EVALUATION OF A RULE-BASED DECISION AID FOR RECREATIONAL TRAVELERS IN AVALANCHE TERRAIN

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ABSTRACT: This paper evaluates a new decision aid for traveling in avalanche terrain. The aid is intended primarily for winter recreationists in Canada and provides guidance in trip selection, route finding and slope evaluation. In contrast to other avalanche decision aids, this tool does not attempt to calculate risk or the probability of triggering an avalanche. Instead, it frames alternatives in terms of prevention value, or the portion of historical accidents that would have been prevented had the victims used the thresholds of the aid as decision criteria.

This paper examines the two components that comprise the decision aid. The first component, the Avaluator Trip Planner, is quantitatively evaluated using 21 years of Canadian avalanche accident data. The second component, the Obvious Clues Method, is quantitatively evaluated for application in Canada by building on a previous analysis of its effectiveness in the United States. Combined, the two components offer a prevention value of over 90% of historical Canadian avalanche accidents. Type I errors by the decision aid (false negative results) are most likely to occur under moderate danger rating and involve small isolated slabs or deep instabilities. The paper concludes by considering the possible impact of the decision aid on future accident trends, and shows that it may be possible to detect a reduction in Canadian avalanche accidents in as little as three to four seasons after recreationists adopt the decision aid.

KEYWORDS: Education, decision-making, risk management, safety

1. INTRODUCTION

Apparently, it was philosopher and poet George Santayana who first said: “Those who do not learn from history are doomed to repeat it.” Somewhere along the way, somebody added the corollary “And those who learn from history are doomed to know that they are repeating it.”

Most people smile when they hear the corollary quote, perhaps because it reminds us that sometimes, even when we know about the past, we don’t always do the right thing.

This phenomenon is vividly clear in avalanche accidents, which are characterized by three recurring themes. First, avalanche victims trigger more than 90% of the avalanches that bury them or their partners. Second, these avalanches are typically triggered under conditions where the hazard would have been obvious even to an avalanche novice (Atkins, 2000; McCammon, 2000, 2002). And third, many avalanche victims (in the U.S., almost half) have formal avalanche training. These recurring themes raise distressing questions about how effectively avalanche education prepares students to manage the conditions that have taken lives in the past.

Traditionally, there have been two approaches to teaching recreationists about avalanches. The first utilizes a knowledge-based strategy aimed at explaining avalanche phenomena and the conditions that give rise to avalanche hazard. Students are taught to apply this knowledge analytically when they assess risk in avalanche terrain.

A second approach utilizes a rule-based strategy that teaches simple algorithms for assessing avalanche hazard. Students learn to recognize specific situational cues, and to use a checklist, arithmetic procedure, or graph to make travel choices.

Research in other fields has consistently shown that knowledge-based methods generally work well for experienced decision makers, whereas rule-based methods often work best for novices (see, for example, Metzger and Parasuraman, 2005; Gonzalez, 2004; Hirt and others, 2003; Maltz and Shinar, 2003; Wiggins and O’Hare, 2003; Kleinmuntz, 1985).

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Interest in rule-based avalanche education has, in recent years, led to the development of a number of quantitative decision aids for travel in avalanche terrain. Among them are the Reduction Method (Munter, 1997), the Stop-or-Go Method (Larcher, 1999), the SnowCard (Engler and Mersch, 2000), the NivoTest (Bolognesi, 2000), and the Obvious Clues Method (McCammon, 2000).

A quantitative evaluation of these methods against 33 years of accident data in the United States by McCammon and Haegeli (2006) found that these methods, had they been used by historical accident victims, would have prevented between 60% and 92% of all accidents in U.S. Other metrics of these methods, such as how well they predict avalanching or accidents, have not yet been evaluated.

In this paper, we evaluate a new decision aid, the Avaluator Trip Planner (ATP). We examine the prevention value of the ATP alone and in combination with the Obvious Clues Method (OCM) when used by Canadian winter recreationists.

2. DESCRIPTION

The Avaluator Trip Planner (Figure 1) is a graphical tool that assists winter recreationists in choosing a travel route based on current avalanche conditions. The ATP was derived from expert opinion regarding travel in avalanche terrain.

To use the ATP, users match the current avalanche danger rating (vertical axis) against the terrain rating of possible trips (horizontal axis). Trips are rated on the Avalanche Terrain Exposure Scale developed by Parks Canada (Statham et al., 2006). Ratings for specific trips are available from Parks Canada and will appear in future guidebooks. Users choose a trip based on color: green (normal caution), yellow (extra caution) and red (not recommended). Details of the ATP can be found in Haegeli et al. (this volume).

