peak of winter on 9 March 2009.

2.2. Flat Field Snow Depth Measurements

Automatic weather stations (AWS) around the Wannengrat and Dischma regions were used to obtain flat field snow depth measurements (HS_{stat}). The stations are part of the Intercantonal Measurement and Information System (IMIS) operated by the WSL Institute of Snow and Avalanche Research SLF [Lehning *et al.*, 1999]. Snow depth is measured automatically with an ultrasonic sensor (mounted on a mast 6 m above ground). The sensor has an accuracy of about 2 cm [Jonas *et al.*, 2008]. While there are several AWSs in the immediate vicinity, for each region, we selected only one AWS with a low terrain horizon and low slope angle (red stars in Figure 1a). Terrain horizons are commonly computed from surrounding terrain elevations to decide if a grid cell of a digital elevation model (DEM) is shaded from the sun or not. Here, we compute horizon angles following the algorithm presented in Helbig *et al.* [2009]. For the Val de Núria region, there was a manual snow depth observation at 9 March 2009 close to an AWS (red star in Figure 1b).

3. Methods

3.1. Aggregating Snow Depth Data

In order to perform a scale-dependent analysis, we determined mean snow depth HS_L in squared domain sizes L of 50, 100, 200, 500, 750, 1000, 1250, 1500, 1750, 2000, 2500, and 3000 m. We assume that this broad range of domain sizes captures a range of spatial snow depth-shaping processes. A domain size L can also be seen as a large-scale model grid cell Δx . By randomly selecting 50 realizations of each L within each region (allowing for overlap) and for each measurement day (Figure 1), we created a total of 3600 snow depth grids for the two Swiss sites and 400 grids for the Spanish site. For the latter we could only average snow depth data up to $L=1500$ m. Note that each of our domain size L has to have at least 75% valid snow depth values. The large number of snow depth grids allows a systematic analysis accounting for a variety of terrain characteristics.

The goal of this study is to develop a parameterization for domain-averaged snow depth HS_L using a single flat field snow depth measurement HS_{stat} . To develop the parameterization, we therefore derived mean flat field snow depth within each domain $HS_{L,flat}$ by averaging all highly resolved flat field snow depth values within each domain of size L . Flat fields were defined as locations where each slope angle $\leq 10^\circ$ within an area of $22 \times 22 \text{ m}^2$ for Wannengrat and Dischma or $11 \times 11 \text{ m}^2$ for Val de Núria [Helbig *et al.*, 2015]. Averaging flat field snow depths within each domain of size L should provide a good proxy for the actual flat field snow depth within that domain. A similar procedure to select flat field sites in highly resolved data sets was suggested by Grünewald and Lehning [2015]. The procedure was derived based on site conditions prescribed when the IMIS station network in Switzerland was set up. The site conditions were chosen in order to obtain reliable flat field snow depth measurements. Here, we had to slightly modify the prescribed 20 m radius surrounding the stations to match the characteristics of the available data sets.

The HS_L values were derived from seven different snow depth data sets acquired in different geographical locations and/or different winters. To identify common trends between snow depth and terrain characteristics therefore requires normalizing the data (Figure 2). We introduce two normalized variables, namely the normalized domain-averaged snow depth $HS_L^{norm} = HS_L / HS_{flatreg}$, with $HS_{flatreg}$ the regional mean of all $HS_{L,flat}$, and the normalized domain-averaged elevation $z_L^{norm} = z_L / z_{flatreg}$, with $z_{flatreg}$ the mean regional elevation of all $HS_{L,flat}$. When normalizing the data in such a manner, overall trends become more apparent since the normalization removes temporal and geographical (i.e., climatic) influences (compare Figures 2a and 2b). Normalization was only required for elevation. Other topographic parameters, such as the mean-squared slope or the sky view factor (see below), do not require normalization since these are derived from elevation differences (gradients).

3.2. Terrain Characteristics

To find the dominant terrain shaping characteristics for HS_L , we derived several terrain parameters from the corresponding summer digital surface model (DSM). For each domain of size L , we derived normalized

Figure 2. (a) Snow depth HS_L as a function of elevation z_L . (b) Normalized snow depth $HS_L^{\text{norm}} = HS_L / HS_{\text{flatreg}}$ as a function of normalized domain-averaged elevation $z_L^{\text{norm}} = z_L / z_{\text{flatreg}}$. Colors indicate the seven different snow depth data sets named by their first two letters and the acquiring year (e.g., “VA09” is Val de Núria 2009). The Spearman correlation r is shown in the top left corner.

domain-averaged elevation ($z_{L,\text{flat}}^{\text{norm}} = z_L / z_{L,\text{flat}}$ and z_L^{norm}), a slope-related parameter, a subgrid correlation length, and the subgrid-parameterized sky view factor which we define in the following. Similar to Helbig *et al.* [2015], we made use of the fact that slope characteristics of real topographies can reasonably well be approximated by Gaussian statistics [Helbig and Löwe, 2012]. Each summer DSM of size $L \times L$ can then be described by only two underlying characteristic length scales, namely a valley-to-peak elevation difference σ (typical height of topographic features), and a lateral extension ξ (typical width of topographic features) describing the correlation length of the summer DSM. Using these two length scales, we derived a terrain parameter related to the mean-squared slope $\mu = \sqrt{2}\sigma / \xi$. It was derived from first partial derivatives of terrain elevations ($\partial_x z, \partial_y z$) in orthogonal directions using $2\mu^2 = (\partial_x z)^2 + (\partial_y z)^2 = \tan^2 \zeta = 4(\sigma / \xi)^2$, as outlined by Löwe and Helbig [2012]. The correlation length of the summer DSM ξ was derived via $\xi = \sqrt{2}\sigma_z / \mu$ using σ_z the standard deviation of the summer DSM. To ensure that enough terrain is included in a domain of size L to obtain reliable domain-averaged variables, the condition $\Delta x \ll \xi \ll L$ must be met [cf., Helbig *et al.*, 2009].

