SPATIAL INTERPOLATION METHODS FOR ESTIMATING EXTREME SNOW SUPPLY

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ABSTRACT: Estimating potential extreme snow supply is one of the most important tasks when planning for large destructive infrequent avalanches. We define it as the amount of snow potentially delivered to a specific area of interest or start zone by precipitation and wind transport over a specified long-term return period (often 100 or 300 years). Extreme snow supply is a key variable for input into dynamic models used to estimate avalanche runout, flow height, impact pressure; and is also an essential part when estimating avalanche hazard. Traditional methods start by applying extreme-value statistics on annual maximum snowpack height data or three-day storm snow totals, and then use various regressions to account for the elevation differences between the relevant start zone and the elevation where the weather station exists. These methods are appropriate for data-rich areas where relevant snowpack height data is available in close proximity to the start zone(s), however errors develop, and judgement is required to account for the spatial variation of snow supply between the start zone(s) and weather stations. We propose a simple and practical method of spatial interpolation for snow supply data based on the fundamental principle that potential snow supply varies more significantly across terrain than it does with elevation. The method involves collecting available snow supply data from various sites (e.g. automated snow height stations, snow pillow stations), adjusting these data to a common elevation using lapse rates, applying extreme value statistics (e.g. Gumbel distributions) to obtain estimates for long term return periods, interpolating spatially to obtain an estimated snow supply surface, determining the interpolated values for the project location (e.g. key avalanche start zones), and again adjusting these values to the elevation of the project avalanche start zones using lapse rates. We also derive new lapse rates from modelled high-resolution snowpack height and snow water equivalent data for nine prominent mountain ranges in Western Canada. Finally, we present two examples where the method was applied to engineering planning projects in Canada and discuss practical applications. These interpolation methods reduce the reliance on engineering judgement, reduce errors originating from spatial variation of snowpack depth across terrain, and potentially lead to better estimations of extreme snow supply.

KEYWORDS: Extreme Snow Supply, Planning, Avalanche Hazard, Climate Data, Snow Climate.

1. INTRODUCTION

"*Estimations of snow supply are considered an essential part of a report on the avalanche hazard for one or more specific paths*" (CAA, 2002b).

Potential snow supply to avalanche start zones directly correlates to the magnitude of potential avalanches which is a key component of hazard (CAA, 2016; Jamieson et al., 2018). Snow supply variables are often used as inputs to dynamic avalanche models that calculate runout, flow height, velocity, and impact pressure. The relevant snow supply variables are typically the annual maximum height of snow (or snow water equivalent), the three-day maximum snowfall amount, or the average release depth for large destructive slab avalanches. This paper focuses on planning and mitigating risk from large extreme avalanches and is not specifically relevant for short-term forecasting of avalanches.

Snow supply data are typically collected from fixed measurement sites that have been operational for long time periods, ideally over several decades. These sites include manual study plots, snow courses, snow pillows, or remote automated weather stations. Often Height of Snow (HS) (i.e. snow depth sensor) or Snow Water Equivalent (SWE) (i.e. cumulative precipitation gauge, snow pillow, or manual snow course) data are available, and average bulk snowpack density (often estimated or measured) may be used to convert between the two. Estimates for average bulk density are typically between 250 and 400 kg/m^3, depending on the snow climate (e.g. coastal, transitional, continental) and site-specific conditions (DeWalle and Rango, 2008; Fierz et al. 2009; Maidment 1992; Singh and Singh, 2001).

The snow supply data are commonly fitted to an extreme value distribution (typically Gumbel) to determine maximum values for return periods useful in planning purposes: 3, 10, 30, 100, and/or 300-year (Jamieson et al., 2018). These extreme value estimates must then be adjusted to account for variation between the fixed site and the relevant avalanche

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start zones. Orientation to prevailing wind, elevation, and spatial variations are the three key factors.

Adjusting snow supply data to account for orientation to prevailing winds requires the application of judgement. Factors such as the size of the fetch (i.e. area where snow may be transported from into the start zone), nearby topography (e.g. ridge features, surrounding peaks), and typical patterns of extreme snowstorms must be accounted for. For example, start zones that are windward to prevailing winds may not be windward to the infrequent extreme snowstorms (Jamieson et al., 2018). Schaerer (2002) proposed that extreme snow supply estimates can be reduced by 30% for windward start zones and potentially increased by up to 50% for lee start zones.