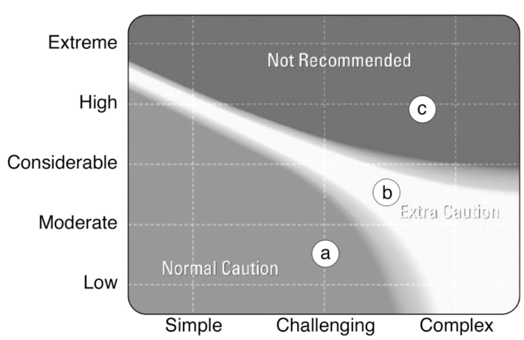

Figure 1. Grayscale rendering of the Avaluator Trip Planner. Region (a) is green, region (b) is yellow, and region (c) is red.

The Obvious Clues Method is a checklist for evaluating avalanche hazard while traveling through avalanche terrain or when evaluating avalanche slopes. Originally developed as a quantitative scale to assess decision making in recreational accidents (McCammon, 2000; 2002), the Obvious Clues Method works by adding up the number of avalanche-related clues that are present (Table 1). Situations with one to two clues suggest normal caution, three to four clues suggests extra caution, and five or more clues are not recommended for travel.

Clue	*Description*
Avalanches	In the area in the last 48 hrs.
Loading	By snow, wind or rain in the last 48 hrs.
Path	Identifiable by a novice.
Terrain trap	Gullies, trees, cliffs or other features that increase severity of being caught.
Rating	Considerable or higher hazard on the current avalanche bulletin.
Unstable snow	Collapsing, cracking, hollow snow or other clear evidence of instability.
Thaw instability	Recent warming of the snow surface due to sun, rain, or warm air.
	TOTAL

Table 1. The Obvious Clues Method for making decisions in avalanche terrain.

In contrast to other avalanche decision aids, the ATP and OCM do not estimate risk, or the likelihood of an avalanche occurring. Instead, they identify the frequency with which the conditions were typical of past accidents.

3. METHODS

One of the obstacles to designing a decision aid for avalanche terrain is the expectation by users that such a device will predict when a slope will avalanche. Avalanche prediction by a simple algorithm is theoretically possible, but its design requires two types of data. The first type comes from accidents where the avalanche was triggered by its victims. Such data is readily available in accident records.

The second type of design data is far more problematic, since it relates to incidents where an avalanche was not triggered. Not only is such data generally unavailable, but the inherent uncertainty in slopes that were traversed once or twice and not triggered compromises the quality of any conclusions drawn from a dichotomous comparison. The result is that without robust nonevent data, we cannot directly assess the predictive value of avalanche decision aids.

In this study, we used prevention value rather than predictive value to assess the effectiveness of decision aids. Our performance metric was the proportion of historical accidents that each method would have prevented, had the avalanche victims used the method as it was intended.

3.1 Evaluating the Avaluator Trip Planner

In determining the prevention value of the ATP, we used Canadian accident data exclusively. Prevention values for the ATP were calculated using two methods.

The first method considered danger ratings and ATES ratings as discrete variables, an interpretation that might be typical of a novice user who does not perceive subtle differences within each rating category. Under this method, we classified accidents by danger rating and ATES trip rating. Plotting accident frequencies in the ATES-danger rating plane of Figure 1, we simply calculated the proportion of accidents that lay below the two color boundaries. Confidence limits for this proportion were computed using a relationship between the *F* distribution and the binomial distribution (Zar, 1999, pp. 527–530), corrected for symmetry around the proportion.

The second method considered ATES ratings and danger ratings as continuous variables, an interpretation that might be typical of advanced users who perceive subtle differences within each rating category. We began by assessing the discrete accident frequencies for bivariate normality. Bivariate normality requires, among other things, that both variables are normally distributed (Stevens, 1996: 243). In other words, not only must both variables follow a normal distribution in their entirety, but for each ATES rating (x) there must be a normal distribution of danger ratings (y) and for each y-value there must be a normal distribution of x-values. To test for normality across the variables, we used the D'Agostino-Pearson K^2 test, which is preferable to other methods when large amounts of tied data are present.

As discussed in Section 5, the hypothesis that the data came from a bivariate normal distribution was not rejected. Thus, all possible accident frequencies could be approximated using the bivariate normal probability density function (PDF):

$$F(z_1, z_2, \rho) = \frac{A(z_1, z_2, \rho)}{2\pi\sqrt{1-\rho^2}} \quad (1)$$

where

$$A(z_1, z_2, \rho) = \exp\left[-\frac{1}{2}\left(\frac{z_1^2 - 2\rho z_1 z_2 + z_2^2}{1-\rho^2}\right)\right] \quad (2)$$

and

$$z_1 = \frac{x - \mu_x}{\sigma_x} \text{ and } z_2 = \frac{y - \mu_y}{\sigma_y}. \quad (3)$$

Here, μ_i is the mean and σ_i is the standard deviation of each sample distribution, and ρ is the correlation coefficient of the two samples.

