ESTIMATING RUTSCHBLOCK STABILITY FROM SNOWMICROPEN MEASUREMENTS

Christine Pielmeier[1], Hans-Peter Marshall[2,3]
[1]WSL Swiss Federal Institute for Snow and Avalanche Research SLF, CH-7260 Davos
[2]Center for Geophysical Investigation of the Shallow Subsurface, Boise State University, Boise, ID, USA
[3]Cold Regions Research and Engineering Laboratory, Hanover, NH, USA

ABSTRACT: Stability prediction from SnowMicroPen (SMP) profiles would support avalanche forecasting operations, since stability information could be gathered more quickly than with standard tests, thereby allowing sampling at higher resolution and over larger spatial scales. In previous studies, the snow properties derived from the SMP have been related to observed snow properties at Rutschblock and compression test failure planes. The goal of this study is to show to what extent Rutschblock stability can be derived from SMP measurements. Our analysis is based on measurements at 36 different sites, which each included a Rutschblock test, a manual profile, and up to 8 adjacent SMP measurements, for a total of 262 SMP profiles. A recently improved SMP analysis procedure is used to estimate the micro-structural and mechanical properties of manually defined weak layers and slab layers. SMP signal quality control and different noise treatment methods are taken into consideration in the analysis. The best and most robust predictor of Rutschblock score is the weak layer compressive strength. In combination with the SMP-estimated density of the slab layer, the cross-validated total accuracy of predicting Rutschblock stability classes is 85% over the entire data set, and 88% when signals with obvious signal dampening (11% of the dataset) are removed. The effect of SMP data quality on the analysis is quantified. The analysis is robust to trends and offsets in the absolute SMP force, which is a frequent signal error but is sensitive to dampened or disturbed SMP force micro variance. Our sensitivity analysis shows that SMP data quality has a significant influence on classification results. It also shows that the best predictor of instability, the weak layer micro-scale compressive strength, is robust to the choice of SMP signal noise removal method.

KEYWORDS: snowpack stability, Rutschblock, micro penetrometer, mechanical properties, avalanche forecasting

1. INTRODUCTION

Snowpack measurements and stability tests are, along with observations of recent avalanche activity and weather history, currently the basis for snowpack stability assessment in most avalanche forecasting operations. The Rutschblock test is currently the standard snowpack stability test in the context of operational avalanche forecasting in Switzerland. The snow properties and the Rutschblock score, an index of snow stability for skier triggering, are the most important parameters for the assessment of current snowpack conditions, itself a basis for forecasting the current avalanche danger.

Schweizer and Jamieson (2003) and Schweizer et al. (2007, 2008) developed a stability classification method based on stability test scores and manual observations of failure interface properties. These studies show the significance of observed snow properties at failure interfaces with respect to snowpack stability.

The SnowMicroPen (SMP), a high-resolution automated penetrometer for snow, measures penetration resistance or snow hardness at the grain scale (Schneebeli and Johnson, 1998). A physical theory for characterizing snow properties from the SMP signal was first introduced by Johnson and Schneebeli (1999). The three basic micro-

Corresponding author address: Christine Pielmeier, Swiss Federal Institute for Snow and Avalanche Research SLF, Flüelastr. 11, CH-7260 Davos, Switzerland; tel: +41-81-4170125; fax: +41-81-4170110; email: pielmeier@slf.ch.

structural parameters are the structural length (L), the deflection at rupture (δ) and the rupture force (f), and from these, mechanical parameters can be derived. Sturm et al. (2004) improved the theory by removing a key assumption, and Marshall (2006) added several improvements including an algorithm for accounting for simultaneous ruptures. Pielmeier and Schweizer (2007) and Pielmeier et al. (2006) applied both versions of the theory in a statistical approach to predict a-priori known weak interfaces from the SMP signal. The classification accuracies in discriminating stable and unstable failure interfaces from SMP signals reached 65% and 70% respectively. Recently, Marshall and Johnson (submitted) significantly improved the SMP analysis procedure. Verified by both extensive Monte-Carlo simulated and observed snow signals, they showed a much higher accuracy when estimating the micro-structural and mechanical parameters than with previous versions of the theory.

