QUANTITATIVELY CAPTURING DECISION-MAKING PRACTICES OF MECHANIZED SKI GUIDES USING GPS TRACKING, AVALANCHE TERRAIN MODELING AND BAYESIAN NETWORKS

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ABSTRACT: Snow avalanches are the primary mountain hazard for mechanized skiing operations. Helicopter and snowcat ski guides are tasked with finding safe terrain to provide guests with enjoyable skiing in a fast-paced and highly dynamic and complex decision environment. Based on years of experience, ski guides have established systematic decision-making practices that streamline the process and limit the potential negative influences that can occur due to time pressure and emotional investment. While guiding teams pass on this expertise through mentorship, the current lack of a quantitative description of the process prevents the development of decision aids. To address this knowledge gap, we collaborated with guides at Canadian Mountain Holidays (CMH) Galena Lodge to catalog and analyze their decision-making process using operational data, GPS tracking, automated avalanche hazard indication mapping, and Bayesian networks. Our initial results use Bayesian networks to model the daily run list decision-making process, where guides code runs as either black (not considered), red (closed), or green (open). To capture the real world decision-making process, we worked with expert guides to build the structure of the decision-making network. Data relevant to run characteristics, current conditions, and prior run list decisions are used to calculate the conditional probability tables of the decision-making model. Our resulting model illustrates the decision-making process and can predict the run list coding with accuracy of roughly 87% compared to 80,854 observed run codes from CMH Galena. These insights provide a baseline for development of future decision-making tools that can offer independent perspectives on operational terrain choices based on historic patterns or as a training tool for newer guides.

KEYWORDS: Decision-making, avalanche terrain modelling, GPS tracking, mechanized skiing, backcountry

1. INTRODUCTION

Snow avalanches are a complex and dynamic natural hazard, responsible for an average of approximately 140 recorded fatalities annually in North America and Europe (Jamieson et al., 2010; Techel et al., 2016; Colorado Avalanche Information Center, 2023). In the majority of avalanche accidents backcountry recreationists are the victims and the avalanche is commonly triggered by a member of the victim's party (Schweizer and Lütschg, 2001). Terrain selection is the primary tool for managing avalanche risk when travelling in the backcountry. A wide range of factors need to be considered to select appropriate terrain, including current avalanche conditions, slope incline, forest density, aspect, elevation, and potential for overhead hazards or terrain traps. The dynamic nature of avalanche hazard conditions and sheer number of influences on avalanche terrain hazard make choosing appropriate terrain challenging.

Due to the complexity of the terrain selection process, there is a desire to develop meaningful decision-making aids for backcountry recreationists. Existing tools such as the Graphical Reduction Method (Munter, 1997), Avaluator (Haegeli et al., 2006), or Skitourenguru (www.skitourenguru.ch) are intended to help recreationist make informed decisions based on basic condition information, such as avalanche danger, and terrain information, primarily based on slope incline. While these tools are effective for general recreationists, their simplicity makes them inappropriate for more complex decision-making scenarios such as in the context of professional guides and advanced recreationists.

For mechanized ski guides in Canada, the decision-making process includes an added layer of operational considerations which increase complexity. Over decades of practice, guides have established sophisticated methods for selecting appropriate terrain specific to their operational context. One example is the daily practice of run coding, where guides determine if a run is closed (red), open for guiding (green), or not-considered (black) as part of their morning meetings (Israelson, 2015). This process helps get the guiding team on the same page for the day and establishes a list of potential terrain that has been deemed appropriate for the day's conditions. Run list coding during the morning meeting gives the opportunity for a consensus based decision process and helps limit emotional and time pressures that can impact decision-making in the field.

Quantitatively capturing the run list coding decision-making process requires a nuanced model that can consider a wide variety of factors. Prior research has used regression analysis as a method for capturing decision-making processes (Sterchi et al, 2019; Thumlert et al., 2018), which assumes that the decision to open or close a run can be represented as a linear combination of factors. These approaches provided a meaningful starting point for capturing the complexity of guiding decisions but are limited by the modelling methods. Data-driven machine learning methods (e.g., Sterchi and Haegeli, 2019) have also shown promise but are prone to detecting spurious relationships, and the black box nature of the algorithms make them difficult to understand and trust. Bayesian networks (BN) offer an attractive alternative to the existing methods due to their ability to use expert knowledge to model complex decision processes.