The maximum proportion (T) of accidents is the volume under the PDF surface bounded by the ATP graph:

$$T = \int_{z_{1(0)}}^{z_{1(1)}} \int_{z_{2(0)}}^{z_{2(1)}} F(z_1, z_2, \rho) dz_1 dz_2 \quad (4)$$

where $z_{1(0)}$ and $z_{2(0)}$ correspond to the lower boudaries of x and y on the ATP graph and $z_{1(1)}$ and $z_{2(1)}$ are the upper boudaries. The prevention value (PV) of each color boundary j on the ATP is the proportion of the PDF volume which lies above the boundary, or

$$PV_j = 1 - \frac{1}{T}\int_{z_{1(0)}}^{z_{1(2)j}} \int_{z_{2(0)}}^{z_{2(2)j}} F(z_1, z_2, \rho) dz_1 dz_2 \quad (5)$$

where $z_{1(2)j}$ and $z_{2(2)j}$ are the maximum values of x and y on boundary (j) mapped into bivariate normal space. Maximum values of x and y were determined by a polynomial regression of the color boundaries.

Closed form solutions of Equations (4) and (5) do not exist, and so we employed the polyhedral approximations

$$T' = \sum_{z_{1(0)}}^{z_{1(1)}} \sum_{z_{2(0)}}^{z_{2(1)}} F(z_1, z_2, \rho) \Delta z_1 \Delta z_2 \quad (6)$$

and

$$PV_j' = 1 - \frac{1}{T'}\sum_{z_{1(0)}}^{z_{1(2)}} \sum_{z_{2(0)}}^{z_{2(2)}} F(z_1, z_2, \rho) \Delta z_1 \Delta z_2 \quad (7)$$

for Equations (4) and (5), where Δz_1 and Δz_2 are the polyhedral cross sectional areas.

3.2 Evaluating the Obvious Clues Method

Avalanche accident data for Canada lacked the information to calculate the prevention value of the OCM directly. Fortunately, a previous investigation had established prevention values for the OCM in the United States (McCammon and Haegeli, 2006). Thus the first step in determining prevention values of the OCM in Canada was to assess the differences between the U.S. and Canadian accident datasets.

The parameters used to compare the two accident data sets are shown in Table 2, along with the type of test used in the comparison. For each parameter, we conducted four comparisons: one within each dataset between fatal and non-fatal accidents and two across the datasets for fatal and non-fatal accidents. The comparison strategy is shown in Figure 2. The null hypothesis of no difference between datasets was rejected when two-sample testing yielded probability $P < 0.05$.

In the 2×2 arrangement shown in Figure 2, probabilities $P_{1(US)}$ and $P_{2(CAN)}$ indicated differences in how consistently these parameters were reported in fatal and non fatal accidents. Probabilities $P_{3(nonfatal)}$ and $P_{4(fatal)}$ indicated differences between parameters across datasets. Significant P values for $P_{4(fatal)}$ were of particular importance, since reporting is generally of higher quality in fatal accidents.

Due to the evolution of snowmobile technology and subsequent changes in snowmobile use patterns in the backcountry, the analysis of avalanche trigger type was restricted to the period 1984–2004 which was common to both datasets. Also, the danger rating of considerable was not widely used in the U.S. and Canada prior to 1995, so only accidents after this date were used in comparing the danger rating parameter between datasets.

In comparing continuous variables, we used the parametric t-test since the number of samples was generally large enough (i.e.

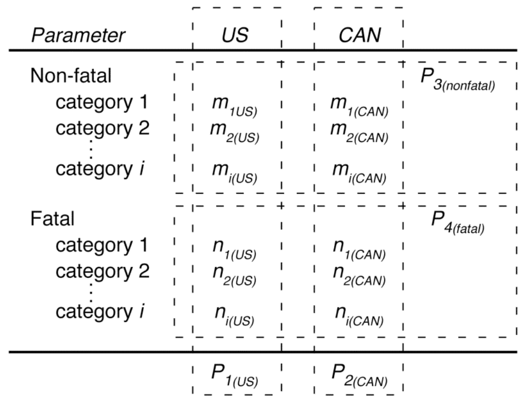

Figure 2. Comparison scheme for U.S. and Canadian accidents. Variables n_i and m_i represent the number of cases in each category.

greater than 100) to justify parametric methods. We compared start zone aspects by computing the angular mean and confidence interval around each mean, following the methods described by Fisher (1999) for grouped circular data.

