Estimating Snow Cover Duration from Ground Temperature

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(Manuscript received 20 December 2014, in final form 20 February 2015)

ABSTRACT

Snow cover duration is commonly derived from snow depth, snow water equivalent, or satellite data. Snow cover duration has more recently also been inferred from ground temperature data. In this study, a probabilistic snow cover duration (SCD) model is introduced that estimates the conditional probability for snow cover given the daily mean and the diurnal range of ground temperature. For the application of the SCD model, 87 Austrian sites in the Alpine region are investigated in the period of 2000 to 2011. The daily range of ground temperature is identified to represent the primary variable in determining the snow cover duration. In the case of a large dataset, however, the inclusion of the daily mean ground temperature as the second given parameter improves results. Rank correlation coefficients of predicted versus observed snow cover duration are typically between 0.8 and 0.9.

1. Introduction

The relative snow cover duration n within a season is a parameter that can be used to describe the snow cover. It is defined here as the sum of days with a snow depth (SD) above a threshold $s = 0$ cm with respect to the total number of days in the considered period and, therefore, can take values from 0 to 1. Knowledge of the duration of the snow-covered period provides different applications. The variation of the snow cover duration can serve as a measure for climate change (e.g., Hantel and Maurer 2011). In vegetation ecology, the duration of the seasonal snow cover limits the length of the vegetation period and can therefore be linked to the occurrence of certain plant communities (Cutler 2011; Gottfried et al. 2011).

The snow cover duration is commonly obtained by measurements of SD or snow water equivalent or from satellite data. It has been shown that ground temperature data can serve as a proxy for snow cover through the insulating effect of snow (Hoelzle et al. 2003; Zhang 2005; Lundquist and Lott 2008; Tyler et al. 2008). When snow is present, the soil does not experience strong diurnal oscillations, whereas snow-free conditions are marked by a more pronounced daily amplitude of ground temperature, as illustrated in Fig. 1a for the measuring site Lunz in Austria. The reduction in the difference between the daily minimum and maximum of ground temperature (daily range of ground temperature ΔGT) in the presence of snow suggests that ground temperature is a suitable predictor for the snow cover condition.

Different approaches exist to infer the snow cover duration from ground temperature. One method involves the definition of both the beginning and the end of the snow season from ground temperature (e.g., Taras et al. 2002; Rixen et al. 2004; Vercauteren et al. 2014). Other methods make use of a combination of criteria for the daily amplitude of ground temperature and the daily mean ground temperature (Gądek and Leszkiewicz 2010; Cutler 2011; Apaloo et al. 2012; Rödder and Kneisel 2012). These methods often include the occurrence of these criteria on consecutive days (Gądek and Leszkiewicz 2010; Cutler 2011). Furthermore, the synchrony with air temperature can be involved in describing snow-free conditions (Zhang 2005). Figure 1b shows the conditional probability of snow with ΔGT as predictor and for the data of all measuring sites. The distribution of the conditional probability suggests that ΔGT alone might not always be sufficient to determine the snow cover. Therefore, the daily mean of ground temperature (MGT) is introduced as a second predictor.

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DOI: 10.1175/JAMC-D-15-0006.1

