Cold Regions Science and Technology 56 (2009) 152–160

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

Assessing changes in the spatial variability of the snowpack fracture propagation propensity over time

Jordy Hendrikx [a,*], Karl Birkeland [b], Martyn Clark [a]

[a] National Institute of Water and Atmospheric Research (NIWA), Christchurch, New Zealand
[b] USDA Forest Service National Avalanche Center, Bozeman, MT 59771, USA

ARTICLE INFO

Article history:
Received 4 July 2008
Accepted 4 December 2008

Keywords:
Spatial variability
Snowpack
Propagation
Avalanche forecasting

ABSTRACT

Understanding the spatial variability in fracture initiation and fracture propagation is critical for avalanching as both are required for an avalanche to release. Most of the previous research looked at the spatial variability of fracture initiation. We focus on understanding the spatial variability of the fracture propagation potential using the Extended Column Test (ECT). This work uses a new overlapping grid methodology which allowed us to make repeat data collection on the same slope to collect data on two separate days at the slope scale from two environmentally different sites (windy and sheltered), thereby capturing temporal changes in the spatial variability of our results. In contrast to previous fracture propagation test research, our data demonstrates considerable spatial variability in fracture propagation potential. Interestingly, at both the windy and sheltered sites the first sampling day demonstrated a relatively random distribution of fracture propagation potential results, while the second sampling day for both sites showed evidence of increased resistance to propagation as well as increased spatial clustering at the scale of our observations. Since distinct clustering or pockets of propagation and non propagation exist on some slopes, the practical implication of our work is that it is often necessary to dig more than one snow pit on suspect slopes to assess stability, and those slopes might be more accurately assessed by widely (greater than 10 m) spaced measurements.
Though our data are limited, these results represent the first statistically demonstrated temporal change in snowpack spatial variability at the slope scale. However, in order to definitively address the question of temporal changes in spatial patterns, much more work is needed on many slopes with varying weak layers and snowpack conditions.

1. Introduction

Seasonal snow varies both temporally and spatially. Both of these aspects of variability have been examined to some extent in previous work for a range of snowpack properties (e.g. resistance (Birkeland et al., 1995); snow water equivalence (Blöschl, 1999; Derksen et al., 2000); snow depth (Dyer and Mote, 2006)). In terms of avalanches, variations in fracture initiation and propagation are important since both are required for an avalanche to release. Most previous research focused on measurements associated with fracture initiation, such as shear tests, compression tests or rutschblock tests (e.g., Conway and Abrahamson, 1984; 1988; Föhn, 1989; Jamieson, 1995; Kronholm, 2004). The recent development of fracture propagation tests (Gauthier and Jamieson, 2006; Simenhois and Birkeland, 2006) allows the assessment of the spatial variability of this property. Understanding the spatial variability of the fracture propagation potential is a crucial step for improving accuracy in field data collection and avalanche forecasting. Our paper focuses on investigating the spatial variability of the fracture propagation potential at the slope scale, and how that spatial variability changes over time.

Previous research demonstrates that the conditions for fracture initiation are highly variable at the slope scale, though the exact amount of variability has been a subject of debate. Schweizer et al. (2008) provide a detailed review of the spatial variability literature, so our review here will be brief. Conway and Abrahamson (1984; 1988) first analyzed the spatial variability snowpack stability at the slope scale by measuring shear strength along fracture lines of recently triggered slab avalanches. Their papers triggered wider interest in the direct examination of the spatial variability of the stability of the snowpack and raised issues about the representativeness of a single snowpack stability observation on a slope. In addition to further shear frame research (Föhn, 1989; Logan et al., 2007), this work led to slope-scale investigations of the variability of rutschblock tests (Jamieson, 1995; Campbell and Jamieson, 2007), small block compression-type tests (Landry, 2002; Stewart and Jamieson, 2002; Landry et al., 2004; Kronholm, 2004; Kronholm and Schweizer, 2003) and penetration resistance (Birkeland, 1990; Birkeland et al., 1995; Birkeland et al., 2004a; Kronholm, 2004; Kronholm et al., 2004).

* Corresponding author.
E-mail address: j.hendrikx@niwa.co.nz (J. Hendrikx).

0165-232X/$ – see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.coldregions.2008.12.001

Recent work utilized the above data for geo-statistical analyses, primarily using semivariograms (Kronholm and Schweizer (2003); Campbell, 2004; Birkeland et al. (2004b); Logan et al. (2007). Results are mixed, with some slopes or layers showing autocorrelation while other slopes or layers did not. However, when autocorrelation exists, the typical correlation length scale is in the order of several meters (<0.5 m to >10 m), despite the different measurement types, different scale triplet (Blöschl and Sivapalan, 1995), and different types of layer (Schweizer et al., 2008). Furthermore, different layers on the same slope sometimes have varying spatial structures (Birkeland et al., 2004b; Kronholm, 2004).

There are far fewer investigations into the spatial variability of fracture propagation propensity. This is partially because tests targeting fracture propagation have only recently been developed (Gauthier and Jamieson, 2006; Simenhois and Birkeland, 2006). However, Johnson and Birkeland (2002) state that shear quality (and closely related fracture character) may provide a qualitative measure of how well a fracture will propagate through a given weak layer, and Schweizer et al. (2008) suggest that shear quality (Johnson and Birkeland, 2002) and fracture character (van Herwijnen and Jamieson, 2002) should show less variability than other test scores. Results from Campbell and Jamieson (2007) demonstrate this reduced variability. Simenhois and Birkeland (2006; 2007) conducted limited slope scale studies of fracture propagation test results. Using the Extended Column Test (ECT), they investigated two slopes and found ECT results to be relatively uniform across those slopes, with variations on one slope explainable by changes in slab properties.

