Mountain snow distribution governed by an altitudinal gradient and terrain roughness

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[1] The heterogeneous mountain snow cover is challenging the eye and the analytical mind of the observer. The snow distribution affects water resources, natural hazards such as avalanches and ecology. While a lot of recent research has helped to better understand this snow distribution and the processes that cause the heterogeneity, it has not yet been possible to predict snow distribution satisfactorily on the basis of terrain parameters alone. We present a model of the mean snow depth in topographic control units as a function of two terrain parameters: the conventional elevation plus a fractal roughness parameter. For this we used a unique data set of high resolution measurements of snow depth from an airborne laser scanner. The model captures the heterogeneous snow distribution by merely analysing the terrain and the mean precipitation. This unusually simple relationship holds for clusters of the snow depths of small topographical units. By applying fractal analysis, we describe the roughness of the terrain and use this parameter for the prediction of snow deposition. Rougher terrain holds less snow than smoother terrain. This finding is important not only for avalanche warning or eco-hydrological applications, but also for reliably predicting how snow water storage may change in the light of the pronounced climate change already ongoing in mountain regions. **Citation:** Lehning, M., T. Grünewald, and M. Schirmer (2011), Mountain snow distribution governed by an altitudinal gradient and terrain roughness, *Geophys. Res. Lett.*, *38*, L19504, doi:10.1029/2011GL048927.

1. Introduction

[2] The snow distribution affects not only the storage of snow water [*Balk and Elder*, 2000] and the avalanche danger [*Schweizer et al.*, 2003], but also the local conditions for plant and animal life [*Wipf et al.*, 2009]. Snow distribution patterns in mountains are shaped by a general altitudinal gradient of precipitation [*Frei and Schaer*, 1998], the locally varying deposition of snow [*Lehning et al.*, 2008] and subsequent redistribution by wind [*Gauer*, 2001] and snow slides [*Bernhardt and Schulz*, 2010; *Sovilla et al.*, 2010]. They are also likely to be severely affected by climate change [*Barnett et al.*, 2005; *Marty*, 2008; *Bavay et al.*, 2009].

[3] Generations of scientists have attempted to identify the most significant characteristics of snow distribution in complex terrain and have made considerable progress in understanding the process of snow deposition [*Lehning et al.*, 2008] or the statistical scaling properties of the snow cover [*Kuchment and Gelfan*, 2001; *Shook and Gray*, 1996; *Mott et al.*, 2011; *Schirmer and Lehning*, 2011]. This includes the persistency of drift features [*Schirmer et al.*, 2011], as well as the role of preferential deposition in the survival of small glaciers [*Dadic et al.*, 2010]. However, one very basic question still remains unanswered: "How much snow is there where on the mountain?". The problem is twofold. First, precipitation gradients (with altitude) in mountains are not well established because (i) the precipitation measurement networks cover higher altitudes insufficiently [*Daly et al.*, 2008; *Blanchet et al.*, 2009], and (ii) the snow precipitation is in general and in particular at higher altitudes difficult to measure [*Sevruk*, 1997]. Second, even if the local precipitation rates were known, the preferential deposition [*Lehning et al.*, 2008] and the snow redistribution mainly by wind makes the assessment even more challenging. Some assumptions tend for example to be made that rock walls with an average slope of more than 60° do not accumulate any snow [*Blöschl and Kirnbauer*, 1992]. It is becoming increasingly feasible to measure snow distribution with airborne and terrestrial laser scanners [*Sovilla et al.*, 2010; *Prokop et al.*, 2008], and thus to analyse distributed snow depths in mountains [*Deems et al.*, 2006; *Trujillo et al.*, 2007; *Grünewald et al.*, 2010]. Such analyses have mainly confirmed the earlier finding [*Erxleben et al.*, 2002; *Schmidt et al.*, 2009] that local terrain parameters do not explain the snow depth distribution. A mechanistic prediction of snow distribution appears possible if the wind transport of snow is modelled [*Lehning et al.*, 2008; *Mott et al.*, 2010; *Mott and Lehning*, 2010], and also in simpler estimates of terrain-based wind effects [*Winstral and Marks*, 2002]. Reliable wind field estimates are however difficult to obtain [*Raderschall et al.*, 2008; *Bernhardt et al.*, 2009] so this approach is unlikely to become operational or have larger scale applications.

