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Enhancing the operational value of snowpack models with visualization design principles

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Abstract. Forecasting snow avalanches requires a reliable stream of field observations, which are often difficult and expensive to collect. Despite the increasing capability of simulating snowpack conditions with physical models, models have seen limited adoption by avalanche forecasters. Feedback from forecasters suggest model data is presented in ways that are difficult to interpret and irrelevant to operational needs. We apply a visualization design framework to enhance the value of snowpack models to avalanche forecasters. An established risk-based workflow for avalanche forecasting is used to define the ways forecasters solve problems with snowpack data. We address common forecasting tasks such as identifying snowpack features related to avalanche problems, summarizing snowpack features within a forecast area, and locating problems in terrain. Examples of visualizations that support these tasks are presented and follow established perceptual and cognitive principles from the field of information visualization. Interactive designs play a critical role in understanding these complex datasets and are well suited for forecasting workflows. Preliminary feedback suggests these design principles produce visualizations that are more relevant and interpretable for avalanche forecasters, but additional operational testing is needed to evaluate their effectiveness. By addressing issues with interpretability and relevance, this work sets the stage for implementing snowpack models into workstations where forecasters can test their operational value and learn their capabilities and deficiencies.

1 Introduction

Numerical environmental and weather prediction models have dramatically transformed the accuracy of weather forecasts and the role of weather forecasters since the 1980s (Benjamin et al., 2019). As model performance improved, forecasting tasks shifted from predicting weather conditions to interpreting and communicating model guidance. A centerpiece in the adoption of prediction models by weather forecasters was the development of workstations that allowed them to work directly with gridded modelled data in combination with in-situ weather observations and remote sensing data (Benjamin et al., 2019). This setup allowed forecasters to visualize model output along with observations and gradually learn the operational value of the models.

The work of avalanche forecasters is similar in nature and complexity to the work of weather forecasters. The objective of avalanche forecasting is to develop an accurate mental model of the current and future nature of avalanche hazard by integrating avalanche, snowpack, and weather information from a variety of sources (Canadian Avalanche Association, 2016b). This assessment is then combined with terrain information to make risk management decisions regarding specific elements at

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risk. The spatial scale of avalanche forecasting can range from individual slopes in backcountry guiding, to groups of avalanche paths when protecting infrastructure, and entire mountain ranges in public avalanche warnings. To assist avalanche forecasters at the higher end of the spatial scale spectrum, physical snowpack models such as Crocus (Brun et al., 1992) and SNOWPACK (Lehning et al., 1999) were developed in the 1990s to provide supplementary data about snowpack conditions. Despite the fact snowpack model developers created numerous operational tools to visualize model output for avalanche forecasters, snowpack models have so far only seen limited adoption into operational workflows when compared to weather prediction models (Morin et al., in press).

Morin et al. (accepted) employed the information quality framework of Bovee et al. (2003) to describe issues with operational snowpack model tools in terms of *accessibility*, *interpretability*, *relevance*, and *integrity* of the information. *Accessibility* to snowpack models is limited by the time constraints in forecasting environments and workstations that are optimally designed for field data rather than model data. Existing tools are also difficult to *interpret* as model output is complex and in their current form require expertise or substantial training to comprehend and utilize. The *relevance* of the information they provide is also questioned, as similar information may be available from other sources. The *integrity* of model output is also difficult to evaluate in an operational setting where there is limited validation data. For example, snowpack models can produce snow stratigraphy profiles for multiple parameters (e.g. grain size, hardness, temperature) at different time intervals at potentially hundreds or thousands of locations. Furthermore, the output from snowpack models are so complex and voluminous that it becomes extremely challenging for operational forecasters to make sense of in its raw form using conventional methods. This has been described as "information overload" and characterizes "big data" environments (De Mauro et al., 2016). As avalanche forecasting requires substantial cognitive effort to continuously maintain a mental model of conditions (Maguire and Percival, 2018), introducing additional complex data can disrupt this process and have adverse effects on performance. Based on their analysis, Morin et al. (in press) aptly conclude that while it was important for researchers to focus on improving the accuracy of snowpack models, we are now at a point where addressing issues with the design of operational tools is critical for making snowpack models truly valuable for avalanche forecasting.

To address the challenges of big data and make it tractable for human analysis, the field of visual analytics blends automatic analysis with human analysis via visual interfaces (Keim et al., 2008). Specifically, visualization in combination with interaction techniques support a process of iterative inquiry into data to support sense-making. This reduces the cognitive work needed to perform analytic tasks by leveraging the pattern detecting abilities of the human visual system for processing complex information that would normally exceed cognitive limits (Ware, 2012). Visual analytics has made complex problems and model output tractable for non-scientists and non-model experts in a variety of domains including physics, business, intelligence analysis, and disaster management (Keim et al., 2008). Effective visualization techniques are particularly valuable for environmental data, which is often complex due its spatiotemporal dimensions and uncertainties (Grainger et al., 2016). For example, studying visualization design principles has improved the interpretability of complex data sets in the fields of meteorology (Rautenhaus et al., 2018; Stauffer et al., 2015) and oceanography (Thyng et al., 2016).

Judging from the success of visual analytics applications in other disciplines of environmental science, we believe that applying a visualization design perspective to snowpack models has the potential to substantially address some of the shortcomings

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that have so far prevented their operational use. In this paper, we present design principles and visualization examples that aim to increase the interpretability and relevance of snowpack models. These design principles are informed by information visualization, operational avalanche forecasting practices, and the unique features of snowpack model data. First, we apply a visualization design framework to the domain of avalanche forecasting to outline principles of how data should be visualized to solve operational problems (Sect. 2). Then we provide examples of visualizations where these principles are applied with snowpack model data (Sect. 3). The validity of the design principles is discussed (Sect. 4) followed by conclusions and recommendations for adoption by avalanche forecasters (Sect. 5).