In order to derive the correct characteristic length scales for the corresponding domain of size L , terrain parameters were extracted from linearly detrended DSM's, similar to Helbig *et al.* [2015]. Using the above mentioned terrain parameters allowed us to compute the domain-averaged sky view factor $F_{\text{sky},L}$. Note that per definition the sky view factor describes the fraction of the radiative flux obtained by an inclined surface from the visible part of the sky to that obtained from a theoretical unobstructed hemisphere. The sky view factor for a surface which is unobstructed by surrounding topography is thus one and decreases to zero the more the surface is obstructed by topography. The domain-averaged sky view factor $F_{\text{sky},L}$ is computed by applying a recently presented subgrid parameterization of the form $F_{\text{sky}} = f(L / \xi, \mu)$ [Helbig and Löwe, 2014]:

$$F_{\text{sky}}(L / \xi, \mu) = \left(1 - \left(1 - \frac{1}{(1 + a\mu^b)^c} \right) e^{-d(L/\xi)^{-2}} \right), \quad (1)$$

The constant parameters are $a = 3.3547$, $b = 1.9988$, $c = 0.2029$, and $d = 5.951$. Equation (1) was developed based on numerically exact sky view factors. They are obtained from anisotropic terrain view factor sums (one-terrain view factor sum), which were computed using the radiosity approach on a large ensemble of Gaussian random fields (GRF) as topography models [Helbig *et al.*, 2009]. The parameterization compared very well to computed sky view factors on additional GRF model topographies with larger and smaller domain sizes than it was developed for. Furthermore, parameterized sky view factors matched domain-averaged sky view factors well on a large variety of real topographies from the United States and from entire Switzerland [Helbig and Löwe, 2014].

To sum up, for each domain of size L , we thus derived four topographic parameters, namely normalized domain-averaged elevation ($z_{L,\text{flat}}^{\text{norm}}$ and z_L^{norm}), mean-squared slope (μ_L), correlation length (ξ_L), and subgrid parameterized sky view factor ($F_{\text{sky},L}$). Furthermore, we used the L / ξ_L ratio, which roughly indicates how many topographic features are included in a domain size of L . When using the parameterization of the sky view factor $F_{\text{sky},L}$ we only used HS_L with $L \geq 500$ m to ensure that the condition $\xi_L \ll L$ was met [e.g., Helbig

and Löwe, 2014]. Excluding snow depth data grids with domain size $L < 500$ m when using $F_{sky,L}$ still allowed us to use 2950 data grids for the development of the parameterization.

3.3. Performance Statistics

To assess the performance of our parameterization, we used various statistical measures. Specifically, we used absolute error measures, namely the Normalized Root-Mean-Square Error (NRMSE) (normalized by the range of data), Mean-Absolute Error (MAE), and the Spearman correlation coefficient r as a measure for correlation. Furthermore, to investigate similarities between the density distributions, we computed probability density functions (pdf) and derive the NRMSE between data and parameterizations $NRMSE_{pdf}$. We also compute the NRMSE for Quantile-Quantile plots $NRMSE_{Q-Q}$ for probabilities with values in $[0.05, 0.95]$.

4. Results and Discussion

4.1. Correlation Between Snow Depth and Topographical Parameters

Combining the data from all data sets and restricting to domain sizes $L \geq 500$ m, the largest correlation was between normalized snow depth HS_L^{norm} and normalized elevation z_L^{norm} (Table 1). Clearly, snow depth increases with elevation, a well-established fact [e.g., Rohrer et al., 1994; Lehning et al., 2011]. Domain-averaged sky view factor negatively correlated with HS_L^{norm} , suggesting that snow depth decreases with increasing $F_{sky,L}$. Since larger domain-averaged sky view factors imply overall flatter terrain in a domain, which does not contain (or numerically resolve) many exposed steep ridges and peaks we would however have expected less snow to accumulate due to wind, incident radiation, or gravitational forces. Given the significant negative correlation between $F_{sky,L}$ and z_L^{norm} (for $L \geq 500$ m, Pearson $r = -0.22$, $p < 0.001$), we therefore hypothesize that the true correlation between snow depth and $F_{sky,L}$ is masked by the correlation with normalized elevation. Note that μ_L and $F_{sky,L}$ showed very similar correlations with opposite signs, which follows from the inverse relationship between μ_L and $F_{sky,L}$ (equation (1)).