Often fixed sites used to collect snow data are located at lower elevations than relevant start zones, and snow supply data must be adjusted for the variation due to the elevation difference using lapse rates. There are several methods commonly used for this adjustment, primarily based on empirical fits to observation datasets.

The spatial variation of snow supply between the fixed study site and the relevant start zone can be significant (e.g. wet versus dry side of a mountain range due to orographic lift). Adjusting for these spatial differences remains based on judgement or not accounted for at all.

This paper aims to reduce the uncertainty and reliance on judgement when accounting for spatial variation by utilizing spatial interpolation techniques. A methodology is proposed for applications where there is likely to be significant spatial variation of snow supply between data sites and the relevant start zone (i.e. the fixed snow data site is not located very close to the start zone), and there are several to many fixed measurement sites in the surrounding region.

2. METHOD

Here we propose a simple methodology for estimating extreme snow supply for a given avalanche start zone. The method uses the spatial interpolation techniques discussed in Section 3 and the lapse rate techniques from Section 4:

a) Collect the relevant annual snow supply data. The ideal data consists of:

- Sites located near the project location.
- Relevant snow supply data (e.g. maximum height of snow, maximum 3-day increase in total snow height, maximum snow water equivalent).
- The data spans many years.
- The sites are generally at a higher elevation (e.g. near treeline). Valley bottom sites are not typically used due to the complication of melting and precipitation falling as rain.

b) Perform quality control and filtering to obtain annual maximum values. Note, there are often long periods of time when stations were not reporting, or contained single erroneous values that must be removed.

c) Adjust these annual maximum snow supply data for the elevation of the study site to a common elevation using lapse rates (Section 4 provides background on lapse rates). The common elevation could be the elevation of the relevant start zone, or the average elevation of the relevant start zones if there are more than one, or an elevation near the local treeline.

d) Fit the snow supply data to a Gumbel extreme value distribution to calculate the relevant extreme snow supply values at the desired return periods (typically 3, 10, 30, 100, or 300-Year).

e) Perform the spatial interpolation (e.g. kriging) in a GIS platform to create an interpolated surface of snow supply data across the region where the relevant avalanche start zone(s) are located. Section 3 further describes spatial interpolation.

f) Find the location of the relevant start zone(s) on the interpolated surface and determine the extreme snow supply data values. Zonal statistics can be useful to summarize the interpolated snow supply raster data depending on the size and area of the relevant start zone(s).

g) Adjust these values from the elevation of the interpolated surface to the elevation of the relevant stat zone, again using lapse rates.

h) Adjust these values for the orientation to the prevailing wind, if required.

3. SPATIAL INTERPOLATION

Several spatial interpolation techniques (e.g. Burrough and McDonnell, 1998) commonly applied in weather data applications include:

- Inverse Distance Weighting (IDW) (e.g. Gandin, 1965),
- Kriging and its variants (e.g. Phillips et al., 1992),
- Smoothing spline interpolation (Hutchinson and Bischof, 1983),
- Nearest neighbour (Thiessen, 1911), or
- Triangulated Irregular Network (TIN) (e.g. Watson and Philip, 1984; Tsai, 1993).

Each of these techniques has advantages and disadvantages, and we have found that kriging or IDW produce the most robust results and are most applicable to highly variable snow supply data. Kriging accounts for spatial correlation between data points making it potentially more accurate for highly variable snow supply data, however it can be computationally intensive. IDW is simple to understand and implement, and is less computationally intensive than kriging, however it doesn't account for spatial correlation of the data. Some comparison studies between interpolation methods have shown a limited effect on overall results, even with the inferior nearest neighbour method showing only an approximate 10% error (e.g. Tabios and Salas, 1985). Another advantage of using these geostatistical techniques - such as kriging - is that they also provide a quantifiable measure of the confidence of these predictions.

4. LAPSE RATES

The method described in Section 2 uses lapse rates - the adjustment of snow supply data by elevation difference - for two parts of the analysis: 1) Adjusting snow supply data collected from fixed sites to a common elevation (e.g. local treeline, 1500 m, 2000 m) to perform the spatial interpolation, and 2) adjusting the snow supply estimate from the interpolated surface to the relevant avalanche start zone.