Where we found significant differences between the U.S. and Canadian accident parameters, we calculated prevention values explicitly across categories within each parameter. Where applicable, we used prevention values for the U.S. directly from a previous study (McCammon and Haegeli, 2006). Parameter prevention values were calculated for the Canadian dataset as

$$\begin{aligned} PV_{i(CAN)} &= \frac{1}{n_i}\left(x_1 + x_2 + \ldots + x_k\right) \\ &= \frac{1}{n_i}\sum_{j=1}^{k} x_j = \frac{1}{n_i}\sum_{j=1}^{k} PV_{i,j(US)} n_j \end{aligned} \tag{8}$$

Parameter	*Categories or variables*	*Test*
Avalanche type	Slab, loose	Yates' corrected χ^2
Trigger classification	Natural, artificial	Yates' corrected χ^2
Trigger type	Non-motorized, motorized	Yates' corrected χ^2
Avalanche climate	Maritime, intermountain/transitional, continental	2×3 contingency table
Danger rating	Low, moderate, considerable, high, extreme	2×5 contingency table
Elevation band	Below treeline, near treeline, above treeline	2×3 contingency table
Number caught	Integer	t-test
FL width	Length in meters	t-test
Slab depth: non-motorized	Depth in meters	t-test
Slab depth: motorized	Depth in meters	t-test
SZ incline	Degrees from horizontal	t-test
Aspect (circular)	Ordinal compass direction	Angular mean and CI

Table 2. Parameters and tests used to compare U.S. and Canadian accident data.

where n_i was the total number of incidents in the Canadian dataset for which that parameter was known, x_j was the number of incidents prevented in each parameter category j, and $PV_{i,j(US)}$ was the prevention value in the U.S. dataset for category j within parameter i, and k was the number of categories within the parameter.

The uncertainty in the prevention value for each parameter was calculated as a cumulative error:

$$\Delta\varepsilon_i = \sqrt{\Delta\varepsilon_1^2 + \Delta\varepsilon_2^2 + ... + \Delta\varepsilon_k^2} = \left[\sum_{j=1}^{k} \Delta\varepsilon_j^2\right]^{1/2} \quad (9)$$

where $\Delta\varepsilon_j$ was the error associated with the prevention value of the j^{th} group within parameter i. Since the contribution of each term to the cumulative error is proportional to its probability of occurring, Eq. 9 can be written

$$\Delta\varepsilon_i = \left[\sum_{j=1}^{k} \Delta\varepsilon_j^2\right]^{1/2} = \frac{1}{m_i}\left[\sum_{j=1}^{k} (n_j c_j)^2\right]^{1/2} \quad (10)$$

where m_i is the total number of cases in parameter i and c_j is the 95% binomial confidence interval of the PV for that category.

At each threshold value, the overall prevention value was calculated as

$$PV_{(CAN)} = \frac{1}{b}\sum_{i=1}^{b} PV_{i,(CAN)} \quad (11)$$

where b was the number of parameters across which the prevention value was being evaluated. Errors in the overall prevention value were calculated using Eq. 9.

3.3 Evaluating the combined ATP and OCM

The combined prevention proportion (PV') for a combination of the ATP and OCM is

$$PV' = PV_1 + PV_2(1 - PV_1) = PV_1 + PV_2 - PV_1 PV_2 \quad (12)$$

where PV_1 is the prevention value of the first tool applied and PV_2 is the prevention value of the second tool applied.

If functional linkages exist between the two tools, so that certain accidents would be consistently prevented by either tool, we would expect the cumulative prevention values to be lower than those calculated by Eq. 12. Unfortunately, identifying such linkages is not possible with the current data.

Uncertainty in the combined prevention value is computed from the error formulation of Eq. 9:

$$c' = \sqrt{c_1^2 + c_2^2 + A_{1,2}^2} \quad (13)$$

where

$$A_{1,2} = (PV_1)(PV_2)\sqrt{\left(\frac{c_1}{PV_1}\right)^2 + \left(\frac{c_2}{PV_2}\right)^2} \, . \quad (14)$$

3.4 Low-frequency accidents

Accident frequencies do not drop to zero in the green region of the ATP, or when the OCM indicates two or fewer clues. Such accidents, which by definition are rare, are of great interest since they reflect conditions where a user may not be fully attendant to the avalanche hazard. Any common features of these low-frequency accidents should be part of the user training for both decision aids.

We evaluated low frequency accidents for both the ATP and OCM using the parameters shown in Table 2. Due to the small number of accidents involved, we employed the non-parametric Mann-Whitney test in place of the *t*-tests listed in Table 2.

