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Data-driven mapping of the potential mountain permafrost distribution

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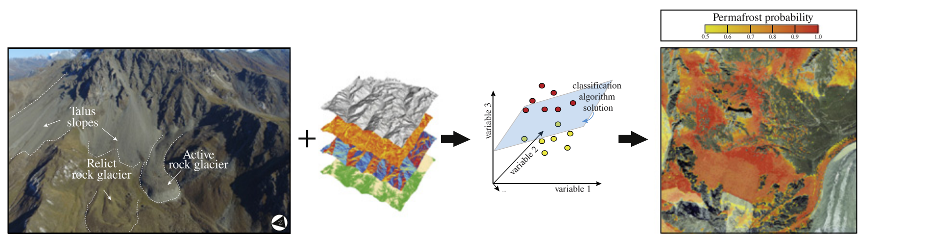
HIGHLIGHTS

- Investigation of an innovative permafrost distribution modelling approach
- Three classifiers belonging to statistics and machine learning were applied.
- Machine learning algorithms provide precise distribution maps at the micro-scale.
- Predicted permafrost distribution is in accordance with the field reality.

GRAPHICAL ABSTRACT



Dataset: positive/negative permafrost evidences and related permafrost predictors

Machine learning classifier (learning from data)

Permafrost prediction

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ABSTRACT

Existing mountain permafrost distribution models generally offer a good overview of the potential extent of this phenomenon at a regional scale. They are however not always able to reproduce the high spatial discontinuity of permafrost at the micro-scale (scale of a specific landform; ten to several hundreds of meters). To overcome this lack, we tested an alternative modelling approach using three classification algorithms belonging to statistics and machine learning: Logistic regression, Support Vector Machines and Random forests. These supervised learning techniques infer a classification function from labelled training data (pixels of permafrost absence and presence) with the aim of predicting the permafrost occurrence where it is unknown. The research was carried out in a 588 km^2 area of the Western Swiss Alps. Permafrost evidences were mapped from ortho-image interpretation (rock glacier inventorying) and field data (mainly geoelectrical and thermal data). The relationship between selected permafrost evidences and permafrost controlling factors was computed with the mentioned techniques. Classification performances, assessed with AUROC, range between 0.81 for Logistic regression, 0.85 with Support Vector Machines and 0.88 with Random forests. The adopted machine learning algorithms have demonstrated to be efficient for permafrost distribution modelling thanks to consistent results compared to the field reality. The high resolution of the input dataset (10 m) allows elaborating maps at the micro-scale with a modelled permafrost spatial distribution less optimistic than classic spatial models. Moreover, the probability output of adopted algorithms offers a more precise overview of the potential distribution of mountain permafrost than proposing simple indexes of the permafrost favorability. These encouraging results also open the way to new possibilities of permafrost data analysis and mapping.

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1. Introduction

Within the 21st century, the Alpine environment is going to experience deep modifications of the cryosphere as a consequence of the increase in air temperatures and the modifications of precipitation regimes. Among the cryospheric components, mountain permafrost describes a ground with temperatures at or below 0°C for two consecutive years (Harris et al., 2009; Beniston et al., 2017). Permafrost in rock walls and sedimentary accumulations may degrade as a consequence of the climate change (Etzelmüller and Frauenfelder, 2009). A thickening of the active layer and a warming of the permafrost body can have various effects on mountain

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slope stabilities, such as an increasing rock fall activity (Gruber and Haeberli, 2007; Ravanel et al., 2010) or a rock glacier acceleration (Kääb et al., 2007; Roer et al., 2008; Delaloye et al., 2010; PERMOS, 2016), leading to an increase of the sediment transfer rates (Lane et al., 2007; Kobierska et al., 2011).

In the European Alps, the periglacial belt is generally marked by the absence of trees, a reduced vegetation cover (where existing essentially made of meadow, mosses and lichens), large volumes of sediment debris, steep slopes and rock faces. Although permafrost may affect all these different types of terrains, its unambiguous morphological manifestation only occurs in active rock glaciers, which are considered as the visible expression of mountain permafrost creep (Haeberli, 1985). Other permafrost indicators are thrust- or push-moraines, corresponding to frozen sediments deformed by the glacier advance during the Little Ice Age, whereas large areas in glacier forefields located in the periglacial belt appear to be unfrozen (Reynard et al., 2003; Harris and Murton, 2005; Kneisel and Kääb, 2007; Bosson et al., 2015). Talus slopes constitute other major landforms of alpine environments where permafrost is generally restricted to the lower half of the slope (e.g. Lambiel and Pieracci, 2008; Otto and Sass, 2006; Scapozza et al., 2011). It is also well established that terrains covered by alpine meadow are generally permafrost free (Haeberli, 1975). The distribution of mountain permafrost is thus extremely discontinuous in mountain areas (see also Ribolini et al., 2010; Otto et al., 2012).