Several lapse rates are commonly used in Western Canada:

- Claus et al. (1984) provide a formula for elevation adjustment on HSW_{30} (30-year estimate for snowpack water equivalent) for areas in British Columbia:

  $$HSW_{30} = 357 - 0.259elev + 0.000501elev^2$$

  $$where\ elev\ is\ the\ elevation\ in\ metres.$$

- McClung (2001) provides regressions for three sub-regions of the Columbia Mountains in Canada which yield lapse rates between 33- and 71-mm SWE / 100 m.

- Jamieson et al. (2018) suggest a simple factor of 5 cm HS for each 100 m difference in elevation between the fixed snow data site and the start zone.

Taking advantage of advances in modern precipitation modelling, we analyzed predictions from the SnowCast model to derive lapse rates in different parts of western Canada. SnowCast incorporates the Canadian Hydrological Model chain with downscaled weather forecasts from the High-Resolution Deterministic Prediction System (HRDPS) model into the Factorial Snow Model (FSM) snow cover model (Marsh et al., 2020). SnowCast provides forecasts of HS and SWE on a 50 m resolution grid across southern BC and Alberta, accounting for localized weather patterns, blowing snow, and solar radiation in complex terrain.

We analyzed gridded HS and SWE SnowCast data for April 1, 2021 (Figure 4-1), when snow coverage was near its peak for the season. We extracted HS and SWE for all grid cells within public forecast regions, selecting only those within 500 m of the local treeline elevation and with a slope angle less than 10°. We excluded cells with snow depths in the top 5th percentile to avoid unrealistic large values in avalanche deposits formed by SnowCast's avalanche module. For each region, we fit a linear model to quantify the relationship between HS/SWE and elevation, using the slope of the regression line to estimate lapse rates. Finally, we averaged the lapse rates for nine prominent mountain ranges. The average lapse rates are shown in cm HS / 100 m in Figure 4-2 and mm SWE / 100 m in Figure 4-3. Table 4-1 also shows the lapse rates along with the average bulk densities from the model.

These lapse rates compare well to previously calculated rates, can be applied specifically to the mountain range where the project site is located, and can be applied to either HS or SWE data depending on what is readily available.

The ratio between the bulk snowpack density and the maximum three-day height of snow increase (HN72) can be used to estimate lapse rates for HN72:

$$\mathbf{Lapse_{HN72}} = \mathbf{Lapse}_{\boldsymbol{HS}}\ \mathbf{x}\ \frac{\boldsymbol{Density_{HS}}}{\boldsymbol{Density_{HN72}}}$$

Where:

$Density_{HS}$ = average bulk density of the snowpack

$Density_{HN72}$ = average density of the three-day snowfall

$Lapse_{HS}$ = Lapse rate used for the depth of the snowpack in centimeters.

