RELATING SPATIAL PATTERNS OF SNOW INSTABILITY TO METEOROLOGICAL DRIVERS

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Abstract

In mountainous regions avalanche hazard threatens people and critical lifelines. In order to mitigate consequences, the avalanche release probability is forecasted for regions of 100 to several 1000 km$^2$. Currently, avalanche forecasting is limited to the regional scale and predicting for smaller areas is hampered by our limited understanding of the variable nature of the mountain snow cover and its ties with weather and terrain characteristics.

To relate spatial patterns of snow instability to meteorological drivers, field measurements at the basin scale were conducted providing quantitative measures and revealing spatial patterns of snow instability. Eventually, the meteorological drivers responsible for the patterns were identified for a specific avalanche situation. As a prerequisite for this approach, however, a quantitative measure to estimate snow instability based on snow mechanical properties had to be established.

As obvious signs of instability are often absent and stability testing is laborious, a promising option to acquire the snow mechanical properties related to instability is the snow micro-penetrometer (SMP). The quality of the SMP-derived snow properties was assessed in comparisons with two other common measurement techniques, modeling of micro-computed tomography derived snow structure and particle tracking of propagation saw tests. Results showed that all snow properties required to model failure initiation and crack propagation are obtained from one SMP signal, but especially with respect to the elastic properties future work is needed.

As a definition of snow instability along the lines of the current understanding of avalanche release processes is lacking, we developed two snow instability criteria for application with snow micro-penetrometer signals. For the first time we developed quantitative measures for failure initiation and crack propagation, the two relevant processes controlling point snow instability. The measures were validated with independent snow instability observations providing confidence in the mechanical approach based on micro-mechanical measurements. Moreover, our results highlight the dependence of snow instability on both, failure initiation and crack propagation.

Based on field data acquired in a basin above tree line ($\leq 0.3$ km$^2$) Davos, Eastern Swiss Alps, during five sampling days we investigated the link between each
of the SMP-derived snow instability measures and simple drivers, such as terrain parameters and snow depth. Among the simple drivers, which explained variations of snow instability to a certain extent, slope aspect was certainly the most prominent driver with a significant influence on the variations under all conditions. The number and type of drivers varied between single days indicating that concluding on avalanche conditions on a specific day is not feasible solely based on terrain characteristics or snow depth. Results for the entire dataset, representing an average over the five sampling days, showed that variations of the propensity of failure initiation were driven by slope angle, while variations of the propensity for crack propagation were best explained by snow depth. Hence, given a specific avalanche situation simple drivers may support extrapolations of snow instability, if the relation between snow instability and simple drivers is known.

Extending the non-spatial analysis with robust geostatistical techniques snow instability variations at the basin scale were quantified. To do so, variations due to differences in terrain parameters and snow depth were modeled with a linear external drift model. The autocorrelation structure of the remaining variation was derived by restricted maximum likelihood estimation. The autocorrelation ranges of the snow instability criteria determined at the basin scale mainly ranged between 5 and 31 m and were comparable to previous studies at smaller scales, primarily at the slope scale. This finding confirmed that autocorrelation ranges of snow instability determined in smaller sampling arrays are meaningful despite often limited spatial extents in slope scale studies. Moreover, as the found autocorrelation ranges were shorter than typical autocorrelation ranges of terrain parameters and terrain induced variations were captured with the external drift model, this study suggests that the identified autocorrelation ranges of 5 to 31 m result from meteorological forcing at the basin scale.

For one exemplary situation (3 March 2011) the meteorological drivers influencing the distribution of snow instability at the basin scale were identified. To this end, the geostatistical analysis was repeated with snow cover model output instead of terrain and snow depth data as covariates. Changing the covariate data did not change the autocorrelation range, as the influence of terrain is implicitly considered in the snow cover model. Including snow cover model data, instead of terrain and snow depth data only, finally allowed searching the meteorological records to identify the parameters responsible for the meteorological forcing. In case of 3 March 2011 differences in precipitation and energy input at the snow surface had caused the observed variations of snow instability. Despite accounting for many micro-meteorological processes and interactions, the spatial snow cover modeling approach still showed deficiencies related to the representation of density and snow depth spatial variations.
To conclude, snow micro-penetrometry provides much needed field data enabling to study snow cover variations and also their temporal evolution, although some discrepancies remain to be solved. More general, data acquired with the SMP allows validating snow properties obtained with other approaches, such as snow cover modeling or remote sensing techniques. The developed snow instability criteria for SMP profiles represent a comprehensive and observer independent method to measure snow instability in the field. The snow instability algorithm may provide input for slope failure models or allow studying the reasons for crack arrest in avalanche prone slopes. Moreover, the approach is not limited to SMP data and may be enhanced with other criteria in future, such as a tensile failure criterion for slab fractures. The basin scale variations modeled with the robust geostatistical approach offer a comprehensive data set to validate the performance of spatial snow cover simulations and to identify weaknesses related to the representation of snow properties. This is certainly required as avalanche forecasting will need to rely on snow cover simulations to include spatial variations. With the benefit of including the meteorological history and characterizing spatial variability, snow cover modelling may enhance forecasting by providing local variations – opening the way for more detailed forecasts in the future.
Kurzfassung

Im Winter sind Verkehrswege und Siedlungen in Gebirgsregionen durch Lawinen bedroht. Um vor der Lawinengefahr zu warnen, beschreiben Lawinenwarndienste die Lawinensituation mit einer Gefahrenstufe, die für Regionen von 100 bis zu mehreren 1000 km$^2$ gilt. Momentan beschränkt sich die Lawinenwarnung auf derartige regionale Prognosen. Vorhersagen für kleinere Gebiete sind schwieriger, da nur wenig über die Variabilität der Schneedecke im Gebirge bekannt ist und man nicht genau weiß, wie Wetterbedingungen und Geländeeigenschaften die räumlichen Schneedeckeneigenschaften beeinflussen.

Um räumliche Variationen der Schneedeckenstabilität mit meteorologischen Einflüssen zu verknüpfen, wurden objektive Feldmessungen in einer kleinen Geländekammer durchgeführt, um die räumliche Verteilung der Schneedeckenstabilität zu untersuchen. Dadurch konnten die meteorologischen Einflüsse abgeleitet werden, die zu den beobachteten Schneedeckenstabilitätsmustern in einer bestimmten Situation geführt hatten. Eine Grundvoraussetzung für diese Vorgehensweise war jedoch die Entwicklung einer quantitativen Messgröße für die Stabilität basierend auf schneemechanischen Eigenschaften.


Da es bisher an einer Definition der Schneedeckenstabilität, die unserem aktuellen Verständnis der Lawinenauslösung folgt, mangelt, wurden zwei quantitative Stabilitätskriterien für das SMP entwickelt. Zum ersten Mal wurden quantitative
Kriterien für die Bruchinitialisierung und für die Bruchausbreitung entwickelt, die die entscheidenden Prozesse für die Schneedeckenstabilität beinhalten. Beide Kriterien wurden mit unabhängigen Stabilitätsbeobachtungen validiert, die ein gewisses Vertrauen in die mechanischen Berechnungen basierend auf den mikro-mechanischen Eigenschaften vermitteln. Ausserdem unterstreichen unsere Ergebnisse die Bedeutung der Bruchinitialisierung und der Bruchausbreitung für die Schneedeckenstabilität.


dem linearen Modell erfasst wurden, liegt es nahe, dass die ermittelten Korrelationslängen von 5 bis 31 m das Ergebnis meteorologischer Einflüsse sind.


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Chapter 1

Introduction

1.1 Motivation

Among the gravity driven natural hazards in mountainous regions are floods, landslides, rockfalls and snow avalanches. Forecasting natural hazards and estimating their damage potential are essential to mitigate the consequences in case of an event (Schweizer et al. 2014a). Prominent examples of infrastructure exposed to avalanche hazard, requiring reliable and detailed forecasts, are public transportation lines, resource industries or residential and recreational areas (Bahnson 1998; Wilhelm et al. 2000; Jamieson and Stethem 2002; Stethem et al. 2003; Hendrikx et al. 2013).

The occurrence of natural hazards, and of snow avalanches in particular, is closely tied to weather conditions including their changeable nature and occasional severity. The sequences of meteorological conditions cause – in connection with terrain characteristics – variations of snow instability which remain to be understood quantitatively.

Snow avalanches occur in mountainous regions all over the globe with at least a seasonal snow cover and are extreme, but rare events. The rare nature of snow avalanches has been discussed by Schweizer (2008) and is suggested to be partly due to the particular nature of the material snow (e.g. McClung 2015). Snow holds a large amount of air pores building around fragile ice structures, which cover with liquid water at the onset of melting. The size and frequency of air pores determines snow density, which is initially related to the size of precipitation particles, but will quickly evolve with external meteorological forcing. Typically, meteorological events affect the topmost part of the snow cover forming stratified layers which are characterized by vertically varying mechanical properties (Colbeck 1991) such as their density, for instance (Fig. 1.1).

Due to a lack of a dense coverage and a high temporal resolution of information on snowpack layering, avalanche forecasting is essentially based on weighing
proxies for snow instability. Considering new snow accumulation, snow temperature and wind, the meteorological conditions are analyzed and combined with available snowpack and terrain data (Schweizer et al. 2003a). Based on point data from models or observations, which are typically available to forecasters, it is not possible to conclude on the scale and the degree of spatial variations of snow instability (e.g. Conway and Abrahamson 1988). Relying on their intuition, however, experienced forecasters are able to interpret observations (LaChapelle 1980) and simulation results to provide the degree of danger within a mountain region. No doubt, snow cover models are capable of modeling variations of snow depth (Mott et al. 2010; Grünewald et al. 2010; Dadic et al. 2010), but modeling snow instability variations remains challenging due to the limited resolution of meteorological data (Rousselot et al. 2010) and model simplifications regarding, for instance, the phenomenological description of snow microstructure (Lehning et al. 2002).

Providing information on variations of snow instability would require knowing the causes of spatial variations as well as their temporal evolution (Logan et al. 2007). Moreover, alternate, possibly measurement based approaches are required to validate such spatial simulations of snow instability, like the ones presented by Rousselot et al. (2010) for the 1999 epochal avalanche cycles in the French Alps. Simulations help us to understand feedback mechanisms in past events, but also allow us to interpret the influence of projected climate scenarios on the snow cover.

Of course, consequences of ongoing climate change were mainly discussed with respect to synoptic scale weather systems (IPCC 2014) – but also in view of a possible increase of weather severity (IPCC 2012). Climate, as considered the aggregate weather conditions in an area, describes the slowly varying meteorological conditions of the atmosphere, including its variations and extremes (Lutgens and Tarbuck 2010). Thus, relevant climatological changes may have consequences for the seasonal snow cover. Regarding averages in the Swiss Alps, altitudinal differences in
snow depth are driven by air temperature below a threshold of about 1400 m, which increased according to Morán-Tejeda et al. (2013); also regional climate model projections suggest a decrease of snow depth for the 21st century at elevations between 1500 and 2000 m (Gobiet et al. 2014). For the occurrence of natural hazards, however, climate extremes are to be considered. Since about 1950 heavy precipitation events and warm as well as cold air temperature extremes have likely increased in Europe and North America (IPCC 2014); in particular strong positive air temperature anomalies during winter at mountain weather stations were observed (Beniston 2005). As a consequence for mountain field sites more melt freeze crusts were observed between mid November and December in a 53-year snow cover record in British Columbia (Bellaire et al. 2013) and increased new snow amounts were reported based on a 30-year Norwegian dataset (Dyrrdal et al. 2013). At lower elevations, however, amounts of solid precipitation decreased in the past decades. With the ongoing climate change the avalanche issue may loose importance at lower elevations due to higher run out elevations, as observed since 1980 in the French alpine regions (Eckert et al. 2010). Avalanche activity, however, did not decrease at higher elevations yet (Dyrrdal et al. 2012); on the contrary, Castebrunet et al. (2014) even modeled an increase of avalanche activity at high elevations in the French Alps for mid and end 21st century climate projections. In future, the projected trends may not cause avalanche issues to simply disappear from hazard maps, but may draw our attention to higher elevations or require alertness to hitherto unknown weather extremes.

Snow cover variations, horizontal or vertical, may be regarded as disorder occurring at scales visible for humans, and scales beyond, often referred to as the micro-scale. Disorder is an inherent property of most naturally occurring materials at a large range of scales (Herrmann and Roux 1990) and in case of snow slab avalanches responsible for the fractures occurring in a weak layer prior to snow slab avalanche release (Schweizer 1999). However, imperfections at the micro-scale alone cannot promote instability, as they are the rule in a porous medium with complex structure. McClung (2015) suggested that, if failure was due to those imperfections, snow would not remain on slopes inclined steeper than the friction angle of 30° (van Herwijnen and Heierli 2009). Many studies focused on the fracture behavior of snow in the past and shed new light on the mechanical processes leading to snow avalanche formation resulting in an accepted framework linking the failure processes at different scales (Schweizer 2014). Before the release of a snow slab avalanche a localization of initially diffuse damage results in a macroscopic failure of a certain area (McClung 1979, 1981). If this macroscopic failure, or initial crack, propagates a slab avalanche releases, which is finally confined by abrupt changes in snow cover properties probably due to terrain variations (Jamieson and Johnston 1992).
As a characteristic of the mountain snow cover, snowpack properties vary at a wide range of scales and consequently provoke differences in snow instability between slopes or areas. To advance our understanding of snow instability and to eventually improve avalanche forecasting a thorough understanding how weather conditions control spatial variations of snow cover properties and how snow property variations are linked to snow instability patterns is required. Due to their interaction with meteorological processes, terrain variations may explain a certain amount of variability, which needs to be known to separate and study the influence of meteorological processes on variations of snow instability. First, however, a definition of snow instability incorporating the relevant fracture mechanical processes and amenable to quantitative analyses is required.

1.2 State of research

To describe the current state of research on variations of snow instability in alpine terrain, we proceed from snow mechanical properties which are required for quantifying snow instability towards the variations seen in field measurements and their causes.

1.2.1 Measuring snow properties

Physical properties of snow play an important role in a wide range of cryospheric applications, reaching from climate sensitivity to water resource estimation. With remote sensing techniques a dense spatial coverage is achieved mainly for bulk or surface properties of the snow cover (Nolin 2010). Snow instability at a certain location, however, initially depends on the vertical variations within the snow cover. Assessing the avalanche hazard the spatial variations of (point) snow instability finally come into play. Hence, both, sufficient vertical and horizontal resolution of snow property measurements are necessary to estimate the distribution of snow instability within an area.

Traditional, manually observed snow profiles only provide indirect, mainly phenomenological observations hindering an estimation of the relevant physical properties, except for snow density or shear strength (Proksch et al. 2015b; Jamieson and Johnston 1993b). Recording profiles with a density cutter or a shear frame, however, is laborious. The most promising approach to measure vertical profiles with high temporal resolution were presented by Schmid et al. (2014), who installed an upward-looking ground-penetrating radar system below the snow cover at a fixed location. A mobile device allowing to measure arrays of vertical profiles of snow mechanical properties is the snow micro-penetrometer (SMP) (Schneebeli
1.2 State of research

and Johnson 1998). With the SMP the penetration resistance of snow is obtained at sub-millimeter resolution. Understanding the connection between the physical properties of snow and their microstructural origin, however, is a general challenge appearing in many snow related contexts (e.g. Shapiro et al. 1997; Schweizer et al. 2003a; Dominé et al. 2011; Löwe et al. 2013). In the past years, advances have been made towards the interpretation of the penetration resistance signal obtained from the SMP (Marshall and Johnson 2009; Löwe and van Herwijnen 2012) and consequently snow density, specific surface area and microstructural correlation length are obtained with reasonable accuracy (Proksch et al. 2015a). Deriving all mechanical snow properties relevant for avalanche release from one SMP signal would allow calculating snow instability directly based on one SMP profile only and eventually enable researchers to obtain many estimates of snow instability within one day.

1.2.2 Deriving point snow instability

Indicators of instability such as recent avalanches, whumpfs or shooting cracks (Fig. 1.2) (Jamieson et al. 2009) are usually considered to estimate snow instability. Often these signs are not observed and in their absence, performing snow instability tests (Schweizer and Jamieson 2010) is considered the method of choice. Another option are stability indices calculated from weak layer shear frame tests (Roch 1966b). With traditional field tests information at the snowpack or ‘pit’ scale (Schweizer and Kronholm 2007) are obtained, but for estimating avalanche hazard the slope or basin scale should be considered. To this end, a metric amenable to quantitative analyses and suited for recording multiple measurements as needed for (geo)statistical analyses is required; thus, classical manual observation methods and stability tests do not qualify.

Alternatively, snow stratigraphy including traditional parameters describing snow structure are obtained from snow cover modeling (Durand et al. 1999; Lehning et al. 2004). However, snow mechanical properties are often not simulated independently, but parameterized on density only. Neither phenomenological parameters like grain type, nor simple parameterizations can reflect the complex structure of snow needed to understand the physical behavior of snow, such as fracture (Löwe et al. 2013).

Kronholm (2004) was the first to obtain quantitative measures in sampling arrays covering a snow slope with the snow micro-penetrrometer. Later, several studies concentrated on the likelihood of initiating a failure in a weak snowpack layer (such as illustrated in Fig. 1.1), termed ‘failure initiation’. Bellaire et al. (2009) and also Pielmeier and Marshall (2009) proposed stability related parameters from measured vertical snow penetration resistance profiles. Pielmeier and Marshall
Introduction

Figure 1.2: A shooting crack accompanied by a ‘whumpf’ like sound observed in the Steintälli field site.

(2009) were able to predict stability classes estimated from rutschblock (RB) tests from penetrometer derived weak layer strength and average slab density with good accuracy provided the weak layer is known. Given the fracture mechanical context of dry-snow slab avalanche release both approaches, however, lack the element of crack propagation, which is considered an important step in the chain of events before avalanche release (Schweizer et al. 2003a).

Clearly, snow stability tests such as the rutschblock or the extended column test (Jamieson and Johnston 1993a; Simenhois and Birkeland 2009) provide information on failure initiation and crack propagation. A quantitative measure for point snow instability, however, is lacking. Such quantitative measures of snow instability should be based on mechanical properties and follow our current understanding of the fracture processes preceding avalanche release. Only then, we may learn about the interaction of snow properties and their control of the avalanche release probability.

1.2.3 Spatial variations of snow instability

The scales on which snow instability varies, reach over several orders of magnitude: from the snowpack or ‘pit’ scale (0.5–5 m) to the mountain range scale (10–100 km)
Avalanche hazard estimation requires snow instability information not only at the pit scale, but the distribution of snow instability at larger scales including fluctuations – not only average stability. Since disorder is considered to be fundamental for the fracture process (Herrmann and Roux 1990), i.e. the scale of spatial variation matters, and hence studying spatial variations of snow properties needs to be envisaged in the context of avalanche formation. If the spatial autocorrelation length is less than the critical length for self-propagating fractures an initial failure might not propagate. Small scale patterns (less than about 1 m) may therefore help prevent avalanche release (Schweizer et al. 2008b). Numerical models suggest that spatial variations of strength properties have a substantial "knock-down" effect on slope stability and that the effect increases with increasing length of spatial correlation of snow properties (Fyffe and Zaiser 2004; Gaume et al. 2014). Field measurements confirming this hypothesis, however, are lacking (Kronholm and Birkeland 2005).

Spatial snow studies generally attempted to characterize spatial continuity – or heterogeneity – of layers and other properties (Kronholm et al. 2004). To cover a slope or a small basin with measurements within one day, snowpack properties or stability information are preferably derived from numerous penetration resistance measurements, because a sequence of several within an hour is possible – in contrast to about one pit per 30–60 minutes when profiling manually. With the snow micropenetrrometer (Schneebeli and Johnson 1998), variations of surface layer hardness (Schweizer et al. 2008a) or surface hoar thickness (Lutz and Birkeland 2011) were studied. However, most studies focused on certain snow properties, leaving open the question how slab and weak layer properties interact and eventually control snow instability.

Whereas warning services can estimate the degree of danger in a region, they can at best provide some information on the locations where the danger is most prominent (Schweizer et al. 2003b). Detailed variations of snow instability are currently not reported in danger forecasts, as many measurements or detailed simulations would be required to do so. Providing information on variations of snow instability would require knowing the causes of spatial variations as well as their temporal evolution (Logan et al. 2007). Several studies addressed these fluctuations in the past, but identifying their causes is not solved, yet (Schweizer et al. 2008b).

## 1.2.4 Causes of spatial variations

The causes of snow instability variations can be subdivided in external and internal drivers acting during and/or after snow deposition (Sturm and Benson 2004). All external drivers are closely related to the meteorological conditions. Already
Seligman (1936) suggested that wind was the most significant cause of variability and indeed, Mott et al. (2010) found precipitation and wind to be the most prominent drivers of snow depth variability. Likewise, the most prominent internal driver, snow metamorphism, depends on the meteorological boundary conditions at the surface. Identifying the meteorological drivers responsible for snow instability variations was attempted during spatial variability studies, but was rather phenomenological (Kronholm et al. 2004) or limited to related snow properties instead (Lutz and Birkeland 2011; Schweizer et al. 2008a).

Snow instability variations beyond the slope scale (5–100 m) have only been addressed rarely (Birkeland 2001; Schweizer et al. 2003b). Results revealed dependencies on terrain parameters, such as elevation or aspect, which typically do not change distinctively at the slope scale. Also snow depth correlated significantly with observed stability at a regional scale. Current research has shown that remote sensing techniques such as laser scanning allow to associate snow deposition patterns with the local wind field (Mott et al. 2010). Also, Schirmer et al. (2011) showed that observed differences in snow depth are explained to a large extent by the average wind speed, altered by terrain. Given the link between snow depth and snow instability reported in regional scale studies, studying so called ‘simple drivers’, such as terrain parameters or snow depth, instead of the process drivers may provide insight in the processes promoting instability. Moreover, relating simple drivers to the above mentioned quantitative measures of snow instability may eventually support decision making in the field, but also enhance interpolations of isolated snow instability measurements as digital elevation models are widely available.

Quantifying patterns of snow instability and identifying the responsible meteorological drivers may improve our understanding of how snow instability varies in space. Finally, a method to do so will also allow us to validate 3D snow cover model simulations, that avalanche forecasting should rely on in future to predict snow instability reliably in complex terrain.

1.3 Goals

Spatial variability of the snow cover is regarded as a main component for avalanche formation – knowing the causes of variability seems the key to improve avalanche forecasting and risk evaluation by providing information on the spatial variation of the danger.

Currently, however, it is not clear how snow instability varies in time and space. Also, we lack a quantitative measure to describe instability and its variations. Only if the spatial distribution of snow instability is measured, variations may be linked to their meteorological causes, which is a long-standing question.
To this end the following goals were defined:

(1) Assess the suitability of the snow micro-penetrometer to provide snow properties relevant for dry-snow slab avalanche release

(2) Define measures of point snow instability considering the processes of failure initiation and crack propagation

(3) Validate the measures of snow instability with independent observations

(4) Measure spatial arrays of snow properties and derive snow instability

(5) Relate point snow instability variations to simple drivers such as terrain parameters

(6) Develop a geostatistical model to quantify spatial snow instability variations at the basin scale

(7) Identify the meteorological drivers responsible for the observed snow instability variations

1.4 Outline

This thesis includes six chapters. After the Introduction, each chapter consists of one scientific contribution. To begin with, in Chapter 2 the preferred snow measurement technique to derive mechanical snow properties is introduced and a comparison with other, current measurement techniques is presented. Based on mechanical snow properties a model to estimate point snow instability is developed and tested in Chapter 3, which is employed to identify simple drivers of snow instability related with terrain parameters and snow depth in Chapter 4. Eventually, a comprehensive geostatistical analysis is performed to determine spatial patterns of snow instability and identify meteorological drivers responsible for the spatial differences (Chapter 5). The last chapter concludes on the findings and offers perspectives for future research.
Chapter 2

Measuring snow properties relevant for snow avalanche release


Abstract

The release of a dry-snow slab avalanche is preceded by a sequence of fractures. The main material properties relevant for the fracture processes are the specific fracture energy and the strength of the weak layer, and the elastic modulus and the density of the overlying slab layers. Recent advances in measurement techniques and data processing now allow to objectively determine these snowpack properties. At the micro-scale, the three dimensional structure of snow samples is obtained from snow micro-tomography ($\mu$CT). By modeling the mechanical behavior based on the snow microstructure under the assumption of linear elasticity, the elastic properties are derived. At the macro-scale, fracture mechanical field tests combined with particle tracking velocimetry (PTV) allow observing the in-situ fracture behavior. Based on the PTV analysis, specific fracture energy and slab effective modulus are derived by fitting an analytical beam equation to the observed deformation field neglecting viscous and plastic deformations. High resolution snow stratigraphy data are obtained from field measurements using the snow micro-penetrometer (SMP). The SMP bridges the gap between both scales since it provides microstructural information for all layers within the snow cover. Using these three techniques, we compiled
a dataset of material properties relevant for slab avalanche release. In many cases we were able to apply at least two of the methods to the same sample. The results show that the different measurement and analysis techniques provide similar values for fracture energy, effective elastic modulus as well as density, even though the measurements were performed at different scales. With reliable methods to determine the key parameters describing the fracture process now being available, snow instability modeling based on either snow cover simulations or spatial field measurements can be envisaged.

2.1 Introduction

Dry-snow slab avalanche release involves a sequence of fractures including failure initiation, meaning the formation of an initial crack in the weak layer beneath the slab, and crack propagation, which finally leads to the detachment of the snow slab (Schweizer et al. 2003a). For both processes, properties of the slab layers and the weak layer are equally important (van Herwijnen and Jamieson 2007b). For failure initiation, the density and the elastic properties of the slab and the strength of the weak layer are believed to be the important properties. For crack propagation, the critical cut length, as it would be measured in a propagation saw test (PST) (Gauthier and Jamieson 2006; Sigrist and Schweizer 2007), is considered the relevant measure. It integrates slab and weak layer properties and can be modeled (Reuter et al. 2015a) using the density and the elastic properties of the slab and the specific fracture energy of the weak layer, which is the resistance to crack propagation (Sigrist and Schweizer 2007).