2 Visualization design principles for avalanche forecasting

2.1 Nested levels of visualization design

The nested model for visualization design described by Munzner (2009) has established itself as a valuable framework for evaluating and designing visualization tools. This framework considers four nested levels where distinct design issues arise, and where issues at one level can cascade to other levels. The issues with operational snowpack model tools identified by Morin et al. (in press) relate to design issues at each level of the nested model. The considerations included in these four levels provide designers with a tangible framework for understanding the users' problems, showing the appropriate information, and presenting it both effectively and efficiently:

1. *Domain situation level.* The domain situation describes the target users, their field of interest, their questions, and their data. A domain has unique vocabulary for describing its data and problems, and usually has an existing workflow for how data is used to solve problems. Issues arise when designers misunderstand the users' needs. For example, existing tools that present snowpack model data may not address the major needs and questions of avalanche forecasters (*relevance*).

2. *Task and data abstraction level.* Task and data abstraction maps domain-specific problems into generic vocabulary that clearly describe what type of data is being visualized and why. Tasks are described with generic verbs (e.g. locate, compare) and data is described with generic nouns and adjectives (e.g. table, network, ordered, categorical). Issues arise when the functions and data types in a design do not solve the intended problem. For example, detailed snow stratigraphy profiles provided by snowpack models may not be the type of information needed for forecasting tasks (*relevance*).

3. *Visual encoding and interaction idiom level.* This level creates visual representations of the data. A distinct visual representation is called an idiom. Data is encoded by arranging it along spatial dimensions and mapping attributes to non-spatial visual features such as colour, size, and shape, while interaction idioms allow the user to change the view. Issues arise when idioms are ineffective at visualizing information. Existing idioms for visualizing snowpack model data are often complex, busy, and difficult for non-model experts to understand (*interpretability*).

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4. *Algorithm level.* This is the level where idioms are produced from raw data with a computer. Issues arise when algorithms are too slow. At the algorithm level, most snowpack model visualizations are time consuming for forecasters because they are poorly integrated into their workstations (*accessibility*).

Munzner (2014) also describes that visualization problems can be attacked from two possible directions within the nested model: top-down approaches that first understand the domain and tasks and then design visual idioms accordingly, and bottom-up approaches that start with developing new algorithms and idioms. Most existing snowpack model visualizations were developed with bottom-up approaches that began with model development followed by the creation of visualizations of the model output. Bottom-up approaches allow novel visualizations that reveal nuances and anomalies in new types of data, but also have the potential to not solve the intended problem (Munzner, 2014). While it is worth considering bottom-up designs that take advantage of the unique capabilities of snowpack models, it is also important to carefully examine the domain and tasks of avalanche forecasting to establish top-down design principles that support forecasting needs.

2.2 Domain of avalanche forecasting

Avalanche forecasting is a common task for all operations that manage short-term avalanche risk (e.g. ski areas, transportation corridors, backcountry warnings, resource extraction). The forecasting process consists of iterative data analysis and is dominated by human judgement and inductive logic (LaChapelle, 1980; McClung, 2002). Statham et al. (2018) surveyed existing operational practices within North American avalanche forecasting operations to develop a standard framework for this process. The resulting *conceptual model of avalanche hazard* (CMAH) identifies the key components of avalanche hazard and provides standard workflow and terminology to guide the forecasting process. The CMAH is a risk-based framework that is consistent with other natural hazard disciplines and can be applied to any scale in space or time. A central part of the CMAH is the concept of avalanche problems that represent individual, identifiable operational concerns that can be described in terms of their potential avalanche type, location, likelihood, and size (Statham et al., 2018). Under the CMAH, avalanche forecasting is viewed as sequentially answering four questions:

1. What type of avalanche problems exist?
2. Where are these problems located in the terrain?
3. How likely is it that an avalanche will occur?
4. How destructive will the avalanche be?

Over the past decade, the CMAH has been widely adopted by all industry sectors in North America (Statham et al., 2018), which clearly indicates that it is a useful model to describe the domain situation of avalanche forecasting.

2.3 Task and data abstractions for snowpack analysis

Given the importance of avalanche problems in avalanche forecasting practices, any operational visualization of data should consider this abstraction to help forecasters identify and characterize avalanche problems. Assessing avalanche problems

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consists of integrating a complex array of data that includes observations of avalanches, snowpack, weather, and terrain (Statham et al., 2018). There is no structured or standardized way this data is used to answer the CMAH questions, as the analysis relies on subjective judgement and heuristics (LaChapelle, 1980), however there are common practices for interpreting field observations. Snowpack models produce data that is analogous to manual snow stratigraphy profiles, which is a key type of field data used by forecasters. Building off familiar visual representations is an effective way for people to understand new types of information (Blackwell, 2001), and thus examining existing practices for visualizing and analyzing snow profiles provides insight into ways snowpack models could be visualized to support forecasting tasks.

Forecasters perform several analysis tasks with snow stratigraphy profiles to help them assess avalanche problems and develop a comprehensive mental model of hazard conditions. Individual snow profiles are either recorded in tables of unstructured text or illustrated as a hardness profiles (Canadian Avalanche Association, 2016a). Forecasters learn to *identify* relevant snowpack *features* in these profiles, and then *compare* multiple snow profiles along with other observations to *summarize* the snowpack conditions within a forecast area. Forecasters summarize snowpack data by writing a concise overview of snowpack conditions in their forecast area. The goal of a written snowpack summary is to organize and reduce data, focusing on average conditions along with potential anomalies and outliers (Canadian Avalanche Association, 2016a). Some operations also illustrate their snowpack summary with generalized stratigraphy profiles for their forecast area (Fig. 1).

Tracking *trends* in snowpack conditions over time is another common forecasting task, which is most often done with tables of text. Temporal trends in the likelihood and size of avalanches are particularly relevant. For example, the InfoEx forecasting workflow allows forecasters to track weak layers in their forecast area with qualitative summaries of their status and depth each day of the season (Haegeli et al., 2014). Simple observed snowpack data is plotted as time series (e.g. daily snowfall at fixed observation sites), but complex data like snowpack structure is rarely visualized temporally.