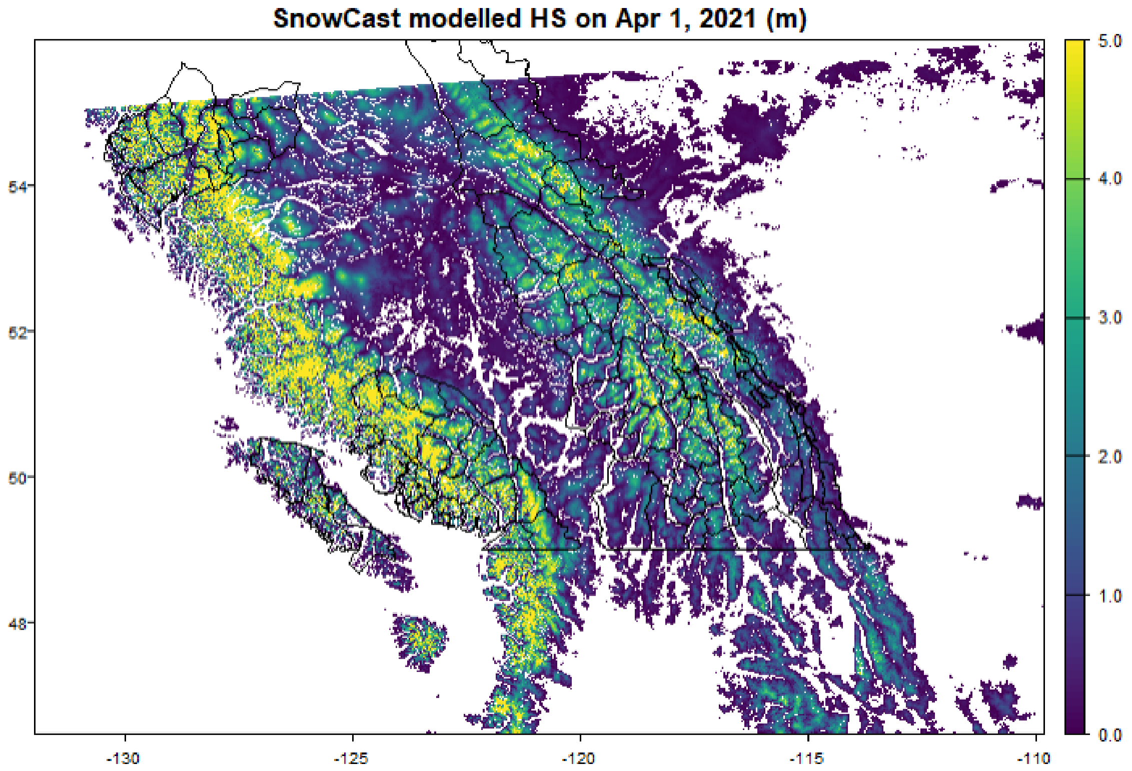

Figure 4-1: SnowCast modelled height of snow data (m) for April 1, 2021 across parts of Western Canada and the United States.

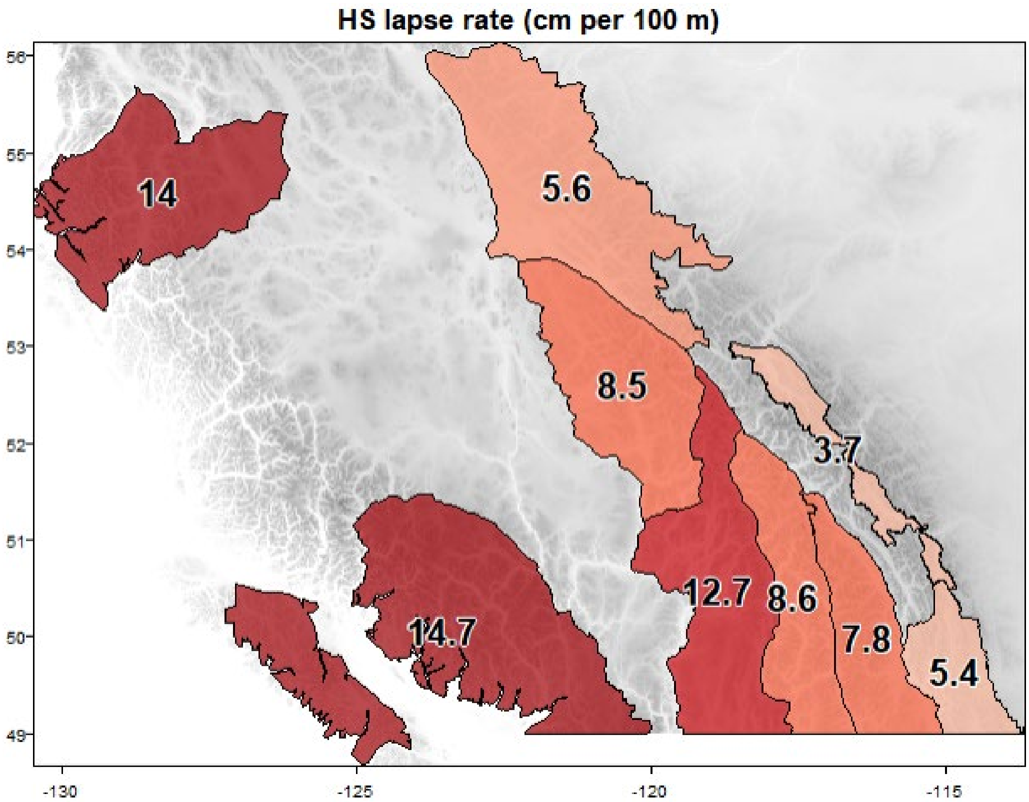

Figure 4-2: Average lapse rates derived from SnowCast modelled snow cover data for April 1, 2021 for nine prominent mountain ranges in Western Canada shown as height of snow per 100 m elevation (cm / 100 m).