Density is measured in the field with a precision of around 5% by weighing a snow sample of a given volume (Proksch et al. 2015b). From micro-tomography images the ice volume fraction is determined in a non-destructive way with high spatial resolution (1 mm) providing the most detailed and accurate measurement to date (Proksch et al. 2015b). Also, Proksch et al. (2015a) have shown that with snow micro-penetrometry (Schneebeli and Johnson 1998) the density of snow is obtained with good precision compared with 3D reconstruction of micro-tomography images (Schneebeli and Sokratov 2004).

With the snow micro-penetrometer (SMP) profiles of penetration resistance are obtained at a resolution of about 250 measurements per mm at a speed of 20 mm s$^{-1}$. Interpreting these fluctuations of penetration resistance as a Poisson shot noise process, force and displacement related parameters of individual snow particles are derived (L"owe and van Herwijnen 2012), which enable us to calculate micromechanical snow properties (Johnson and Schneebeli 1999).

With respect to snow instability modeling, the elastic modulus is probably the
most delicate of the mentioned parameters, since experimental values of the effective modulus for seasonal snow spread over at least two orders of magnitude (Mellor 1975). The Young’s modulus is defined as the initial slope in the stress-strain relation and hence, precise values may only be obtained for small displacements. Elastic properties of snow were determined in shear (e.g. Schweizer 1998), torsional shear (Camponovo and Schweizer 2001), tensile (e.g. Narita 1980) and compression (e.g. Scapozza 2004) experiments. Reported values of the elastic modulus range between about 1 and 100 MPa for typical densities of seasonal snow and snow temperatures between -5°C and -20°C (Schweizer 1998; Camponovo and Schweizer 2001; Scapozza 2004; Sigrist et al. 2006; Reiweger and Schweizer 2010). Experiments at various snow temperatures are required to characterize the elastic behavior, because the dependence of the elastic properties on snow temperature varies in particular when approaching the melting point. Also, experiments with insufficient measurement resolution do not reveal the true Young’s modulus, as the initial elastic deformation at small stresses cannot be resolved. Hence, most appropriate values of the Young’s modulus are obtained with highly dynamic experiments – such as ”high frequency vibration” (Mellor 1975) or wave propagation experiments (Capelli et al. 2015). Alternatively, sample-based modeling with finite elements allows deriving an elastic modulus of snow based on the elastic properties of ice. To do so, the stresses due to a prescribed displacement field were modeled from 3D reconstructed micro-computed tomography images by Schneebeli (2004). Still, also this approach apparently holds some uncertainties due to segmentation thresholds and assuming isotropic material properties.

The specific fracture energy $w_f$ of weak snowpack layers was modeled from fracture mechanical field experiments or calculated from lab experiments. First calculations were presented by Kirchner et al. (2002) who applied tensile and shear forces to natural snow samples and derived the critical fracture toughnesses in tension and shear. From carefully prepared snow samples and known snow structure Sigrist (2006) simulated the fracture behavior and obtained values of $(0.04 \pm 0.02)$ J m$^{-2}$. LeBaron and Miller (2014) were the first, who reported values of fracture energy from 3D micro-tomography reconstructions of snow samples. They calculated the critical energy release rate $G_c \propto 2 w_f$ along the minimum cut surface following the idea of Hagenmuller et al. (2014), who defined an area separating a sample at minimum energy cost, and suggested a value of about 0.03 J m$^{-2}$. Values obtained from field experiments range between 0.01 and 2 J m$^{-2}$ (Sigrist and Schweizer 2007; Schweizer et al. 2011). McClung (2015) discussed the differences in view of strain rate dependencies during experiments and presented estimates of fracture energy from the shear fracture model of Palmer and Rice (1973) based on a large field dataset yielding values between 0.01 and 0.2 J m$^{-2}$. Many studies used
the propagation saw test (Gauthier and Jamieson 2006; Sigrist and Schweizer 2007), which is due to its geometry and the well defined loading state the best suited snow stability test for modeling purposes. By assuming the bending of the slab over the weak layer as linear elastic the specific fracture energy may be derived from changes in strain energy. With this approach Sigrist and Schweizer (2007) reported \( w_f = 0.07 \pm 0.02 \text{ J m}^{-2} \) and Schweizer et al. (2011) obtained \( w_f = 1.3 \pm 0.8 \text{ J m}^{-2} \) for different sets of weak layers. The striking differences could partly be explained by the choice of elastic moduli used for the FE simulations. Also Gauthier and Jamieson (2010) reported values of the specific fracture energy from a dataset of 170 PSTs described in Gauthier and Jamieson (2008b). The fracture energies were obtained with an analytical expression presented by Sigrist (2006) and had a median of \( w_f \approx 0.03 \text{ J m}^{-2} \). Requiring assumptions about the bulk effective modulus of the slab when determining the fracture energy, being a weak layer property, is a drawback of this method. This is circumvented by the particle tracking velocimetry (PTV) technique where the displacement field in a propagation saw test (PST) is analyzed. Bulk effective modulus of the slab and the specific fracture energy of the weak layer are both determined simultaneously (van Herwijnen and Heierli 2010), however, at rather low strain rates involving delayed elastic deformation components. Considering several slab layers overlying one weak layer Reuter et al. (2015a) calculated the critical crack length of a PST from the effective bulk modulus of the slab and the specific fracture energy of the weak layer, both SMP-derived, with an error of a few cm.

In the field, the snow mechanical properties of slab layers and the weak layer relevant for slab avalanche release modeling can be measured with either snow micro-penetrometry or analyzing the deformation field by particle tracking of propagation saw tests. Due to different specimen sizes and measurement time scales values obtained with the two methods, however, differ. Our aim is to compare values of density, elastic modulus and fracture energy obtained from both methods and snow micro-tomography derived values. To this end, we use two datasets at different measurement scales relating PST and \( \mu \text{CT} \) with SMP, respectively.

## 2.2 Methods

### 2.2.1 Experimental data

The PST-SMP field dataset consists of field measurements that were conducted in the Swiss Alps around Davos on six days during the winter seasons between 2010 and 2013. On each of these days, SMP measurements and propagation saw test (PST) experiments were performed in close proximity to allow direct comparisons. The ex-
Experimental procedure included performing a manual snow profile, including manual density measurements (CAA 2007), conducting several SMP measurements along a contour line of the slope, preparation of snow columns with the saw cut end close to an SMP measurement and PTV analysis of PST experiments. The snow properties derived from this dataset refer to the macro-scale, i.e. snow layers on the order of 1 to 10 cm.

For comparison to the micro-scale we build on a lab dataset of µCT and SMP measurements previously presented by Riche and Schneebeli (2013). This dataset consists of natural snow samples and nature identical snow samples obtained from the ‘snow maker’ (Schleef et al. 2014) and was – along with other Arctic and Antarctic samples – analyzed by Proksch et al. (2015a), who provide a sketch (Fig. 2a therein) of the original measurement setup used by Riche and Schneebeli (2013). From the center of the snow samples, one µCT sample (≤ 0.5 cm³) was extracted and up to four SMP measurements were taken around the location of the µCT sample allowing direct comparisons. In this dataset measured parameters of snow structure correspond to layer thicknesses of several mm.

In order to compare the snow properties measured with different methods we use linear correlations and report the coefficient of determination $R^2$. In the case of linear regressions we also provide the $p$-values of regression coefficients to describe the significance of the regression slope and the intercept.

### 2.2.2 Micro-computed tomography of snow

Micro-computed tomography (µCT) allows the full reconstruction of the 3D microstructure of snow (Schneebeli and Sokratov 2004). The 27 snow samples from the µCT-SMP lab dataset were all analyzed as described in the following.

µCT scans were performed with a nominal resolution (pixel size) between 10 µm for new snow samples and 18 µm for depth hoar. The size of the scanned volume was selected manually to ensure representative volumes are measured and ranged between $(5.9 \text{ mm})^3$ for new snow and $(7.1 \text{ mm})^3$ for depth hoar. The attenuation image (gray scale image) resulting from each scan was filtered using a Gaussian filter ($\sigma = 1$ voxel, kernel half-width = 2 voxels following Kerbrat et al. (2008)) and then segmented into a binary image. The threshold for segmentation was constant for each sample and determined visually. The snow density of the µCT sample equals the ice volume fraction of the binary µCT image times the density of ice. The elastic moduli were computed from segmented µCT images by finite element modeling (Garboczi 1998). The stresses due to linear elastic behavior observed under displacement constraints were calculated with the finite element method for the ice matrix, assuming material properties of ice. At the upper end of the sample
a vertical strain of $\epsilon = 0.1\%$ was prescribed. The elastic modulus was determined by averaging modeled stresses and strains over the sample volume following the definition for an effective modulus (Torquato 2002) and hence, the obtained effective modulus refers to an isotropic linear elastic modulus in compression, as we neglected microstructural anisotropy. Also with the SMP and also the PTV technique isotropy is assumed. This simplification may be acceptable for this study, but the validity of this assumption in view of the existing microstructural anisotropy of snow remains to be shown in the future, in particular at small scales.

2.2.3 Snow micro-penetrometry

The snow micro-penetrometer (SMP), which contains a high-resolution force sensor being driven into the snow cover at constant speed, measures the penetration resistance of snow layers. By interpreting fluctuations of the penetration resistance as a Poisson shot noise process as proposed by Löwe and van Herwijnen (2012) the SMP signal can be decomposed into three microstructural parameters, namely the rupture force $f$, the deflection at rupture $\delta$ and the structural element size $L$. The parameters were calculated over a moving window $w$ of 2.5 mm with 50% overlap and then averaged over layers which were manually introduced after visual SMP signal inspection. By visual inspection signals of lower quality (according to Pielmeier and Marshall 2009) were excluded.

The density was derived from the median penetration resistance and the structural element length following the work by Proksch et al. (2015a) who improved earlier algorithms by including the microstructural parameter $L$. Hence, snow samples having the same penetration resistance may have different densities, because their approach considers, how ice and air are arranged. To give an example, many smaller structures with weaker bonds yield lower penetration resistance than fewer larger crystals, covering the same ice volume, but having stronger bonds resulting in higher penetration resistance.

The micromechanical modulus was calculated from the microstructural parameters $f$, $\delta$ and $L$ according to Johnson and Schneebeli (1999). For comparison with the PTV derived effective modulus, the effective bulk modulus of the slab was calculated with a FE model simulating a layered snow column bending over a crack similar to the situation in a PST (Reuter et al. 2015a).

The specific fracture energy was determined by integrating the penetration force over a 2.5 mm window and taking the minimum over the distance of the weak layer (Reuter et al. 2015a).
2.2.4 Propagation saw test and particle tracking

All PST experiments had the same dimensions (cross-slope width: 0.3 m, up-slope length: 1.2 m), but had slope normal, rather than vertical, column ends. A crack was cut into the weak layer in up-slope direction with a 2 mm thick snow saw until a self-propagating crack started at a certain crack length, the critical cut length $r_c$. Numerous black markers were inserted in the snow above and below the weak layer and experiments were recorded with a video camera fixed on a tripod. Displacements were derived with particle tracking velocimetry (PTV) for each marker between the original state of the markers and their position during the increase of the crack. The mechanical energy was calculated according to van Herwijnen and Heierli (2010) including the product of the load and the displacements summed up over all snow slab layers for a number of frames (usually between 5 and 15) of the recorded movie. Snow layer density and thickness were available from an adjacent manual snow profile. From the obtained pairs of mechanical energy and corresponding crack length the effective modulus of the snow slab is obtained by fitting an analytic expression for the mechanical strain energy provided by Heierli (2008). The first derivative of the fitted analytic expression, including the effective modulus, with respect to the crack length at the onset of propagation yields the specific fracture energy of the weak layer (van Herwijnen and Heierli 2010).

2.3 Results and discussion

The snow properties involved in snow instability estimation and modeling, namely snow density, modulus and specific fracture energy, were derived from microtomography images, snow micro-penetration signals and particle tracking velocimetry of propagation saw tests. In the following we present the results of our analysis for each property and then compare our results with previous studies, address observed differences and discuss the uncertainties of the current approaches.

2.3.1 Density

Twenty seven snow samples were both, scanned in the $\mu$CT and measured with the snow micro-penetrometer ($\mu$CT-SMP dataset). Snow density was obtained from the ice volume fraction of the binary $\mu$CT images and from SMP penetration resistance measurements. Snow densities derived from the SMP signal were clearly related to those obtained from the $\mu$CT ($R^2 = 0.74$, $p_{\text{slope}} < 0.01$; Fig. 2.1). Sources of uncertainty of $\mu$CT derived snow density are among others related to the segmentation process to obtain binary images and the measurement resolution, which was chosen according to the complexity of the snow structure. The relative agreement of
Figure 2.1: \( \mu \)CT and SMP-derived density with linear regression for 27 snow samples of the \( \mu \)CT-SMP dataset covering a broad range of different snow types (by colors) according to Fierz et al. (2009).

Volumetric measurements with density cutters and \( \mu \)CT measurements are within 5–9% as reported by Proksch et al. (2015b). Assuming the \( \mu \)CT as the more accurate measurement and hence considering it producing ‘true’ values the accuracy of SMP-derived density was estimated to 18% (RMSE) and 15% (MAE). The observed RMSE is slightly higher than the previously reported RMSE of 11% by Proksch et al. (2015a), although we used the parametrization presented in their work. Differences may be due to the larger scatter for alpine snow samples presented here compared to their dataset containing Alpine as well as Arctic and Antarctic samples.

2.3.2 Effective modulus

The linear elastic modulus derived from \( \mu \)CT images with the finite element method ranged between 3 MPa and 0.6 GPa. The elastic modulus increased with increasing density in Fig. 2.2a (solid circles), for the same data as shown in Fig. 2.1 \((R^2 = 0.84)\).

Our \( \mu \)CT-derived values of the elastic modulus are in the same range as values previously modeled by Schneebeli (2004): 62–228 MPa for a density of 234 kg m\(^{-3}\), but different microstructure due to temperature-gradient metamorphism. Both FE-model experiments were conducted at small deformations \( \epsilon = 0.1 \% \) under the assumption of linear elasticity. The parametrization presented by Sigrist et al. (2006) based on vibrational measurements at high strain rates of about 100 Hz are close to the FE simulation results. Scapozza (2004) estimated the modulus from the stress...
Table 2.1: Exponential fit models for dependence of the effective modulus $E$ on density $\rho$: $E = p_1 \cdot \exp(p_2 \cdot \rho)$ for both datasets: $\mu$CT-SMP and PST-SMP. Subscripts CT, SMP and PTV indicate $\mu$CT, SMP or PTV-derived values, respectively. The two other subscripts refer to the parametrization by Scapozza (2004) and Sigrist (2006).

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<td>0.84</td>
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<td>$E_{\text{SMP}}$</td>
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<td>–</td>
</tr>
<tr>
<td>$E_{\text{Sigrist}}$</td>
<td>0.1800</td>
<td>0.0149</td>
<td>–</td>
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<tr>
<td>$E_{\text{PTV}}$</td>
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<tr>
<td>$E_{\text{SMP}}$</td>
<td>0.0783</td>
<td>0.0084</td>
<td>0.67</td>
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increase observed at small deformations ($\epsilon = 0.125\%$). The parametrization with density he proposed yields lower values of the modulus, more modestly increasing with density (Table 2.1).

The differences compared to the FE modeled modulus may be related to the rather low strain rates in his experiments ranging between $10^{-6}$ s$^{-1}$ and $10^{-3}$ s$^{-1}$, which his parametrization was based on.

We also present the effective modulus calculated from SMP measurements, which had been performed adjacent to the $\mu$CT scans, in Fig. 2.2a. The values ranged between 0.16 and 12 MPa and increased with density. Obviously, also the scatter increased with density yielding an $R^2$ of 0.28. Compared with $\mu$CT-derived values, the SMP-derived values were about two orders of magnitude lower.

Also, SMP-derived values were lower than the parametrizations by Sigrist et al. (2006) and Scapozza (2004). The increase of the SMP-derived effective modulus with density, i.e. the slopes in Fig. 2.2a were between the parametrization presented by Sigrist et al. (2006) and Scapozza (2004) (Table 2.1). The strain rates occurring at the tip of the SMP during a measurement are $\dot{\epsilon} \approx 10$ s$^{-1}$ assuming a typical deflection at rupture $\delta = 10^{-5}$ m, a typical structural element size $L = 10^{-4}$ m and the penetration velocity of the SMP $(20 \times 10^{-3}$ m s$^{-1}$). Considering the strain rates involved with the SMP measurement the obtained values correspond to an effective modulus, as to determine the true Young’s modulus strain rates above approx. 100 s$^{-1}$ (Sigrist 2006, p. 51f.) are required.

The SMP-derived values exhibited more scatter than FE-model results of $\mu$CT images according to the $R^2$ (Table 2.1) and in both cases, the $\mu$CT and the SMP-derived modulus, the scatter increased with density. This is expected, as density alone cannot completely describe the complex snow structure (e.g. Shapiro et al. 1997; Schweizer et al. 2003a; Schneebeli 2004; Löwe et al. 2013); in other words snow structure does not only depend on density. For small densities, which often
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consist of precipitation particles, density is a proxy of the effective modulus. In contrast, at higher densities there are obviously more possible snow structures with the same density exhibiting different mechanical behavior.

Figure 2.2: (a) Elastic modulus versus density, both computed from $\mu$CT for 26 snow samples of the lab $\mu$CT-SMP dataset by solid circles and effective modulus versus density, both computed from SMP signals adjacent to the $\mu$CT samples by open circles (colors indicating grain types). Grain type abbreviations according to Fierz et al. (2009). Empirical relation found by Scapozza (2004) by dashed line and by Sigrist et al. (2006) by dash-dotted line. (b) Effective modulus versus density computed from the field dataset by SMP signal analysis and PTV analysis (colors indicate field sites). Black lines represent exponential relationships (Table 2.1).

From SMP measurements and PTV analysis we obtained bulk effective moduli for the PST-SMP field dataset (Fig. 2.2b). With the PTV method, some stratigraphic information is implicitly preserved, meaning that a bulk effective modulus is determined describing the slab as a layered material. To be able to compare with SMP-derived moduli, we calculated the bulk effective modulus with a FE model simulating the bending behavior of a beam identical to the PST. PTV and the SMP-derived values of the bulk effective modulus showed both an increase with snow density (Table 2.1). The scatter for PTV and the SMP-derived values was similar, which is reflected in similar values of the coefficient of determination $R^2$ (Table 2.1).

We obtained for both methods, i.e. from SMP signal analysis and the PTV analysis, lower effective moduli than for the $\mu$CT derived elastic modulus or than reported by Scapozza (2004). As strain rates for the PST are low, we anticipated that effective moduli derived with the PTV analysis would be low, and certainly lower than Young’s modulus. Effective moduli derived from the SMP signals, however, are lower than PTV derived values and possibly too low considering that the strain
rate in front of the cone tip is $\dot{\epsilon} \approx 10\, s^{-1}$. Due to the lack of a reference measurement we could not calibrate the SMP-derived effective modulus and thus, we present the micromechanical modulus as obtained according to Johnson and Schneebeli (1999).

During the PST experiment snow does not behave purely linear elastic, but visco-elastic and/or plastic behavior are involved. In case of a PST van Herwijnen et al. (2015) reported an average observed displacement $\approx 6 \times 10^{-4}\, m$, an average slab thickness of 0.5 m and a typical time scale for the bending of 1.5 s, yielding a strain rate of about $\dot{\epsilon} \approx 10^{-4}\, s^{-1}$. Snow fails brittle for strain rates above around $10^{-3}\, s^{-1}$ (Narita 1980; Schweizer 1998; Camponovo and Schweizer 2001). In Fig. 2.3 stress-strain curves for a high strain rate showing brittle failure (green line) and for a low strain rate showing failure with subsequent strain softening (dark yellow line) are presented. The Young’s modulus is defined as the slope in the stress-strain diagram at the origin. In case an experiment is conducted at strain rates lower than the ductile-to-brittle transition (cf. dark yellow line in Fig. 2.3) and the measurement resolution is not high enough to resolve the initial slope of the stress-strain curve, we may not be able to observe the Young’s modulus, but only an effective modulus. The observed effective modulus is lower, as more (not only reversible) deformation occurs leading to a weaker increase of stress with strain.

**Figure 2.3:** Schematic of the failure behavior of snow at different strain rates above (green line) and below (dark yellow line) the ductile-to-brittle transition based on results by Schweizer (1998). Star indicates peak stress and arrow indicates fracture.

As in the lab $\mu$CT-SMP dataset, SMP measurements were performed adjacent to $\mu$CT measurements in the same snow sample a direct comparison of SMP and $\mu$CT-derived elastic moduli is possible (Fig. 2.4a). Also, by means of finite element modeling a bulk effective modulus was derived from SMP measurements in a layered snow slab, allowing a direct comparison with PTV derived moduli (Fig. 2.4b).

$\mu$CT derived elastic moduli are higher by factor of about 64 than SMP-derived elastic moduli (Fig. 2.4a). The $\mu$CT derived elastic modulus was not linearly correlated with the SMP-derived modulus ($R^2 = 0.07$, $p_{\text{slope}} = 0.19$).

According to Fig. 2.4, the SMP-derived values of the effective modulus were
not sufficiently related with the \( \mu \)CT elastic modulus referring to a sample volume of \( \leq 0.5 \text{ cm}^3 \). The poor agreement of SMP values with \( \mu \)CT are probably due to the large amount of scatter seen in Fig. 2.4a. In fact, the deviations of the \( \mu \)CT and the SMP-derived moduli from their trend lines with density shown in Fig. 2.2a do not compensate, since corresponding samples are not on the same side of the trendline for SMP and \( \mu \)CT values. In addition, the correlation of \( \mu \)CT and SMP-derived density was not perfect \( (R^2 = 0.74; \text{Fig. 2.1}) \), and hence, the correlation of each parameter with density (Fig. 2.2a) is lost in the direct comparison (Fig. 2.4a). To reduce the scatter seen in plots of the modulus vs. density further microstructural parameters possibly need to be included into the parametrization of the SMP modulus. This finding does not come with surprise, as the dependencies of physical properties on snow structure represent open questions in related fields requiring more sophisticated models than simple parametrizations with density (e.g. Dominé et al. 2011; Calonne et al. 2012).

With the PTV method the effective modulus was determined for a bending snow column of \( \leq 0.1 \text{ m}^3 \). The values obtained with the PTV method were correlated with the effective modulus derived from SMP measurements \( (R^2 = 0.66, p_{\text{slope}} < 0.01; \text{Fig. 2.4b}) \). Data collected on 28 February 2012 with sample ID ‘120228,STEI’ are from a thick (approx. 50 cm) and dense slab of 325 kg m\(^{-3}\) on average. On the other sampling days slabs were considerably softer with mean densities below 300 kg m\(^{-3}\).
2.3 Results and discussion

2.3.3 Fracture energy

The specific fracture energy, the crucial property of the weak layer, describes the amount of energy needed to expand a crack over a given distance in the weak layer. The specific fracture energy derived from the SMP signal compared reasonably well with the fracture energy derived from PTV ($R^2 = 0.68$, $p_{\text{slope}} < 0.01$; Fig. 2.5).

![Figure 2.5: Weak layer fracture energy derived from SMP and PTV measurements; colors indicating different field days and sites. Three outlying PTV measurements with fracture energies exceeding 1 J m$^{-2}$ excluded.](image)

PTV derived values are similarly high as values reported by Schweizer et al. (2011) ($w_f = 1.3 \pm 0.8$ J m$^{-2}$), who modeled the specific fracture energy with finite element simulations with effective moduli from SMP microstructural parameters derived after Marshall and Johnson (2009). In general, our PTV values overestimated the specific fracture energy as they are higher than literature values for ice, e.g. Schulson and Duval (2009, p. 206) estimated $w_f \approx 0.32$ J m$^{-2}$.

Lower values of fracture energy $w_f = 0.07 \pm 0.02$ J m$^{-2}$ were obtained by Sigrist and Schweizer (2007), who used a FE model with SMP-derived values of the modulus adjusted to their dynamic experiments at 100 Hz (Sigrist et al. 2006). Two additional, rather novel approaches are based on $\mu$CT and field measurements: LeBaron and Miller (2014) presented values of 0.03 J m$^{-2}$ based on $\mu$CT reconstructions of snow samples and calculations of the critical energy release rate along the minimum cut surface (Hagenmuller et al. 2014). Their calculations are based on the linear elastic assumption and secondary fractures away from the ‘cut’ area were neglected, despite possibly contributing to the fracture energy as well. Moreover, McClung (2015) demonstrated that the specific fracture energy may be obtained from field measurements based on the shear fracture model originally introduced by Palmer...
and Rice (1973). For his avalanche crown dataset he obtained values between 0.08 and 0.36 J m$^{-2}$ and similarly for a large dataset of 591 PSTs he obtained values between 0.04 and 0.1 J m$^{-2}$.

The discrepancies between the values of fracture energy determined with the PTV approach and values from literature or previous studies possibly stem from the non-elastic deformation in the overhanging part of the slab during the PST experiment. Still, the PST mimics the behavior of snow prior to slab avalanche release possibly including some non-elastic deformation. From this point of view, values obtained with the PTV method are again effective values. In fact, with the PTV method fracture energy values are derived from the change of mechanical strain energy under the linear elastic assumption of the anticrack model (Heierli 2008) and hence exceed the commonly reported range in literature.

2.4 Conclusions

Objective and fast measurements of snow-mechanical properties are required to advance snow instability modeling. We presented data acquired with three different methods SMP, $\mu$CT and PTV. Based on the two shared datasets differences of derived density, effective modulus and fracture energy due to the methodology were investigated – revealing promising results, but also discrepancies, which remain to be solved.

Snow density was reproduced with the SMP and the data were well in line with the data derived from $\mu$CT image analysis for a broad range of Alpine snow types.

Also, SMP-derived values of the effective modulus increased with density; the increases were similar to the curves obtained from $\mu$CT and PTV data for previous parametrizations of the effective modulus with snow density. The direct comparison between $\mu$CT and SMP-derived effective moduli suggests that the parametrization of the effective modulus from the SMP-derived micromechanical parameters may not be sufficient. The increasing scatter of the modulus with density in the $\mu$CT-SMP dataset and the groupings of snow types indicate a dependence on snow structure apart from density. To include appropriate snow-structural parameters, a more thorough understanding of the response of the SMP tip during penetration of a snow structure may be helpful. Presently, the only remaining option to calibrate the SMP-derived effective modulus is with PTV-derived mechanical properties.