3.5 Measuring accident reduction trends

If the ATP and OCM become widely adopted, how long will it take to detect an accident prevention trend? As we discussed in the beginning of this section, non-event back-country use data is not generally available, and so it is not possible to directly monitor any decrease in avalanche accident rates.

However, Fleiss, Tytun and Ury (1980) and Ury and Fleis (1980) described a method for estimating minimum sample size to detect proportion differences between unequal populations. We modified their method to estimate how many seasons would elapse before an accident prevention trend would become statistically significant.

Viewed as two populations, past accidents and future accidents are characterized by some number of incidents (n_i) where enough information is present to rate the incident according to the ATP or OCM. There is also a proportion of incidents (p_i) that represents accidents that occurred at scores above the prevention threshold. Assuming that the reporting rate of incidents (γ) stays approximately the same over the period of analysis, we need only calculate the number of future reported incidents (n_1) to determine how many seasons ($S = n_1/\gamma$) will elapse before a set difference ($\delta = |p_1 - p_2|$) in the prevention values becomes significant. The percent drop in the proportion of accidents above the threshold value (H) is simply $H = 1 - p_1/p_2$).

The method described by Fleiss, Tytun and Ury (1980) and Ury and Fleiss (1980) estimates the smaller sample as

$$n_1 = \frac{n}{4}\left[1+\sqrt{1+\frac{2(r+1)}{rn\delta}}\right]^2, \qquad (15)$$

where $r = n_2/n_1$. The sample size parameter is

$$n = \frac{1}{r\delta^2}\left[t_{\alpha(2),\infty}\sqrt{(r+1)p'q'} + t_{\beta(1),\infty}\sqrt{rp_1q_1 + rp_2q_2}\right]^2 \quad (16)$$

Here, $t_{\alpha(2),\infty}$ is the value of the t distribution evaluated as a two-tailed probability (α) of a Type I error for infinite degrees of freedom, and $t_{\beta(1),\infty}$ is the value of the t distribution evaluated at the one-tailed probability (β) of a Type II error. The variable p' is the proportion average and q' is the complement average

$$p' = \frac{p_1 + p_2}{2}, \quad q' = \frac{q_1 + q_2}{2} \qquad (17)$$

where $q_i = 1 - p_i$. Since the population of existing accidents (n_2) is known, we solved Eq. 15 numerically for r, from which n_1 and subsequently S could be computed directly.

4. DATA

Our analysis of the ATP and OCM utilized avalanche accident data from two sources. Information on Canadian accidents came from records maintained by the Canadian Avalanche Association. We considered only those accidents that involved skiing and snowboarding (excluding lift-assisted and mechanized), snowshoeing, hiking, or climbing. We excluded commercial, custodial, highway and residential incidents from the analysis. The Canadian dataset included 697 avalanche incidents from 1984 – 2005, and reported 423 people caught and 182 people killed.

The accident dataset for the United States used in this study was derived from the national records of the Colorado Avalanche Information Center. The data covers the period 1972 – 2004, and includes a total of 751 incidents, involving 1408 people caught and 518 people killed. We considered only recreational accidents, and excluded incidents related to commercial guiding, custodial groups, highway and residential activities and ski patrol or avalanche control operations.

5. RESULTS

5.1 Prevention values: Avaluator Trip Planner

There were 203 Canadian cases where both the trip-level ATES rating and the danger rating were known. Figure 3 shows the frequency of accidents, and the arrangement used to calculate the discrete prevention values. Curves A and B represent the color boundaries, and the dotted line indicates the boundaries of the Avaluator card. Prevention values for boundaries A and B, computed as discrete proportions (PV_1), appear in Table 3.

The first step in computing continuous prevention values for boundaries A and B was to test for bivariate normality using a piecewise D'Agostino-Pearson test. The distribution of both ATES ratings and avalanche danger ratings did not reject normality (P = 0.258 and 0.474 respectively). P-values for distributions within each x and y value ranged from 0.258 to 0.923, and likewise did not reject normality. The calculated bivariate normal distribution is shown in Figure 3. Parameters for the bivariate distribution were μ_x= 2.3; σ_x= 0.573; μ_y= 2.9; σ_y= 0.815; ρ = -0.02; P = 0.754).