Applying the improved theory by Marshall and Johnson (submitted) to a dataset comprised of snow profiles, Rutschblock tests and SMP measurements, we obtain more accurate and robust predictors of stability from the SMP signals. Furthermore, the effect of signal quality control and SMP signal noise filtering on the accuracy of the results is shown.

2. DATA AND QUALITY

2.1 Data

The 36 combined profiles were taken in dry snow conditions between December 2007 and March 2008 in the Swiss Canton of Graubünden (Figure 1). All locations were chosen for the operational assessment of regional avalanche danger. Altitudes range between 2000 and 2600 m a.s.l. and the slope angles range between 30 and 40°. The majority of the profiles were taken on north facing slopes (NW-N-NE: 69%, SE-S-SW: 15%, E: 6%, W: 11%).

A combined profile consists of one manual profile with at least one vertical and one slope-perpendicular SMP measurement adjacent to it, as well as a Rutschblock test with up to six SMP measurements at its perimeter and one in the middle of the block. 262 SMP measurements are available for analysis. The 36 observed Rutschblock scores range from 1 to 7.

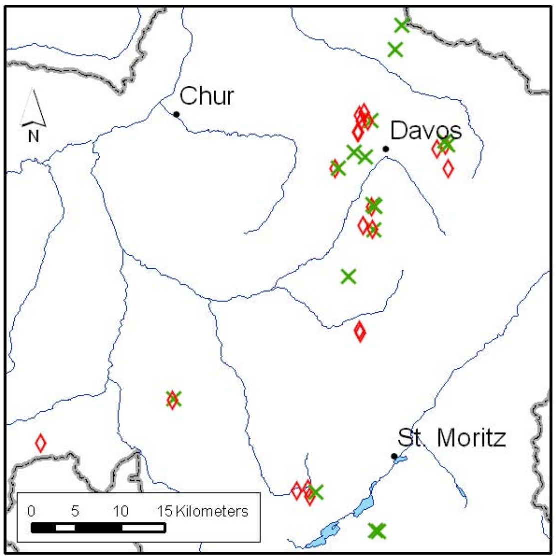

Fig. 1: Map of a portion of the Swiss Canton Graubünden showing the profile locations. Red diamonds represent Rutschblock scores ≤ 3 and RB 4 whole block (n=20), green crosses represent Rutschblock scores 4 partial break and RB scores 5-7 (n=16).

Figure 2 shows the range and frequency of the 36 observed snowpack types (Schweizer and Lütschg, 2001).

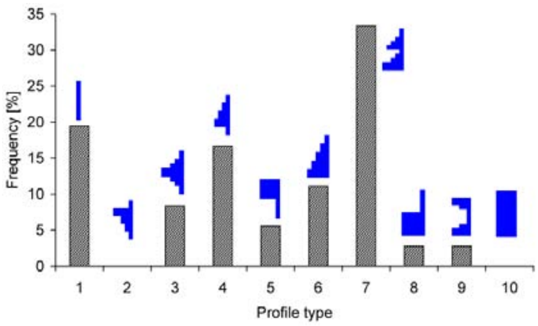

Fig. 2: The distribution of the 36 snow profiles in terms of profile types (blue icons). There is an equal split between profiles with weak (type 1-5) and consolidated basal layers (type 6-10).

2.2 SMP data quality

All 262 SMP measurements were qualitatively checked for obvious signal errors and classified into four quality categories (Table 1).

Tab. 1: Categories and distribution of SMP data quality.

Quality	*Type of SMP signal error*	*N [%]*
Q1	None	158 [60%]
Q2	Trend or offset in absolute SMP force	75 [29%]
Q3	Dampened or disturbed SMP force micro-variance	5 [2%]
Q4	Both, Q2 and Q3	24 [9%]

Amongst the 36 profiles were 5 profiles that had no first quality SMP measurement at all. Signal errors may stem from a variety of sources such as a frozen SMP measuring tip, a defect sensor or a defect coax cable. The sources of error are not specified here, but the data quality is accounted for in the analysis to show the effect on the accuracy of the results.

3. METHODS

3.1 Field methods

Manual snow profiles were taken according to the International Classification for Seasonal Snow on the Ground (Colbeck et al., 1990). Three different stability tests were taken adjacent to the manual profile: one Rutschblock test (RB), two Extended Column tests (ECT) and two Compression tests (CT). Figure 3 shows the experimental design of the combined profiles. The ECT and CT scores are not the subject of this study, but are analyzed in a comparison of stability tests by Winkler and Schweizer (2008).