[4] The hypothesis put forward here is that terrain roughness might be used to characterize snow distribution given the qualitative observation that rough and rocky terrain has often thin snow when compared to smoother terrain (e.g., a meadow) in the same area [*Wirz et al.*, 2011]. The idea of using a non-local (roughness) parameter is also based on the observation that the simple terrain characteristics typically fail because they only look at local terrain parameters as, e.g., derived for one grid point of a digital elevation model (DEM) and that good correlation with terrain parameters requires averaging [*Jost et al.*, 2007]. In the following, we analyze airborne laser scan data on snow depth distributions in two Alpine catchments and show how the mean snow depth in sub-areas is explained by elevation and a fractal roughness parameter.

2. Experimental Area and Definition of Topographic Units

[5] A visual inspection of topography and the associated snow distribution at our study sites in the central Swiss Alps

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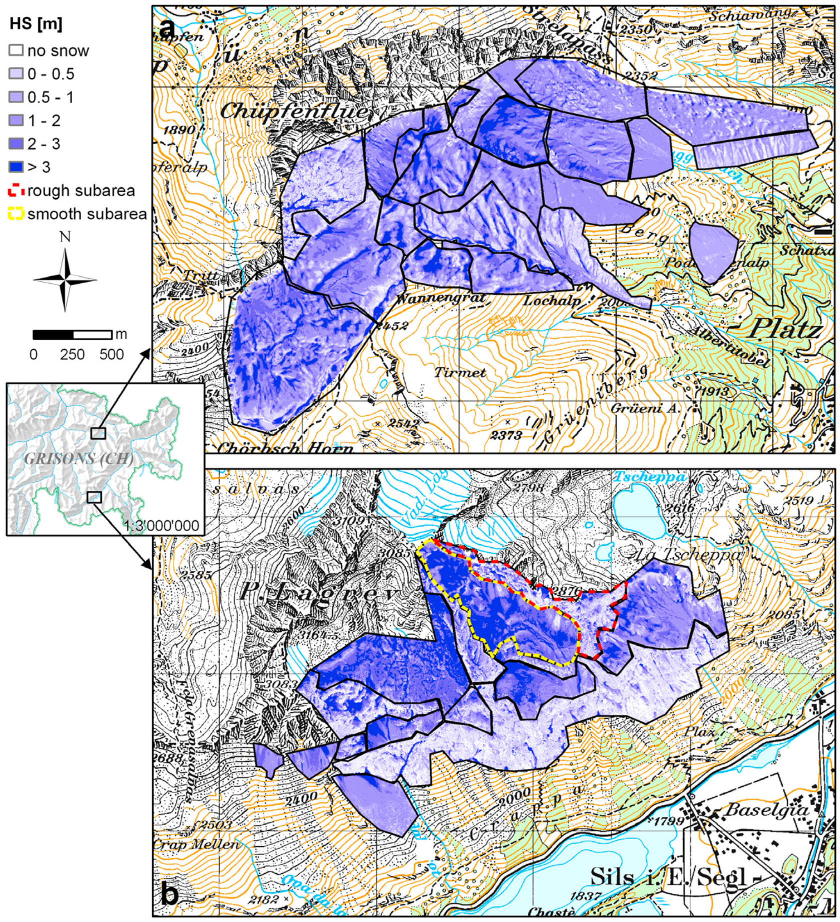

Figure 1. Situation of study plots in Switzerland (inset) and snow depth in the "Wannengrat" (April 9, 2009) and "Lagrev" (April 7, 2009) areas with sub-areas (black lines). Maps reproduced with permission (Swisstopo, JA100118). A smooth and rough sub-area are shown as examples from Lagrev and are used to generate the terrain variograms in Figure 3.

