Snow mechanical properties variability at the slope scale, implication for snow mechanical modeling

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Abstract. Snow avalanches represent a natural hazard ~~for infrastructures~~ to infrastructure and backcountry recreationists. Risk assessment of avalanche hazard is difficult due to the sparse nature of available observations informing on snowpack mechanical and geophysical properties and overall stability. The spatial variability of these properties also adds complexity to ~~the decision-making~~ decision making and route finding in avalanche terrain for mountain users. Snow cover models can simulate snow mechanical properties with good accuracy at fairly good spatial resolution (around 100 m). However, monitoring small-scale variability at the slope scale (5-50 m) remains critical, since slope stability and the possible size of an avalanche are governed by that scale. To better understand and estimate the spatial variability at the slope scale, this work explores links between snow mechanical properties and microtopographic indicators. ~~Four~~ Six spatial snow surveys were ~~carried out at two study sites~~ conducted in two study areas across Canada. ~~First, we compared the covariance models of snow mechanical properties and stability metrics between surveys. Then, we estimated snow mechanical properties, including point snow stability, using GAM spatial models (Generalized Additives Models) with microtopographic indicators as covariates.~~ Snow mechanical properties such as snow density, elastic modulus ~~, shear modulus and snow microstructural~~ and shear strength were estimated from a high-resolution snow penetrometer (SMP) at multiple locations over several studied slopes, in Rogers Pass, British-Columbia, and Mt Albert, Québec. Point snow stability such as the skier crack length, critical propagation crack length and a skier stability index were derived using the snow mechanical properties from SMP measurements. Microtopographic indicators such as the topographic position index (TPI), vegetation height and proximity, ~~up-wind slope index (wind exposed/sheltered area)~~ wind-exposed slope index and potential radiation index were derived from Uncrewed Aerial Vehicles (UAV) surveys with sub-meter resolution. We computed the variogram and fractal dimension of snow mechanical properties and stability metrics and compared it between them. The comparison showed some similarities in the correlation distances and fractal dimensions between the slab thickness and the slab snow density and also between the weak layer ~~microstructural~~ strength and the stability metrics. We estimated snow mechanical properties, including point snow stability, using GAM spatial models (Generalized Additives Models) with microtopographic indicators as covariates. The use of covariates in GAM models suggested that microtopographic indicators can be ~~use to estimate~~ used to estimate with fair precision the variation of the snow mechanical

properties, ~~and with less precision,~~ but not the stability metrics. We observed a difference in spatial pattern between the slab and the weak layer that should be considered in snow mechanical modeling.

1 Introduction

Snow avalanches represent a natural hazard ~~for infrastructures~~ to infrastructure and backcountry recreationists across mountainous areas all across the world (Stethem et al., 2003; Techel et al., 2016). Snow avalanches can be divided into different types~~of avalanches~~: wet, dry, non-cohesive or slab avalanches. However, dry-snow slab avalanches are the most difficult to predict and ~~the ones causing~~ are responsible for the most fatalities (Techel et al., 2016). They require a shear crack usually initiated by a person or new ~~stresses from snowfall or warming~~ snowfall in a weak porous layer underneath a cohesive snow slab. Then, the crack must ~~be at a critical length~~ reach a critical size in order to self-propagate across the slope for a slab avalanche to occur. Practitioners and forecasters estimate the probability and size of an avalanche from ~~punctual~~ point-scale information on weak layers and slab properties across different scales. However, the sparse ~~and punctual~~ nature of available observations on snowpack properties makes the forecasting of ~~dry snow~~ slab avalanches difficult (Hägeli and McClung, 2004). The snow spatial variability at different scales also adds complexity to this challenging task by adding uncertainty on whether the properties measured in the field are representatives of the slab and weak layer system (Schweizer et al., 2008a).

The spatial variability of snow properties is well documented in climate studies (e.g. Harper and Bradford, 2003), glacier dynamics (e.g. Pulwicki et al., 2018), snow hydrology (e.g. Deems et al., 2006), mountain meteorology ~~(Mott et al., 2011)~~ (e.g. Mott et al., 2011), permafrost (e.g. Wirz et al., 2011) and snow ~~avalanche (e.g. Schweizer et al., 2008a). Several studies have looked at~~ (e.g. Schweizer et al., 2008a). Numerous studies have investigated the spatial distribution of snow depth and its water equivalent to ~~feed~~ support hydrological models (e.g. Deems et al., 2006; Grünewald et al., 2010; Schirmer et al., 2011; Winstral et al., 2002). Some ~~authors~~ researchers went further to estimate and analyze the spatial pattern of snow depth (Deems et al., 2006; Mott et al., 2011; Schirmer and Lehning, 2011; Trujillo et al., 2007). They analyzed the scaling properties and the fractal dimension of the snow depth, which can be estimated with the slope of a log-log variogram or with the periodogram of the spatial signal. The idea behind the scaling properties and fractal dimension is that many scales can define a spatial pattern instead of one scale like the correlation length in a variogram. Fractal dimension ~~can also characterize~~ also characterizes the roughness or smoothness of a spatial pattern ~~over~~ across multiple scales. These ~~authors~~ researchers compared the fractal dimension of snow depth with the fractal dimension of topographic indicators and vegetation. However, no ~~study has studied~~ studies have explored the fractal dimension of snow mechanical properties. Most ~~of these studies are mainly based~~ studies have relied on LiDAR or manual snow probe surveys to estimate ~~the~~ snow depth. However, snow depth is not a ~~good~~ sufficient indicator of the conditions required for snow avalanches to occur.

There are ~~better~~ more effective indicators, such as snow stability tests, to estimate the conditions for snow avalanches. These tests are widely used in the avalanche industry to assess snow stability and, ultimately, snow avalanche hazard. ~~The result of these tests represents~~ These tests provide a qualitative evaluation of the mechanical interaction between the cohesive slab and the weak layer. Some studies ~~investigate~~ investigated the variability of several snow stability tests on an avalanche-prone slope (Kronholm and Schweizer, 2003; Birkeland, 2001; Campbell and Jamieson, 2007). ~~These results demonstrate~~ They demonstrated a variation in the test results and spatial patterns with variograms and correlation distances around 5-20 m. However, these snow stability tests do not provide information on the snow mechanical properties of the slab and the weak layer. ~~Snow stability tests are also~~ Additionaly, these tests are time-consuming, ~~causing the~~ leading to limited spatial sampling density and extent ~~to be relatively small~~ for statistical analysis, around ~~20 m and below~~ 30 ~~measurements. The~~ m measurements covering 20 m. To address this limitation, the high-resolution snow ~~penetrometer, Snowmicropen~~ micro-penetrometer (SMP) ~~,~~ ~~is~~ was used to characterize the mechanical and structural properties of the snow, ~~such as the thickness of the slab and the weak layer~~ including slab and weak layer thickness, density, ~~the density, the~~ elastic modulus, and ~~the~~ microstructural strength of the weak layer (Proksch et al., 2015; Löwe and van Herwijnen, 2012; Johnson and Schneebeli, 1999). Several ~~authors~~ studies characterized stability based on snow mechanical properties of the slab and the weak layer (Föhn, 1987; Gaume and Reuter, 2017; Reuter et al., 2015b; Monti et al., 2016; Schweizer and Reuter, 2015; Reuter and Schweizer, 2018; Rosendahl and Weißgraeber, 2020). Gaume and Reuter (2017) proposed a stability index that ~~represents~~ accounts for both failure initiation and propagation propensity~~with~~ , using an analytical method ~~that can be easily applied~~ applicable to SMP profiles.

The SMP was used in snow spatial studies because it can rapidly and accurately measure the mechanical properties of the snow relevant to snow stability on a slope prone to avalanche (Bellaire and Schweizer, 2011; Feick et al., 2007; Kronholm and Schweizer, 2003; Landry et al., 2004; Lutz et al., 2007; Lutz and Birkeland, 2011). These studies ~~report~~ reported spatial patterns of weak layer properties with ~~a correlation distance~~ correlation distances ranging from 0.5 to 20 m. However, the sampling density ~~and the spatial extent~~ of the survey ~~were around 20 to 50 m for the spatial extent and~~ was between 20 to 50 SMP measurements depending on the studies ~~. Reuter et al. (2016) also~~ and the spatial extent was covering 20 to 50 m. Reuter et al. (2016) used stability metrics based on SMP-derived snow mechanical properties ~~derived from the SMP~~ to show spatial patterns of snow stability with a ~~larger~~ higher sampling density and extent compared to the other studies. The correlation distance obtained from this study was still in the same range as the others with some exceptions between 40 and 60 m. The differences in spatial patterns of snow instability ~~differed between the surveys , and these results~~ among surveys were attributed to ~~the different~~ various meteorological processes interacting with the terrain and ~~the~~ snow cover (e.g. Schweizer et al., 2008a; Reuter et al., 2016).

~~From these results~~Based on these findings, several studies have simulated artificial spatial patterns of the weak layer in mechanical models to ~~explain~~ understand the effect of the spatial variability of the weak layer on the slope stability, given the likelihood of an avalanche (Gaume et al., 2014, 2013; Kronholm and Birkeland, 2005; Fyffe and Zaiser, 2004). Gaume et al. (2015) used the same method to estimate the propensity for tensile failure in the slab and the relationship with the size of ~~the~~ avalanche release. These studies ~~were based on the assumption~~ typically assumed that the spatial patterns of the weak layer ranged from 0.5 to 10 m, with the other parameters being constant for simplicity. ~~Bellaire and Schweizer (2011) suggested~~ Kronholm (2004) and Bellaire and Schweizer (2011) demonstrated that the spatial patterns of the weak layer and the slab could have different correlation distances for the same survey, resulting in some cases in a smoother slab variation than the weak layer or the opposite. However, the spatial extent of the snow sampling was relatively small, only twice as the measured correlation length, and could affect the estimation of the correlation length (e.g. Dale and Fortin, 2014; Skøien and

Blöschl, 2006). ~~The slab and the weak layer could have a different spatial pattern, resulting in some cases with a slab variation smoother than the weak layer or the opposite.~~ This matter should be further explored with a spatial sampling extent greater than 20 m in order to improve the implementation of snow variability in mechanical models.

Spatial patterns of snow properties can ~~also~~ be explained and estimated by statistical models with exploratory spatial variables. In the past, environmental variables were mapped using a linear regression model and kriging with external drift. Several studies used kriging to map point snow stability, such as snow stability test results, SMP-derived mechanical properties, and stability metrics (Birkeland, 2001; Mullen and Birkeland, 2008; Reuter et al., 2015a; Schweizer and Kronholm, 2007). These studies ~~showed~~ demonstrated that point snow stability can be ~~partially explained~~ spatially estimated using topographic indicators such as aspect, altitude, and slope angle on the regional ~~/ massif~~ scale. These ~~topographic indicators can express~~ indicators capture the complex interactions between ~~the meteorological process and the terrain~~ meteorological processes and terrain features, such as ~~wind deposition from lee / windward slopes and~~ snow deposition by wind and the influence of solar radiation on the snow surface between different slopes (Reuter et al., 2016). However, ~~spatially autocorrelated residuals remained from these statistical models using topographic indicators. This remaining~~ despite the use of statistical models incorporating topographic indicators, spatially autocorrelated residuals persisted. This residual spatial variability could be ~~explained and estimated by~~ attributed to other spatial phenomena ~~on~~ at a smaller scale. ~~At~~

In studies focused on the slope scale, ~~other authors~~ researchers successfully explained and estimated the spatial variability of snow depth~~where slope~~, even in cases where slope angle, aspect, and ~~altitude remained mostly stable~~ elevation remained relatively constant (e.g. Deems et al., 2006; Grünewald et al., 2010; Pulwicki et al., 2018; Revuelto et al., 2020; Meloche et al., 2022; Trujillo et al., 2007; Winstral et al., 2002). They used in their studies microtopographic indicators such as the shape of the slope (topographic position index TPI), vegetation index and microclimate indexes such as wind exposure (Winstral index) or the potential of solar radiation. Guy and Birkeland (2013) ~~has shown the potential to use microtopography to spatially estimate~~ related these terrain parameters to potential trigger zones, but the characterization of their potential trigger was ~~only with~~ limited to the presence of depth hoar layers. However, the presence of depth hoar crystals is insufficient to characterize snow stability~~is insufficient and~~, which requires more information on snow mechanical properties for the slab and the weak layer. These mechanical properties can be accurately measured with the SMP (Reuter et al., 2019). ~~No studies~~ Reuter et al. (2016) have linked snow stability ~~and~~ from SMP-derived snow mechanical properties with microtopography indicators ~~in spatial modeling. This could lead to an improvement of the potential avalanche size mapping (Veitinger et al., 2016), but integrating variations of the snow mechanical properties as input in snow mechanical modeling. Also, the spatial studies cited above~~ at the basin scale. While previous spatial studies explored linear relations between point snow stability and topographic indicators, ~~but Reuter et al. (2016) suggests that non-linear relationships should be explored. Other statistical models like General Additive Models (GAM's) can represent~~ Reuter et al. (2016) suggested that the relation between point snow stability and topographic indicators could be non-linear~~relationships and should be explored~~.

The snow mechanical variability can also affect the overall slope stability with the so-called knockdown effect (Fyffe and Zaiser, 2004; Gaume et al., 2014; Kronholm and Schweizer, 2003; Schweizer et al., 2008a)~~, promoting an overall failure of the slope with long-scale spatial variation of snow mechanical properties. Spatial~~. This effect denotes that variations in weak layer strength can cause the slope to fail before the load reaches the corresponding average strength, and this effect is more prominent with a longer correlation length. Additionally, spatial variation in snow can ~~also affect~~ influence the size of the avalanche release (Gaume et al., 2015)~~, when small-scale~~. Small-scale variation can promote slab tensile failure and smaller avalanches.

It is necessary to spatially explain and estimate the mechanical properties of ~~the snow and the stability of the~~ snow and snow stability snow with microtopography indicators at the slope scale. This study is based on the limitations and suggestions of Reuter et al. (2016), who ~~was able to predict the spatial variation~~ modeled the spatial patterns of two stability metrics at ~~a larger~~ the basin scale with terrain-based indicators such as slope angle, aspect and elevation. This work ~~will attempt to predict the~~ aims to estimate spatial variation at a smaller scale using microtopographic indicators ~~with a~~ through non-linear regression. As such, the ~~main objectives~~ first objective of this paper ~~are~~ is to compare the scaling effect of the snow mechanical properties and the stability metrics for slopes prone to avalanches with different characteristics~~and spatially estimate the~~. The second objective is to spatially estimate snow spatial variability using microtopography indicators. ~~A supplementary objective will be to compare the parametrization of snow mechanical properties in relation to~~ An additional objective is to compare our dataset with two empirical power law fits from the literature (Bažant et al., 2003; McClung, 2009), which estimate the shear strength of the weak layer and slab density from the slab thickness~~to our dataset to improve snow mechanical modeling~~.