The ability of modelling the spatial distribution of such a complex phenomenon became an important task for the alpine permafrost research during the last two decades. First empirico-statistical models were based on simple approaches (such as linear regression) and offered a good overview of the potential distribution of mountain permafrost at the regional scale (i.e. Hoelzle, 1994; Ebohon and Schrott, 2008; Avian and Kellerer-Pirklbauer, 2012). These models are generally thresholding the occurrence of permafrost on the basis of a restricted number of topographical and climatic parameters (i.e. altitude of rock glacier fronts for a given orientation) and are validated with measurements of the ground surface temperature, which may be subject to bias. The availability of an increasing amount of high resolution data (generally derived from high resolution digital elevation models) opened then the way to new complex statistical models able to deal with a large number of predictors (i.e. Boeckli et al., 2012; Schöner et al., 2012; Magnin et al., 2015; Azócar et al., 2016; Sattler et al., 2016). Although they offer a good overview of the permafrost distribution at local scale (i.e. scale of a valley side), these models do not reflect the great heterogeneity of the phenomenon at the scale of a specific landform (the micro-scale; covering ten to several hundreds of meters).

To address the need of an improved prediction of the permafrost extent at the micro-scale, we propose an alternative approach, which employs classification algorithms belonging to statistics and machine learning, namely Logistic regression, Support Vector Machines and Random forests. These algorithms can deal with complex and high dimensional datasets (Bishop, 2006) and they derive functional dependencies directly from data without appealing to physical models (Hastie et al., 2009). They have successfully been adopted for mapping the spatial distribution of several natural phenomena (i.e. Amatulli et al., 2013; Varley et al., 2016). In the periglacial research such techniques have been already used for geomorphological mapping (Luoto and Hjort, 2005), landform characterization (Marmion et al., 2008) or permafrost mapping using satellite images (Ou et al., 2016). Accordingly, we collected field observations indicating the known presence or the known absence of mountain permafrost and related topo-climatic data for a specific area of the Western Swiss Alps. The dataset built was analyzed and used to investigate the potential of machine learning techniques for mapping the high spatial discontinuity of mountain permafrost. Furthermore, as the potential permafrost distribution in rockwalls had already been successfully modelled in other studies (i.e. Gruber et al., 2004; Noetzli et al., 2007; Magnin et al., 2015), the present work focuses only on sedimentary accumulations.

2. Materials and methods

2.1. Permafrost evidences and explanatory variables

This study was carried out in a sector of the Western Valais Alps (Switzerland) covering a regular grid of 588 km^2, with more than 60% above the theoretical permafrost lower limit of 2500 m.a.s.l., delimiting the lower boundary of the periglacial belt in the area (Lambiel and Reynard, 2001).

We used evidences of known permafrost presence or absence collected since the mid-1990s by the Universities of Lausanne and Fribourg as training data for employed machine learning algorithms (Fig. 1). These evidences have been obtained from two distinct sources:

- *Rock glacier inventories*. Permafrost presence or absence can be derived from rock glacier maps, based on their activity. Indeed, active or inactive rock glaciers suggest the existence of permafrost conditions, whereas relict ones indicate its absence (see Haeberli, 1985; Humlum, 1996; Barsch, 2012). For this study, we employed some existing inventories (Delaloye and Morand, 1998; Morand, 2000; Lambiel and Reynard, 2003), for which rock glaciers were mapped directly in the field. Some additional rock glaciers located within the study area were also added through ortho-image interpretation. All rock glacier limits were then corrected with a comparison with recent orthophotos (Swissimage, from swisstopo) and their activity was verified with the analysis of geomorphic signatures and InSAR signals (Delaloye et al., 2007; Barboux et al., 2014).
- *Geoelectrical and thermal data*. Direct-current (DC) resistivity methods are well established tools for detecting permafrost in sediments (Hauck and Kneisel, 2008). Electrical resistivity tomography (ERT) is especially often utilized to detect ground ice and characterize frozen materials in permafrost environments (e.g. Hauck et al., 2003; Hilbich et al., 2009; Otto et al., 2012). In addition, permafrost can also be inferred from ground surface temperature measurements (Hoelzle et al., 1999; Carturan et al., 2015). Coupling geoelectrical and thermal data can thus improve the reliability of permafrost mapping. Following the procedure employed by Lambiel (2006, p. 95) and Scapozza et al. (2011), we compiled and combined geoelectrical and thermal data collected in the framework of different studies aiming at detecting and mapping ground ice in permafrost environments – mainly talus slopes and glacier forefields – of our study area (Marescot et al., 2003; Reynard et al., 2003; Delaloye, 2004; Delaloye and Lambiel, 2005, 2008; Lambiel, 2006; Lambiel and Pieracci, 2008; Scapozza et al., 2011; Scapozza, 2013; Staub et al., 2015). Completed by thermal measurements gathered for the Swiss Permafrost Monitoring Network (PERMOS, 2016) and by other unpublished projects, these data were used to map the permafrost extension in the prospected landforms. This provided to the classification algorithms additional training examples also located outside rock glaciers. Negative training observations (known permafrost absence) resulted not only from in-situ measurements indicating warm conditions or absence of ground ice, but also from expert knowledge. We particularly used the conclusions of Lambiel and Pieracci (2008) and Scapozza et al. (2011) that showed the general absence of permafrost in the upper half of talus slopes.

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