In this study, the weak layer depth and the stability were determined by the Rutschblock test as described by Föhn (1987). The RB score (1 to 7), release type (whole block vs. partial break/edge) and fracture surface character (clean vs. rough/irregular) were observed (Schweizer, 2002). Within the immediate vicinity of the manual profile (5 to 20 cm), two slope perpendicular and one vertical SMP measurement were taken. Up to six SMP measurements were taken at the perimeter and in the center of the Rutschblock area (Figure 3).

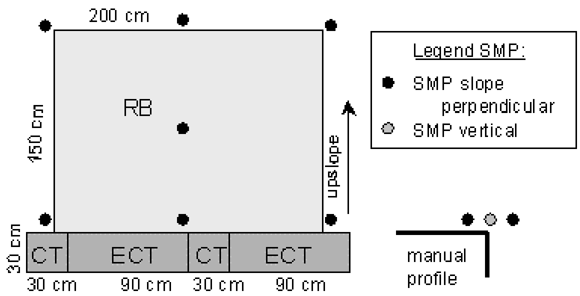

Fig 3: Experimental design of combined profiles, where one manual profile was taken with three adjacent SMP measurements along with one RB, two ECT and two CT tests with seven adjacent SMP measurements.

3.2 Analysis methods

Stability classification

Unstable und stable profiles were classified according to the RB scores. Profiles are classified unstable with RB scores 1 to 3 independent of release type and RB score 4, if release type is whole block (n=140). Profiles are classified stable with RB score 4, if release type is partial break and RB scores 5 to 7 independent of release type (n=122). This entails a small difference to the previously used stability classification (Pielmeier et al., 2006), where profiles with RB 4 and release type whole block were considered stable.

SMP signal analysis

By graphically superimposing the manual profile onto the slope-perpendicular SMP measurement that is closest to the manual profile, the layer boundaries at the failure interface are manually delineated (aided by vertical SMP measurements). Furthermore, all SMP measurements from one site were graphically aligned to track the failure interface. An example of the manual delineation of the weak layer (WL), the transitional layer (TL), the adjacent layer (AL) and the slab layer (SL) is shown in Figure 4.

The SMP signal is first filtered to reduce signal noise. Three different methods are applied to the raw SMP signal: a static threshold of 0.023 N rupture force (based on the fluctuations in air measurements), a dynamic threshold of 10% of the maximum rupture force, and a combination of both. In addition to data quality, the filter type is also accounted for in the analysis to show the effect on the accuracy of the results.

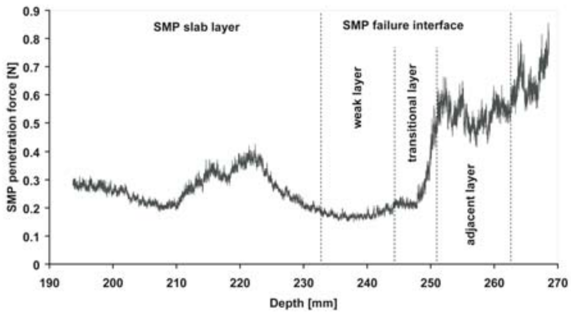

Fig 4: Section of an SMP profile showing manually depicted layer boundaries at a failure interface.

The calculated SMP parameters based on Marshall and Johnson (submitted) are: rupture force (f), deflection at rupture (d), structural element length (L), force normal to tip (F), probability of contact (Pc), number of elements engaged (Ne), number of elements available (Na), mean force (Fm), total force at peak (F_T), stiffness (k), micro-scale elastic modulus (Emicro), micro-scale compressive strength (Smicro), measured number of ruptures (Nm) and total number of ruptures (N_T). Also, the texture index (TI) (Schneebeli et al., 1999), the slab layer mean density (rho) (Pielmeier, 2003), and the depth of the weak layer are calculated.