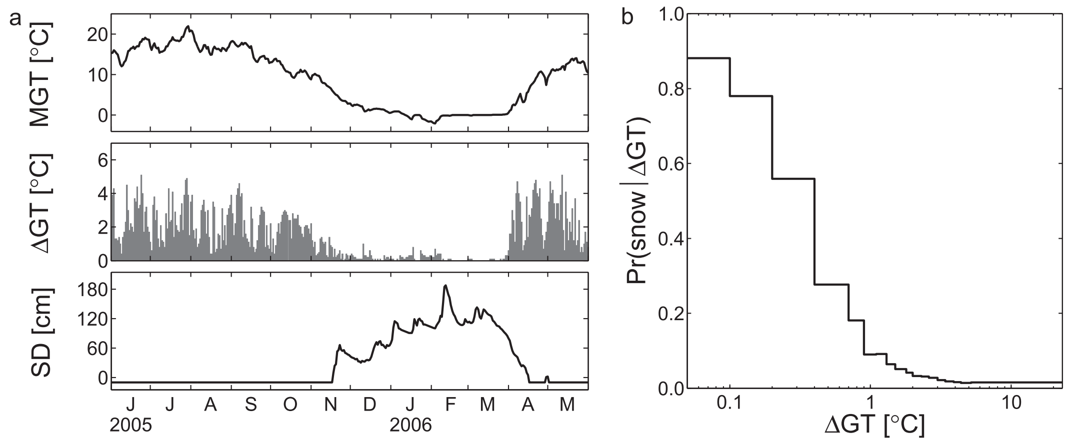

FIG. 1. (a) Time series of the daily MGT, the daily ΔGT, and the SD for the Lunz site (612 m MSL) in the snow year 2005/06. Snow-free conditions are represented by SD = −10 cm. (b) Conditional probability (Pr) of snow with ΔGT as given parameter. The probability was computed with the data of all 87 sites in both the calibration and the application period (2000–11). Note that ΔGT is displayed on a logarithmic scale. For the definition of the conditional probability see section 2b.

The aspect of gradually dividing ΔGT intervals along MGT is a new approach in the context of estimating the snow cover duration.

2. Method

a. Data and study area

The dataset includes 87 Austrian sites in the Alpine region. These sites cover altitudes ranging between 118 and 2304 m above mean sea level (MSL). For detailed information on the measuring sites see Teubner (2013). The data consist of daily SD measurements and hourly ground temperature data. Snow depth was determined with a snow-measuring stick, and ground temperature was obtained by Fenwal Electronics Co. thermistors with a precision of ±0.1°C located at 10 cm depth. Of the 87 sites, 53 possess a continuous time series of 10–11 years within the period of investigation (2000–11). Therefore, the snow cover duration (SCD) model was first tested on the dataset of the 53 sites and then was applied to all 87 sites. In both cases, the data were divided into a calibration period (January 2000–May 2005) and an application period (June 2005–May 2011). In this study, a snow year (whole year) refers to the period from the beginning of June to the end of May. The cold season is represented either by the short interval of December–February (DJF) or by the interval from November to April (NDJFMA).

b. SCD model

The statistical model consists of two steps: 1) the computation of the conditional probability of snow and 2) the determination of a threshold for this probability. Input variables for the model calibration are SD, ΔGT, and MGT. For the determination of the conditional probability of snow, it is necessary to define interval limits for the ground temperature variables. We use quantiles of ΔGT and MGT as interval boundaries. This has the advantage that there are sufficient data in every interval.

The conditional probability (Pr) of an event A (snow) for all possible combinations B_i of ΔGT and MGT can be written as (see, e.g., DeGroot and Schervish 2002)

$$\Pr(A|B_i) = \frac{\Pr(AB_i)}{\Pr(B_i)}.$$

The conditional probability is computed with both predictors ΔGT and MGT, or with ΔGT alone. An example of Pr with ΔGT as the given parameter is displayed in Fig. 1b for the data of all 87 sites for both calibration and application period. In the case of the SCD model the conditional probability of snow with two predictors (ΔGT and MGT) is illustrated in Fig. 2a for the data of all 87 sites. The model was applied to the winter seasons from November to April in the calibration period. The graph shows that the probability of snow is highest for low values of ΔGT and for MGT ranging between −7° and 4°C. Furthermore, the figure reveals a clear reduction of the conditional probability at MGT = 0°C. The range of ΔGT intervals with a high probability of snow is higher for MGT values below 0°C than above 0°C. Figure 2b shows the corresponding relative frequency of the data points for each interval combination. The intervals where ΔGT lies between 0° and 0.1°C and