Polynomial regression yielded the following relationships for curves A and B:

$$y_A = 0.167x^2 - 1.333x + 5.329, \qquad (18)$$

$$y_B = -0.521x^4 + 2.768x^3 - 5.278x^2 + 3.088x + 3.780 \qquad (19)$$

with correlation coefficients 0.999 for curve A and 0.998 for curve B. Using the polyhedral approximations of Eqs. 6 and 7 with polyhe-

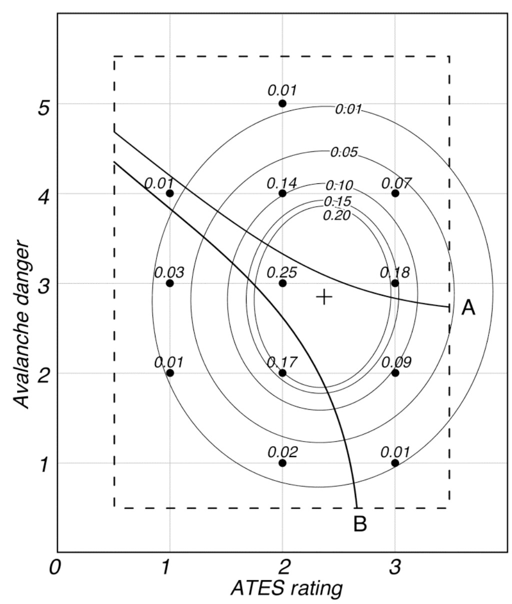

Figure 3. The Avaluator Trip Planner and Canadian accident frequencies (n = 203). Curves A and B represent color boundaries. Also shown are frequency contours of the bivariate normal distribution, with its center marked by a "+" symbol.

Boundary	PV_1	PV_2
A	40 ± 7%	36%
B	76 ± 6%	75%

Table 3. Prevention values derived from discrete (PV_1) and bivariate (PV_2) analyses.

dron dimensions $\Delta x = \Delta y = 0.01$ resulted in the continuous prevention values (PV_2) shown in Table 3. It is likely that prevention values PV_2 are close to the ultimate prevention values of the ATP.

5.2 Prevention values: Obvious Clues Method

Because we could not calculate prevention values for the OCM in Canada directly, we used data from U.S. accidents (n = 252) as a surrogate dataset. Comparative results of the U.S. and Canadian accident datasets appear in Table 4.

Avalanche accident data from the U.S. appears to be fairly consistent across fatal and non-fatal accidents, as evidenced by $P_{1(US)}$ values generally greater than 0.05. The number of people caught and fracture line width are the only exceptions. In contrast, there appear to be many differences in the Canadian accident data between fatal and nonfatal accidents ($P_{2(CAN)}$). One possible source of these differences may be the inclusion in the Canadian dataset of incidents where an avalanche was deliberately triggered and no one was caught. Further evidence for over reporting of less serious incidents in the Canadian dataset can be seen in the values for $P_{3(nonfatal)}$, which shows many differences between U.S. and Canadian nonfatal accidents. Many of these differences vanish when we consider only fatal accidents, where reporting is generally of higher quality. Thus it appears that fatal accidents provide the most consistent standard for comparing the two datasets.

Avalanche type, trigger type, number of people caught, slab depth and start zone incline are roughly equivalent between the U.S. and Canadian datasets. Thus no adjustment appears necessary for these parameters in calculating PV for the OCM in Canada.

Trigger classification in the Canadian dataset disproportionately reports fatal avalanches as naturally triggered, a pattern that is not observed in Canadian nonfatal accidents or in U.S. accidents. Jamieson and Geldsetzer (1996: p.11) discuss reporting issues in Canadian accidents with regard to this parameter. In general, it appears that about 7% of avalanche accidents in the combined datasets result from natural releases and about 93% are triggered by the victims.

Avalanche climate, danger rating and elevation band of accidents appear to be fundamentally different between the two data sets. Thus any calculation of the prevention value for the OCM in Canada should take into account differences in these three parameters.

Results for the comparison of start zone aspect in avalanche accidents are shown in Figure 4. Angular means for the U.S. and Canada are very nearly equal, but Canadian accidents show a greater circular standard deviation (114° versus 82° in the U.S. data, reflected in the length of the mean vector).

We computed prevention values of the OCM in Canada by applying Eqs. 8 – 10. Results are shown in Table 5. Note that a threshold of OC ≤ 3 appears to be relatively constant over these three parameters, with somewhat more variability for OC ≤ 4. Thresholds of five and above appear impractical as OCM decision guides, since prevention values vary significantly (20% and higher) across the parameters shown in Table 5.

Parameter	$P_{1(US)}$	$P_{2(CAN)}$	$P_{3(nonfatal)}$	$P_{4(fatal)}$
Avalanche type	0.766	0.438	**0.016**	0.762
Trigger classification	0.181	**< 0.001**	0.676	**< 0.001**
Trigger type	0.166	**< 0.001**	**< 0.001**	0.179
Avalanche climate	0.155	0.918	**< 0.001**	**0.021**
Danger rating	0.964	**< 0.001**	**0.001**	**<0.001**
Elevation band	0.118	0.963	**< 0.001**	**0.002**
Number caught	**0.016**	**0.015**	**< 0.001**	0.366
FL width	**0.037**	**< 0.001**	**0.031**	**0.027**
Slab depth: non-motor.	0.311	**0.016**	**< 0.001**	0.390
Slab depth: motorized	0.153	0.277	0.200	0.267
SZ incline	0.469	**0.019**	**< 0.001**	0.145

Table 4. Comparison results from U.S. and Canadian accident datasets. *P*-values correspond to comparisons in Table 2 and Figure 2. Statistically significant differences appear in bold type.