Recent research shows our understanding of fracture propagation is evolving (Heierli et al., 2008), and the relationship of ECT results to

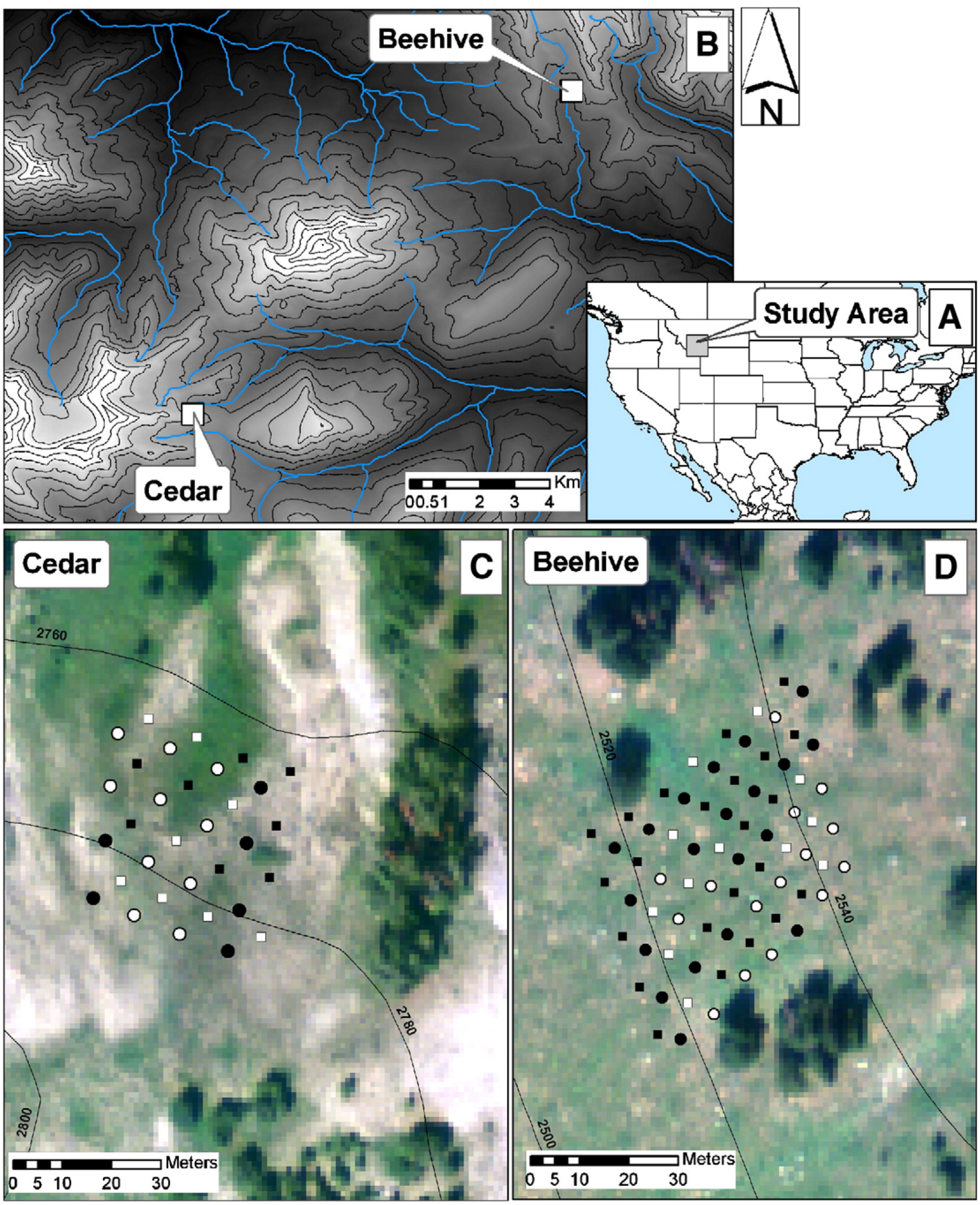


Fig. 1. (A) Map of North America, showing the United States and the field area in southwestern Montana. (B) Elevation map with 100 m contour intervals, showing the locations of the two field sites; Beehive and Cedar. Inset maps of Cedar (C) and Beehive (D) with the field data from day 1 at both sites shown as squares and day 2 as circles, where white symbols are ECTN and black symbols are ECTP (illustrates the overlapping grids), 20 m contour intervals are also shown and data is presented on an aerial photograph of the area showing vegetation and general slope surroundings.

actual fracture propagation is not known. In the ECT the fracture is initiated over a length of approximately 30 cm and then may propagate an additional 60 cm. We do not know how propagation across this relatively short distance relates to the longer slope-scale propagations required for avalanche release, so we must treat our ECT results as an *index* of fracture propagation rather than an actual measure of fracture propagation.

Despite the extensive body of work on spatial variability, few studies have assessed temporal changes in that spatial variability. Such work is important from a practical sense because it informs avalanche practitioners the extent to which observed patterns tend to persist over time. Changing patterns would offer additional challenges for those attempting to predict slope stability. Birkeland and Landry (2002) first looked at this problem and analyzed limited data to suggest that spatial variability might increase through time, but they could not form strong conclusions. The work by Logan et al. (2007) focussed on this problem with a specialized sampling strategy on two given slopes. While some measures of spatial variability of shear frame test results (such as the interquartile range) increased through time, they found other evidence of temporal changes of spatial variability was limited.

Our research has two primary goals. First, we investigate the slope scale spatial variability of fracture propagation potential using the ECT. Second, we attempt to quantify temporal changes in that spatial variability. Our field sites include one slope that is relatively protected from the wind and another that is highly wind affected. Our work involves developing a new field sampling strategy, as well as utilizing new data analysis techniques to quantify whether our results are clustered or random.

2. Study area

We collected data on 2 days at each of the two field sites. These two sites are both situated in southwestern Montana, USA near the resort town of Big Sky (Fig. 1). Located within the intermountain avalanche climate zone, the sites typically exhibit a variety of avalanche and snowpack conditions, including persistent weak layers (Mock and Birkeland, 2000). This research targeted persistent weak layers or near surface weaknesses. The two sites exhibited differences in exposure to the wind, with one site representing typical sheltered conditions (where most of the previous spatial variability work has been undertaken), while the other represented a highly wind exposed location.

Our first site is located in the lower reaches of Beehive Basin (111.3867 W, 45.3177 N) at an elevation of 2520 m on a WSW (average 253°) aspect. The Beehive slope is a wind sheltered slope approximately 70 m wide and 80 m high with trees on the northern and southern edges. This site has an average slope angle of 30°, decreasing to 26° towards the top and displaying a small amount of cross slope curvature with aspects ranging from 238° to 262°. Our second site is located below the lower slopes of the east ridge of Mt. Cedar (111.4838 W, 45.2350 N) at an elevation of 2770 m on a NNE (average 022°) aspect. The Cedar slope is a wind swept slope approximately 60 m wide and 50 m high with trees on the eastern and northern edges. The Cedar site has an average slope angle of 29° and has a small amount of cross slope curvature with aspect ranging from 018° to 030°.