To help forecasters answering the four key questions about avalanche problems posed by the CMAH, visualizations of snowpack model data should help forecasters *identify*, *compare*, and *summarize* snowpack *features* and highlight *trends* over time.

2.4 Information visualization principles

The field of information visualization studies how to leverage the human visual system to off-load cognitive work and visualize information effectively. Information visualization principles should be considered when designing the visual appearance and interactive components of tools for snowpack model data (i.e. the visual encoding and interaction idiom level of the nested model). These principles consider effective ways of representing data visually and are explained in greater detail in textbooks by Ware (2012) and Munzner (2014). The following list summarizes information visualization principles that are relevant when visualizing snowpack model data:

– When representing information visually, designers encode data to visual features such as: spatial position, size, color, or shape among others. Color can be further divided into hue (the actual color), luminance (the brightness or darkness of a

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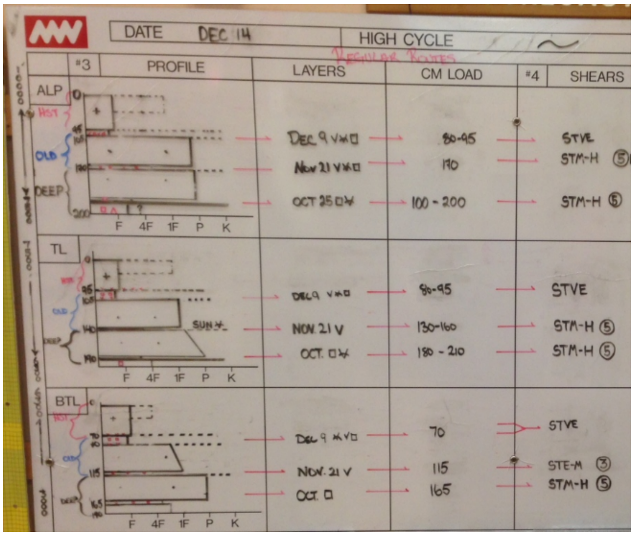

Figure 1. Snowpack conditions within a large forecast area are summarized with generalized snow profiles highlighting important snowpack features at different elevation bands (Photo: Mike Wiegele Helicopter Skiing).

color), and saturation (the intensity of the color). Through years of perception studies, standard guidelines for mapping these visual features to data types have been established (Cleveland and McGill, 1984).

– Visual encodings should present data in ways that match the capabilities of our visual system. Hence, categorical and ordered data should be encoded with visual features that match human visual aptitudes. For example, when using colours, hues should be used for categorical attributes such as avalanche problem types and luminance (lightness or brightness) should be used for ordered attributes such as avalanche likelihood.

– Designs should prioritize the importance of information and encode data to visual features that are perceived more quickly, accurately, and draw our attention to make this information more salient (i.e. noticeable) and discriminable (Cleveland and McGill, 1984). Spatial position is perceived the fastest and most accurately, and thus the most important attributes should be encoded by their position in a visualization. After spatial position, designs should consider the hierarchy of salience for non-spatial visual features. For example, size features such as length and area are more salient than colour features such as hue, luminance, and saturation. For a comprehensive breakdown of this hierarchy see Munzner (2014).

– Choose designs that are accessible and effective for common types of colour blindness. For example, red-green colour blindness (deuteranopes) affects roughly 8 % of males of European descent (Birch, 2012).

– Interaction reduces cognitive load and helps users understand data by asking questions and performing queries. A practical guideline for designing interaction idioms is the visual information seeking mantra of Shneiderman (1996): “overview first, zoom and filter, then details on demand”. The initial visualization should provide an overview of the

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entire dataset, and then the interactions should allow the users to change the view to see subsets of the data, and then visualize details about features of interest. This design approach offers users a flexible way to explore data, while being able to maintain a sense of context and orientation.

– Comparison tasks are often more effective when seeing multiple frames in a single side-by-side view rather than changing views over time. The human perceptual system is effective at reading spatial information in parallel, whereas changing views with animations or multiple tabs relies on human memory and results in substantial cognitive load (Ware, 2012).

– Visualization idioms should present data with the smallest number of spatial dimensions, avoiding three-dimensional visualizations and using one-dimensional lists where possible. Displaying three-dimensional data on planar surfaces has numerous issues with depth-perception and over plotting (Ware, 2012).

3 Applications of visualization design principles

This section presents applications of the visualization design principles using simulated snowpack data for 8 January 2018 in Glacier National Park, Canada. On this day the avalanche danger rating was considerable at all elevation bands with two avalanche problems (Parks Canada, 2018): a storm slab problem at all elevations (size 1 to 2 avalanches were possible to likely) and a persistent slab problem at treeline and below treeline elevations (size 1 to 3 avalanche were possible to likely). Simulated profiles were produced by forcing the physical snowpack model SNOWPACK (Lehning et al., 1999) with gridded meteorological data from the Canadian HRDPS numerical weather prediction model (Milbrandt et al., 2016). Meteorological data was extracted at 236 grid points in the park and at each grid point a single flat field profile and four virtual slope profiles were simulated (38 ° slopes in four cardinal directions). A total of 1180 profiles covering an area of $1354\,\mathrm{km}^2$ provide a sample data set to present visualizations of regional snowpack conditions.

3.1 Identify snowpack structure patterns with colour

Snowpack features related to avalanche problems should be easy to identify in visualizations of snowpack structure. The standard colour palette for snow grains (i.e. Fierz et al., 2009) creates undesired emphasis on certain types of snow. Important features such as thin weak layers have relatively low perceptual salience while less important features such as melt forms and ice formations have relatively high salience. The colours also make it difficult for individuals with colour blindness to distinguish important features.