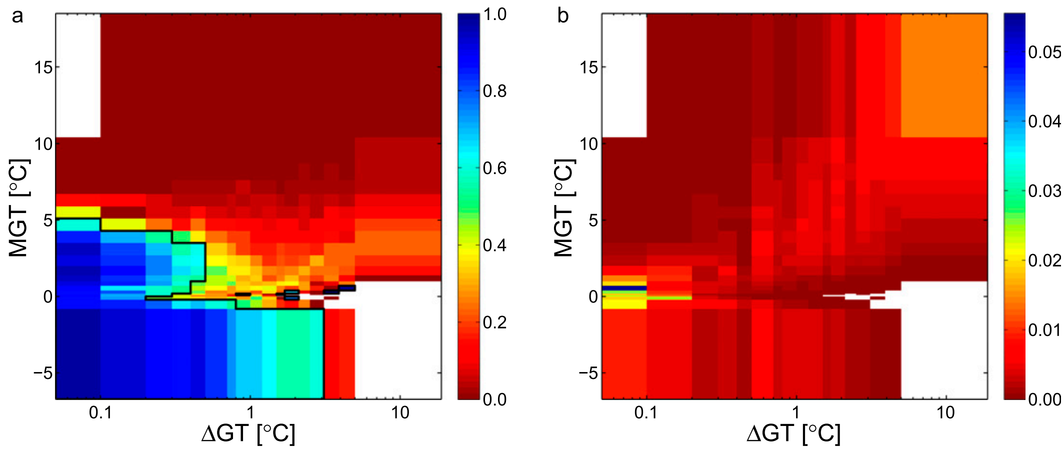

FIG. 2. (a) Conditional probability (color coded) of snow for the given parameters of the daily MGT and the daily ΔGT. The probability was determined simultaneously for all 87 sites (general model) for the winter seasons NDJFMA in the calibration period (January 2000–May 2005). The enclosed area (black line) represents the interval combinations with a conditional probability above the optimal threshold. (b) Corresponding relative frequency of ground temperature data. Note that ΔGT is displayed on a logarithmic scale.

MGT lies between 0° and 1°C exhibit the highest number of data points. This reflects the fact that the energy-intensive freezing and melting processes stabilize the temperature around the freezing level.

The second step is to find an optimal threshold for the conditional probability of snow above which the model assumes snow. For this purpose, we first define an arbitrary threshold (e.g., 0.5). As one can see from Fig. 2a, certain combinations of ΔGT and MGT yield probabilities above this threshold. For each day on which ΔGT and MGT lie within the region with probabilities above this threshold snow cover is predicted. Since the occurrence of snow is known from SD measurements, we can verify for each day of the season whether the model prediction is correct. Wrong predictions can either be false alarms or missed events and are evaluated for different probability thresholds. If the threshold is chosen to be too low, there are more false alarms than missed events, and vice versa. The optimal threshold is defined such that it minimizes the absolute value of the difference between the frequencies of missed events and false alarms. For the conditional probability in Fig. 2a, which was calculated from the data of all 87 sites, the optimal threshold yields $\mathrm{Pr} = 0.52$ and corresponds to a set of ΔGT and MGT intervals that is indicated by the black line.

Once the model is calibrated, the SCD can be calculated for intervals outside the calibration period. The method was applied to single sites (individual model) or to all sites simultaneously (general model). While the individual model calculates station-specific optimal thresholds, the general model determines a single optimal threshold from the data of all sites. In addition, the interval for the model calibration was varied. For evaluation intervals shorter than one year, the model was calibrated either from the data of the considered interval alone or from the data of the whole year.

c. *Statistical analysis*

The modeled SCD was compared with the observed SCD using correlation coefficients. In addition, a linear regression analysis was carried out to describe the output of the SCD model. When computing the SCD for the short winter seasons from December to February, data points accumulate near $n = 1$. In this case, the relative SCD is not normally distributed. To be able to compare the results of the different evaluation intervals, Spearman's rank correlation coefficients were calculated for all model applications. Furthermore, the regression analysis was omitted for the short winter seasons.

The data were checked for outliers. To account for outliers in the hourly ground temperature dataset, data points below the 2% quantile and above the 98% quantile were excluded for each month.

3. Results

The results of the SCD model with two predictors for the winter seasons of NDJFMA are shown in Figs. 3–5. The first two graphs differ in the model type (individual vs general) and were determined for the subset of 53 sites. The third graph displays the application of the general model to all 87 sites. The SCD model was also calculated for whole years and the