5.3 Prevention values: combined ATP & OCM

Combined prevention values of the various threshold combinations for the ATP and OCM are shown in Table 6. Continuous PV values for the ATP were used to calculate *PV′* since these values likely approximate the theoretical limit PV for the ATP. Thus, the prevention values shown in Table 6 should be considered maximums that are ob-

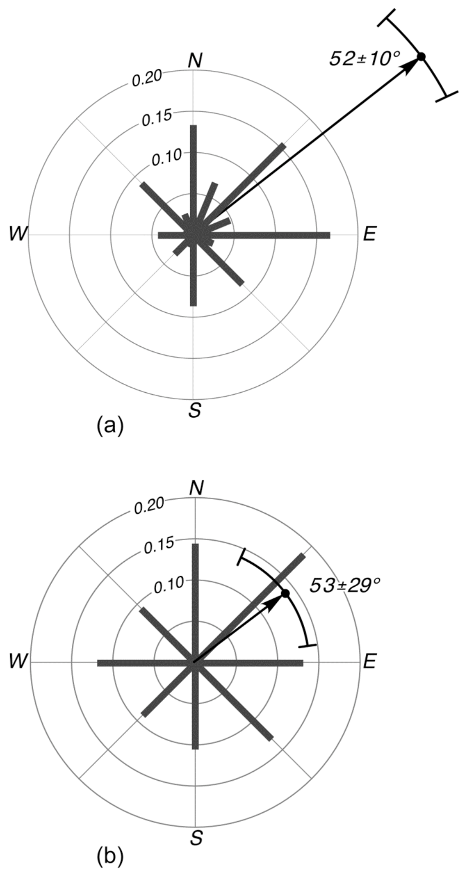

Figure 4. Frequency histograms for start zone aspect in a) the U.S. dataset and b) the Canadian dataset. Angular mean vectors include the 95% confidence interval.

tained under ideal conditions.

The combination of the ATP and OCM compares favorably with decision aids developed in Europe, and evaluated for use in the United States by McCammon and Haegeli (2006). European prevention values ranged from a low of 60±5% (Reduction Method) to a high of 86±4% (SnowCard).

Parameter	*≤ 3*	*≤ 4*
Climate	0.92±0.04	0.75±0.04
Elev. Band	0.92±0.04	0.76±0.06
Danger	0.88±0.05	0.69±0.06
Avg.	0.90±0.04	0.74±0.05

Table 5. Prevention values of the OCM calculated relative to Canadian accidents.

ATP boundary	*OC threshold*	*PV ’± CI’*
A	≤ 3	0.94 ± 0.04
	≤ 4	0.83 ± 0.06
B	≤ 3	0.96 ± 0.04
	≤ 4	0.93 ± 0.07

Table 6. Prevention values of the combined ATP and OCM.

5.4 Low-frequency accidents

The green region of the ATP in Figure 1 and three or fewer clues in the OCM represent conditions where users are urged to use “normal caution.” Although they are rare, accidents do occur under these conditions.

In comparing low-frequency and high-frequency accidents in the ATP, we found no statistical difference between avalanche type (P = 0.624), trigger classifier (P = 0.316), trigger type (P = 0.313), avalanche climate (P = 0.521), elevation band (P = 0.294), number of people caught (P = 0.982), start zone incline (P = 0.149), or start zone aspect (both angular means lay within each other’s confidence intervals).

However, differences in slab depth, fracture line width and danger rating suggest that low-frequency accidents have a number of characteristic features.

Slabs in low-frequency accidents were shallower than in high-frequency accidents (mean difference 0.2 m, P = 0.002). Fracture lines appeared to be possibly smaller (P = 0.071), with fracture line width in low-frequency accidents averaging 68.8 m (σ = 99.6 m), compared to 104.5 m (σ = 160.2 m) in high-frequency accidents.

Low-frequency accidents under the OCM showed a similar pattern, with most occurring disproportionately during times of moderate hazard (P < 0.001). Generally fewer people were entrained in the avalanche in low-frequency accidents (P = 0.064).

Notably, there were four low-frequency accidents where large avalanches (FL width > 100m) were triggered when OC ≤ 3. All of these cases involved deep instabilities, moderate avalanche danger, and probable triggering from a shallow area on the slope.