SMP-derived effective modulus and fracture energy were linearly correlated with PTV-derived values. However, PTV-derived fracture energy values were certainly too high compared with other studies reporting values between 0.03 and 0.4 J m$^{-2}$ and literature values of ice ($w_f = 0.32$ J m$^{-2}$). This overestimation is likely due to the linear elastic assumption of the anticrack model, which the analysis of the
displacement field observed in a PST relies on. To conclude, fracture energy values obtained from SMP signal analysis seem realistic as they are in the range reported in literature and are correlated with independent estimates from the PST analyzed with the PTV method.

Our results demonstrate that the snow micro-penetrrometer provides us with a method to quickly sample the snow properties relevant to failure initiation and crack propagation. All properties needed to model snow instability, namely density and modulus of the slab layers, as well as fracture energy and strength (c.f. Marshall and Johnson 2009) of the weak layer are derived from one SMP signal.
Chapter 3

A process-based approach for point snow instability estimation


Abstract

Snow instability data provide information about the mechanical state of the snow cover and are essential for forecasting snow avalanches. So far, direct observations of instability (recent avalanches, shooting cracks or whumpf sounds) are complemented with field tests such as the rutschblock test, since no measurement method for instability exists. We propose a new approach based on snow mechanical properties derived from the snow micro-penetrometer that takes into account the two essential processes during dry-snow avalanche release: failure initiation and crack propagation. To estimate the propensity of failure initiation we define a stress-based failure criterion, whereas the propensity of crack propagation is described by the critical cut length as obtained with a propagation saw test. The input parameters include layer thickness, snow density, effective elastic modulus, strength and specific fracture energy of the weak layer – all derived from the penetration-force signal acquired with the snow micro-penetrrometer. Both instability measures were validated with independent field data and correlated well with results from field tests. Comparisons with observed signs of instability clearly indicated that a snowpack is only prone to avalanche if the two separate conditions for failure initiation and crack propagation are fulfilled. To our knowledge, this is the first time that an objective method for estimating snow instability has been proposed. The approach can either be used directly based on field measurements with the snow micro-penetrrometer, or be im-
A process-based approach for point snow instability estimation implemented in numerical snow cover models. With an objective measure of instability at hand, the problem of spatial variations of instability and its causes can now be tackled.

3.1 Introduction

Snow slope stability describes the mechanical state of the snow cover on an inclined slope and is inversely related to the probability of avalanche release (McClung and Schäerer 1993). For a given time, depth within the snowpack, and location on a slope, snow stability can be described as the balance between snow strength and stress termed stability index (Roch 1966a). This index has been widely used (e.g. Conway and Abrahamson 1984; Perla et al. 1982) and refined by taking into account triggering by an additional load such as a skier (Föhn 1987). Whereas, the skier stability index has been shown to be related to the probability of skier triggering (Jamieson 1995), this critical stress approach does not take into account that slope failure requires crack propagation. While failure initiation may depend on stress only, the propagation of cracks requires deformation energy (Bazant and Planas 1998). Furthermore, on a slope, strength and stress are spatially variable; these variations are fundamental to the fracture process (Schweizer et al. 2003a). Around locally failed areas, stress concentrations will form and drive crack propagation, and eventually cause catastrophic failure before the average material strength is reached. This observation has been termed knock-down effect (Fyffe and Zaiser 2004) and partly explains why the stability index derived from measurements at or near natural slab avalanches often indicated stable conditions (Perla 1977).

Not surprisingly, the link between point observations of snow stability and snow slope stability is not clear, yet (e.g. Bellaire and Schweizer 2011). Scale issues due to different measurement scales, the so-called support and knowledge gaps between the processes involved at both scales have complicated bringing together point and slope scale snow instability results (Schweizer et al. 2008b). The point stability scale is not even well defined. Failure initiation refers to the collective failing of snow grains, or bonds between grains, on the scale of centimeters and the onset of a self-propagating crack in a weak snow layer called crack propagation. A common scale for both processes is the snowpack scale which spans about one square meter (Schweizer and Kronholm 2007), which in the following we will refer to when we use the term point snow instability.

The stability index assumes a transition from stable to unstable when driving forces are no longer balanced by resisting forces. However, this approach is questionable, primarily since dry-snow slab avalanche release is the result of a series of fractures and snow properties are spatially variable. In a fracture mechanical view,
to describe a material’s resistance to crack propagation, flaw size and toughness need to be considered additionally to the stresses (Anderson 2005). With the introduction of the propagation saw test (PST) (Gauthier and Jamieson 2006; Sigrist and Schweizer 2007) all these properties can be obtained from field data. PST experiments to study propagating cracks have confirmed deformation of the slab to substantially contribute to the mechanical energy consumed by crack extension (van Herwijnen et al. 2010). Further, Gauthier and Jamieson (2008b) have shown that the critical crack length together with the fracture result are related to slope instability. In particular, cracks propagating to the end of the column after saw cut lengths less than 50% of the column length were clear indicators of high crack propagation propensity.

There is presently no objective measurement of snow instability. Instead, recent avalanches, whumpfs or shooting cracks are considered indicators of instability (Jamieson et al. 2009), but these observations are rare. In their absence, the remaining option to gather field data on snow instability is snow instability testing (Schweizer and Jamieson 2010). The rutschblock (RB) is a traditional snow stability test (Schweizer 2002). The RB score was found indicative of the failure initiation propensity, the RB release type of the crack propagation propensity (Schweizer et al. 2008c). Whereas the RB release type only represents an ordinal rank, the propagation saw test (PST) gives a metric value, the critical cut length, which eases quantitative analysis. A combination of the results of both tests therefore seems appropriate for snow instability assessment.

Several studies focused on snow instability in the past, thereby either concentrating on failure initiation or crack propagation. Both, Bellaire et al. (2009) and Pielmeier and Marshall (2009) derived stability related parameters from measured snow micro-penetrometer resistance profiles. They found that weak layer strength and average slab density predicted with good accuracy stability classes estimated from RB tests.

Under the assumption of a uniform slab on a rigid substratum Heierli (2008) presented estimates of critical crack lengths obtained from recalculation of PST field experiments. Yet, averaging slab properties is a strong simplification and Schweizer (1993) pointed out the importance of slab properties for failure initiation. By means of linear elastic finite element (FE) simulations of typical snow profile types Habermann et al. (2008) found the stress at the depth of the weak layer to vary by a factor of 2 compared to a uniform slab. McClung (2009) suggested an alternative model to estimate the critical crack length by considering a finite fracture process zone.

Several numerical approaches focusing on avalanche release (for a summary see Podolskiy et al. 2013) have been made but only a few incorporate both fracture processes. Among the latest were Gaume et al. (2013a) who presented a Mohr–
Coulomb failure criterion based model taking into account variations of weak layer shear strength and stress redistribution by slab elasticity. Only lately, a possible refinement of the classical stability index by accounting for strength variations and their knock-down effect including a derivation of a critical crack length was presented (Gaume et al. 2014).

Predicting snow instability requires snow properties obtained either from field measurements or from snow cover modeling. In the field, the method of choice is the snow micro-penetrometer (SMP) (Schneebeli and Johnson 1998) that allows deriving micro-structural and micro-mechanical properties from the penetration force-distance signal (Johnson and Schneebeli 1999). Marshall and Johnson (2009) showed that values of snow density, elastic modulus and strength derived from snow micro-penetrometer signals compared well with literature data. Interpreting the oscillation of the penetration force as a Poisson shot-noise process Löwe and van Herwijnen (2012) suggested a more robust method to extract the micro-structural parameters. Their method was employed by Proksch et al. (2015a) who developed a reliable parameterization of snow density applicable to a wide range of snow types. Reuter et al. (2013) showed that with the snow micro-penetrometer apart from snow density and effective modulus also the specific fracture energy of the weak layer can be derived. Comparing the results for mechanical properties obtained with snow micro-tomography (Schneebeli 2004) to those with particle tracking velocimetry of propagation saw tests (van Herwijnen et al. 2010) they substantiated the reliability of SMP-derived parameters.

Alternatively, snow cover models provide snow structural information allowing snow instability modeling (Durand et al. 1999; Lehning et al. 2004). However, snow mechanical properties are often not simulated independently, but parameterized on density only. Schweizer et al. (2006) refined the skier’s stability index implemented in the snow cover model SNOWPACK and validated it with field observations. By first identifying the potential weakness in a simulated profile and then assessing its stability. Monti et al. (2014) improved this approach to classify profiles into three classes of snow instability: poor, fair and good.

Given the fracture mechanical context of dry-snow slab avalanche release and the lack of an objective measure of instability, we propose that a description of instability should take into account the two essential processes in slab avalanche release, i.e., failure initiation and crack propagation, and be based on snow mechanical properties measured with the snow micro-penetrometer. Our goal is to provide an observer-independent methodology applicable to field measurements of snow stratigraphy. To this end we introduce a two-step calculation of a stability criterion and a critical crack length based on snow mechanical properties measured with the SMP. Then, we will validate the performance of our approach with field experiments of
snow instability. Finally, we will show how classical snow instability observations may be interpreted in terms of failure initiation and crack propagation.

3.2 Methods

First, we present the experimental data, and then we describe how the mechanical field data acquired with the snow micro-penetrometer was analyzed, before we introduce the new approach to derive snow instability.

3.2.1 Field data

Two data sets of SMP measurements were exploited to test the performance of the failure initiation (A) and the crack propagation (B) part of our approach. Data set A was originally presented by Bellaire et al. (2009). As metadata on snow instability was only available for a share of the data, 64 SMP measurements were kept for further analysis. They were all performed in close proximity (<0.5 m) to a RB test. The main results of a RB test, which is a point observation, are score and release type (Fig. 3.1). We used the score for validating the failure initiation propensity (Schweizer and Jamieson 2010).

**Figure 3.1:** Sketch presenting the rutschblock (RB) test as it is seen looking upslope: after isolating a block of snow 2 m wide and 1.5 m upslope it is loaded progressively by a skier. The loading steps and scores are described in the inset. The release type was not considered here.
Data set B consists of 31 SMP measurements which have been performed in a distance less than 30 cm from the lower end of the column of propagation saw tests (PST) (Fig. 3.2). Data were collected on 7 different days. We filmed the fractures in the PSTs to precisely determine the onset of propagation by measuring the critical cut length in the pictures as a criterion of crack propagation. Both data sets also include manually observed snow profiles including snow grain type and size and hand hardness index for each manually identified layer. In addition, 77 out of the 95 field records in total contain information on either type or absence of signs of instability.

![Figure 3.2: Sketch presenting the propagation saw test (PST) as it is seen looking upslope: after isolating a column 30 cm wide and at least 1.2 m upslope, the weak layer is cut with a snow saw from its lower end continuing upslope. Possible fracture results are described in the inset. Here, we only consider tests where the fracture went to the end of the column “End”.

3.2.2 Snow micro-penetrometer

With the snow micro-penetrometer (SMP) a penetration resistance profile is recorded to a depth well below the weak layer at submillimeter resolution. Based on the detailed manually observed snow profile layers were defined from the corresponding sections of the signal, namely slab layers, a weak layer and a basal layer. As every layer is later represented in a finite element (FE) model and the resolution of the SMP is higher than the one needed for FE simulations, we deal with layers for
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Figure 3.3: Penetration resistance (black) as measured with the SMP vs. snow depth. Slab layers (S1–S5) shaded in light green, weak layer (WL) shaded in light red, basal layer (B) shaded in light orange. 50 mm of air signal cut off.

In the sake of shorter computation times, Fig. 3.3 shows an example of a SMP signal with manually assigned snow layer boundaries.

Applying the shot-noise model by Löwe and van Herwijnen (2012) snow microstructural parameters, namely the rupture force $f$, the deflection at rupture $\delta$ and the structural element size $L$ were calculated over a moving window $w$ of 2.5 mm with 50% overlap and then averaged over the layer. Snow density was calculated as described in Proksch et al. (2015a):

$$\rho = a_1 + a_2 \log \left( \tilde{F} \right) + a_3 L \log \left( \tilde{F} \right) + a_4 L,$$

(3.1)

where $a_i$ are coefficients, $F$ is the penetration resistance and tilde denotes the median. The micro-mechanical effective modulus and strength were calculated according to Johnson and Schneebeli (1999):

$$E = \frac{f}{\delta L},$$

(3.2)

and

$$\sigma = \frac{f}{L^2}.$$  

(3.3)

The specific fracture energy of the weak layer (WL) was calculated as the minimum of the penetration resistance integrated across the window size $w$ within the weak
layer (Reuter et al. 2013):

\[ w_f = \min_{w_L} \int_{-\frac{w}{2}}^{\frac{w}{2}} F \, dz. \]  

(3.4)

The penetration depth PS was calculated from Eq. 3.5 by integrating the penetration resistance \( F \) from the snow surface to PS until a threshold absorbed energy \( e_a = 0.036 \, \text{J} \) is reached. The value of \( e_a \) has been determined by comparison of SMP profiles with concurrently observed penetration depth (Schweizer and Reuter 2015):

\[ e_a = \int_0^{PS} F(z) \, dz. \]  

(3.5)

### 3.2.3 Modeling

In the following, the modeling approach to calculate estimates of the failure initiation and the crack propagation propensity of a certain slab–weak layer combination is described and validated. The mechanical properties required as input are obtained from the SMP signal as described above.

#### Failure initiation

A strength-over-stress criterion \( S \) describes the propensity of the weak layer to fail in the case of an additional load:

\[ S = \frac{\sigma_{WL}}{\Delta \tau}, \]  

(3.6)

with \( \sigma_{WL} \) being the strength of the weak layer and \( \Delta \tau \) being the maximum additional shear stress at the depth of the weak layer due to skier loading. The strength of the weak layer is approximated by the micro-mechanical strength derived from the snow micro-penetrometer signal in the weak layer; i.e., we cannot use the slope-parallel shear strength because the SMP is an indentation test measuring an effective strength resulting from the mixed-mode breaking of bonds at the tip. The maximum shear stress at the depth of the weak layer was modeled with the 2-D linear elastic finite element model originally designed by Habermann et al. (2008) to calculate the shear stress at the depth of the weak layer below a layered slab due to the weight of a skier. \( S \) may be interpreted as an indicator of failure initiation with low (high) values being associated with high (low) likelihood of initiating a failure. Note, the stability criterion \( S \) is not expected to yield typical values of the skier’s stability index (\(< 1 \) for “unstable”, \(> 1.5 \) for “stable”) (Jamieson and Johnston 1998). One reason is that SMP-derived strength values are about 2 orders of magnitude larger than values of shear strength reported in literature (Marshall and Johnson 2009). As the SMP measurement is a small-scale indentation test, the difference between
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Figure 3.4: (a) FE model to simulate the maximum shear stress at the depth of the weak layer consisting of three slab layers (green), the weak layer (red) and a basal layer below (orange) inclined by the slope angle $\alpha$. Triangles indicate fixed nodes. The applied strip load $P$ is illustrated by black arrows pointing towards the snow surface. The axes of the coordinate system are indicated by arrows. (b) Maximum shear stress from FE simulations (dots) and from the analytical solution (line) for a uniform slab with density $200 \text{ kg m}^{-3}$ and a slope angle of $38^\circ$ vs. slab thickness $H$.

strength values measured with the SMP and the shear frame test (Jamieson and Johnston 2001) may be attributed to sample size and type of loading.

The 2-D FE model by Habermann et al. (2008) has been adopted to include all relevant slab layers – usually about 5–10 layers. The geometry of the model (Fig. 3.4a) was chosen such that the length of the modeled section of the snowpack (10 m) is at least 1 order of magnitude larger than the average depth of the weak layer to keep boundary effects small. The model consists of multiple layers including slab and basal layers as well as an embedded weak layer corresponding to the layering identified in the SMP signal. The layers are inclined by the slope angle $\alpha$. Nodes at the lower end (on the right of Fig. 3.4a) and at the snow–soil interface were fixed in both coordinate directions.

The model domain was divided into 2-D, quadrilateral plane strain elements having eight nodes each. The mesh consisted of 75 nodes in the horizontal and 100 nodes in the vertical per meter. The model has been implemented in ANSYS workbench to calculate the maximum shear stress within the weak layer. We assumed plane strain as stresses in the direction normal to the $x$–$y$ plane are smaller than within and linear elastic behavior as the loading rate is high considering skier loading. The skier load was modeled as a static strip load $P$ of 780 N spread over a width $a$ of 0.2 m. To account for skier penetration, we assumed the layers within the penetration depth to be compacted to a density of $300 \text{ kg m}^{-3}$ with a corresponding elastic modulus of 16 MPa according to Scapozza (2004); the thickness of those slab
layers was adjusted so that the mass remained the same. All snow layers in the FE model were assigned thickness, density and effective modulus values as derived from the SMP signal. A fixed value of the Poisson’s ratio was chosen ($\nu = 0.25$), as its influence is small compared to our measurement uncertainties for density or elastic modulus. From the modeled linear elastic behavior, the maximum shear stress within the weak layer was computed yielding $\Delta \tau$ of Eq. 3.6, i.e., not considering the stress due to the weight of the slab.

The FE model was tested to reproduce the analytical solution of McClung and Schweizer (1999) for the shear stress for a strip load on a finite area $\tau(\theta, H)$ where $\theta$ and $H$ are 2-D polar coordinates. To do so, the maximum shear stress at a certain depth $H$ was determined by varying $\theta$. The FE model was run with a Poisson’s ratio of $\nu = 0.49$, as the analytical solution assumes an incompressible half space. The slab was not stratified, but uniform having a density of 200 kg m$^{-3}$. Hence, the solution is independent of the elastic modulus. The simulation results for different slab thickness $H$ are presented in Fig. 3.4b together with the analytical solution. The FE model reproduced the maximum shear stress as obtained with the analytical solution very well ($R^2 = 0.94$, regression slope $m = 1.2$) especially for slab depth larger than the width of skier load (0.2 m).

Crack propagation

In order to estimate the crack propagation propensity the critical crack length as measured in a PST experiment was calculated for a weak layer embedded by a layered slab and a basal layer.

A theoretical expression (Eq. 3.7) linking the fracture energy of the weak layer, the elastic modulus of the slab and the critical crack length for a self-propagating crack is obtained by replacing the mechanical energy in Griffith’s criterion with the total energy of the slab–weak layer system found by Heierli (2008) and was presented in detail by Schweizer et al. (2011). The formulation of the total mechanical energy of the slab–weak layer system has been proven to describe the released mechanical energy of the slab in a PST reasonably well (van Herwijnen et al. 2010):

$$w_f (E, r_c) = \frac{H}{2E} \left[ w_0 + w_1 \frac{r_c}{H} + w_2 \left( \frac{r_c}{H} \right)^2 + w_3 \left( \frac{r_c}{H} \right)^3 + w_4 \left( \frac{r_c}{H} \right)^4 \right], \quad (3.7)$$

with

$$w_0 = \frac{3\eta^2}{4} \tau^2,$$
$$w_1 = \left( \pi \gamma + \frac{3\eta}{2} \right) \tau^2 + 3\eta^2 \tau \sigma + \pi \gamma \sigma^2,$$
$$w_2 = \tau^2 + \frac{9\eta}{2} \tau \sigma + 3\eta^2 \sigma^2,$$
$$w_3 = 3\eta \sigma^2,$$
$$w_4 = 3\sigma^2.$$
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**Figure 3.5:** The polynomial’s (Eq. 5) discriminant vs. slab density for typical values of slab thickness (colors); different line styles indicate flat terrain (dashed) and a slope inclined by $\alpha = 38^\circ$ (solid lines).

$\tau = -\rho g H \sin(\alpha)$ the shear stress, $\sigma = -\rho g H \cos(\alpha)$ the normal stress, $\gamma = 1$ the elastic mismatch parameter, which is about 1 according to Heierli (2008), $\eta = \sqrt{4(1 + \nu)}/5$ and $\nu = 0.25$. Provided the elastic modulus $E$, the density $\rho$ and the thickness of the slab $H$, the fracture energy of the weak layer $w_f$, and the slope angle $\alpha$ are known, the calculation of the critical crack length $r_c$ reduces to finding the roots of Eq. 3.7. This fourth degree polynomial of $r_c$ has real, ever positive coefficients. Figure 3.5 illustrates the dependence of the polynomial’s discriminant on slab thickness and density, which is the case if a dependence of the elastic modulus on density is assumed. As the polynomial’s discriminant does not change sign for typical values of density (and the elastic modulus), solutions consist of a pair of complex conjugated and two real roots. A physically meaningful solution of $r_c$ is obtained, if the complex roots and the one with an unexpected sign are discarded.

To relax the assumption of a uniform, i.e., not stratified, slab a FE model was designed to determine the equivalent bulk modulus $E'$ of a stratified slab (Fig. 3.6a). The model performed a stepwise calculation of the mechanical strain energy $M$ of a stratified slab due to bending over an increasing crack of length $r$. In order to recover an equivalent bulk modulus $E'$, in a next step the pairs of mechanical energy and crack length $(M, r)$ were fitted with a theoretical expression of the total mechanical
energy of the slab $M$ (Heierli 2008):

$$M(E', r) = \frac{\pi \gamma r^2}{4E'} \left( \tau^2 + \sigma^2 \right) - \frac{r^3}{6E'H} \left[ \lambda_{\tau\tau} \tau^2 + \lambda_{\sigma\tau} \tau \sigma + \lambda_{\sigma\sigma} \sigma^2 \right], \quad (3.8)$$

with

$$\begin{align*}
\lambda_{\tau\tau} &= 1 + \frac{9}{4} \eta \left( \frac{r}{H} \right) - 1 + \frac{9}{4} \eta^2 \left( \frac{r}{H} \right)^2 \\
\lambda_{\tau\sigma} &= \frac{9}{2} \eta + \frac{9}{4} \eta^2 \left( \frac{r}{H} \right) - 1 \\
\lambda_{\sigma\sigma} &= 3 \eta^2 + \frac{9}{2} \eta \frac{r}{H} + \frac{9}{5} \left( \frac{r}{H} \right)^2.
\end{align*}$$

The FE model consists of stratified layers, which were assigned SMP-derived values of density, effective modulus and thickness (Fig. 3.6a). The Poisson’s ratio was kept constant ($\nu = 0.25$). Due to its geometry (only considering slab layers) and boundary conditions (rigid support along the ligament length ($L-r$)), the FE model only considers the behavior of the slab layers as described with the formulation of the total mechanical energy of the slab–weak layer system, neglecting deformation in the weak or basal layers. In our model, the deflecting beam never got in touch with the basal layer, which, however, may be the case in field experiments, in particular with soft slabs. The FE model reproduced the theoretical formulation very well ($R^2 = 0.85$), especially for crack lengths $r$ greater or equal the thickness of the overlying slab $H$ (Fig. 3.6a). With the bulk equivalent modulus $E'$, we find the exact solution of Eq. 3.7 and obtain the critical crack length $r_c$ for the specific slab–weak layer combination.

**Figure 3.6:** (a) The FE model to calculate the equivalent effective modulus contains as many slab layers as necessary to reflect the stratigraphy found in the SMP signal. Triangles indicate fixed nodes. The beam of length $L$ is overhanging a crack of length $r$ and is inclined by the slope angle $\alpha$. (a) Mechanical energy $M$ over the ratio of crack length and slab thickness ($r/H$) modeled with FE (dots) and calculated from the analytical solution (line) for a homogeneous slab with density $200 \text{ kg m}^{-3}$ and a slope angle of $30^\circ$. 
3.3 Results

In the following, both model parts predicting the propensity of the snowpack to failure initiation and crack propagation are evaluated with the two independent data sets (A and B).

3.3.1 Failure initiation

For each of the 66 SMP profiles with corresponding RB test (data set A) the failure initiation criterion $S$ was calculated. SMP-derived density, effective modulus, strength and layer thickness were used to drive the FE model. For the comparison with the RB score, we grouped scores 1 and 2 as well as 6 and 7 because scores 1 and 7 were observed infrequently. The criterion $S$ increased with increasing RB score (Fig. 3.7a). If for a given $S$ there was no overlap of the boxes, the predictive power of $S$ would obviously be very good. Although this is not the case, the medians of the failure initiation criterion (indicated by gray lines) per RB score increased monotonically with increasing RB scores. This monotonic increase is reflected in a high Spearman rank correlation coefficient ($r_s > 0.9$). If results are grouped (Fig. 3.7b) by scores in two stability classes of RB $< 4$ and RB $\geq 4$, a threshold previously found to separate lower and higher stability (e.g. Schweizer and Jamieson 2003), the criterion $S$ discriminated well between the two classes (Wilcoxon rank sum test, level of significance $p = 0.01$) with a classification tree splitting value of $S = 133$.

3.3.2 Crack propagation

All 31 SMP signals from data set B were analyzed and the critical cut length $r_c$ was calculated from Eq. 3.7 with SMP-derived mechanical properties being density, effective modulus, specific fracture energy and layer thickness. In Fig. 3.8 the results are contrasted with the critical crack lengths measured in the field in the PST experiments adjacent to the SMP measurements. On the left, (Fig. 3.8a) model results are shown for the case of a uniform slab; i.e., density and effective modulus were averaged to show the effect of neglecting the stratigraphy of the slab. Modeled values overestimated the critical cut length yielding a rather fair Pearson correlation coefficient of $r_p = 0.58$ and a coefficient of determination of $R^2 = 0.29$. Only for a few experiments were modeled and observed crack lengths similar, indicating that assuming a uniform slab is not a good approximation. In fact, Fig. 3.8b shows that the agreement between model results and observations improved if the stratification of the slab was taken into account. All identified slab layers were assigned the corresponding density and effective modulus obtained from SMP signal processing and input in the FE model to determine the bulk effective modulus of the slab.
The modeled values of critical crack length were clearly related to the measured values ($r_p = 0.83$) as indicated by the collapse of the linear regression on the 1:1 line (Fig. 8b). The regression slope was well-defined ($p < 0.01$) with some scatter ($R^2 = 0.50$) indicating the uncertainty involved with the presented approach. The critical crack length was predicted with a root mean squared error of 7 cm, a mean absolute error of 2 cm and a mean absolute percentage error of 9%.