2 Data and methods

2.1 Study sites

In order to spatially estimate the spatial variability of snow using microtopography indicators, we ~~choose three study sites according to~~ selected four study sites based on their specific microtopography and microclimate context. The first study site ~~was~~ is located on Mount Albert in Gaspésie National Park, Québec, Canada (Fig. 1~~b~~a). The winter climate of the region is characterized by extreme changes caused by 1) low-pressure continental systems that bring heavy snowfall up to 100 cm in 48 hours followed by Artic cold air masses with strong ~~northwestern~~ northwesterly winds, 2) warm and wet air masses coming from the south creating rain-on-snow events (Meloche et al., 2018). The study site is named Arete de Roc (AR) and is located in a subalpine/tundra area heavily affected by wind and snow transport compared to the other sites. This site has a high ~~soil~~ ground roughness with large boulders and small trees (1 m high). The slope angle is ~~constant~~ uniform (33°) with a convex roll at the top and a concavity at the bottom (Fig. 1). Two other surveys in Mt Albert at Épaule du Mur (EP) ~~is added~~ were added only for our supplementary objective, ~~adding~~ which will add more dense and thicker slabs in our comparison to ~~classic~~ the parameterization of snow mechanical properties ~~parametrization~~ in relation to slab thickness (Bažant et al., 2003; McClung, 2009). ~~These~~ However, these two surveys were not used ~~for the spatial analysis because their~~ in the variogram analysis and spatial modeling due to their insufficient spatial density and extent ~~are insufficient~~ compared to the other surveys. They were added to the study only to obtain more data points for Figure 3.

Two study sites are in Glacier National Park, located in Rogers Pass, British Columbia, Canada (Fig. 1). Our study sites are on Mount Fidelity, which receives heavy ~~snowfall~~ snow precipitation (Hägeli and McClung, 2003), and has a snow cover of around 2-3 m and sometimes up to 4 m. The Mount Fidelity area is classified as a ~~Transitional~~ transitional snow and avalanche climate influenced by warm and wet air masses from the Pacific that bring heavy snowfall and cold air masses from the ~~North~~north, leading to the development of persistent weak layers (Hägeli and McClung, 2003). This study area experiences annually several persistent weak layers consisting of buried surface hoars or facets, relevant for stability assessment~~purposes~~. The first study site at Mount Fidelity is located just above the tree line at ~~2300 m .~~2020 m a.s.l on a shoulder named Round Hill (RH). This site is an alpine area with low soil roughness (Fig. 1). The slope angle is relatively low (near 25°), with ~~longer and smoother~~ long and smooth convex rolls around 20-30m. The last study site, Jim Bay Corner (JBC), is located below the tree line at 1830 m ~~.~~a.s.l. It is an open forested area with relatively low ~~soil~~ ground roughness with small shrubs. The site has 10 m tall trees which ~~created~~ create some shaded areas and the slope angle is relatively constant (near 20°) with small convex rolls around 5-10 m (Fig. 1).

2.2 Data collection and sampling strategies

~~This study presents 4~~ For the spatial analysis, this study presents four snow spatial surveys collected during winter 2021-2022 (Fig. 1): 25 February 2022 at the Arête de Roc site (AR22-PP), 27 January 2022 at the Round Hill site (RH22-PP), 19 January 2022 at Jim Bay corner (JBC22-SH), and 24 January 2022 at Jim bay corner (JBC22-PP). ~~A summary of these surveys will be presented first in 3.1~~Two more surveys were added for the comparison of different parametrizations of snow mechanical properties: 24 Janvier 2019 at Épaule du Mur (EP19-FC) and 29 Février 2020 at Épaule du Mur (EP20-DF). Snow mechanical properties were measured using the high-resolution SMP. To compare the spatial ~~pattern~~ patterns of snow mechanical properties and snow stability, each SMP measurement was made following a sampling scheme~~following~~ , according to the concept of the scale triplet which is the support, spacing, and extent described by Blöschl and Sivapalan (1995). The support is the diameter of the SMP ~~penetration cone~~ tip which is around 5 mm~~with a 1 mm vertical resolution. This ensures~~ , guaranteeing a proper estimation of the ~~snow mechanical properties because they are linked to their microstructural properties at the mm scale~~microstructural properties of the snow. A minimum spacing of 2 m and a study site extent ~~of~~ covering around 60 to 100 m were chosen ~~in order for~~ to allow the spacing to be at least half of the ~~estimated correlation length reported by the literature~~ expected correlation length and the extent ~~needs~~ to be two to five times the ~~estimated correlation , which is~~ expected correlation length. The expected correlation length has been reported to be around 5-20 m ~~reported by~~ from several studies (Bellaire and Schweizer, 2011; Lutz et al., 2007; Reuter et al., 2016; Schweizer and Reuter, 2015). This method ensures a ~~proper estimation~~ reliable estimate of the spatial pattern, defined by ~~the~~ both spatial variance and ~~the~~ autocorrelation distance (Skøien and Blöschl, 2006; Dale and Fortin, 2014). Our sampling scheme also needs to be adequate for the second objective, which is the spatial estimation of snow mechanical properties and stability metrics using microtopographic indicators. Therefore, the sampling scheme was adjusted for each specific study site ~~in order~~ to obtain a representative distribution of microtopographic indicator values while respecting the scale triplets mentioned above. The sampling was conducted by randomly traversing the study site while adhering to the minimum spacing, and also by characterizing the down and cross-slope for an isotropic sampling. The sampling was stopped when the study site was almost covered with 60 to 80 SMP measurements. The resulting sampling is shown in Figure 1. Random sampling ~~helps to have a good estimation of spatial parameters with limited samples~~ contributes to

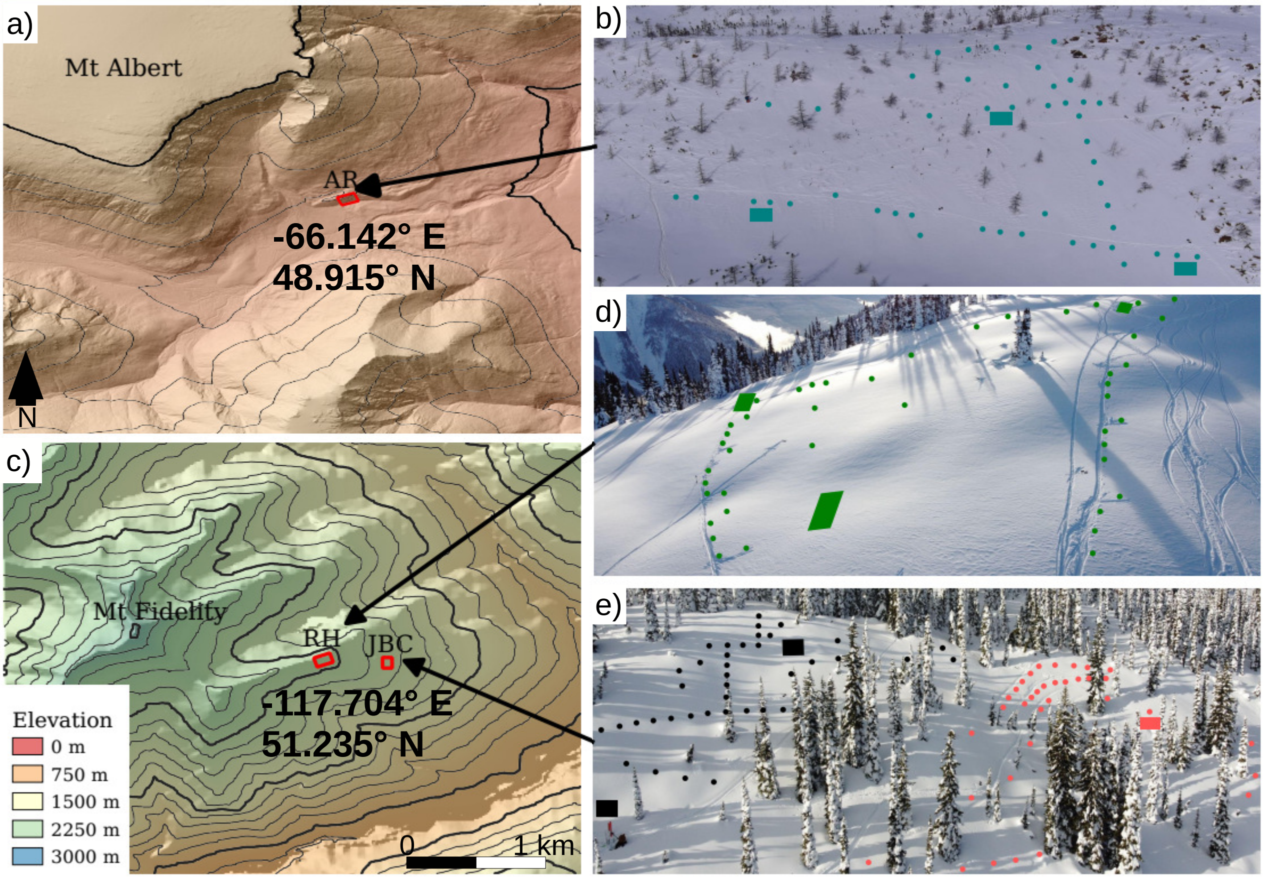

Figure 1. Map of the study area of a) Mount Albert, Québec, Canada, ~~representing~~ with the study site b) Arête de Roc with the 25 February 2022 survey in blue (AR). c) Mount Fidelity study area, British Columbia, Canada, with ~~the study~~ sites: d) Round Hill (RH) with the 27 January 2022 survey in green and e) Jim Bay corner (JBC) with the 19 January 2022 survey in red and the 24 January 2022 survey in black. The aerial photography is from the UAV flight of each study site and the snow spatial sampling is represented by circles for the locations of SMP measurements and the squares are the snow profile locations.

obtain a robust estimation of the correlation length with limited SMP measurements (Kronholm and Birkeland, 2007; Skøien and Blöschl, 2006).

~~In order to correctly interpret~~ To ensure an accurate interpretation of the SMP signal, the weak layer needed to be identified and characterized from a ~~"test"~~ snow profile. Full characterization of the snow stratigraphy was not needed for our analysis, so a shorter version ~~that we called the "test"~~ of snow profile was used to optimize the time ~~on~~ in the field. Two or three ~~test~~ snow profiles were ~~made~~ conducted per snow spatial survey, spaced at least 20 m apart and positioned next to SMP measurements (Fig. 1). In each test snow profile, we first performed two compression ~~snow~~ tests to identify the weak layer (Canadian Avalanche Association, 2016). The weak layer was attributed to the uppermost compression test results ~~which were~~ consistent in both compression tests. Then, we visually characterized the types and sizes of the snow grains of the weak layer~~, and finally~~. Finally, a propagation saw test was performed to measure the critical crack length of the weak layer (Gauthier and Jamieson, 2008). ~~We considered every layer~~ Layers situated above the weak layer ~~to be~~ were considered part of the slab. This assessment ~~enables us to correctly~~ allowed us to accurately identify the weak layer ~~to~~ in the nearest SMP profile and ~~then identify the weak layer~~ subsequently in the remaining SMP profiles. Each snow measurement, SMP or snow profile, was georeferenced using a GNSS receiver with centimeter accuracy. ~~In addition to snow measurements~~Furthermore, for each study site, aerial imagery was captured by a quad-rotor UAV with RGB sensor ~~for each study site~~ to characterize the topography both in the summer and ~~in~~ winter on the same day ~~of~~ as the spatial snow survey~~to characterize the snow surface~~. Ground / surface models were generated using a *structure from motion (sfm)* photogrammetry algorithm (Westoby et al., 2012) with ground and snow control points~~to georeference~~, ensuring georeferenced models with centimeter accuracy (< 2 cm in x,y and < 5 cm in z).

2.3 Snow mechanical properties and stability metrics

This section ~~will present~~ describes the workflow used to process every SMP profile~~in order to obtain~~, extracting several snow mechanical properties needed for stability assessment. Three stability metrics were ~~then found using~~ derived from these snow mechanical properties. Figure 2 presents the summary of this workflow.

2.3.1 SMP signal processing and snow properties

Each SMP signal was visually interpreted to identify ~~the~~ distinct layers. First, the weak layer was identified on the SMP signal next to the snow profile, ~~with the corresponding depth of the~~ based on the failure depth in the corresponding compression test. Then homogeneous layers above the weak layer were classified into slab layers (S_1, S_2,...S_i). This procedure was repeated ~~to the rest of~~ for the remaining SMP signal. To obtain the macroscopic mechanical properties ~~of snow~~ for each snow layer, the SMP signal was analyzed using a Poisson shot noise model with a moving window of 2.5 mm (Löwe and van Herwijnen, 2012). This analysis ~~is~~ was used to recover microstructural parameters~~such as~~, including the peak force F, the deflection at rupture δ, and the element length L (Löwe and van Herwijnen, 2012). Then, each structural and macroscopic snow mechanical property ~~needed to estimate~~ necessary for estimating the stability metrics can be retrieved: the slab thickness D, the weak layer thickness D_{wl}, the slab density ρ, the weak layer density ρ_{wl}, the elastic modulus of the slab E and the shear strength of the weak layer τ_p. ~~First~~Specifically, the slab thickness D and the weak layer thickness D_{wl} are ~~extracted directly~~ directly extracted from the

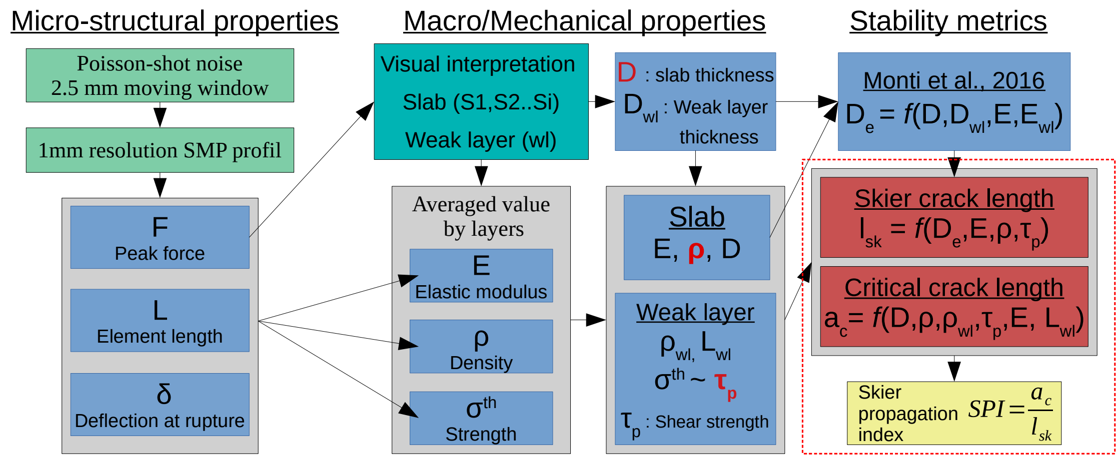

Figure 2. Schematic representation of the workflow used to process the SMP signal to obtain the snow mechanical properties and the stability metrics. The variables and the dashed square in red are the snow mechanical properties and the three stability metrics that will be analyzed and spatially estimated in this work. The parameters of the weak layer are denoted by the subscript X_{wl}.