The objective of this paper is to present a BN based decision-making model for run list coding at a mechanized guiding operation. We explore the factors that influence run list decisions and the relationships within the decision-making process. The quantitative foundation of the BN is based on 7 seasons of operational data as well as high resolution avalanche terrain modelling. We also test the use of the BN as a decision support tool for predicting run codes based on current conditions and local run characteristics.

2. METHODS

2.1 *Bayesian networks*

Bayesian networks (BN), also known as belief networks or probabilistic graphical models, are a type of statistical model that are used to represent and analyze uncertain complex relationships among multiple variables that include both inputs and outputs. The foundation of a BN is called a directed acyclic graph (DAG), which illustrates the variables (nodes) and relationships between variables (arcs). The assumptions of a Bayesian Network are that the arcs between nodes represent relationships, the graphical structure cannot contain any cycles, and nodes that are not connected by an arc are assumed to be conditionally independent given their parents (Fenton & Neil, 2019; Scutari, M. and Denis, J., 2021). One major advantage of a Bayesian Network over other types of modern machine learning algorithms is that the structure of the network can be constructed based on input from domain experts, which allows the network to take on a form which is authentic to real world decision-making thought processes.

The quantitative foundation of the model is based on conditional probability tables (CPT) for each node, which can be estimated manually or based on observed data. This type of model has been applied in a variety of fields, including medical diagnosis and operational risk analysis (Fenton and Neil, 2019). Once a BN has been estimated, it can be used for a variety of tasks related to probabilistic inference, prediction, and decision support, which make BNs well suited to our task of modeling an uncertain decision-making scenario.

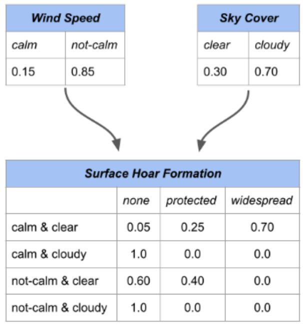

Figure 1: Simple BN example illustrating conditional probability tables.

As a simple example of a BN, consider the probability of surface hoar formation given wind speed and sky cover (Figure 1). The CPT for the parent nodes, sky cover and wind speed, are based on their observed or estimated frequencies. The CPT for the child node, surface hoar, includes each combination of levels from the parent nodes. This means that CPTs can grow very large for nodes with many parents or with parent nodes that have many levels. Based on the CPT for surface hoar, when conditions are calm and clear the conditional probability of widespread surface hoar growth is 70 %.

2.2 *Study area*

Canadian Mountain Holidays (CMH) Galena Lodge is a mechanized skiing operation located in the Selkirk Mountains near Trout Lake, BC, Canada. The Selkirk Mountains typically have a transitional snowpack, prone to persistent weak layers of surface hoar and faceted layers associated with icy crusts (Haegeli & McClung, 2007). Most of the terrain in the CMH Galena tenure is forested, but there are also high alpine zones with glaciated ski runs. Within their roughly 1200 km^2 tenure are 295 individual ski runs, which are individually coded as black, red, or green each day.

2.3 *Decision-making data*

Capturing the critical factors for the CMH Galena run list decision-making process required a variety of different data sets which can be grouped into factors that characterize the terrain within each ski run or characterize the current conditions. In addition, operational logistics play a large role in the decision-making process for mechanized guides.

Run characteristics

The data we used to characterize avalanche terrain at CMH Galena include elevation, forest cover, potential avalanche release areas, and runout impact