### 3.3.3 Validation with signs of instability

Model results were further compared with independent field observations of signs of instability such as whumpfs, shooting cracks and recent avalanches. Both data sets (A and B) included records of such field observations which we grouped in three categories: whumpfs, shooting cracks with or without whumpfs (“cracks”) or “all signs” (whumpfs, cracks and recent avalanches); i.e., fresh avalanches were only observed simultaneously with whumpfs and cracks (Fig. 3.9). To jointly relate
### 3.3 Results

Figure 3.8: Critical crack lengths $r_c$ predicted from Eq. 3.7 are contrasted with critical crack lengths measured in the field ($N = 31$). Experiments grouped by date and location with colors. Solid line shows linear regression, dashed line indicates the 1:1 line.

(a) Slab stratigraphy neglected (average density, average effective modulus). (b) Density and effective modulus of each snow layer taken into account by FE simulation.

Our modeled estimates of instability to the observations of instability we contrasted the propensity to crack propagation, i.e., modeled critical crack length, and failure initiation, i.e., initiation criterion $S$, in Fig. 3.9. Signs of instability were primarily present in the lower left of Fig. 3.9, i.e., for low values of the failure initiation criterion and the critical crack length. Vice versa no signs of instability were reported if both criteria yielded high values (upper right). This finding suggests that both criteria, the one for failure initiation and the one for crack propagation, are linked to snow instability. A classification tree with the two independent variables $S$ and $r_c$ yielded splits of $S = 234$ and $r_c = 0.41$ m which separate between the cases with and without concurrently observed signs of instability (Fig. 3.9). These thresholds divide the plot into four quadrants. In the lower left quadrant all 35 cases with signs of instability as well as 10 cases without signs of instability were found. Our split value ($S = 234$) for the initiation criterion $S$ is very similar to the one found by Schweizer and Reuter (2015) who reported a value of 212. In regard to the modeled critical crack length, Gauthier and Jamieson (2008a) suggested a value of <50% of the column length which in their study corresponded to 50 cm. Assuming crack propagation to be likely (two lower quadrants) or failure initiation to be easy (two left quadrants) does not distinguish sharply between signs of instability present or absent. However, if both criteria had low values unstable snow conditions were observed (lower left quadrant).
3.4 Discussion

In our present understanding avalanche release is seen as a sequence of fractures. To capture the two most important steps preceding the detachment of a snow slab we addressed the stress at the depth of a potential weakness with the failure initiation criterion $S$ and the critical crack size for self-propagation with the critical crack length $r_c$. We presented a model approach to derive both quantities from snow micropenetrometer signals which is a fast method to acquire information on mechanical properties in the field.

Assessing the performance of the model approach with two different field tests (RB and PST) yielded plausible results. However, the main source of uncertainty is related to the mechanical properties needed as input for the model. Snow density, effective modulus and specific fracture energy were all determined from SMP measurements. Uncertainties related to the determination of these mechanical properties have recently been addressed by Proksch et al. (2015a) and Reuter et al. (2013) and lie within $10 - 20\%$ for density and fracture energy. Other SMP error sources are known, so erroneous signals were identified and discarded. Some errors were user-
related such as mechanical disturbances. Other unavoidable errors such as signal drift due to strong temperature changes in the snowpack or stick slip of the rod at high snow densities were rare.

The SMP-derived failure initiation criterion $S$ performed well based on the evaluation with rutschblock tests, yielding a better correlation than the one lately observed by Schweizer and Reuter (2015) using the compression test. They concluded that the dimensions of the compression test and the type of loading are not ideal for modeling purposes. While the RB test includes six different loading steps, the load is only increased twice in a compression test, but numerous taps are performed within the same loading range. The loading of the RB and consequently the stress exerted on the weak layer increases monotonically with the score (score four and five have the same load). This is reflected in the fair discrimination of RB scores four and five with the failure initiation criterion $S$. Furthermore, RB loading steps are ordinal numbers; i.e., they can be ranked, but they do not follow a known relation with stability. Hence, the stress in the weak layer increases stepwise in the experiment, whereas the modeled stability is continuous. The box plots in Fig. 3.7 group modeled values of failure initiation ($S$) with rutschblock classes. The monotonic increase of the medians suggests that the criterion $S$ reflects the propensity of failure initiation in a weak layer below a layered slab. Correlations of the rutschblock release type were neither significant with the initiation criterion $S$ ($r_s = 0.11, p = 0.39$), nor with the modeled critical cut length ($r_s = 0.04, p = 0.76$).

The critical cut length was modeled with an accuracy of a few centimeters (RMSE of 7 cm). It was shown that the slab layering played an important role in the process of crack propagation. Only with the introduction of the bulk effective modulus imitating the bending behavior of a layered slab measured critical cut lengths were reproduced with good accuracy (Fig. 3.8). Until now, research on snow instability had mainly focused on weak layer or average slab properties (Bellaire et al. 2009; Pielmeier and Marshall 2009), and field studies quantifying the influence of snow layering on snow instability (Reuter and Schweizer 2012) were rare. Alternatively, the critical value of the crack length could have been determined by stepwise increasing the crack length in an FE model until the critical energy release rate reaches the specific fracture energy of the weak layer. This approach, comparable to that of Mahajan and Joshi (2008), however, was not followed due to its high computational expenses, as repeated meshing for every single iteration step would be costly.

The introduced FE models assumed linear elastic behavior and were confined to two dimensions. These assumptions are in contrast with our knowledge that snow is a porous medium consisting of a non-isotropic ice/air matrix, exhibiting plastic, elastic and viscous behavior at the macro scale. However, as loading rates in RB
tests and PSTs are high, linear elastic assumptions are justified – for the rutschblock test at least at a certain depth below the snow surface. Two-dimensional modeling seems sufficient, as three-dimensional modeling is not advantageous due to the lack of experimental orthotropic material properties at this point of time.

### 3.5 Conclusions

We have developed a novel approach to determine quantitative estimates of both, the failure initiation and crack propagation propensity of the snowpack based on mechanical properties derived from objective snow micro-penetrometer measurements. Based on the current understanding of dry-snow slab avalanche release it includes the mechanical properties of all relevant layers embedding the weak layer to make predictions on the propensity of initiating a failure and spreading the crack in a weak layer within the snowpack. The presented approach is process-based, observer-independent and relies on measurements of mechanical properties.

The performance of the two novel measures of instability has been assessed in comparisons with two different data sets of field tests (rutschblock and propagation saw test). Both measures of instability, the stress criterion $S$ as well as the critical crack length $r_c$ were well correlated with the results of field tests. In addition, the importance of slab layering especially with respect to crack propagation has been shown. The comparison of our modeled estimates of snow instability with field observations of signs of instability clearly indicated that a snowpack is unstable only in case of high failure initiation as well as high crack propagation propensity. Although we anticipated this finding, i.e., that both conditions have to be fulfilled, we are not aware, to the best of our knowledge, that it has been demonstrated before.

Recent field studies have frequently focused on identifying spatial variations of snow instability and its drivers, which requires an objective measure of instability, which was so far lacking. With the observer-independent method (we presented taking into account both failure initiation and crack propagation processes) it will become possible to resolve causes of spatial snow instability variations. With respect to operational application in the context of avalanche forecasting, our approach based on field measurements could be employed, provided a robust and reliable snow micro-penetrometer is at hand which additionally allows remote data transfer and automatic processing, or be implemented in numerical snow cover models.
Acknowledgements:

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Chapter 4

Relating simple drivers to snow instability


Abstract

Snow layers form during and after accumulation due to the interaction of meteorological and physical processes. It is known that the vertical structure and also the lateral continuity of layers depend on these processes and the boundaries set by the terrain. This study addresses the variations seen among vertical penetration resistance profiles and investigates possible forcings at the basin scale. In the past years we acquired a unique dataset with 613 snow micro-penetrometer (SMP) resistance measurements covering a variety of dry-snow conditions. With recent advances in signal processing all snow layer properties required for snow instability modelling are extracted from a SMP signal so that quantitative metrics of the propensity to failure initiation and crack propagation can be calculated. The modeled values of instability corresponded well with field test results obtained during the measurement campaigns and the verified, local danger. We then analyzed whether snow instability was related to simple drivers such as slope aspect, snow depth and slope angle. In general, aspect was the most prominent driver as on all field days we found associations of our measures of snow instability with aspect. For ‘old’ slab layers the relation between aspect and snow instability was more pronounced than for recently deposited slab layers. However, the relationships between drivers and our measures of snow instability varied depending on whether we analyzed the single
field days separately or jointly. Considering all field days jointly, which reflects mean trends over varying snowpack conditions, slope angle was weakly related to the failure initiation propensity and snow depth to the crack propagation propensity. Our findings suggest that with SMP field measurements differences in snow conditions can be resolved which relate to the failure initiation and crack propagation propensity relevant for snow instability assessment. Our analysis of terrain and snow depth data showed that readily and widely available simple drivers have the potential to enhance snow instability predictions from point measurements at the basin scale.

4.1 Introduction

Classical snow instability observations require an in-depth knowledge on site selection (e.g. Landry et al. 2004; Schweizer and Jamieson 2010), snow profiling technique and above all interpretation (e.g. Schweizer and Jamieson 2007). As we often already know the general avalanche conditions within a region, but are interested in local differences, we may look at the drivers responsible for snow instability patterns. The causes (or drivers) of spatial variations in snow instability, and in general of snowpack properties, can be divided into external and internal agents acting during and/or after deposition (Sturm and Benson 2004). These process drivers include precipitation, wind, radiation, temperature and snow metamorphism; they all cause spatial variations mainly by interacting with terrain (Schweizer et al. 2008b). Whereas at the slope scale, the causes of spatial variations are difficult to explain since typical drivers such as radiation do hardly vary, the problem is perceived to be somewhat less complex at the basin scale (for a definition of scales used in spatial variability studies see Schweizer and Kronholm (2007)). In fact, at the scale of a basin, covering several slopes within a subregion of a valley, it has been shown that, for example, differences in snow depth can be explained to a large extent by the average wind speed, altered by terrain (Schirmer et al. 2011). Just by applying a simple terrain parameter based model (Winstrol et al. 2002) they were able to reproduce general snow accumulation patterns at the basin scale. Therefore, we hypothesize that at the basin scale variations of snowpack properties relating to instability may be mainly due to varying topography so that simple drivers such as terrain parameters can be considered instead of the process drivers to explain observed spatial patterns. In contrast, this assumption does not hold at the slope scale, where these variations of topography simply do not exist.

Exploiting simple drivers such as terrain parameters or snow depth for snow instability estimation may be useful when making decisions in the field or interpolating snow instability information. Snow instability assessment is principally based on weighing meteorological conditions such as new snow accumulation, snow tem-
4.1 Introduction

Accounting for detailed terrain characteristics is key for accurately modeling incoming global radiation (Helbig et al. 2010) and thus snow temperatures, but also for assessing snow accumulation which is forced by local, terrain induced winds (Dadic et al. 2010). As both, the radiation balance and snow accumulation are closely tied to terrain parameters, the terrain parameters aspect and slope angle are believed to shape snow instability patterns (Schweizer et al. 2008b). Moreover, slope angle is not only an important parameter of incoming shortwave radiation, but also directly determines the stress state within the snowpack. Snow depth is suspected to be an indicator of snow instability, just as recurring snow depth patterns are shaped by terrain and average weather conditions (Grünwald et al. 2010). Above all simple drivers have the great advantage that they are readily and widely available.

Various studies have investigated associations between snow instability and simple drivers such as slope aspect, snow depth and slope angle. At the slope scale, (Campbell and Jamieson 2007) performed Rutschblock (RB) tests on rather uniform slopes with small differences in either aspect, snow depth or slope angle. Their results were mostly inconclusive, as on most slopes they could not find a clear relation between RB score and snow depth, aspect or slope angle. Furthermore, when correlations were present, e.g. for snow depth and slope angle, they were either positive or negative. Birkeland et al. (1995) measured snow strength with a digital resistograph as an indicator of snow instability on two different slopes. Whereas they found no relation between snow depth and snow strength at one site, they suspected less complex terrain characteristics at a second site to cause a significant relation between snow depth and snow strength.

At the regional scale, however, some studies identified relations between snow stability test results or specific snow instability related properties and terrain parameters. Birkeland (2001) was among the first to investigate the dependence of snow instability on terrain and found lower stability results in high elevation north-facing slopes. His results also indicate that differences evolve with time, i.e. variable weather conditions shape the snowpack and introduce terrain driven differences. Schweizer et al. (2003b) analyzed snow instability observations from five periods during a winter season covering a mountain region as well. Among the simple drivers specified above they found that snow depth was the best indicator of snow instability. Assessing the predictive power of meteorological and snowpack properties for observed snow instability, Zeidler and Jamieson (2004) also found snow depth to be a significant driver for instability, which they described with a skier stability index.

At the basin scale, Schweizer et al. (2008a) performed manual observations of snow surface properties and measurements of penetration resistance with the snow micro-penetrrometer (SMP) (Schneebeli and Johnson 1998). With the penetration
resistance measurements (four per manual observation) they found a larger amount of variation in snow surface properties than with manual observations indicating that variation depends on measurement support, the area represented by each sample. They also explored the causes of the snow surface hardness variations based on measurements of a nearby automatic weather station. Whereas their analysis of the causes of variability at the slope scale was mainly inconclusive, they observed a general trend to lower penetration resistance in the topmost 2 cm and lower slopescale variation after a snowfall event and higher resistance and variability during a subsequent period of fair weather.

Buried surface hoar layers can cause widespread avalanching and periods of poor snow stability. Hence, a couple of studies focused on how terrain parameters drive the distribution of surface hoar. Lutz and Birkeland (2011) modeled the radiation budget in forest openings including the sky visibility and found that spatial differences of measured surface hoar size depended thereof. Feick et al. (2007) and Borish et al. (2012) identified a correlation between elevation and surface hoar crystal size and snow instability estimates, which both attributed to local wind regimes. Schweizer and Kronholm (2007), on the other hand, found aspect and slope angle to be more indicative for the presence of surface hoar at the regional scale. Slope angle and aspect were also rated as important drivers of surface hoar formation and persistence by Helbig and van Herwijnen (2012) who modeled surface hoar size in complex terrain based on simple terrain characteristics. Horton et al. (2015) observed surface hoar sizes at a regional scale; they suggested air humidity, wind speed and surface temperature to be responsible for surface hoar formation along elevation bands. Their model results obtained from snow cover modelling coupled to numerical weather prediction output, however, were less conclusive.

In summary, the above mentioned spatial variability studies investigated if simple terrain characteristics or snow depth were associated with either snow instability observations or weak layer properties. In particular cases, such as the formation of surface hoar, drivers were identified. With regard to snow instability, however, weak layer and slab layer properties interact together which complicates the influences of drivers. Currently, it is not clear whether and when differences in snow instability can be explained by simple drivers. Snow depth distributions in catchments or basins have successfully been modelled, but with a focus on estimating snow water equivalent or ablation rather than on snow instability prediction. Winstral et al. (2009) obtained realistic snow depth distributions from terrain, vegetation and wind data in catchments of 0.26 km$^2$ to 14 km$^2$ by including the upwind topography and employing a sheltering index. Mott and Lehning (2010) even included micrometeorological processes such as preferential deposition and true redistribution and were able to model small-scale deposition patterns, such as dunes and cornices. Ter-
4.1 Introduction

Terrestrial laser scanning (TLS) is widely used to measure the spatial distribution of snow depositions (Prokop 2008) and study ablation rates (Grünewald et al. 2010). Modeled snow distributions have been validated with this technique and exhibited recurring patterns with elevation, slope and aspect being the most important predictors (Grünewald et al. 2013). Grünewald et al. (2010) compared terrestrial and airborne laser scans from the same area and found a deviation of around 10 cm depending on the incident angle of the beam and footprint size. Using LIDAR methods spatial distributions of snow depth can be measured with high spatial resolution.

A link between spatial distributions of snow depth and snow instability that could support snow instability mapping in data sparse areas, however, is pending. Also, a detailed comparison between snow instability and terrain parameters seems interesting since digital elevation models are widely available and may enhance spatial snow instability mapping. Both ideas, however, require a method for closely spaced snow instability measurements or spatially distributed snow instability modeling for comparison with LIDAR snow depth measurements or terrain parameters from digital elevation models.

The snow micro-penetrometer offers an objective way to measure snow mechanical properties relevant for slab avalanche release at high spatial resolution (Reuter et al. 2013) and to derive measures of instability (Schweizer and Reuter 2015). In particular, a recently developed approach to determine the propensity of failure initiation and crack propagation now allows evaluating field measurements of snow stratigraphy in view of snow instability (Reuter et al. 2015a). With this approach we are now able to obtain observer independent metrics of snow instability in a rapid way allowing spatial sampling with more than 100 measurements per day – exceeding former frequencies of manual stability observations.

To investigate whether snow instability is tied to simple drivers, we present snowpack and terrain data from five situations in a small basin. For every situation snow instability was derived from more than 100 SMP profiles with the approach described by Reuter et al. (2015a) which allows assessing the influence of potential drivers on the propensity of failure initiation and crack propagation separately. The drivers include slope aspect, snow depth and slope angle. Driver data were available at high-resolution for the entire basin from an elevation model with 1 m horizontal resolution and repeated laser scans of the snow surface resulting in snow surface elevation models with the same resolution. Results showed associations between simple drivers and snow instability with potential to support snow instability mapping in data sparse areas.
4.2 Methods

In the following we describe our field data set, the processing of SMP signals including the derivation of snow instability, the derivation of terrain and snow depth data and the multiple regression analysis of simple drivers.

4.2.1 Field data

In the winter seasons between 2010 and 2013 we carried out five field campaigns at the Steintälli field site above Davos (Switzerland) under different snow conditions. The field site is located in a bowl draining to the east above a small ski area. The entire sampling area spans about 400 m \( \times \) 400 m and was divided into 25 cells (Fig. 4.1) each of which has six measurement locations. Hence, considering the framework for spatial variability studies introduced by Blöschl and Sivapalan (1995), our sampling design has an extent (the longest distance between two measurement locations, or the area covered by the study) of several hundred meters, a variable spacing (the distance between measurement locations) ranging from 3 to about 80 m, and a support (the area or volume over which each measurement is integrated) of about 1 cm\(^2\).

We recorded snow depth, slope angle and aspect of the snow surface at every SMP measurement location (Fig. 4.1). Also, GPS coordinates were recorded at the corner points. Nine manual snow profiles were concurrently observed including snow grain type and size, and hand hardness index. The profiles were complemented with stability tests and provide a valuable benchmark for snow instability. Stability tests included the propagation saw test (Gauthier and Jamieson 2008b), the extended column test (Simenhois and Birkeland 2009) and the compression test (Jamieson and Johnston 1996). On each day, we also verified the avalanche danger forecast based on common field observations such as signs of instability (e.g. Jamieson et al. 2009; Haladuick et al. 2014); the verified danger level is described according to the European avalanche danger scale: ‘low’ (1), ‘moderate’ (2), ‘considerable’ (3), ‘high’ (4) and ‘very high’ (5).

4.2.2 SMP signal analysis

In order to derive snow mechanical properties from SMP penetration resistance profiles, the signal was processed to obtain the characteristic set of microstructural parameters, namely rupture force \( (f) \), deflection at rupture \( (\delta) \) and structural element size \( (L) \) (Löwe and van Herwijnen 2012). This step involved 2.5 mm moving window averaging with an overlap of 50% and eventually yields a resolution of 1.25 mm. For the sake of shorter computation times we reduced the resolution again and intro-
Figure 4.1: On the left, photography of the Steintälli field site (looking towards the southwest) with 3 out of 25 cells, one with field staff at work (No. 16) and two (No. 17 and No. 21) with sampling locations (red dots). On the right, map showing the field site with sampling locations (contour line interval is 20 m). Red dots indicating SMP profiles and measurements of terrain parameters and snow depth.

duced layers. By comparing the SMP signal to the manual snow profiles, with a particular focus on the most critical weakness found in stability tests, every SMP signal was divided into several slab layers, a weak layer and a basal layer. For those layers the average mechanical properties were calculated as follows. Snow density $\rho$ was derived after Proksch et al. (2015a) who refined previous penetration resistance based approaches by including the structural element length $L$:

$$\rho = a_1 + a_2 \log \left( \tilde{F} \right) + a_3 L \log \left( \tilde{F} \right) + a_4 L,$$

(4.1)

where $a_i$ are coefficients, $F$ is the penetration resistance and tilde denotes the median. The weak layer fracture energy $w_f$ was derived after Reuter et al. (2013) who showed that integrating the penetration resistance over a window of 2.5 mm and taking the minimum across the weak layer yielded plausible values compared with particle tracking velocimetry results of propagation saw tests van (van Herwijnen and Heierli 2010). From the micro-structural parameters, deflection at rupture $\delta$, structural element size $L$ and rupture force $f$, the effective modulus $E$ and the strength $\sigma$ were calculated after Johnson and Schneebeli (1999):

$$E = \frac{f}{\delta L},$$

(4.2)

$$\sigma = \frac{f}{L^2}.$$  

(4.3)

Thus, at every SMP measurement location, snow stratigraphy was characterized by the relevant mechanical properties: $\rho$ and $E$ for the slab layers, $w_f$ and $\sigma_{WL}$ for the weak layer, and $\rho$ and $E$ for the basal layers. Following the recently presented approach by Reuter et al. (2015a) the failure initiation criterion and the critical crack length were derived as estimates of snow instability.
4.2.3 Failure initiation criterion

As described by Reuter et al. (2015a), a criterion $S$ describing the likelihood of initiating a failure at the depth of the weak layer was defined as:

$$S = \frac{\sigma_{WL}}{\Delta\tau},$$

(4.4)

with $\sigma_{WL}$ the strength of the weak layer and $\Delta\tau$ the maximum shear stress within the weak layer due to skier loading only. The maximum shear stress under the stratified slab was modeled by a finite element simulation (Habermann et al. 2008).

As SMP derived values of strength are larger by about two orders of magnitude than values of shear strength found in literature (Marshall and Johnson 2009), the values of $S$ are much higher than typical values of e.g. the skier stability index (Jamieson and Johnston 1998). Nonetheless, Reuter et al. (2015a) showed that $S$ was clearly related to Rutschblock scores.

4.2.4 Crack propagation propensity

The snowpack’s propensity to support crack propagation in a weak layer may be estimated as the critical crack length $r_c$ for unstable crack propagation. The critical crack length was obtained by finding the real, positive root of the formulation of the specific fracture energy $w_f$ given by Eq. 4 in (Schweizer et al. 2011):

$$w_f(E, r_c) = \frac{H}{2E} \left[ w_0 + w_1 \frac{r_c}{H} + w_2 \left( \frac{r_c}{H} \right)^2 + w_3 \left( \frac{r_c}{H} \right)^3 + w_4 \left( \frac{r_c}{H} \right)^4 \right],$$

(4.5)

with

$$w_0 = \frac{3\eta^2}{4} \tau^2,$$

$$w_1 = \left( \pi \gamma + \frac{3\eta}{2} \right) \tau^2 + 3\eta^2 \tau \sigma + \pi \gamma \sigma^2,$$

$$w_2 = \tau^2 + 9\eta^2 \tau \sigma + 3\eta^2 \sigma^2,$$

$$w_3 = 3\eta \sigma^2,$$

$$w_4 = 3\sigma^2,$$

with $E$ the elastic modulus, $H$ the slab thickness, $\eta = \sqrt{4(1+\nu)/5}$, $\gamma = 1$ the elastic mismatch parameter, $\nu$ the Poisson’s ratio, $\tau = -\rho g H \sin(\alpha)$ the shear stress and $\sigma = -\rho g H \cos(\alpha)$ the normal stress including density $\rho$, gravity $g$ and slope angle $\alpha$. This approach requires an assumption about the elastic modulus $E$ of the entire slab, i.e. the bulk modulus. Following Reuter et al. (2015a) we used the bulk effective modulus obtained from finite element simulations to account for snow stratigraphy, as assuming a uniform slab results in inaccurate estimates of the mechanical deformation energy (Schweizer et al. 2011).
4.2 Methods

4.2.5 Drivers

Our list of drivers is confined to easily available parameters and hence only includes slope aspect, snow depth and slope angle. The influence of each of these drivers may be on snowpack properties directly and/or indirectly by affecting the meteorological processes and thereby shaping snowpack properties.

Slope aspect and slope angle

Slope aspect and slope angle of the snow surface were available from manual observations at every SMP measurement location, but also from a 1 m-resolution digital elevation model (DEM) covering the Steintälli field site. The digital elevation model data were used to compare the terrain properties at the sampling locations with the distribution characteristic of the basin.

Slope aspects are not equally represented in our field site according to calculations from digital elevation model data (Fig. 4.2a). Our samples show the same uneven distribution with considerably more members between north-east and south than between south-west and north in a clockwise sense. We consider our samples representative of the field site, as distributions have similar characteristics, sampling locations were selected randomly in the 25 grid cells and the observation density is about one per 1000 m$^2$ on average.

Rather than splitting the compass rose into four or eight sections and introducing classes, we introduced continuous weighting functions for aspects. We used the first two terms of a Fourier series expansion (Fig. 4.3) to characterize the observed aspects. The aspect variable $asp_{E-W}$ gives aspects with a westerly component a lower weight ($asp_{E-W} = -1$) than those with an easterly component ($asp_{E-W} = 1$). We consider this variable as our field site lies in a small basin which opens to the east and is sheltered to the west. The aspect variable $asp_{N-S}$ weighs northerly ($asp_{N-S} = 1$) against southerly aspects ($asp_{N-S} = -1$). This transformation basically models the course of the sun. For example, for the aspect SE ($= 135^\circ$) the values of the aspect variables are $asp_{E-W}(135^\circ) = 0.71$ and $asp_{N-S}(135^\circ) = -0.71$, whereas for E ($= 90^\circ$) they are 1 and 0, respectively.

Our samples of slope angles were almost normally distributed with a maximum ($N = 187$) in the range of 15–20$^\circ$ (Fig. 4.2b). From digital elevation model data of the entire field site we know that the distribution of slope angles also peaks between 15$^\circ$ and 20$^\circ$ indicating that our samples are representative of the field site characteristics.
Snow depth and slab depth

The distribution of snow depth in our data set was almost normally distributed with a mean of 1.65 m and was slightly skewed to lower values (median 1.52 m). Also for the snow depth, our samples can be considered as representative of the field site’s snow depth distribution as laser scan derived snow depths of the same day had very similar almost Gaussian distributions (Fig. 4.2c). We explore snow depth data from manual measurements close to SMP measurement locations and repeated laser scans of the Steintälli field site. Snow distribution in the Steintälli basin was determined by terrestrial laser scanning (TLS) using the Riegl LPM-321 device operating at 905 nm (Veitinger et al. 2014). Prokop (2008) and Prokop et al.
Figure 4.3: Aspect weighting variables $asp_{E-W}$ (full line) and $asp_{N-S}$ (dotted line) as derived from the two first terms of a Fourier series expansion. The variable $asp_{E-W}$ weighs easterly ($asp_{E-W} = 1$) with westerly aspects ($asp_{E-W} = -1$) and $asp_{N-S}$ weighs northerly ($asp_{N-S} = 1$) with southerly aspects ($asp_{N-S} = -1$).