To uncover the true correlation between snow depth and sky view factor therefore required detrending, the mean snow depth HS_L to remove the masking elevation trend. To do so, we first created a combined and sorted normalized elevation vector and divided it into N_w nonoverlapping windows containing an equal number of data points. These windows can be seen as normalized elevation bands of varying width. Then, for each window w , we determined the detrended snow depth by dividing the domain-averaged snow depth HS_L by the mean flat field snow depth $HS_{flatreg}$ within w for each data set separately: $HS_L^{detrend} = HS_L / HS_{flatreg} [z_L^{norm} \in w]$. Essentially, this procedure corresponds to removing a moving mean trend, which we deemed appropriate since the real elevation trend of snow depth is nonlinear and unknown [e.g., Grünwald et al., 2014].

When removing the elevation trend from HS_L in this manner (using $N_w = 50$) and when only incorporating domain sizes $L \geq 500$ m, we found a weak but significant positive correlation between $F_{sky,L}$ and $HS_L^{detrend}$ (Table 1 and Figure 3). Overall, we now find the opposite and more intuitive trend than before, namely that snow depth increases with increasing $F_{sky,L}$, i.e., with overall flatter topography in a domain. Note that μ_L again correlated similarly well with detrended snow depth.

The value of the Spearman correlation coefficient r between $F_{sky,L}$ and $HS_L^{detrend}$ was mostly insensitive to N_w (Figure 4a). However, for $N_w > 300$ the correlation coefficient decreased toward zero since for such a large number of windows the underlying $F_{sky,L}$ trend is also removed. On the contrary, for $N_w < 3$ the correlation coefficient became negative since the dominant elevation trend was not adequately removed. For $N_w = 50$ the r value is reliable.

Table 1. Correlation Statistics Between Topographic Parameters and Normalized Domain-Averaged Snow Depth HS_L^{norm} for $L \geq 500$ m and Detrended Domain-Averaged Snow Depth $HS_L^{detrend}$ for $L \geq 500$ m and $N_w = 50$ (See Section 4.1)^a

	z_L^{norm}	$F_{sky,L}$	μ_L	L/ξ_L	L
Normalized Domain-Averaged Snow Depth					
Spearman r	0.65	-0.22	0.18	0.13	0.04
p Value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Detrended Domain-Averaged Snow Depth					
Spearman r	-0.006	0.12	0.14	0.05	0.10
p Value	0.76	< 0.001	< 0.001	0.013	< 0.001

^aThe topographic parameters consist of normalized domain-averaged terrain elevations $z_L^{norm} = z_L / z_{flatreg}$, subgrid parameterized sky view factor $F_{sky,L}$, mean-squared slope μ_L , and the ratio of domain size and correlation length L/ξ_L and domain-size L .

number of windows the underlying $F_{sky,L}$ trend is also removed. On the contrary, for $N_w < 3$ the correlation coefficient became negative since the dominant elevation trend was not adequately removed. For $N_w = 50$ the r value is reliable.

The overall goal is to develop a parameterization independent of specific grid cell size, which is why we used all domain sizes L . Nevertheless, we found that correlations between $HS_L^{detrend}$ and $F_{sky,L}$ increased with

Figure 3. Detrended domain-averaged snow depth $HS_L^{\text{detrend}} = HS_L / HS_{\text{flatreg}} [z_L^{\text{norm}} \in w]$ as a function of subgrid parameterized sky view factors $F_{\text{sky},L}$ for $L \geq 500$ m. We used $N_w = 50$ nonoverlapping windows. Colors show normalized domain-averaged elevation $z_L^{\text{norm}} = z_L / z_{\text{flatreg}}$. The black line shows the moving mean with 50 windows.

increasing domain size L (Figure 4b), when more terrain is included in the domain (larger L/ξ_L ratio), and $r > 0.1$ for $L > 1000$ m. This is consistent with results presented by Helbig and Löwe [2014], who found that parameterized and computed domain-averaged $F_{\text{sky},L}$ on real topographies agree better for larger L and larger L/ξ_L ratios. Furthermore, Melvold and Skaugen [2013]; Helbig et al. [2015] also suggested a lower limit of $L \geq 1000$ m necessary to minimize scatter when computing the standard deviation of snow depth for coarse-scale grid cells.

4.2. Parameterization of Domain-Averaged Snow Depth

The correlation analysis above suggests that a parameterization of domain-averaged snow depth HS_L based on topographical parameters and regional averages of flat field snow depth HS_{flatreg} is feasible. Since elevation correlated best with snow depth, it seems obvious that any parameterization will have to include elevation. Linear lapse rates are the easiest choice for altitudinal lapse rates of many meteorological parameters, e.g., linear lapse rates are already well-established to describe the decrease of air temperature with elevation. Here, the choice of a linear lapse rate for snow depth was also based on observed, mostly positive correlations between elevation and measured snow depth [e.g., Turcan, 1975; Grünwald et al., 2014; Kirchner et al., 2014] as well as between elevation and precipitation gauges [e.g., Sevruck and Mieglistz, 2002]. Note however that topographic and climate conditions of upper and lower gauges can clearly affect computed precipitation gradients Sevruck and Mieglistz [e.g., 2002].

Figure 4. Correlation coefficient r between detrended domain-averaged snow depth HS_L^{detrend} and parameterized sky view factors $F_{\text{sky},L}$ for (a) a range of number of normalized domain-averaged elevation (z_L^{norm}) nonoverlapping windows N_w and (b) for the given domain size L .