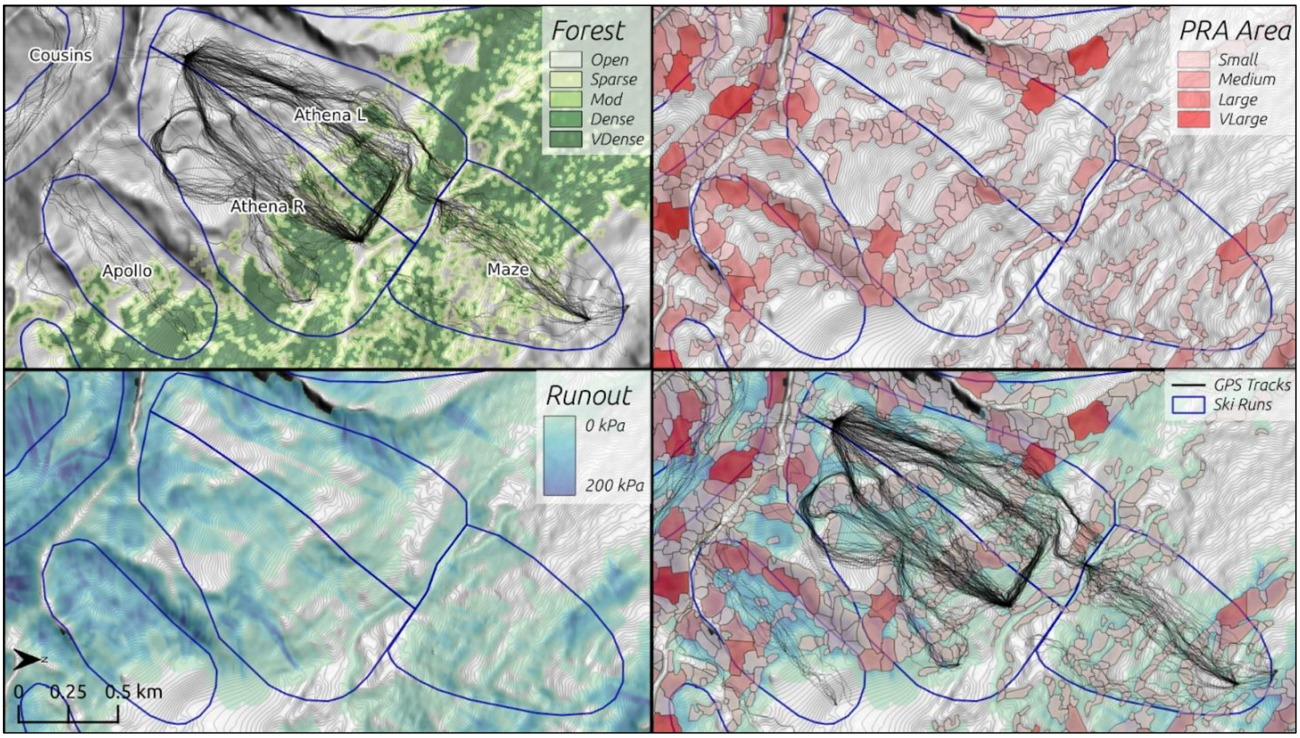

Figure 2: Avalanche hazard indication mapping outputs with forest density (top left), potential release areas (top right), RAMMS impact pressure (bottom left), PRA and runout with GPS tracking data (bottom right).

pressures. Elevation data come from a SPOT 6 satellite stereophotogrammetry 5 m DEM and forest cover is estimated using land cover classification of Rapid Eye 5 m satellite imagery (Sykes et al., 2022). We used a potential release area (PRA) model to estimate the extent and size of avalanche start zones based on slope angle, aspect, curvature, roughness, and forest density (Bühler et al., 2018, Sykes et al., 2022). To quantify exposure to overhead hazard, we used RAMMS (Christen et al., 2010, Bühler et al., 2022) to simulate the runout distance, velocity, impact pressure, and flow height for every individual avalanche originating from the 111,937 PRA polygons identified in the CMH Galena tenure. Our simulations were based on a frequent avalanche scenario that used a release depth of 50 cm.

Starting in the winter of 2015/2016 the Simon Fraser University Avalanche Research Program has collaborated with several mechanized ski guiding operations in Western Canada to collect GPS tracking information. The GPS trackers are custom designed units which continuously track guides over the course of a week (Thumlert et al., 2018). At CMH Galena we have collected 15,111 GPS tracks over 7 seasons (1 season is missing due to COVID-19 restrictions). We leverage the GPS tracking data in our run list decision-making model by using the GPS track coordinates to extract terrain characteristics for each run. This method is more accurate than using the predefined run polygons (Figure 2) because it limits the spatial extent of the terrain characterization to only the portion of the run polygon that has been skied by a guide during the period of record.