(Figure 1) suggests that terrain sub-units can be defined that have similar characteristics distinct from those of neighboring units. Such sub-units may be a rock face, a bowl, a ridge or a meadow. Here we analyze the mean snow depths in distinct topographical sub-units at the sites. The snow depths as derived from airborne laser scans have a mean accuracy of at least 0.1 meters [*Schirmer et al.*, 2011]. Note that in hydrology, it has been a successful concept to work with "hydrological response units", in which grid points are lumped together according to their similarity in terms of their hydrological response [*Rinaldo et al.*, 2006]. Figure 1 shows the sub-areas defined manually for our two investigation areas. Until it will be possible to decompose the terrain automatically, e.g., by clustering methods, suitable sub-areas can easily be found by visual inspection.

3. The Altitudinal Gradient of Snow Depths

[6] Snow depth deviation (from the total area mean snow depth), ΔHS, in the sub-areas was analyzed using elevation as the explanatory variable (Figure 2). Elevation explains only about 20% in mean snow depth ($r^2 = 0.21$) variability, although elevation is typically used as the only explanatory variable [*Grünewald and Lehning*, 2011]. The most significant deviations from a linear correlation are for sub-areas with rough terrain, as defined below. A significant deviation was also found for a sub-area, where a large avalanche had redistributed snow from steeper areas to less steep areas. The analysis shows that elevation is an important variable in snow depth distribution but only explains a small part of the variation in mean snow depth. Our data reduction through clustering in sub-areas already improved the model: a comparison to a model using the original data at the 1 m grid resolution shows that only 10% of the variance is explained if individual data points are considered at the measurement resolution.

4. Introduction of the Roughness Parameter

[7] For all sub-areas, scaling parameters were determined [*Sun et al.*, 2006] to describe the local roughness of the terrain. Terrain characteristics have long been described using scaling quantities. However, while it is common to describe snow – atmosphere exchange with the aerodynamic roughness [e.g., *Yang et al.*, 1997], the use of geometric terrain scaling to make predictions on snow distribution is novel. Here we use scaling quantities derived from the semi-variance (*SV*) plot, which is basically a second-order structure function defined by:

$$SV(x) = \frac{1}{2N(x)} \sum_{i,j \in N(x)} (z(i) - z(j))^2. \tag{1}$$

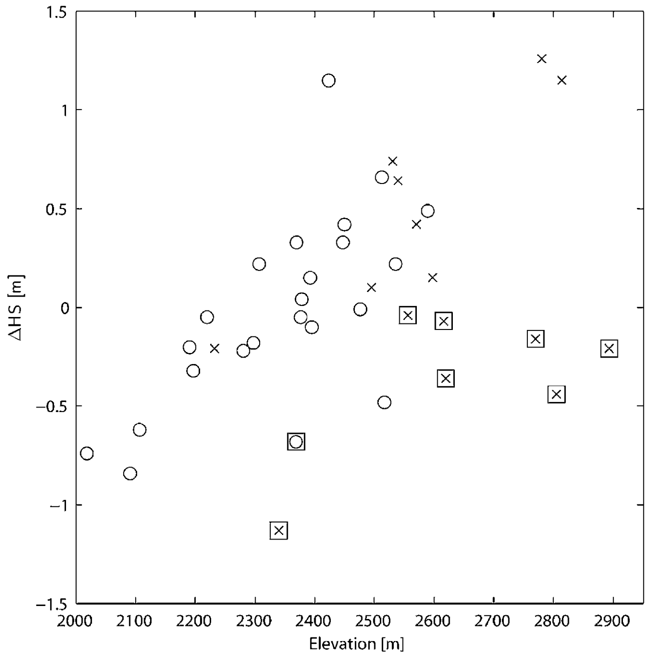

Figure 2. Scatterplot of elevation and snow depth scaled by mean snow depth, ΔHS. Crosses (circles) refer to observations in the Lagrev (Wannengrat) area. The observations marked with a rectangle are from a rough surface, with γ larger 0.3 m.