2.5 Spatial modeling

2.5.1 Covariates processing

The second objective of this study is to explore the link between microtopographic indicators and snow mechanical properties and stability metrics ~~to explain and~~ in order to estimate snow spatial variability. The scale of these microtopographic indicators is defined by the size of the moving window used to derive them. Different sizes of moving windows were used to allow for a multiscale approach ~~in~~ describing the spatial process (e.g. Revuelto et al., 2020; Meloche et al., 2022; Veitinger et al., 2014). The ~~different sizes of the moving window~~ choice of different window sizes used in this study ~~are~~ is based on the literature and will be developed further below. Microtopography indicators are used as exploratory spatial variables and will be referred to as covariates in the spatial model. These covariates were ~~generated~~ derived from a digital terrain and surface model (DTM/DSM) generated ~~by photogrammetry with~~ through photogrammetry using the UAV imagery. The classification between the ground and the vegetation was performed manually ~~by visual inspectionbecause the~~ through visual inspection, given the small extent of the study site~~is small. Canopy models were also generated for every~~. Additionally, canopy models were generated for each snow study site by differentiating the DSM from the DTM. Snow depth maps were generated using a snow surface model (DSM_{snow}) and compared to the DTM model to retrieve the snow depth for each spatial snow survey.

All covariates ~~are~~ were raster data with an original spatial resolution below 0.1 m and were upscaled to a spatial resolution of 0.5 m. The final resolution of the spatial model ~~is~~ was the same as the covariates. The choice of covariates ~~is~~ was based on multiple studies that focus on spatial variation of snow depth that will be described below. Three groups of covariates, terrain shape, vegetation and microclimate, are presented in Table 1. ~~We choose two indicators~~ Two indicators were chosen to

Table 1. Covariates used for the spatial models with the source (DTM/DSM) and additional parameters.

Covariates	Abbr	
~~Easting and northing xy NA Python implementation Terrain slope Slope NA Qgis~~ Topographic Position index	TPI515	
Topographic Position index	TPI2550	
Vector ruggedness measure	VRM5	
Vector ruggedness measure	VRM15	
Vector ruggedness measure	VRM25	
Terrain slope angle	Slope	
Convexity	Convex	
Canopy height	Cano	
Distance to canopy	Dist-cano	R
Incoming solar radiation	Rad	~~Hourly time steps~~ Potanti
~~Snow depth H_s $DSM_{snow} - DTM$ Qgis~~ Winstral index	S_x	
Snow depth	H_s	
Easting and northing	xy	

describe the terrain shape, the topographic position index TPI and the vector ruggedness measure ~~. The topographic position index~~ VRM. The TPI is a slope descriptor indicating ridges, valleys or slopes at a given scale, ~~it refers to~~ referencing the position in elevation relative to ~~the neighbor~~ neighboring cells (Weiss, 2001). The TPI ~~is~~ was measured between a minimum radius and a maximum radius with weighted distance from the maximum radius (~~less important) (~~Table 1). The vector ruggedness measure VRM indicates the ruggedness of the terrain independently of ~~the slope~~ slope angle and aspect. The ruggedness ~~is derived with~~ was derived as the sum of elevation differences with ~~the neighbor~~ neighboring cells, but then decoupled with ~~the slope~~ slope angle and aspect, ~~meaning~~ which means that a flat and a steep slope could be homogeneous with low ruggedness ~~(?)~~ (Sappington et al., 2007). These two indicators ~~are widely used in the literature~~ were used to explain and estimate ~~the~~ snow depth (e.g. Revuelto et al., 2020; Meloche et al., 2022; Veitinger et al., 2014). The sizes of the different moving windows were chosen based on the values used in these studies to have a multiscale approach (Table 1). We ~~also~~ used the slope angle and convexity of the terrain ~~and also convexity~~ as exploratory variables. Vegetation also has an impact on the spatial variation of snow depth (Deems et al., 2006), we choose to use the canopy height for the influence of shrubs (around 0.3 and 0.5 m) and small trees (around 1 or 2 m) because ~~the snowpack~~ snow cover can be up to 3 or 4 m in some areas ~~in~~ of JBC and RH. Only trees above ~~5m~~ 5 m were masked from the study sites. We ~~use~~ used the radial proximity to vegetation greater than 2 m, to represent proximity to trees. Some authors also found that solar radiation (e.g. Lutz and Birkeland, 2011) and wind exposure (e.g. Winstral et al., 2002) were important ~~to spatially estimate~~ in spatially estimating snow properties. We selected as covariates the ~~potential of~~ potentially incoming solar radiation~~, the algorithm simulates~~. The algorithm simulated over a DSM (including trees), the trajectory of the sun in the sky based on the time of the year and the latitude of the study site. The

Each smooth function represents a combination of linear terms fitted to a covariate x_j. The order of the smooth function ~~defined~~ determines the non-linear degree or the *wigliness* of the fitted GAM. We ~~choose to keep the order low~~ kept a low order ($k = 3$) to avoid overfitting and non-realistic variation. ~~Although~~ While stepwise procedures are ~~widely~~ commonly used, they lack stability compared to newer methods such as shrinkage and boosting procedures (Hesterberg et al., 2008). We ~~choose to use~~ used the double penalty approach as a shrinkage method proposed by Marra and Wood (2011)~~. This method~~, which adds a smoothing parameter for each covariate spline function. This method is implemented in the ~~package~~ *mgcv* package in R. We ~~repeated this~~ applied this described method for six response variables ~~,~~ Y: the three snow mechanical properties ~~, the~~ (slab thickness D, slab density ρ_{slab}, and the shear strength of the weak layer τ_p~~, and also~~) and the three stability metrics ~~described above, which are the~~ (skier crack length l_{sk}, ~~the~~ critical crack length a_c and ~~the~~ skier propagation index SPI~~. These response variables were estimated with~~). The estimation of these response variables used GAM's ~~using~~ with the 13 covariates listed in Table 1.

The performance of our models was ~~assessed~~ evaluated with the root mean square error RMSE and the mean absolute error MAE using a 10-fold cross-validation approach. This ~~procedure splits the sample randomly~~ involves randomly splitting the sample into 10 subsets~~and fits~~, fitting the model to the 9 subsets~~and compares~~, comparing it to the remaining subset, ~~this procedure is repeated~~ and repeating this procedure 10 times. The percentage of deviance explained (sum of squared errors) ~~is~~ was computed to demonstrate the amount of total variance accounted by the model, this metric is more suited for non-linear model compared to R^2, which is still shown in the results for comparison. Once our model ~~is~~ was fitted (and cross-validated) and the covariates ~~are selected, we estimate~~ were selected, the response variable was estimated for every location at each study site on a 0.5 m resolution grid. A smaller resolution will not be in line with the assumption of homogeneous snowpack for the computation of the skier crack l_{sk} and the critical crack length a_c. All statistical computations were performed in R (R Core, 2013).

3 Results

3.1 Summary of spatial snow surveys

The first spatial snow survey ~~is~~ was conducted at the AR site. A weak layer of precipitation particles with an observed grain size of 0.5 - 1 mm was investigated on 25 February 2022 (AR22-PP), with 45 SMP measurements and a spatial extent of 71 m. The average slab thickness was ~~on average~~ 0.28 m ~~with a high mean density of~~ and the mean slab density was relatively high: 252 kg m^{-3} (Table 2). ~~This study site is highly wind-affected, especially in the upper part of the slope with a higher slab density. The bottom of the slope is more protected from the wind, whereas the slab is softer with a lower density.~~

At the RH site (RH22-PP), a weak layer of precipitation particles with an observed grain size of ~~between~~ 0.5 ~~and~~ to 1 mm was found beneath a relatively ~~fresh and~~ soft snow slab~~, with a~~. The mean slab thickness ~~of~~ was 0.19 m and ~~a mean density of~~ the mean density was 171 kg m^{-3}. This survey~~was done~~, conducted on 27 January 2022~~with~~, included 64 SMP measurements and covered a spatial extent of 116 m. The slab ~~for this survey is made up of one layer of homogeneous~~ consisted of one

Table 2. Summary for the snow measurements of all ~~four~~ spatial surveys. The results of the compression test CT results and the propagation saw test PST are shown according to the standards of Canadian Avalanche Association (2016).

Surveys	Date	Mean D & ρ	Weak layer	Nb SMP	Extent	CT	PST (m)
AR22-PP	~~2022-02-25~~ 25 Feb 2022	0.28 m & 252 kg m^{-3}	PP 0.5-1 mm	45	71 m	CTM11 (RP) down 0.25 m CTH23 (RP) down 0.54 m CTH22 (RP) down 0.35 m	0.9/1.5 END 1.42/1.5 END 1.22/1.5 END
RH22-PP	~~2022-01-27~~ 27 Jan 2022	0.19 m & 171 kg m^{-3}	PP 0.5-1 mm	64	116 m	CTM19 (RP) down 0.22 m CTM19 (RP) down 0.22 m CTH22 (RP) down 0.24 m	0.8/1.5 END 0.28/1.5 SF 1.38/1.5 END
JBC22-SH	~~2022-01-19~~ 19 Jan 2022	0.39 m & 188 kg m^{-3}	SH 1-2 mm	53	102 m	CTH21 (RP) down 0.39 m CTM12 (RP) down 0.5 m	1.28/1.5 END 1.46/1.5 END
JBC22-PP	~~2022-01-24~~ 24 Jan 2022	0.21 m & 166 kg m^{-3}	PP 0.5-1 mm	55	74 m	CTM13 (RP) down 0.25 m CTM16 (RP) down 0.24 m	1.24/1.5 END 1.41/1.5 END
EP20-DF	~~2020-02-29~~ 29 Fev 2020	0.32 m & 241 kg m^{-3}	DF 0.5-1 mm	38	45 m	CTH23 (RP) down 0.38 m CTH24 (RP) down 0.45 m	- -
EP19-FC	~~2019-01-24~~ 24 Jan 2019	0.85 m & 333 kg m^{-3}	FC 1 mm	22	48 m	CTH20 (SP) down 0.82 m CTM22 (RP) down 0.88 m	- -

homogeneous layer of storm snow, and both the slab and the weak layer ~~are~~ originated from the same meteorological event. ~~We were able to conduct~~

We conducted two spatial snow surveys at the JBC site in two different areas of the site. The first survey at this site ~~was done on January~~ took place on 19 ~~,~~ January 2022 (JBC22-SH) when there was a ~~weak persistent~~ persistent weak layer of buried surface ~~hoars~~ hoar of size 1-2 mm. The slab ~~is~~ was composed of multiple layers ~~, given~~ with a mean slab thickness of 0.39 m and a mean density of 188 kg m^{-3} above the surface hoar crystals. This survey ~~consists~~ consisted of 53 SMP measurements~~and~~ , covering a spatial extent of 102 m. The second ~~field survey was carried out in a snowpack~~ survey (JBC22-PP) was characterized by a weak layer of precipitation particles buried under a fresh snow slab of 0.21 m ~~and~~ thickness and an average slab density of 166 kg m^{-3}~~on average, which comes from~~ , deposited by the same meteorological event as RH22-PP. This survey ~~was carried out on 24 January 2022 (JBC22-PP) with~~ included 55 SMP measurements and ~~a spatial extent of~~ the spatial extent was 74 m (Table 2).

~~Figure 3 demonstrates slab density ρ and the~~ The last two surveys presented in Table 2 were added to the study to obtain more data points in Figure 3. The snow spatial survey EP20-DF had a mean slab thickness of 0.32 m and slab density of 241 kg m^{-3}, similar to AR22-PP. The snow spatial survey EP19-FC recorded the highest mean slab thickness of 0.85 m and the highest mean slab density of 333 kg m^{-3}. Although the number of SMP measurements and spatial extent were not sufficient for spatial analysis, these surveys provided valuable data points characterized by higher slab thickness D, contributing to a reliable assessment of the two empirical power law fits (Bažant et al., 2003; McClung, 2009).

Figure 3 shows slab density ρ and weak layer shear strength τ_p in relation to slab thickness D. These relations are ~~well defined in snow science, as the~~ often established, as snow density and ~~the~~ snow strength should increase as the ~~snow weight increases. Figure 3 shows our data set compared to two empirical power law fits (Bažant et al., 2003; McClung, 2009), which are used to parameterize realistic snow mechanical values in relation to the slab thickness. Two other power laws were fitted to the slab density~~ slab load increases. We fitted two power laws to our SMP-derived dataset, and compared them with two other empirical power laws commonly used in the literature (Bažant et al., 2003; McClung, 2009). Figure 3 indicates a poor fit for both parameters (ρ and ~~weak layer shear strength τ_p. Figure 3-a agrees well with our 'softer-slab' surveys~~). The power law from McClung (2009) was better suited for the two surveys characterized with relatively low density (ρ < 250 kg m^{-3}), which were conducted at Mount Fidelity ~~, but could easily be adjusted by increasing the initial density in the power law for the survey where the mean density is higher. Surveys~~ (Figure 3-a). The surveys with higher density (ρ > 250 kg m^{-3}) were on Mount Albert, which is a heavily wind-exposed area that could explain these highly dense slabs. Figure 3-b shows some surveys ~~align well~~ aligned with the two power laws, especially the surveys from Mount Fidelity (circles). ~~The "stronger" surveys (crosses) from Mount Albert could also be fitted if the initial cohesion is increased.~~ However, the Mount Albert surveys ~~contained~~ exhibited more variability compared to the Mount Fidelity surveys. ~~Our dataset demonstrates that, in~~ In general, our data set ~~fits approximately the power-law fits, but~~ fitted poorly with the power laws from the literature, and a lot of variability remained in each survey. The intra-survey variability and implication for snow mechanical modeling will be discussed in section 4.1.