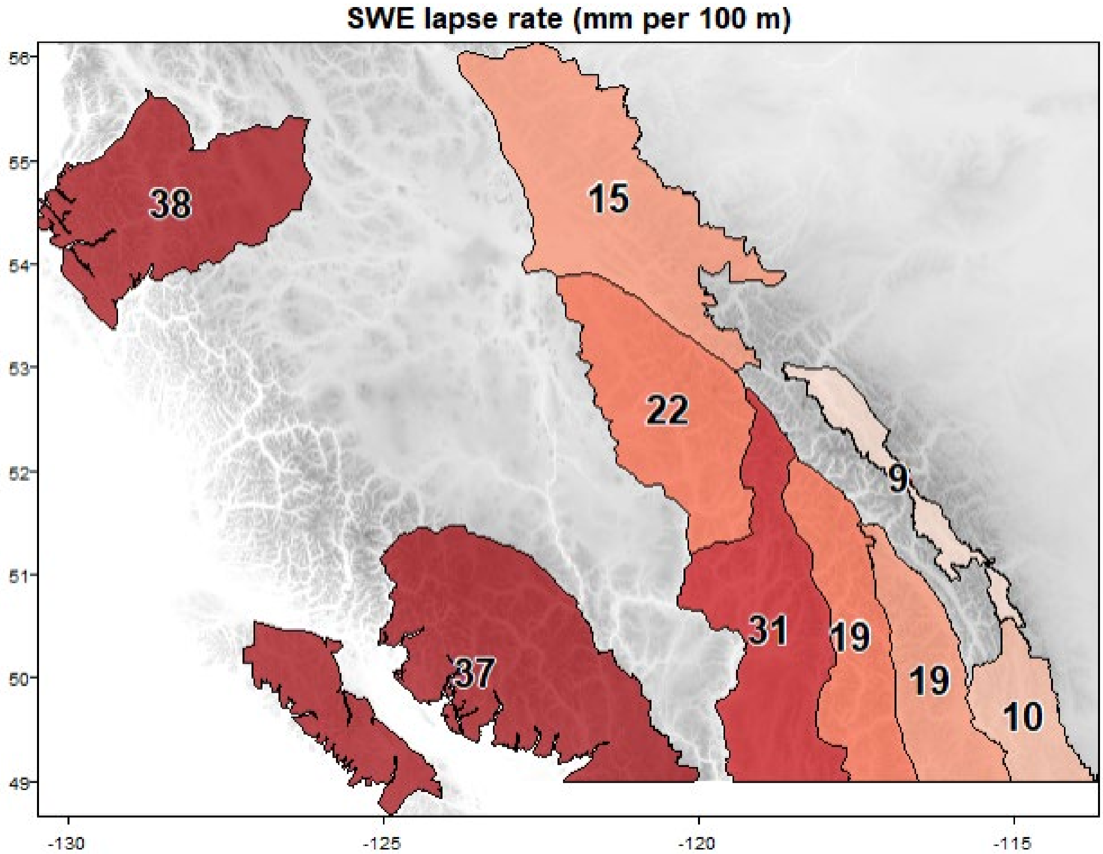

Figure 4-3: Average lapse rates derived from SnowCast modelled snow cover data for April 1, 2021 for nine prominent mountain ranges in Western Canada shown in snow water equivalent per 100 m elevation (mm / 100 m).

Table 4-1: Average lapse rates for nine prominent mountain ranges in Western Canada shown in height of snowpack (HS) and snow water equivalent (SWE). The average bulk density to convert between the two estimates is also shown.

Mountain Range	***HS (cm)***	***SWE (mm)***	***Density (kg/m^3)***
South Rockies	5.4	10.2	187.8
Selkirks	8.6	19.3	225.0
Central Rockies	3.7	8.7	237.0
Monashees	12.7	30.8	243.0
Purcells	7.8	19.2	244.7
South Coast	14.7	36.7	250.0
Cariboos	8.5	22.2	260.8
North Rockies	5.6	14.6	261.5
North Coast	14.0	38.4	274.3

5. APPLICATION

Next, we show two examples where this methodology was applied to engineering planning projects in Canada: 1) Kananaskis Country, Alberta, and 2) Stewart, British Columbia.