Based on the seven snow depth data sets and using all L , i.e., $L \geq 50$ m, we obtained an average lapse rate of 0.0014 (i.e., 14 cm/100 m), thus we formulated the first parameterization (P1) for HS_L as

$$HS_L = HS_{flatreg} + 0.0014 (z_L - z_{flatreg}), \quad (2)$$

or in terms of the two normalized variables HS_L^{norm} and z_L^{norm} :

$$HS_L^{norm} = 1 + \frac{0.0014 z_{flatreg}}{HS_{flatreg}} (z_L^{norm} - 1).$$

The constant lapse rate in equation (2), as well as all fit parameters presented below, were obtained from nonlinear regression analysis by robust M-estimators using iterated reweighted least squares (see R v3.2.3 statistical programming language [R Core Team, 2015] and its robustbase v0.92-5 package [Rousseeuw et al., 2015]). Thus, assuming a linear lapse rate essentially corresponds to assuming that HS_L scales linearly with z_L . Note that our rather steep lapse rate of 14 cm/100 m compares reasonably well with previously reported lapse rates. For instance, *Kirchner et al.* [2014] obtained a lapse rate at peak of winter of 15 cm/100 m from LIDAR measured snow depth from snowline to about 3300 m on the west slope of the Southern Sierra Nevada (equivalent to about 60 mm SWE/100 m). Based on long-term of snow water equivalent measurements in a basin of the Swiss Alps, *Rohrer et al.* [1994] found similar overall linear increases between 70 and 80 mm SWE/100 m depending on terrain aspect of the measurement stations.

While accounting for elevation is obviously required, the results from the correlation analysis presented above (section 4.1) suggest that there are also other significant topographic dependencies. Once the elevation trend in snow depth was removed remaining significant correlations between detrended snow depth and these topographic parameters became obvious (Table 1). The two largest correlations were obtained for the subgrid sky view factor $F_{sky,L}$ and mean-squared slope μ_L . Even though the correlations were very similar for both terrain parameters, we selected $F_{sky,L}$ rather than μ_L because $F_{sky,L}$ is an intuitive measure over unresolved topography. Furthermore, the subgrid parameterization for the sky view factor was previously used to parameterize the influence of unresolved topography on the surface radiation balance in complex terrain [*Helbig and Löwe*, 2012] and most recently to scale coarse-scale wind speeds for unresolved sheltering/exposure [*Helbig et al.*, 2016]. It is thus a terrain parameter which can be used to scale subgrid influences of topography in coarse flat grid cells. Our second parameterization (P2) for HS_L therefore includes the subgrid parameterized sky view factor $F_{sky,L}$. Furthermore, we relaxed the linear assumption and describe the elevation trend with a power law:

$$HS_L = HS_{flatreg} \frac{g}{(1 + k(1 - F_{sky,L})^l)} \left(\frac{z_L}{z_{flatreg}} \right)^h, \quad (3)$$

or again in terms of the two normalized variables HS_L^{norm} and z_L^{norm} :

$$HS_L^{norm} = \frac{g}{(1 + k(1 - F_{sky,L})^l)} (z_L^{norm})^h,$$

with constant fit parameters $g = 0.8674$, $h = 2.3108$, $k = 561.7908$, and $l = 4.9613$. Thus, P2 combines two power law relationships, one for normalized elevation (derived using $L \geq 50$ m) and one for the subgrid parameterized sky view factor (derived using $L \geq 500$ m).

Overall, our second parameterization outperformed the linear lapse rate (Table 2). Only for a few data sets some performance measures were better when using P1, for instance for Val de Núria. However, the overall performance of P2 was clearly better than P1 (see “all” in Table 2). Thus, a linear lapse rate model is not the most appropriate to estimate domain-averaged snow depth. Clearly, one reason is that a constant lapse rate cannot be used over the entire elevation range. Indeed, based on snow depth measurements, *Grünwald et al.* [2014], *Kirchner et al.* [2014], and *Turcan* [1975] found that snow depth decreases above a certain elevation, while, using numerical weather prediction (NWP) forecasted seasonal snowfall, *Vionnet et al.* [2016] showed that the increase in precipitation with elevation may also become less steep or level out above a certain elevation. These results suggest that a linear lapse rate model would perform more poorly at higher elevations. However, P2 outperformed P1 over the entire elevation range (Figure 5), suggesting that a parameterization combining elevation and subgrid sky view factor is more robust than a

Table 2. Performance Measures for the Two Snow Depth Parameterizations P1 and P2, Using Flat Field Means of Highly Resolved Snow Depth for Each Region $HS_{flatreg}$, i.e., Equations (2) and (3)^a