3. Methods

3.1. Field data

At the Beehive site we performed 35 sets of snow stability and fracture propagation potential tests each day, and at the Cedar site we performed 16 sets of tests per day. The number of pits was less at the Cedar site because of access logistics and the size of the slope limited our sampling. At both sites, we spaced tests 10 m apart in a regular rectangular (Beehive) or square (Cedar) gridded layout. For Beehive this was achieved with a grid of 5×7 snow tests (extent 40 m wide×60 m high) and for Cedar with a grid of 4×4 (extent 30 m wide×30 m high). Care was taken to minimise the disturbance to the snow between the 10 m grid locations. At the end of the first day, this resulted in observations every 10 m within the grid and an area of approximately 80 m^2 of undisturbed snow between observation points. On the second day at each field site the rectangular or square grid was off-set by 5 m up and across the slope, so that tests were performed in the middle of the 80 m^2 of undisturbed snow (Fig. 2).

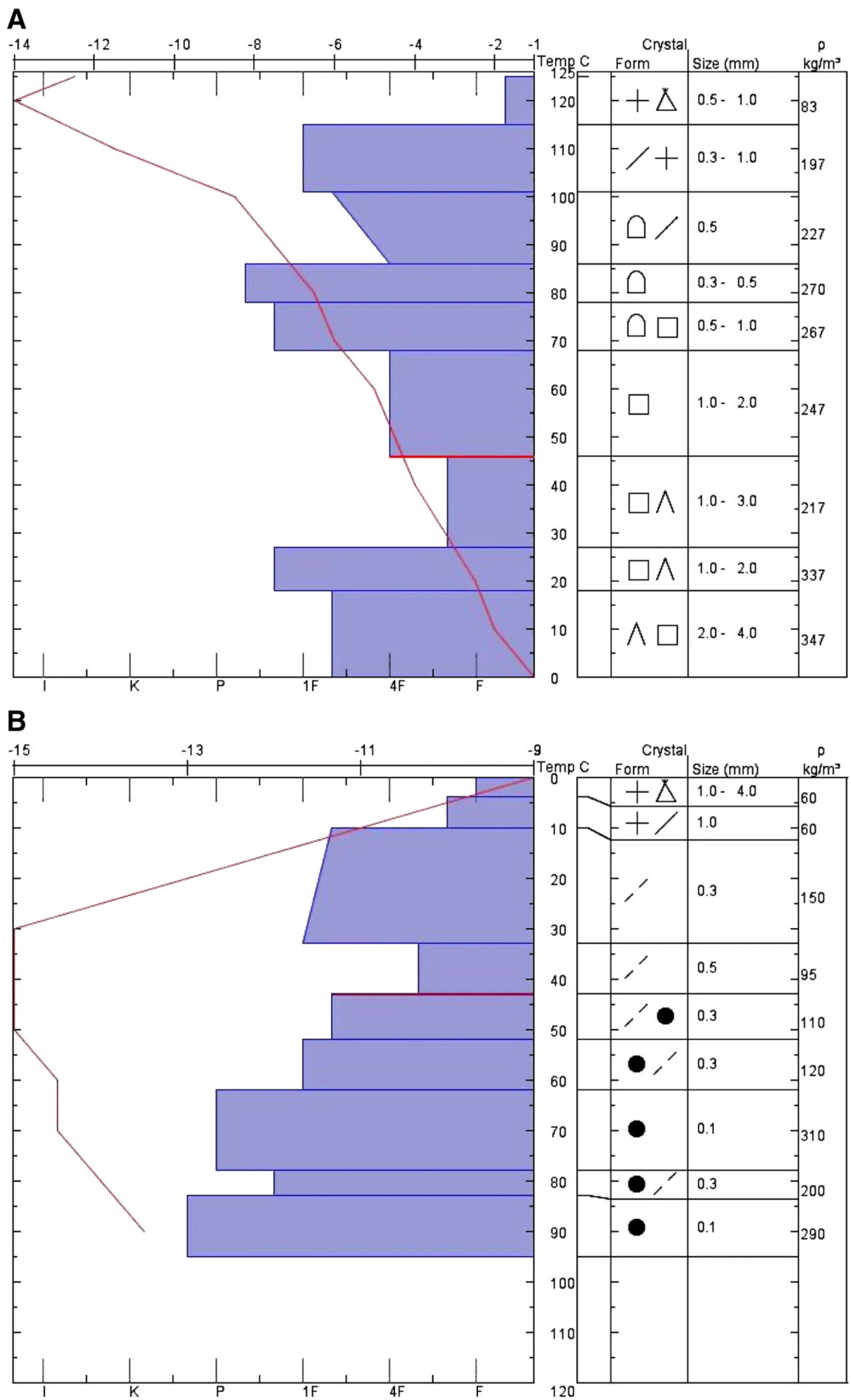
Fig. 2. Photo from day 2 at Beehive, showing the day 2 snow pits and the remnants of the day 1 snowpits in between and below the grid illustrating the 10 m spacing in the grid, and the 5 m offset layout for the second day.

Our second day's observations allowed us to assess temporal changes on the slope. This technique differed from those used by Birkeland and Landry (2002) and Logan et al. (2007), and offered both advantages and disadvantages. The advantages are that our technique maximized the extent of our sampling, and also allowed us to sample the same part of a slope rather than adjacent parts of the same slope as had been done previously. However, a possible problem is that our first day's data collection, which involved walking between grid points on the slope (Fig. 2), might affect our second day's observations. Birkeland and Landry (2002) hypothesized that one of the mechanisms for temporal changes in spatial variability could be creep, and Logan (2005) found some evidence for this for shear frame results in his data analyses. Our sampling technique likely affected creep on our slope and therefore may have affected the patterns we observed. However, no perfect technique for such temporal analyses currently exists.

The time between the two sampling days varied between the sites. The snowpack at the Beehive site contained a persistent weak layer of faceted grains (Fig. 3), so we waited longer between the days. At this site our first data collection effort was on 5 February 2008, with our second day on 14 February. At the Cedar site the snowpack did not contain persistent weaknesses. Instead, the layers of interest consisted of a variety of wind deposited layers sitting on relatively lower density snow (Fig. 3). As such, we waited only 4 days between samples at this site, with our first day on 7 February 2008 and the second day on 11 February. The snow profiles were undertaken at both sites on both days, at the lower left corner of the grid (when observed from down slope).

At the Beehive site each of the 35 snow tests included at least one stuffblock (SB) test (Birkeland and Johnson, 1999) and one extended column test (ECT) (Simenhois and Birkeland, 2006) using the stuffblock method to create the load increments. At the Cedar site each of the 16 snow tests included at least one compression test (CT)

Fig. 3. (A) Snow profile at Beehive showing the relatively shallow snowpack with persistent weaknesses, and the location of the fracture at the bottom of the layer of faceted grains (at 46 cm). (B) Snow profile at Cedar day showing the deeper snowpack with multiple wind deposited layers and the location of the fracture at the bottom of the layer of relatively lower density snow (43 cm down from the surface).