5.1 Kananaskis Alberta

First, annual snow water equivalent data from snow pillows and height of snow data from remote automated weather stations were collected from a variety of fixed sites in the Alberta Parks Kananaskis region. Figure 5-1 shows the locations of the fixed snow data sites. The data were filtered to obtain the annual maximum values for all years with available data. Average bulk density of 300 kg/m^3 was used to convert the snow water equivalent to height of snow.

Second, the annual maximum height of snow was adjusted to a common elevation of 2000 m using the Jamieson et al. (2018) 5 cm / 100 m elevation factor. For example, the Sunshine Environment Canada weather station is located at 2187 m, so the height of snow was reduced by 9.4 cm ((2187 m – 2000 m) x 5 cm / 100 m) to account for the elevation difference between the station and the common elevation of 2000 m.

Third, the data were fitted to a Gumbel extreme value distribution to determine the extreme potential height of snow for 3, 10, 30, 100, and 300-Year return periods.

Fourth, the project required estimates for the 100-Year return period extreme snowpack depth, so these 100-year values were used for the spatial interpolation. The geographic information system QGIS was used to perform the kriging interpolation which is also shown in Figure 5-1.

Fifth, values from the 100-year interpolation were extracted at the locations of the relevant avalanche start zones (Figure 5-1 red polygons). For example, the 100-year value for the avalanche path start zone near the "Burstall Pass" weather station was found to be 240 cm.

Lastly, these 100-year return period estimates were adjusted for any elevation differences between the avalanche start zone at 2700 m and the common 2000 m elevation used for the interpolation. The 5 cm / 100 m factor was used resulting in an estimated 275 cm maximum 100-year height of snow. And the estimates were adjusted based on judgement for the start zone orientation to the prevailing winds.

Overall, the spatial interpolation shown in Figure 5-1 shows deeper snowpacks in the southwest part of the region which would be expected due to orographic lift on the side of the mountain range first encountering most storm systems.

5.2 Stewart British Columbia

Figure 5-2 shows the results from the methodology applied to a similar engineering project near Stewart BC. Again the spatial interpolation shows deeper snowpacks on the coastal side of the mountain range and shallower snowpacks more inland. The interpolation also accounts for the known deeper snowpack areas around the Granduc Mine.

6. DISCUSSION

While the reliance on engineering judgement to interpolate spatially between weather stations and project sites can be reduced, the proposed methods do not eliminate it. Judgement is still required to account for the start zone orientation to prevailing winds and for the effect of prominent terrain features. Further, the proposed methods - and all similar methods relying on snow supply data acquired from fixed sites - work well with higher density and close proximity of data sites relative to the project location. In other words, spatial interpolation methods break down and the effectiveness is reduced when snow supply data are sparse. Manual measurements from site visits, interviews to capture local knowledge, using modelled precipitation data (e.g. PRISM Climate Data), and/or the application of judgement can provide options.

The proposed methods have been developed for local, project-specific analysis. However, extreme snow depth maps can be constructed for large regions (e.g. British Columbia, Western Canada). Such maps have been created in Austria (e.g. Schellander and Hell, 2018) where planners and engineers can acquire extreme snow depth estimates for any location in the country adjusted for the relevant start zone elevation. A logical next step would be the creation of these extreme snow supply maps for the mountainous regions of Canada.

7. CONCLUSIONS

This paper has outlined a methodology for estimating extreme snow supply in avalanche start zones, which is critical for understanding and mitigating avalanche risk. By integrating spatial interpolation techniques and elevation lapse rates, the proposed approach reduces some of the reliance on professional judgment, especially when dealing with significant spatial variations in snow supply. While the methodology has the potential to enhance accuracy, it does not entirely eliminate the need for professional judgment. The approach is most effective when there is a high density of snow data sites in close proximity to the project location. However, in areas with sparse data, additional measures such as manual measurements, interviews, or modelled precipitation data may be necessary to improve reliability. The development of extreme snow depth maps for larger regions, similar to those in Austria, represents a promising avenue for future research and application, potentially benefiting planners and engineers across the mountainous regions of Canada.

Figure 5-1: Spatial interpolation of the 100-Year extreme height of snow data shown as the transparent green to brown overlay. Darker green represents deeper snowpacks (335 cm) and light brown represents thinner snowpacks (125 cm). The figure also shows the fixed weather sites (green circles), the relevant avalanche paths for the project are (red polygons), the provincial border (purple line), the Trans-Canada Highway #1 (orange line), and Alberta Highway 742 (brown line).