Data Set	Parameterization	r	MAE (cm)	NRMSE (%)	NRMSE _{pdf} (%)	NRMSE _{Q-Q} (%)
VA09	P1 equation (2)	0.48	19.7	12.4	20.5	8.5
	P2 equation (3)	0.48	22.5	14.1	25.8	21.2
WA15	P1 equation (2)	0.72	20.1	13.0	21.8	23.0
	P2 equation (3)	0.74	13.7	9.0	19.2	11.4
DI15	P1 equation (2)	0.83	39.2	16.8	34.3	33.2
	P2 equation (3)	0.83	27.0	12.1	24.5	13.3
WA13	P1 equation (2)	0.83	25.5	13.0	27.0	15.7
	P2 equation (3)	0.83	18.8	10.5	20.4	8.5
DI13	P1 equation (2)	0.73	15.9	9.7	18.8	20.7
	P2 equation (3)	0.77	15.8	8.9	18.5	18.5
WA12	P1 equation (2)	0.56	29.8	14.6	24.5	35.6
	P2 equation (3)	0.60	16.1	9.3	13.1	8.5
DI12	P1 equation (2)	0.77	50.7	15.3	29.3	29.4
	P2 equation (3)	0.77	30.4	10.6	19.8	13.0
All	P1 equation (2)	0.87	29.3	7.7	17.2	14.9
	P2 equation (3)	0.88	20.5	5.7	14.2	3.1

^aAll data area used for $L \geq 500$ m. Spearman correlations coefficient r , Mean Absolute Error (MAE), Normalized Root Mean Squared Error (NRMSE), NRMSE for probability density functions (NRMSE_{pdf}), and NRMSE of Quantile-Quantile (NRMSE_{Q-Q}) plots for probabilities in [0.05,0.95] are shown. Data sets are named by their first two letters and the acquiring year (e.g., "VA09" is Val de Núria 2009). Best statistic measures are marked in bold.

linear lapse rate. *Kirchner et al.* [2014] also found deviations from a linear lapse rate already at intermediate elevations, which they explained with local topographic impacts consisting of different aspect and steepness characteristics. Note, that all subgrid parameterizations for snow depth presented here were developed for peak of winter snow depth data.

4.3. Estimating Domain-Averaged Snow Depth From Flat Field Measurements

The constant lapse rate parameterization can directly be applied to estimate domain-averaged snow depth from single flat field measurements by substituting HS_{stat} for $HS_{flatreg}$ and z_{stat} for $z_{flatreg}$ in equation (2):

Figure 5. Performance statistics between domain-averaged and parameterized snow depth HS_L using a linear elevation trend P1 (equation (2)) and our combined parameterization consisting of a power law for normalized elevation and one for the subgrid parameterized sky view factor P2 (equation (3)) as a function of mean domain-averaged normalized elevation z_L^{norm} . Depicted statistics are (a) Correlation coefficient r , (b) MAE, (c) NRMSE, and (d) NRMSE for probability density functions (pdf) (NRMSE_{pdf}) for all data sets and for domain sizes $L \geq 500$ m. We used 10 windows allowing for 75% overlap.

$$HS_L^{P1} = HS_{stat} + 0.0014 (z_L - z_{stat}) . \quad (4)$$

The second parameterization (equation (3)) presented above, on the other hand, is of the form $HS_L^{norm} = HS_L / HS_{flatreg} \propto f(z_L^{norm}, F_{sky,L}) = f(z_L / z_{flatreg}, F_{sky,L})$ and can thus also be used to estimate domain-averaged snow depth HS_L . However, this requires two regional mean values, namely $HS_{flatreg}$ and $z_{flatreg}$. This can be circumvented by evaluating the parameterization at the location of the single flat field snow depth measurement HS_{stat} and solving for $HS_{flatreg}$, i.e., $HS_{flatreg} \propto HS_{stat} / f(z_{stat} / z_{flatreg}, F_{sky,stat})$. By inserting this value in the parameterization, the domain-averaged snow depth HS_L can be derived without requiring $HS_{flatreg}$:

$$HS_L^{P2} = HS_{stat} \frac{(1 + k(1 - F_{sky,stat})^I)}{(1 + k(1 - F_{sky,L})^I)} \cdot \left(\frac{z_L}{z_{stat}}\right)^h, \quad (5)$$

The advantage of first deriving relationships between regional means of highly resolved flat field snow depth measurements and topographic parameters (equations (2) and (3)) thus becomes clear since we only had to reformulate both equations to obtain equations for domain-averaged snow depth HS_L using single flat field snow depth measurements as input. It is now possible to estimate HS_L from HS_{stat} by only using easy to derive topographic parameters. In equation (5), we introduced the sky view factor at the flat field site $F_{sky,stat}$. Note, that $F_{sky,stat}$ is not a subgrid parameter as the $F_{sky,L}$ in equation (1). It is the sky view factor computed for the station grid cell on a fine-scale DEM. We used a 25 m DEM covering the two Swiss AWS (see <http://www.swisstopo.ch>) and a 5 m DEM covering the Spanish weather station (<https://www.ign.es/ign/main/index.do?locale=en>). Here, we compute the sky view factor for that surface patch from numerically exact anisotropic terrain view factor sums (for computational details cf., Helbig et al. [2009]). A close approximation can easily be computed from integrating around the horizon in a sloped coordinate system [cf., Manners et al., 2012]. If the site would be a true flat field site, without any obstruction in a 360° field of view, $F_{sky,stat}$ would equal one. On most flat field sites in mountainous terrain this is however not the case. A $F_{sky,stat}$ lower than one means a site is sheltered and HS_{stat} is increased in order to correct for a possible reduced precipitation (see equation (5)).