Since the unit of decision-making for the run list coding is an individual ski run, we needed to simplify the terrain information for each run into a single number summary for each terrain characteristic. For elevation we specified the elevation band (alpine, treeline, below treeline) with the largest proportion of GPS locations within each run as the primary elevation band. Forest cover was summarized based on the percentage of GPS locations that are forested and split into categories of 0-25%, 25-50%, 50-75%, or 75-100%. PRA and runout zones were summarized by taking the 95th percentile of the distribution for each run and then categorizing each run by PRA size (0-10,000 m^2, 10,000-15,000 m^2, 15,000-20,000 m^2, > 20,000 m^2) and runout pressure (0-50 kPa, 50-100 kPa, 100-150 kPa, > 150 kPa). Using the 95th percentile gives an estimate of the higher end of avalanche release area and runout exposure.

The final component of run characterization comes from survey data capturing guides' perception of the terrain (Wakefield et al., 2020). This survey contains a wealth of information from CMH guides but so far, we have incorporated only a limited subset including a) whether weak layers are intentionally managed by destroying them on the surface using skier traffic, b) whether a run has significant crevasse hazard, and c) the approximate flight distance required to access each cluster of ski runs within the tenure. These factors help to incorporate real world operational considerations that have an impact on the decision-making process which are independent from the terrain hazard or avalanche hazard conditions.

Avalanche conditions data

There are a multitude of condition factors that could impact run coding at CMH Galena, but in this manuscript we only present a relatively sparse model that focuses on the major decision drivers. We selected the variables based on the operational experience of Roger Atkins and also looked for relationships within the data. The highest level conditions variables we included in the present study are a) height of new snow over the past 72 hours (HN72), b) time of season (early-winter, mid-winter, etc.), c) total number of avalanche observations over the past 72 hours (0, 1-5, 5-10, 10-20, >20), and d) maximum size of avalanche observations in the past 72 hours (D1-1.5, D2-2.5, D3-3.5, D4-5). These variables are calculated based on CMH Galena's internal weather and avalanche safety observation records.

To capture the guiding team's understanding of the avalanche hazard conditions, we extracted avalanche problem, likelihood, and size information from their morning assessments. We elected to separate likelihood and size information for persistent and non-persistent avalanche problems to capture the effect of different types of avalanche problems on the decision-making process more accurately. The variables included in our decision-making model represent a) whether a persistent or deep persistent avalanche problem is present, b) the typical likelihood and maximum expected size for persistent avalanche problems, and c) the typical likelihood and maximum expected size for non-persistent avalanche problems. We elected not to include the avalanche danger rating in the model because the individual components of the hazard assessment process (likelihood and size) are more relevant to run list coding than the overall summary danger rating.

Run coding

The daily run codes are the output variables for this decision-making network. We split the possible outcomes of run coding into two variables, one capturing whether a run was considered for the day (black vs not-black) and a second capturing whether the run was closed or open for guiding on that day (red vs green). Black codes represent non-events (i.e., default) describing the situation when guides do not think the run is worth discussing during their roughly 15 minute run coding meeting. The reasons for not discussing a run (black code) include insufficient snow coverage on a run, the run being too far away given the current flying conditions, the terrain being obviously too hazardous to consider for the current conditions, or too much uncertainty for making an informed decision. Hence, the causes of a run not being coded differ from a run being coded red versus green. Preferences and biases of individual guides can also impact whether a run is coded as black.

We also included run coding variables from the prior day as input to the daily run code. This represents the iterative nature of the run coding where codes are updated daily based on prior observations and new information for the current day. Including these variables is realistic to the real world decision-making process and allows us to more explicitly identify periods of transition within the run coding.

2.4 Decision-making network

We designed and evaluated the BN in the R program for statistical computing (R Core Team, 2021) using the packages 'bnlearn' (Scutari and Denis, 2021), 'gRain' (Højsgaard, S., 2012), 'caret' (Kuhn, M., 2008), and 'pROC' (Robin et al., 2011).

Design of network

The main driver for deciding what nodes to include in the BN and how to set arcs between nodes was the expert opinion of Roger Atkins. The primary objective is to capture realistic patterns of decision-making in the arc pathways within the BN. We then use the data described in the previous section to calculate the conditional probability distributions of the BN based on the structure provided by our domain expert.