(2008) demonstrated the suitability of this scanner for snow depth measurements in alpine terrain. Grünewald et al. (2010), by comparing TLS with Tachymeter measurements, established a mean deviation of 4 cm with a standard deviation of 5 cm at distances up to 250 m. In order to georeference the scans, we installed six reflector plates at different distances and angles from the scanner position. The plates were attached to existing weather stations or drilled into rockwalls; this assured stable positions over the three-year measurement period. The laser scanner was mounted on a tripod on a small hill overlooking the Steintälli basin. The tripod was installed on solid rock to minimize vibration effects due to wind and keep errors due to settling and tilting small. In order to obtain snow depth, elevations measured with the laser scanner were subtracted from a digital terrain model created with the same technique. As scan data were available at very high resolution, the presented maps have a horizontal resolution of 1 m. Some areas of the field site cannot be seen from this location and hence the TLS data do not cover the entire area. Data gaps were filled by nearest neighbor interpolation.

In addition to snow depth we also considered slab depth. Slab depth which is equivalent to the depth of the weak layer was derived from SMP measurements. Slab depth affects failure initiation as well as crack propagation propensity (van Herwijnen and Jamieson 2007a) so that spatial variations of instability may well be related to slab depth. However, slab depth cannot be considered as readily available
variable, and we therefore did not include it in the multiple linear regression analysis (see below), but only performed a simple correlation analysis.

Representativity of field samples

In order to assess if the samples we collected in the field were representative of the basin we compared our field sample distributions of aspect, slope angle and snow depth with the distribution of the terrain parameters from the DEM and of snow depth from TLS. Therefore, we resampled the DEM as well as the TLS data 100 times each in the sampling area to obtain comparable sample sizes and performed a U-Test (Table 4.1). In nine out of fifteen cases the majority of the repeated tests indicated that our field samples were representative of the entire basin. On 3 March 2011 and 13 February 2012 samples were representative for all parameters, whereas this was not always the case on the other field days. Still, comparing the distributions visually (Fig. 4.2) suggests that distributions were rather similar.

Table 4.1: Percentage of representative cases of field samples according to the U-Test for terrain parameters and snow depth by field days.

<table>
<thead>
<tr>
<th>Date</th>
<th>Slope angle</th>
<th>Aspect</th>
<th>Snow depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 January 2011</td>
<td>97</td>
<td>85</td>
<td>33</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>95</td>
<td>87</td>
<td>76</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>77</td>
<td>65</td>
<td>96</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>29</td>
<td>9</td>
<td>59</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>4</td>
<td>27</td>
<td>11</td>
</tr>
</tbody>
</table>

4.2.6 Relating snow instability to simple drivers

In order to assess the predictive power of simple drivers for point snow instability, we used a stepwise method of multiple linear regressions (MLR) (Draper and Smith 1998). The presumed drivers slope angle, aspect and snow depth were fed into MLR models as predictors. The dependent variable was either the modeled failure initiation criterion $S$ or the modeled critical crack length $r_c$. For this analysis a regression model was created by stepwise increasing the number of predictors until the predictive power did no longer improve significantly resulting in a final model (F-Test, significance level $p = 0.05$). We report the $p$-values for testing if a coefficient is not zero. Only drivers with $p$-values $p < 0.05$ appear in the final model and the reported $p$-values refer to the final model. For excluded predictors the $p$-value is reported that would result if the predictor was included in the final model. We consider drivers as relevant if their regression coefficient standard error $\Delta(r) < 50\%$ and their $p$-value $p < 0.05$. 


Moreover, the Pearson correlation coefficient $r_p$, the Spearman rank order correlation coefficient $r_s$ and the value of significance $p$ of the regression slope assuming significance for $p < 0.05$ are presented to describe the strength of linear relations.

### 4.3 Results

#### 4.3.1 General avalanche conditions

Three out of five field campaigns we carried out on days with ‘moderate’ avalanche danger. In one case the avalanche danger was rated ‘low’ and in another case ‘considerable’ (Table 4.2). In Fig. 4.4 we present maps of snow depth anomaly from the daily mean with modeled point snow instability estimates for 3 March 2011 and 13 February 2012. On these days the danger level was ‘considerable’ and ‘moderate’, respectively, which is reflected in both instability criteria: on 3 March 2011 the average modeled critical crack length ($r_c = 26$ cm) was lower than on 13 February 2012 ($r_c = 48$ cm). Also the average of the failure initiation criterion yielded lower values on 3 March 2011 ($S = 167$) than on 13 February 2012 ($S = 238$).

**Table 4.2:** Overview showing the number of SMP field measurements, the verified danger level and the days since the last snowfall for the field campaigns.

<table>
<thead>
<tr>
<th>Date</th>
<th>No. SMP</th>
<th>Danger level</th>
<th>Days since snowfall</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 January 2011</td>
<td>125</td>
<td>low</td>
<td>2 days</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>110</td>
<td>considerable</td>
<td>4 days</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>119</td>
<td>moderate</td>
<td>19 days</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>102</td>
<td>moderate</td>
<td>1 day</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>157</td>
<td>moderate</td>
<td>3 days</td>
</tr>
</tbody>
</table>

Overall, the modeled critical crack length was lowest for days with ‘considerable’ avalanche danger with a median of $r_c = 0.26$ m (Fig. 4.5). In those cases when the avalanche danger was rated ‘moderate’ the median critical crack length was $r_c = 0.42$ m. Interestingly, modeled values of $r_c$ were lower on 28 January 2011 (median $r_c = 0.36$ m), when the avalanche danger was rated ‘low’. Also, the results of the crack propagation tests rather indicated that cracks may propagate: PST 46/120cm END on an east-facing slope, ECT 11/11 on a south-facing slope and ECT 23/pp on a north-facing slope. But due to the soft slab, widespread crack propagation was deemed unlikely. We measured an average penetration force of 0.07 N and a density of 112 kg m$^{-3}$ of the surface slab layer with the SMP. About one month later, on 3 March 2011, the same weak layer was buried deeper and the danger level was ‘considerable’. On this day, we observed several whumpfs and also modeled short critical crack lengths (orange box in Fig. 4.5) confirming an increased
**Figure 4.4:** Maps of snow depth anomaly, i.e. deviations from the daily mean snow depth for the Steintälli field site for 3 March 2011 (a, b) and 13 February 2012 (c, d). In addition, the modeled critical crack length $r_c$ (a, c) and the failure initiation criterion $S$ (b, d) are shown by circles; area of circles scales with magnitude of the values. Numbers indicate Swiss coordinates (in meters), i.e. an area of 550 m × 550 m is shown. Contour line spacing is 20 m of elevation.

propensity for crack propagation. A similar tendency was observed for the stability criterion $S$. However, the differences between the danger levels ‘moderate’ and ‘considerable’ were not as pronounced.

### 4.3.2 Simple drivers

We investigated the predictive power of slope aspect, snow depth and slope angle for the two modeled metrics of snow instability, and also related them to slab depth.
4.3 Results

Figure 4.5: Modeled critical crack length by verified avalanche danger level (N = 613). Width of boxes corresponds to the number of cases (see Table 4.2); whiskers extend to the most extreme data points not considered outliers (crosses) within 1.5 times the interquartile range above the 3rd and below the 1st quartile.

In the following we present the results for the specific drivers, first by analyzing the field days all together, then by comparing the characteristics of the single field days.

Slope aspect

Considering all five field campaigns together, the aspect variable \( asp_{N-S} \) was not significantly related to our measures of instability. The aspect variable \( asp_{E-W} \), however, showed statistically significant negative relations meaning that on slopes with aspects in the eastern half-space lower values of both, modeled critical crack length and stability criterion \( S \) were observed (Table 4.3). The polar plot in Fig. 4.6 shows the distribution of modeled critical crack length by aspect for the entire dataset. A slightly higher density of lower and intermediate values was found in the east-south-eastern (ESE) sector which together with the east-north-eastern (ENE) is contrasted with the NNE and SSE sectors and the NNW and the SSW sectors. The western sectors (WNW and WSW) had few cases and less influence on the trend of the aspect variable \( asp_{E-W} \). The polar plot for the failure initiation criterion \( S \) looked similar.

Considering the single days, both aspect variables were significant on 13 February 2012 (i.e. the \( p \)-values of the regression coefficients were < 0.05) and hence aspect can be rated a dominant driver of both criteria, the failure initiation criterion and the critical crack length (columns two to five in Table 4.3). On the other days, however, at most one aspect variable was identified as a driver. On 13 February
Relating simple drivers to snow instability

Figure 4.6: Distribution of modeled critical crack length \( r_c \) by aspect (degrees from North) for all field measurements. Bright colors indicate short cut lengths (N=613). Eight outliers \((r_c > 0.8 \text{ m})\) not shown.

2012 no new snow had been recorded since 18 days and meteorological processes such as radiation or snow drift had shaped the snowpack since. On the other field days upper slab layers were only 2 to 4 days old. On 9 March 2012, for instance, the snowfall had stopped the night before the field measurements were performed. On this day only the category \( asp_{E-W} \) was significant, other drivers were not significant. On the other hand, on 10 January 2013, the relation between the criteria of snowpack stability and \( asp_{N-S} \) was positive with lower stability on south-facing (than north-facing) slopes.

Fig. 4.4 contrasts the propensity for failure initiation and crack propagation of two situations. On 3 March 2011 (upper panels) \( asp_{N-S} \) was not a relevant driver, whereas on 13 February 2012 (lower panels) \( asp_{N-S} \) was a significant driver of both snow instability criteria. On 13 February 2012 values were lower in the central part than in the south-facing slopes in the northern part of the field site (lower panels). On 3 March 2011, however, this trend towards higher values of snow stability on south-facing slopes (upper panels) was not significant (Table 4.3).

Snow depth

Considering all five field campaigns together, snow depth was positively related with the modeled critical crack length (Table 4.3), i.e. with a deep snowpack significantly lower propensity for crack propagation was modeled (Fig. 4.7). The correlation was fair \((r_p = 0.20)\), but the linear trend was significant \((p < 0.01)\). On the other hand, the relation between snow depth and the failure initiation criterion was not
Table 4.3: The \( p \)-values of the regression coefficients between potential drivers and the modeled critical crack length \( r_c \) as well as the stability criterion \( S \) shown for single field days and the entire dataset (‘all’). Potential drivers: \( asp_{E-W} \) and \( asp_{N-S} \), i.e. aspects in the eastern (northern) vs. aspects in the western (southern) half-space, snow depth and slope angle. Bold values indicate significance on a level of 5% and a regression coefficient standard error \( \Delta(r) < 50 \% \). Black colors denote a positive, blue colors a negative relationship.

<table>
<thead>
<tr>
<th>Date</th>
<th>( asp_{E-W} )</th>
<th>( asp_{N-S} )</th>
<th>Snow depth</th>
<th>Slope angle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( r_c )</td>
<td>( S )</td>
<td>( r_c )</td>
<td>( S )</td>
</tr>
<tr>
<td>28 January 2011</td>
<td>0.18</td>
<td>0.01</td>
<td>0.08</td>
<td>0.47</td>
</tr>
<tr>
<td>3 March 2011</td>
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<td>0.02</td>
<td>0.58</td>
<td>0.48</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>0.01</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>9 March 2012</td>
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<td>0.01</td>
<td>0.41</td>
<td>0.14</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>0.88</td>
<td>0.82</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>All days</td>
<td>0.01</td>
<td>0.01</td>
<td>0.47</td>
<td>0.45</td>
</tr>
</tbody>
</table>

significant for the entire dataset.

In contrast to the findings for the entire dataset, snow depth was not related to the modeled critical crack length (Table 4.3) on any of the single days. Considering the other measure of instability, snow depth was positively related to the instability criterion \( S \) in two cases, namely on 28 January 2011 and 10 January 2013 (Table 4.3); this means the thicker the snowpack the harder failure initiation. On 3 March 2011, however, snow depth was negatively correlated with the instability criterion \( S \).

In Fig. 4.4 snow depth anomalies from the daily mean are overlain with the modeled critical crack length and the failure initiation criterion. The distribution of snow depth was very similar on both days (and also on the other days; not shown). Consistent features were found in the northwestern corner of the maps where three finger-like features indicate large snow depths and in the central part where undulations of snow depth appear going from south to north. To some extent also the distributions of crack propagation and failure initiation propensity recurred. For both criteria the highest values were found on the south-facing slopes with a shallow snowpack. In the central part, however, differences of snow instability were not as clearly related to variations in snow depth. In summary, to some extent, large scale snow instability variations across our field site may be explained by snow depth variations, but features at a smaller scale, i.e. at the scale of tens of meters, do not seem to be related to patterns of snow depth.

Slope angle

If all field days were considered jointly, slope angle was related to the failure initiation criterion, but not to the propensity of crack propagation. The sign of the regression
Relating simple drivers to snow instability

Coefficient (Table 4.3) indicated that on steeper slopes failures can be initiated more easily. Fig. 4.8 shows the distribution of the failure initiation criterion $S$ for classes of slope angles. The median failure initiation criterion per class tended to decrease with increasing slope angle indicating easier failure initiation on steeper slopes ($r_p = 0.79$, $p = 0.03$). However, for the class with slope angles between 30 and 35°, including the steepest slopes we sample, the median value of $S$ was slightly higher than for the preceding class; this increase is likely due to the fact that this class contains a small number of cases ($N = 40$) from south-facing slopes with rather high values of $S$.

Considering the single days, in three out of the four cases when slope angle was a driver of modeled snow instability, steeper slopes had higher values of critical crack length $r_c$ or stability criterion $S$ (Table 4.3). However, in our field site most steep slopes (> 30°) are found on southerly aspects. Often we observed that slopes on southerly aspects were less unstable, which may shift the proportion of unstable slopes among steep slopes towards more stable.

Slab depth

Performing a correlation analysis with slab depth led to very consistent, positive significant relations with the failure initiation criterion $S$ ($p$-values $p < 0.05$ on all single days). Also, when considering the entire dataset slab depth was a significant positive driver with $p < 0.01$.

The crack propagation propensity was in three out of five cases significantly

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**Figure 4.7**: Modeled critical crack length versus manually measured snow depth for all field days, indicated by different colors ($N=613$). Eight outliers ($r_c > 0.8$ m) not shown.
4.3 Results

**Figure 4.8:** Failure initiation criterion $S$ for all field days versus classes of slope angle. Class ‘$< 10^\circ$’ covering $0 \leq \alpha < 10^\circ$, Class ‘$< 15^\circ$’ covering $10 \leq \alpha < 15^\circ$ etc. Number of members per class on the top (N=613). Five outliers ($S > 900$) not shown.

related with slab depth, but not considering the entire dataset ($p=0.35$). In two cases (13 February 2012 and 9 March 2012) the relation was negative, i.e. below thicker slabs shorter critical crack lengths were modeled. In one case (3 March 2011), the relation was positive, in other words, below shallow slabs short critical crack lengths were modeled. There are plausible explanations for these seemingly contradictory findings. On one hand, thicker slabs release more energy and usually have shorter crack lengths given the same weak layer properties. On the other hand, weak layers below thicker slabs are stronger, i.e. have higher specific fracture energy resulting in longer critical crack lengths. However, based on our simple analysis we cannot tell which process, higher slab load or higher specific fracture energy, caused the relations we observed.

Slab depth was not correlated with snow depth ($r_p=-0.14$), i.e. snow depth should not be considered as an indicator of slab depth. Relationships of snow depth with the failure initiation criterion $S$ existed on single days as shown above, but no clear relation was found for the entire dataset including all five field days. In cases when slab depth (i.e. weak layer depth) is known, for instance, when measuring or observing snow stratigraphy, more information on snow instability is already available and we would not rely on simple drivers.
4.4 Discussion

The layered structure of the snowpack suggests that temporary influences of external (e.g. wind) and internal (e.g. metamorphism) processes cause differences in layer properties (Schweizer et al. 2008b). The presented work aims at analyzing if simple drivers, which combine external and internal processes, are suitable for predicting differences in snow instability at the basin scale. With available objective measures of snow instability (Reuter et al. 2015a), we were for the first time able to relate multiple objective measures of snow instability with terrain parameters and measurements of snow depth.

The failure initiation and the crack propagation propensity within the basin were mapped for two situations with danger level ‘moderate’ (13 February 2012) and ‘considerable’ (3 March 2011) (Fig. 4.4). Whereas the failure initiation criterion $S$ was quite variable on 3 March 2011 and on 13 February 2012, the modeled critical crack length $r_c$ showed less variable results on both days. On both days several locations existed where a failure could have been initiated, but on 13 February 2012 the crack propagating probability was lower than on 3 March 2011 where especially in the central part of our field site modeled critical crack lengths were short. These qualitative results at the basin scale highlight the importance of the two separate processes, failure initiation and crack propagation with respect to snow instability. However, only a spatial analysis may allow assessing the influence of spatial variations on avalanche release.

Snow instability distributions within a region were investigated by Schweizer et al. (2003b) who evaluated manual observations and snow profiles from five field campaigns with varying avalanche conditions. They found distinct snow instability distributions for the three danger levels ‘low’, ‘moderate’ and ‘considerable’. In our limited data set covering only 5 days we also obtained stability distributions (Fig. 4.5). The distributions were well representing the danger levels ‘considerable’ and ‘moderate’. Still, our snow instability criteria did not reflect the lower propagation propensity on one day with danger level ‘low’, which may be due to the slab properties the algorithm currently still neglects, possibly the tensile strength of the slab. The results for our snow instability criteria showed the same behavior as in Schweizer et al. (2003b). Except for one situation on 28 January 2011 when due to a soft and low cohesion slab widespread avalanching was unlikely.

In our analysis, time spans between field campaigns and the last snowfall (deposition of the topmost slab layers) ranged from 1 to 19 days. On 13 February 2012 when the upper part of the slab was 19 days old, aspect was clearly a dominant driver. Both aspect variables were significant for both instability criteria. In the cases of more recently deposited slabs, differences in snow instability were not as
much associated with slope aspect. Also right after storms, like on 9 March 2012, only one driver was found to be significant. Both results suggest that with aging of the slab layers the influence of the driver slope aspect on snow instability grew. Similar results were already presented by Birkeland (2001) who identified more drivers in his field campaigns after variable weather conditions than after sustained snow storms. Schweizer et al. (2008a) also observed less variation right after storms than after a subsequent fair weather period. Snow instability patterns are supposed to be caused by terrain and weather conditions as atmospheric processes in combination with terrain set the boundary conditions for the evolution of the mountain snowpack Schweizer et al. (2008b). The incoming radiation on a slope is a function of the incident angle. Hence, slope aspect plays a major role for the heat energy input into the snowpack and controls snow temperature and hence affects stability (Reuter and Schweizer 2012). Also, snow deposition depends on slope aspect which is consequently anticipated to be a driver of snow density and hence stiffness. Differences in snow instability were in all cases related to aspect. This finding is in line with previous research, for instance with Schweizer et al. (2003b) who observed that often differences in snow instability were explained by aspect. Two variables were introduced explaining differences between easterly and westerly aspects which are likely caused by wind, and between northerly and southerly aspects which are likely caused by incoming shortwave radiation but also wind direction. We found that on east-facing slopes the propensity of failure initiation was higher in four out of five cases and of crack propagation in two out of five cases. With respect to north-south differences the aspect variable indicated significant trends in two cases, once with higher values on north-facing slopes than on south-facing ones, and once vice versa.

Finding the reason for this discrepancy, would involve a more detailed analysis of all ingredients controlling our measures of snow instability and their history, which is beyond the scope of this work. Already in a former study by Schweizer and Kronholm (2007) aspect was an important driver of weak layer presence. They explained surface hoar presence in one region with slope angle and the absolute deviation from north – similar to our aspect variable $asp_{N-S}$.

Also in our cases we found weak layers to be present over the entire basin, however, with varying strength and specific fracture energy. Internal processes such as sintering and metamorphism suggest that deeper snowpacks have weak layers which are stronger and not as prone to fracture under loading compared to shallower snowpacks (Jamieson et al. 2007). Snow depth was not related to the modeled critical crack length (Table 4.3) on any of the single days, but for the entire dataset snow depth was a significant driver. The failure initiation criterion was on three out of five field days driven by snow depth – with varying sign of correlation. Considering the entire dataset including all 5 days, a relation between snow depth and the failure
Relating simple drivers to snow instability

The initiation criterion was not found. Hence, on a single day, an association between snow depth and snow instability does not always exist, whereas on average, when we compare many different snow conditions we may observe a trend of increasing values of snowpack stability with increasing snow depth – controlled by the crack propagation propensity. Considering both, failure initiation and crack propagation as required ingredients of snow instability our findings agree with frequently reported significant positive correlations between snow depth and snow stability for different observation times and field sites with varying snowpack conditions at the regional scale (e.g. Schweizer et al. 2003b; Zeidler and Jamieson 2004). An anticipated relation between the failure initiation criterion and snow depth on average, i.e. for the entire dataset, was not confirmed. Our measurements of snow depth were not even correlated with slab depth, which is closely tied to failure initiation.

We found recurring patterns of snow depth in accordance with previous studies (Grünewald et al. 2010). Also, some patterns of the crack propagation and failure initiation propensity recurred. Values were highest on south-facing slopes with a shallow snowpack in the northern part of our field site, whereas differences of snow instability were not as clearly related to variations of snow depth within the central part of our basin. It seems that snow depth variations can explain patterns of snow instability on a larger scale, such as across our field site, but are not necessarily indicative of small scale variations of snow instability at the scale of tens of meters.

We excluded slab depth from the MLR analysis, as it is no simple driver, i.e. there is no widespread data available on the depth of the weak layer. Automated, repeated LIDAR measurements could provide this piece of information, provided the exact burial time of the relevant weak layer is known and snow settlement is negligible.

Slope angle affects the incident solar radiation and hence partly controls snow temperature. Snow instability also directly depends on slope angle, as with slope incline the stress state due to loading shifts towards higher shear and lower normal stresses. On single days, we observed three times positive and once negative relations with our measures of snow instability in the four cases when slope angle was a driver. This finding is somewhat counterintuitive. If we consider, for example, the definition of the skier stability index where the shear stress increases with increasing slope angle, lower values of the skier stability index are expected on steeper slopes. However, the distribution of steep slopes (>30°) within our field site is imbalanced towards considerably more cases on south-facing slopes. In other words, the stability might have been simply less critical on the south-facing slopes which at the same time are the steepest ones we usually sample. Thus, results for single days are questionable. The entire dataset representing many different snowpack conditions, however, showed that the slope angle played a significant role in controlling the
failure initiation propensity. Decreasing values of the failure initiation criterion $S$, i.e. failure is more likely, were associated with increasing slope angle. In the past, studies investigating the role of the slope angle as a potential driver of snow instability found contradicting results. Previous studies presented field data on the crack propagation propensity (Gauthier and Jamieson 2008a; Heierli et al. 2011), on the propensity of failure initiation based on ECT scores on slopes (e.g. Simenhois et al. 2012) and on snow instability in general (Schweizer et al. 2003b) and did not find a significant relation with slope angle. Jamieson (1999) and Campbell and Jamieson (2007), however, found a correlation of decreasing compression and Rutschblock test scores with increasing slope angle, respectively. In this study, however, snow instability was modeled with a two-step approach considering failure initiation and crack propagation, two important requirements for slab avalanche release. Our results suggest a slight increase of the failure initiation propensity with slope angle, which is the first step in the chain of events preceding avalanche release.

The data on simple drivers we presented were determined from manual field observations with typical observation uncertainties of about 5° for aspects, 1 cm for snow depth and 3° for slope angles. Snow instability data were derived from post-processed snow micro-penetrrometer signals representing several sources of uncertainty. The uncertainty can be assessed in comparisons with experimental data and yields about 2 cm for modeled critical crack lengths (RMSE) and about one Rutschblock score for the modeled failure initiation criterion (Reuter et al. 2015a); this roughly corresponds to an uncertainty $\Delta(S) \approx 40$. The snow depth derived from TLS measurements has an accuracy of about 10 cm (Grünewald et al. 2010).

4.5 Conclusions

We presented an application of a new method to derive point snow instability from SMP measurements allowing observer-independent measurements of snow instability. By performing multiple spatially distributed snow micro-penetrrometer measurements in a small alpine basin we obtained a unique dataset covering 5 different avalanche situations. Maps from 2 different snow instability situations provided a qualitative picture of the spatial distribution of snow instability with respect to the propensity of failure initiation and crack propagation. Our measures of snow instability were able to reproduce snow instability distributions characteristic of the avalanche danger level as observed in previous studies.

Following our hypothesis that simple drivers may explain differences in snow instability to a significant extent, we related our objective measurements of snow instability to simple drivers, rather than process drivers: slope aspect, snow depth and slope angle. The most prominent driver was slope aspect. We observed that
the older the slab was, the more differences of snow instability were reflected in the driver aspect. In our field site significant differences of snow instability existed between east-facing and west-facing slopes. On single field days a stepwise MLR analysis showed different relationships, positive and negative, between drivers and our measures of snow instability depending on the situation. Applying the analysis on the entire dataset which contains many different snow conditions revealed that snow depth was a driver of the crack propagation propensity and slope angle was a driver of the failure initiation propensity. Briefly, on average, thicker snowpacks tended to produce longer critical crack lengths and on steeper slopes failure initiation was easier. Our results compared well with previous studies identifying aspect and snow depth as important drivers of snow instability at the slope as well as at the regional scale. Furthermore, slab depth was very clearly positively related with the failure initiation criterion $S$ confirming that a failure is more easily initiated below a shallow slab.

Also, this study sheds new light on the role of the slope angle in view of snow instability, which was often controversially discussed. Our results suggest that slope angle mainly controls the propensity of failure initiation and thus influences snow instability since both criteria need to be fulfilled for avalanche formation (Reuter et al. 2015a). In our field data set the modeled critical crack length, however, never significantly decreased with increasing slope angle. This trend was anticipated from the knock-down function presented by Gaume et al. (2014), but was not verified in the field, yet.