When using a single flat field snow depth measurement to estimate domain-averaged snow depth HS_L , performance measures obviously changed compared to using regional mean flat field snow depth $HS_{flatreg}$ to estimate HS_L (compare Tables 2 and 3). Interestingly, for P1 (equations (2) and (4)) performance improved for three of the data sets as well as for the combined data set ("all") (Figure 6a). For the second parameterization P2 (equations (3) and (5)), on the other hand, performance decreased for all but one data set as well as for the combined data set (Figure 6b). The overall performance improvement for P1 was unexpected as surely a single flat field snow depth measurement is less representative than the regional mean of $HS_{L,flat}$. Nevertheless, for most data sets as well as the combined data set overall performance statistics were again better for P2 than for P1 (Table 3).

Table 3. The Same Performance Measures as in Table 2 for the Two Snow Depth Parameterizations P1 and P2^a

Data Set	Parameterization	<i>r</i>	MAE (cm)	NRMSE (%)	NRMSE _{pdf} (%)	NRMSE _{Q-Q} (%)
VA09	P1 equation (4)	0.48	29.2	16.9	27.9	28.0
	P2 equation (5)	0.48	25.0	15.4	28.3	25.5
WA15	P1 equation (4)	0.72	22.0	13.9	22.7	25.4
	P2 equation (5)	0.74	19.0	12.4	20.5	21.3
DI15	P1 equation (4)	0.83	28.1	12.5	25.3	14.0
	P2 equation (5)	0.83	27.5	12.3	25.0	13.7
WA13	P1 equation (4)	0.83	55.8	26.2	32.9	40.4
	P2 equation (5)	0.83	52.8	25.6	35.1	39.3
DI13	P1 equation (4)	0.73	23.8	12.5	25.5	32.2
	P2 equation (5)	0.77	25.3	13.0	25.1	34.8
WA12	P1 equation (4)	0.56	16.0	9.1	16.1	11.4
	P2 equation (5)	0.60	16.2	9.4	13.1	9.0
DI12	P1 equation (4)	0.77	25.2	10.5	12.6	11.5
	P2 equation (5)	0.77	24.5	10.2	11.2	9.0
All	P1 equation (4)	0.71	28.5	7.7	13.6	4.4
	P2 equation (5)	0.73	27.3	7.5	12.9	6.6

^aHowever, now single flat field measurements HS_{stat} are used, i.e., equations (4) and (5). Best statistic measures are marked in bold.

Figure 6. Relative errors between a range of performance measures (X) obtained for (a) linear elevation trend parameterization P1 and (b) our combined parameterization consisting of a power law for normalized elevation and one for the subgrid parameterized sky view factor P2. $X_{flatreg}$ indicates applying the parameterizations using the regional mean flat field snow depth measurements (equations (2) and (3)). X_{stat} indicates applying the reformulated parameterizations using single flat field snow depth measurements (equations (4) and (5)). Data sets are named by their first two letters and the acquiring year (e.g., “VA09” is Val de Núria 2009).

With more representative flat field snow depth measurements, the performance of P1 and P2 could further improve. Performance statistics should however be evaluated using the parameterizations applying the regional means of flat field snow depth measurements (equations (2) and (3)) rather than using the parameterizations applying a single flat field snow depth measurement (equations (4) and (5)). Using single flat field measurements only, introduces unknown errors from either measurement devices or local site characteristics which might bias the performance. For instance, if the single flat field station is exposed to wind resulting in a reduced snow depth, this is not corrected for in our parameterizations. With this in mind and knowing that our parameterizations were derived based on highly resolved high-quality snow depth data, i.e., not using locally measured flat field snow depth, the results presented here are very encouraging.

5. Conclusion and Outlook

We presented a simple method to scale a flat field snow depth measurement to derive mean snow depth in a coarse-scale grid cell over complex, alpine topography. We compared two parameterizations with varying complexity, namely a commonly applied simple linear lapse rate and a parameterization based on a power law elevation trend scaled with subgrid parameterized sky view factor. Input parameters are easy to derive terrain parameters in combination with a representative flat field snow depth measurement.

Overall, the more complex parameterization performed better than a linear lapse rate. Including a factor based on the subgrid parameterized sky view factor in the parameterization corrects for the diminishing snow depth at higher elevation, where the sky view factor generally decreases. Nevertheless, the increase in snow depth with elevation is the most important trend to account for, which can better be approximated with a power law. We conclude that for grid cell sizes $L > 1000$ m it is possible to describe subgrid terrain influences on domain-averaged snow depth since local variability is mainly averaged out. For smaller grid cell sizes, fine-scale modelling is required to account for local topographic influences. The presented

parameterization can thus be used in coarse-scale models to more realistically depict mean snow depth in grid cells over complex topography, for instance as input for fractional snow-covered area parameterizations [e.g., Helbig et al., 2015].

Our parameterizations were derived based on highly resolved high-quality snow depth data. However, they were evaluated using both a single point snow depth measurement for each region as well as a regional mean of flat field high-resolution snow depth measurements. Performances between measured and parameterized snow depth decreased for the parameterizations when applying a single flat field snow depth measurement. This decrease was expected since single flat field snow depth measurements are less representative and may introduce unknown errors. Nevertheless, the overall reasonable performance suggest that single flat field snow depth measurements can be used to estimate domain-averaged snow depth. While at first this might seem to contradict the findings of Grünwald and Lehning [2015], this is not actually the case since they only compared flat field snow depth to mean snow depth of the surrounding terrain, without any topographic scaling.

