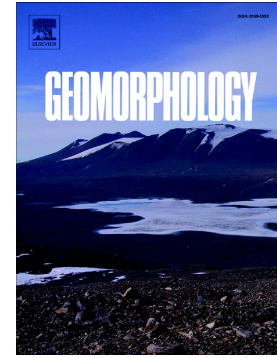


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Title: Assessing the utility of regionalized rock-mass geomechanical properties in rockfall susceptibility modelling in an alpine environment

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Author Contributions

conceptualization: GB, CC, AB, TA; funding acquisition: TA; methodology: GB, CC, AB, TA; investigation and formal analysis: GB; supervision: CC, AB, TA; writing – initial draft: GB; writing – reviewing and editing: GB, CC, AB, TA.

Conflict of Interest

Authors declare no conflict of interest.

Abstract

The main goal of this study was to develop a reliable rockfall susceptibility map for Valchiavenna (275 km²), located in the Italian Central Alps, through the introduction of outcrop-scale geomechanical properties (Joint Volumetric Count-Jv, rock mass Weathering Index-Wi and Equivalent Permeability-Keq) as spatially distributed predictors. Specific objectives were: (i) to increase the representativeness over the study area of an existing geomechanical dataset by adding new surveys, (ii) to effectively regionalize the geomechanical properties (iii) to evaluate the performance and the physical plausibility of a rockfall susceptibility model combining geomechanical, topographical, geomorphological, and geological predictors.

We optimized new survey locations by means of Spatial Simulated Annealing (SSA) and Multivariate Environmental Similarity Surface (MESS). For the regionalization of

predictors we tested several interpolation techniques and evaluated them through performance indices and leave-one-out-validation. We performed the susceptibility analysis using rockfall data from the official Italian inventory, later updated with several field-mapped rockfalls, and different combinations of predictors. We applied Generalized Additive Models, which we evaluated through spatial k-fold cross-validation in terms of model performance (AUROC) and physical plausibility. Also, we investigated the importance of the predictors in the model through penalization and the calculation of the mean decrease of deviance explained (mDD%) upon recursive removal of each predictor.

Through SSA we added 25 survey locations that reduced the study area with negative MESS from 26.2% to 15.9%. We calculated the geomechanical predictor maps applying ordinary kriging to Jv (NRMSE= 13.7%) and Wi (NRMSE= 14.5%) and using Thin Plate Splines for Keq (NRMSE= 13.5%).

The model containing the geomechanical predictors resulted in acceptable rockfall discrimination capabilities (mean AUROC>0.7), with high-susceptibility areas located in plausible geomorphological contexts, characterized by currently active deformations (verified by means of InSAR data), which were not revealed by the topographic predictors alone. Regarding importance, Jv showed an mDD% of 7.5% comparable to those of secondary topographic predictors (e.g., profile curvature, northness), while Wi and Keq were penalized out of the model. Models built with the non-updated inventory resulted in physically implausible susceptibility maps and predictor behaviour (unreasonable smoothing functions), highlighting a model bias.

Keywords

Joint Volumetric Count, Permeability, Weathering, Generalized Additive Models

1. Introduction

In mountainous environments, rockfalls are a widespread and frequent instability type, strongly affecting human society and infrastructures. In geologically complex alpine areas, such as the Valchiavenna (Central Italian Alps), the challenge is to identify differences in failure probability amongst adjacent cliffs, and to understand why different portions of the same rock mass behave differently (Matasci et al., 2018). Where the climatic and topographic contexts are similar, variability in rockfall activity should be investigated in terms of local hydro-mechanical characteristics (Coe and Harp, 2007; Matasci et al., 2011; McColl, 2012; Falli et al., 2012).

In literature rock mass instabilities are investigated at different scales: (i) at the slope scale, by means of physically-based numerical models (Gischig et al., 2011; Brideau et al., 2011; Wang and Ni, 2014; Morcioni et al., 2020); (ii) at the medium scale, including contiguous slopes, either by means of ground-based monitoring systems, such as LiDAR (Gigli et al., 2014; Dunham et al., 2017; Matasci et al., 2015; 2018), or with the pioneering use of augmented reality (Zhang et al., 2019); (iii) at the regional scale, by means of hybrid physically and statistically based approaches (Frattoni et al., 2008), multi-criteria decision-making methods (Cignetti et al., 2020), and statistical and machine-learning methods (Messenzehl et al., 2017; Zhou et al., 2018; Losasso and Sdao, 2018; Fanos and Pradhan, 2019; Rossi et al., 2021).

Regional-scale susceptibility approaches considering only topographic predictors may suffer from a strong generalization of the processes, as these phenomena reflect a complex interplay of numerous processes acting at different spatial-temporal scales (Messenzehl et al., 2017). Nonetheless, including other types of predictors, relevant to the landslide type and volume, is challenging. Geo-structural and geomechanical properties are difficult to interpolate (Reichenbach et al., 2018), primarily due to raw data limited availability and suitable coverage over large areas. These types of

datasets are usually collected either in relation to local problems or clustered close to roads and infrastructures, hence not representative of the properties' variability and not suitable for interpolation. Therefore, strategies for the design of optimal sampling schemes (i.e., efficient and effective in terms of time, budget, and quantity/quality of sampled points) to update or even create geological-environmental datasets become necessary. Several of such options are available in the digital soil mapping literature (see Brus, 2019 for a comprehensive review).

The rock mass system mechanical behavior derives from the interaction of topographic, tectonic, glacial loading-unloading and exhumation generated stresses, acting at several spatial and temporal scales and preferential directions (Ballantyne, 2002; Jaboyedoff et al., 2011; McColl, 2012; Loye et al., 2012; Ballantyne and Stone, 2013; Ambrosi and Crosta, 2006; Leith et al., 2014). The stress history materializes in the rock mass geomechanical properties, primarily controlling rock slope stability and long-term equilibrium (McColl, 2012). This explains why geomechanical properties are more relevant than readily available terrain attributes (e.g., lithology, slope aspect) for the understanding and modelling of rock slope degrading processes (Krautblatter and Moore 2014). Fracture density, water circulation and weathering conditions are widely recognized as crucial geomechanical properties for rock slope instability (Moore et al., 2009; Ballantyne, 2002; Matasci et al., 2011; Jaboyedoff et al., 2011; McColl, 2012; Wei et al., 2014; Krautblatter and Moore, 2014; Scott and Wohl, 2019; Hartmayer, 2020).

In rock masses, the presence of discontinuities of different origin creates an anisotropic strength severely affecting rock slope stability (Coe and Harp, 2007). Also, deformability is more influenced by joints than by intact-rock properties (Jaboyedoff et al., 2004). Fracture density and orientation control valley morphology and rock mass-wasting processes (Leith et al., 2012; Loye et al., 2012); in general, slopes with

closely spaced fractures are more susceptible to rock slope instability (Scott and Wohl, 2019). Rock mass fracturing characteristics are traditionally considered in susceptibility models in the form of the distance from faults predictor (Hong et al., 2016; Du et al., 2017; Yi et al., 2020; Rabby and Li, 2020). However, for rockfalls, the local fracture pattern and the spatial variation of the geometrical characteristics of jointing are crucial predisposing factors (Volkwein et al., 2011; Corominas et al., 2014; Wang et al., 2021). Therefore, the distance to fault predictor suffers of two major shortcomings. Firstly, it is commonly based on “subjective” distance classes depending on the modeler sensitivity, thus not guaranteeing to reproduce the joint network spatial variation correctly. Secondly, it seldom considers the state of activity and size of the fault zones, thus omitting to distinguish areas with different fracturing patterns in terms of e.g., local joints orientation, aperture and spacing (although similar distance to fault). For this reason, the fracture density (e.g., in the form of the Joint Volumetric Count, J_v) is considered an appealing property to be used as predictor in a regional analysis.

Weathering is another factor affecting the instability of rock slopes and rock mass quality (Eberhardt et al., 2005; Ceryan et al., 2007; Zimmer et al., 2012; Mišćević and Vlastelica, 2014; Krautblatter and Moore, 2014). Weathering acts by extending the existing micro-defects of rock masses, nucleating new fractures and decreasing the toughness, cohesion and frictional resistance of existing fractures (Ballantyne, 2002; Viles, 2013; Krautblatter and Moore, 2014). Therefore, the process triggers a feedback loop, since it provides additional surfaces and opens up pathways for weathering processes (McColl, 2012; Scott and Wohl, 2019). Weathering can be added in a regional analysis deriving a spatial map of the weathering index.

The rock mass hydromechanical behavior is dominated by the fracture system as the intact rock permeability can be considered negligible (Baghbanan and Jing,

2007). Rock mass permeability influences slope stability in a complex dual relationship: time-dependent crack damage and fracture growth enhance rock mass permeability (Riva et al., 2017; Grämiger et al., 2017), which in turn controls infiltration, discharge, and pore pressure changes. Due to the difficulties in quantifying rock mass hydrogeological conditions objectively, they are usually included in a qualitative way in most of the rock mass classification systems, especially when applied to slope stability problems (Pantelidis, 2009). Moreover, differential weakening processes and stress redistribution may lead to variations in hydraulic conductivity and drainage patterns (Crosta et al., 2013; Wei et al., 2014). It is worth exploring a qualitative-quantitative hybrid approach, considering both the density of drainage and infiltration structures and an equivalent permeability calculated from field data.

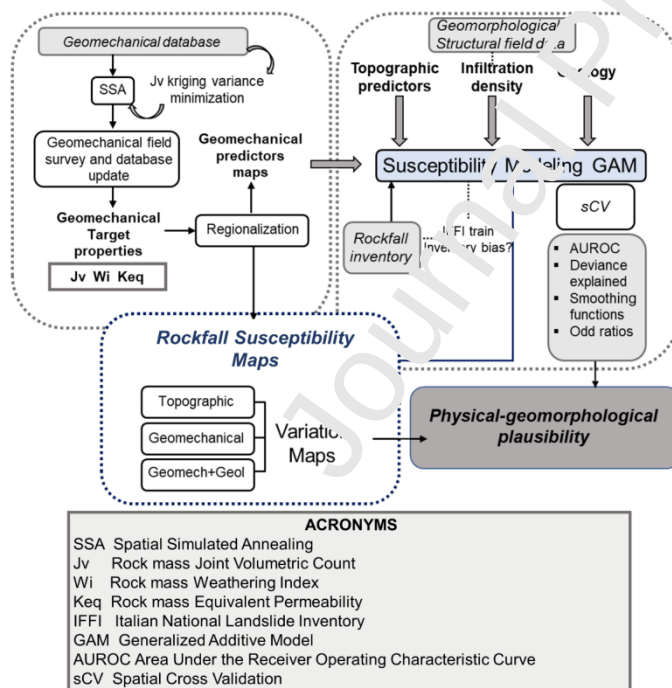


Figure 1. Workflow representing the main phases of the work

Introducing high-quality and relevant geo-environmental predictors into susceptibility models, is a known challenge, especially for landslides involving rock slopes (Reichenbach et al., 2018). The overarching goal of the study was to test the influence of some geomechanical properties on rockfall susceptibility in an Alpine environment. Specific objectives, summarized in Figure 1, were: (i) to update and review an available geomechanical dataset for Valchiavenna (SO, Italy) through the optimal selection of additional sampling sites and the execution of geomechanical surveys; (ii) to calculate three geomechanical target properties, namely Joint Volumetric Count (Jv), rock-mass weathering index (W_i) and rock-mass equivalent permeability (K_{eq}), derived from post-processing the field-surveyed geomechanical data, and to regionalize them over the study area; (iii) to implement these regionalized geomechanical properties as predictors in a rockfall susceptibility model developed by means of Generalized Additive Models (GAM). The main thread guiding the entire procedure was the evaluation of the geomorphological-geological plausibility of the outputs, often disregarded when dealing with landslide susceptibility assessment (Steger et al., 2016a). Moreover, uncertainties related to the geomechanical and rockfall inventory inputs were investigated. To the authors' knowledge, this research represents the first attempt to upscale local rock mass geomechanical properties in a regional susceptibility analysis.