Statistical analysis

To find the best classifier for unstable and stable RB results from the SMP records, we use the classification tree method (Breiman et al., 1984). A total of 16 parameters are calculated for each SMP profile at increments of 1 mm using a 5 mm window. The mean value of these 16 parameters is calculated for the manually defined weak layer, the upper slab layer, and the difference of both. Together with the weak layer depth, a total of 49 variables were tested for their ability to correctly classify the profile based on the RB score. A cross-validation analysis was performed by subdividing the data set into 10 balanced independent subsets, on which the classifications were performed. This analysis indicated that a 2-node tree, using 2 variables, was statistically significant. We therefore focus below on the classification accuracy using 1 and 2 explanatory variables.

4. RESULTS

<u>*4.1 Classification*</u>

From the 49 variables used in the univariate classification tree analysis, the ten best predictors of unstable and stable profiles are given in Table 2.

Tab. 2: The ten best classifiers from univariate classification tree analysis. TA is the total accuracy, SA is the stable accuracy, UA is the unstable accuracy. At the split value of the SMP parameter the classification changes from stable to unstable or vice versa. A number one in the "≥" column means the split was greater or equal than the value to be stable, a zero means less than the split value is stable.

SMP Parameter	*TA [%]*	*SA [%]*	*UA [%]*	*Split value*	≥
WL_Smicro	83.5	79.5	87.5	0.0755 N mm^{-2}	1
SL_Pc	79.8	89.7	70.0	0.13 [prob.]	0
WL_Nm	77.2	73.1	81.3	14 [#]	1
WL_Na	77.2	73.1	81.3	33 [#]	1
WL_Emicro	77.2	92.3	62.5	1.44 N mm^{-2}	1
WL_L	77.2	73.1	81.3	1.09 mm	0
WL_N_T	76.6	69.2	83.8	82 [#]	1
WL_f	75.3	65.4	85.0	0.10 N	1
WL_k	74.1	87.2	61.3	1.45 N mm^{-1}	1
WL_depth	73.4	74.4	72.5	200 mm	1

The single best predictor is the weak layer micro-scale compressive strength (WL_Smicro), with values greater or equal to 0.0755 N mm^{-2} classified as stable, and less than 0.0755 N mm^{-2} as unstable, with a total classification accuracy of 83.5% (stable accuracy 79.5%, unstable accuracy 87.5%).

Figure 5 shows the distributions for WL_Smicro for all 262 SMP profiles (all SMP data qualities) and for WL_Smicro according to unstable and stable Rutschblock stability classes.

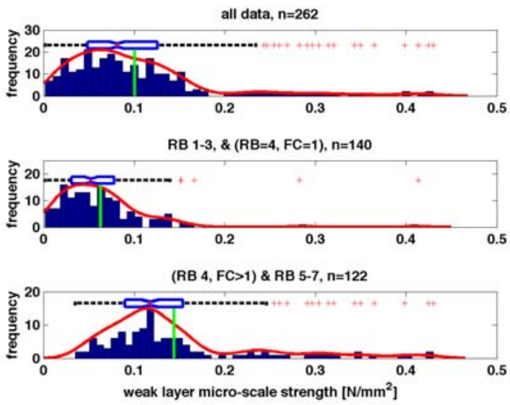

Fig. 5: Histograms of the WL_Smicro for all data (top), for the unstable RB class and for the stable RB class. The distributions of WL_Smicro for unstable and stable conditions are significantly different.

From the multivariate classification tree analysis of the 49 variables, the second-best variable to predict unstable and stable profiles (with WL_Smicro as first variable) is the slab layer mean density (SL_rho). The second-best variables with the 12 highest total accuracies are given in Table 3. Also, the total accuracies in terms of the data quality classes are shown.

Tab. 3: Total accuracies obtained from the multivariate tree analysis (with WL_Smicro as first variable). The total accuracy is shown for the 12 best second variables, also as a function of SMP data quality.