3.2 Comparison of spatial patterns

For all spatial snow surveys, the empirical variogram showed smaller correlation lengths for the slab thickness compared to other properties, ranging from 5 to 10 m (Fig. 4). The ~~slab density variograms were also small and similar to~~ variograms for the slab density exhibited correlation length in the same range as for the slab thickness~~variogram~~ , particularly for JBC22-PP and RH22-PP, with 5 and 8 m, respectively. These two spatial snow surveys had the same weak layer and slab meteorological deposition event characterized by a new ~~snowfall~~ snow instability. The correlation length for the slab thickness and slab density at AR22-PP ~~is~~ was 10 m, with the same type of new ~~snowfall~~ snow instability. The ~~last one at the Jim Bay corner (~~variogram for the slab density at JBC22-SH ~~) has longer correlation lengths of around 20 to 30 m. The empirical variogram for this survey shows a correlation around 20 m, but shows significant variability that makes the estimation less reliable compared to the other empirical variograms (Fig. 4). The variogram~~ was the only survey that had a longer correlation length of 34 m. Variograms of the slab density from JBC22-SH, JBC22-PP and AR22-PP ~~also had fractal characteristicswith a stabilization of the variance around 20~~ appeared to exhibit fractal characteristics. These variograms showed a distinct plateau of variance around 10-20 m, followed by an increase in variance around ~~30~~ 30-40 m, indicating a multiscale pattern around these two distances (10 and 40 m~~. If we look at the variogram of the shear strength~~). Variograms of the weak layer ~~, the four spatial snow surveys had~~ shear strength indicated a longer correlation length around 20 m compared to slab properties, which are around 10 m. ~~The~~ In

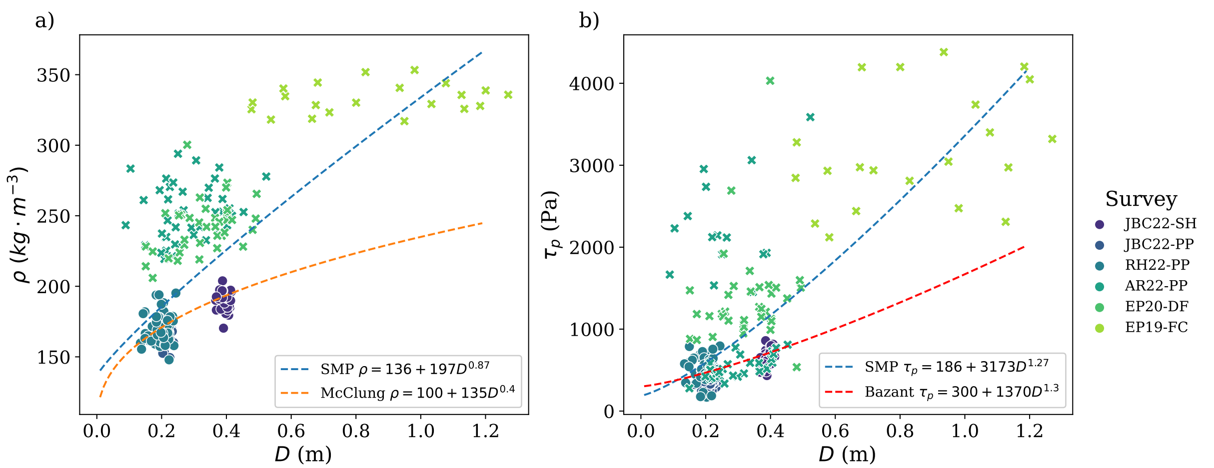

Figure 3. ~~SMP derived~~ SMP-derived for a) slab density ρ_{slab} ~~(a)~~ and b) weak layer shear strength τ_p ~~(b)~~ in relation to the slab thickness D for each SMP measurement of all spatial survey. The full circles represent the SMP values ~~in~~ from Mount Fidelity, British Columbia, and the crosses are from the surveys ~~in~~ from Mount Albert, Québec. A power law in blue was fitted to the SMP-derived values of all ~~the~~ surveys, with ~~, respectively, a) 0.5~~ R^2 = 0.5 for ρ, and ~~b) 0.4~~ R^2 = 0.4 for τ_p, respectively. ~~a)~~ The orange power law ~~fit~~ in (a) represents ρ compared to D, with an initial density of 100 kg m^{-3} from McClung (2009). ~~b)~~ The red power law is the power law in (b) for τ_p from Bažant et al. (2003) ~~reported to~~ who used Mohr-Coulomb ~~criterion~~ relation with an initial cohesion of 300 Pa (Gaume et al., 2014).

the JBC22-PP and RH22-PP surveys, which shared the same meteorological deposition event, ~~had a~~ the variance stabilized at 20 m without any further increase in variance. The other surveys (JBC22-SH and AR22-PP) had longer correlation lengths and showed fractal characteristics with no stabilization in variance ~~with increasing sampling distance . The type of variogram models that were fit was mostly~~ as the sampling distance increased. The primarily used variogram models were spherical and exponential, ~~which exhibit~~ characterized by a rapid increase in variance for ~~small~~ short distances. These models ~~are typically~~ tend to be less smooth than Gaussian models~~(~~, which have a smaller variance for short distances~~), which~~ . Gaussian models were fitted for slab thickness at JBC22-SH and slab density at JBC22-PP. ~~However, these two fitted Gaussian models still showed a shorter correlation (> 5 m).~~ In general, the correlation lengths ~~are~~ tended to be shorter for the thickness and density of the slab compared to the shear strength of the weak layer ~~for~~ in each snow spatial survey.

At first glance, all the correlation lengths for the stability metrics ~~are around 20 m, thus longer than~~ were longer than those for the slab properties. Surveys at the Jim Bay corner (JBC22-SH and JBC22-PP) ~~had smaller correlation lengths of~~ showed correlation lengths around 20 m ~~compared to the other two surveys with longer correlation lengths of around 30-40 m~~ (Fig. 5). The ~~same similarity can be observed for the correlation length of the critical crack lengthand also for the skier index. The skier index is the ratio between the critical crack length and the skier crack length, so this result is quite expected~~other two surveys (AR22-PP and RH22-PP) exhibited an empirical variogram that did not show a clear plateau of variance to determine a correlation length. These surveys either had a longer correlation length than the spatial extent of the sampling or showed a fractal behavior over multiple scales. The correlation length of the stability metrics ~~is around~~ ranged from 10 to 20 m, ~~but some~~

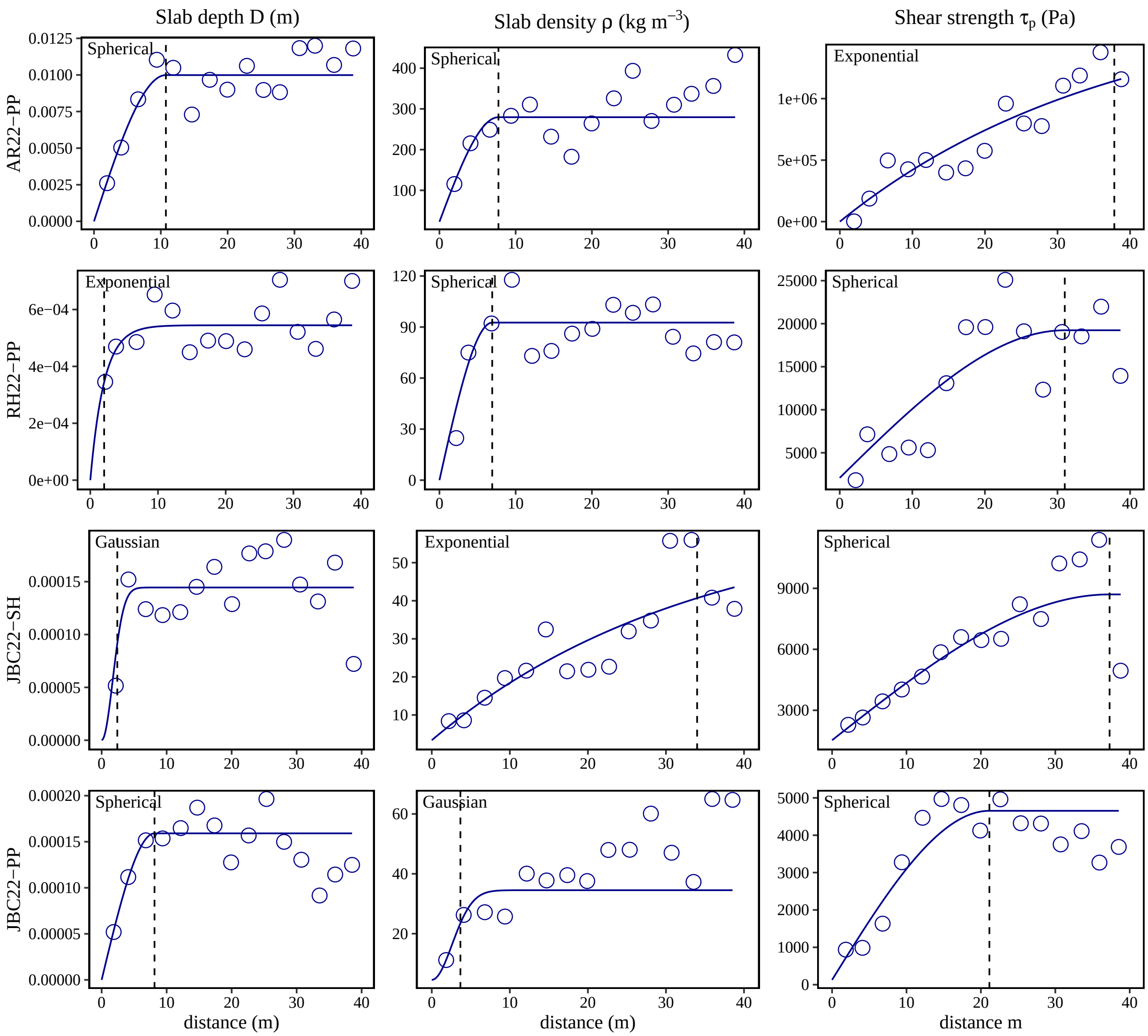

Figure 4. Experimental ~~variogram~~ variograms (circles) and fitted variogram models (line) for the snow mechanical properties. Note that the square root of the variance gives the absolute variation. The vertical dashed line in each variogram is the range for the fitted variogram model to the experimental variogram.

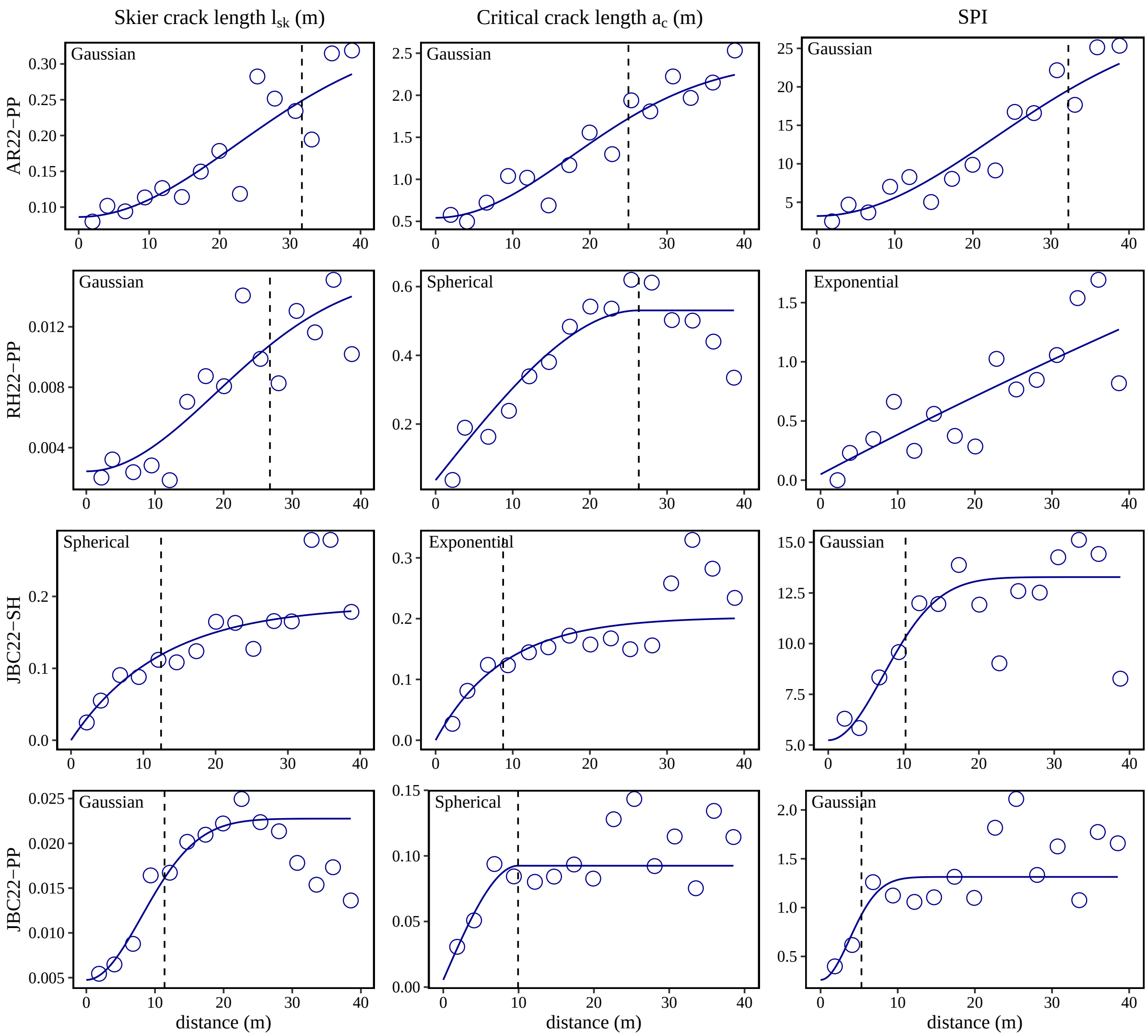

Figure 5. Experimental ~~variogram~~ variograms (circles) and fitted variogram models (line) for the stability metrics. Note that the square root of the variance gives the absolute variation. The vertical dashed line in each variogram is the range fitted for the theoretical variogram (line) to the empirical variogram (circles).

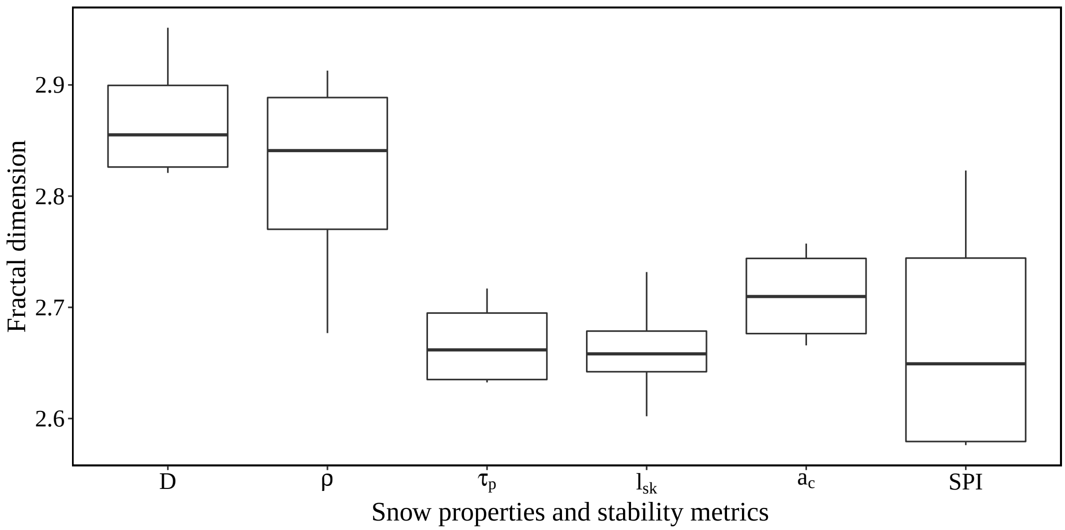

Figure 6. Boxplot of fractal dimension for snow mechanical properties and stability metrics with the four surveys in each boxplot.