A
-14 -12 -10 -8 -6 -4 -2 -1
Temp C
Crystal
Form
Size (mm)
ρ kg/m³
125 120 110 100 90 80 70 60 50 40 30 20 10 0
0.5 - 1.0
83
0.3 - 1.0
197
0.5
227
0.3 - 0.5
270
0.5 - 1.0
267
1.0 - 2.0
247
1.0 - 3.0
217
1.0 - 2.0
337
2.0 - 4.0
347
I K P 1F 4F F
B
-15 -13 -11 -9
Temp C
Crystal
Form
Size (mm)
ρ kg/m³
0 10 20 30 40 50 60 70 80 90 100 110 120
1.0 - 4.0
60
1.0
60
0.3
150
0.5
95
0.3
110
0.3
120
0.1
310
0.3
200
0.1
290
I K P 1F 4F F

(Jamieson, 1999) and one ECT. In each case the support was 0.09 m^2 (SB or CT) and 0.27 m^2 (ECT). At both sites on both days for every test the following parameters were also recorded: shear quality (Johnson, and Birkeland, 2002), fracture character (van Herwijnen and Jamieson, 2002), snow depth, depth to failure, aspect and slope angle. The same person performed all the tests at one location on both days. At the Beehive site an additional set of 10 snow depth and SnowMicroPen (SMP) observations were made for every third snow test, resulting in 120 SMP and snow depth measurements. These latter measurements are not utilized in this paper.

3.2. Data analysis

We analyzed both sites (Beehive and Cedar) in the same way. Both sets of data have two observation days, and each day has been treated as a separate data set, with changes between the days regarded as temporal changes to the same slope. Our analysis concentrates on the spatial variability of the propagation or non-propagation of the ECT test rather than the stability test score as in previous work.

When the ECT results are plotted on the grid, we wanted to determine if there was a spatial pattern in the results. If a pattern is present, then is the pattern spatially clustered, random or dispersed, and at what spatial scales is this pattern discernible? We used two methods to address this issue; Moran's *I* (Moran, 1948; Fischer et al., 1996) and a Modified Ripley's *K* (Ripley, 1981; Cressie, 1993) using a Monte Carlo simulation.

3.2.1. Moran's I

Moran's *I* coefficient of spatial autocorrelation summarizes a complete spatial distribution into a single number (Moran, 1948). Moran's *I* is a weighted correlation coefficient used to detect departures from spatial randomness, where departures from randomness indicate spatial patterns such as clusters (Fischer et al., 1996).

The *Spatial Autocorrelation: Moran's I* tool in the spatial statistics tool bar in ArcGIS 9.2 was used in this analysis. The tool measures spatial autocorrelation on both feature locations and feature values simultaneously, calculating the Moran's *I* value and a *Z* score. The null hypothesis of this tool states that “there is no spatial clustering of the values” and when the *Z* score is greater than the desired significance level, the null hypothesis can be rejected. In this paper we consider both the 10% and 5% significance level. Inspection of the Moran's *I* indicated if the features exhibit a dispersed (values nearer −1.0) or clustered pattern (values nearer +1.0).

3.2.2. Modified Ripley's K using Monte Carlo simulation

Ripley's *K* function has been used for a wide range of applications to summarise a given point pattern, test hypotheses about the pattern, or estimate parameters and fit models (Ripley, 1981; Cressie, 1993). In contrast to Moran's *I*, Ripley's *K* summarises the spatial dependence over a range of distances. This is desirable for our analysis since Moran's *I* provides no information on spatial scales of clustering or dispersion, or if this changes at different spatial scales.

For a given grid we first identified a set of “events” (for our data an event was where an ECT did not propagate (ECTN)), resulting in a binary grid. The fraction of events was calculated for a given search radius around each event, and the average fraction of events for a given search radius was calculated as a function of the area of the study area domain (as defined by outer edge of points) within the circle. This can be summarized by Eq. (1):

$$E = \frac{\sum_{i=1}^{n} Ai.Fi}{\sum_{i=1}^{n} Ai} \tag{1}$$

where *E* is the average fraction of events for a given search radii around each measurement location, *Ai* is the area of the *i*-th circle within the study domain, and *Fi* is the fraction of events within a circle, relative to number of measurements within the circle. Eq. (1) accounts for edge effects by weighting the fraction of events (*Fi*) by the area of the study domain within the search radius (*Ai*).

The average fraction of events for a given search radii (*E*) was then computed for multiple search radii. A spatial signature is produced by simply plotting *E* for multiple distances. If the average fraction of events for a particular evaluation distance is greater than the average fraction of events throughout the study domain, the distribution is considered clustered at that distance. Comparing the fraction of events at a given distance to the average fraction of events over the study domain assumes that the process is spatially homogenous at the scale of the study domain — for example, differences in propagation potential within the study domain can result from trends in propagation potential at the scale of the study domain. However, the field data only allow testing of spatial clustering at spatial scales smaller than the extent of the study domain.

Confidence bounds for spatial clustering are produced using Monte Carlo trials. This approach is novel in snow science, but it is not unique and has been used in other disciplines to calculate confidence envelopes with Ripley's *K* (e.g. in ecology; Wiegand and Moloney, 2004). Monte Carlo trials test if the underlying spatial process was purely random. To make this assessment 1000 random grids were generated by re-sampling (without replacement) from the field data. This maintained the same *average*propagation probability as the field data for every one of the 1000 random grids. Essentially this process simply re-shuffled the field data 1000 times, such that the distribution of spatial structures and corresponding spatial signature in the 1000 random grids only occurs due to chance. The spatial signature for each of the 1000 random grids provides 1000 different summaries of *E* against distance, and these 1000 plots of the spatial signature are used to construct confidence bounds at the 5, 10, 90 and 95 percentiles.

4. Results

The field data for both days at Beehive and Cedar are presented in Fig. 4 and summarised in Table 1. At both sites the second day's observations were made 5 m up slope and 5 m across slope (to the right) when viewed from the bottom of the slope. Qualitative inspection of the field data suggests there is some spatial structure at both Beehive and Cedar.

We considered that the patterns in ECTP and ECTN were not solely due to random variations and that there might be a discernable pattern at a given scale in the field data. We also observed changes in the spatial pattern between Day 1 and Day 2 at each of the sites. At Beehive we noticed a decrease in ECTP results to the right and upper parts of the slope. At Cedar the central part of the slope showed a decrease in the number of ECTP results. Furthermore, there is a difference in the mean drop height (in cm) and number of taps for the ECTP results on the 2 days, with Beehive increasing from 42 cm on day 1 to 50 cm on day 2, and Cedar increasing from 5 taps to 14 taps for ECTP results (Table 1).