In both the ATP and the OCM, it appears that low-frequency accidents are of two types, both of which occur during periods of moderate or lower avalanche danger. The first type of accident involves an isolated slab, usually small enough to catch a single person but large enough to bury them.

The second type of low-frequency accident appears to involve a deep instability that is triggered from a shallow point in the snowpack. These avalanches release over large areas and in all cases have proven fatal for the victims.

5.5 Future accident trends

We've shown that the ATP and OCM combination has the potential to prevent many accidents. But how widespread will the use of this system need to be before an accident reduction trend can be detected, and how much time will elapse before such a trend is detectable?

Table 7 shows the results of numerically solving Eq. 15 for the minimum detectable magnitude of change (H) and the percentage of avalanche victims who would need to be using the device in order to produce that change (= $H \div PV'$). For this calculation, we chose an intermediate prevention value (PV' = 0.90), which is roughly the midpoint between the most conservative threshold [ATP(B)+OCM(≤3)] and the least conservative threshold [ATP(A)+OCM(≤4)]. We used the existing population of accidents for which ATP scores were known (n_2=203) as a comparison basis, and chose the probability of Type I and Type II errors as $\alpha = \beta = 0.05$. We also assumed that reporting rates (γ) remained fixed at 2003/2004 levels (about 21 well-documented accidents per year in Canada).

As one would expect, accident reductions in the first one or two seasons following the introduction of the Avaluator will have to be substantial in order to be detectable – the proportion of accidents above the least conservative threshold must drop by 30% or more. This corresponds to more than a third of all avalanche victims using the Avaluator to guide their decisions. If we assume that avalanche involvement is a random sampling process among the backcountry population, this translates into more than a third of all backcountry recreationists in Canada using the Avaluator routinely. More realistic is a reduction trend that becomes apparent in three to four years. Here, a minimum of one out of every four backcountry users would have to be making route decisions using the Avaluator. Beyond about five years, the minimum detectable change flattens out significantly, and accident reductions, unless they are pronounced, are unlikely to be apparent against the background of gradual changes in backcountry use.

S	*H*	*% victims*
1	0.41	46%
2	0.29	32%
3	0.24	27%
4	0.21	23%
5	0.19	21%
7	0.17	19%
10	0.16	18%

Table 7. Number of seasons (S) before a minimum change in magnitude (H) becomes a detectable trend in avalanche accident prevention. Also shown is the minimum percent of victims who would need to be using the Avaluator to effect this change.

6. DISCUSSION

It appears that both the ATP and OCM have the potential to significantly reduce avalanche accidents. In the most permissive configuration (ATP boundary A and OC ≤ 4), the combination of decision aids would prevent approximately as many accidents as the highest-performing European decision aid (SnowCard). In the most conservative configuration (ATP boundary B and OC ≤ 3), the combination of decision aids would prevent up to 98% of historical avalanche accidents in Canada.

An important feature of the ATP and OCM is that their prevention value at the recommended thresholds is not greatly affected by avalanche climate or elevation band. Moreover, the OCM retains a high prevention value even at avalanche danger ratings of low and moderate – a characteristic that makes it unique among decision aids for avalanche terrain. As such, it is well suited to novices who want a simple and universal tool to help them avoid most hazardous conditions. Of particular interest is the finding that anomalous accidents most commonly occur during periods of moderate or low hazard, and involve either small isolated slabs or deep instabilities. Teaching students to recognize these conditions will serve to sharpen their understanding of snowpack and terrain issues.

An important distinction between the ATP+OCM and other methods is that both tools are primarily awareness tools, rather than predictive tools. In other words, users cannot use these tools to predict if a slope will avalanche. They can, instead, use the tools to identify when they are entering a situation where their decisions are critical, and where they may need advanced skills to navigate the hazard. Neither the ATP nor the OCM is a go/no go decision aid.

Finally, if backcountry users widely adopt these decision aids, it may be possible to see accident reductions within several seasons. As usual, future trends will be easier to detect if reporting and documentation are improved. But ultimately, the most important metric of success will be how widely adopted these tools become, and whether or not they are still preventing accidents years from now.

7. CONCLUSIONS

As noted in the introduction, avalanche education is something of an experiment in how well we can learn from the past. In this paper, we've presented two tools for making decisions in avalanche terrain. These tools help users avoid mistakes that have taken lives in the past. We've shown that these decision tools are robust across avalanche climates, elevation bands and danger ratings, and when combined, can prevent around 90% of historical accidents in Canada. We've also shown that the use of these tools can result in accident prevention trends that are detectable with a few seasons. By that time, we should know how well these tools were embraced by users, and how many avalanche accidents they actually prevented. And then, we will know how well have learned from history.

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