where $N(x)$ is the number of point pairs (i, j) in each distance class x. In particular, we investigated (i) the variance on a scale of 1 m (i.e., the measurement resolution) expressed by the semi-variogram intercept, γ, and (ii) the roughness parameter D (fractal dimension) for the summer terrain. D is for a surface related to the slope α of the semi-variogram by:

$$D = 3 - \frac{\alpha}{2}. \quad (2)$$

[8] The parameters γ and α are determined by a logarithmic least squares fit to the semi-variance curve. Examples of semi-variograms for two sub-areas, a rough one and a smooth one, are given in Figure 3. The sub-areas have also been marked in Figure 1. From the figure it can be seen that the linear fit allows a very reliable estimate of γ and α. A small slope of the semi-variogram (large D) is usually associated with greater roughness [*Sun et al.*, 2006]. In addition to altitude and the scaling parameters γ and D, we investigated the most obvious topographic parameters *slope* and *northing*, where *northing* is defined as the *angle formed by the projection of the normal to the surface onto the horizontal plane with North*. The average value for a sub-area was determined by the most frequent value in a histogram with 10 degree intervals.

[9] A stepwise regression model starting with the five parameters elevation (h), γ, D, *slope* and *northing* eliminates the parameter *slope* as non-significant. The rejection of slope is probably because of (i) a strong correlation with γ and (ii) less explanatory power than γ with respect to ΔHS. The first acceptable model retains the four-parameters (each parameter significant at the 1% level) h, γ, D and *northing*:

$$\Delta\widetilde{HS} = 0.83\,\tilde{h} - 1.18\,\tilde{\gamma} - 0.18\,\widetilde{northing} + 0.49\,\tilde{D}. \quad (3)$$

Note that in equation (3) the variables have been normalized (tilde) to zero mean and a standard deviation of 1 such that the coefficients become directly comparable. This four parameter model is a good model in the sense that it has a high explanatory power (adjusted $r^2 = 0.79$) and that the residuals have zero mean, are normally distributed and uncorrelated (not shown). Since 38 data points are fitted with four parameters, a simpler model is searched by eliminating less significant parameters. It turns out that if only the parameters γ and h are retained, most of the variance can be explained. This "best choice" two-parameter model, in which the altitude, h, is preferably complemented by γ in the predictive equation (4) explains 73% of the variance (adjusted $r^2 = 0.71$):

$$\Delta HS = -5.13 + 2.3610^{-3} h - 1.37\gamma. \quad (4)$$

[10] Normalizing the variables results in:

$$\Delta\widetilde{HS} = 0.00 + 0.87\,\tilde{h} - 0.82\,\tilde{\gamma}. \quad (5)$$

The corresponding two-dimensional residual plot (Figure 4) suggests a stable model, given the relatively small number of topographical units (38). This is confirmed by a robust regression, which yields basically identical coefficients and further supported by a standard residual analysis (not shown). Note that the two-parameter model can explain a major part of the local snow depth variation despite the fact that a model with either of the parameters alone only explains a very small fraction. Also note that γ is highly correlated ($r^2 = 0.76$) with the more commonly used roughness parameter D. The fact that γ has a little more