Results from the Moran's *I* analysis for Beehive Day 1 and Cedar Day 1 both indicate, through the low *Z* score, that the point pattern of ECT results shows no coherent spatial pattern and can be considered random (Table 1). The results for Beehive Day 2 and Cedar Day 2 indicate that there is less than a 5% likelihood that the clustered point pattern is the result of random chance, where a *Z* score of 1.65 is 10%, 1.96 is 5% and 2.58 is 1%. While the Moran's *I* value is low at Beehive and Cedar (0.02 and 0.03 respectively) the high *Z* score (2.13 and 2.11) suggests that there is greater than 95% chance that this point pattern is not the result of random chance. Thus, our results suggest a temporal change from a random pattern to a more spatially organized pattern of ECT results at the scale of our observations for both of our sites.

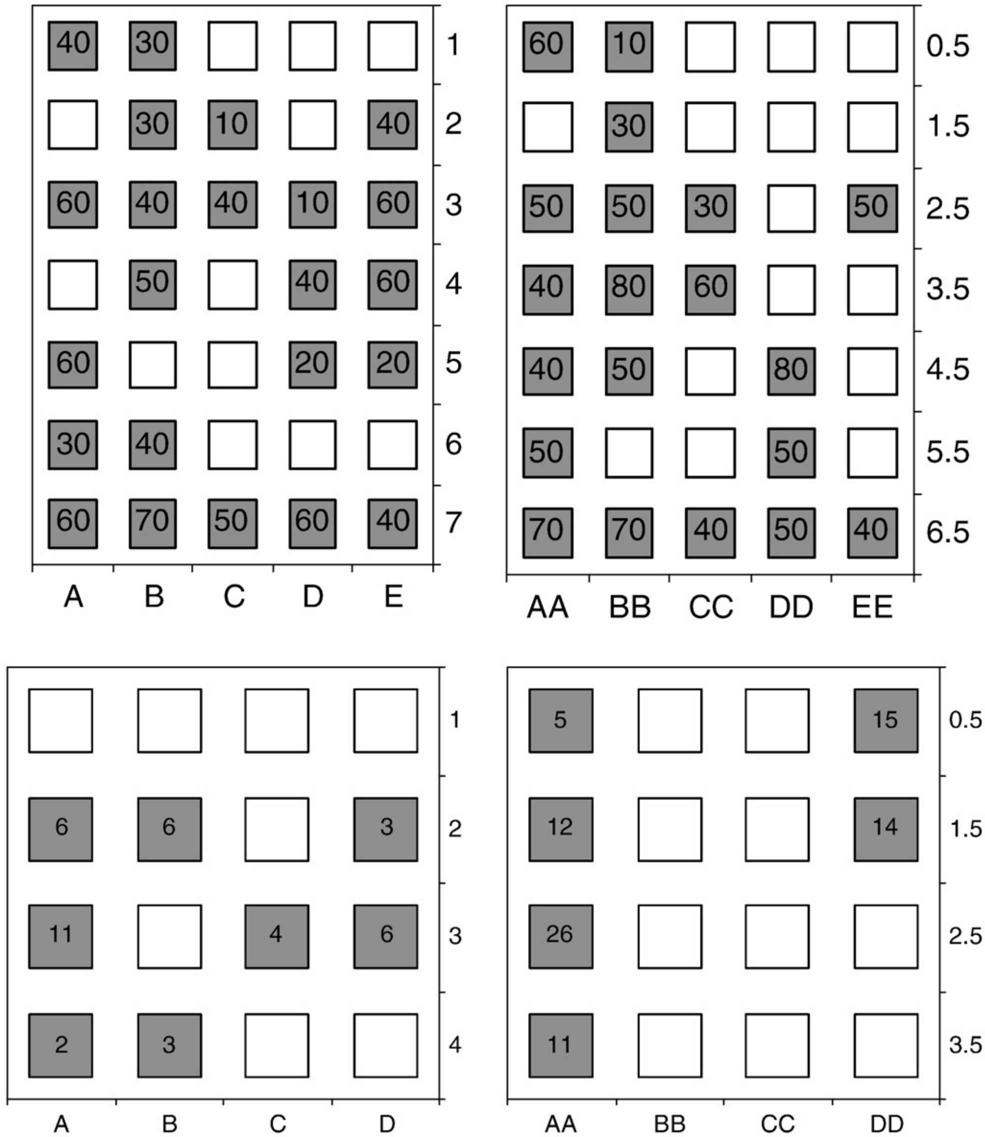


Fig. 4. Data from Day 1 (left) and Day 2 (right) at Beehive (top row) and Cedar (bottom row) as viewed from the bottom of the slope. Where the ECT propagated it is shown in gray and the drop height (in cm) is shown for Beehive (top row) and the number of taps for Cedar (bottom row). Note that the spacing between each observation is 10 m and the grid on the second day was off set by 5 m up slope and 5 m to the right.

Our Ripley's *K* Monte Carlo simulations or "spatial signatures" reinforce the Moran's *I* results, as well as providing additional information on the distances at which clustering or dispersion might be occurring. Fig. 5 (Beehive) and Fig. 6 (Cedar) show plots of the spatial signature from the two days with *E* against distance for the original field data (thick black line), the 1000 random grids (thin grey lines), and the 5, 10, 90, and 95 percentile lines (thick grey lines). Results are shown for two cases: in the first case (left plots) the event is defined as where the pit did not propagate (ECTN), and in the second case (right plots) the event is defined as where the pit did propagate (ECTP). The top (bottom) set of plots show results for the first (second) field day. If the field data is outside the confidence limits, then it is unlikely (less than 5 or 10% chance) that the observed spatial patterns in the field data are random at the specified distance. Values above the top grey line indicate clustered data while values below the bottom grey line represent dispersed data at those distances.

The field data for Day 1 at Beehive (Fig. 5, top row) lie mostly within the 10 and 90 percentile confidence limits. However, there are

Table 1
Beehive and Cedar data, showing the number of observations, ECTP, ECTN, mean drop height or number of taps for ECTP, standard deviation for ECTP results, Moran's *I*, *Z* score and Moran's summary comment.