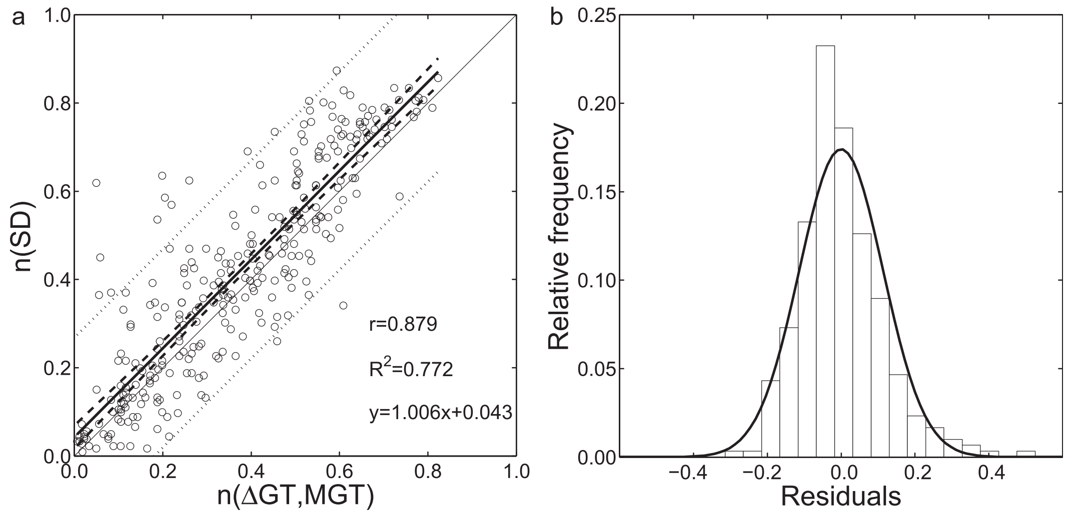

FIG. 3. (a) Plot of observed relative snow cover duration [n(SD)] against modeled relative snow cover duration [n(ΔGT, MGT)] for the subset of 53 sites. The SCD model was computed for the winter seasons NDJFMA in the application period (June 2005–July 2011). The model was determined from the data of the considered interval of NDJFMA and was derived separately for each station (individual model). A single point represents the SCD for one site and for one season. Therefore, each site is represented by a maximum of six data points. The data were fitted with a linear regression model (thick solid line). Further, the 95% confidence interval (thick dashed lines), the 95% prediction interval (thin dotted lines), and the Spearman's rank correlation coefficient r are shown. The thin solid line indicates the identity line. (b) Histogram of the residuals for the linear regression in (a). The solid line represents the theoretical probability density function.

short winter seasons from December to February. The resulting Spearman's rank correlation coefficients are summarized in Table 1.

Figure 3a shows that the observed relative SCD is in general well represented by the SCD model. This is indicated by the high value of the correlation coefficient of $r = 0.879$ and the location of the linear regression line, which runs almost parallel to the identity line. The intercept of the linear regression indicates that on average the SCD model slightly underestimates the true snow cover conditions. Figure 3b shows that the histogram of the residuals in Fig. 3a cannot be distinguished from a normal distribution (Kolmogorov–Smirnov test; significance level $p > 0.05$).

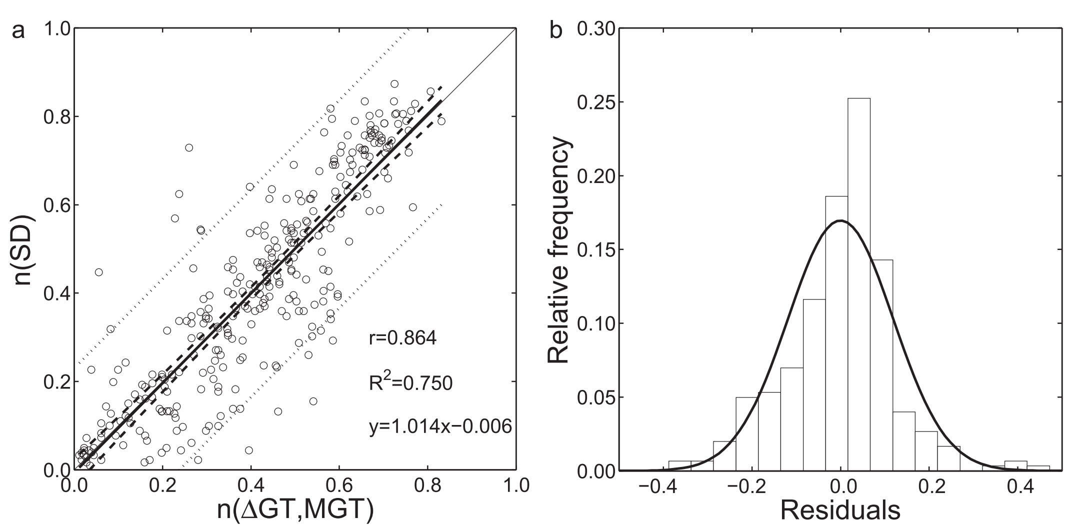

FIG. 4. As in Fig. 3, but for an SCD model that was derived from the data of the 53 sites simultaneously (general model).