~~are around 30 to 40 m, which is quite large~~ which is longer compared to the slab properties (Fig. 5). The ~~variogram model used is mostly~~ most frequently used variogram model was spherical, but ~~also Gaussian~~ Gaussian models were also applied for the skier crack length (JBC22-PP, RH22-PP, AR22-PP) and skier index (JBC22-SH, JBC22-PP). Gaussian models were ~~fitted more~~ more frequently fitted to stability metrics than to snow properties, ~~showing~~ suggesting smoother spatial patterns for the stability metrics. The variogram for the stability metrics ~~shares~~ exhibited more similarities with the variogram of the weak layer shear strength rather than the slab properties.

The fractal dimensions for the snow properties ~~showed~~ indicated a difference in surface ~~roughness or~~ complexity between the slab properties, the weak layer properties, and the stability metrics (Fig. 6). The slab properties ~~have~~ had higher fractal dimensions~~of~~, around 2.85, ~~thus~~ indicating a higher surface complexity, compared to the weak layer and the stability metrics, which ~~yield~~ had a similar fractal dimension ~~of~~ around 2.7. ~~The values for~~ Despite the stability metrics ~~are computed from the~~ being computed from both slab mechanical properties and weak layer properties, ~~but the values of fractal dimension seem to be in the same range as those for~~ their fractal dimension values were closer to those of the weak layer rather than the slab. These results suggest that the spatial patterns of the stability metrics ~~are~~ were more similar to ~~the spatial pattern~~ those of the weak layer than ~~to the spatial pattern~~ those of the slab properties.

3.3 Spatial modeling

The spatial models created by ~~GAMs were able to explain~~ the GAMs explained some of the variance of the response variable, but ~~not~~ far from entirely. The R^2 and the percentage of deviance explained ~~range~~ ranged from 0.17 to 0.84 and from 22 to 84 % (Table 3 - 4). ~~As for the average , it is approximately around~~ On average for all models, the R^2 was approximately 0.5 and the percentage of deviance was 55 %. The average R^2 ~~is~~ was 0.47 for snow properties and 0.55 for stability metrics, ~~but~~ and

Table 3. Summary of the spatial models, model ~~selection~~selections, and performance metrics for the snow properties. The performance metrics are the following: R^2, the percentage of deviance % dev, scale, the cross-validated Root-mean-squared-error CV RMSE, and the cross-validated mean-absolute-error CV MAE. The symbols next to the covariates refer to the significance levels of the p-value: > 0.1 ".", < 0.05 "*", < 0.01 "**", < 0.001 "***".

Site	Snow prop.	Covariates	R^2	% dev	scale	CV RMSE	CV MAE
JBC22-SH	D	TPI2550* + VRM25 + VRM5* + H_s* + Convex. + Dist-cano* + S_x*	0.35	42.9	9.57e-5	0.01	0.01
JBC22-SH	ρ_{slab}	Slope** + VRM15*** + H_s* + Convex*** + Dist-cano*	0.57	64.1	12.22	7.91	4.78
JBC22-SH	τ_p	(x+y)* + Slope* + TPI515* + VRM15** + VRM5* + Convex* + Cano.	0.50	66.2	3762.3	66.29	51.70
JBC22-PP	D	VRM5. + Cano*	0.17	22.2	0.0001	0.01	0.01
JBC22-PP	ρ_{slab}	Slope** + TPI515** + TPI2550*** + VRM25** + VRM15** + VRM5* + H_s. + S_x.	0.64	69.6	15.13	6.32	5.00v
JBC22-PP	τ_p	(x+y)*** + TPI2550*** + VRM25** + VRM15 + VRM5*** + Dist-cano** + S_x*	0.76	80.4	864.78	41.32	30.79
RH22-PP	D	(x+y)*** + Slope* + TPI515*** + TPI2550* + Cano** + Dist-cano** + S_x**	0.54	60	0.0002	0.03	0.02
RH22-PP	ρ_{slab}	(x+y)** + Slope. + TPI515. + VRM15** + Convex*** + Cano*	0.32	38.2	64.99	11.39	8.51
RH22-PP	τ_p	(x+y)** + TPI2550*** + VRM25* + VRM5** + Rad* + Cano**	0.42	48.3	10463	128.37	99.70
AR22-PP	D	(x+y). + VRM15* + VRM5. + Cano.	0.28	36.2	0.006	0.12	0.10
AR22-PP	ρ_{slab}	(x+y)** + TPI2550. + H_s. + Convex**	0.41	46.8	216.77	21.78	21.80
AR22-PP	τ_p	(x+y)*** + Slope* + TPI2550*** + VRM5* + Convex*** + Dist-cano*	0.72	76.7	2.157e5	752.70	578.88

the average percentage of deviance explained ~~is~~ was the same at 55 %. The performance of the models was assessed with a 10-fold cross-validated RMSE and MAE. The cross-validated RMSE and MAE for the slab thickness D were mostly 1-2 cm except for 12 cm at AR22-PP and were around 4 to 27 kg m^{-3} for the slab density. The RMSE and MAE for the shear strength ~~range~~ ranged from 30 to 128 Pa except for 752 Pa for AR22-PP, but this snow spatial survey was also the one ~~with the more~~ which had the highest variance (500 to 3500 Pa).

The spatial surfaces estimated by the GAM models in JBC22-SH for the snow mechanical properties are presented in Figure 7. The estimated ~~surface~~ surfaces for the slab thickness and density ~~had~~ exhibited a similar variation with ~~the same~~ comparable maximum and minimum areas. ~~The~~ However, the estimated surface for the shear strength of the weak layer ~~differs~~ differed

Table 4. Summary of the spatial models, model selection and performance metrics for the stability metrics. The performance metrics are the following: R^2, the percentage of deviance % dev, scale, the cross-validated Root-mean-squared-error CV RMSE, and the cross-validated mean-absolute-error CV MAE. The symbols next to the covariates refer to the significance levels of the p-value: > 0.1 ".", < 0.05 "*", < 0.01 "**", < 0.001 "***".

Site	Stab. metrics	Covariates	R^2	% dev	scale	CV RMSE	CV MAE
JBC22-SH	l_{sk}	(x+y)* + Slope** + VRM15*** + VRM5. + Convex.	0.58	64.8	0.06	0.48	0.22
JBC22-SH	A_c	Slope*** + TPI515** + TPI2550* + VRM15*** + VRM** + H_s***	0.60	65.9	0.06	0.20	0.14
JBC22-SH	SPI	Slope** + VRM15* + VRM15** + H_s*	0.35	40.3	6.66	2.5	1.89
JBC22-PP	l_{sk}	(x+y)*** + TPI2550** + VRM25** + VRM5** + S_x*	0.60	65.1	0.006	0.10	0.07
JBC22-PP	A_c	(x+y)* + TPI515*** + VRM5*** + H_s. + Rad** + S_x*	0.74	77.7	0.02	0.15	0.11
JBC22-PP	SPI	(x+y)** + TPI515*** + VRM5*** + Rad** + S_x*	0.84	87	0.20	0.36	0.27
RH22-PP	l_{sk}	(x+y)*** + TPI2550** + VRM25** + VRM15* + VRM5* + Rad* + Cano*	0.51	57.1	0.004	0.11	0.08
RH22-PP	A_c	VRM25** + VRM5**	0.25	28.7	0.39	0.60	0.47
RH22-PP	SPI	(x+y)*** + VRM25*** + Rad. + Convex**	0.43	48.5	0.61	1.23	0.85
AR22-PP	l_{sk}	(x+y)** + VRM25*	0.22	27.5	3.2	2.97	1.85
AR22-PP	A_c	TPI2550*** + VRM15* + Convex* + Cano. + S_x.	0.65	69.1	0.61	1.26	1.01
AR22-PP	SPI	TPI2550*** + Convex**	0.66	68.7	5.14	4.29	3.31

slightly from the slab properties. This ~~result also~~ finding reinforces the above results, ~~showing~~ indicating that the spatial pattern of the weak layer ~~differs~~ differed from the slab properties in our dataset. Estimation errors for critical crack length ~~are around~~ ranged 0.11 to 0.60 m, except for 1.2 m for AR22-PP. The RMSE and MAE for the skier propagation index ranged from 0.27 to 4, ~~which is very variable and quite high~~ showing significant variability and relatively high values for an index. The estimation errors for the stability metrics were ~~high and~~ notably high, demonstrating that the model estimations were not reliable compared to the snow mechanical properties. However, Figure 8 ~~shows~~ suggests that some outliers might ~~overestimate RSME~~contributed to overestimating the RSME, particularly with low values of l_{sk} and high SPI values (SPI $\approx$ 10). The spatial patterns of the stability metrics ~~indicate~~ revealed two major weak spots represented by two clusters of low SPI values near zero, located on the north side (right) and northwest (upper-middle). These weak spots ~~correspond~~ corresponded to areas with lower shear strength values and slightly thicker and higher-density slabs.

There are no clear covariates selected by the model for every site, snow properties, or stability metrics. However, some covariates were ~~used more often~~ selected more frequently by the spatial models than others. The most ~~used covariates~~ frequently

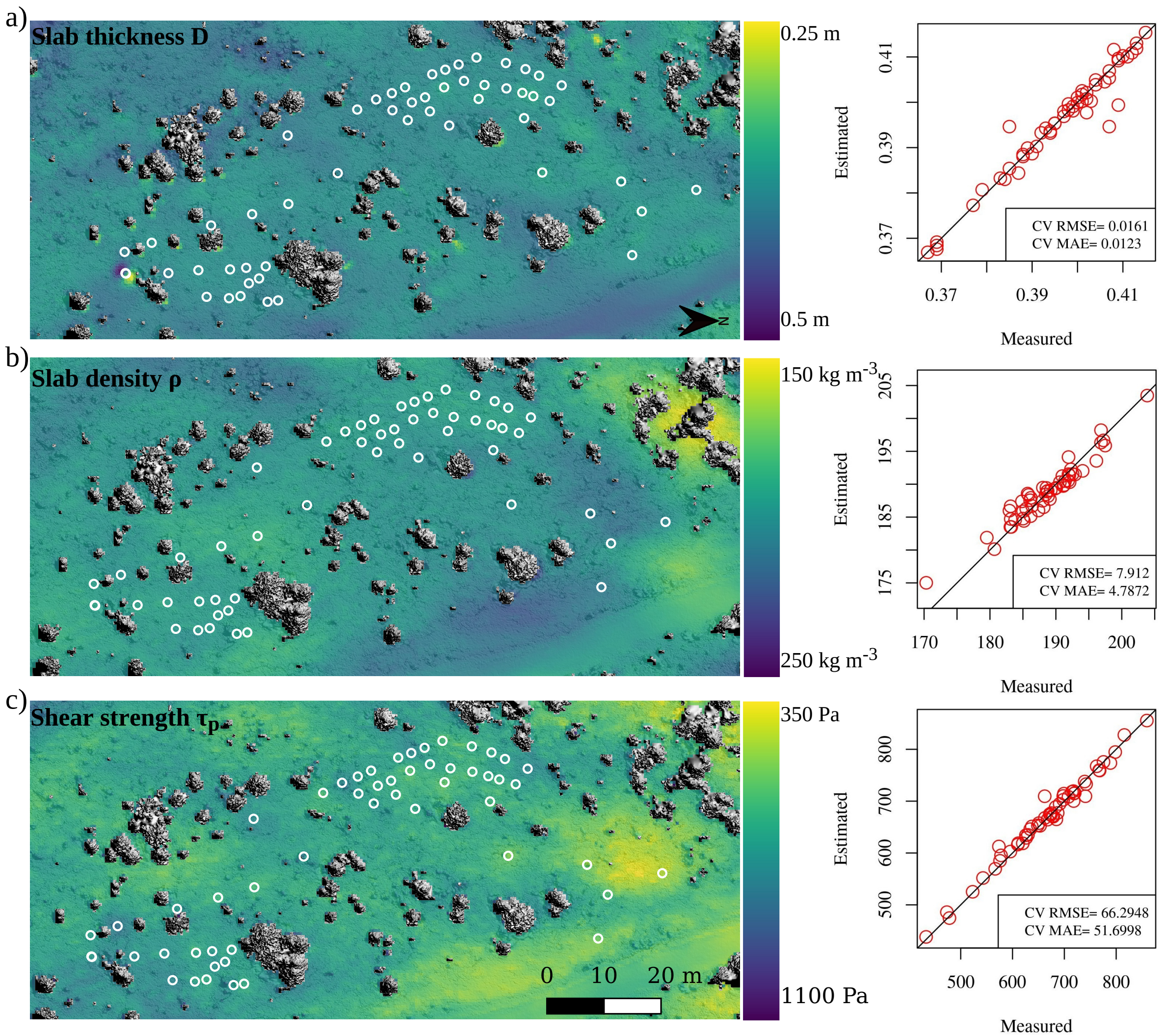

Figure 7. Spatial estimation for the snow mechanical properties a) slab thickness D, b) slab density ρ, c) shear strength τ_p at the Jim ~~bay~~ Bay corner on 19 January 2022 (surface hoar layer - 1mm). The cross-validated root mean squared error RMSE and the mean absolute error MAE are shown next to the map of each property. The ~~grey~~ gray shading ~~in~~ on the background map represents a canopy shading only for the visualization of trees.

used covariates by the models, for both snow properties and stability metrics, were multiscale TPI and VRM, but their usage ~~is quite variable~~ varied depending on the scale (Fig. 9). ~~The~~ Spatial models for the shear strength of the weak layer appeared to ~~use~~ select mainly TPI2550 and VRM5~~compared to the~~ , whereas for slab density, ~~which used mainly~~ VRM15 and convexity ~~. The canopy height was used~~ were chosen predominantly. Canopy height was selected in the snow properties models~~but not really~~ , but rarely in the stability metrics models. The easting and northing coordinates (xy) were widely used in the models~~showing~~