Site/day	No. Obs	ECTP	ECTN	Mean drop height or number of taps	Std dev	Moran's *I*	*Z* score	Morans *I* summary comment
Beehive day 1	35	23	12	42 cm	17	−0.04	−0.64	The pattern is neither clustered nor dispersed. (i.e. random)
Beehive day 2	35	20	15	50 cm	17	0.02	2.13	There is less than a 5% likelihood that this clustered pattern is the result of random chance
Cedar day 1	16	8	8	5 taps	2.9	−0.05	0.42	The pattern is neither clustered nor dispersed. (i.e. random)
Cedar day 2	16	6	10	14 taps	6.9	0.03	2.11	There is less than a 5% likelihood that this clustered pattern is the result of random chance

some distances at which it is likely that either clustering (greater than 90%) or dispersion (less than 10%) is occurring. ECTN on day 1 is dispersed (10% confidence interval) at distances greater than 30 m and less than 50 m, while at distances greater than 50 m there is a suggestion of clustering. ECTP on day 1 is dispersed (10% confidence interval) at distances greater than 25 m and less than 40 m, while at distances greater than 50 m there is a slight tendency to show clustering.

Day 2 at Beehive (Fig. 5, bottom row) shows a temporal change toward increased spatial organization. The field data are close, and often exceed the 90 and 95 percentile confidence limits at various distances. Our results show that there is strong evidence that ECTN results on day 2 are clustered at distances less than 30 m and at distances greater than 45 m. ECTP on day 2 is also likely to be clustered (95% confidence interval) at distances less than 15 m and at distances greater than 45 m.

Similar to the changes observed for Beehive, the data from Cedar also show a temporal change toward increased spatial organization. Our Day 1 data (Fig. 6, top row) lie in the middle of the distribution, suggesting a relatively random spatial distribution. The only exception is the slightest tendency to show clustering at distances between 30 and 35 m in the ECTP results, but this evidence is not strong.

In contrast, Day 2 at Cedar (Fig. 6, bottom row) shows that the field data for ECTN is predominantly clustered, especially at distances less than 20 m, and often exceeds the 90 and 95 percentile confidence limits at various distances. ECTP on day 2 has an interesting pattern. Those results are likely to be clustered (95% confidence interval) at distances less than 15 m and are likely to be dispersed at distances greater than 22 m but less than 30 m.

The Monte Carlo approach provides a novel method for analyzing the clustering or dispersion of ECT results. This technique reinforced our Moran's *I* results which suggested that both sites demonstrated temporal changes from more spatially random patterns to more spatially organized patterns at the scale of our observations. However, the Monte Carlo approach also provided additional information by allowing us to quantify the distances over which the spatial organization (either clustering or dispersion) was occurring.

5. Discussion and conclusions

Our data demonstrate that considerable spatial variability exists in ECT results under some conditions (Fig. 4 and Table 1). This contrasts with previous work by Simenhois and Birkeland (2006; 2007) which suggested relatively uniform ECT results at the slope scale. These results also appear to run counter to analyses showing extremely low false stable rates (around 3%) found for ECT test results for a large database (Simenhois and Birkeland, 2006; 2007). In our study some slopes exhibited around 50% ECTP and 50% ECTN results, suggesting either a false-stable or a false-unstable rate of about 50% for those particular slopes. Thus, on many slopes the ECT appears to provide stability data with reasonable confidence, but there are some slopes (such as the slopes in this research) where the spatial variability of results cast doubt on the ability of any one test to accurately assess the slope stability. The differences between the results presented here and those from previous work may be due in part to the extent of this work, which is greater than that of previous studies. There may also be differences in the variability of the ECT results related to the layer on which the fracture is occurring and the setting or climatic region in

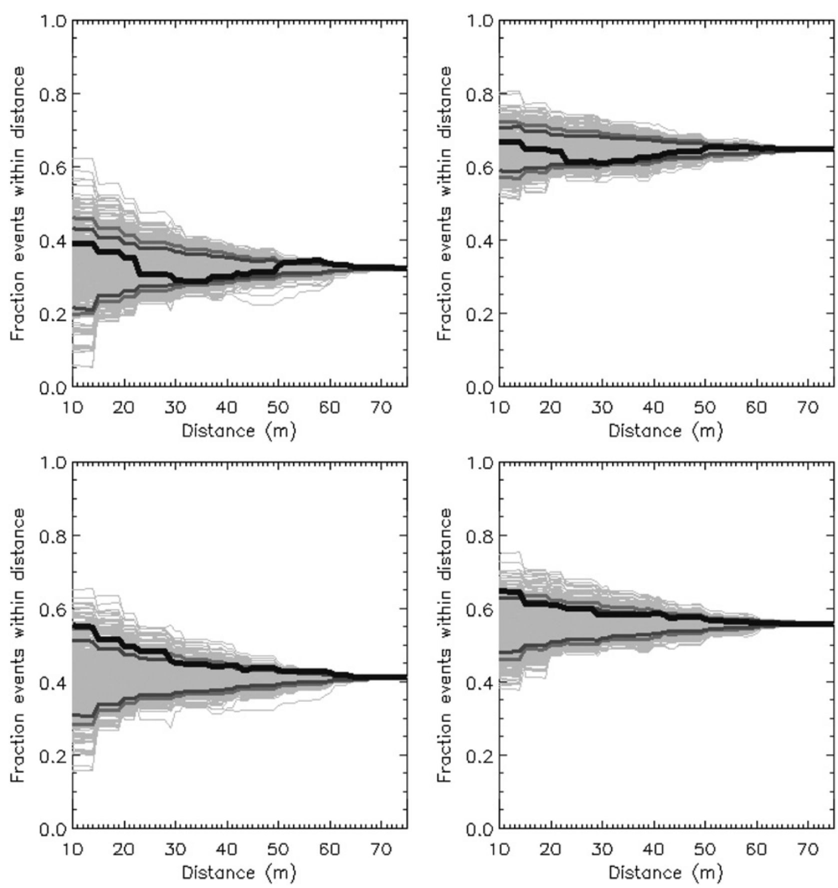


Fig. 5. Ripley's *K* Monte Carlo simulations "Spatial signatures" for data from Beehive. Left column = Events ECTN. Right column = Events ECTP. Top row = Day 1 (23 ECTP). Bottom row = Day 2 (20 ECTP). The thick black line is the observed data, thin grey lines represent 1000 random grids, and thick grey lines are the 5th, 10th, 90th, and 95th percentile from the random simulations.