We propose a perception-informed colour palette for snow grain types that emphasize features related to avalanche problems (Table 1). Similar perception-informed colour palettes have been proposed to improve the interpretation of visualizations in meteorology and oceanography (Stauffer et al., 2015; Thyng et al., 2016). The proposed colour palette groups grain types into four categories based on their role in avalanche problems: persistent weak layers (surface hoar and depth hoar), new snow layers (precipitation particles and decomposing and fragmented particles), bulk layers (rounded grains and faceted crystals), and melt and ice form layers. These groups were visually related using analogous color schemes (e.g. the hues are perceptually close

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to each other) that remained visually discriminable. The visual salience of these groups was adjusted using properties of color such as how dark they appear (i.e. luminance) and how vivid the colors are (i.e. saturation). In this way a visual hierarchy of importance was created. Weak layers that tend to take up the smallest area were made the most salient by using strong contrast against other grain types, next new snow was made salient. Finally, the other layers formed the lowest level of perceptual salience and serve as a neutral background. All colors were made to be perceptually distinct. Accessibility for common types of colour blindness was also considered (see Table 1). Unique colours were also assigned to melt-freeze crust and rounding faceted particles, as distinguishing these sub-classes was deemed meaningful for avalanche forecasters. A simplified colour palette was also designed using only the four main categories of grain types non-model experts (Table 2). The simplified palette uses analogous colours to the full palette and maintains a similar visual hierarchy.

Table 1. A perception-informed colour palette for snow grain types that emphasizes features related to avalanche problems and is effective in grayscale and for common types of colour blindness.

Grain type	Standard	Perception -informed	Grayscale	Deutera-nomaly	Deutera-nopia	Hex code
Surface hoar (SH)						#ff0000
Depth hoar (DH)						#0078ff
Precipitation particles (PP)						#ffde00
Decomposing and fragmented particles (DF)						#f1f501
Rounded grains (RG)						#ffccd9
Rounding faceted particles (FCxr)						#dacef4
Faceted crystals (FC)						#b2edff
Melt forms (MF)						#d5ebb5
Melt-freeze crust (MFcr)						#addd8e
Ice formations (IF)						#a3ddbb

Table 2. Simplified colour palette for groups of grain types related to avalanche problems.

Group	Grain types	Colour	Hex code
Persistent weak layers	SH, DH		#95258f
New snow layers	PP, DF		#ffde00
Bulk layers	RG, FCxr, FC		#dacef4
Melt and ice layers	MF, MFcr, IF		#d5ebb5

The colour palettes were tested with common visualization idioms such as hardness and timeseries profiles (Fig. 2). Comparing the standard and redesigned colour palettes shows how the new palettes simplify the interpretation of the profiles by drawing attention to the most important snowpack features on 8 January 2018. The increased salience of the thin depth hoar layers highlights a potential persistent slab avalanche problem and the new snow highlights a potential storm slab avalanche problem.

3.2 Identify avalanche problem types from multiple profiles

Visualizing information from an ensemble of snow profiles is an effective way to identify snowpack patterns in a forecast area. Identification and summarization tasks can be done fast and effectively by deriving visual summary statistics from distributed visual information. For example, humans can visually calculate correlation coefficients, clusters, and averages with their visual perception systems (Szafir et al., 2016). The volume and continuity of data produced by snowpack models offers new opportunities for summarizing snowpack structure that are not possible with human observed snow profiles. When

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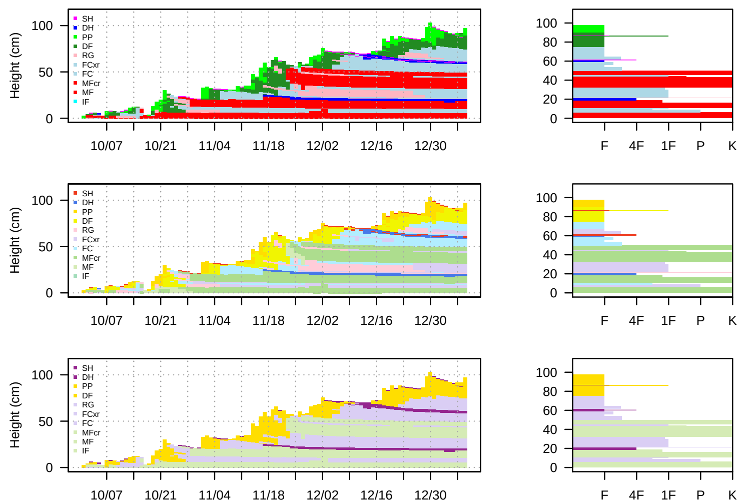

Figure 2. Comparison of timeline and stratigraphy profiles with standard colours for grain types, perception-informed colours for grain types (Table 1), and perception-informed colours for grain type groups (Table 2).

used in combination with a colour palette that emphasizes snowpack features related to avalanche problems, profile ensemble visualizations can help forecasters identify prominent avalanche problem types.

A simple and powerful summary is obtained by plotting multiple grain type profiles side-by-side (Fig. 3). In this example, 1180 profiles are sorted from thinnest to thickest and over 46 000 individual snow layers are shown in a single view. Despite the large volume of data, and a few prominent snowpack features pop-out and attention is drawn to the main snowpack patterns in the forecast area. Since this visualization is specifically designed for the task of identifying potential avalanche problem types, other idioms are required for visualizing geospatial patterns in a meaningful way (see Sect. 3.3).

Another summary visualization that draws attention to potential avalanche problem types is produced by aggregating layers by their age or deposition date (Fig. 4). Simulated profiles can be aligned and aggregated by the deposition date of each layer to summarize the main features amongst a set of profiles. The prevalence of different grain types is determined by counting the percentage of profiles containing grain types for each day the season. Grain types associated with persistent weak layers are emphasized with a diverging horizontal scale to distinguish them from other grain types. The persistent weak layers are also easier to notice in this visualization because they occupy a greater area than in Fig. 2 and 3 where their size is proportional to layer thickness. While it is also possible to produce an aggregated stratigraphy profile from aligned layers (e.g. Hagenmuller and Pilloix, 2016; Herla et al., in preparation), this requires complex data transformations and assumptions about averaging layer properties. The layer prevalence visualization in Fig. 4 is simple to implement and supports the task of identifying potential avalanche problem types.