The proposed parameterizations were developed using data sets of high-resolution snow depth data from three different geographical regions, in two distinct climatic regions and from four different winter seasons. By pooling all data and only using normalized snow depth and elevation values, in principle the proposed parameterizations are not bound by specific geographic regions. Nevertheless, to confirm our results, our method should be evaluated in other areas. Furthermore, since we only investigated snow depth data at peak of winter, future efforts to confirm or improve the results obtained here will require including other periods during the accumulation and the ablation season, once more spatial snow depth data become available [e.g., Deems et al., 2013]. Since we used spatial snow depth data on the ground at peak of winter, this implies that all processes leading to the snow depth distribution at peak winter were implicitly parameterized, including snow redistribution due to wind, spatially variable settling rates or snow relocation due to avalanches. At this point, it is unconfirmed if our presented method can also be used to scale coarse solid precipitation input as e.g., from a NWP model. While developing a parameterization for precipitation based on spatial radar measurements would be a solution, thus far radar observations lack the required accuracy, in particular close to the ground [e.g., Scipion et al., 2013]. Thus, as a first approximation, we believe our method can also be used to scale solid precipitation input (once transformed to snow depth) in coarse-scale models, which until now do not account for the underlying unresolved topography.

Acknowledgments

We would like to thank Yves Bühler and Thomas Grünwald for ADS and ALS data preparation, respectively. The authors thank Samuel Morin and two other anonymous reviewers for helpful comments on the manuscript. This study was partly funded by the Federal Office of the Environment FOEN. The data used in this study are listed in the references.

References

- Bühler, Y., M. Marty, and C. Ginzler (2012), High resolution DEM generation in high-alpine terrain using airborne remote sensing techniques, *Trans. GIS*, 16(5), 635–647.
- Bühler, Y., M. Marty, L. Egli, J. Veitinger, T. Jonas, P. Thee, and C. Ginzler (2015), Snow depth mapping in high-alpine catchments using digital photogrammetry, *Cryosphere*, 9, 229–243, doi:10.5194/tc-9-229-2015.
- Deems, J. S., T. Painter, and D. Finnegan (2013), Lidar measurement of snow depth: A review, *J. Glaciol.*, 59, 467–479.
- Farinotti, D., L. Longuevergne, G. Moholdt, D. Duethmann, T. Mölg, T. Bolch, S. Vorogushyn, and A. Güntner (2015), Substantial glacier mass loss in the Tien Shan over the past 50 years, *Nat. Geosci.*, 8, 716–722, doi:10.1038/ngeo2513.
- Goovaerts, P. (2000), Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall, *J. Hydrol.*, 228, 113–129.
- Grünwald, T., and M. Lehning (2015), Are flat-field snow depth measurements representative? A comparison of selected index sites with areal snow depth measurements at the small catchment scale, *Hydrol. Processes*, 29, 1717–1728, doi:10.1002/hyp.10295.
- Grünwald, T., J. Stötter, J. Pomeroy, R. Dadić, I. Moreno Banos, J. Marturia, M. Spross, C. Hopkinson, P. Burlando, and M. Lehning (2013), Statistical modelling of the snow depth distribution in open alpine terrain, *Hydrol. Earth Syst. Sci.*, 17, 3005–3021.
- Grünwald, T., Y. Bühler, and M. Lehning (2014), Elevation dependency of mountain snow depth, *Cryosphere*, 8, 2381–2394, doi:10.5194/tc-8-2381-2014.
- Helbig, N., and H. Löwe (2012), Shortwave radiation parameterization scheme for subgrid topography, *J. Geophys. Res.*, 117, D03112, doi:10.1029/2011JD016465.
- Helbig, N., and H. Löwe (2014), Parameterization of the spatially averaged sky view factor in complex topography, *J. Geophys. Res. Atmos.*, 119, 4616–4625, doi:10.1002/2013JD020892.
- Helbig, N., H. Löwe, and M. Lehning (2009), Radiosity approach for the surface radiation balance in complex terrain, *J. Atmos. Sci.*, 66, 2900–2912, doi:10.1175/2009JAS2940.1.
- Helbig, N., A. van Herwijnen, J. Magnusson, and T. Jonas (2015), Fractional snow-covered area parameterization over complex topography, *Hydrol. Earth Syst. Sci.*, 19, 1339–1351, doi:10.5194/hess-19-1339-2015.
- Helbig, N., R. Mott, A. van Herwijnen, A. Winstral, and T. Jonas (2016), Parameterizing surface wind speed over complex topography, *J. Geophys. Res. Atmos.*, 121, doi:10.1002/2016JD025593, in press.
- Jonas, T., C. Rixen, M. Sturm, and V. Stoeckli (2008), How alpine plant growth is linked to snow cover and climate variability, *J. Geophys. Res.*, 113, G03013, doi:10.1029/2007JG000680.
- Jonas, T., C. Marty, and J. Magnusson (2009), Estimating the snow water equivalent from snow depth measurements in the Swiss alps, *J. Hydrol.*, 378, 161–167, doi:10.1016/j.jhydrol.2009.09.021.