Recurring patterns of snow depth could only to some extent explain differences in snow instability. To better resolve small scale patterns of snow instability and explore relations with external drivers a geostatistical analysis of the presented dataset will be required.

To sum up, simple drivers exist and may help to enhance our predictions of snow instability, but we should bear in mind the influences to avoid over-interpreting. Certainly, micro-meteorological and snow cover modelling have the potential to account for external and internal drivers separately and will be a logical next step. Nonetheless, due to their good availability and their ties with the processes influencing snow instability exploring the role of simple drivers seems worthwhile. The processes shaping the mountain snowpack and hence controlling snow instability are complex and may not be reflected in a set of drivers. With this in mind the results may be valuable for snow instability estimations, where direct information of snow instability is lacking between point observations, e.g. when applying forecasting models in data sparse areas or verifying snow instability distributions from measured data in large areas.
Acknowledgements:
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Chapter 5

Snow instability patterns at the scale of a small basin


Abstract

Spatial and temporal variations are inherent characteristics of the alpine snow cover. Spatial heterogeneity is supposed to control the avalanche release probability by either hindering extensive crack propagation or facilitating localized failure initiation. Though a link between spatial snow instability variations and meteorological forcing is anticipated, it has not been quantitatively shown yet. We recorded snow penetration resistance profiles with the snow micro-penetrometer at an alpine field site during five field campaigns in Eastern Switzerland. For each of about 150 vertical profiles sampled per day two snow instability criteria were calculated. For both criteria we analyzed their spatial structure and predicted snow instability in the basin by external drift kriging. The regression models were based on terrain and snow depth data. Slope aspect was the most prominent driver, but significant covariates varied depending on the situation. Residual autocorrelation ranges were shorter than the ones of the terrain suggesting external influences possibly due to meteorological forcing. To explore the causes of the instability patterns we repeated the geostatistical analysis with snow cover model output as covariate data for one case. The observed variations of snow instability were related to variations in slab layer properties which were caused by preferential deposition of precipitation and differences in energy input at the snow surface during the formation period of the slab layers. Our results suggest that 3D snow cover modelling allows reproducing
some of the snow property variations related to snow instability, but in future work all relevant micro-meteorological spatial interactions should be considered.

## 5.1 Introduction

Predicting snow instability in time and space is hampered by our limited knowledge of the inherently variable nature of the mountain snowpack. Based on point observations or modelling at specific locations we can typically not conclude on the scale and degree of spatial variations of instability (e.g. Conway and Abrahamson 1988; Jamieson and Johnston 1993a). For reliable spatial prediction one would need to know the drivers of instability as well as their temporal evolution. In other words, a link between the observed variations of snowpack properties and the meteorological drivers, such as precipitation, wind and radiation, and terrain has to be established. Once the link is established, i.e. we know how meteorological drivers cause variations in snowpack properties and thereby control stability, it will become possible to anticipate stability variations based on the type of meteorological conditions. Of course, extrapolation can be circumvented, if the spatial patterns of snowpack properties could be captured by either (airborne) remote sensing techniques or by modelling the snow cover over 3D terrain. The latter would certainly be the most elegant approach, provided the model includes a snow instability module so that snow instability patterns can be predicted, but requires meteorological input data distributed on a high resolution terrain model.

Spatial variations, or more generally disorder, are considered to be fundamental for the fracture process (Anderson 2005) and hence studying spatial variations is to be envisaged in the context of avalanche formation (Schweizer et al. 2008b). At the slope scale, the scale and degree of spatial variations is supposed to control the avalanche release probability by either facilitating localized failure initiation or hindering extensive crack propagation. However, the role of spatial variations in overall slope instability remained so far purely conceptual and rather hypothetical (Kronholm and Schweizer 2003) – though numerical simulations confirmed some of the anticipated relations between, for instance, the correlation length of snow properties and avalanche size (e.g. Fyffe and Zaiser 2004; Gaume et al. 2015b; Kronholm and Birkeland 2005). Variations beyond the slope scale may control the size of slab avalanches by confining their outline since propagating cracks may arrest at distinct discontinuities of the snowpack in particular where terrain properties change.

At the slope scale, most studies aiming at characterizing snow cover variability and studying its causes or its relation to snow instability were first based on arrays of stability tests (e.g. Campbell and Jamieson 2007; Conway and Abrahamson 1984; Föhn 1989; Jamieson and Johnston 1993a). More recently, snow cover data were
gathered with the snow micro-penetrometer allowing a higher sampling rate and terrain coverage than with stability tests. Most studies investigated the spatial variations of layer properties (e.g. Kronholm et al. 2004; Lutz and Birkeland 2011), but some also addressed snow instability variations (e.g. Hendrikx et al. 2009; Simenhois and Birkeland 2009).

Birkeland et al. (2004a) reported the absence of linear spatial trends of the penetration resistance of buried surface hoar layers on two slopes in Montana. A later geostatistical analysis (Birkeland et al. 2004b), however, revealed spatial autocorrelation of weak layer penetration resistance on one slope after log-transformation and outlier removal. Birkeland et al. (2004b) discussed the challenges involved with spatial snowpack data and with geostatistical data analysis in this field. Although the snow cover can be approximated as a substratum of unique and spatially continuous layers (Kronholm et al. 2004), each layer’s properties may vary significantly in space. For this reason geostatistical analysis techniques are promising, but they require robust regression techniques (Papritz et al. 2013) and the right choice of the sampling design to resolve prevailing snow cover variations, despite safety concerns and time constraints (Elder et al. 2009). Different sampling designs were analyzed by Kronholm and Birkeland (2007) who highlighted the need for sufficient resolution and recommended to include some randomness in stratified grids. Birkeland et al. (2004b) reported slab layer properties had an autocorrelation range of a couple of meters, but only in a few cases spatial patterns were identified at all in the residuals of the linear trend model. At the slope scale also Lutz et al. (2007) analyzed weak layer penetration resistance for two cases and found similar autocorrelation ranges as Kronholm et al. (2004) who reported typical values of between four and eleven meters. In contrast, repeated weekly measurements of weak layer strength using the shear frame on two slopes initially showed weak autocorrelation at very short ranges of about one meter and was smoothened to a random field after only two weeks (Logan et al. 2007). The observed temporal evolution may have been caused by internal processes such as sintering, as external forcing due to variations in terrain properties was absent – as is typically the case at the slope scale.

Kronholm et al. (2004) attributed rather uniform weak layer properties and more variable slab layer properties to calm weather during the weak layer formation period and rather windy conditions thereafter. Relating meteorological parameters to snow properties directly is not straightforward due to the temporal aspect (Logan et al. 2007). Snow layers form during certain weather periods and are subject to metamorphism thereafter. That’s why in the past, indicators have been used summarizing the meteorological influence such as the sum of energy fluxes at the snow surface (Reuter and Schweizer 2012) or the variation in wind speed, which was considered a potential measure of turbulence. Schweizer et al. (2008a) attempted to
relate the variation in penetration resistance of the surface layer to the standard deviation of 10-min maximum wind speed – but found no significant correlation. Also, the role of terrain, vegetation and micro-meteorological characteristics on surface hoar thickness in a forest opening has been studied by Lutz and Birkeland (2011). They reported autocorrelation ranges of several meters for the thickness of surface hoar layers on a slope they sampled repeatedly with the snow micro-penetrrometer.

Studies investigating the spatial structure of objective measures of snow instability are rare, not least because point snow instability is considered to result of a non-trivial interaction of weak and slab layer properties. Bellaire and Schweizer (2011) used a SMP-derived parameter presented by Bellaire et al. (2009) and determined an autocorrelation range of several meters in seven out of eleven field campaigns at the slope scale, but could not identify a relation with slope instability. Recently, Schweizer and Reuter (2015) reanalyzed the dataset of Bellaire and Schweizer (2011) and applied a refined snow instability algorithm accounting for slab and weak layer properties yielding a fair correlation with compression test scores. Still, they were not able to relate their point stability results to slope stability despite a geostatistical analysis. Hendrikx et al. (2009) assessed clustering of extended column test propagation results as a measure of point snow instability and found that out of four slopes in total two were clustered and two were not. They suggested that the observed clustering into propagation and non-propagation areas on the slopes may explain weak layer fracturing without subsequent release as reported by Birkeland et al. (2006); cracks may initiate but then arrest in strong areas of the slope.

At the basin scale, contrary to the slope scale, topographic variations are clearly more pronounced and for that reason drivers such as radiation or snow transport by wind cause variations in snow properties (Schweizer and Kronholm 2007). Schirmer et al. (2011) showed that snow depth variations within a basin were altered by average wind speed and terrain. Winstral et al. (2002) successfully reproduced basin scale snow accumulation patterns from a model based on simple terrain parameters. By modelling wind events with flow fields derived from an atmospheric model even small scale features such as dunes measured with terrestrial laser scans were reproduced (Mott and Lehning 2010). As such small scale variations are resolved, their approach promises that given high temporal resolution also snow stratigraphy may spatially be well resolved, so it may possible to identify meteorological causes for spatial variations of stratigraphy – or even instability.

So far, however, only a small number of studies have addressed the causes of snow instability variations. At the scale of a mountain range, Birkeland (2001) suggested that aspect and elevation may serve as predictors of snow instability. Schweizer et al. (2003b) also related stability to terrain while analyzing stability
patterns at the regional scale, however on different sampling days different patterns with regard to aspect and elevation were observed. They found increasing point stability with increasing snow depth and identified the primary weakness to be due to a cold period causing faceting around crusts within the snowpack. Relating objective measures of snow instability to aspect, slope angle and snow depth (Reuter et al. 2015b) partly explained snow instability variations in a non-spatial analysis with different combinations of these parameters. These findings may provide guidance for investigating causes of instability and in general help to enhance instability predictions.

Two approaches can be generally thought of in order to obtain the spatial structure of snow instability, interpolation of the target variable from point measurements of the target variable or modelling of the target variable on gridded, possibly interpolated explanatory data.

The first approach, that is based on field measurements, was hampered in the past by inadequate measures of snow instability and/or small sample sizes not amenable to geostatistical analysis (e.g. Bellaire and Schweizer 2011; Campbell and Jamieson 2007). With developments in field measurement techniques, however, snow properties can be measured observer independently (Schneebeli et al. 1999) and with good accuracy (Proksch et al. 2015a). These developments allowed the first geostatistical analyses of snow layer properties such as penetration resistance (e.g. Kronholm et al. 2004). Concurrently, SMP-derived metrics such as the micro-structural compressive strength (Johnson and Schneebeli 1999) were related to stability test results (Bellaire et al. 2009; Pielmeier and Marshall 2009; Pielmeier and Schweizer 2007). More recently, two criteria of instability were suggested that relate to the two key processes in dry-snow slab avalanche release (failure initiation and crack propagation); the two metrics were clearly related to independent observations of instability (Reuter et al. 2015a).

To interpolate field measurements, geostatistical methods were preferred over simple regression techniques to interpolate observations of snow properties or snow instability. One reason for the preference is that snow instability observations are time consuming which limits exhaustive sampling to achieve densely spaced observations that would allow simple interpolation. Also, experience suggests that patterns of snow instability exist and hence, methods to obtain measures of autocorrelation were chosen (Kronholm 2004). In order to describe the spatial distribution of weak layer properties, maps of weak layer penetration resistance were presented and qualitatively related to arrays of point stability observations (Schweizer et al. 2008b). Bellaire (2010) described the spatial autocorrelation based on topographic coordinates and interpolated weak layer strength by ordinary kriging. Based on his data first maps of snow instability were presented by Schweizer and Reuter (2015) who
introduced a simple index of instability considering the mechanical interplay of the weak layer and the slab.

Geostatistical modelling approaches taking into account so called covariate information, i.e. additional information indicative of the quantity to be predicted and available on the entire interpolation grid, were applied to snow depth distributions by Gaume et al. (2013b). They presented spatial interpolations of annual maxima of the 3-day sum of precipitation based on climate regions and elevations as covariates in the French Alps. In order to interpolate surface air temperatures over Switzerland, Frei (2014) divided surface air temperature variations into meteorological meaningful ‘background’ and ‘residual’ patterns and eventually performed spatial interpolations by weighting residuals for topographic effects. In complex terrain the spatial interpolation of meteorological parameters may profit from correlations with any kind of environmental parameters so that kriging techniques are widely used in meteorological applications (e.g. Perćec Tadic 2010). Hence, including covariate information for spatial interpolation currently seems the most appropriate approach in cases of different scale processes being superimposed in complex terrain.

With regard to the second approach, modelling snow layer properties from gridded meteorological data in space and time builds upon modelling of snow stratigraphy in one vertical dimension, and preferably includes spatial interactions such as preferential deposition and redistribution of snow or radiative processes (Lehning et al. 2006). Meanwhile models simulating the surface radiation balance in complex terrain are available and their performance under clear and overcast skies was validated with measured radiation components yielding good agreements (Helbig et al. 2010). Also, snow accumulation features were reproduced by snow transport models (Vionnet et al. 2014), even resolving small scale features such as dunes, if a sufficient resolution (5 m) was chosen (Mott and Lehning 2010).

Once the spatial structure of snow stratigraphy is obtained, these data can be used as input into mechanical models that take into account the spatial interactions between gridded point instability data in order to simulate snow slope instability and eventually predict avalanche release. For instance, Gaume et al. (2014) applied stochastic finite element simulations to model slope instability from weak layer heterogeneity. They demonstrated a knock-down effect on slope instability depending among others on the coefficient of variation of weak layer cohesion. The influence of the coefficient of variation of weak layer shear strength was earlier described by Fyffe and Zaiser (2004), who used a cellular automaton model for the investigation of snow slope instability. Kronholm and Birkeland (2005) used measured shear strength distributions for their cellular automaton model with modifications regarding the distributions of initial shear strength values to investigate the size of the fractured area. By keeping snowpack parameters constant, but varying the spatial
structure they obtained results indicating that large scale spatial structures favor crack propagation. They noted that field measurements confirming the hypothesis are still lacking.

Basin scale snow instability variations were only rarely studied and their causes are largely unknown. By applying advanced geostatistical methods to objective metrics of snow instability, we aim at identifying spatial patterns of snow instability and their drivers at the basin scale. We analyze a field dataset consisting of five campaigns comprising data on snow depth, terrain and snow properties mainly acquired with the snow micro-penetrometer in a small basin above treeline. From our field measurements we modeled the autocorrelation structure of snow instability using snow depth and terrain data as covariates. In order to identify patterns of snow instability we performed external drift kriging and mapped the variations of instability. Furthermore, we used modelled snow properties as covariates and repeated the geostatistical analysis. This approach, using snow cover model output, allows making an initial attempt to explore the causes of the observed patterns of instability by tracking back how the meteorological conditions shaped the snow layer properties.

5.2 Methods

In the following sections we describe the field data collection, explain the SMP signal processing, introduce the two snow instability criteria used and provide a detailed description of the geostatistical methods for spatial interpolation. With regard to the field data, essentially the same data have been analyzed non-spatially by Reuter et al. (2015b). Then the meteorological data and snow cover model setup are described.

5.2.1 Field data

Throughout the winter seasons between 2010 and 2013 we sampled the Steintälli basin above Davos (Eastern Swiss Alps; 46.81° N, 9.79° E) thirteen times but only for five of the field campaigns we acquired a complete dataset (Table 5.1). Measurements were performed at 150 locations according to a sampling design spanning about 400 m × 400 m presented in Fig. 5.1. Our field records contain profiles of snow penetration resistance measured with the snow micro-penetrometer, locations measured with differential GPS, manual measurements of aspect, snow depth and slope angle, terrestrial laser scans, manual snow profiles and snow instability observations. The sampling design consists of 25 partly randomized cell arrays allowing for subsequent measurements and easy orientation during data collection in the field.
while sampling most diverse distance pairs, called lag distances in the geostatistical context. The distribution of lag distances is presented in the histogram of Fig. 5.2. For distances between 10 m and 380 m at least 100 lag pairs are available per bin given a bin width of 10 m. Hence the selected design provides a reasonably dense coverage for studying local differences of snow properties at the basin scale. With regard to the scale triplet (Blöschl and Sivapalan 1995), the support was on the order of $10^{-5}$ m$^2$, corresponding to the area of the SMP tip, the minimum spacing 3 m and the maximum extent was about 500 m.

**Table 5.1:** Overview over the sampling days including name of the field site, the number of the used SMP device, the total number of recorded signals and the danger level estimate. The first five field day were analyzed.

<table>
<thead>
<tr>
<th>Date</th>
<th>Field site</th>
<th>SMP device</th>
<th>Number of SMPs</th>
<th>Danger level in area</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 January 2011</td>
<td>Steintälli</td>
<td>21</td>
<td>125</td>
<td>low</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>Steintälli</td>
<td>21</td>
<td>110</td>
<td>considerable</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>Steintälli</td>
<td>21</td>
<td>119</td>
<td>moderate</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>Steintälli</td>
<td>21</td>
<td>102</td>
<td>moderate</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>Steintälli</td>
<td>33</td>
<td>157</td>
<td>moderate</td>
</tr>
<tr>
<td>22 January 2013</td>
<td>Latschüel</td>
<td>33</td>
<td>150</td>
<td>moderate-considerable</td>
</tr>
<tr>
<td>10 January 2014</td>
<td>Steintälli</td>
<td>33</td>
<td>114</td>
<td>considerable</td>
</tr>
<tr>
<td>22 January 2014</td>
<td>Latschüel</td>
<td>33</td>
<td>144</td>
<td>considerable</td>
</tr>
<tr>
<td>06 February 2014</td>
<td>Steintälli</td>
<td>33</td>
<td>149</td>
<td>moderate-considerable</td>
</tr>
<tr>
<td>25 March 2014</td>
<td>Steintälli</td>
<td>33</td>
<td>150</td>
<td>considerable</td>
</tr>
<tr>
<td>21 January 2015</td>
<td>Steintälli</td>
<td>33</td>
<td>156</td>
<td>moderate</td>
</tr>
<tr>
<td>11 February 2015</td>
<td>Steintälli</td>
<td>33</td>
<td>144</td>
<td>considerable</td>
</tr>
</tbody>
</table>

To obtain accurate measurement locations we performed differential GPS measurements yielding coordinates with sub-meter accuracy at the corner points. The other sampling locations in a grid cell were then determined with a measuring tape and compass northing. Further terrain parameters including slope angle and aspect were measured manually. Snow depth was measured with a probe at every measurement location but is also available from a terrestrial laser scan.

During all field campaigns a terrestrial laser scan was performed from an exposed location overlooking the Steintälli (Fig. 5.1). We used the Riegl LPM-321 device operating at 905 nm (Veitinger et al. 2014). The suitability of this device was demonstrated by Prokop (2008) and Prokop et al. (2008). Its accuracy was determined by Grünewald et al. (2010) in comparisons with Tachymeter measurements at distances up to 250 m (mean deviation of 4 cm and standard deviation of 5 cm). In order to minimize vibration effects due to wind and keep errors due to settling and tilting small, the device was installed on a tripod on solid rock. To facilitate geo-referencing of the scans we had installed reflecting plates in rock walls or attached to weather stations at different distances and angles from the measurement.
Figure 5.1: On the left, map of field site showing all 25 cells (blues boxes with numbering along the sides) each with L-shaped sampling array (red points) including 6 SMP measurements and measurements of terrain parameters and snow depth. Manual snow profiles were conducted at corner points of the "L" in cells 1, 5, 7, 9, 13, 17, 19, 21 and 25, GPS measurements in all cells at corner points. Contour line interval is 20 m, cell size is 80 m. On the right, view of the field site below the Strela summit (orange overlay) from the SE. Laser scan location by black dot, weather stations by black triangles. L-shaped sampling design illustrated in lower right; distances from corner point in meters.

Figure 5.2: Histogram of lag distances of measurements performed on the 3 March 2011.

location. Eventually, the spatial distribution of snow depth was calculated by subtracting a digital terrain model obtained with the TLS sampling technique as well. The resulting snow depth data have a resolution of 1 m. However, due to terrain shading in grid cells 1 to 5 (Fig. 5.1) some areas are not covered.

Concurrent snow instability observations included nine snow profiles in grid cells
Snow instability patterns at the scale of a small basin

1, 5, 7, 9, 13, 17, 19, 21 and 25 as well as stability tests and observations of signs of instability. The snow profiles were performed following the ICSSG guidelines (Fierz et al. 2009) and contain information on snow layering, grain type and size and hand hardness index. An exemplary snow profile representing the characteristic snowpack layering for each sampling day is provided in the Appendix (Fig. A.1). We performed propagation saw tests (Gauthier and Jamieson 2008a), extended column tests (Simenhois and Birkeland 2009) and compression tests (Jamieson and Johnston 1996). Signs of instability (e.g. Haladuick et al. 2014; Jamieson et al. 2009) were recorded with time and location.

The avalanche danger forecast was verified based on our snow instability observations in the field (Schweizer et al. 2003b) and is described according to the European avalanche danger scale increasing from low (1), moderate (2), considerable (3), high (4), to very high (5) (Meister 1995).

5.2.2 Snow micro-penetrometer signal analysis

The snow micro-penetrometer (SMP) is a constant speed penetrometer which allows to record micro-structural and mechanical snow profile information. The signal we obtain from an SMP measurement is a depth-resistance record. Due to the high measuring frequency of about 250 samples per mm and a constant penetration speed of 20 mm s$^{-1}$ the penetration resistance signal may be interpreted as a Poisson shot noise process, which allows to recover the following properties from the signal: rupture force, deflection at rupture and structural element size (Löwe and van Herwijnen 2012). After 2.5 mm moving window averaging and an overlap of 50% the effective resolution is eventually 1.25 mm. In order to reduce computation times we introduced layers and assigned mean values obtained from the moving window averaging. The layering was consistent at the field site and hence, we selected the same slab layers and the same weak layer, according to the most prominent weakness found in stability tests and manual snow profiles. The layer properties included snow density $\rho$ derived following Proksch et al. (2015a), the weak layer fracture energy $w_f$ calculated according to Reuter et al. (2015a), and the effective modulus $E$ and the strength $\sigma$ as described by Johnson and Schneebeli (1999).

Thus, at every SMP measurement location, snow stratigraphy was characterized by the relevant mechanical properties: $\rho$ and $E$ for the slab layers, $w_f$ and $\sigma_{WL}$ for the weak layer, and $\rho$ and $E$ for the basal layers. Following the recently presented approach by Reuter et al. (2015a) the failure initiation criterion $S$ and the critical crack length $r_c$ were derived as estimates of snow instability.
5.2 Methods

5.2.3 Snow instability criteria

A criterion $S$ describing the likelihood of initiating a failure at the depth of the weak layer was defined by Reuter et al. (2015a) as:

$$S = \frac{\sigma_{WL}}{\Delta\tau},$$

where $\sigma_{WL}$ is the strength of the weak layer and $\Delta\tau$ the maximum shear stress within the weak layer due to skier loading only. The maximum shear stress under the stratified slab was obtained with a linear elastic finite element simulation.

The critical crack length $r_c$ for unstable crack propagation is regarded as a criterion for the snowpack’s propensity to support crack propagation in a weak layer (e.g. Sigrist and Schweizer 2007). The critical crack length was obtained as the solution of an analytical beam equation for a uniform slab. The stratigraphic properties of the slab were accounted for by deriving the bulk effective modulus from a finite element simulation of the stratified slab, as assuming a uniform slab yields unrealistic estimates of the mechanical deformation energy Reuter et al. (2015a).

5.2.4 Covariates for statistical modelling

To improve predictions between sampling locations we used slope aspect, slope angle, snow depth and elevation which have been confirmed to be potential drivers of snow instability at the basin scale Reuter et al. (2015b). These potential drivers will be used as covariates of our trend models (see below) as they have a physical relationship with the response variables, our two snow instability metrics, we attempt to model. Slope aspect, slope angle and elevation were available from a 1 m-resolution digital elevation model covering the Steintälli field site. The elevations of field measurement locations were determined with measured coordinates from the locations in the DEM, whereas for slope aspect and slope angle the manual measurements were used. Snow depth data were available from manual measurements at every measurement location and repeated laser scans of the Steintälli field site (Veitinger et al. 2014). Due to its circular nature slope aspect (0-360°) is not amenable to statistical analysis and was hence decomposed into four periodic B-splines for each aspect category, thus peaking at the distinct aspects (E, N, W, S) and reaching zero at their opponent aspect (W, S, E, N). If aspect was a significant covariate, only two non-opponent B-splines were included as the B-spline of the opponent aspect is redundant each.


5.2.5 Geostatistical analyses

Spatial autocorrelation

Exploring an underlying spatially continuous phenomenon in a finite sample of measured values and predicting for un-sampled locations based on the identified spatial structure is the core aim of geostatistical techniques (Webster and Oliver 2007). With regard to snow instability at the basin scale, we are first interested in the prediction of values of snow instability at locations we did not sample in order to map snow instability in an alpine basin. Second, an analysis of prediction errors is required to assess the uncertainty involved with the mapping but also to compare predictions based on two types of covariate data: terrain and snow depth information from a digital elevation model (DEM) and from terrestrial laser scans (TLS) on one hand, and snow cover model output on the other.

For the prediction of the two instability metrics over our study area we will develop a geostatistical (or spatial) model $Y$ that divides the instability variations into a physical meaningful `background’ (based on the above mentioned covariates) and `residual’ patterns and then perform spatial interpolations based on the background field and residual patterns (Frei 2014; Nussbaum et al. 2014). The background field (describing the external drift) was modelled as a linear regression model, whereas the residual field, the second part describing the autocorrelation, was modeled as a stationary autocorrelated Gaussian random field. The workflow we followed is presented in Fig. 5.3.

![Flowchart presenting the workflow followed within the geostatistical analysis to model the spatial structure of snow instability. From SMP-derived snow properties (blue box) the snow instability criteria ($S$ and $r_c$) were derived. The regression model is built on the significant covariates (elevation and snow depth, for instance) selected from the four covariates available from DEM (orange boxes) or TLS data (green box). The spatial structure was modeled as a linear regression model and a residual autocorrelation.](image)

The background field, represented by a linear external drift model, is determined
by processes varying smoothly with topographic features, such as solar radiation depending on slope angle and aspect, leading to rather large scale patterns. Smaller scale variations imprinted on the background field, for instance snow accumulation patterns caused by wind, e.g. dunes, may be captured by the residual autocorrelation.