SMP Parameter	*Q1 [%]*	*Q2 [%]*	*Q3,Q4 [%]*	*Q1,Q2 [%]*	*Q1,Q2, Q3,Q4 [%]*
SL_rho	85.44	89.33	75.86	88.00	85.50
SL_TI	84.18	85.33	68.97	84.55	82.82
SL_f	85.44	81.33	65.52	84.12	82.06
WL_L	84.18	84.00	82.76	84.12	83.97
WL_Na	83.54	82.67	82.76	83.26	83.21
WL_S	84.81	80.00	79.31	83.26	82.82
WL_Nm	81.01	81.33	82.76	81.12	81.30
WL_N_T	81.65	80.00	82.76	81.12	81.30
WL_Pc	82.28	76.00	72.41	80.26	79.39
WL_Fm	77.85	84.00	72.41	79.83	79.01
SL_Pc	84.81	69.33	68.97	79.83	78.63
WL_depth	83.54	70.67	72.41	79.40	78.63

From the classification tree analysis shown in Figure 6, the SMP failure interfaces are predicted to be stable if the WL_Smicro ≥ 0.0755 N mm^{-2} and the SL_rho ≤ 320.6 kg m^{-3}.

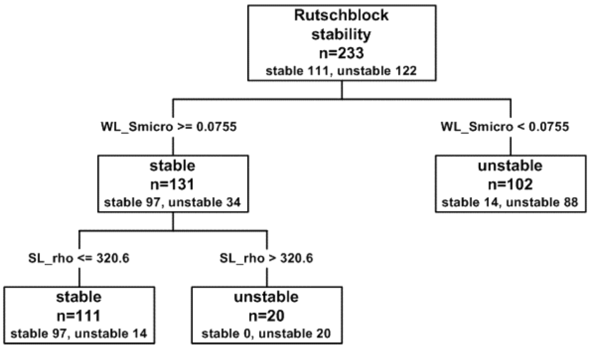

Fig. 6: Classification tree for unstable/stable dataset (n=233, Q1 and Q2 data). The cross-validation analysis indicated that the 2-node tree, using 2 variables is statistically significant.

Figure 7 shows all data along with the split values gained from the classification tree analysis, as a function of data quality. The total classification accuracy for all data is 85.5%.

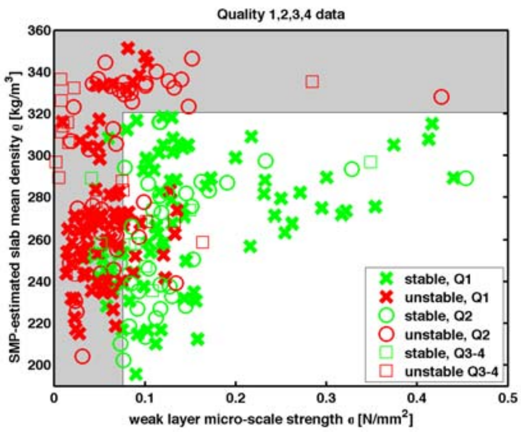

Fig. 7: Plot values of WL_Smicro as a function of SL_rho for all SMP data quality classes. The grey shaded area is the two variable best classification for RB stability classes unstable. The different symbols indicate SMP data quality.

4.2 Sensitivity analysis

Sensitivity to SMP data quality
For the univariate classification, with WL_Smicro as best classifier (Table 2), the accuracies are calculated for three different SMP data quality classes. Table 4 shows lower accuracies for Q2 data than for Q1 data, and even lower accuracies for Q3 and Q4 data.

Tab. 4: The classification accuracies for WL_Smicro in terms of SMP data quality. TA is the total accuracy, SA is the stable accuracy, UA is the unstable accuracy, and n is the number of SMP profiles in the group.

SMP data quality	*TA [%]*	*SA [%]*	*UA [%]*	*n*
Q1	83.54	79.49	87.50	158
Q2	74.67	78.79	71.43	75
Q3 & Q4	68.97	72.73	66.67	29

For the multivariate classification, with WL_Smicro and SL_rho as best classifiers (Table 3), the accuracies are less sensitive to data quality, as shown in Table 5.

Tab. 5: The classification accuracies for combined WL_Smicro and SL_rho in terms of SMP data quality classes. TA is the total accuracy, SA is the stable accuracy and UA is the unstable accuracy.

Classification accuracies	*Q1*	*Q2*	*Q3, Q4*	*Q1, Q2*	*Q1,Q2, Q3,Q4*
TA [%]	85.44	89.33	75.86	88.00	85.50
SA [%]	79.49	87.88	45.46	87.40	78.12
UA [%]	91.25	90.48	94.44	88.50	91.38

The multivariate classification is robust to Q2 data (29% of all data), where the signal error is a trend or an offset in absolute SMP force. Q1 and Q2 data together yield a total accuracy of 88%. Q3 and Q4 data significantly reduce the total classification accuracy by misclassifying more than half of the stable cases. However, the accuracies obtained using all data together are still acceptable and much higher than expected (total accuracy = 85.5%), indicating that this method may be applicable to large datasets not manually classified by quality, which may be too time consuming to do in some cases.