We constructed the DAG based on the thought process of using three different types of relationships to set arcs (Figure 3). First are arcs between run characteristic nodes, which represent the natural physical relationships in avalanche terrain and operational relationships in the guide survey nodes. Second are arcs between condition variables, which represent the relationships between observations and guides' assessments, which are roughly modelled after the theoretical foundation of the conceptual model of avalanche hazard (Statham et al., 2010). Third are decision arcs that connect nodes that could have a direct impact on how a run is coded. Each of these three types of arcs are included in the BN for different purposes, but all are relevant for our decision-making scenario.

Evaluation of network

To assess how well our decision-making network matches real world decisions, we used the BN as a predictive tool to calculate daily probabilities of runs being coded black, red, or green based on run characteristics and avalanche conditions. We used 70% (n = 188,654) of our dataset to estimate the BN model (i.e, calculate the conditional probability tables) and 30% (n = 80,854) to test the prediction accuracy. Using the BN as a predictive tool can be done in a variety of different ways, we set the nodes 'run considered' (black vs not-black) and 'run open [for guiding]' (red vs green) as the output nodes and used all other nodes as inputs for the calculations.

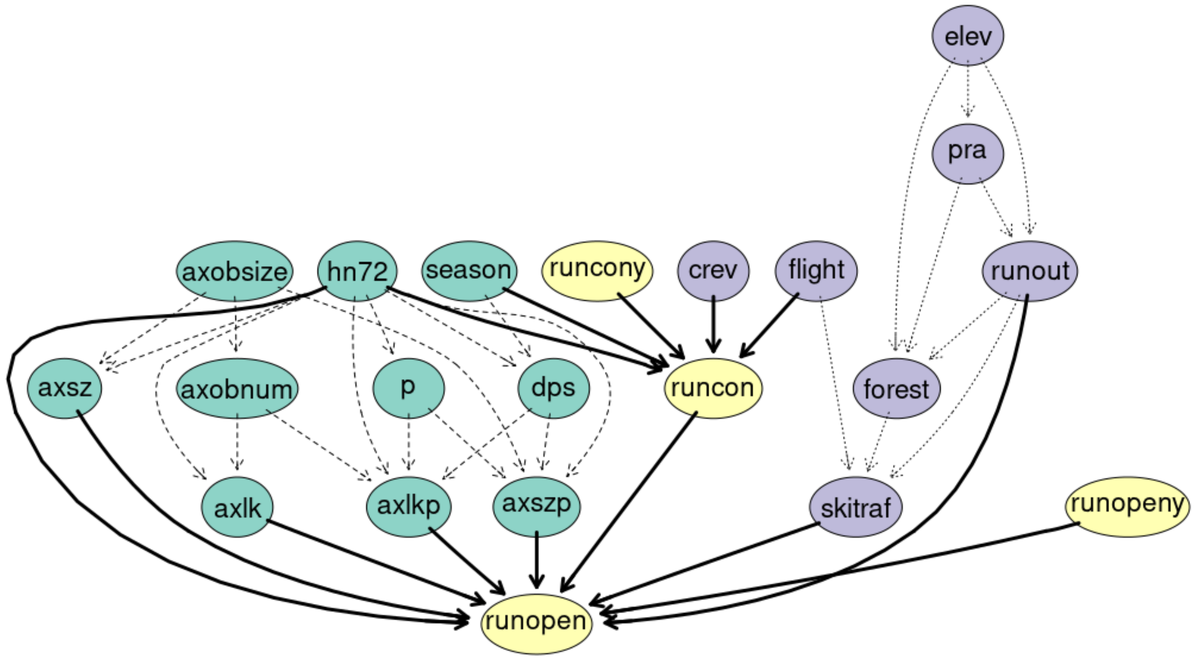

Figure 3: Directed acyclic graph (DAG) for run list decision-making model. Green nodes are condition variables, purple are run characteristics, and yellow are run code variables. Dashed arcs are based on hazard assessment, dotted arcs represent physical relationships between terrain nodes, and solid arcs represent decision pathways.

Hence, for each run and day, the run characteristic nodes were set to the local values for a specific run and the condition nodes to the current conditions for that day to predict the run code. Based on the results of the predictions we calculated the area under the receiver operating curve (AUROC) to set the thresholds for classifying the probability estimates into class estimates and used a confusion matrix to assess the performance of the BN.