2. Geological Setting

Valchiavenna (northern Italy, Province of Sondrio) is a structural-glacial valley of about 275 km², located in the Central Alps (Figure 2). It is characterized by the convergence of two orthogonal tributary valleys in correspondence of the town of Chiavenna: San Giacomo Valley (N-S), and Bregaglia Valley (E-W), both connecting Italy to Switzerland. These two valleys differ in terms of geostructural settings and slope morphologies (Figure 2).

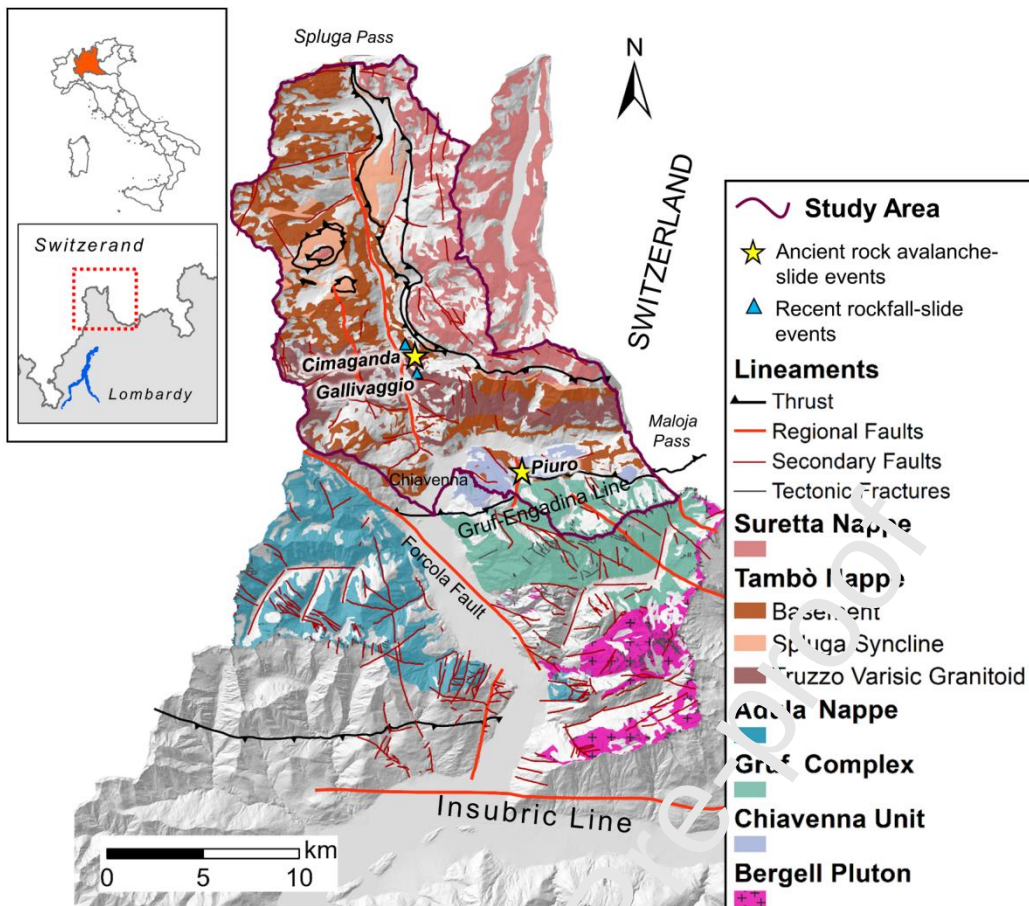


Figure 2. Location of the study area (Lombardy region, Italy) and geo-structural map of the study area (CROP Project, Montrasio & Sciesa, 1978). Grey filled areas represent Quaternary deposits

The San Giacomo Valley is predominantly characterized by the sub-horizontal thrust contact between the tabular gneissic bodies of the Tambò and Suretta nappes, both Penninic. The two nappes feature a gently NE-dipping schistosity and similar polycyclic and poly-metamorphic paragneiss lithologies, intercalated with minor orthogneiss and ultramafic layers (Montrasio & Sciesa, 1988; Nussbaum et al., 1998). Their crystalline basements are separated by the Permo-Mesozoic metasedimentary cover, of the Spluga Syncline, showing the typical facies of the Briançonnais domain (Baudin et al., 1993) with metapelites, micaschists, carbonates and quartzites. Outcrops of these lithologies are frequent in the northern part of the San Giacomo Valley, resulting in a wide, open morphology with large flat surfaces at mid-high elevations (1500-2000 m a.s.l.). Conversely, the southern part of the San Giacomo Valley is shaped by the presence of the Variscan Truzzo Metagranite, intruded into the

Tambò Nappe, resulting in a narrow morphology with steep slopes (Tantardini et al., 2013).

The Tambò-Suretta structural contact extends through the northern slope of the Bregaglia Valley, where it is clearly visible at an elevation of around 2000 m a.s.l. In contrast, the southern slope is characterized by the presence of the Penninic granulite-migmatite Gruf Complex in structural contact with the ophiolitic Chiavenna Unit, marked by the sub-vertical mylonitic zone called Gruf Line (Galli et al., 2013). The Gruf Line could be interpreted as the brittle-ductile elongation of the Engadine Line (Wenk, 1984). In its south-eastern sector, the Gruf Complex was intruded in a compressional tectonic regime (Berger et al., 1990) by the Periadriatic Bergell Pluton (Tibaldi and Pasquarè, 2013). The Gruf Complex is composed of biotite-feldspar migmatitic gneiss, often characterized by augen-texture and granitic enclaves (Pigazzi et al., 2022). The Chiavenna Unit is interpreted as the result of the youngest basic oceanic magmatism in the Alps (Huber and Marquer, 1998; Liati et al., 2003) and mainly includes ultramafic lithologies (e.g., metaperidotites, amphibolites, metagabbros).

The structural framework of the area is characterized by the presence of three main regional tectonic alignments (Figure 2), namely the Insubric Line (WNW-ESE), the Forcola Fault (NW-SE) and the Gruf-Engadine Line (NE-SW). At the slope scale, they reveal themselves through pervasive and recognizable discontinuity sets, overprinted and steepened by late alpine brittle-ductile deformation phases which produced an extensive fracturing pattern expressed by normal faults (Ferrari et al., 2014). The structural setting of Bregaglia Valley is dominated by three main ductile shear zones related to Gruf Complex, carrying identical mineral association suggesting a contemporaneous development (Galli et al., 2013).

As described by Tantardini et al. (2013), during the Last Glacial Maximum - LGM (from 30 to 18 ky BP, Lambeck et al., 2002, Schaefer et al., 2006) San Giacomo and Engadina-Bregaglia glaciers merged in the area of Chiavenna forming a single glacier flowing southwards. The Engadina-Bregaglia glacier was characterized by a greater thickness than San Giacomo glacier, which was consequently partially squeezed and stretched along the western slope of Chiavenna Valley. Throughout the deglaciation phase, several lateral glaciers detached from the major San Giacomo glacial tongue and advanced towards the major valley. According to the Alpine Permafrost Index Map (APIM, Boeckli et al., 2012) permafrost is present in the area, localized at high altitudes (approximately from and above 2500 m a.s.l.) but it was not directly accounted in the present study.

The interplay between tectonic processes and glacial cyclical debuttressing (Grämiger et al., 2017), following the retreat of the Engadine-Bregaglia and San Giacomo glaciers (Tantardini et al., 2013), is crucial in defining the present-day slope dynamics in the study area. Both the San Giacomo and the Bregaglia Valley are characterized by several DSGSD (Deep Seated Gravitational Slope Deformations) with different "maturity" and field evidence (Tantardini, 2016). Associated to these wider and slower processes, secondary more rapid phenomena such as rock avalanches, rockslides and rockfalls could occur (Figure 2). In the study area, the most ancient known events of this kind are the Cimaganda rock avalanche in the San Giacomo Valley, which probably occurred in the IX century (with an estimated volume of 7.5 Mm³, Mazzoccola, 1993), and the 1618 Piuro landslide (Schuster and Highland, 2007; Pigazzi et al., 2022) on the southern slope of Bregaglia Valley (with an estimated volume between 6 and 9 Mm³ Pigazzi et al., 2022). These historical events aside, the community living in Valchiavenna frequently faces several instabilities and their associated damages and risks. The most recent events are the Cimaganda

reactivation in 2012 (with a volume of ca. 20.000 m³, Morcioni et al., 2020), the Cengalo rockslide-rock avalanche occurred in Bondasca Valley (tributary of Bregaglia Valley in its Swiss segment) in 2017 but affecting the whole Bregaglia Valley (with a detached volume of ca. 3 Mm³ Mergili et al., 2020) and the Gallivaggio rockfall in 2018 (with a volume of ca. 5000 m³, Carlà et al., 2019).

3. Materials and methods

3.1 Data

3.1.1 Land surface data

In this study the Digital Terrain Model (DTM) made available by Regione Lombardia was used (<http://www.geoportale.regione.lombardia.it/>). It has a 5 m x 5 m horizontal resolution and is the result of several airborne LiDAR surveys (2008-2009; 2010-2011; 2013-2015). Regarding geology, for the study area, a map is available at a 1:50,000 scale (Crop Project, Montrasio and Sciesa, 1988), including both geo-structural (Figure 2) and lithological descriptions (Figure 3a). In addition, SqueeSARTM data (TRE Altimira) are available in the region. They consist of permanent (PS) and distributed (DS) scatterers, reporting line-of-sight (LOS) displacement rate. Data are available in both ascending (track=15, mean LOS=40.64°) and descending (track=66, mean LOS=36.94° and track=168, mean LOS=42.4°) geometries. In detail, data were derived from Sentinel 1A/B radar since October 2014 to February 2021 and were made available for this study by Regione Lombardia within the framework, of the ongoing A.M.AL.PI.18 Interreg Project (<https://progetti.interreg-italiasvizzera.eu/it/b/78/alpiinmovimentomovimentonellealpiuero>).