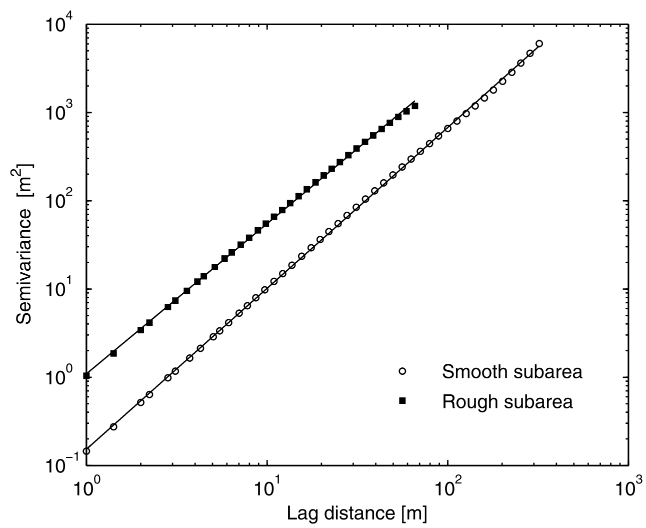

Figure 3. Variograms for a rough and smooth sub-area as marked in Figure 1. The linear fit to the data defines the magnitude of roughness, γ. The observations marked with a rectangle are from rougher surfaces ($\gamma > m^2$).

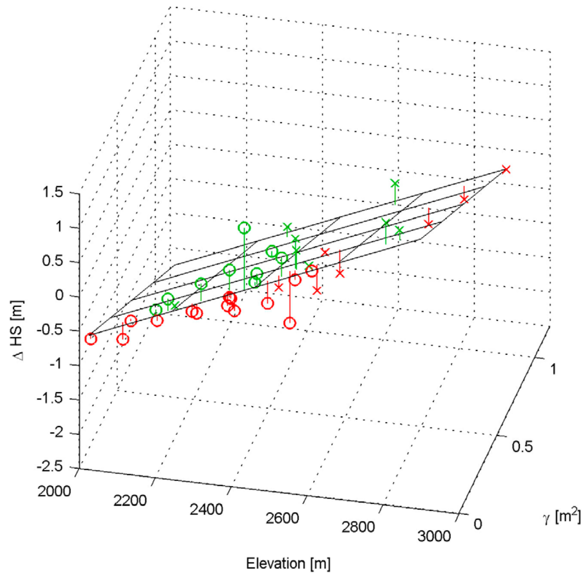

Figure 4. Linear regression for ΔHS with elevation and γ as predictors. Observations with negative residuals are plotted in red, while positive residuals are in green. Crosses (circles) refer to observations in the Lagrev (Wannengrat) area.

explanatory power than D suggests that it is the small scale roughness, which is most important. γ, which is often also called the magnitude of roughness, gives the terrain variation at the measurement scale (1 m).

5. Conclusions

[11] We have shown that the relative distribution of snow depth is governed by topographical control units, which are characterized by their summer terrain surface roughness and a general gradient in altitude. The roughness can be described by parameters derived from a semivariance scaling analysis. The influence of roughness may present a combination of two physical effects: i) in alpine terrain, there is a close relationship between roughness and mean slope angle, which has also been confirmed in our study (not shown). However, mean slope angle does not have the same explanatory power as the roughness. This suggests that a further physical mechanism is at work. We hypothesize that ii) wind exposed areas are typically rougher than sheltered areas in this type of terrain since sheltered areas also accumulate more fine particles in the summer and tend to develop soils easier. The roughness parameter would therefore measure the combined effect of terrain steepness and soil development, which has to be tested by future investigations.

[12] The analysis presented here is based on a relatively small number of control units and in only two small areas in the central Swiss Alps. Based on our physical process understanding, we believe the dependence of snow distribution on altitude and surface roughness to be a universal feature. This needs, however, to be tested with larger data sets in future in different climates and other mountain environments.

[13] The analysis has thus far been restricted to the peak of winter snow distribution. In how far the results can be transferred to individual storms [*Schirmer et al.*, 2011], still needs to be explored. A typical snow deposition during a single storm is likely to be similar to the peak of winter snow distribution [*Schirmer and Lehning*, 2011] and it can also be expected that the terrain roughness parameters will play a significant explanatory role.

[14] Overall, the simple relationship presented here predicts how the distribution of winter snow can be mapped onto topographic control units. These units can exclusively be described by their summer terrain digital elevation model. This is very relevant for forecasting how much snow is where, which will first help hydrological, climatological and meteorological analyses.

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