Sensitivity to SMP noise removal methods
The classification accuracies for WL_Smicro (Table 2) are calculated for three different SMP signal noise removal methods: a static filter, a dynamic filter and a combination of both. Table 6 shows that the classification accuracies are not sensitive to the selected filter.

Tab. 6: The classification accuracies for WL_Smicro from univariate analysis in terms of SMP noise removal methods for Q1 data.

SMP filter type	*TA [%]*	*SA [%]*	*UA [%]*	*n*
static	83.54	79.49	87.50	158
dynamic	84.81	78.49	90.00	158
static & dynamic	83.54	79.49	87.50	158

5. DISCUSSION

Future work involves the application of the classification model to a larger dataset and the analysis of the spatial variability of the SMP measurements in relation to Rutschblock score and release type. The results of the adjacent compression tests and extended column tests will be included in the analysis. A systematic catalogue of data quality classes for SMP users will be developed and an algorithm to detect errors in the SMP force micro-variance will be tested. Furthermore, the sensitivity study will be extended to older versions of the SMP theory.

Since the results for micro-scale strength are robust to the suggested SMP signal noise filter methods, we suggest that SMP users apply the simplest method, a static filter with a rupture force threshold value of 0.023 N, and focus on the strength parameter for stability applications.

Figure 7 shows the total, unstable and stable accuracies for all WL_Smicro split values calculated from an unweighted classification tree. Future work also entails the analysis and discussion of a cost function where false stable predictions can perhaps be optimized at an acceptable cost of false alarms.

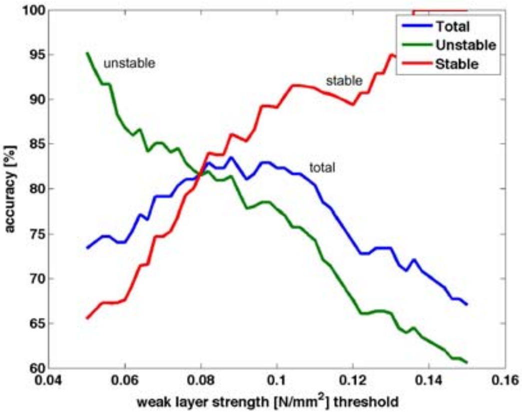

Fig. 7: Total accuracy together with unstable and stable accuracies for WL_Smicro threshold values. By increasing the accuracy for unstable predictions (green curve), the accuracy of the stable predictions decreases (red curve), which means a loss of credibility. In how far can unstable predictions be optimized?

6. CONCLUSION

Applying an improved SMP signal interpretation theory to a combined dataset of snow profiles, SMP measurements and Rutschblock tests, significant indicators of snowpack instabilities are derived from SMP measurements. The weak layer micro-scale compressive strength is the single most significant parameter. Combined with the second-best parameter from multivariate analysis - the slab layer mean density - the total classification accuracy is 88% where 11.5% of the profiles are classified false unstable (false alarms) and 12.6% are classified false stable (misses). The presented classification model is an improvement to previous studies.

The sensitivity studies for SMP data quality showed that the classification model is robust to trends and offsets in the SMP mean force (i.e., Q2 SMP data). This is by far the most frequent signal error encountered (29% of all data, Table 1). But, the classification is somewhat sensitive to a dampened or disturbed SMP force micro variance (Q3 and Q4 data,11% of all data). Furthermore, the best classifier, weak layer micro-scale compressive strength, is robust to the choice of SMP signal noise removal methods.

It is shown that SMP data quality control is critical when interpreting SMP data. It becomes even more important when snowpack stability datasets with SMP measurements are compared. A simple and robust SMP signal noise removal method is suggested. The results of the study provide a basis for the automated detection of potentially weak interfaces in snowpacks from SMP measurements.