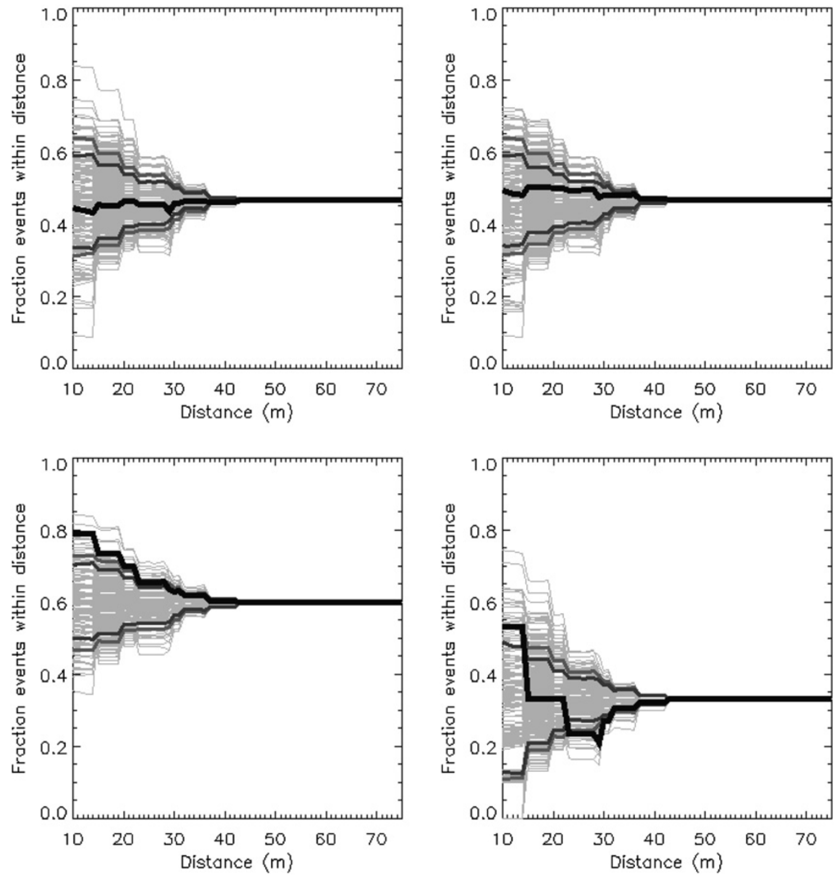


Fig. 6. Ripley's *K* Monte Carlo simulations "Spatial signatures" for data from Cedar. Left column = Events ECTN. Right column = Events ECTP. Top row = Day 1 (8 ECTP). Bottom row = Day 2 (6 ECTP). The thick black line is the observed data, thin grey lines represent 1000 random grids, and thick grey lines are the 5th, 10th, 90th, and 95th percentile from the random simulations.

which the slope is situated. However, at this point we cannot definitively explain the differences between this paper and previous research. Our work on this subject is ongoing, and we hope that ongoing field work will provide new insights.

Though we use two different methods for analyzing our fracture propagation data, both methods indicate the same trend in results. In each case the initial sampling day demonstrated a relatively random distribution of ECT results, while the second sampling day for both the Beehive and Cedar sites showed evidence of increased spatial clustering at the scale of our observations. Our results are encouraging because they are the first statistically demonstrated documentation of a temporal change in spatial variability of fracture propagation (as indexed by the ECT) at the slope scale. However, we have only collected data from two slopes, and we only have two snapshots of each slope. In order to definitively address the question of temporal changes in spatial patterns, we need much more work on many slopes with varying weak layers and snowpack conditions.

Our work has practical implications. First, clustering of propagation and non-propagation may partially explain some non-avalanche events (Birkeland et al., 2006a, b). In these cases fractures initiated and propagated for some distance, but avalanches did not immediately release. Perhaps strong zones that resisted fracture propagation were partially responsible for these events. Second, since distinct clustering or pockets of propagation and non propagation exist on some slopes it seems prudent to follow the recommendations of Birkeland and Chabot (2006) to dig more than one snow pit on suspect slopes. Knowing the spatial variability or degree of clustering on a slope and the correlation length scale of this clustering would allow the assessment of the most beneficial spacing to minimise false stable results and maximise representative data collection. Schweizer et al. (2008) state that multiple snow pits on the same slope should be spaced out further apart than the correlation length scale (which is unknown), but recommended that two tests should be spaced out at least 10 m in order to get independent results (inferring a correlation length scale of less than 10 m). However, the degree of spatial variability is not currently known for a given slope, a given layer, how it changes over time, or in relation to environmental factors of the specific slope, and no reliable guidance exists for assisting observers in identifying the correlation length. Since our results still show evidence of clustering when tests are 10 m apart, some slopes might be more accurately assessed by more widely spaced measurements. The implicit implication here is that slopes should be viewed as a whole and when observers are considering where they would like to place their representative snow pits they should consider which two locations would best represent this slope.

More data are needed to document the spatial and temporal variability of the snow pack in a number of different locations, slopes, settings and environmental conditions. These are required to define a typical correlation length scale for a specific scenario or environment, in order to provide guidance on the optimal spacing of multiple snow pits on a given slope. However, these data are not yet available, so assessing avalanche conditions using snowpits continues to be an experience-based exercise requiring a conservative approach.

Acknowledgements

We would like to gratefully acknowledge the support from the New Zealand Royal Society International Science and Technology Linkages Fund for the travel funding, support from the US Forest Service National Avalanche Centre, the land owners for access to their property at Beehive Basin (Lewis Bishop), the Yellowstone Club for access to one of the field sites and providing two patrollers (Doug Catherine and Doug McCabe) to help dig and take observations, and the assistance from the forecasters at the Gallatin National Forest Avalanche Centre (Ron Johnson) and students from Montana State University (Tara Chesley, Jared Nelson, and Patrick Staron).

References

Birkeland, K.W., 1990. The spatial variability of snow resistance on potential avalanche slopes. M.S. thesis, Department of Earth Sciences, Montana State University, Bozeman, MT, USA, 99 pp.

Birkeland, K.W., Johnson, R.F., 1999. The stuffblock snow stability test: comparability with the rutschblock, usefulness in different snow climates, and repeatability between observers. Cold Regions Science and Technology 30, 115–123.

Birkeland, K.W., Landry, C., 2002. Changes in spatial patterns of snow stability through time. In: Stevens, J.R. (Ed.), Proceedings of the 2002 International Snow Science Workshop, Penticton BC, Canada, pp. 482–490.

Birkeland, K.W., Chabot, D., 2006. Minimizing "false-stable" stability test results: why digging more snowpits is a good idea. In: Gleason, J.A. (Ed.), Proceedings of the 2006 International Snow Science Workshop, Telluride, Colorado, USA, pp. 498–504.

Birkeland, K.W., Hansen, H.J., Brown, R.L., 1995. The spatial variability of snow resistance on potential avalanche slopes. Journal of Glaciology 41 (137), 183–189.

Birkeland, K.W., Kronholm, K., Schneebeli, M., Pielemeier, C., 2004a. Changes in the shear strength and micro-penetration hardness of a buried surface hoar layer. Annals of Glaciology 38, 223–228.