The visualizations in Fig. 3 and 4 use colour and position to draw attention to snowpack features that relate to the storm slab and persistent slab avalanche problems on 8 January 2018. The storm slab problem is apparent from the yellow new snow

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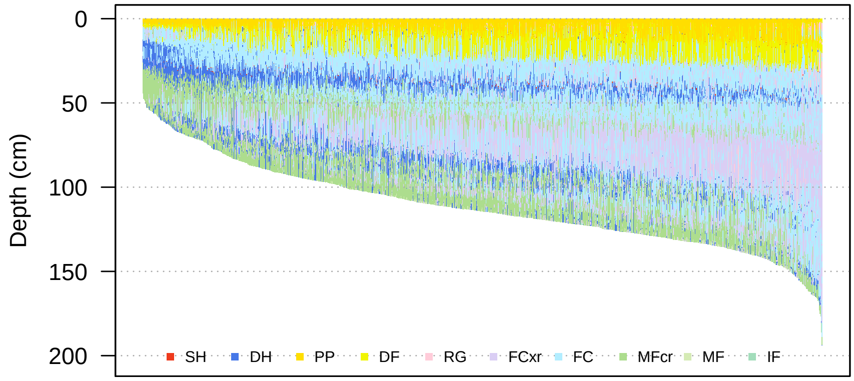

Figure 3. Snowpack layers from 1180 simulated profiles are summarized by plotting grain type stratigraphies side-by-side and sorting the profiles from thinnest to thickest. Grain types are coloured using the perception-informed palette from Table 1.

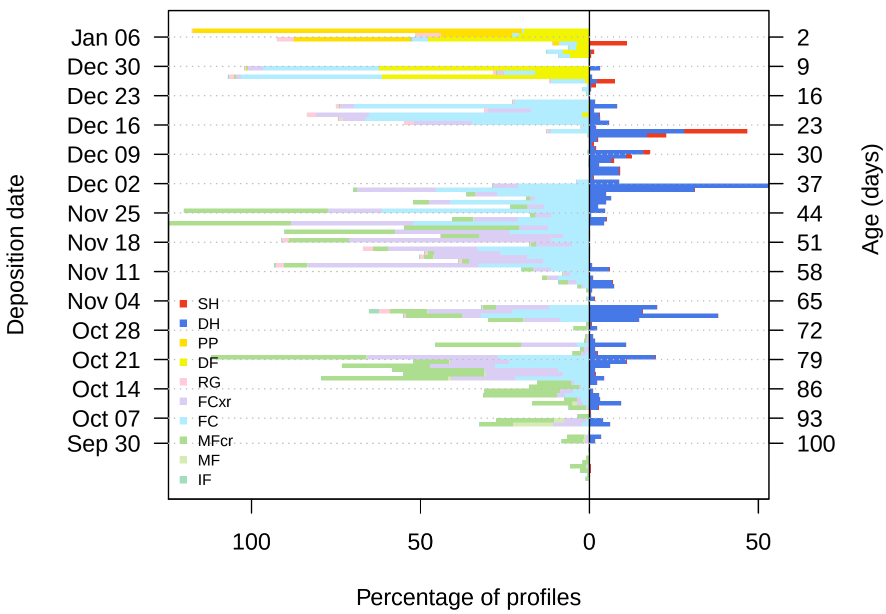

Figure 4. Prevalence of snowpack layers from 1180 simulated profiles by aggregating layers by their age. A diverging scale distinguishes the percentage of profiles with layers containing persistent grain types (i.e. surface hoar and depth hoar) on the right from the percentage of profiles with layers containing other grain types on the left. Grain types are coloured using the perception-informed palette from Table 1.

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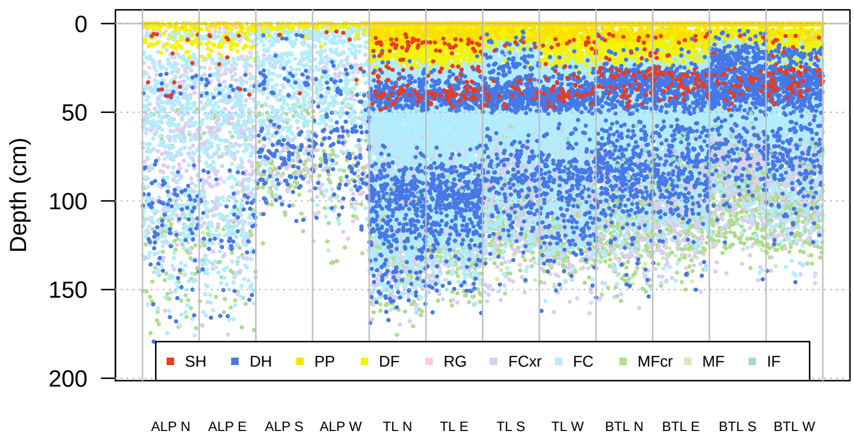

Figure 5. Snowpack layers from 1180 simulated profiles partitioned into terrain class bins for elevation band and aspect. Elevation bins include alpine (ALP), treeline (TL), and below treeline (BTL) and aspect bins include four cardinal directions (north, east, south, west). Each layer is given a random horizontal position within the bin to allow visual summary statistics. Grain types are coloured using the perception-informed palette from Table 1.

grains on the surface and a potential persistent slab avalanche problem is apparent from the salient surface hoar and depth hoar layers that are buried 30 to 50 cm below the surface (Fig. 3) and formed in early December 2017 (Fig. 4).

3.3 Locate avalanche problems in terrain

When locating avalanche problems in terrain, the description of the terrain depends on the context and scale of the forecast (Statham et al., 2018). For example, regional forecasters describe terrain by elevation bands and aspects while highway forecasters reference named avalanche paths. Partitioning snowpack data into distinct terrain classes and comparing side-by-side views of the data for each terrain class is an effective way visualize complex geospatial patterns. High-dimension (3D) visualizations are tempting to characterize mountainous terrain, particularly with high density model datasets, but there is large potential for misinterpretation on two-dimensional displays due to depth perception issues and over-plotting (Ware, 2012). Instead, using eyes to simultaneously compare visualizations for different types of terrain has low cognitive load and less potential for misinterpretation.