The response variables were the SMP-derived failure initiation criterion $S$ and the critical crack length $r_c$. Covariate data available for the area of the sampling domain consisted of DEM data, providing aspect, slope angle, elevation and the topographic coordinates, and TLS data providing the current snow depth at the time of our field campaigns. For the geostatistical analysis only significant covariates were selected.

Snow instability was derived from SMP measurements at locations $s = (s_1, s_2)$ giving an array of observed values $y(s)$ for each of both instability criteria $S$ and $r_c$. Covariate information $x(s)$ was collected at the locations of the SMP measurements in the field. Hence, $y$ and $s$ have length $n$ and $x$ has size $(n,p)$, with $n$ being the number of observations and $p$ the number of covariate variables.

The spatial model $Y(s)$ that describes the variations in our observations at the field measurement locations $s$ has the following form:

$$Y(s) = x(s)^T \beta + Z(s) + \epsilon(s),$$

where $x(s)^T \beta$ describes the external drift with coefficients $\beta$, $Z(s)$ is a spatially stationary autocorrelated Gaussian process with zero mean and covariance $\text{cov}(Z)$, and un-correlated fluctuations $\epsilon(s)$ with zero mean, i.e. independently distributed errors.

As our data set does not contain a large number of replicated measurements at the same locations, we cannot separate measurement errors and sub-grid fluctuations. Hence, we ignore $\epsilon(s)$ and all fluctuations from the autocorrelated variation are summarized in the ‘nugget’ variance $\tau^2$; hence, the covariance of $Z$ can be given as:

$$\text{cov}(Z) = \sigma^2 V_\rho + \tau^2 I,$$

with $V_\rho$ being the correlation matrix and $I$ the identity matrix, $\sigma^2$ is the variance of the autocorrelated variation (also called the sill variance) in $Z$ and $\tau^2$ the nugget variance of $Z(s)$ that cannot be resolved with the chosen sampling design plus measurement errors.

To select significant covariates, we performed stepwise multiple linear regressions between the response variables $y$ and the covariates $x$ and provide the adjusted coefficient of determination $R^2_a$. The quality of the external drift model was assessed by residual diagnostics to ensure the spatial stationarity assumption is fulfilled (Diggle and Ribeiro 2007). In case, residuals showed non-stationary behavior (i.e. con-
siderable drift with increasing fitted values) the response was log-transformed for the spatial autocorrelation analysis and eventually back transformed for the spatial prediction. Based on their correlation we assured that redundant covariates were excluded. With the Akaike information criterion we ensure that model improvement by including additional covariates is exhausted (Draper and Smith 1998).

Whereas it is common practice to derive the autocorrelation structure from the experimental variogram that relates the residuals of an external drift model to the lag distances (Webster and Oliver 2007), this approach is not well suited for data including significant outliers. As in our field data records outlying observations are not rare, they will affect estimates of the external drift model and the autocorrelation parameters. Methods insensitive to outliers are therefore preferred to obtain robust statistical estimates. Papritz et al. (2013) presented a robust approach for identifying the autocorrelation structure of a Gaussian random field which has been applied by Nussbaum et al. (2014) to soil data. We followed their procedure to obtain robust estimates of the covariance parameters of the variogram \( V \) of the residuals of our external drift model, with lag distances \( u \), nugget variance \( \tau^2 \) summarizing fluctuations and measurement errors, signal variance \( \sigma^2 \) of the autocorrelation and correlation function \( \rho_a \); the latter includes the range \( r_a \):

\[
V(u) = \frac{1}{2}\text{var}(Z(s) - Z(s - u)) = \sigma^2(1 - \rho_a(u)) + \tau^2. \tag{5.4}
\]

The most likely variogram parameters fitting the variogram \( V \) can be determined by optimizing the log-likelihood function \( L(y; \sigma^2, \tau^2, r_a, \beta) \) relating the model parameters with their joint probability of the multivariate distribution \( f(y; \sigma^2, \tau^2, r_a, \beta) \). Under the assumption of \( y \) being Gaussian with a linear trend the joint probability density function \( f(y; \sigma^2, \tau^2, r_a, \beta) \) is explicit,

\[
L = -\frac{1}{2}[\ln(2\pi)+\ln(\det(\sigma^2 V_a + \tau^2 I))+(y - x^T\beta)^T(\sigma^2 V_a + \tau^2 I)^{-1}(y - x^T\beta)]. \tag{5.5}
\]

Maximizing this equation yields a system of equations for the regression coefficients and the covariance parameters. By generalized least squares estimation both, the regression coefficients \( \beta \) and the covariance parameters \( (\sigma^2, \tau^2, r_a) \) are obtained (Papritz 2013). In addition, also resampled partitions of the data were used to optimize the profile likelihood function (Restricted Maximum Likelihood Estimation) to reduce the nuisance in small samples as ours. In our case the equivalent number of independent observations (49) is about less than one third of the nominal sample size \( \approx 150 \). By taking into account the autocorrelation of 11,175 variogram sample pairs from only 150 different sampling locations the maximum likelihood estimation approach brings a large benefit as it yields less biased variance estimators compared to ordinary least squares fitting techniques.
5.2 Methods

We obviously do not know the spatial structure of snow instability, i.e. whether snow instability has a rough or rather smooth surface representation in the terrain. To not limit ourselves to a specific correlation function, we selected the most appropriate one from the Matérn ‘family’ of correlation functions (Diggle and Ribeiro 2007). The shape parameter $\eta$ varied $\eta = [0.5, 1.5, 2.5]$; a value of $\eta = 0.5$ corresponds to the exponential variogram representing a rather rough surface, whereas the higher values of the shape parameter yield two smoother fitting models being once ($\eta = 1.5$) or twice differentiable ($\eta = 2.5$). The choice between the models was taken based on the maximized restricted log-likelihood. Apart from different surface roughness models, staying within the Matérn family allows comparisons of the covariance parameters such as the resulting autocorrelation range. The computation was carried out in R (R Core Team 2013).

Spatial prediction

In order to map snow instability variations within the Steintälli, we use the spatial model described above including the autocorrelation structure and perform external drift kriging to obtain predictions of snow instability (Papritz 2013).

The predicted surface $\hat{Y}$ is generated for all locations $s_0$, also those without observations, by combining the underlying external drift model with the estimated coefficients $\hat{\beta}$ and the estimated covariance structure of the data:

$$\hat{Y}(s_0) = x(s_0)^T\hat{\beta} + \gamma_\alpha(s - s_0)^T(\text{cov}_\alpha(Z(s)))^{-1}\tilde{Z}(s),$$

where the second term on the right contains a vector $\hat{\gamma}$ of estimated covariance between $Z(s)$ and $Z(s_0)$, the estimated covariance matrix of the Gaussian process at sampled locations $Z(s)$ and the vector with the kriging predictions (estimated residuals) of sampled locations $\tilde{Z}(s)$. The superscript ‘hat’ indicates that values from the REML algorithm are used and the subscript ‘a’ indicates that the covariance parameters enter the estimation of the function. Thus, the prediction compromises between the external drift, i.e. the background field, and the autocorrelation structure observed in the measurement data. In other words, it depends on the properties of the target location $x(s_0)$, i.e. the covariates at the target location, but also on the sampling locations $s$, i.e. the sampling design, and on the identified covariance structure, i.e. the covariance model parameters summarized by the subscript ‘a’ (autocorrelation structure). Thus, the background field gives a first estimation and then the interpolation is refined with the autocorrelation structure, in other words, we add estimates of the fluctuations we obtained from the analysis of the residual patterns.

As the parameters we chose as covariates partly explain the snow instability variations, they may enhance the prediction at locations we did not sample by
introducing local differences which would be missed by ordinary regression lacking covariate information. If, however, the geostatistical analysis does not reveal a spatial dependence, the external drift kriging would simply reduce to a multiple linear regression of the drift model $x^T \beta$.

The quality of the predictions is assessed by comparing the predictions at the locations, where the measurements were performed with the 10-fold cross validation approach. After separating the observed data into ten random samples, the model is refitted from nine out of ten samples and compared to the omitted tenth of the observations. Repeating the procedure ten times gives an estimate of the prediction accuracy.

5.2.6 Snow cover modelling and identification of meteorological drivers

The model system Alpine3D (Lehning et al. 2006) was used to model the snow cover and its properties in the Steintälli basin based on the micro-meteorological conditions. To this end, a digital elevation and a land-cover model, both at a resolution of 4 m in the horizontal, were used (Bühler et al. 2012). Therefore, the meteorological input data are interpolated on the digital elevation and land-cover models yielding a 4 m resolution. The Alpine3D model system provides three modules which include the interaction of micro-meteorological processes. The modules are related to preferential deposition and redistribution of snow (snow transport), to the energy balance (radiation module), and to internal processes in the snow cover (SNOWPACK). Only if the first two spatially interacting processes (snow transport and radiation) are included, spatial variations in snow properties are expected to be simulated. In the following, we refer to the data sources and the model setup in detail.

The model system was driven with data from four automatic weather stations (AWS) located within and around the Steintälli study site between 2440 and 2492 m a.s.l. (see Fig. 5.1) and at the Weissfluhjoch study plot (2540 m, 3 km to the northeast of Steintälli) (not shown in Fig. 5.1). Meteorological input contained air temperature and relative humidity (Rotronic MP100H HygroClip, ventilated), wind speed and direction (YOUNG wind monitor and Lambrecht combined wind sensor 14512), incoming short and long wave radiation (Campbell CNR1), and precipitation (Lambrecht Joss-Tongini). The meteorological input data were interpolated on a grid with size 600 m × 600 m covering the area of field measurements at a resolution of 4 m (module MeteoI/O) (Bavay and Egger 2014). In case data gaps longer than one day existed the data of the AWS were excluded in that particular period. Data gaps shorter than one day were filled by linear interpolation. Variables were filtered by introducing reasonable lower and upper limits, e.g. 5 and 100%
for relative humidity. Air temperature was interpolated with an elevation lapse rate of 8 K/1000 m and by inverse distance weighting. From air temperature and relative humidity the dew point temperature was calculated, interpolated over the grid by inverse distance weighting and retransformed into relative humidity. Wind speed was distributed over the grid by applying an elevation lapse rate based on all AWS data and performing inverse distance weighting. Furthermore, the wind speed was corrected at grid points for sheltering of the slope from the wind direction based on aspect, slope angle and exposure (terrain curvature) (Liston and Elder 2006). After correcting for under-catch (Schmucki et al. 2014) precipitation values were distributed over the grid by inverse distance weighting and including a constant elevation lapse rate. To account for preferential deposition during snowfalls a correction based on terrain and average wind direction was applied over the grid (Winstral et al. 2002).

Spatial variations of micro-meteorological processes are also caused by radiation differences. Measurement values from the reference AWS located within the Steintälli (grid cell 9 in Fig. 5.1) provided incoming short and long wave radiation. Short wave radiation was split into diffuse and direct radiation (Erbs et al. 1982). The contribution of direct short wave radiation on every grid point was calculated including shading effects based on the DEM. Adding the diffuse part, which is assumed constant over the modelling domain, and accounting for additional terrain reflections by introducing a terrain view factor and the albedo of the reflecting terrain amounts to the complete short wave radiation received at a grid point. Long wave radiation values from all AWS were averaged after correction with a constant elevation lapse rate (-0.031 W (m²m⁻¹)) (Marty et al. 2002).

Snow properties were modeled by the snow cover model SNOWPACK running within the model framework of Alpine3D. The modelling time step was 60 min after resampling the data from the AWS with a sampling rate of either 10 min or 30 min. The model was initiated on 24 September the year before, when no snow was present at the AWS and ran until the day of the field measurement campaign. Neumann boundary conditions for estimating the snow surface temperature and atmospheric stability corrections for estimating turbulent exchange were the preferred adjustments concerning the energy balance model (Stössel et al. 2010).

The snow properties obtained from snow cover modelling include the weak layer shear strength (Jamieson and Johnston 2001), the shear stress at the depth of the weak layer, the load of the slab, the average density of the slab, the slab thickness and the skier stability index (Jamieson and Johnston 1998). A principle component analysis was performed on these snow properties to evaluate whether they are suited as covariates for the snow instability criteria obtained from snow micropenetrometer field measurements – for 3 March 2011 when simulated snow properties
were available. Then, the geostatistical analysis from above was carried out on the first principle components, including regression model development, determination of covariance parameters and modelling error estimation by cross-validation. The cross-validation errors provide information on the predictive power of the spatial model including covariates as obtained from the snow cover model. In case, a similar quality of prediction as with terrain and snow depth data is achieved, snow cover properties may be used interchangeably with terrain parameters.

Snow cover model data have the advantage that they implicitly contain the records of meteorological data of the season. Hence, basing the geostatistical model on covariates from snow cover model output will enable us to search the meteorological records for the significant meteorological driving agents – i.e. causes of variations. Because in our model setup differences due to spatial interactions are only created by variations in snow transport and radiation, we only selected snow cover properties of the Alpine3D output that were linked to either snow transport or radiation. These properties include the precipitation mass and modeled wind speed, the energy input at the snow surface and the snowpack’s internal energy change. The variables were averaged over the weak or slab layer formation period depending on whether they refer to a weak or a slab layer property. A simple correlation analysis facilitated the search for significant drivers. We report the coefficient of determination ($R^2$) as a measure of correlation and variance, which is the square of the correlation coefficient in the case of linear correlation.

5.3 Results

In the following we present the model results for the external drift model, the spatial autocorrelation of the snow instability parameters and the spatial predictions of the two snow instability metrics for the Steintälli basin. Finally, we report the meteorological variables identified as drivers of snow instability variations for 3 March 2011.

5.3.1 External drift model

First, we developed multiple linear regression models for both instability criteria and all five field campaigns considering the five variables: topographic coordinates, snow depth, slope angle, elevation and aspect. Table 5.2 gives an overview on the different regression models. The most important terrain related driving agent was aspect, which was included in the regression models in all cases. However, the regression models in general differed; they contained the coordinates, the slope angle and the elevation as significant covariates in seven cases, whereas the snow depth
5.3 Results

Table 5.2: Regression and covariance fitting models for all five field campaigns and the two response variables $S$ and $r_c$. Furthermore, the information whether the response variable was log-transformed (yes/no), the adjusted coefficient of determination ($R^2_a$) of the regression model, the shape parameter of the Matérn model ($\eta$), the range estimated from the covariance model and the restricted log-likelihood (log-lik) are given.

<table>
<thead>
<tr>
<th>Date</th>
<th>Criterion</th>
<th>Significant covariates</th>
<th>log $R^2_a$</th>
<th>$\eta$</th>
<th>Range</th>
<th>log-lik</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 January 2011</td>
<td>$S$</td>
<td>snow depth, elevation, aspect</td>
<td>yes</td>
<td>0.45</td>
<td>2.5</td>
<td>31 m</td>
</tr>
<tr>
<td>28 January 2011</td>
<td>$r_c$</td>
<td>coordinates, slope angle, elevation, aspect</td>
<td>no</td>
<td>0.19</td>
<td>2.5</td>
<td>68 m</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>$S$</td>
<td>coordinates, snow depth, slope angle, aspect</td>
<td>yes</td>
<td>0.30</td>
<td>2.5</td>
<td>5 m</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>$r_c$</td>
<td>snow depth, slope angle, aspect</td>
<td>no</td>
<td>0.13</td>
<td>2.5</td>
<td>7 m</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>$S$</td>
<td>coordinates, snow depth, slope angle, elevation, aspect</td>
<td>yes</td>
<td>0.56</td>
<td>0.5</td>
<td>15 m</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>$r_c$</td>
<td>coordinates, slope angle, elevation, aspect</td>
<td>yes</td>
<td>0.45</td>
<td>0.5</td>
<td>10 m</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>$S$</td>
<td>coordinates, snow depth, elevation, aspect</td>
<td>yes</td>
<td>0.51</td>
<td>0.5</td>
<td>26 m</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>$r_c$</td>
<td>coordinates, elevation, aspect</td>
<td>no</td>
<td>0.33</td>
<td>0.5</td>
<td>7 m</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>$S$</td>
<td>snow depth, slope angle, elevation, aspect</td>
<td>yes</td>
<td>0.44</td>
<td>0.5</td>
<td>10 m</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>$r_c$</td>
<td>coordinates, slope angle, aspect</td>
<td>no</td>
<td>0.12</td>
<td>0.5</td>
<td>26 m</td>
</tr>
</tbody>
</table>

entered the regression model in six cases. In most cases a similar set of covariates described the background field of the two instability criteria on a single day. Hence, the agents varied depending on the situation which is in line with the findings of Reuter et al. (2015b). For instance, on 3 March 2011 a quite well settled slab sat on top of a four-day-old weak layer of facets partly grown to depth hoar crystals, whereas on 13 February 2012 a thinner, poorly bonded slab covered smaller, 19-days-old faceted crystals. Meteorological processes altered by terrain had caused different vertical snowpack structures in both situations which are then reflected in different sets of driving agents.

In all cases the adjusted coefficient of determination $R^2_a$ was higher for the failure initiation criterion than for the critical crack length. This indicates that the external drift model better explained the spatial variability in case of the failure initiation criterion. It is not surprising that not all the variance observed in a basin can be explained by a linear regression model. Even though the values of $R^2_a$ for the regression analysis are modest, a spatial structure may still exist, which eventually will yield good predictions.
5.3.2 Spatial autocorrelation

The residuals of the multiple linear regressions showed in all cases spatial autocorrelation even though not as distinct in some cases according to the restricted log-likelihood (Table 5.2, Fig. 5.4 and 5.5). The covariance models fitting the variograms best were either the exponential model (equal to Matérn with $\eta = 0.5$) representing a rough surface, or the twice differentiable Matérn model with $\eta = 2.5$, representing a smooth surface. With the chosen sampling design autocorrelation ranges between 3 and 250 m can be resolved, where the minimum is the shortest lag pair and the maximum is approximated as half of the maximum extent. On 28 January 2011 the autocorrelation ranges were rather large with 31 m for $S$ and 68 m for $r_c$ compared to 3 March 2011 when 5 m and 7 m were modeled. On both days the small scale fluctuations (i.e. the nugget variance), which summarize measurement errors plus sub-grid scale fluctuations, were modeled as smooth surfaces. On the remaining days, namely 13 February 2012, 9 March 2012 and 10 January 2013, the autocorrelation ranges varied between 7 m and 26 m and the best fitting covariance function was the exponential model. Hence on these three days, stronger small scale fluctuations were superimposed on the autocorrelation ranges of both instability criteria, as both snow instability criteria were modeled as rough surfaces. Assuming the measurement error was the same on all days, we can conclude that sub-grid scale fluctuations were stronger on these days than on 28 January and 3 March 2011.

In all cases autocorrelation models fitted the residuals of the crack length better than the failure initiation criterion which is reflected in higher values of the restricted log-likelihood (Table 5.2). A large amount of variation of the failure initiation criterion was already explained by terrain and snow depth variations, corresponding to higher $R^2_a$ for the external drift model of the failure initiation criterion. In case of the critical crack length, less variation was captured by the external drift model, but the covariance models performed better than for the failure initiation criterion, corresponding to higher values of the restricted log-likelihood. Hence, the remaining residual variation was partly captured in the second step when modelling the autocorrelation.

5.3.3 Spatial prediction

Based on the external drift model and the autocorrelation structure identified for both snow instability criteria we calculated spatial predictions for both snow instability criteria and analyzed the prediction errors to assess the uncertainty involved with the mapping. The results of the external drift kriging predictions and their errors are summarized in Table 5.3. The average predicted values of the failure initiation criterion were within 10% of the SMP-derived values at the measurement
Figure 5.4: Covariance models of the modeled failure initiation criterion for all five field campaigns estimated with the restricted maximum likelihood method.
**Figure 5.5:** Covariance models of the modeled critical crack length for all five field campaigns estimated with the restricted maximum likelihood method.
Table 5.3: Measured and predicted values with mean and standard deviation (std) of the two instability criteria $S$ and $r_c$ for the measurement locations on the five field days. Prediction errors from 10-fold cross validation including root mean square error (RMSE) and mean absolute error (MAE).

<table>
<thead>
<tr>
<th>Date</th>
<th>Criterion</th>
<th>Measurement $(\text{mean} \pm \text{std})$</th>
<th>Prediction $(\text{mean} \pm \text{std})$</th>
<th>Prediction RMSE</th>
<th>Prediction MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>28 January 2011</td>
<td>$S$</td>
<td>$188 \pm 120$</td>
<td>$173 \pm 82$</td>
<td>93</td>
<td>58</td>
</tr>
<tr>
<td>28 January 2011</td>
<td>$r_c$</td>
<td>$(38 \pm 10) \text{ cm}$</td>
<td>$(38 \pm 7) \text{ cm}$</td>
<td>9 cm</td>
<td>6 cm</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>$S$</td>
<td>$167 \pm 145$</td>
<td>$149 \pm 62$</td>
<td>140</td>
<td>67</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>$r_c$</td>
<td>$(26 \pm 9) \text{ cm}$</td>
<td>$(26 \pm 5) \text{ cm}$</td>
<td>10 cm</td>
<td>7 cm</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>$S$</td>
<td>$207 \pm 208$</td>
<td>$194 \pm 179$</td>
<td>127</td>
<td>76</td>
</tr>
<tr>
<td>13 February 2012</td>
<td>$r_c$</td>
<td>$(46 \pm 15) \text{ cm}$</td>
<td>$(45 \pm 10) \text{ cm}$</td>
<td>10 cm</td>
<td>7 cm</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>$S$</td>
<td>$231 \pm 165$</td>
<td>$226 \pm 163$</td>
<td>141</td>
<td>90</td>
</tr>
<tr>
<td>9 March 2012</td>
<td>$r_c$</td>
<td>$(46 \pm 15) \text{ cm}$</td>
<td>$(45 \pm 10) \text{ cm}$</td>
<td>13 cm</td>
<td>10 cm</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>$S$</td>
<td>$365 \pm 196$</td>
<td>$340 \pm 135$</td>
<td>148</td>
<td>114</td>
</tr>
<tr>
<td>10 January 2013</td>
<td>$r_c$</td>
<td>$(41 \pm 8) \text{ cm}$</td>
<td>$(41 \pm 5) \text{ cm}$</td>
<td>8 cm</td>
<td>6 cm</td>
</tr>
</tbody>
</table>

locations. They were all considerably larger than the errors for the critical crack length. On all days, the average predicted values of the critical crack lengths at the measurements locations were within $\pm 1 \text{ cm}$ of the SMP-derived critical crack lengths.

SMP-derived values and values predicted with 10-fold cross validation of the failure initiation criterion and the critical crack length are contrasted in scatter-plots in Fig. 5.6 and 5.7, respectively. The smoothing spline is close to the 1:1 line in the plots where the point density is high. Deviations from the 1:1 line were largest in case of the failure initiation criterion on 9 March 2012 and 10 January 2013 (Fig. 5.6), which is reflected in the highest mean absolute errors (MAE = 90 and MAE = 114, respectively) of the predicted failure initiation criterion on the two days (Table 5.3). For the critical crack length, the deviation of the smoothing spline from the 1:1 line was less pronounced (Fig. 5.7), with the largest mean absolute error on 9 March 2012 (MAE = 10 cm). Plots for SMP-derived and predicted critical crack length showed few scatter (Fig. 5.7), except on 9 March 2012, which is in line with low root mean square prediction errors only slightly larger than the SMP-derived critical crack length modelling error, namely RMSE = 7 cm and MAE = 2 cm as reported by Reuter et al. (2015a). The smallest error (RMSE = 8 cm) was obtained on 10 January 2013, when the autocorrelation was modelled with the highest restricted log-likelihood (Table 5.2).

Summing up, predictions of the failure initiation criterion were less reliable compared to the spatial predictions of the critical crack length. While with the external drift model a larger amount of variation of the failure initiation criterion
was captured than in case of the critical crack length, the residuals of the failure initiation criterion were less clearly autocorrelated and the fits of the covariance model performed less well according to the values of restricted log-likelihood in Table 5.2. The lower level of residual autocorrelation is one reason for the less reliable predictions for the failure initiation criterion apart from an inherently higher

\[ \text{MAE}_{\text{CV}} = 56 \]
\[ \text{RMSE}_{\text{CV}} = 93 \]

\[ \text{MAE}_{\text{CV}} = 67 \]
\[ \text{RMSE}_{\text{CV}} = 140 \]

\[ \text{MAE}_{\text{CV}} = 76 \]
\[ \text{RMSE}_{\text{CV}} = 127 \]

\[ \text{MAE}_{\text{CV}} = 90 \]
\[ \text{RMSE}_{\text{CV}} = 141 \]

\[ \text{MAE}_{\text{CV}} = 114 \]
\[ \text{RMSE}_{\text{CV}} = 148 \]
5.3 Results

Figure 5.7: Comparisons of SMP-derived and predicted critical crack length $r_c$ (m) from cross validation (CV) (dots) with smoothing spline in red and 1:1 line in black (dashed) for all five field campaigns. Yellow bulb covers one standard deviation of the data.

variance in the failure initiation criterion indicated by the scatter in Fig. 5.6.

Furthermore, Fig. 5.6 and 5.7 illustrate the non-spatial distribution of modeled snow instability criteria at the measurement locations which is highlighted by a bulb around the mean with one standard deviation. For example, on 13 February 2012 the propensity of failure initiation was generally high as the point cloud is located
in the lower left and most values are below the threshold of 234 reported by Reuter et al. (2015a). However, the scatter was large indicated by the large size of the bulb. In contrast, the propensity for crack propagation was not very pronounced due to generally intermediate to high values of the critical crack length (0.4–0.6 m) according to the threshold of 0.41 m reported by Reuter et al. (2015a).