- Kirchner, P. B., R. C. Bales, N. P. Molotch, J. Flanagan, and Q. Guo (2014), LiDAR measurement of seasonal snow accumulation along an elevation gradient in the southern Sierra Nevada, California, *Hydrol. Earth Syst. Sci.*, **18**, 4261–4275, doi:10.5194/hess-18-4261-2014.
- Lehning, M., P. Bartelt, B. Brown, T. Russi, U. Stöckli, and M. Zimmerli (1999), Snowpack model calculations for avalanche warning based upon a new network of weather and snow stations, *Cold Reg. Sci. Technol.*, **30**, 145–157.
- Lehning, M., T. Grünwald, and M. Schirmer (2011), Mountain snow distribution governed by an altitudinal gradient and terrain roughness, *Geophys. Res. Lett.*, **38**, L19504, doi:10.1029/2011GL048927.
- Löwe, H., and N. Helbig (2012), Quasi-analytical treatment of spatially averaged radiation transfer in complex topography, *J. Geophys. Res.*, **117**, D19101, doi:10.1029/2012JD018181.
- Manners, J., S. B. Vosper, and N. Roberts (2012), Radiative transfer over resolved topographic features for high resolution weather prediction, *Q. J. R. Meteorol. Soc.*, **138**(664), 720–733, doi:10.1002/qj.956.
- Martinez, J., and A. Rango (1991), Indirect evaluation of snow reserves in mountain basins, in *Snow, Hydrology and Forest in High Alpine Areas (Proceedings of the Vienna Symposium)*, vol. 205, pp. 111–120, IAHS Publ., Vienna.
- Melvold, K., and T. Skaugen (2013), Multiscale spatial variability of lidar-derived and modeled snow depth on Hardangervidda, Norway, *Ann. Glaciol.*, **54**(62), 273–281.
- Moreno Banos, I., A. Ruiz Garcia, J. Marturia I Alavedra, P. Oller I Figueras, J. Pina Iglesias, C. Garcia Selles, P. Martinez I Figueras, and J. Talaya Lopez (2009), Snowpack depth modelling and water availability from lidar measurements in eastern pyrenees, in *Proceedings of the International Snow Science Workshop ISSW 2009 Europe, 27 September-2 October 2009, Davos, Switzerland*, edited by J. Schweizer and A. van Herwijnen, pp. 202–206, International Snow Science Workshop ISSW, Davos, Switzerland, 27 September - 2 October 2009, Swiss Federal Institute for Forest, Snow and Landscape Research WSL.
- Mott, R., D. Scipion, M. Schneebeli, N. Dawes, A. Berne, and M. Lehning (2014), Orographic effects on snow deposition patterns in mountainous terrain, *J. Geophys. Res. Atmos.*, **119**, 1419–1439, doi:10.1002/2013JD019880.
- R Core Team (2015), *R: A Language and Environment for Statistical Computing*, R Found. for Stat. Comput., Vienna, Austria.
- Roesch, A., M. Wild, H. Gilgen, and A. Ohmura (2001), A new snow cover fraction parameterization for the ECHAM4 GCM, *Clim. Dyn.*, **17**, 933–946.
- Rohrer, M., L. Braun, and H. Lang (1994), Long-term records of snow cover water equivalent in the Swiss Alps 1. Analysis, *Nord. Hydrol.*, **25**, 53–64.
- Rousseeuw, P., C. Croux, V. Todorov, A. Ruckstuhl, M. Salibián-Barrera, T. Verbeke, M. Koller, and M. Maechler (2015), *robustbase: Basic Robust Statistics*, R package version 0.92-5. [Available at <http://CRAN.R-project.org/package=robustbase>.]
- Schweizer, J., J. Jamieson, and M. Schneebeli (2003), Snow avalanche formation, *Rev. Geophys.*, **41**(4), 1016, doi:10.1029/2002RG000123.
- Scipion, D. E., R. Mott, M. Lehning, M. Schneebeli, and A. Berne (2013), Seasonal small-scale spatial variability in alpine snowfall and snow accumulation, *Water Resour. Res.*, **49**, 1446–1457, doi:10.1002/wrcr.20135.
- Sevruk, B., and K. Miegilitz (2002), The effect of topography, season and weather situation on daily precipitation gradients in 60 Swiss valleys, *Water Sci. Technol.*, **45**(2), 41–48.
- Turcan, J. (1975), Snow storage distribution in mountain watersheds, in *Proceedings of the Moscow Snow and Ice-Symposium Neige et Glaces, Moscow, Russia, August 1971*, vol. 104, pp. 335–340, IAHS AISH Publ. No. 104.
- Vionnet, V., I. D. Etchevers, M. Lafaysse, L. Queno, Y. Seity, and E. E. Bazile (2016), Numerical weather forecasts at kilometer scale in the French alps: Evaluation and application for snowpack modeling, *J. Hydrometeorol.*, **17**(10), 2591–2614.
- Voegeli, C., M. Lehning, N. Wever, and M. Bavay (2016), Scaling precipitation input to spatially distributed hydrological models by measured snow distribution, *Front. Earth Sci.*, **4**(108), 108, doi:10.3389/feart.2016.00108.
- Whiteman, C. D. (2000), *Mountain Meteorology: Fundamentals and Applications*, Oxford Univ. Press, Oxford University Press Inc, New York, N. Y.