To provide insight into the spatial distribution of avalanche problem characteristics, the simulated profiles from Glacier National Park were partitioned into bins for elevation band and aspect classes to support regional-scale forecasting (Fig. 5). A randomized horizontal position (i.e. jitter) was applied to each layer to reduce over-plotting and randomize the order within a

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bin. The jitter plot allows the user to derive visual summary statistics about the snowpack structure in each terrain class and make comparisons between different terrain bins such as:

- snow depth generally increases with elevation, except for south and west facing slopes in the alpine,
- there is more new snow on north and east aspects,
- buried surface hoar layers are more prevalent on north and east aspects, and
- the early December 2017 weak layer is more prevalent at treeline and below treeline elevations.

These types of visual patterns could help forecasters localize avalanche problems in their terrain. Different types of terrain bins could be applied for other forecasting contexts to highlight differences between relevant types of terrain. Examples include sub-regions, avalanche paths, or classes of ski terrain (e.g. Sterchi et al., 2019).

3.4 Compare distributions of avalanche size and likelihood

Avalanche size is easily visualized by aligning layers by depth rather than height. Layer depth is more relevant to forecasting avalanches than layer height, as weak layer depths correlate to the destructive potential of slab avalanches (McClung, 2009). From an information visualization perspective, comparisons are more effective on aligned scales, and thus aligning layers by depth allows users to browse the distribution of depths for specific weak layers. From the distribution of layer depths in Fig. 3 and Fig. 5, forecasters could estimate the potential sizes of storm slab and persistent slab avalanches.

The CMAH defines the likelihood of avalanches as a combination of *sensitivity to triggers* and *spatial distribution* (Statham et al., 2018), making it a relatively difficult attribute to visualize. Options for visualizing avalanche likelihood include encoding related attributes with visual features such as shape, size, or motion in any of the previous idioms or by designing new idioms that focus specifically on likelihood. Information about the *spatial distribution* of a problem can be derived by counting relevant features amongst a set of profiles (e.g. Fig. 4). *Sensitivity to triggers* is an assessment of snowpack instability, which snowpack models estimate using stability indexes based on the mechanical and structural properties of the layers (Schweizer et al., 2006). We derive a relative measure of sensitivity to triggers (S) from SNOWPACK's structural stability index (SSI). The SSI combines a stress-strength ratio with differences in hardness and grain size to calculate a value between 0 and 6, where lower values correspond to less stable layers. To visually emphasize unstable layers, SSI was transformed into a relative measure of sensitivity to triggers:

$$S \propto exp^{-SSI} \tag{1}$$

where the SSI for each layer is scaled inverse exponentially to produce an ordered variable that correlates with the sensitivity categories from the CMAH (i.e. unreactive, stubborn, reactive, touchy). This transformation produces values between 0 and 1 and exaggerates differences for weak layers with low SSI. The numeric value of the sensitivity measure does not have an interpretable meaning but illustrates relative patterns when applied in visualizations.

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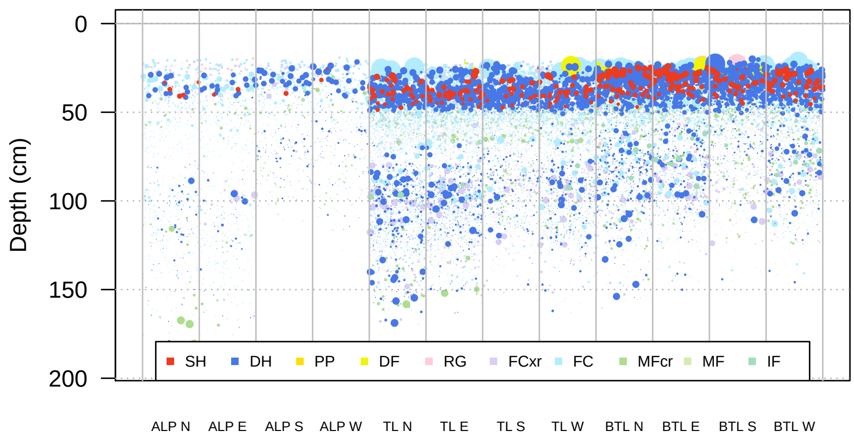

Figure 6. Providing information about the likelihood of persistent slabs avalanches by scaling the size of each layer's dot with its sensitivity to triggers (derived from the structural stability index). Snowpack layers from 1180 simulated profiles are partitioned into terrain class bins for elevation band and aspect. Elevation bins include alpine (ALP), treeline (TL), and below treeline (BTL) and aspect bins include four cardinal directions (north, east, south, west). Each layer is given a random horizontal position within the bin to allow visual summary statistics. Grain types are coloured using the perception-informed palette from Table 1.

We present two examples of visualizing likelihood information with this relative measure for sensitivity to triggers. The terrain class visualization in Fig. 5 was modified to scale the dot size of each layer to its sensitivity to triggers (Fig. 6). This creates greater emphasis on sensitive weak layers, where the number and size of weak layer dots in a terrain bin relate to the likelihood of persistent slab avalanches in that type of terrain. Another visualization specifically designed for likelihood is given in Fig. 7, where the left panel provides information about the spatial distribution of each layer and the right panel provides information about their sensitivity to triggers. Spatial distribution is shown by the prevalence of each layer by age (i.e. Fig. 4), while sensitivity to triggers is shown with the distribution of the relative sensitivity of each layer by age. The side-by-side comparison of spatial distribution and sensitivity to triggers provides information about the potential likelihood of persistent slab avalanche problems. For example, the weak layers that formed in early December 2017 are more widely distributed and sensitive to triggers than the weak layers that formed in late October (i.e. avalanches are more likely).

It is important to note that we are presenting these likelihood visualizations more to illustrate the concept than as a practical decision aid. It is known that the modelled stability index does not provide meaningful information about layers near the surface where storm slab avalanches occur (Schweizer et al., 2006), and Monti et al. (2014) has highlighted issues between the modelled stability indices and field observations of snowpack instability.