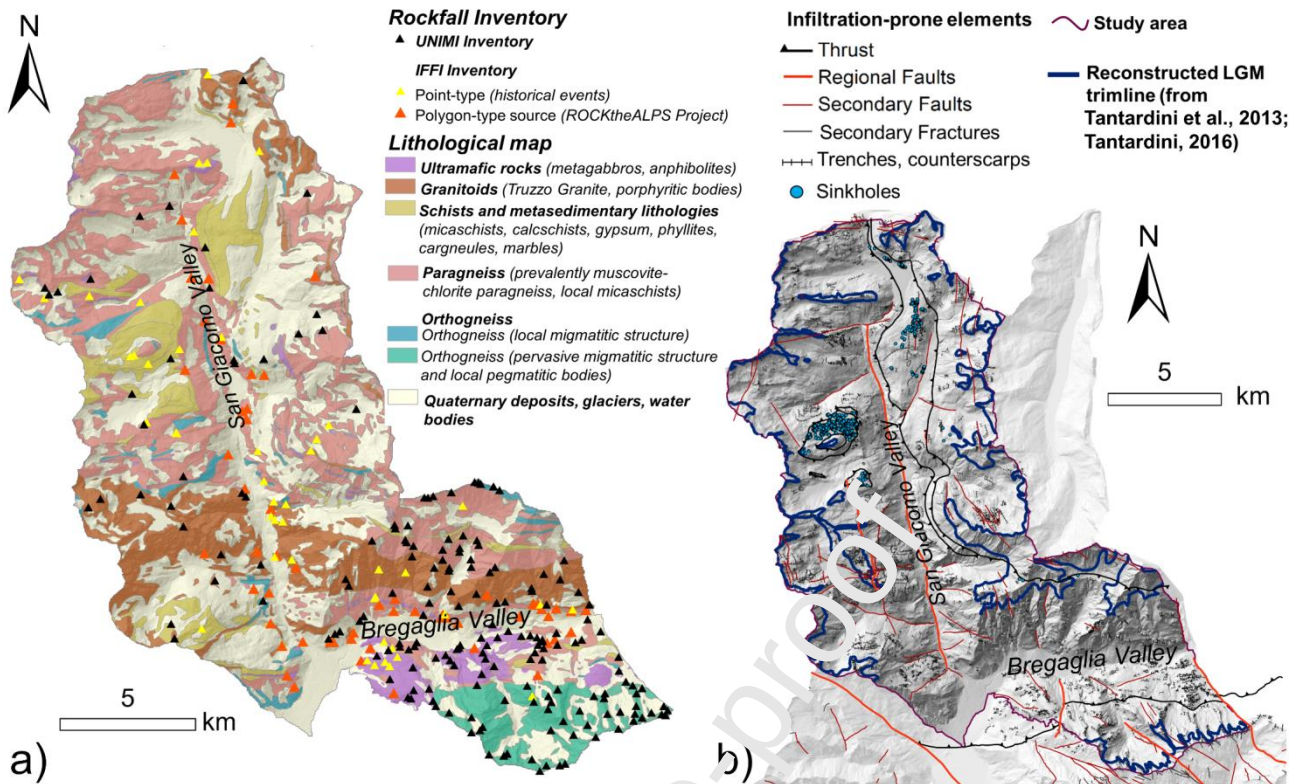


Figure 3 a) Lithological map of the study area, bearing rockfall source location (CROP Project, Montrasio & Sciesa, 1988); b) Shaded relief map of the study area, comprehending the reconstructed LGM trimline (Tantardini et al., 2013; Tantardini, 2016) and the infiltration-prone elements used for the infiltration density predictor creation (Section 3.5.1)

3.1.2 Rockfall data

Rockfall data (Figure 3a) were the result of the integration of two different rockfall inventories. The first is the freely available IFFI dataset (Inventario Fenomeni Franosi in Italia, <https://www.progettoiffi.isprambiente.it/>) in which rockfalls are partly recorded as points (labelled as “historical events”) and partly as polygons (reporting both the source and the accumulation areas). For the IFFI “historical events” each point represented the georeferenced highest point of the crown (<https://www.progettoiffi.isprambiente.it/en/methodology/>). For the IFFI “polygon-type” dataset, the source points were interpreted as the highest points of the source area polygons within the project ROCKtheALPS 2019. These source points were also made available through an open-source dataset (<https://www.alpine-space.org/projects/rockthealps/en/home>). The second inventory is a

geomorphological dataset (hereafter UNIMI inventory), comprising several additional rockfall scarps and deposits and covering remote locations of the study area. The latter was extracted from a detailed geomorphological-structural map of the area, derived from field surveys conducted at a 1:10,000 scale, integrated with remote sensing. All surveys were carried out in the period 2002-2020 in the framework of the Valchiavenna Project (Sfondrini and Pasquare, 2011), several MSc theses, the Ph.D. studies of Tantardini (2016), and within the A.M.AL.PI.18 Interreg Project.

3.1.3 Geomechanical data

A dataset of 128 geomechanical surveys conducted between 2002 and 2019 was available for the study area prior to this work (database of the geoengineering research group of the Dept. of Earth Sciences, Università degli Studi di Milano). This dataset was the result of detailed geomechanical campaigns carried out by different surveyors. Each record was acquired according to the International Society of Rock Mechanics (ISRM) Suggested Methods (ISRM, 1978). Records include both primary variables (e.g., Joint Roughness Coefficient JRC, Schmidt Hammer rebounds, joint spacing, orientation, aperture, persistence) and derived rock mass quality indices (e.g., Rock Mass Rating RMR, Geological Strength Index GSI). The main limitation of this dataset consists in a clustering of data along the main valley floors (i.e., easily accessible areas).

3.2 Target geomechanical properties

To produce a statistically-based susceptibility model, it was necessary to resolve the complexity of the rock mass system by means of measurable and independent variables. Among the several rock mass and joint metrics measurable on an outcrop, the focus fell on three main target properties: Joint Volumetric Count J_v (fractures/m³), Weathering index W_i (-), and Equivalent Permeability K_{eq} (m/s), all

representative of rather shallow conditions of the rock masses. Geomechanical surveys were carried out on outcrops with lengths ranging approximately from 10 m up to 150 m. As the median length of the rockfall scarps collected in the UNIMI inventory was 126 m, the geomechanical survey sites dimensions were considered representative of the investigated instability phenomena.

Joint Volumetric Count represents the volumetric fracturing degree of a rock mass and is defined as the number of joints intersecting a volume of 1 m³. This parameter can be obtained from the measured average spacing of each joint set (Palmstrom, 1982). It is independent of the discontinuity type, being a proxy not only of the tectonic history but also of the other stress redistribution processes acting on rock slopes at a local level.

The weathering index represents the rock mass weathering conditions. It is calculated as the ratio of Schmidt Hammer rebounds on natural and abraded joint surfaces, following the relationship linking rebounds and surface age of exposure (e.g., Stahl et al., 2013; Stahl and Tye, 2020). This index represents the weathering predisposition of the rock masses, which is strictly connected to rock mineralogy and weak planes, given similar microclimate and topography (Hall et al., 2012).

K_{eq} was derived from the permeability tensor $\bar{K}$ introduced by Kiraly (1969) and modified by Coli et al. (2008):

$$\bar{K} = \frac{g}{12\nu} \sum_{i=1}^N f_i e^3_i [I - \vec{n}_i \times \vec{n}_i] \quad \text{Eq. 1}$$

where g is gravity (9.81 m/s²), ν is the kinematic viscosity of water (3.2x10⁻⁶ m²/s), N is the total number of discontinuity sets, f is the average frequency of the i^{th} set of discontinuities (m⁻¹), e is the average hydraulic aperture of the i^{th} set of discontinuities (m), I is the identity matrix and $\vec{n}|_{n_1, n_2, n_3}$ is the dimensionless unitary vector normal

to the average plane of the discontinuity set. The authors used the hydraulic aperture defined by Barton (2004 a,b) to account for mechanical aperture reduction related to joint roughness. Finally, once obtained the tensor $\bar{K}$, the three components of the principal diagonal were used to calculate K_{eq} as (Guo et al., 2015):

$$K_{eq} = \sqrt[3]{k_{11}k_{22}k_{33}} \quad \text{Eq. 2}$$

As K_{eq} calculation is strongly based on joint apertures measured in each geomechanical survey site, it consequently represents the hydrogeological behavior of the rock mass at the outcrop scale.

3.3 Expansion of the geomechanical dataset

Due to clustering along main valleys, the spatial distribution of the pre-existing geomechanical surveys was not fully suitable for regionalization. Therefore, the model-based Spatial Simulated Annealing - SSA (Van Groeningen, 1999) procedure, proposed by Brus (2019) was adopted to increase the number of survey points and simultaneously improve the spatial distribution of the dataset. SSA is an iterative random search procedure (Brus, 2019) that optimizes a custom target function based on the pre-existing survey sites. Due to incomplete data collection, J_v was the only target property calculable at all survey sites. For this reason, a preliminary regionalization of J_v was performed by means of ordinary kriging – already used to regionalize geomechanical parameters in the upper part of San Giacomo Valley (Ferrari et al. 2012, 2014) – and used the associated prediction error variance as the target function to obtain 25 new survey locations. Additional details on SSA parametrization can be found in the Supplementary Material.

Detailed geomechanical field analyses were performed at each new location and contextually some pre-existing sites were revisited to acquire missing parameters to obtain J_v , W_i and K_{eq} . Minor offsets from the exact SSA sites were due to logistic

choices (e.g., vegetation cover, terrain stability conditions, surveyors' safety), while in three cases the selected survey sites were not accessible. In such situation close and accessible areas with similar characteristics in terms of geological unit and slope aspect were alternatively selected. Moreover, before and after conducting the field surveys, the Multivariate Environmental Similarity Surface (MESS; Elith et al., 2010) was calculated based on several environmental covariates (elevation, aspect, slope, longitude, latitude) and using the R package *dismo* (Hijmans, 2013). The goal was to attest if, besides kriging variance minimization, the newly acquired information would improve the representativeness of the geomechanical dataset in the studied, complex, mountain environment. The algorithm returns a pixel-based MESS value. The higher this value, the more common the environment of the point (pixel). Negative values indicate a novel environment, meaning one or more covariates are not fully represented by the survey locations (Camacho et al., 2017).

3.4 Regionalization of the geomechanical properties

Prior to regionalization, the pairwise correlations (Pearson's correlation coefficients and p -values of t -tests) among geomechanical properties and with environmental variables such as elevation, latitude, longitude, slope and aspect - in terms of northness = $\cos(\text{aspect})$ and eastness = $\sin(\text{aspect})$ - was analyzed to find preliminary patterns in the dataset. Following different deterministic (inverse distance weighting, thin plate spline), geostatistical (ordinary kriging, kriging with external drift) and regression (multiple linear regression, geographically weighted regression) regionalization techniques were evaluated. For the predicted K_{eq} map, a minimum cut-off was added. Values lower than the typical values of intact rock permeability (according to the underlying lithology) were substituted with the intact rock values, i.e. the lowest possible value for the rock mass. Intact rock permeability values were derived from various sources (Brace, 1980; Kovacs, 1981; Morrow et al., 1994; Evans

et al., 1997; Selvadurai et al., 2005; Sperl and Trckova, 2008; Milsch et al., 2011; Najser et al., 2011; Leclère et al., 2015; Sen et al., 2015; Duan et al., 2017; Sarout et al., 2017).

The regionalization was performed in R, at a 50 m x 50 m horizontal resolution, and applied a bilinear interpolation for resampling to DTM resolution. Moreover, regionalization performances were assessed with a leave-one-out cross-validation (LOO-CV) by calculating goodness-of-fit and error metrics (correlation coefficient r of modelled and observed values, and NRMSE- Normalized Root Mean Square Error). Based on performance indices and spatial patterns, the most reliable maps were selected as geomechanical predictors for susceptibility modeling.

3.5 Rockfall susceptibility modeling

3.5.1 Modelling algorithm

Rockfall susceptibility was modelled using Generalized Additive Models (GAM).

Generalized Additive Models are a semi-parametric extension of Generalized Linear Models - GLM (Hastie and Tibshirani, 1990). GAMs extend the parametric assumption of GLMs by replacing some, or all, of the parametric terms with smooth functions (Simpson, 2018). GAMs are used to study the relationships between a response variable (absence/presence of landslides) and a set of explanatory variables x , both categorical and numerical (Hosmer and Lemeshow, 2000). The response variable is not modelled directly but by means of the logit of the conditional probability $p(x)$:

$$\text{logit}(p) = \ln \frac{p(x)}{1 - p(x)} = \ln(\text{odds}) \quad \text{Eq. 3}$$

The odds or likelihood ratio represents the ratio between the probability p that the dependent variable is 1 and the probability $1-p$ that the dependent variable is 0.

While in GLMs logits are modelled linearly, in GAMs they have a more general form (Brenning et al., 2015):

$$\text{logit}(p) = \alpha + f_1(x_1) + \dots + f_j(x_j) \quad \text{Eq. 4}$$

where $f(x)$ is a non-linear transform of the explanatory variables and could be obtained by using smooth functions. In other terms, GAMs are able to represent non-linear predictor-response relationships while maintaining interpretability through their additive structure (Goetz et al., 2011, 2015). Interpretability was necessary to assess the behavior and plausibility of geomechanical predictors. Analyses were performed in R using the *mgcv* package (Wood, 2017).