RESULTS

2.5 Decision-making network

Our decision-making network aimed at capturing the daily run list coding at CMH Galena contains 21 nodes and 39 arcs (Figure 3). Overall, the network represents the complexity of the decision-making process by containing many potential pathways to the run coding nodes - run considered (runcon) and run open (runopen). This realistically represents the real world decision-making process, where the driving factor for the coding of runs depends on a multitude of factors related to the current conditions and the local run characteristics.

Input nodes - run characteristics

The highest level node in the run characteristics is primary elevation band (elev). Elevation is connected by arcs to potential release area (pra), runout pressure (runout), and percent of forest cover (forest). The relationships here assume that higher elevations are associated with larger avalanche release areas, higher potential impact pressures, and lower percentage of forested terrain. PRA is connected by arcs to runout and forest, indicating that larger release areas are associated with higher impact pressures and lower percentages of forested terrain. Runout pressure has a relationship with both percentage of forest cover and whether runs are maintained using skier traffic (skitraf) by CMH guides. Based on conversations with Roger Atkins, overhead hazard and runout are major considerations when selecting runs to be mitigated by skier traffic. Their goal being to make those runs available for skiing during elevated avalanche hazard conditions without being exposed to potential large natural avalanches releasing overhead. Forest is also directly connected to skier traffic because forest cover can break up potential avalanche start zones into multiple smaller start zones, which are more suitable for this type of mitigation. Flight distance from the CMH lodge also has an arc into skier traffic mitigation since this type of mitigation is only meaningful for more easily accessible runs closer to the lodge.

Input nodes - conditions

The relationships among the condition variables are driven by the avalanche hazard assessment process. The primary weather condition variable in the BN is the height of new snow within 72 hours (hn72). This captures the amount of new snow loading on top of the existing snowpack and has arcs connected to avalanche size, avalanche likelihood, status of persistent or deep persistent avalanche problems, the likelihood of persistent avalanches, and the size of persistent avalanches. Time of season (season) is a secondary condition variable that is oriented