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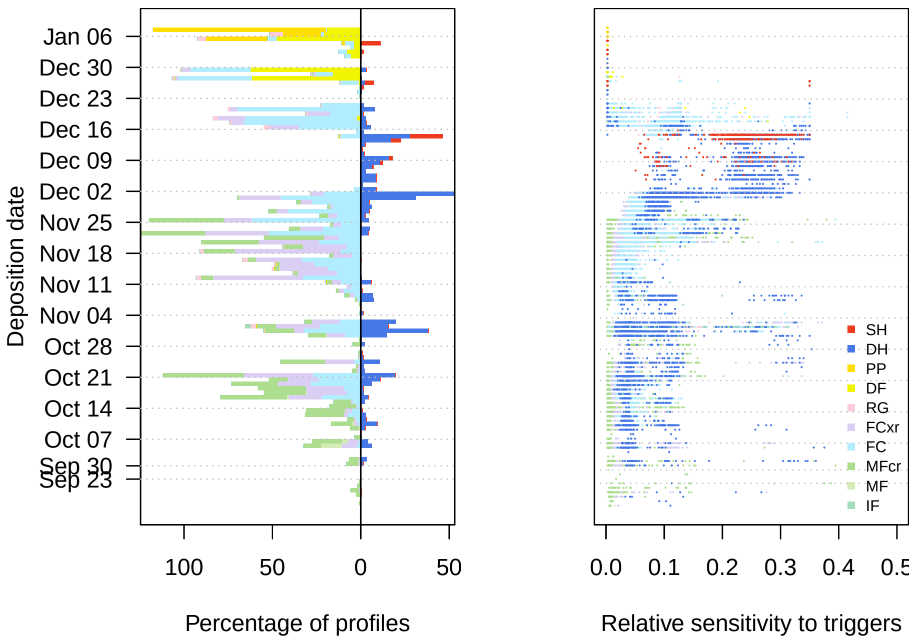

Figure 7. Combining visualizations of spatial distribution and sensitivity to triggers to provide information about the likelihood of avalanches. Both visualizations aggregate the layers by age and colour them by grain type. The left panel shows spatial distribution by counting the number of profiles with different grain types (see Fig. 4) and the right panel shows the distribution of sensitivity to triggers for these same layers as derived from the structural stability index. Grain types are coloured using the perception-informed palette from Table 1.

3.5 Interactive dashboard

Visualizations presented in this section were combined into an interactive dashboard using Tableau data visualization software (Fig. 8 and available online in Code and data availability). The dashboard facilitates the sequential questions of the CMAH by following the "overview first, zoom and filter, details on demand" mantra (Shneiderman, 1996) via interactions that allow the user to change the view by selecting visual features and filters from the legend. The initial view (Fig. 8a) consists of the layer prevalence visualization (Fig. 4), the profile summary visualization (Fig. 3), and the location in terrain visualization (Fig. 5). The combination of these visualizations provides a visual overview of the snowpack structure to support the first question in the CMAH – identifying potential avalanche problem types (Fig. 8a). After identifying potential avalanche problem types from the overview visualizations, users select layers of concern from the layer prevalence panel to update the visualizations. Once a layer of concern is selected, the layer is highlighted in the other panels to provide details about the location in terrain and the distribution of avalanche sizes (Fig. 8b). Horizontal bars show the median depth of the selected layer in each terrain class for comparison of potential avalanche sizes. A tooltip allows the user to hover over any visual feature and see details such as the grain type, deposition date, and depth in a pop-up window. In Fig. 8b, the user has selected all the layers that formed between 2 and 15 December 2017 to investigate the persistent slab avalanche problem. The profile summary shows the position of this