3.5.2 Response variable

The binary response variable (i.e. rockfall presence/absence) was obtained from the rockfall inventory (Sect. 3.1.3). To uniquely identify each rockfall, despite the different sources, each event was summarized in a point feature. For the IFFI dataset, each point represented the georeferenced highest point of the crown, both for the “historical” (59 events) and “polygon-type” (47 events) features (<https://www.progettoiffi.isprambiente.it/en/methodology/>). For the UNIMI dataset, 137 out of the 185 available rockfall events were associated with a mapped scarp or crown in the geomorphological map; in such cases the representative rockfall point was chosen as the bisector of the scarp. When this feature was not available (48 out of 185 events), the point was placed in correspondence of the highest elevation of the mapped rockfall deposit body. It was assumed that the base of the rockfall scarp could have geomechanical conditions similar to the upper crown; however, it may introduce a possible positional inaccuracy for 16.5% of the inventory.

As absence sampling is equally crucial (Bornaetxea et al., 2018; Knevels et al., 2020), a 1:1 ratio was used to randomly extract the absence locations from all “eligible”

areas, masking urban areas, glaciers and water bodies, quaternary deposits and areas within an 80-m buffer from rockfall points and scarp lines. This buffer represents the average radius of the rockfall scarps surveyed in the study area. A 1:1 ratio was adopted for the extraction of absence points, following the guidelines of Hong et al. (2019), who found that this ratio is optimal when the “eligible” area approaches the 99% of the modelling domain (in the present case study the percentage was 92.3%).

3.5.3 Predictors

Three groups of predictors were considered: topographic, geological, and geomechanical predictors. The topographic ones are the most commonly used predictors in landslide susceptibility studies (Van Westen, 2008; Reichenbach et al., 2018) as they are considered as proxies for the slope’s climatic, hydrological, and stress conditions. Elevation, slope, northness, eastness, profile curvature, plan curvature, and SAGA Topographic Wetness Index (SWI) were derived from the available DTM using the RSAGA package (Brenning et al., 2018). Geomechanical predictors were the previously regionalized J_v , W_i and K_{eq} properties. K_{eq} was strongly based on joint apertures, and consequently represents the hydrogeological behavior of the rock mass at the outcrop scale.

To assess hydrogeological processes on rock mass instability in a broader context, an infiltration density predictor was introduced too. It was defined as the density of geomorphological-structural elements prone to infiltration, such as regional lineaments, trenches and counterscarps, and sinkholes (Figure 3b). This information was derived from the detailed structural-geomorphological map (1:10000 scale) of the area (Sect. 3.1.3) and calculated on a 5 m x 5 m pixel basis to be consistent with the resolution of the other predictors. This predictor may be interpreted as a proxy for the infiltration and draining behavior of slopes. Lineaments and morpho-structures localize

joint weathering and water supply to the rock mass (Walter et al., 2012; Wei et al., 2014; Scott and Wohl, 2019), thus representing weaknesses where geomorphic and gravitational processes are preferentially initiated and propagated (Loye et al., 2012). The infiltration density map and the maps of the topographic predictors are presented in the Supplementary Material.

Geology-related predictors are often included as they are classified in the basic geological maps available for the area (i.e., along with their unit's regional names); this may lead to unclear relationship with landslide susceptibility, hampering the transferability of the proposed modelling approach to different areas (Reichenbach et al., 2018). Moreover, very detailed geological maps may result impractical in statistically-based susceptibility modelling: the large number of classes and the limited spatial extension of some of them may result in an inadequate model validation (Segoni et al., 2020, Dornik et al., 2022). An appropriate representation of geology should be representative of the mechanical behavior of the investigated materials, thus a reclassification in terms of – measured or reasonably assumed – physical and geotechnical properties is advisable (Catani et al. 2005; Van Westen, 2008; Henriques et al., 2015; Segoni et al. 2018; 2020). Another option could be a qualitative ranking describing the relative strength of rock types (Reichenbach et al., 2018). In this study the geological map available for the study area (refer to Sect. 3.1.2 and Figure 3a) was reclassified into five classes following a lithological criterion (Catani et al. 2005; Henriques et al., 2015; Youssef et al. 2016; Samia et al., 2018; Segoni et al. 2018; 2020; Dornik et al., 2022; Panahi et al., 2022). The rationale behind the classification relies on the mineralogical association and rock mass textures and structures, which together govern its mechanical response (Segoni et al., 2020). The five classes are: (i) Paragneiss, including densely foliated muscovite-chlorite paragneiss with local layer of micaschists mainly constituting the Tambò and Suretta

Nappes; (ii) Granitoids, including the Truzzo Metagranite and porphyritic bodies from Suretta Nappe basement outcropping in the NE part of the study area; (iii) Orthogneiss, including mostly the Gruf Complex migmatitic gneisses and pegmatitic bodies and the orthogneiss layers with a local migmatitic structure from Tambò and Suretta Nappes; (iv), Schists and metasedimentary lithologies (micaschists, calcschists, gypsum, phyllites, canergules, marbles, quartzites) grouped together as with limited spatial extension and all mainly belonging to the Spluga Syncline; (v) Ultramafic rocks (mainly metagabbros and amphibolites), primarily constituting the Chiavenna Unit and secondarily present as local layers in the Tambò and Suretta Nappes. The class adopted as the modelling reference was the most abundant in the study area (Paragneiss).

3.5.4 Modelling options

Using these predictor sets, three models were set up and compared: a topography-based model (TOPO), a topographic-geomechanical model (GM), and a topographic-geomechanical-geological model (GM+GEO). To achieve a good trade-off between model size and fit, variable selection through shrinkage was adopted, which is an option available in the *mgcv* implementation of the GAM. Predictors with low or no influence on the model would thus be penalized out of the model. Topographic predictors that were removed from the TOPO model were not further considered in the successive GM and GM+GEO models. The relationships between rockfall occurrence and predictors were analyzed through the associated smoothing functions by means of CSF (Component Smoothing Function) plots and odds ratios for geological categories. Odds ratios for categorical variables represent the chance of an outcome, given a certain class in comparison to a reference one. A class with an odds ratio < 1 represents a lower chance of a modelled outcome (rockfalls) in comparison to the

reference class, an odds ratio >1 a higher chance, and an odds ratio around 1 means no relationship (Knevels et al., 2020).

3.5.5 Model performance and predictor importance

Model performance was assessed through a spatial k -fold cross-validation (sCV) to estimate, the area under the receiver operating characteristic curve (AUROC), a widely applied performance measure for landslide susceptibility models (Corominas et al., 2014; Reichenbach et al., 2018). Spatial cross-validation is preferable when dealing with spatial data, which are often subject to spatial autocorrelation (Brenning, 2005, 2012b). A spatial partitioning based on k -means clustering of coordinates was applied to derive $k=5$ folds and, to obtain results that are independent of a particular partitioning, this procedure was repeated $=100$ times. The sCV was implemented using the R package *sperrorest* (Brenning, 2012a). As a measure of spatial transferability, the interquartile range (IQR) of the test-set AUROC values was analyzed (Petschko et al., 2014).

Furthermore, the predictors' CSFs from each cross-validation run were compared with the corresponding smoothing function obtained on the entire dataset, to assess coherence and robustness of their behavior. For the GM+GEO model, the variability of geology odds ratios from the different CV runs was assessed too.

To investigate the importance of predictors, the penalization frequency coming from the application of the shrinkage option was combined with the mean decrease in deviance explained (mDD%), calculated as in Knevels et al., (2020). The shrinkage option was set to penalize out of the model all the variables showing effective degrees of freedom below 0.7. Moreover, concurvity between the smoothers was assessed, i.e. the generalization of multicollinearity; high concurvity values may lead to unstable parameter estimation (Amodio et al., 2014).

3.5.6 Susceptibility maps and geomorphological plausibility

To allow a straightforward comparison between model outputs derived from different predictors sets, susceptibility maps were reclassified into five susceptibility classes (as in e.g., Camera et al., 2021), namely 0.0–0.3 “very Low”, 0.3–0.5 “low”, 0.5–0.7 “medium”, 0.7–0.9 “high”, 0.9–1.0 “very high”.

Spatial patterns in susceptibility maps were critically analyzed for geomorphological plausibility. Furthermore, differences between susceptibility maps obtained with different predictor sets were explored and possible relationships to geomorphological and geo-structural features examined.

To explore the physical plausibility of the derived maps, they were also compared with Sentinel-1 SAR data (PS/DS mean annual velocities). Although these types of data are mainly suitable for the investigation of slow deformations, in particular deep-seated gravitational slope deformation (DSGSD; Frattini et al., 2018), they could also be useful to study more rapid phenomena such as rockfalls. Indeed, slow deformations are considered as proxies for various processes relevant for slope stability (e.g., hydrogeological circulation, creep, neotectonics) and are usually associated to the nucleation of secondary, shallower instabilities (Crippa et al., 2020).

3.5.7 Uncertainty related to the inventory

As the used rockfall inventory integrates two different sources, the opportunity arose to evaluate the effects of potential biases in the official inventory. The IFFI inventory (see Sect. 3.1.2) was compiled starting from administration reports and multi-temporal aerial photographs, therefore it could be affected by an underrepresentation of rockfalls in remote areas (Guzzetti et al., 1999; Steger et al., 2016a, 2021) and by an obliteration of geomorphic features in forested area (Steger

et al., 2017). Model performance, the behavior of predictors, and predicted susceptibility patterns of the GM and GM+GEO models were compared using the IFFI inventory as the training set and the UNIMI inventory as test set. The model was cross-validated as in Sect. 3.5.5 to assess model performance as well.

4. Results

4.1 Geomechanical properties: sampling

The preliminary results of the Jv regionalization, performed by means of ordinary kriging (Figures 4a and 4b), were used as input data for optimal survey sites selection. Figure 4c shows the SSA-selected sites and the survey locations consequently used in addition to the old dataset.

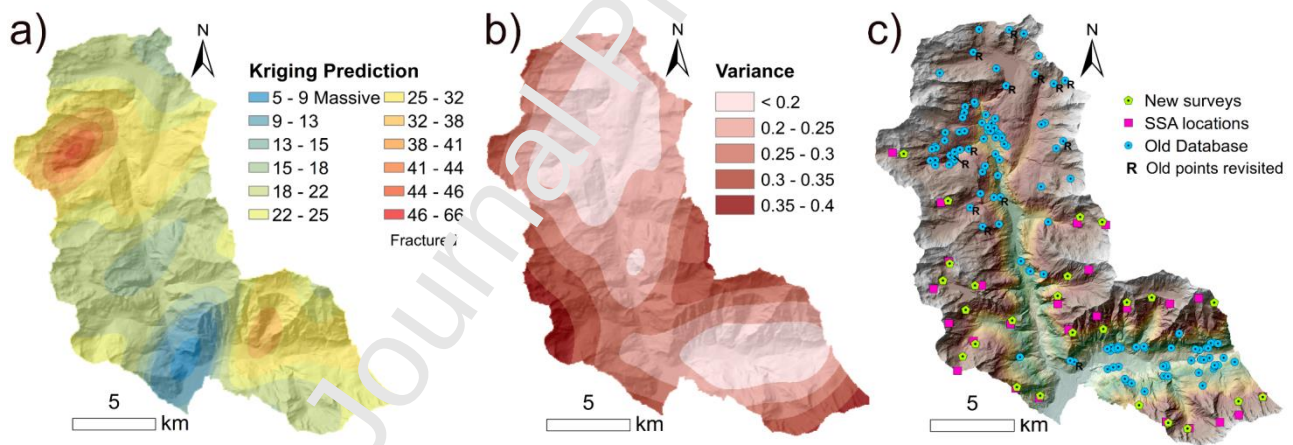


Figure 4. a) Jv prediction by ordinary kriging pre-field survey; b) Jv associated kriging variance pre-field survey; c) map showing old database locations, revisited old sites, SSA selected locations, new survey locations

Regarding the MESS resulting maps, the updated inventory enhanced the similarity and the representativeness of the geomechanical dataset, particularly on the Southern slope of Bregaglia Valley and the upper Western slope of San Giacomo Valley (Figure 5a and 5b). The addition of the new sites limited negative values of MESS to 15.9% of the study area in comparison to the 26.2% associated to the original dataset. The new surveyed sites allowed the geomechanical dataset to be updated and homogenized for the regionalization phase.