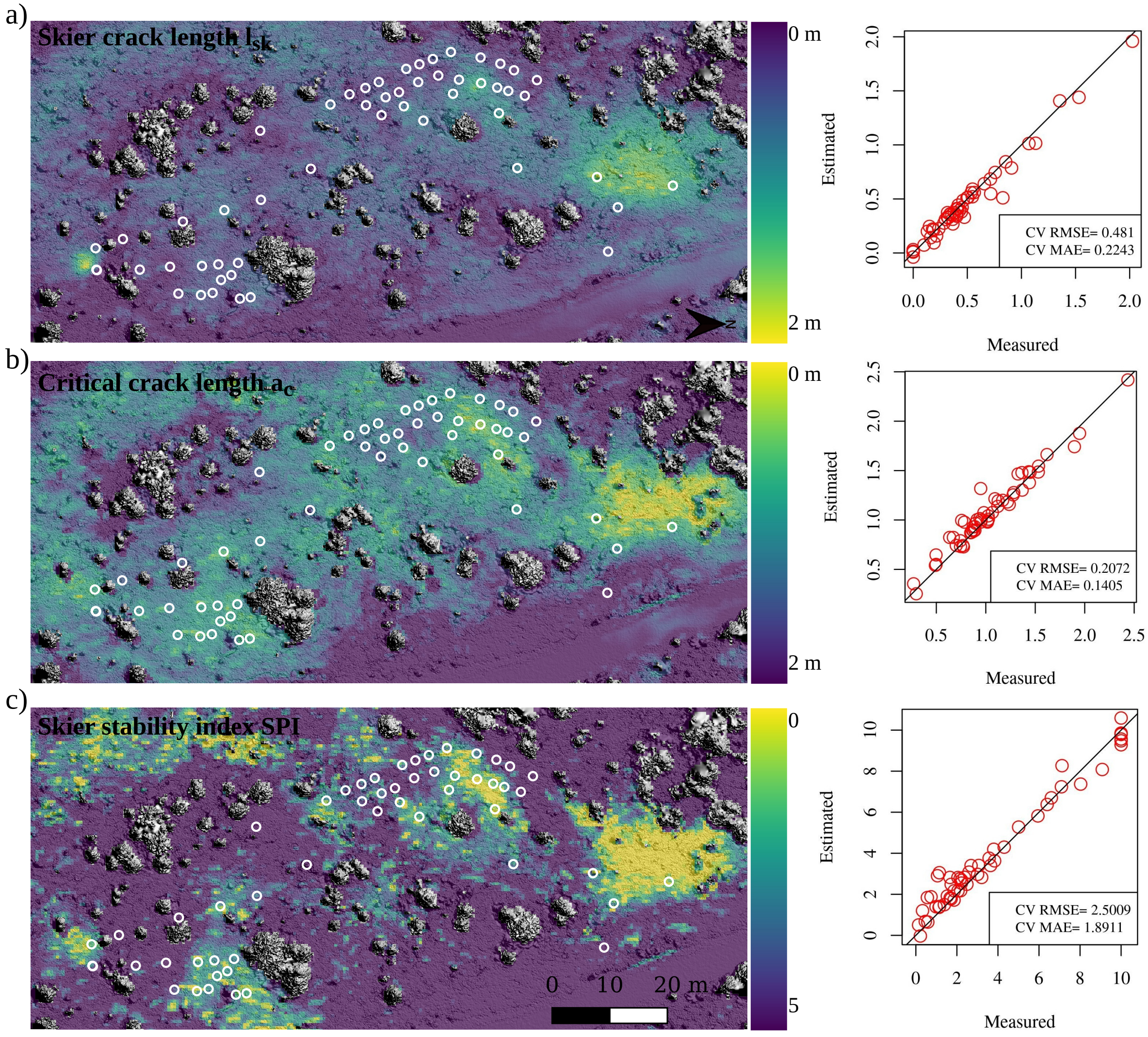

Figure 8. Spatial estimation for the stability metrics a) skier crack length l_{sk}, b) critical crack length a_c, and c) Skier propagation index SPI at the Jim ~~bay~~ Bay corner on ~~2022-01-19~~ 19 January 2022 (surface hoar layer - 1mm). Cross-validated root mean squared error RMSE and mean absolute error MAE are shown next to the map of each metric. The grey shading ~~in~~ on the background map represents a canopy shading only for the visualization of trees.

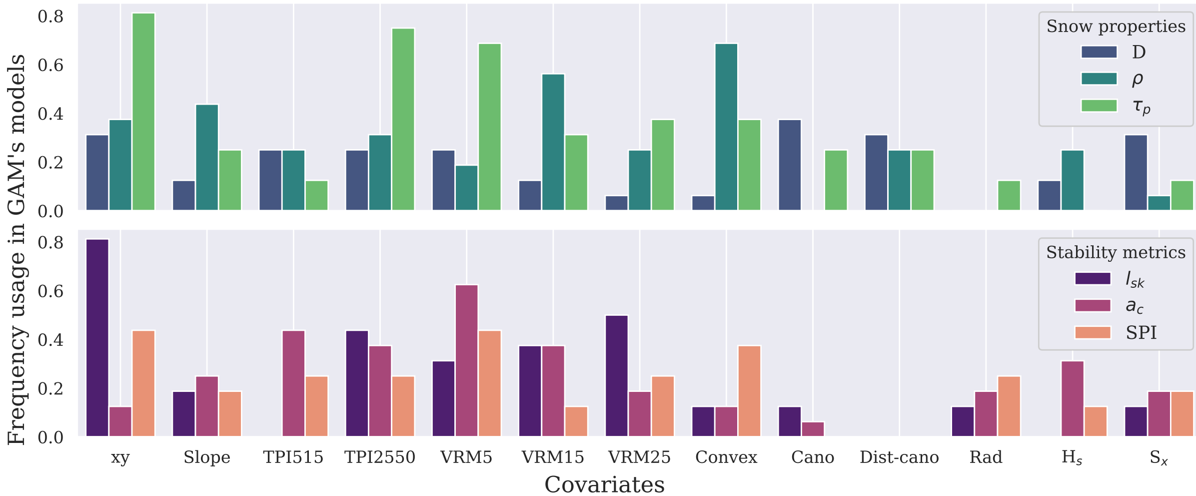

Figure 9. The frequency usage of covariates in the GAM spatial models, the frequency is weighted with the significance levels of the p-value.

, indicating the presence of spatially autocorrelated residuals. Surprisingly, snow depth was not used as ~~much~~ frequently as other covariates. ~~These results showed~~ Convexity was selected numerous times, especially for the slab density, but almost never for the slab thickness. Overall, these results indicate that there are no universal covariates or specific covariates for snow properties or stability metrics ~~. However, these results demonstrate the utility of using these covariates to spatially estimate the snow properties, and also stability metricswith less precision~~that could be extrapolated to other sites. The selection of covariates by the spatial models was site-specific and also specific to different snow properties. The spatial models presented using microtopography indicators were fairly reliable for estimating absolute values of snow properties and not reliable for the stability metrics, but rather for capturing relative spatial variability.

4 Discussion

4.1 Snow mechanical parametrization

Our study aligns with the well-known relationship between slab thickness and slab density, attributed to snow settlement . The comparison of spatial patterns between surveys indicated that these two properties exhibited similar trends in their variogram, the fractal dimension, and their covariates used for spatial modeling. For further research, the empirical power law fit $\rho \sim 100 + 135D^{0.4}$ suggested by McClung (2009) provides a simple approach to obtain average values that represent the interaction between these two properties for mechanical simulation (e.g. Gaume and Reuter, 2017) . The power law fitted to our SMP-derived data set appears to yield better average values for denser slabs in wind-exposed areas. However, it is important to note that these power laws fitted poorly with our dataset, indicating that significant variability remains. Nevertheless, these power laws could be used in snow mechanical model to generate a slab density variation according to the spatial pattern of the slab thickness. Until now in snow mechanical modeling research, the spatial variation of snow properties was limited to the weak layer. Our study shows a distinction between the spatial variation of the slab properties and the weak layer, already observed by Kronholm (2004) and Bellaire and Schweizer (2011). We propose accounting for both slab properties variation and weak layer variation since spatial patterns can differ between them.

Weak layer variations exhibited longer correlation lengths (smoother spatial pattern) than slab variations, and the increase in shear strength did not necessarily match the increase in the slab thickness. In general, shear strength should increase with slab thickness due to the slab load, but some variation was still present in our dataset (Figure 3). The interaction between slab thickness and shear strength can be described with a power law $\tau_p \sim c + 1370D^{1.3}$ (Bažant et al., 2003), reported according to the Mohr-Coulomb relation with initial cohesion c (300 Pa in Figure 3) (Gaume et al., 2014). This power law represented well the average values of the survey from Mount Fidelity, but our fitted power law could also be used for thicker (denser) slabs in wind-exposed areas. However, the four power laws tested did not adequately capture the variability in values for a specific spatial survey. The constant parameter must be adjusted for each spatial survey to fit the values. Overall, these power laws should be used with caution to estimate the average snow values (strength and density) if only the slab thickness is available.

Gaume et al. (2013) proposed a method to generate a weak layer with spatial heterogeneity. The method generates a random field with a specified mean, variance, and correlation length for the cohesion of the weak layer, where the shear strength of the weak layer is defined by a Mohr-Coulomb relation. The friction term of the Mohr-Coulomb, which incorporates the slab load, was added to the cohesion to obtain the shear strength. Although their fiction term was constant due to a constant slab thickness, the method can be easily adapted to accommodate a variable friction term, reflecting a variation in slab thickness. This adaptation would enable the specification of two distinct random fields for the properties of the slab and the weak layer while ensuring consistency with load of the slab. This method still requires input values for mean, variance, and correlation length. The empirical power law can estimate mean values, but according to our dataset, the variance is not well represented (Fig. 3). Future work should explore the possibility to estimate variance and correlation length of snow properties using the covariance of microtopography combined with distributed snow cover model. Such approaches could contribute to more realistic simulations in avalanche modeling, enhancing forecasting capabilities for both the probability of skier triggering and the size of avalanche releases.

4.2 Spatial modeling

This study gathers a unique dataset ~~describing~~ characterizing the spatial variation of snow mechanical properties and stability metrics at four different study sites. The comparison of ~~the~~ variograms and fractal dimensions ~~demonstrates that the slab properties (depth and density) vary at a different scale compared to the~~ highlights differences in scale between slab properties and weak layer properties and stability metrics (smoother ~~pattern~~patterns). Spatial GAM ~~modeling was used to spatially predict with good~~ models were used to estimate with fair accuracy the snow mechanical properties using microtopography~~and with less precision the stability metrics~~. However, ~~Our spatial modeling did not fully explain the variance of each response variable. Some spatial variances remain unexplained , but could also be attributed~~ the spatial modeling of the stability metrics was poor and not reliable. Additionally, a portion of spatial variances remained unexplained by the models, potentially due to non-spatial variances, such as instrument error or our processing data strategy. This strategy ~~includes~~ included a visual interpretation of the layer in the SMP resistance profile~~. A~~ , as misclassification or misidentification of the weak layer boundaries can ~~influence our results by adding non-spatial variance to our dataset. However, we used the SMP parameter L in~~ impact the result. Nevertheless, the modification of using the parameterization F_{wl} proposed by ~~(Richter et al., 2019)~~ Richter et al. (2019) instead of the ~~thickness of the weak layer~~ weak layer thickness for the computation of the critical crack length ~~(Gaume et al., 2017) . This modification makes our~~ makes the method less dependent on ~~the~~ weak layer thickness, ~~which was visually identified for each SMP profile. The RMSE was still quite high for the stability metrics and, thus less reliable for spatial estimation purposes. The SPI values were quite low (<0.5) for some areas in the spatial survey. If we had sampled these areas walking with the SMP, these areas should have been triggered, but nothing happened. This indicates that the stability metrics estimations are too pessimistic. We are not sure where the error might be, maybe in the SMP processing or the spatial modeling, or maybe both. However,~~ enhancing its robustness. While the cross-validated RMSE for ~~the~~ snow mechanical properties ~~was good with reliable precisionaccording to the properties (Table 3), indicating that the SMP processing for~~ suggests sufficient precision, the ~~snow mechanical properties is good, as well as the GAM spatial modeling compared to the stability metrics~~ high RMSE for stability metrics indicates that the spatial modeling of these metrics is not reliable (Table 3). Future work could use spatial estimations of the snow mechanical properties to compute the stability metrics from the spatial field of snow properties.

The cross-validation procedure ~~is~~ was performed by randomly selecting 10 subsets. ~~The random selection could take into account a minimum distance between observations (i.e our correlation length)~~ Future work should consider the correlation length during the random selection of subsets in cross-validation procedures to ensure complete ~~independent subsetsbefore computing the RMSE and MAE, and could bias the estimation of the~~ independence between subsets. This could improve the reliability of RMSE and MAE estimations. However, our 10-fold cross-validation (repeated 10 times) still provides a reliable estimation of the performance of our models. ~~Future work should take this into account.~~

4.3 Microtopographic covariates

This study aimed to use microtopographic covariates ~~to spatially predict snow spatial variation~~ for spatial estimations of snow spatial variability and stability. Our GAM spatial modeling did not reveal a universal covariate that ~~predicts~~ could spatially estimate both snow mechanical properties or stability metrics. The study of Reuter et al. (2016), based on larger-scale terrain-based covariates, did not find a ~~universal covariate to predict~~ consistent covariate in all surveys to estimate instability at the basin scale. They reported that the slope aspect was selected as a ~~predictor~~ estimator by the model in all of their surveys, but each survey used a different combination of covariates. ~~Like the study of Reuter et al. (2016)~~In the present study, the selection of covariates was specific to each survey with no clear trend or takeaway regarding the choice of covariates. ~~Surprisingly~~Notably, snow depth was not a ~~good~~ reliable spatial estimator of snow mechanical properties and stability metrics~~. Reuter et al. (2016) also reported that all their terrain-related covariates were used in 7 of their surveys, but snow depth was only in six of them. In our study , snow depth was only used to predict slab depth and slab density but the model never selected snow depth to predict the shear strength of the weak layer. A possible explanation could be that~~ , a finding consistent with the study

Reuter et al. (2016). The limited selection of snow depth as an estimator in our study might be attributed to the homogeneity of the dataset regarding snow depth or the weak layer~~spatial variation is not related~~'s spatial variation being unrelated to the snow accumulation process~~, or that our dataset was too homogeneous regarding snow depth. AR22-PP is~~. It is also noteworthy that, despite AR22-PP being a wind-exposed ~~study siteand, surprisingly~~site, the GAM model did not select the Winstral index S_x as ~~good predictor. The~~ a predictor. This could be related to the research distance in S_x ~~represents the scale of the indicator and the one selected in the study might be~~ being too large (100 m)~~. Using multiple scales like in the case of~~, and adjusting the scale of this indicator, similar to TPI and VRM, could ~~change~~ reveal S_x as a significant covariate, especially at the wind-exposed site (AR22-PP).