To visualize the spatial distribution of snow instability the prediction was carried out across the entire Steintälli basin. The results were mapped and are presented in Fig. 5.8 and 5.9. Blue colors indicate values above the thresholds reported by Reuter et al. (2015a), i.e. high values of snow stability, red colors indicate values below these thresholds, i.e. low values of snow stability. As shown above snow instability variations were partly explained by snow depth and terrain parameters (Table 5.2). Apparently, snow instability patterns followed terrain features, i.e. areas with similar values of snow instability were found in areas with similar topography, which is reflected in Fig. 5.8 and 5.9. For instance, on 28 January 2011, when slope angle and aspect were both covariates, a flat area slightly northeast and a rather flat area near the AWS in the center of the sampling area (Fig. 5.1) had lower values of the critical crack length compared with the rest of the sampling domain (Fig. 5.9). In view of the crack propagation propensity on all days except on 3 March 2011 intermediate to high values of the critical crack length were modeled (Fig. 5.9). On 3 March 2011 lower critical crack lengths were predicted in the center of the basin than in the north on the south-facing slopes. With regard to failure initiation that pattern, meaning lower values in the center of the basin than on the south-facing slopes, was observed more frequently, namely on 3 March 2011, 13 February 2012 and 9 March 2012 (Fig. 5.8). On the other two days the pattern was reversed with lower values of the failure initiation criterion on the south-facing slopes in the north of the basin. Moreover, 3 March 2011 was the only day with both snow instability criteria yielding below threshold values in most of the sampling area (red colors in Fig. 5.8 and 5.9). In fact, that day the avalanche danger level was highest among all field campaigns and verified to have been ‘considerable’. On the other sampling days the avalanche danger level was lower, i.e. ‘low’ or ‘moderate’.

The uncertainty of the interpolation of the snow instability criteria at the field site is presented in Fig. 5.10 for 9 March 2012 by the root mean squared prediction errors. It is obvious that prediction errors of the critical crack length are smaller within the entire sampling area and slightly beyond, whereas the uncertainty of the predicted failure initiation criterion increases quickly away from sampled locations. In case of the failure initiation criterion, variations depend stronger on terrain, than on the autocorrelation structure compared to the critical crack length, as presented in sections 5.3.1 and 5.3.2. Hence varying the terrain, which is equivalent to moving away from sampling locations, increases the prediction uncertainty more rapidly in
5.3 Results

Figure 5.8: Maps of the failure initiation criterion predicted with external drift kriging for all five field campaigns for the Steintälli field site. Axes are labeled with Swiss coordinates (in meters). Triangle indicates an AWS at an elevated point on the ridge.
Figure 5.9: Maps of the critical cut length predicted with external drift kriging for all five field campaigns for the Steintälli field site. Axes are labeled with Swiss coordinates (in meters). Triangle indicates an AWS at an elevated point on the ridge.
5.3 Results

101 case of the failure initiation criterion.

Figure 5.10: Selected maps presenting the standard prediction error of the failure initiation criterion (left) and the critical crack length (right) for 9 March 2012. Axes are labeled with Swiss coordinates (in meters). Triangle indicates an AWS at an elevated point on the ridge.

5.3.4 Identifying causes of snow instability variations

Aiming at identifying meteorological drivers, we built the geostatistical model (section 5.2.5) on snow cover covariate data, which were modeled from meteorological input with Alpine3D. For one specific case, 3 March 2011, we made an initial attempt to identify the drivers of snow instability variations by tracking back the meteorological conditions. To this end, the geostatistical analysis, we had performed hitherto, was repeated with snow cover related covariates instead of terrain parameters and snow depth; as the covariates we selected the first two components of a principle component analysis applied to the SNOWPACK output variables: weak layer shear strength, shear stress at the depth of the weak layer, load of the slab, average density of the slab, slab thickness and the skier stability index.

For both snow instability criteria, the load due to the weight of the slab and the shear stress at the depth of the weak layer described the snow instability variations in the basin. Both parameters are based on slope angle, density and the thickness of the slab. The regression model was significantly better than a regression based on topographic coordinates only (Akaike information criterion). The covariance models fitting the variograms best indicated a smooth surface (corresponding to Matérn with $\eta = 2.5$) and the range was derived to 5 m for $S$ and 7 m for $r_c$ (Table 5.4). From 10-fold cross-validation we obtained similar prediction errors as with the terrain based statistical model (RMSE = 143 for the failure initiation criterion and RMSE = 10 cm
Table 5.4: Results of the geostatistical analyses based on snow cover modelling derived covariates. For 3 March 2011 for both response variables $S$ and $r_c$ the variables included in the PCA components (covariates) are presented. Furthermore, the information whether the response variable was log-transformed (yes/no), the adjusted coefficient of determination ($R^2_a$) of the regression model and the range estimated from the covariance model are given. In case of the failure initiation criterion $S$ the regression analysis failed.

<table>
<thead>
<tr>
<th>Date</th>
<th>Criterion</th>
<th>Covariates</th>
<th>log $R^2_a$</th>
<th>Covariance function</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 March 2011</td>
<td>$S$</td>
<td>load, weak layer shear stress</td>
<td>yes</td>
<td>Matérn, $\eta = 2.5$</td>
<td>5 m</td>
</tr>
<tr>
<td>3 March 2011</td>
<td>$r_c$</td>
<td>load, weak layer shear stress</td>
<td>no</td>
<td>Matérn, $\eta = 2.5$</td>
<td>7 m</td>
</tr>
</tbody>
</table>

For the obtained snow instability variations on 3 March 2011, we were finally searching for the meteorological drivers that had caused the variations of slab load and weak layer stress. These two slab properties mostly depend on snow density and slab thickness. The meteorological variables were integrated over the slab formation period between 24 January and 3 March 2011, as both, slab density and thickness are slab parameters. A linear regression analysis indicates that the slab thickness was related to the total sum of precipitation ($R^2 = 0.64$) (Fig. 5.11a) and the total energy input at the snow surface ($R^2 = 0.58$) during the slab formation period (Fig. 5.11b) at the sampling locations. The average density of the slab was rather driven by the energy input at the snow surface ($R^2 = 0.52$) (Fig. 5.11c) than by the total sum of precipitation ($R^2 < 0.01$) during the slab formation period.

With smaller amounts of precipitation and higher energy inputs at the same time thinner slabs had developed in the south and southeast-facing slopes in the northern part of the sampling area resulting in a lower propensity for crack propagation on these slopes (Fig. 5.9). In this area, also the propensity for failure initiation was lowest. The relatively long critical crack lengths on the slopes of northern aspect, e.g. in the southernmost grid cell (Fig. 5.9), can also be explained with lower slab densities caused by a significantly lower energy input due to the aspect-related differences in radiation (Fig. 5.11d).

Interestingly, the skier stability index $SK_{38}$ was not included into PCA since it was slightly negatively correlated ($R^2 = 0.05$) with our failure initiation criterion $S$ – although they are based on the same parameters. Furthermore, $SK_{38}$ modelled with SNOWPACK was previously validated and found to be related to observed snow instability (Schweizer et al. 2006). To find the reason for this discrepancy we contrasted the key model parameters with the measured opponents.

In Fig. 5.12a we compare average slab densities as measured with the SMP and
Figure 5.11: Slab thickness and average slab density versus sum of precipitation and sum of energy fluxes at the snow surface during the slab formation period. All values obtained from snow cover modelling. Colors indicate aspect and the numbers refer to the grid cells presented with the sampling design in Fig. 5.1.

modeled with Alpine3D. The variations produced by the snow cover model ranged from 145 to 200 kg m$^{-3}$ and considerably underestimated the variations measured with the SMP (145–390 kg m$^{-3}$) (Fig. 5.12a). Furthermore, the modeled variations in snow depth were much less prominent than actually observed with the TLS measurements – though the average snow depths agreed well (Alpine3D: 1.37 m, TLS: 1.44 m; not shown). The less prominent snow depth variations may have contributed to the low variation in modeled snow density.

In Fig. 5.12b we contrast modeled shear strength and SMP-derived strength. Note, the SMP-derived values are about two orders of magnitude higher, because SMP-derived strength rather refers to the compression than to the shear mode and values are not calibrated. In the snow cover module the calculation of the shear
strength of persistent weak layers is based on snow density $\rho$:

$$\tau_s = a\left(\frac{\rho}{\rho_{\text{ice}}}\right)^b,$$

with $a = 18.5$ kPa and $b = 2.11$, and $\rho_{\text{ice}}$ the density of ice (Jamieson and Johnston 2001). Performing a robust linear regression of the SMP-derived strength for the part of snow density data containing many measurements ($175$–$280$ kg m$^{-3}$), yielded a coefficient $a = 2.3$ MPa and an exponent $b = 2.49$. The similar exponents indicate that the increase of SMP-derived strength with density is in line with the shear frame measurements by Jamieson and Johnston (2001). The modeled values of shear strength, however, showed little variation since the parameterization is primarily based on snow density, which was underestimated by the model.

In summary, the overall low variation in density seems to be responsible for the lack of correlation between the modeled skier stability index and our initiation criterion.

5.4 Discussion

A geostatistical approach to predict snow instability at the basin scale was applied to snow property data from five field campaigns collected with the snow micro-penetrrometer in a small basin above treeline. The data were recently presented by Reuter et al. (2015b) who performed a first non-spatial analysis to explore potential
5.4 Discussion

drivers, mainly terrain and snow depth. Building on their work, the current study aims at describing the spatial variations of snow instability at the basin scale and finally at identifying the causes. To this end, a robust maximum likelihood estimation technique was applied to determine the coefficients of an external drift model and evaluate the spatial autocorrelation structure, which were both used to eventually predict snow instability from point measurements.

5.4.1 External drift model

Terrain is a prominent driver of snow instability at the basin scale and with slope aspect, in particular, observed variations of snow instability were partly explained on all sampling days. This finding agrees well with previous studies at scales beyond the slope scale (Birkeland 2001; Schweizer and Kronholm 2007; Schweizer et al. 2003b). Similarly it has been shown that terrain is the most important driver for snow depth (e.g. Schirmer et al. 2011), which is to some extent related to snow instability (Reuter et al. 2015b; Schweizer et al. 2003b).

For every situation the best fitting model for the available driving agents was chosen by stepwise regression to only include significant driving agents in the models, by the Akaike information criterion to compromise between overfitting and information gain. The regression models varied compared to the previous study by Reuter et al. (2015b) as we had to log-transform the response variable in some cases (Table 5.2) to make sure the assumption of weak stationarity was fulfilled for further geostatistical analysis and also as we included topographic coordinates. Prior to the analysis, it was not clear which set of covariates controlled the distribution of snow instability, and the covariates had to be chosen for each situation separately. Although aspect was always among the significant covariates, its influence on snow instability variations varied, for example, north-facing slopes may be more stable than south-facing slopes (10 January 2013) or vice versa (13 February 2012) (Fig. 5.8 and 5.9). The lack of a general rule characterizing the distribution of snow instability at all times, agrees with our picture of snow instability varying in time and space (McClung and Schweizer 1999). Meteorological processes vary in time, interact with terrain and thus cause spatially and temporally varying snow physical properties.

5.4.2 Spatial autocorrelation

Our snow instability criteria include several snow physical properties and hence comprise processes on different temporal and spatial scales (Schweizer and Kronholm 2007). The chosen geostatistical approach divides variations of snow instability into a background field consisting of terrain parameters or snow depth representing a
constant or seasonal average and residual patterns partly due to meteorological forcing. With our sampling design having an extent of about 500 m we identified autocorrelation ranges between 5 and 26 m, except for one case of 68 m. These values are similar to the ranges for instability related parameters determined at the slope scale in previous studies: \( r_a = 2–8 \) m at an extent of 19 m (Bellaire and Schweizer 2011), \( r_a = 2–8 \) m at an extent of 19 m (Schweizer and Reuter 2015) and \( r_a = 1–13 \) m at extents of 23 and 37 m (Lutz et al. 2007). Obviously, ranges determined previously – though in some cases half the extent – were meaningful, as typical ranges found in the present study at an extent of 500 m were not considerably larger. Comparing with the terrain, obtained ranges were typically shorter than the autocorrelation range of the terrain in the Steintälli area, which has values between 47 and 102 m depending on direction. As snow instability variations due to terrain were modeled with the external drift model and autocorrelation ranges are shorter than the scale on which terrain varies, obtained autocorrelation ranges are suggested to be due to micro-meteorological processes causing slope scale variations. The smoothness of the variations modeled by the shape parameter of the fitted covariance model varied between the field days, but was always the same for both instability criteria – reflecting the small scale variability at the particular sampling day. However, strong stability variations below three meters have not frequently been observed. Birkeland et al. (2010) revisited 25 studies in search for an optimal distance for stability test spacing and found only in 2 out of 25 studies strong snow instability variations below 5 m.

### 5.4.3 Spatial prediction

For all sampling days, we performed external drift kriging predictions from multiple regressions based on terrain and snow depth data and the remaining residual autocorrelation. Typically, uncertainties – determined with 10-fold cross validation – were larger for the failure initiation criterion than for the critical crack length. According to higher adjusted \( R_a^2 \) the external drift model explained more variation of the failure initiation criterion than of the critical crack length. However, the residuals of the critical crack length were more clearly autocorrelated as reflected in higher values of the restricted log-likelihood which yielded a better prediction performance in the end. Also, possibly due to inherently more scattering of the failure initiation criterion itself compared with the critical crack length, the prediction did not reach the same performance. The cross validation prediction errors yielded similar values as the root mean square error of 7 cm of the method to derive the critical crack length from an SMP signal (Reuter et al. 2015a). Hence snow instability may be mapped reliably based on our data.
After first maps had been presented for snow instability related indices at the slope scale (Bellaire 2010; Kronholm and Schweizer 2003; Schweizer et al. 2008b; Schweizer and Reuter 2015), we presented detailed maps of snow instability variations based on field measurements and external drift kriging predictions at the basin scale. Supporting earlier studies based on snow stability observations (Birkeland 2001; Schweizer et al. 2003b) our maps showed that variations of snow instability followed terrain features. The maps may be interpreted according to the sequence of avalanche release processes in the sense that if failure initiation is likely, the crack propagation propensity has to be considered, highlighting the importance of both processes to promote snow instability (Schweizer et al. 2003a). However, at increasing distances from the sampling locations interpretation requires more caution in particular for maps of the failure initiation criterion.

5.4.4 Causes of snow instability variations

Proxy data for snow instability estimation typically include meteorological data (Perla 1970), but the predictive power is limited if concluding from meteorological data on avalanche hazard (Schweizer and Föhn 1996). The approach of predicting snow instability variations from meteorological data is basically hampered by the temporal and spatial variations of the snow cover and the missing interaction with terrain. For example, Schirmer et al. (2009) made an attempt to include spatial variations in their forecasting model by considering the SNOWPACK output for two rather than one AWS and corresponding virtual slope simulations, but the prediction performance did not improve – suggesting the modelled variation was not sufficiently meaningful.

To consider the temporal influence of the meteorological forcing and the spatial interactions of meteorological processes with terrain, we repeated the geostatistical analysis with covariates of snow cover data modeled with Alpine3D for the field campaign of 3 March 2011. If the spatial predictions of the failure initiation criterion and the critical crack length were based on snow cover model rather than terrain and snow depth data, the same autocorrelation ranges, the same type of autocorrelation representing a rather smooth surface and similar cross-validation model errors were obtained. These results suggest that 3D snow cover modelling with Alpine3D is able to mimic variations of snow properties due to meteorological forcing interacting with terrain – but not variations of snow instability. However, this might be feasible as Mott et al. (2011a) have shown for snow ablation which depends on similarly complex micro-meteorological processes.

To identify the meteorological processes which shaped the observed variations of snow instability we analyzed meteorological variables. Preferential deposition of
precipitation and differences in the energy input at the snow surface controlled the thickness and the density of the slab. The differences in snow instability (Fig. 5.9) were eventually explained with variations in total amount of precipitation or the energy input at the snow surface during the formation period of the slab (Fig. 5.11). In agreement with Kozak et al. (2003), who was able to relate snow layer hardness to snow and air temperature indices or radiation, variations of snow density were related to the energy input at the snow surface and influenced snow instability. Also, relations of the total amount of precipitation with slab thickness and density were plausible and intuitive, so we are confident that precipitation and energy input at the snow surface were mainly responsible for the variations of instability we found on this particular sampling day.

Comparing the snow cover model output with our measurements, we found that the variations of snow density, snow strength and snow depth modelled with Alpine3D were smaller than measured with the SMP or TLS. The findings suggest that the model is able to mimic snow property variations, but does not cover all processes leading to variations of snow instability nor fully capture their influence. We anticipate an improvement in snow cover model performance, once a full description of short and long wave reflections (Helbig et al. 2010) and an atmospheric flow field to account for all snow transport processes are considered (Mott et al. 2011b). Moreover, the comparison of SMP-derived snow strength with the shear strength parametrization of Jamieson and Johnston (2001) supports previous findings that the snow micro-penetrrometer is a reliable field measurement tool to acquire snow properties (Marshall and Johnson 2009; van Herwijnen et al. 2009; Proksch et al. 2015a; Reuter et al. 2015a).

5.5 Conclusions

We derived two snow instability criteria from stratified snow micro-penetrrometer measurements within a basin and performed robust geostatistical analyses for five sampling days with the aim to describe spatial patterns and identify their causes. Using external drift kriging we interpolated the snow instability measures at the basin scale and provide first exemplary maps.

The external drift model was based on terrain and snow depth, i.e. a constant or seasonal average, respectively. Significant covariates, among which slope aspect was the most prominent, varied depending on the situation. In other words, there is no general rule how terrain parameters relate to snow instability. The sets of covariates explained more variation of the failure initiation criterion than of the critical crack length. In contrast, the residual patterns of the critical crack length were more clearly autocorrelated than in case of the failure initiation criterion. For this reason
and possibly due to less scatter of the SMP-derived critical crack length, its spatial prediction was more reliable. The resulting maps clearly showed how the propensity for failure initiation and crack propagation varied in our study site depending on terrain. Only when both snow instability criteria yielded below threshold values in most of the sampling area, the avalanche danger rating was ‘considerable’ indicating critical conditions. For both criteria we modeled rather short autocorrelation ranges (5–31 m, and once 68 m) similar to the ranges found in previous slope scale studies and clearly below the autocorrelation ranges of the terrain. We conclude that previously determined ranges at the slope scale were meaningful, despite short extents in sampling designs. Snow instability variations due to terrain were captured with the external drift model and autocorrelation ranges were shorter than those of the terrain. This finding suggests the autocorrelated variations were due to micro-meteorological processes causing variations at the slope scale.

For one situation we identified the meteorological forcing responsible for the observed snow instability variations at the basin scale. Repeating the geostatistical analysis with modeled snow cover data as covariates we obtained the same autocorrelation ranges and similar prediction errors for both instability criteria. This approach allowed us for the first time to track back potential causes for the variations of snow instability. The observed variations were mainly due to variations in slab layer properties which in the case of 3 March 2011 were caused by preferential deposition of precipitation and energy input at the snow surface during the formation period of the slab layers.

Our results demonstrate the value of 3D snow cover modelling for enhancing snow instability predictions. Despite this benefit, comparisons with field measurements showed that with our model setup the variations of snow cover properties such as density, snow depth and snow strength were underestimated. This shortcoming calls for more advanced snow cover modelling to better resolve micro-meteorological spatial interactions which are required to capture realistic variations of snow cover properties. In order to fully exploit the potential of snow cover modelling for snow instability prediction, all possible meteorological spatial interactions should be considered in future work. Furthermore, the spatial variability data can be used for realistic simulations with slope failure models.
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Chapter 6

Conclusions and Outlook

6.1 Conclusions

Snow property variations are an inherent characteristic of the mountain snow cover and control the instability of the snowpack. A quantitative understanding of the causes of these variations of snow instability is required for a deterministic modeling approach aiming at resolving snow instability variations and model validation.

Snow instability – according to our current understanding of avalanche release – is determined by the probability of initiating a failure in a weak layer and its eventual propagation. Both processes may be modeled based on snow stability tests, which are the only method to observe snow instability in the absence of obvious signs of instability such as ‘whumpfs’, ‘shooting cracks’ and current avalanching. This modeling approach requires meaningful snow cover data, preferably collected with the snow micro-penetrometer, which allows resolving the vertical stratification of the snow cover and covering an area of a small basin with measurement arrays during one day. The quality of snow micro-penetrometer derived input parameters was assessed in comparisons with current measurement techniques, including micro-computed tomography of snow samples and particle tracking velocimetry of field experiments (chapter 2). SMP-derived snow properties were related with the values obtained from the two other techniques, but especially with respect to the effective modulus discrepancies remain to be solved.

Based on these snow micro-penetrometer derived properties two measures of snow instability were developed. Both measures, the failure initiation criterion and the critical crack length are quantitative criteria providing a means for observer independent snow instability measurements in the field. The performance of both measures was assessed in comparisons with two field data sets containing rutschblock scores and critical crack lengths observed in propagation saw tests. In both cases significant correlations provided evidence that with this approach the propensity for
failure initiation and crack propagation in the snowpack can be estimated. Additionally, independent observations of signs of instability confirmed the relevance of both criteria and highlighted the dependence of snow instability on both, failure initiation and crack propagation. This was anticipated as both processes are the relevant steps in the chain of events leading to avalanche release, but had not been demonstrated quantitatively, yet. Moreover, for the first time, an observer independent method for snow instability assessment in the field exists – which is one step forward towards a comprehensive definition of snow instability.

The process-based approach for snow instability assessment was applied to vertical profiles obtained with the snow micro-penetrometer at specific locations in a basin. The sampling locations were predefined according to a semi-randomized sampling design and were mostly representative in view of the terrain characteristics of the basin. This allowed to compare the snow instability criteria derived from the penetration resistance profiles with the verified avalanche danger level for the area of the basin. The snow instability distributions found with the presented approach resembled the instability distributions characteristic of the avalanche danger level found in previous studies. Relating our snow instability measures with terrain and snow depth data, which are expected to explain snow instability variations to a certain extent at the basin scale, we found that aspect was the most prominent driver appearing as driver on all sampling days. Snow depth and slope angle did not appear as consistently. The findings that between the sampling days the sets of significant drivers and the sign of the relationships (positive or negative coupling) varied, indicate that general statements concluding from terrain or snow depth characteristics on the snow instability distribution are not feasible on a specific day. Considering the entire data set, i.e. averaging over the five sampling days, showed that snow depth variations explained differences of the crack propagation propensity and that the propensity of failure initiation was driven by slope angle and slab depth. To conclude, in case snow instability information are available, simple drivers may support spatial extrapolation. In case instability data are not available and hence, a link between the drivers and the specific situation cannot be established, still trends may be estimated from the average drivers.

By means of robust geostatistical analyses we aimed at quantifying spatial snow instability variations based on our quantitative, SMP-derived snow instability measures and identify the meteorological forcing responsible for the variations at the basin scale. In order to quantify spatial variations we based the external drift models on the relationships between simple drivers such as terrain and snow depth. In line with the results from the non-spatial analysis (chapter 4), the derived external drift model confirmed that aspect was the most prominent driver of snow instability at the basin scale – despite including elevation and the topographic coordinates as
6.2 Outlook

From the results of the present thesis starting points for further research may be provided.

Snow cover properties are important for a wide range of cryospheric applications. With respect to snow instability especially density, effective modulus, fracture energy and strength are among the crucial mechanical properties. Results from SMP and µCT comparisons were promising, but the increasing scatter of the modulus with density in the µCT-SMP dataset and the grouping of snow types suggested a dependency of the modulus on other parameters than density. To obtain a robust
parametrization for the SMP-derived modulus and including appropriate structural parameters, first the interpretation of the response of the SMP tip during penetration of a snow structure needs to be improved. Hagenmuller (2014) already addressed the issue with first simulations of a cone penetrating a well-defined granular geometry.

Definitions for snow instability may be given following the current understanding of snow avalanche release. To do so, we introduced two SMP-derived criteria for failure initiation and crack propagation. However, in the validation with signs of instability some cases remained in which neither criterion reflected the observed stability correctly. This suggests that one element of snow instability is missing. In fact, we also regularly observe crack arrest in propagation saw tests instead of full propagation to the end of the column, although a critical weak layer is present. Obviously the tensile strength of slab needs to be accounted for, as it is important for the propagation of cracks in weak layers (Schweizer et al. 2014b). Incorporating this aspect may improve the description of snow instability at the pit scale.

The presented, or an enhanced algorithm for SMP signals in the future does not only pave the way for analyzing the spatial variation, but also the temporal evolution of snow stratigraphy. Repeated measurements in study plots may provide a comprehensive dataset for validating snow layer properties simulated by snow cover models.

With respect to the slope scale, definitions of snow instability are mainly based on manual observations (Bellaire and Schweizer 2011; Schweizer and Reuter 2015). In order to base the definition on comprehensive, objective criteria we need to advance our understanding of slope stability. To do so, the present study offers a dataset which enables us to drive and validate slope failure models as presented by Gaume et al. (2015a). Moreover, with a field measurement method to determine snow instability from SMP signals we may also gather field data to address the open question of crack arrest and avalanche size. According to previous research propagating cracks do not only arrest at topographical and morphological features, but may also stop due to changes in snowpack properties.

Regarding the regional scale, knowing the drivers of snow instability variations for a specific situation possibly from simulations or field measurements, spatial variations of snow instability may be estimated based on simple drivers due to their wide availability. In data sparse areas, where terrain or even snow depth data are available, this low cost option may provide clues, how snow instability varies.

Snow instability forecasting is based on snow cover and meteorological data. Temporal and spatial variations and their interaction with terrain generally complicate the prediction of snow instability variations. The most elegant way to advance snow instability forecasting and include spatial variations is by spatial snow cover modeling based on gridded meteorological data. This thesis provides starting points
to advance towards spatial snow instability prediction.

Further research is required to enhance the spatial modeling of snow properties, such as snow density. With respect to modeling the micro-meteorological processes shaping spatial variations of snow properties more sophisticated routines are available (Mott et al. 2011a), but require testing with measured snow cover data. The presented snow micro-penetrrometer data offers an option to perform these comparisons. Concerning parameterizations of snow mechanical properties, a profound understanding of the links between snow microstructure and the physical properties is required. The first steps towards a comprehensive description of the physical parameters and snow microstructure is on the way (e.g. Calonne et al. 2014; Löwe et al. 2013). Improving relationships between mechanical properties and snow structure, however, possibly requires a new set of parameters to characterize snow structure in snow cover models (Carmagnola et al. 2014).
Appendix A

Additional data
Figure A.1: SMP profiles (orange) recorded at the corner point of grid cell 9 for each field day overlain by traditional snow profile data including hand hardness index (blue), snow depth $H$ (cm), grain type $F$ and grain size $E$ (mm). Critical weakness highlighted in orange and characterized by the Compression Test (CT) result: CT score and fracture type.
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