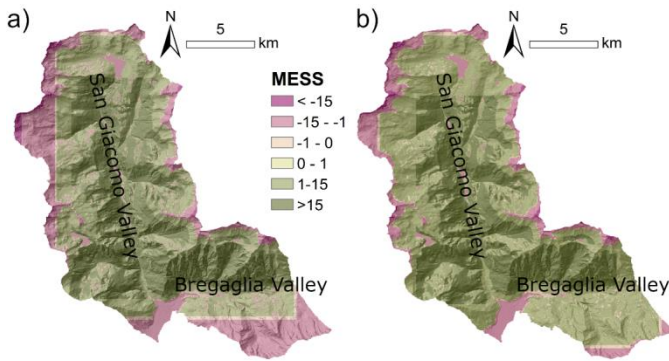


Figure 5. MESS values before(a) and after (b) field survey

4.2 Geomechanical properties: regionalization

Since linear relationships between target properties and environmental covariates were not statistically significant (p values >0.05), properties were not regionalized with MLR or KED.

For J_v , ordinary kriging outperformed the other techniques (associated map in Figure 6a). The variogram was best fit by an anisotropic exponential model with a nugget effect of 0.14 and a maximum range of 12 km in the NW-SE direction. The LOO-CV correlation between observations and predictions increased from 0.43 (pre-field survey) to 0.49 (post-field survey), while NRMSE decreased from 14.1% to 13.7%. Globally, the associated variance (Figure 6b) decreased too, mainly due to decreases at high altitudes and in the Bregaglia Valley. In the same Figure 6b, a slight increase in variance can be noticed locally, in the NE part of the San Giacomo Valley. These results demonstrated that the adopted sampling strategy was successful in reducing the error (i.e., uncertainty) associated to this predictor.

For the regionalization of the weathering index, even if the best performance was obtained adopting a GWR technique that included the latitude covariate ($r=0.51$, NRMSE=14.0%), the resulting map showed an unrealistically homogeneous spatial pattern, characterized by large bands of equal values cutting the slopes morphology.

Conversely, the W_i variability observed at the outcrop scale (i.e., on discontinuities with different orientation and aspect) showed an average variation from the mean value adopted for the interpolation of about 11% (even over the 20% for some of the outcrops investigated, i.e., for 14% of the dataset). The associated map is presented in the Supplementary Material. For these reasons, the map obtained applying an isotropic ordinary kriging (Figure 6c) was considered more reliable, despite a slightly worse performance ($r=0.47$, $\text{NRMSE}=14.5\%$). The variography of W_i resulted in an isotropic spherical variogram with a nugget effect of 0.0075. The shorter range (3125 m) and lag (750 m) in comparison to J_v suggested a more local connotation of this property. A possible interpretation could be that W_i expresses the local microclimate, while J_v is the reflection, at the outcrop scale, of the regional structural and tectonic framework. These results are geologically plausible, as no evidence of a weathering grade anisotropy was ever observed or reported in field surveys.

The regionalization of the K_{eq} index (Figure 6d) showed the poorest performance and the highest uncertainty. Its best output was obtained through a TPS method including altitude as covariate ($r=0.16$, $\text{NRMSE}=18.5\%$).

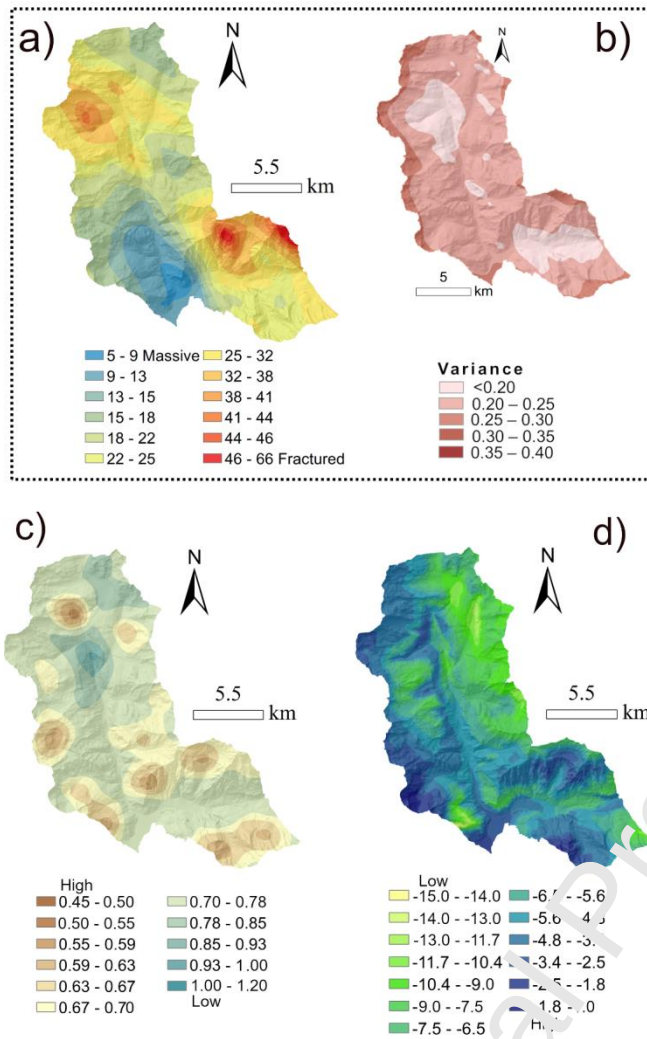


Figure 6. a) J_v predictions and b) associated kriging variance post-field survey; c) W_i predicted map by means of OK; d) Keq predicted map by means of TPS

4.3 Susceptibility model: Predictor-response relationships

Variable penalization resulted in the exclusion of the predictors eastness and plan curvature from the TOPO model fitted on all data and in most sCV runs (penalization frequency of 67.0% and 86.6%, respectively). Therefore, these predictors were excluded from the successive GM and GM+GEO models. As the predictor-response relationships were almost always maintained through the GM and the GM+GEO models, in the current section the focus is on the GM+GEO model results. Figure 7 shows the CSF plots reflecting the behavior of the different predictors

in the model, while Figure 8 presents the penalization frequency and mDD% variations amongst the different CV runs.

In the GM+GEO model, elevation and slope resulted the most important predictors, with high selection frequencies (100% and 80.4%, respectively) and mDD% values of 24.5% and 17.7% on the entire dataset. For rock slopes located at low and medium elevations, the elevation CSF shows an almost linear decreasing behavior. This result is consistent with the highly incised valley morphology characterized by active rock walls at the bottom, originated in response to the glacial evolution of the area. The secondary small increase between 2000 and 2200 m a.s.l. could be linked to the transition between glacial terraces, characterized by soil-dominated slopes, and high elevation sub-vertical rock walls. Coherently, rockfall susceptibility increased towards higher slope angles. Profile curvature, SWI and northness were almost always included (100%, 100%, and 80.4%, respectively) and shows a mDD% in the all-points based model around 11% for profile curvature and SWI, and 10% for northness. The associated CSF indicates that the modelled rockfall likelihood was highest for concave slopes with small upslope draining areas. North and south facing slopes had the highest modelled rockfall likelihood, slightly higher for the former. North-facing slopes are characterized by the lowest daily temperatures, leading to precipitation-derived water freezing in joints and, for the highest rock walls, to the possible occurrence of alpine permafrost. Consequent thawing may occur during summer days, likely driving rock mass detachments. Conversely, south-facing rock walls are the most exposed to diurnal cycles of temperature and should experience the highest frequencies of wetting and drying as well as snowmelt.

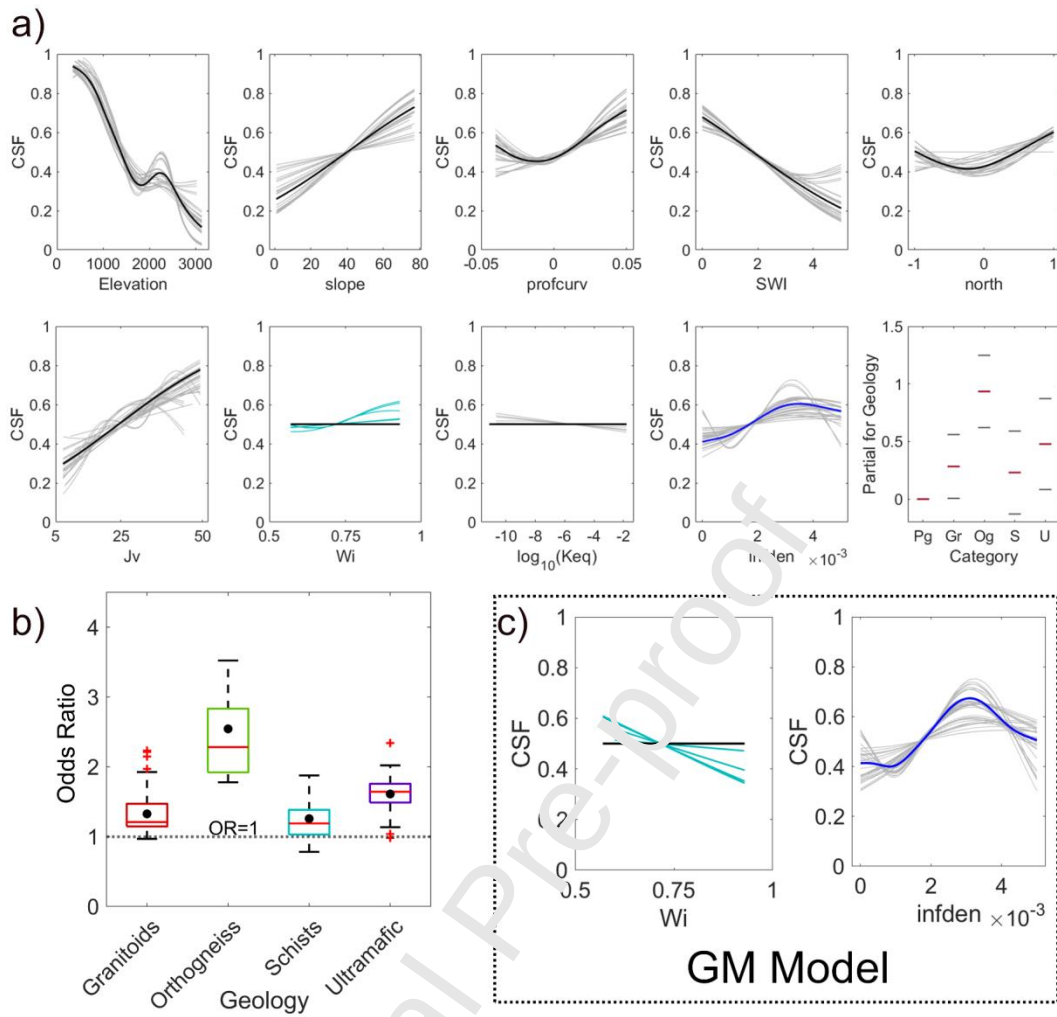


Figure 7. Smoothing functions and odds ratios extracted from all the sCV runs (grey lines –light blue for Wi – for smoothing functions and boxplot for odds ratios) and from the model fitted on all data (black line – blue for in.den – for smoothing functions and black dots for odds ratios). a) Smoothing function for the predictors included in the GM+GEO Model; b) Odds ratios for the geological predictor; c) Wi and Infiltration density smoothing functions from all the sCV runs and from the model fitted on all data for the GM Model

Regarding geomechanical predictors, rockfall susceptibility increased linearly with increasing Jv both in the all-points-based model and in the sCV runs (sCV selection frequency 96.4%, mDD% 7.5% using all data). Rock mass fracture density therefore has a quite strong influence on rockfall susceptibility predictions, comparable to the topographic predictors. The modelled functional relationship remained stable across sCV runs, indicating that the relationship is spatially transferable within the study area.