Unfortunately, no link could be made between our only persistent weak layer survey consisting of surface hoar crystals (JBC22-SH) and the remaining non-persistent weak layer surveys. A bigger dataset is needed to demonstrate clear differences between ~~alpine/forested areas and persistent /~~persistent vs. non-persistent weak layers, as well as between alpine vs. forested areas. The covariates TPI and VRM ~~are the best~~ emerged as the most significant covariates for estimating snow properties, this was also observed by previous studies using spatial models (random forest) ~~to spatially estimate snow depth~~ for snow depth estimation (Meloche et al., 2022; Revuelto et al., 2020). The ~~best scale~~ , optimal scale or window size ~~, of~~ for TPI and VRM ~~for prediction seems to be changing~~ varied depending on the study site, snow properties and stability metrics. Future work with a ~~larger~~ more extensive dataset should investigate ~~if the best scale is related~~ whether the optimal scale is linked to the specific scale of ~~the terrain~~ terrain features at each site, the scale of the meteorological process affecting the slab and the weak layer, or ~~interaction with both. Still, the multiscale covariate TPI associated with terrain shape appears to be a good spatial estimator for backcountry recreationists. VRM could also be a good estimator for backcountry recreationists, but it could be more difficult to identify with snow-covered terrain. Weak layer spatial variability remains the main information for monitoring the spatial occurrence of snow instability, but the difficulty of quickly assessing the weak layer spatial pattern in the field for backcountry recreationists remains a challenge~~a combination of both factors.

4.4 ~~Snow mechanical parametrization and modeling~~

~~Our study agrees with the well-known relationship between the slab thickness and the slab density due to snow settlement . The comparison of the spatial pattern between surveys shows that these two properties exhibit the same spatial pattern in the variogram, the fractal dimension, and their covariates used for spatial modeling. For further study, the empirical power-law fit $\rho \sim 100 + 135D^{0.4}$ suggested by McClung (2009) is a good way to easily represent the interaction between these two properties to obtain realistic snow values for mechanical simulation (e.g. Gaume and Reuter, 2017) . However, our SMP power law fit could be better represent denser slabs in wind-exposed areas. The power-law fit could also be used to generate the slab density based on the spatial pattern of the slab thickness if some variation is included in the simulation. Until now in snow mechanical modeling, the spatial variation of snow properties was limited to the weak layer. Our study shows that there is a difference between the spatial variation of the slab properties and the weak layer in our dataset. This difference was previously observed by Bellaire and Schweizer (2011), in their spatial survey conduct over a smaller extent. Our study shows the need to account for both slab properties variation and weak layer variation because spatial patterns can differ from each other.~~

~~Our study shows that the weak layer variation was smoother than the slab and the increase in shear strength did not necessarily match the increase in the slab thickness. In general, shear strength should increase with slab thickness due to the slab weight, but some variation was still present in our dataset (Figure 3). The interaction between slab thickness and shear strength can be described with a power law $\tau_p \sim c + 1370D^{1.3}$ (Bažant et al., 2003), but it was reported according to~~ The transferability of our results to different sites is not feasible. The selection of covariates by the ~~Mohr-Coulomb criterion with initial cohesion c (300 Pa in Figure 3) (Gaume et al., 2014). These power laws represent well the average values of the survey from Mount Fidelity, but our fitted power laws could also be used for thicker (denser) slabs in wind-exposed areas. However, these power laws did not adequately capture the variability in values for a specific spatial survey. The constant parameter needs to be adjusted for every spatial survey to fit the values. These power laws could be used to estimate the average snow values if only the slab thickness is available, but a stochastic process could be added to generate a more realistic variability.~~

~~Gaume et al. (2013) proposed a method to generate a weak layer with spatial heterogeneity. The method generates a random field with a specified mean, variance, and correlation length for the cohesion of the weak layerin the Mohr-Coulomb relation. The friction term of the Mohr-Coulomb, which incorporates the slab thickness, is added to the cohesion to obtain the shear strength. Their fiction term was constant because the slab thickness was constant, but this method could easily be adapted with a variable friction term following a variation in the thickness of the slab. These methods would allow two different random fields to be specified for both the properties of the slab and the weak layerwhile respecting the friction regarding the slab thickness. This method still needs a mean, variance, and correlation length as input. The empirical power law can estimate mean values, but according to our dataset, the variance is not well represented (Fig. 3). Future work should explore the possibility of estimating the variance and the correlation length using the covariance of microtopography combined with the snow cover model outputs. These methods could lead to more realistic simulations in avalanche modelingfor forecasting purposes, both for the probability of skier triggering and the avalanche release size~~model was specific to each site, snow properties and stability metrics. As demonstrated by Reuter et al. (2016), the interaction between meteorological processes and terrain leads to distinct spatial variation in snow properties across different surveys. These micrometeorological processes vary between sites and differences emerge not only between slab deposition patterns, but crucially, between different types of weak layer. More spatial snow surveys are needed to gather a robust dataset to highlight trends in spatial pattern between different types of weak layer, slab deposition, microtopographic, and microclimatic contexts. To obtain a more robust dataset, future research should aim for an equivalent or higher sampling density and extent presented in this study (60 and more SMP covering 80 m extent). Lowering the sampling density and extent could compromise the estimation of the experimental variogram and the spatial modeling. An alternative approach to sampling with fewer SMP measurements could be to incorporate distributed 3D snow cover modeling tools like ALPINE3D. This avenue was explored by (Reuter et al., 2016), but acknowledged the need to improve performance in distributed snow cover modeling. Implementing 3D snow cover modeling has the potential to capture a portion of these site-specific micrometeorological processes without requiring an extensive spatial survey of SMP measurements.

5 Conclusion

The study provides insights into the spatial variability of ~~mechanical properties has been measured, compared, and estimated in this study~~snow mechanical properties and stability metrics. First, we show that in our dataset, the slab properties exhibit spatial patterns that were different from the weak layer spatial patterns. In fact, the slab properties, both the slab thickness and density, had smaller correlation lengths in their ~~variogram~~ variograms than the weak layer strength. The slab properties had higher fractal dimensions than the weak layer strength, which demonstrates a more "rough" spatial surface. Secondly, ~~we estimated the spatial variability of snow mechanical properties and also some stability metrics using spatial variables of microtopography . Estimates were reliable and precise for~~ spatial modeling using microtopography variables allows for the estimation of snow mechanical properties ~~, but not for stability metrics~~with reasonable accuracy, although the reliability of stability metric estimations was poor and not reliable. We also show the utility of using microtopography to estimate snow spatial variability~~. However, no microtopographic indicators were predominantly used to give advice to backcountry recreationists. The use of microtopography seems to be~~ , but the selection of the indicators was specific to each study site and snow properties. The ~~use~~ spatial models did not predominantly select microtopographic indicators, resulting in no possible extrapolation to other sites or advice to backcountry recreationists. Future research could explore the capability of multiscale microtopographic indicators, ~~such as~~ like the topographic position index ~~TPI and the~~ (TPI) and vector ruggedness measure ~~VRM, should be explored in future work~~ (VRM), to estimate spatial patterns of snow mechanical properties ~~as input for snow mechanical models. This could lead~~ with 3D snow cover modeling. This may contribute to the development of predictive methods ~~in~~ for operational avalanche forecasting services~~to estimate the avalanche release size using~~ , potentially estimating avalanche release sizes through snow cover modeling and mechanical models. Additional work is needed ~~on stability occurrence with respect to microtopography indicators to help backcountry recreationists find a safer downhill and uphill route~~to gather a robust dataset regarding the spatial pattern of snow mechanical properties in order to elucidate trends between different types of weak layers and terrain features.

Code and data availability. The code and the data are available upon request.

Author contributions. FM conceptualized and led the research, wrote the code for the processing and analysis of the data, and drafted the manuscript. FG and AL conceptualized the research and reviewed the manuscript. AL provided the major part of the funds for the project.

Competing interests. Alexandre Langlois is a member of the editorial board of The Cryosphere

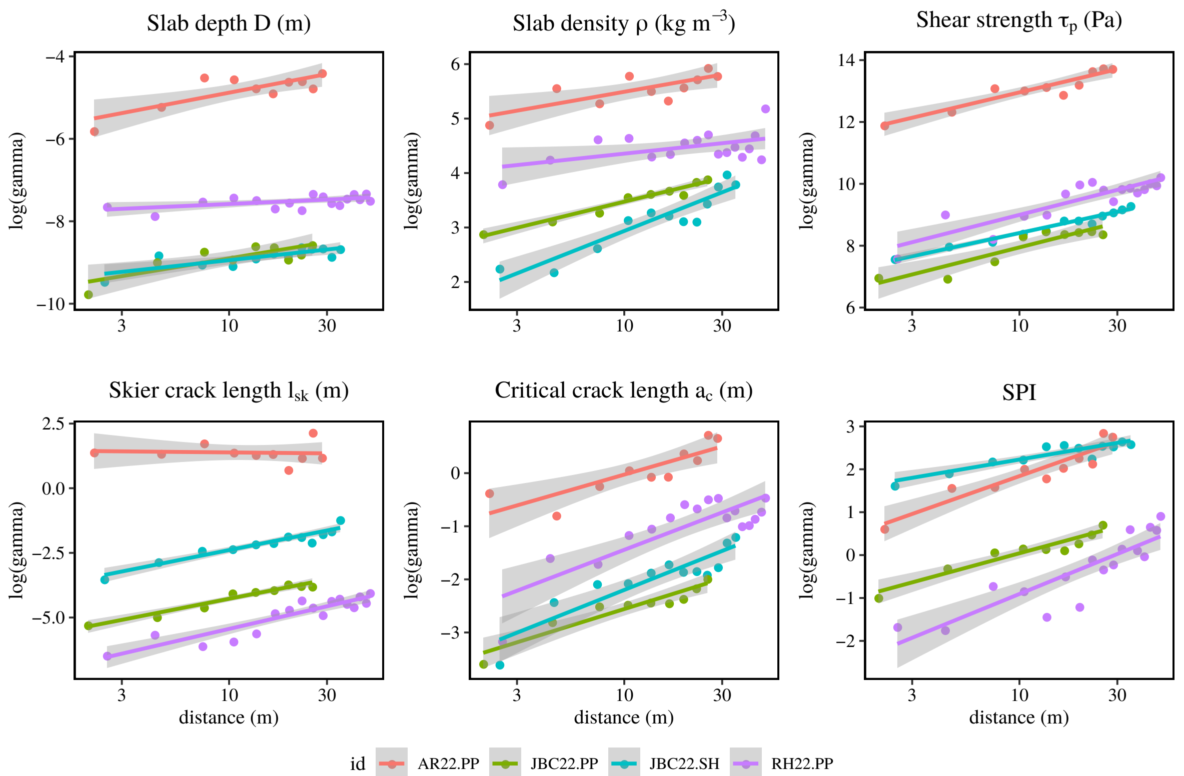

Figure A1. Log-Log variogram of snow mechanical properties and stability metrics for every snow spatial surveys. The fractal dimension is computed from the slope of the regression line. The gamma represented the variance for each variable. The unit is specified in each title.

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Appendix A

The log-log variograms needed to calculate the fractal dimension ~~are presented in the Appendix~~in Figure 6 are presented below (Figure A1).

References

Bažant, Z. P., Zi, G., and McClung, D.: Size effect law and fracture mechanics of the triggering of dry snow slab avalanches, Journal of Geophysical Research: Solid Earth, 108, https://doi.org/10.1029/2002jb001884, 2003.

Bellaire, S. and Schweizer, J.: Measuring spatial variations of weak layer and slab properties with regard to snow slope stability, Cold Regions Science and Technology, 65, 234–241, https://doi.org/10.1016/J.COLDREGIONS.2010.08.013, 2011.

Birkeland, K. W.: Spatial patterns of snow stability throughout a small mountain range, Journal of Glaciology, 47, 176–186, https://doi.org/10.3189/172756501781832250, 2001.

Blöschl, G. and Sivapalan, M.: Scale issues in hydrological modelling: A review, Hydrological Processes, 9, 251–290, https://doi.org/10.1002/hyp.3360090305, 1995.

Calonne, N., Richter, B., Löwe, H., Cetti, C., Judith, Herwijnen, A. V., Fierz, C., Jaggi, M., and Schneebeli, M.: The RHOSSA campaign: Monitoring the seasonal evolution of an alpine snowpack up to daily resolution, in Prep., pp. 1–30, 2019.

Campbell, C. and Jamieson, B.: Spatial variability of slab stability and fracture characteristics within avalanche start zones, Cold Regions Science and Technology, 47, 134–147, https://doi.org/10.1016/j.coldregions.2006.08.015, 2007.

Canadian Avalanche Association: Observations guidelines and recording standards for weather, snowpack and avalanches, Tech. rep., Revelstoke, 2016.

Chilès, J.-P. and Delfiner, P.: Geostatistics: Modelling Spatial Uncertainty, John Wiley & Sons, Ltd, New-York, 1999.

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., and Böhner, J.: System for Automated Geoscientific Analyses (SAGA) v. 2.1.4, Geoscientific Model Development, 8, 1991–2007, https://doi.org/10.5194/GMD-8-1991-2015, 2015.

Dale, M. R. T. and Fortin, M.-J.: Spatial Analysis : A guide for Ecologists, Cambridge University Press, 2nd edn., 2014.

Deems, J. S., Fassnacht, S. R., and Elder, K. J.: Fractal distribution of snow depth from lidar data, Journal of Hydrometeorology, 7, 285–297, https://doi.org/10.1175/JHM487.1, 2006.

Feick, S., Kronholm, K., and Schweizer, J.: Field observations on spatial variability of surface hoar at the basin scale, Journal of Geophysical Research: Earth Surface, 112, 1–16, https://doi.org/10.1029/2006JF000587, 2007.

Föhn, P.: The stability index and various triggering mechanisms, IAHS, 162, 195–214, 1987.

Fyffe, B. and Zaiser, M.: The effects of snow variability on slab avalanche release, Cold Regions Science and Technology, 40, 229–242, https://doi.org/10.1016/j.coldregions.2004.08.004, 2004.

Gao, J. and Xia, Z. G.: Fractals in physical geography, Progress in Physical Geography, 20, 178–191, https://doi.org/10.1177/030913339602000204, 1996.

Gaume, J. and Reuter, B.: Assessing snow instability in skier-triggered snow slab avalanches by combining failure initiation and crack propagation, Cold Regions Science and Technology, 144, 6–15, https://doi.org/10.1016/j.coldregions.2017.05.011, 2017.

Gaume, J., Chambon, G., Eckert, N., and Naaim, M.: Influence of weak-layer heterogeneity on snow slab avalanche release: Application to the evaluation of avalanche release depths, Journal of Glaciology, 59, 423–437, https://doi.org/10.3189/2013JoG12J161, 2013.