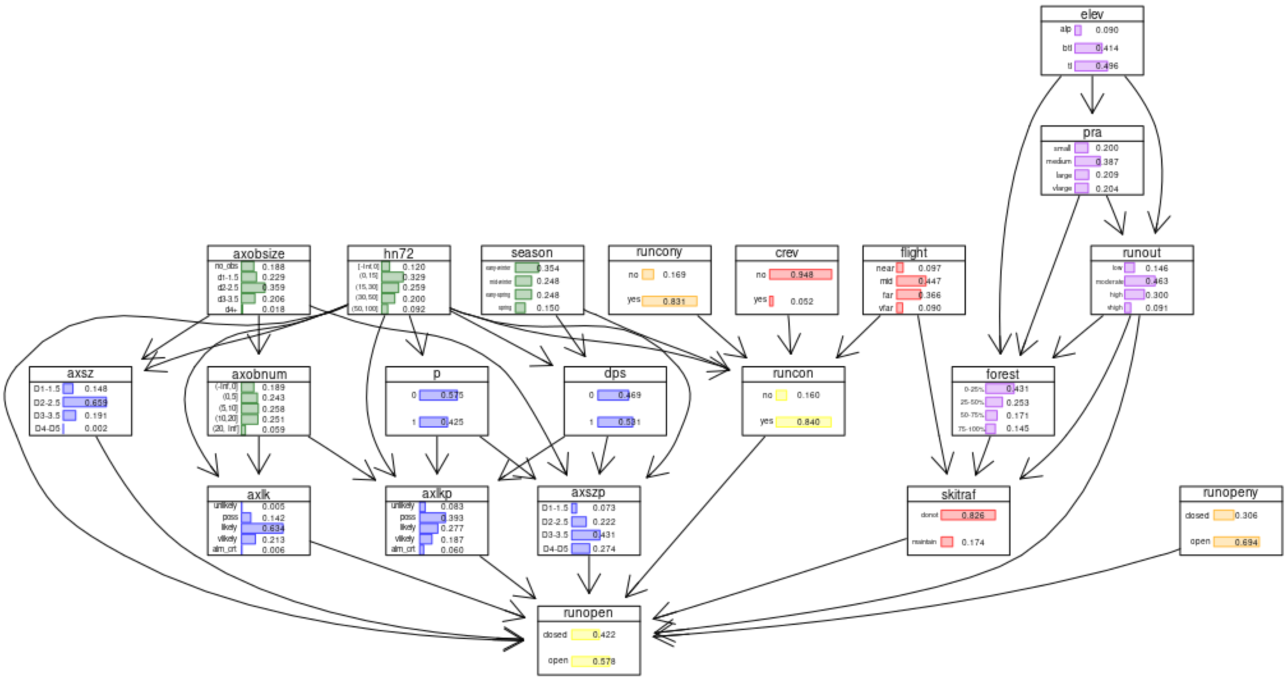

Figure 4: Initial state of the conditional probability tables for each node in the BN. Green color bar plots are weather or conditions observations, blue are avalanche hazard assessments, purple are avalanche run characteristics, red are operational data, orange prior conditions, and yellow are output decision nodes.

towards the development of snowpack characteristics over the course of a winter season. Season is connected to the status of deep persistent avalanche problems, which tends to be less likely in the early winter and more likely in the mid-winter, early-spring, and spring. The number of avalanche observations (axobnum) and maximum size of avalanche observations (axobsize) within 72 hours capture the guides' field observations, with an arc connected from avalanche size to number of avalanches. This arc supports the relationship that an increase in observed avalanche size is typically related to an increase in total number of observations. Arcs connect observed avalanche size to expected avalanche size for persistent and non-persistent avalanche problems. Similarly, arcs connect the number of observed avalanches to expected avalanche likelihood for both persistent and non-persistent avalanche problems. The status of persistent and deep persistent avalanche problems are each connected with arcs to persistent avalanche likelihood and size.

Output nodes

Whether a run is discussed on a given day (i.e., coded black or not) is represented by the run considered node (runcon). Input arcs for this node are hn72, time of season, crevasse (crev), flight distance, and whether the run was considered yesterday (runcony). Each of these input arcs represents an independent reason why a run could be coded black.

The status of a run being closed (red) or open for guiding (green) is captured by the run open node. This node has input arcs from hn72, avalanche size, avalanche likelihood, persistent avalanche size, persistent avalanche likelihood, runout, skier traffic mitigation, run considered, and the status of run open from the prior day (runopeny). By combining condition variables, run characteristics, and prior status we aimed to capture the range of potential factors that could impact run coding for different types of runs.

2.6 Network evaluation

The AUROC analysis for the 'run considered' node found and area under the curve of 0.92 and determined that if a run had a probability of ≥ 13.7% of being black then it should be classified black. The confusion matrix showed that the overall accuracy of the black run coding is 87.6% (Table 1). Additional accuracy metrics are shown in Table 1, which provide insight into how the model performs compared to the observed run coding from CMH guides and give estimates of how often the model is overpredicting (false positive rate) and underpredicting (false negative rate) the run coding.

For the run open node we predict the probability of a run being closed (red) or open (green) for guiding. The AUROC analysis has an area under the curve of 0.92 and determined the optimal classification threshold to be 47.9%. The overall accuracy for run open is 86.7% (Table 1). The true negative rate and true positive rate are very similar compared to the run considered node. However, the false positive rate is much higher for the run considered node, indicating that the model has a higher rate of overprediction for a run being coded black versus red.

Table 1: BN predictive confusion matrix results.

Output Node	*Overall Accuracy*	*True positive rate*	*True negative rate*	*False positive rate*	*False negative rate*
runcon	87.6 %	82.8 %	88.6 %	40.0 %	3.9 %
runopen	86.7 %	84.7 %	87.6 %	24.9 %	7.2 %

3. DISCUSSION

Our primary focus in developing a decision-making network for the daily run list coding at CMH Galena was to have the structure of the model match the real world decision-making process as closely as possible. The overall prediction accuracy of roughly 87% illustrates that BNs have the potential to accurately capture complex decision processes based on the knowledge of domain experts. While the BN was developed based on the decision-making process at CMH Galena, the approach can be applied to other guiding operations based on their local run characteristics and conditions.

Compared to prior approaches to analyze decision-making of mechanized guides which utilized regression analyses (Sterchi et al, 2019; Thumlert et al., 2018), the results of our model are much more intuitive to interpret. Despite being a complex model with 19 unique input nodes that are used to predict the run coding, the graphical structure of the model and careful justification of relationships makes the BN digestible for field practitioners, which improves the likelihood of being adopted as an operational tool.