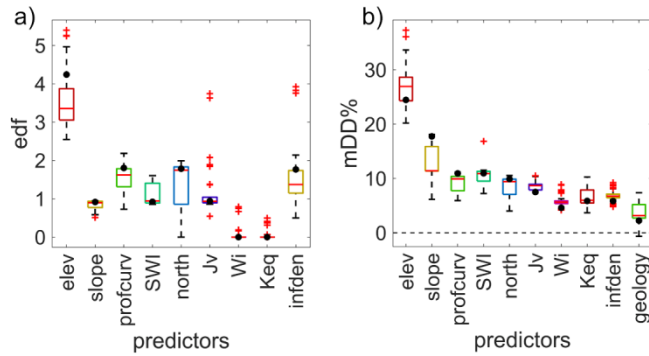


Figure 8. Effective degrees of freedom (edf) and mDD% for each predictor for the GM+GEO model. Boxplots represent values from the sCV runs, while superimposed black dots are estimated using all data

Wi and Keq demonstrated a more unstable behavior. They were penalized out of the model using all data, and out of all sCV models (except for the outliers in Figure 8a; mDD% consistently <10%). Overall, these two predictors resulted of relatively minor importance compared to Jv.

The hydrogeological influence on rockfall susceptibility could still be represented using the infiltration density predictor. It was included in almost all models (penalization frequency 5.2%) and achieved an mDD% of 5.8% using all data. The associated smoothing function showed an increasing behavior for low to medium values and the reaching of a plateau at a value of approximately 3×10^{-3} number of elements per m^2 both for the all-points-based model and for most of the sCV runs (Figure 7a). In few cases the curve resulted in a bell shape, not physically meaningful and possibly attributable to the train-test splitting.

Considering the geological predictor, with an odds ratio of 2.5 (p -value=0.002) in the model fitted with the entire dataset, orthogneiss class (i.e., migmatitic gneisses lithology) was associated with a statistically significative (p -value of 0.002) higher chance of rockfall occurrence than the most abundant class (paragneiss). All the other lithologies showed odds ratios close to 1 meaning a similar chance of rockfall

occurrence as the paragneiss lithology (Figure 7b). The overall mDD% of geology was relatively low (2.3% with all data, up to 7.4% in sCV runs).

Within the GM+GEO model, the concavity among continuous predictors resulted to be acceptable, with a maximum value of 0.59. Although almost identical to the GM+GEO model discussed above, the GM model was characterized by two differences in terms of predictor behavior (Figure 7c): (i) in some sCV runs the W_i predictor had an opposite behavior; (ii) the infiltration density predictor had a slightly decreasing susceptibility at the highest infiltration density values. This may be attributable to a large variability of the dataset at the highest values, potentially smoothed with the introduction of geology, rather than to a real physical meaning. Furthermore, all the geomechanical predictors and infiltration density had a higher deviance explained (of the order of 2-3%).

4.4 Susceptibility model performance

Figure 9 shows the performance of the three models. The prediction performance of the TOPO model (mean AUROC of 0.68 in sCV) indicates a poor discrimination capacity, while those of the GM and GM+GEO models (mean AUROC of 0.71 and 0.72, respectively) can be regarded as acceptable, according to Hosmer et al. (2013). Considering the IQR of AUROC across sCV runs, the GM model showed the best spatial transferability, followed by GM+GEO. This may be linked to the fact that the lithological classes are not uniformly distributed in the study area, leading to a higher heterogeneity between training and test samples and thus to a lower spatial transferability (Guzzetti et al., 2006; Petschko et al., 2014). These results highlight that geomechanical (J_v) and geomorphological-hydrogeological (infiltration density) predictors improved model performance, allowing a deeper and more process-oriented understanding of the phenomena.

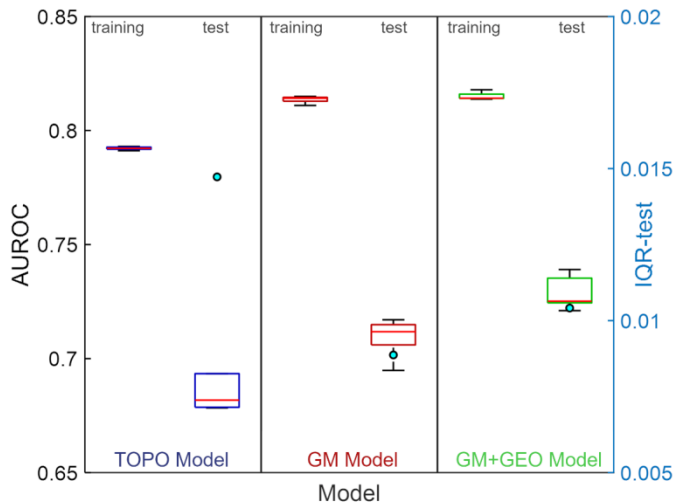


Figure 9. Performance of the three models (TOPO, GM and GM+GEO) in the sCV runs (repetitions), expressed in terms of AUROC values (primary y-axis) for both the training and the test set and IQR (secondary y-axis) for the test set only

4.5 Susceptibility maps and geomorphological plausibility

The three output susceptibility maps are shown in Figure 10. The spatial pattern of susceptibility in the TOPO model (Figure 10a) showed a concentration of the “very high” and “high” susceptibility classes mostly at the principal and secondary valleys bottoms. The percentages of the “very high” and “high” classes in the GM model (Figure 10b) remained almost equal to the TOPO model. However, their spatial distribution changed, including also some lateral valleys and rock walls and ridges at higher elevations. The spatial pattern in the GM+GEO model (Figure 10c) was very similar to the GM model, except for a slightly higher susceptibility in correspondence of the Gruf complex in the southern slope of Bregaglia Valley. Both the GM and GM+GEO models showed a better discrimination than the TOPO model, as the “medium” susceptibility class, which can be considered as the most ambiguous, was less widespread in both models.

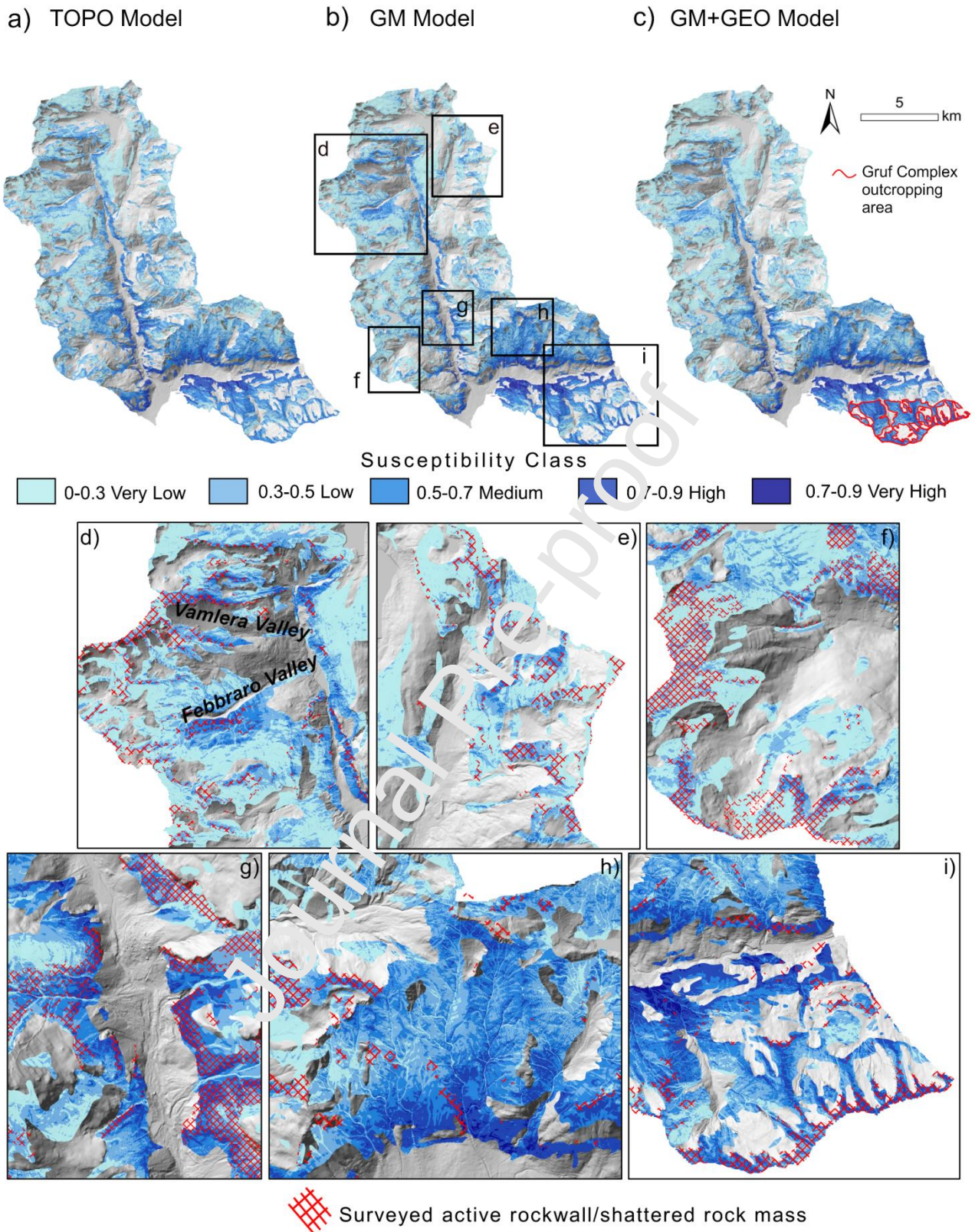


Figure 10. Susceptibility maps obtained from a) Topographic b) Geomechanical c) Geomechanical-geological models; d)-i) Extracts of the geomechanical susceptibility map, with superimposed active rock walls surveyed in the field

By qualitatively comparing the GM model output map with the surveyed active rock walls and very shattered rock masses in the available geomorphological maps of the area, in most cases a good agreement with the “very high” and “high” susceptibility classes was observed (Figure 10d-i). Some mismatches are still present, probably due to the different scales of the survey (1:10,000) and the geological map used to discriminate rock masses and quaternary deposits (1:50,000). In some areas, limitations related to restricted visibility (e.g., complex topography, dense vegetation) may also have affected field mapping.