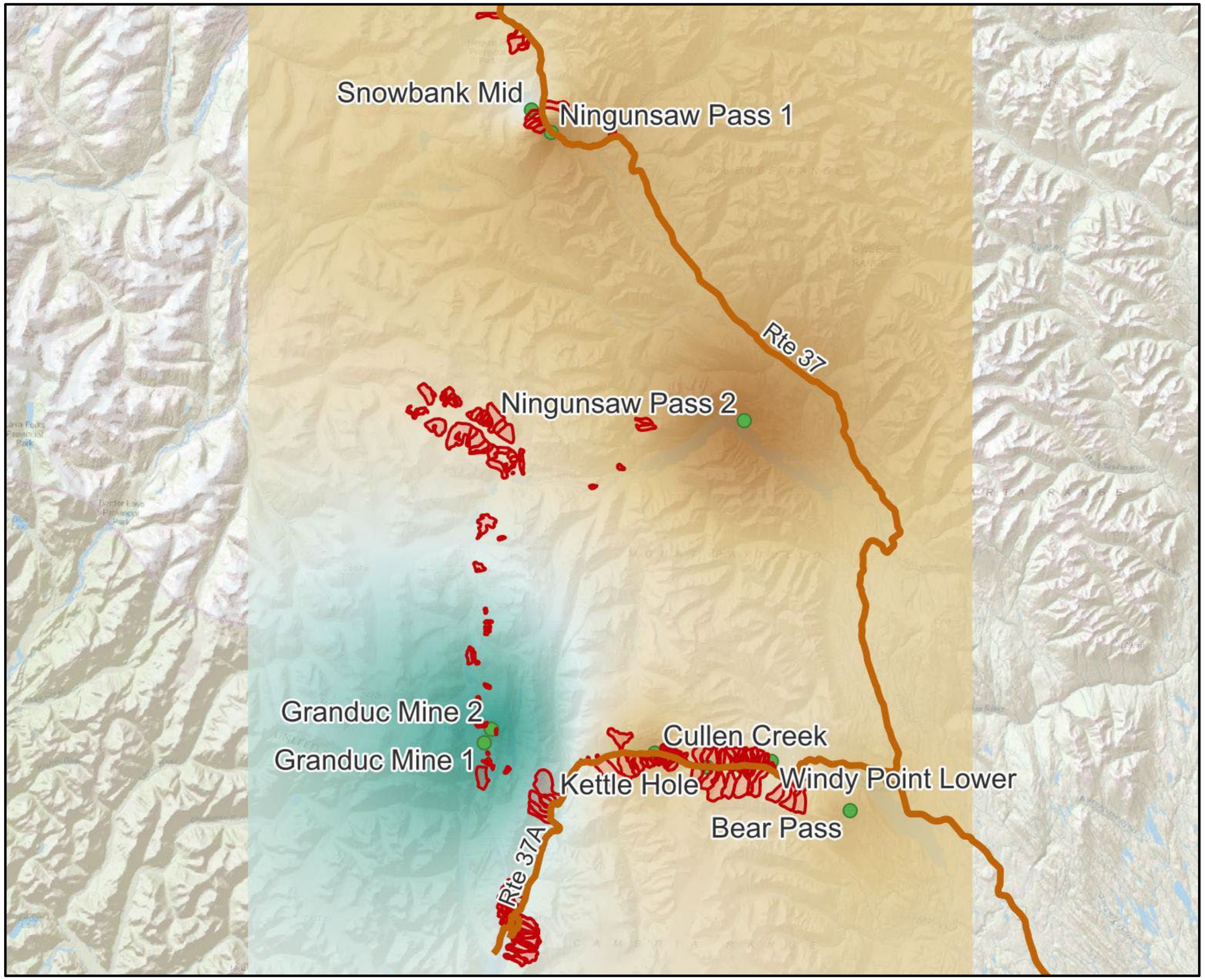

Figure 5-2: Spatial interpolation of the 100-Year extreme height of snow data shown as the transparent green to brown overlay. Darker green represents deeper snowpacks (945 cm) and light brown represents thinner snowpacks (390 cm). The figure also shows the fixed weather sites (green circles), the relevant avalanche paths for the project (red polygons), and BC highways (orange lines).

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