While we are encouraged by the initial predictive performance of the model, the false positive rate for predicting whether a run is considered and whether a run is closed is high, at 40% and 24.9% respectively. This means that the model is more likely to predict that a run is not considered (black) or that a run is closed (red) compared to the observed data. The tendency to overestimate black and red run coding could indicate that our current model is missing critical decision-making factors. For practical purposes, coding a run as either black or red results in the run not being available for guiding that day, which means the BN trends towards predicting a conservative run list. From a risk management perspective, we would prefer the model to be biased towards predicting more conservative run list codings.

3.1 Applications

Our BN could be deployed as a decision support tool that provides guides with predicted run code probabilities for each run based on current conditions. Applying the BN in this way could expedite the run coding process and would ground guide's decisions in the observed operational behavior that is captured in the 7 seasons of data that the model is based on. The model could also be used to develop tools to help train new guides based on the existing practices of the operation.

To illustrate how a BN can be applied as a decision support tool, we can set evidence and observe changes in conditional probabilities of run codes. In the initial state, the BN predicts the probability of runs being closed is 42.2 % (Figure 4), which represents the average probability across all runs and all conditions. If we want to explore the general probability of being closed for runs with very high runout exposure, we can set evidence in the network (runout = 'vhigh'). The BN fixes the state of the runout node at 'vhigh' and propagates that information throughout the network to update the conditional probability tables of all nodes. The updated probability of a run being closed is now 49.9% (i.e., above the AUROC threshold of 47.9%), which means that these runs are generally coded closed (Figure 5). Setting evidence for more information about the conditions allows us to provide condition-specific run code estimates. For example, if hn72 is 40 cm, persistent avalanche likelihood is likely, and persistent avalanche size is D3-3.5 the updated probability of a run being closed is 64.5% (Figure 5). As a counter example, during periods without active loading (hn72 = 0 cm) and lower likelihood for persistent avalanches (axlkp = unlikely) the probability of runs with very high runout exposure being closed drops to 42.3% (Figure 5). By setting evidence for specific run characteristics and condition information the BN produces more precise and realistic conditional probability estimates for run code.

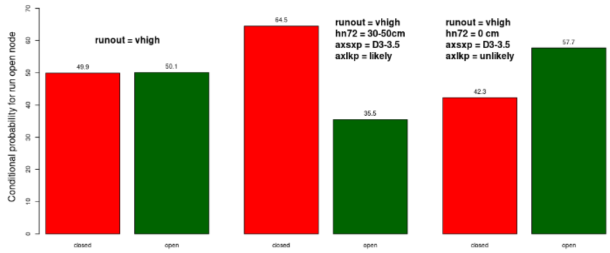

Figure 5: Run closed probability estimates with evidence: 1) runout = 'vhigh' (left). 2) runout = 'vhigh', hn72 = 30-50 cm, axszp = 'D3-3.5' and axlkp = 'likely' (center). 3) runout = 'vhigh', hn72 = 0 cm, axszp = 'D3-3.5' and axlkp = 'unlikely' (right).

4. CONCLUSIONS

This research illustrates how Bayesian networks can be applied as a tool to capture complex real world decision-making processes in the context of avalanche risk management. We use a variety of input data sets to capture decision-making influences, including weather and avalanche observations, avalanche hazard assessments, avalanche terrain modeling, GPS tracks, and guide survey data. The combination of having a nuanced decision-making model that mimics the real world process and high quality input data allows us to predict run list coding at CMH Galena with accuracies of roughly 87%.

Future research will aim to further refine this decision-making model and apply these methods to additional decision-making scenarios encountered by mechanized ski guides, including daily run selection and slope scale terrain selection. The ability to work with expert guides to build a decision-making model that realistically captures their decision-making process is the greatest single advantage of this method. Bayesian networks show great promise for eliciting expert-based avalanche risk management processes and providing a quantitative framework to develop decision support tools. Further applications could include capturing operational avalanche forecasting practices or decisions to open or close transportation corridors. The development of decision support tools for these uncertain and often high consequence risk assessments could help improve accuracy, consistency, and transparency in the avalanche industry.

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