The difference map of the TOPO and GM models and of the GM and the GM+GEO models are shown in Figure 11a and 11b, respectively. The first points out how the introduction of geomechanical predictors led to increased susceptibilities in some geomorphologically relevant areas. One of these areas is located in the proximity to the DSGSD of the Febbraro and Variera valleys in the upper Western part of San Giacomo Valley (Figure 11 c-d-e). Another area is located along the ridge drawn by Mt. Emet (Figure 11f) and Mt. Maier in the upper Eastern part of the San Giacomo Valley. This area is characterized by two interacting DSGSDs, associated to secondary rockslides and active rock glaciers (Crippa et al., 2020). The last area includes the regional thrust separating the Suretta and Tambò nappes on the Northern slope of the Bregaglia Valley (Figure 11g). The decrease in susceptibility in the central-lower part of San Giacomo Valley is linked either to a combination of low J_v and infiltration density values or to the bell shape of the CSF associated to infiltration density (see Section 4.3). In particular, the SW area corresponds to the Truzzo Granite unit, which is characterized by more massive (i.e., with fewer joint sets) and mechanically resistant rock masses compared to the other lithologies of the study area. However, as visible in the susceptibility maps in Figure 10, this did not mean that these slopes are totally not susceptible (“medium” and “high” susceptibility classes are still

present) rather than the geomechanical predictors did not favor instability. The variation map between the GM and the GM+GEO models (Figure 11b) highlights a further increase of susceptibility in the Southern part of the Bregaglia Valley, due to the peculiar characteristics of the Gruf Complex (Figure 11h-i), already discussed in Section 2 (e.g., migmatitic structure, ductile shear zones, mechanical contrasts)

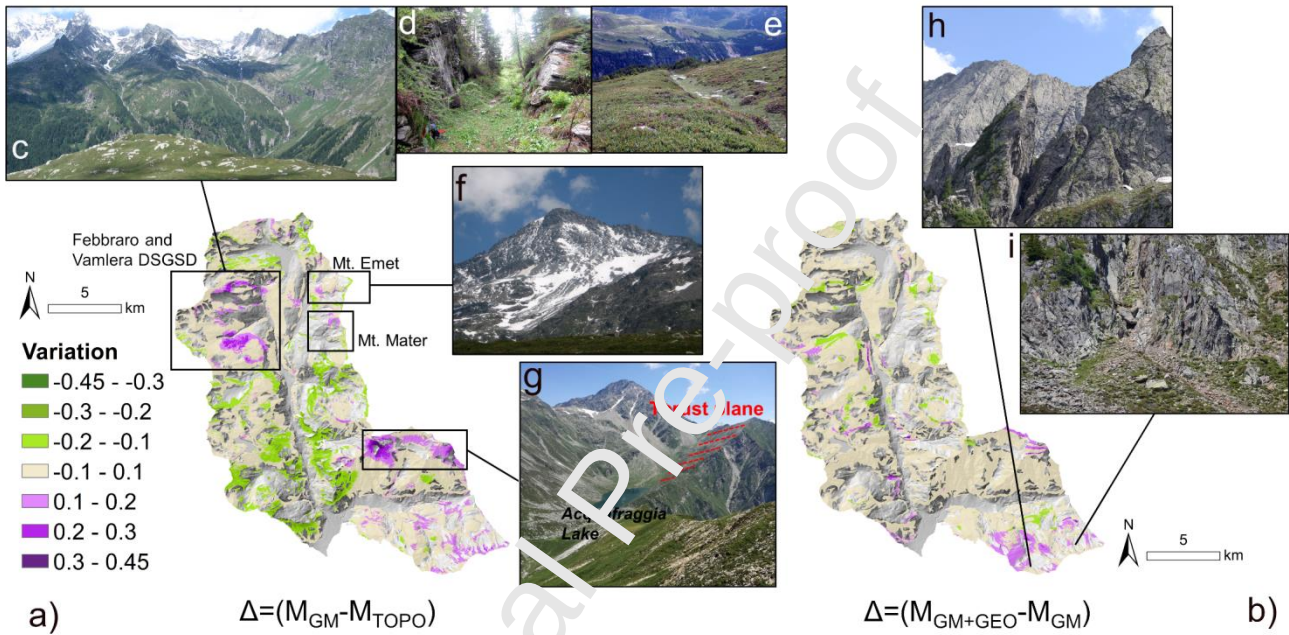


Figure 11. a) Difference map between geomechanical and topographic model b) Difference map between geomechanical and geomechanical-geological model; c),d),e),f),g),h),i) Photographs of the mentioned locations, from the Engineering geology group of University of Milan

The comparison between the difference map between the TOPO and GM models with the PS/DS mean annual velocities, obtained from SqueeSARTM data for the period 2014-2021 (Figure 12a-c), showed that all the above-mentioned areas are associated with recent deformation and displacements along the LOS line. Mean annual velocities can overcome 10mm/y along some morpho-structures such as trenches, counterscarps, and structural lineaments. Due to the less favorable exposure of the Bregaglia Valley to the satellites, evidence of movement can be detected primarily on the northern slope, especially on west dipping facets (Fig 12c). These present-day deformation patterns are a good clue for the identification of gravitationally active

contexts, in which large and small instabilities coexist, further validating the GM rockfall susceptibility maps.

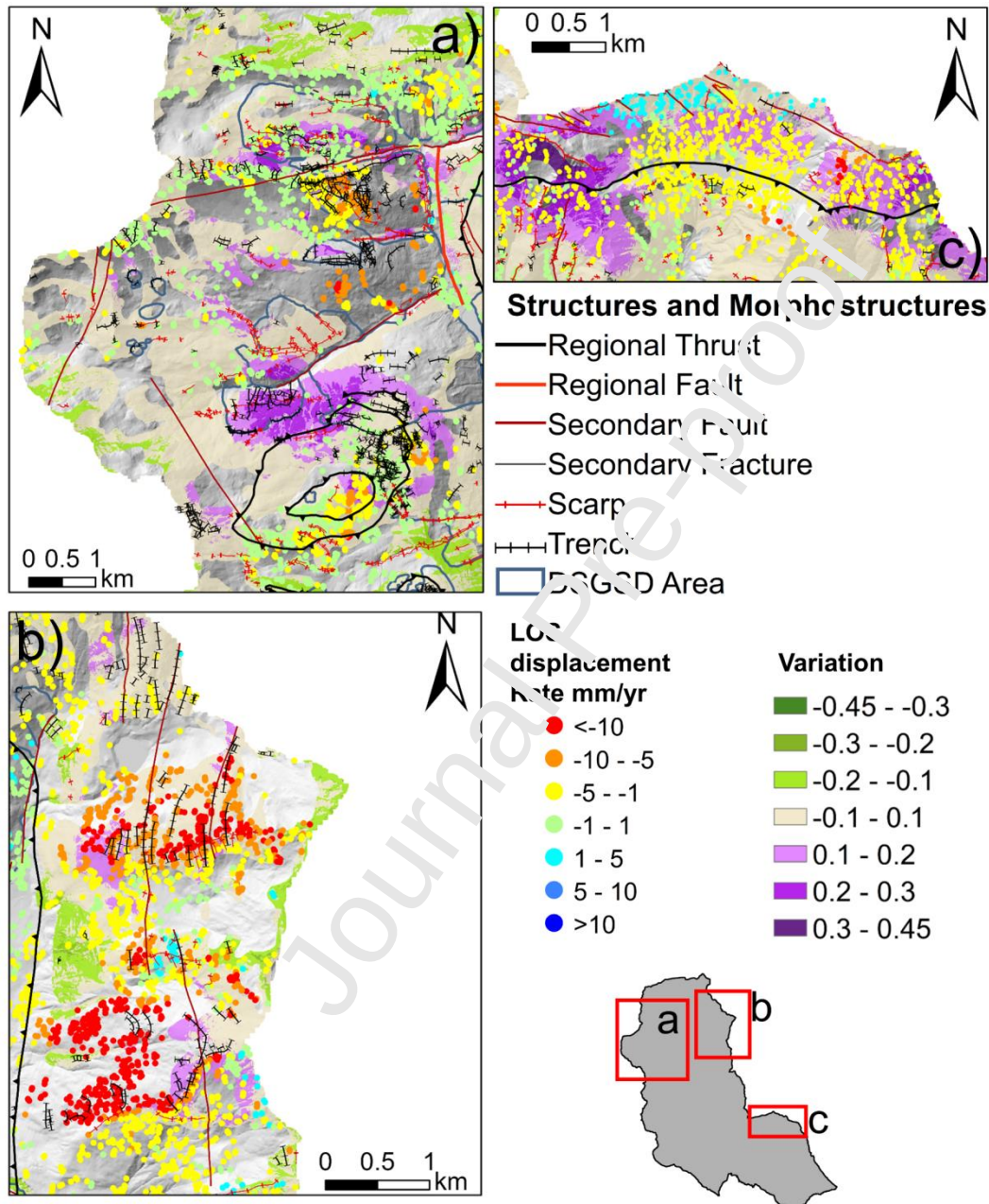


Figure 12. Difference map between geomechanical and topographic model with superimposed morpho-structures and PS/DS derived from inSAR a) Febbraro and Vamlara DSGSDs b) Mount Emet and Mater c) Regional thrust area close to the Acquafraggia Lake

4.6 Inventory-related uncertainty

The GM and GM+GEO models based on the only IFFI inventory showed a predictive performance in terms of mean AUROC of 0.77 and 0.75, respectively. Despite these quite good performances, physically distorted, unrealistic relationships between the J_v and infiltration density predictors and susceptibility were observed (Figure 13 a-b). The smoothing functions show a behavior opposite to the expected

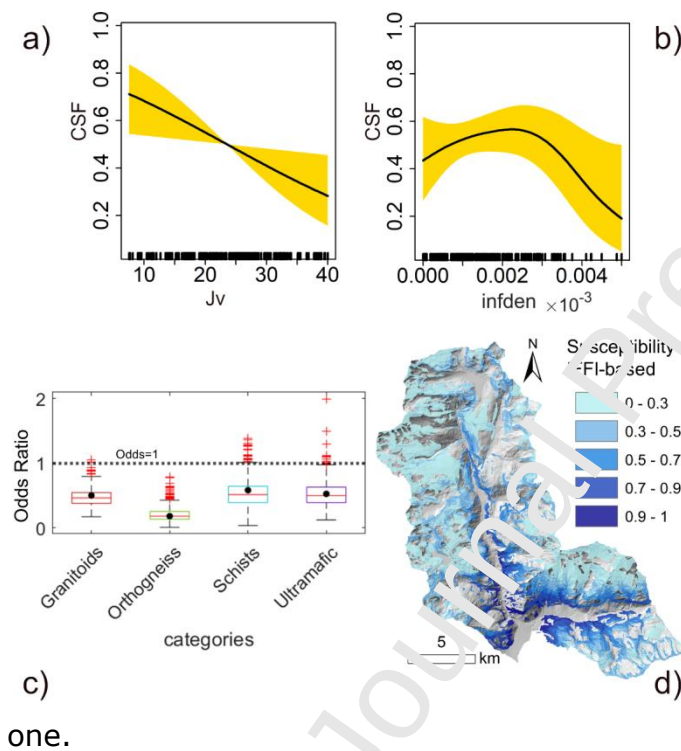


Figure 13. a) Smoothing function for J_v and b) infiltration density from the geomechanical model based on the IFFI data. Confidence bands are shown in yellow; c) Odds ratio variation among sCV repetitions of the GM+GEO model performed on the IFFI inventory. Black dots represent the odds ratios estimated using all IFFI points; d) Geomechanical model output map based on the IFFI inventory

Limiting the training set to the IFFI database also affected the relationships between rockfall susceptibility and lithology. The orthogneiss category (Figure 13c)

became the least susceptible lithology within this model, contrary to the results obtained with the complete inventory. Moreover, implausible rockfall susceptibility maps were obtained, with elevated susceptibilities concentrated only near the valley bottom (Figure 13d).

Both the GM and GM+GEO models had low AUROC values of 0.69 and 0.61, respectively, on the UNIMI inventory as test set. These results revealed a bias in the IFFI inventory, mainly compiled with operational purposes and thus linked to damage reported and elements at risk.

5. Discussion and Outlook

5.1 Regionalized geomechanical properties in the susceptibility assessment process: utility and issues

This study focused on the acquisition and inclusion of geo-environmental data specifically suited for rockfalls in a susceptibility assessment process, as suggested by Reichenbach et al. (2018). In particular, it proposed to transfer the geomechanical properties relevant at the outcrop scale in a regional scale analysis, traditionally based on topographic predictors, to assess the potential additional value of this approach in terms of model interpretability. The well-established Generalized Additive Models, already successfully applied in the landslide susceptibility field (Goetz et al., 2011, 2015; Muenchow et al., 2012; Petschko et al., 2014; Knevels et al., 2020) were used for the aim. The technique has the advantage of allowing the interpretation of model behavior (Brenning, 2012).