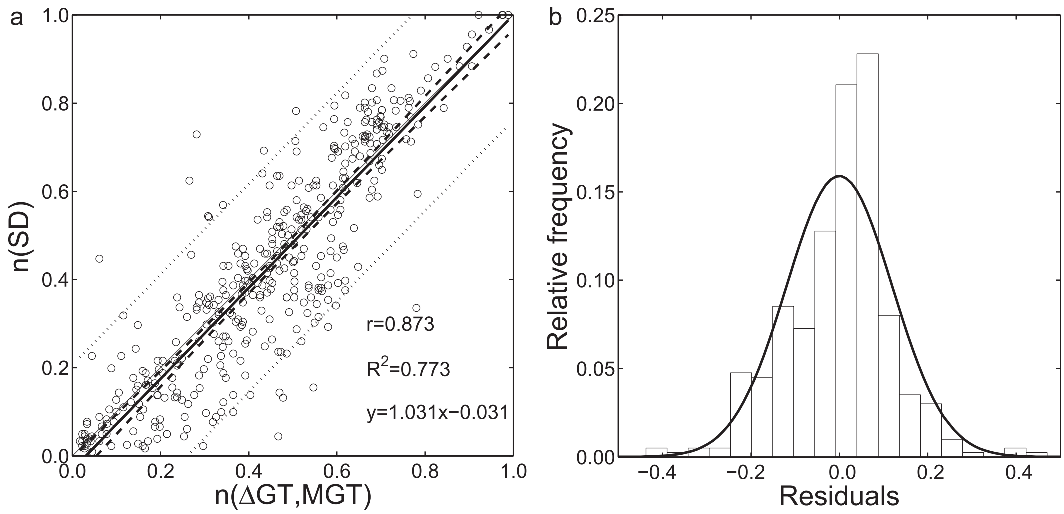

FIG. 5. As in Fig. 4, but for all 87 sites. The corresponding conditional probability is displayed in Fig. 2.

In comparing the individual model in Fig. 3 with the general model in Fig. 4 it becomes apparent that the general model yields similar results. Although the correlation coefficient appears to be slightly reduced, the linear regression almost coincides with the line of equality.

The application of the general model to all 87 sites is displayed in Fig. 5. The graphs show that the SCD is well represented by the general SCD model. Even with the added sites, for which the computation of an individual model with two predictors was not possible because of insufficient data, the application of the model results in a high correlation coefficient.

Table 1 gives an overview for all applications of the SCD model. The correlation coefficients range between 0.779 and 0.897, indicating a strong linear relationship for all shown variations of the model. The slope of the linear regression lines that were calculated for the evaluation intervals of a whole year and NDJFMA varies between 0.804 and 1.063, with a median of 1.019. The values of the intercept range between −0.092 and 0.051, with a median of −0.006. In comparing the different variations of the SCD model, we found that the regression lines are all close to the identity line. This result agrees with the choice of a probability threshold that balances the frequencies of missed events and false alarms.

The correlation coefficients for the subset of 53 sites reveal that in most cases the individual model with ΔGT as the only predictor is superior to the individual model with two given parameters. In contrast, the general model with ΔGT and MGT as predictors results in slightly higher correlation coefficients than the general model with ΔGT alone. This is also true for the application of the general model to all 87 sites. Despite the generally high correlation coefficients, we observed that the computation of the SCD for DJF appears to result in a lower correlation coefficient than for the two other evaluation intervals of NDJFMA and whole year. Further we found that the variation of the intervals for the model calibration (whole year, NDJFMA, or DJF) does not show a clear pattern.

The different applications of the SCD model in Table 1 were also calculated for the thresholds of $s = 1, 2, 3, \ldots,$ 10 cm (data not shown). We found that the correlation coefficients for $s = 1$ cm and $s = 2$ cm yield higher values than for $s = 0$ cm in some cases of the model application but do not present a clear trend. In contrast, the correlation coefficients for $s \geq 3$ cm decrease with increasing s for all variations of the SCD model.