7. ACKNOWLEDGEMENTS

The study was carried out during a research exchange visit at the Center for Snow and Avalanche Studies, Silverton, CO and was partially funded by the Swiss National Science Foundation research fellowship stipend no. IZK020-122784/1. We thank C. Landry and C. McAlpin for hosting the visit. Further we would like to acknowledge F. Techel, M. Oberhammer, K. Winkler and S. Bellaire for field assistance as well as A. Moser, A. Beeli and M. Ulmer for technical support. C. Landry and J. Schweizer gave valuable feedback on the manuscript.

8. REFERENCES

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1984. Classification and Regression Trees. CRC Press, Boca Raton, USA, 368 pp.

Colbeck, S.C., Akitaya, E., Armstrong, R., Gubler, H., Lafeuille, J., Lied, K., McClung, D., Morris, E., 1990. The International Classification for Seasonal Snow on the Ground. International Association of Scientific Hydrology. International Commission on Snow and Ice, Wallingford, Oxfordshire, 23 pp.

Föhn, P.M.B., 1987. The Rutschblock as a practical tool for slope stability evaluation. In: B. Salm and H. Gubler (Editors), Symposium at Davos 1986 - Avalanche Formation, Movement and Effects, IAHS Publ., 162. International Association of Hydrological Sciences, Wallingford, Oxfordshire, U.K., pp. 223-228.

Johnson, J.B., Schneebeli, M., 1999. Characterizing the micro structural and micro mechanical properties of snow. Cold Reg. Sci. Technol., 30, 91-100.

Kronholm, K., 2004. Spatial variability of snow mechanical properties with regard to avalanche formation. Ph.D. thesis, University of Zürich, Zürich, 158 pp.

Marshall, H.P., Johnson, J.B., submitted. Accurate inversion of high resolution snow penetrometer signals for microstructural and micromechanical properties. J. of Geophysical Resarch - Earth Surface.

Marshall, H.P., 2006. Snowpack spatial variability: towards understanding its effect on remote sensing measurements and snow slope stability. Ph.D. thesis, University of Colorado at Boulder, 264 pp.

Pielmeier, C., Schweizer, J., 2007. Snowpack stability information derived from the SnowMicroPen signal. Cold Regions Science and Technology 47: 102-107.

Pielmeier, C., Marshall, H.P, Schweizer, J., 2006. Improvements in the application of the SnowMicroPen to derive stability information for avalanche forecasting. Proceedings of the Int. Snow Science Workshop 2006, Telluride CO, USA. 187-192.

Pielmeier, C., 2003. Textural and mechanical variability of mountain snowpacks. PhD thesis, University of Berne, 127 pp.

Schneebeli, M., Pielmeier, C., Johnson, J.B., 1999. Measuring snow microstructure and hardness using a high resolution penetrometer. Cold Reg. Sci. Technol., 30, 101-114.

Schneebeli, M., Johnson, J.B., 1998. A constant-speed penetrometer for high-resolution snow stratigraphy. Ann. Glaciol., 18, 193-198.

Schweizer, J., McCammon, I.A., Jamieson J.B., 2008. Snowpack observations and fracture concepts for skier-triggering of dry-snow slab avalanches. Cold Reg. Sci. Technol., 51, 112-121.

Schweizer, J., Jamieson, B., Fierz, C., 2007. A threshold sum approach to stability evaluation of manual snow profiles. Cold Reg. Sci. Technol. 47 (1-2), 54-63.

Schweizer, J., Jamieson J.B., 2003. Snowpack properties for snow profile analysis. Cold Reg. Sci. Technol., 37, 233-241.

Schweizer, J., 2002. The Rutschblock test-Procedure and application in Switzerland. The Avalanche Review, 20(5), 1, 14-15.

Schweizer, J., Lütschg, M., 2001. Characteristics of human-triggered avalanches. Cold Reg. Sci. Technol., 33, 147-162.

Sturm, M., Johnson, J., Holmgren, J., 2004. Variations in the mechanical properties of arctic and subarctic snow at local (1-m) to regional (100-km) scales. Proceedings of the International Symposium on Snow Monitoring and Avalanches (ISSMA-2004), Manali, India, pp. 233-238.

Winkler, K., Schweizer, J., 2008. Comparison of different snow stability tests including the Extended Column Test. Proceedings of the Int. Snow Science Workshop, Whistler BC, CAN (this issue).