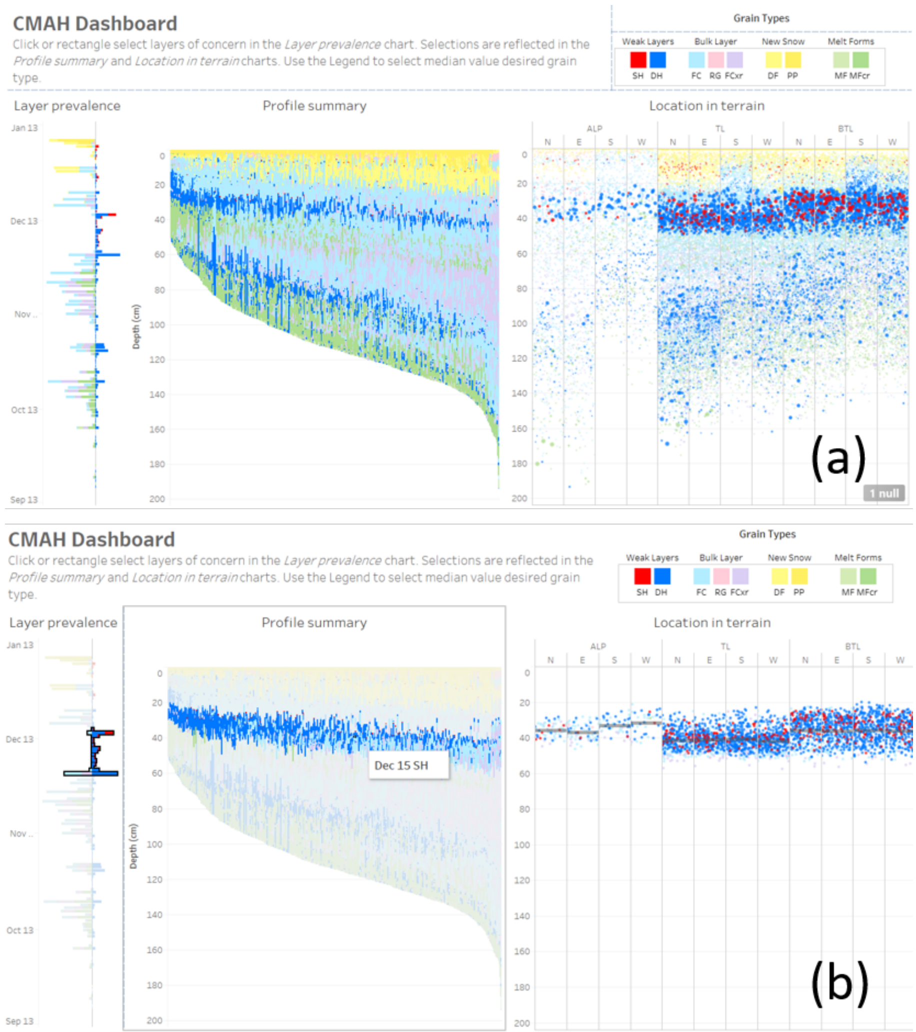

Figure 8. Screenshots of an interactive dashboard that provides visualizations of layer prevalence, profile summary, and location in terrain. The initial view (a) provides and overview of the entire dataset for the user to assess potential avalanche problems and then (b) the updated view after the user has selected layers that formed between 2 and 15 December 2017 to explore details about the distribution and depth of the persistent slab avalanche problem.

layer in the snowpack and the location in terrain visualization shows the layer is more prevalent at treeline and below treeline, with median depths of $40\,\mathrm{cm}$ at treeline and $35\,\mathrm{cm}$ below treeline.

4 Validating visualization designs

While the principles outline in Sect. 2 are a good foundation for designing meaningful visualizations, user testing is critical to ensure the visualizations have the desired effects. We presented the visualizations from the previous section to avalanche forecasters at ten workshop-style presentations, tested real-time prototypes with three helicopter skiing operations over two winters, and ran an exercise where five users performed basic tasks with the interactive dashboard. Following the nested model for visualization design framework of Munzner (2009) again, we present the feedback that we received at each design level separately.

At the domain situation level, creating links between snowpack models and the CMAH addresses operational challenges faced by avalanche forecasters (Statham et al., 2018). Reflecting the broad adoption of the CMAH, the proposition of using snowpack models to characterize avalanche problems has gained more interest from the Canadian forecasting community than snowpack model tools produced over the past decade. The CMAH may not characterize the domain situation for all possible snowpack model users, as problems such as terrain selection or civil protection likely require distinct design considerations.

At the task and data abstraction level, the visualization of snowpack summaries has received consistent positive feedback from forecasters. The side-by-side profile summary (Fig. 3) visualizes snowpack patterns in a way that is not possible with traditional snow profile data and can help forecasters build a mental model of the snowpack structure in their forecast area. Other operational tasks could benefit from bottom-up designs that leverage the spatial and temporal coverage of snowpack models, such as using stratigraphy timelines to visualize temporal trends.

At the visualization and interaction idiom level, some forecasters suggested reducing the number of colours in snow profile visualizations to make them easier to interpret. The perception-informed colour palettes (Table 1 and 2) achieve this while following established perceptual and cognitive principles to draw attention to the most important features. The user testing exercise evaluated the users' ability to interpret the visualizations by performing simple tasks with the interactive dashboard. Four out of five participants correctly performed task such as comparing snow height over different elevations, identifying the depth of prominent weak layers, and summarizing new snow amounts. The remaining participant made mistakes with filtering and selection, highlighting the importance of designing interactions that are simple and intuitive.

At the algorithm level, the operational prototypes provided daily updated visualizations in a timely manner with fast response time for interactions. The main concern at the algorithm level was the prototypes were accessed externally from existing workstations, which created a major barrier to access. Integrating snowpack model visualizations into forecasting workstations is a critical next step. Testing in an operational setting would allow further validation at the domain and abstraction levels by measuring user adoption and observing how designs are used to perform operational tasks. Although the designs presented in this paper follow established visualization principles, testing in real forecasting scenarios is needed to validate their actual operational value.

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5 Conclusions

We present visualization design principles that increase the *interpretability* and *relevance* of snowpack model outputs. These are two of the four major perceived issues with operational snowpack model tools identified by Morin et al. (in press). The nested model for visualization design (Munzner, 2009) provides a framework for defining the domain of avalanche forecasting and the necessary tasks that are needed to analyze data. Tasks required to assess avalanche hazard are described by applying the widely adopted conceptual model of avalanche hazard (Statham et al., 2018). From these tasks, we apply information visualization principles to design visual representations of snowpack model data in ways that leverage the human visual system to understand the complex nature of the data. Preliminary feedback from avalanche forecasters suggests these designs are easier to interpret and provide more relevant information than previous visualizations of snowpack model data.

A key idea in these designs is shifting from bottom-up scientific visualizations towards information visualizations that address user needs. As highlighted by Grainger et al. (2016), other types of environmental models would likely see improved adoption by shifting towards information visualization. When using numeric models as a tool for assessing natural hazards, visualizations will be more effective when the designers make links to established risk frameworks and carefully consider the tasks performed by operational decision makers.

A critical next step is implementing these designs into operational forecasting workflows. By addressing issues with the interpretability and relevance of snowpack model data, these designs will allow forecasters to learn the capabilities and deficiencies of snowpack models in a meaningful way. The same design principles should be considered when visualizing other types of avalanche and snowpack data, as the same domain situation and task abstractions apply when analyzing field observations. Interaction idioms should play an important role in understanding of complex model data, as they allow users to perform custom queries, test and validate hypotheses, and discover inconsistencies and anomalies. Interactions that compare model data with observation data would be particularly powerful in building trust in the models and addressing issues with their integrity. This process was critical in the adoption and trust in numeric weather predictions models by meteorologists (Benjamin et al., 2019), and just like meteorologists, avalanche forecasters could become active participants in model validation and improvement.

. The code and data used to produce the visualizations are published as a data file containing the simulated profiles and an R script that produces each of the visualizations. The interactive dashboard is available at https://avalancheresearch.ca/pubs/2019_horton_snowpackvis.

. All authors worked on the conceptualization of this paper. SH prepared the data and software, SN contributed to visualization ideas and designs, and PH provided supervision. SH prepared the manuscript with review and editing from the other authors.

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