Birkeland, K.W., Kronholm, K., Logan, S., 2004b. A comparison of the spatial structure of the penetration resistance of snow layers in two different snow climates. Proceedings of the 2004 International Symposium on Snow Monitoring and Avalanches. Snow and Avalanche Study Establishment, Manali, India, pp. 3–11.

Birkeland, K.W., Kronholm, K., Logan, S., Schweizer, J., 2006a. Field measurements of sintering after fracture of snowpack weak layers. Geophysical Research Letters 33, L03501. doi:10.1029/2005GL025104.

Birkeland, K.W., Savage, S., Trautman, S., Kronholm, K., Logan, S., Schweizer, J., 2006b. Uncertainties in assessing the stability of fractured slopes. In: Gleason, J.A. (Ed.), Proceedings of the 2006 International Snow Science Workshop, Telluride, Colorado, USA, pp. 29–37.

Blöschl, G., 1999. Scaling issues in snow hydrology. Hydrological Processes 13 (14–15), 2149–2175.

Blöschl, G., Sivapalan, M., 1995. Scale issues in hydrological modelling — a review. Hydrological Processes 9, 251–290.

Campbell, C., 2004. Spatial variability of slab stability and fracture properties in avalanche start zones. MSc Thesis, University of Calgary, Calgary, AB, Canada, 248 pp.

Campbell, C., Jamieson, B., 2007. Spatial variability of slab stability and fracture characteristics within avalanche start zones. Cold Regions Science and Technology 47 (1–2), 134–147.

Conway, H., Abrahamson, J., 1984. Snow Stability Index. Journal of Glaciology 30 (106), 321–327.

Conway, H., Abrahamson, J., 1988. Snow-slope stability — a probabilistic approach. Journal of Glaciology 34 (117), 170–177.

Cressie, N.A.C., 1993. Statistics for Spatial Data. Wiley, New York. 900 pp.

Derksen, C., LeDrew, E., Goodison, B., 2000. Temporal and spatial variability of North American prairie snow cover (1988–1995) inferred from passive microwave-derived snow water equivalent imagery. Water Resources Research 36 (1), 255–266.

Dyer, L.J., Mote, T.L., 2006. Spatial variability and trends in snow depth over North America. Geophysical Research Letters 33, L16503.

Fischer, M.M., Scholten, H.J., European, D.U., 1996. Spatial Analytical Perspectives on GIS. Taylor Francis Ltd., London. 267 pp.

Föhn, P.M.B., 1989. Snow cover stability tests and the areal variability of snow strength. In: Canadian Avalanche Association (Ed.), Proceedings of the 1988 International Snow Science Workshop, Whistler, B.C., Canada, pp. 262–273.

Gauthier, D., Jamieson, B., 2006. Evaluating a prototype field test for weak layer fracture and failure propagation. In: Gleason, J.A. (Ed.), Proceedings of the 2006 International Snow Science Workshop, Telluride, Colorado, USA, pp. 107–116.

Heierli, J., Gumbsch, P., Zaiser, M., 2008. Anticrack nucleation as triggering mechanism for snow slab avalanches. Science 321 (5886), 240–243.

Jamieson, J.B., 1995. Avalanche prediction for persistent snow slabs. PhD Thesis, University of Calgary, Calgary AB, Canada, 258 pp.

Jamieson, J.B., 1999. The compression test — after 25 years. The Avalanche Review 18, 10–12.

Johnson, R.F., Birkeland, K.W., 2002. Integrating shear quality into stability test results. In: Stevens, J.R. (Ed.), Proceedings of the 2002 International Snow Science Workshop, Penticton BC, Canada, pp. 508–513.

Kronholm, K., 2004. Spatial variability of snow mechanical properties with regard to avalanche formation. PhD Thesis, University of Zurich, Zurich, Switzerland, 192pp.

Kronholm, K., Schweizer, J., 2003. Snow stability variation on small slopes. Cold Regions Science and Technology 37 (3), 453–465.

Kronholm, K., Schneebeli, M., Schweizer, J., 2004. Spatial variability of micropenetration resistance in snow layers on a small slope. Annals Glaciology 38, 202–208.

Landry, C.C., 2002. Spatial variations in snow stability on uniform slopes: implications for extrapolation to surrounding terrain. M.Sc. Thesis, Montana State University, Bozeman, MT, USA, 194 pp.

Landry, C., Birkeland, K., Hansen, K., Borkowski, J., Brown, R., Aspinall, R., 2004. Variations in snow strength and stability on uniform slopes. Cold Regions Science and Technology 39 (2–3), 205–218.

Logan, S., 2005. Temporal changes in the spatial patterns of weak layer shear strength and stability on uniform slopes. M.Sc. Thesis, Montana State University, Bozeman, MT, USA, 157 pp.

Logan, S., Birkeland, K.W., Kronholm, K., Hansen, K., 2007. Temporal changes in the slope-scale spatial variability of the shear strength of buried surface hoar layers. Cold Regions Science and Technology 47 (1–2), 148–158.

Mock, C.J., Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. Bulletin of the American Meteorological Society 81 (10), 2367–2392.

Moran, P.A.P., 1948. The interpretation of statistical maps. Journal of the Royal statistical Society B 10, 243–251.

Ripley, B.D., 1981. Spatial Statistics. Wiley, New York.

Schweizer, J., Kronholm, K., Jamieson, B., Birkeland, K.W., 2008. Review of spatial variability of snowpack properties and its importance for avalanche formation. Cold Regions Science and Technology 51 (2–3), 253–272.

Simenhois, R., Birkeland, K.W., 2006. The extended column test: a field test for fracture initiation and propagation. In: Gleason, J.A. (Ed.), Proceedings of the 2006 International Snow Science Workshop, Telluride, Colorado, USA, pp. 79–85.

Simenhois, R., Birkeland, K.W., 2007. An update on the Extended Column Test: new recording standards and additional data analyses. The Avalanche Review 26 (2) December 2007.

Stewart, K., Jamieson, J.B., 2002. Spatial variability of slab stability in avalanche start zones. In: Stevens, J.R. (Ed.), Proceedings of the 2002 International Snow Science Workshop, Penticton BC, Canada, pp. 544–548.

van Herwijnen, A., Jamieson, J.B., 2002. Interpretating fracture character in stability tests. In: Stevens, J.R. (Ed.), Proceedings of the 2002 International Snow Science Workshop, Penticton BC, Canada, pp. 514–522.

Wiegand, T., Moloney, K.A., 2004. Rings, circles and null-models for point pattern analysis in ecology. Oikos 104, 209–229.