Gaume, J., Schweizer, J., Herwijnen, A., Chambon, G., Reuter, B., Eckert, N., and Naaim, M.: Evaluation of slope stability with respect to snowpack spatial variability, Journal of Geophysical Research: Earth Surface, 119, 1783–1799, https://doi.org/10.1002/2014jf003193, 2014.

Gaume, J., Chambon, G., Eckert, N., Naaim, M., and Schweizer, J.: Influence of weak layer heterogeneity and slab properties on slab tensile failure propensity and avalanche release area, Cryosphere, 9, 795–804, https://doi.org/10.5194/tc-9-795-2015, 2015.

Gaume, J., Van Herwijnen, A., Chambon, G., Wever, N., and Schweizer, J.: Snow fracture in relation to slab avalanche release: Critical state for the onset of crack propagation, Cryosphere, 11, 217–228, https://doi.org/10.5194/tc-11-217-2017, 2017.

Gauthier, D. and Jamieson, B.: Evaluation of a prototype field test for fracture and failure propagation propensity in weak snowpack layers, Cold Regions Science and Technology, 51, 87–97, https://doi.org/10.1016/J.COLDREGIONS.2007.04.005, 2008.

Grünewald, T., Schirmer, M., Mott, R., and Lehning, M.: Spatial and temporal variability of snow depth and ablation rates in a small mountain catchment, Cryosphere, 4, 215–225, https://doi.org/10.5194/tc-4-215-2010, 2010.

Guy, Z. M. and Birkeland, K. W.: Relating complex terrain to potential avalanche trigger locations, Cold Regions Science and Technology, 86, 1–13, https://doi.org/10.1016/j.coldregions.2012.10.008, 2013.

Habermann, M., Schweizer, J., and Jamieson, J. B.: Influence of snowpack layering on human-triggered snow slab avalanche release, Cold Regions Science and Technology, 54, 176–182, https://doi.org/10.1016/j.coldregions.2008.05.003, 2008.

Hägeli, P. and McClung, D. M.: Avalanche characteristics of a transitional snow climate-Columbia Mountains, British Columbia, Canada, Cold Regions Science and Technology, 37, 255–276, https://doi.org/10.1016/S0165-232X(03)00069-7, 2003.

Hägeli, P. and McClung, D. M.: Hierarchy theory as a conceptual framework for scale issues in avalanche forecast modeling, Annals of Glaciology, 38, 209–214, https://doi.org/10.3189/172756404781815266, 2004.

Harper, J. T. and Bradford, J. H.: Snow stratigraphy over a uniform depositional surface: Spatial variability and measurement tools, Cold Regions Science and Technology, 37, 289–298, https://doi.org/10.1016/S0165-232X(03)00071-5, 2003.

Hesterberg, T., Choi, N. H., Meier, L., and Fraley, C.: Least angle and l1 penalized regression: A review, https://doi.org/10.1214/08-SS035, 2, 61–93, https://doi.org/10.1214/08-SS035, 2008.

Johnson, J. B. and Schneebeli, M.: Characterizing the microstructural and micromechanical properties of snow, Cold Regions Science and Technology, 30, 91–100, https://doi.org/10.1016/S0165-232X(99)00013-0, 1999.

Kronholm, K.: Spatial Variability of Snow Mechanical Properties with regard to avalanche formation, Ph.D. thesis, University of Zurich, Zurich, 2004.

Kronholm, K. and Birkeland, K. W.: Integrating spatial patterns into a snow avalanche cellular automata model, Geophysical Research Letters, 32, https://doi.org/10.1029/2005GL024373, 2005.

Kronholm, K. and Birkeland, K. W.: Reliability of sampling designs for spatial snow surveys, Computers and Geosciences, 33, 1097–1110, https://doi.org/10.1016/j.cageo.2006.10.004, 2007.

Kronholm, K. and Schweizer, J.: Snow stability variation on small slopes, Cold Regions Science and Technology, 37, 453–465, https://doi.org/10.1016/S0165-232X(03)00084-3, 2003.

Landry, C., Birkeland, K., Hansen, K., Borkowski, J., Brown, R., and Aspinall, R.: Variations in snow strength and stability on uniform slopes, Cold Regions Science and Technology, 39, 205–218, https://doi.org/10.1016/j.coldregions.2003.12.003, 2004.

Löwe, H. and van Herwijnen, A.: A Poisson shot noise model for micro-penetration of snow, Cold Regions Science and Technology, 70, 62–70, https://doi.org/10.1016/j.coldregions.2011.09.001, 2012.

Lutz, E. and Birkeland, K. W.: Spatial patterns of surface hoar properties and incoming radiation on an inclined forest opening, Journal of Glaciology, 57, 355–366, https://doi.org/10.3189/002214311796405843, 2011.

Lutz, E., Birkeland, K. W., Kronholm, K., Hansen, K., and Aspinall, R.: Surface hoar characteristics derived from a snow micropenetrometer using moving window statistical operations, Cold Regions Science and Technology, 47, 118–133, https://doi.org/10.1016/j.coldregions.2006.08.021, 2007.

Marra, G. and Wood, S. N.: Practical variable selection for generalized additive models, Computational Statistics and Data Analysis, 55, 2372–2387, https://doi.org/10.1016/j.csda.2011.02.004, 2011.

McClung, D. M.: Dimensions of dry snow slab avalanches from field measurements, Journal of Geophysical Research: Earth Surface, 114, https://doi.org/10.1029/2007JF000941, 2009.

Meloche, F., Gauthier, F., Langlois, A., and Boucher, D.: The Northeastern Rainy Continental snow climate: A snow climate classification for the Gaspé Peninsula, Québec, Canada, in: International Snow Science Workshop, Innsbruck, Austria, pp. 1025–1029, 2018.

Meloche, J., Langlois, A., Rutter, N., McLennan, D., Royer, A., Billecocq, P., and Ponomarenko, S.: High-resolution snow depth prediction using Random Forest algorithm with topographic parameters: A case study in the Greiner watershed, Nunavut, Hydrological Processes, 36, e14 546, https://doi.org/10.1002/HYP.14546, 2022.

Monti, F., Gaume, J., Van Herwijnen, A., and Schweizer, J.: Snow instability evaluation: Calculating the skier-induced stress in a multi-layered snowpack, Natural Hazards and Earth System Sciences, 16, 775–788, https://doi.org/10.5194/nhess-16-775-2016, 2016.

Mott, R., Schirmer, M., and Lehning, M.: Scaling properties of wind and snow depth distribution in an Alpine catchment, Journal of Geophysical Research Atmospheres, 116, 1–8, https://doi.org/10.1029/2010JD014886, 2011.

Mullen, R. S. and Birkeland, K. W.: Mixed Effect and Spatial Correlation Models for Analyzing a Regional Spatial dataset, International snow science workshop, p. 8, 2008.

Nussbaum, M., Walthert, L., Fraefel, M., Greiner, L., and Papritz, A.: Mapping of soil properties at high resolution in Switzerland using boosted geoadditive models, SOIL, 3, 191–210, https://doi.org/10.5194/SOIL-3-191-2017, 2017.

Pebesma, E. J.: Multivariable geostatistics in S: the gstat package, Computers & Geosciences, 30, 683–691, https://doi.org/10.1016/j.cageo.2004.03.012, 2004.

Pielmeier, C. and Marshall, H. P.: Rutschblock-scale snowpack stability derived from multiple quality-controlled SnowMicroPen measurements, Cold Regions Science and Technology, 59, 178–184, https://doi.org/10.1016/j.coldregions.2009.06.005, 2009.

Proksch, M., Löwe, H., and Schneebeli, M.: Density, specific surface area, and correlation length of snow measured by high-resolution penetrometry, Journal of Geophysical Research: Earth Surface, 120, 346–362, https://doi.org/10.1002/2014JF003266, 2015.

Pulwicki, A., Flowers, G. E., Radic, V., and Bingham, D.: Estimating winter balance and its uncertainty from direct measurements of snow depth and density on alpine glaciers, Journal of Glaciology, 64, 781–795, https://doi.org/10.1017/JOG.2018.68, 2018.

R Core: R : A language and environment for statistical computing, 2013.

Reuter, B. and Schweizer, J.: Describing Snow Instability by Failure Initiation, Crack Propagation, and Slab Tensile Support, Geophysical Research Letters, 45, 7019–7027, https://doi.org/10.1029/2018GL078069, 2018.

Reuter, B., Herwijnen, A. V., and Schweizer, J.: Simple drivers of snow instability, Cold Regions Science and Technology, 120, 168–178, http://dx.doi.org/10.1016/j.coldregions.2015.06.016, 2015a.

Reuter, B., Schweizer, J., and Van Herwijnen, A.: A process-based approach to estimate point snow instability, Cryosphere, 9, 837–847, https://doi.org/10.5194/tc-9-837-2015, 2015b.

Reuter, B., Richter, B., and Schweizer, J.: Snow instability patterns at the scale of a small basin, Journal of Geophysical Research: Earth Surface, 121, 257–282, https://doi.org/10.1002/2015JF003700, 2016.

Reuter, B., Proksch, M., Löwe, H., Van Herwijnen, A., and Schweizer, J.: Comparing measurements of snow mechanical properties relevant for slab avalanche release, Journal of Glaciology, 65, 55–67, https://doi.org/10.1017/jog.2018.93, 2019.

Revuelto, J., Billecocq, P., Tuzet, F., Cluzet, B., Lamare, M., Larue, F., and Dumont, M.: Random forests as a tool to understand the snow depth distribution and its evolution in mountain areas, Hydrological Processes, pp. 1–18, https://doi.org/10.1002/hyp.13951, 2020.

Richter, B., Schweizer, J., Rotach, M., and van Herwijnen, A.: Validating modeled critical crack length for crack propagation in the snow cover model SNOWPACK, The Cryosphere Discussions, pp. 1–21, https://doi.org/10.5194/tc-2019-97, 2019.

Rosendahl, P. L. and Weißgraeber, P.: Modeling snow slab avalanches caused by weak-layer failure - Part 2: Coupled mixed-mode criterion for skier-triggered anticracks, Cryosphere, 14, 131–145, https://doi.org/10.5194/tc-14-131-2020, 2020.

Sappington, J. M., Longshore, K. M., and Thompson, D. B.: Quantifying Landscape Ruggedness for Animal Habitat Analysis: A Case Study Using Bighorn Sheep in the Mojave Desert, The Journal of Wildlife Management, 71, 1419–1426, https://doi.org/10.2193/2005-723, 2007.

Schirmer, M. and Lehning, M.: Persistence in intra-annual snow depth distribution: 2.Fractal analysis of snow depth development, Water Resources Research, 47, 1–14, https://doi.org/10.1029/2010WR009429, 2011.

Schirmer, M., Wirz, V., Clifton, A., and Lehning, M.: Persistence in intra-annual snow depth distribution: 1.Measurements and topographic control, Water Resources Research, 47, 1–16, https://doi.org/10.1029/2010WR009426, 2011.

Schweizer, J. and Kronholm, K.: Snow cover spatial variability at multiple scales: Characteristics of a layer of buried surface hoar, Cold Regions Science and Technology, 47, 207–223, https://doi.org/10.1016/j.coldregions.2006.09.002, 2007.

Schweizer, J. and Reuter, B.: A new index combining weak layer and slab properties for snow instability prediction, Natural Hazards and Earth System Sciences, 15, 109–118, https://doi.org/10.5194/nhess-15-109-2015, 2015.

Schweizer, J., Kronholm, K., Jamieson, J. B., and Birkeland, K. W.: Review of spatial variability of snowpack properties and its importance for avalanche formation, Cold Regions Science and Technology, 51, 253–272, https://doi.org/10.1016/j.coldregions.2007.04.009, 2008a.

Schweizer, J., McCammon, I., and Jamieson, J. B.: Snowpack observations and fracture concepts for skier-triggering of dry-snow slab avalanches, Cold Regions Science and Technology, 51, 112–121, https://doi.org/10.1016/J.COLDREGIONS.2007.04.019, 2008b.

Skøien, J. O. and Blöschl, G.: Sampling scale effects in random fields and implications for environmental monitoring, Environmental Monitoring and Assessment, 114, 521–552, https://doi.org/10.1007/s10661-006-4939-z, 2006.

Stethem, C., Jamieson, B., Schaerer, P., Liverman, D., Germain, D., and Walker, S.: Snow avalanche hazard in Canada - A review, Natural Hazards, 28, 487–515, https://doi.org/10.1023/A:1022998512227, 2003.

Techel, F., Jarry, F., Kronthaler, G., Mitterer, S., Nairz, P., Pavšek, M., Valt, M., and Darms, G.: Avalanche fatalities in the European Alps: Long-term trends and statistics, Geographica Helvetica, 71, 147–159, https://doi.org/10.5194/gh-71-147-2016, 2016.

Trujillo, E., Ramírez, J. A., and Elder, K. J.: Topographic, meteorologic, and canopy controls on the scaling characteristics of the spatial distribution of snow depth fields, Water Resources Research, 43, https://doi.org/10.1029/2006WR005317, 2007.

Veitinger, J., Sovilla, B., and Purves, R. S.: Influence of snow depth distribution on surface roughness in alpine terrain: A multi-scale approach, Cryosphere, 8, 547–569, https://doi.org/10.5194/tc-8-547-2014, 2014.

Veitinger, J., Stuart Purves, R., and Sovilla, B.: Potential slab avalanche release area identification from estimated winter terrain: A multi-scale, fuzzy logic approach, Natural Hazards and Earth System Sciences, 16, 2211–2225, https://doi.org/10.5194/nhess-16-2211-2016, 2016.

Weiss, a.: Topographic position and landforms analysis, Poster presentation, ESRI User Conference, San Diego, CA, 64, 227 – 245, http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Topographic+Position+and+Landforms+Analysis#0, 2001.

Weißgraeber, P. and Rosendahl, P. L.: A closed-form model for layered snow slabs, https://doi.org/10.5194/tc-2022-140.

Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., and Reynolds, J. M.: ‘Structure-from-Motion’ photogrammetry: A low-cost, effective tool for geoscience applications, Geomorphology, 179, 300–314, https://doi.org/10.1016/J.GEOMORPH.2012.08.021, 2012.

Winstral, A., Elder, K., and Davis, R. E.: Spatial snow modeling of wind-redistributed snow using terrain-based parameters, Journal of Hydrometeorology, 3, 524–538, https://doi.org/10.1175/1525-7541(2002)003<0524:SSMOWR>2.0.CO;2, 2002.

Wirz, V., Schirmer, M., Gruber, S., and Lehning, M.: Spatio-temporal measurements and analysis of snow depth in a rock face, Cryosphere, 5, 893–905, https://doi.org/10.5194/tc-5-893-2011, 2011.

Wood, S. N.: Generalized Additive Models, Chapman and Hall/CRC, https://doi.org/10.1201/9781420010404/GENERALIZED-ADDITIVE-MODELS-SIMON-WOOD, 2006.