4. Discussion and conclusions

In this study, we describe a statistical snow cover duration model that predicts snow cover solely from ground temperature. The results for a network of 87 Austrian stations show that the SCD model agrees well with the observed relative SCD. This was quantified using rank correlation as the main verification measure. The model was applied to individual stations as well as to the whole network simultaneously. It was found that for individual stations the diurnal ground temperature range ΔGT alone is already sufficient to predict the snow cover. The addition of the mean ground temperature MGT did not noticeably improve results. When applied to the whole station network the inclusion of MGT has proven beneficial.

The method of choosing a threshold for ΔGT to infer the SCD has been successfully applied to a small

TABLE 1. Spearman's rank correlation coefficient r, slope b_1, and intercept b_0 of the linear regression for observed vs modeled SCD. The model, which was determined with two [labeled (ΔGT, MGT)] or with one given parameter [labeled (ΔGT)], was applied to the subset of 53 sites or to all 87 sites and was calculated for three different evaluation intervals: whole year, NDJFMA, and DJF. The model was calibrated with different intervals (whole year, DJF, or NDJFMA) as indicated in parentheses. All statistics were calculated with data from the application period.

Model	Sites	Parameter	Whole year (whole year)	NDJFMA (NDJFMA)	NDJFMA (whole year)	DJF (DJF)	DJF (whole year)
Individual (ΔGT, MGT)	53	r	0.888	0.879	0.874	0.779	0.798
		b_1	0.979	1.006	0.951		
		b_0	0.021	0.043	0.051		
General (ΔGT, MGT)	53	r	0.861	0.864	0.861	0.836	0.828
		b_1	1.029	1.014	1.017		
		b_0	−0.007	−0.006	−0.016		
Individual (ΔGT)	53	r	0.872	0.897	0.881	0.827	0.837
		b_1	0.804	0.949	0.925		
		b_0	0.025	0.015	0.017		
General (ΔGT)	53	r	0.853	0.856	0.856	0.807	0.810
		b_1	1.047	1.050	1.050		
		b_0	−0.009	−0.019	−0.019		
General (ΔGT, MGT)	87	r	0.875	0.873	0.871	0.829	0.827
		b_1	1.053	1.031	1.020		
		b_0	−0.005	−0.031	−0.004		
General (ΔGT)	87	r	0.814	0.853	0.841	0.793	0.788
		b_1	0.839	1.025	1.063		
		b_0	−0.001	−0.012	−0.092		

number of sites (Hoelzle et al. 2003; Sawada et al. 2003; Rödder and Kneisel 2012; Vercauteren et al. 2014). When combining ΔGT with MGT to detect the snow cover condition, one or two interval limits for MGT are often defined around 0°C (Gądek and Leszkiewicz 2010; Cutler 2011; Apaloo et al. 2012; Schmid et al. 2012). The SCD model with two predictors allows a clearer discrimination of intervals with a high probability of snow. Through the model calibration by balancing the number of missed events and false alarms, the SCD model represents an automated method that can be applied to other datasets with different measurement depths of ground temperature with reasonable effort. A shallower measurement depth could potentially be beneficial for the performance of the model since temperature time lag errors may be smaller. Radiation may affect measurements near the surface, however.

A common problem in analyzing snow cover data is related to the spatial heterogeneity. Particularly during snowmelt, the patchy snow cover can cause a representation error of the local measurements. Snowdrift may result in snow conditions at the measuring site that are not representative of its surroundings. Since there is typically no documentation of these problems, we have to assume that patchiness does not induce systematic errors in our analysis. The applied model calibration may at least partly address this issue. Most likely is that patchiness has contributed to the noisiness in our evaluation and, therefore, has lowered the performance of the SCD model.

The SCD model relies on the definition of the threshold s for the snow depth. We found that the correlation coefficients for observed against modeled SCD decrease for $s \geq 3$ cm. The reason for this is the increasing number of snow-free cases that still relate to low values of ΔGT. Although a higher value of s can diminish the effect of a patchy snow cover, increasing s above a certain threshold also reduces the sensitivity of the model. Therefore, a low SD threshold seems appropriate for manual SD measurements. For acoustic SD measurements, which can experience difficulties in detecting snow-free conditions (Ryan et al. 2008), higher SD thresholds might be more appropriate when applying the SCD model.

Acknowledgments. Ground temperature and snow-depth data were provided by the Zentralanstalt für Meteorologie und Geodynamik, Austria (ZAMG). Thanks are given to Christian Maurer and Reinhard Böhm for detailed information on the ZAMG dataset.

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