Two underlying assumptions on geomechanical predictors are worth discussing. The first one is the time-invariance of geomechanical predictors. Even if the considered geomechanical properties could be reasonably assumed as stationary in terms of temporal validity of the susceptibility map, this assumption does not consider

the short-term evolution of the investigated systems. This is particularly true when linking weathering to rock slope instabilities. The low influence of weathering grade on rockfall susceptibility obtained in the models seems to confirm the work of Viles (2013), who concluded that the inherent temporal non-linearity of rock mass weathering processes hampers the possibility to make predictions or generalizations about how a change in the weathering component of rock mass would influence its stability. On the one hand, Samia et al. (2017) demonstrated that landslides do follow landslides in a path-dependency perspective. This could likewise be assumed when dealing with rock masses, as the detachment of rock blocks may redistribute the local in-situ stresses and partially modify the kinematic confinement degree, potentially driving fracture propagation and coalescence (McBeck et al., 2021), rock mass dilation (Brideau and Stead, 2012) and joint aperture (and thus permeability) variation (Lei et al., 2020). On the other hand, an improvement of the rock mass mechanical conditions may occur after a rockfall. Whether the unstable mass was totally detached, the newly exposed rock surface (which was previously at a higher depth inside the rock wall) could be less weathered (Huisman et al., 2006) and, as joint aperture and frequency decrease with depth, less permeable (Snow, 1968; Zhang., 2013). Attempting to introduce in the analysis these non-linear and feedback processes would require a dated multitemporal inventory combined with a dataset recording both pre-failure and post-failure geomechanical conditions.

Secondly, it was assumed that an average representative value for J_v , W_i and K_{eq} could be assigned to the sites representing the survey. This generalization to the rock mass scale allowed to regionalize J_v and W_i by means of geostatistical technique, already applied in some previous studies aimed at regionalizing some geomechanical properties (Ferrari et al., 2012; 2014; 2019; Pinheiro et al., 2016, 2018; Eivazy et al., 2017; Bajni et al., 2021). Although the regionalization of W_i had a good performance,

its values showed a limited range (from 0.5 to 1.0). These homogeneous values may indicate that the area was not subject to a sufficient differential weathering to robustly influence rockfall occurrence. In contrast, the regionalization of K_{eq} was more challenging and led to less encouraging results. This could be linked to the inclusion of joints' aperture in the permeability tensor calculation, for which an average value may not be the best solution. Variability in aperture is one of the most challenging problems in slope design and management (Price, 2016) and it cannot be considered either constant or scale invariant (Baghbanan and Jing, 2008). It could be highly variable over short distances, due to the presence of asperities at different scales modulating the effective volume available for water flow. The high uncertainty associated to K_{eq} regionalization could be the reason why it was excluded from the rockfall susceptibility models. Therefore, more precise and spatially more detailed estimates of K_{eq} than those available may therefore still improve the rockfall susceptibility map in the future. In absence of in-situ tests supporting the calibration of K_{eq} values obtained from the permeability tensor (as in Coli et al., 2008 and Oge, 2017), it is more suitable to use this property in outcrop-scale studies rather than in regional assessments. At such detailed scale it is possible and reasonable to capture and represent its own short-range variability. For basin or regional scale studies, this gap could be addressed by integrating a synthetic Discrete Fracture Network (DFN) or with the emerging application of infrared thermography (Pappalardo, 2018).

5.2 Geomorphological and physical plausibility of the outputs

With the addition of geomechanical predictors, model performance showed a slight enhancement in terms of AUROC. Besides quantitative performance, the inclusion improves the geomorphological plausibility of the output maps, often disregarded but essential for their effective utilization (Sterlacchini et al., 2011; Goetz et al., 2015; Steger et al., 2016a; Reichenbach et al., 2018; Camera et al., 2021).

Deepening the knowledge on local geomechanical conditions and including geomechanical predictors in the susceptibility model led to a more process-oriented understanding of the susceptibility spatial patterns. This should be introduced in the cost-benefit tradeoff when planning an intense field campaign. Compared to the topographic model, the rockfall susceptibility map deriving from the GM model showed a consistent redistribution of the “very high” and “high” susceptibility classes in some relevant, geomorphological plausible contexts. These results were further verified through the observation of the present-day slope deformation patterns by means of SAR data.

Regarding the inclusion of the geological component, one may argue that orthogneiss is in general a more resistant lithology than paragneiss. However, in the study area, orthogneisses mainly belong to the Gruf Complex. This is a poly-metamorphic highly foliated migmatitic body, (Galli et al., 2013), thus characterized by mechanical and mineralogical contrasts (e.g., due to the augen texture), as well as weak zones. As demonstrated by De Vilder et al. (2017), not only the wider geology but also the local scale lithological and mineralogical variability control rock mass wasting processes.

5.3 Susceptibility modelling related uncertainties

Any landslide susceptibility assessment has a level of uncertainty coming from different sources; this is a topic already addressed in different ways by several authors and considered crucial (Guzzetti et al., 2006; Rossi et al., 2010; Petschko et al., 2014). The principal source of uncertainty in the procedure was linked to the regionalization of the geomechanical predictors, potentially responsible of interpolation errors that can propagate into the susceptibility model. Moreover, the geomechanical dataset itself was compiled by different surveyors, therefore the study includes unquantified uncertainties related to subjectivity during field work. On the

one hand, each predictor was presented and discussed according to its regionalization performance and error metrics, giving a quantifiable indication of the reliability of the associated predictors maps. On the other hand, the quantification of the kriging variance associated to J_v was used to optimize the new geomechanical survey location by means of the SSA algorithm. It was demonstrated that this approach can successfully reduce the uncertainties related to regionalization by comparing J_v kriging variance and MESS scores before and after the field survey.

The rockfall inventory used in this study comes from the integration of the institutional IFFI inventory and the one derived from several years of detailed geomorphological field mapping. On the one hand, the integration of the two sources had the aim of reducing the epistemic uncertainty related to inventory completeness. On the other hand, choosing rockfall point sources alternatively as the scarp/crown bisector or as the highest point of the deposit may introduce an issue of positional inaccuracy on an inventory portion (specifically, for the 16.5%). However, some studies highlighted that using either the scarp or a random point inside the landslide polygon resulted in similar and comparable results in terms of susceptibility model performance (e.g., Petschko et al., 2013, 2016). By using the IFFI dataset only to train the model, physically implausible relationships with geomechanical predictors and geology, and consequently implausible susceptibility patterns, were obtained. This is linked to how the IFFI inventory was compiled in the study area (i.e., in relation to elements at risk and damages reported by the administration in charge), thus reproducing data collection effects (as defined by Steger et al., 2021) rather than physically driven processes. These results agree with the findings of Steger et al. (2016a, 2017), who underlined the necessity of supporting quantitative performance measures with geomorphological plausibility; this is crucial to avoid misleading high quantitative performances deriving from strongly biased inventories.

6. Conclusions

The study highlighted that including geomechanical predictors in a rockfall susceptibility model could improve the geomorphological plausibility of the resulting map, with a redistribution of the highest susceptibility values in some relevant environmental contexts. The plausibility assessment of the output maps, conducted by means of secondary products such as variation maps and comparison with SAR data, could improve the readability and the communication of the results to potential users. Understanding the physical and geomorphological underlying context is necessary to suggest where to concentrate time and resources at the local scale. In such framework, models able to analyze the non-linear relationships between the predictors and instability occurrence, such as GAMs, were essential. It was verified that quantitative performance measures of a susceptibility model do not guarantee its geomorphological and physical plausibility; an in-depth critical analysis of the results in light of the environmental context is necessary.

The uncertainty evaluation conducted in this study proved to be useful to: (i) plan an effective field survey to acquire new data, representative of the geomechanical context of the study area; (ii) determine the regionalization quality and associated error of the geomechanical predictors implemented in the susceptibility model; (iii) assess the official rockfall inventory limitations and incompleteness in a complex mountainous environment.

The study results demonstrate that rockfall susceptibility can be analyzed by means of non-linear statistical models. However, to obtain reliable results, efforts should be made to derive regionalized maps of geomechanical predictors and complete rockfall inventories. The lack of these conditions can lead to erroneous outputs that could compromise an effective management of hazard and risk related to these phenomena. Further improvements to the models could come from the inclusion

of climatic variables. These variables could also provide insights, through time-dependent maps, on the evolution of the analyzed processes under climate change. However, multi-temporal inventories and long time series of meteorological data are necessary to derive such variables.

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Data availability

The Digital Terrain Model used in this study is publicly available at <http://www.geoportale.regione.lombardia.it/>. The IFFI rockfall inventory is publicly available at <https://www.progettoiffi.isprambiente.it/> and the relative source points for the polygon-type rockfalls are available at <https://www.arcgis.com/apps/webappviewer/index.html?id=f0908d087e4f483c8c4b705c4ed4dd51> from the project ROCKtheALPS 2019, Interreg Alpine Space, alpine-space.eu/projects/rockthealps/.

Geomechanical data and UNIMI rockfall inventory are products continuously updated by the Geoengineering Group of the Università degli Studi di Milano and may be accessible upon reasonable request to the authors. SAR data were made available

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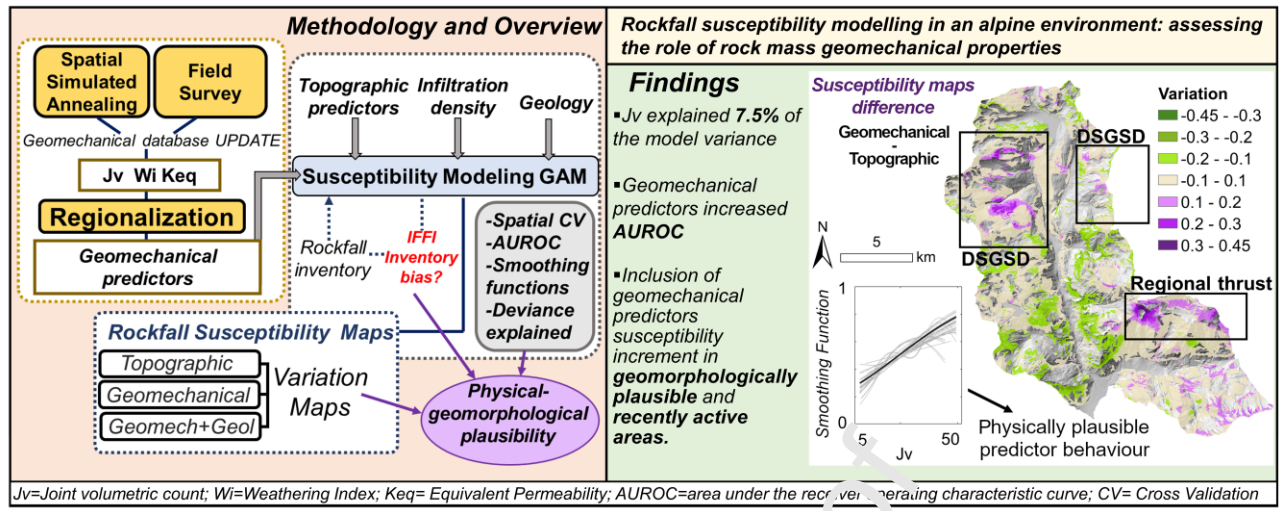
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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Graphical abstract



Highlights

- Geomechanical predictors are introduced in a rockfall susceptibility analysis
- Geomechanical predictors improve model performance quantitatively
- Geomechanical predictors improve the output map geomorphological plausibility
- J_v is the most relevant geomechanical predictor explaining 7.5% of model variance
- Model results highlighted a bias in the Italian Landslide Inventory (IFFI)