REGIONAL SCALE STATISTICAL MAPPING OF SNOW AVALANCHE LIKELIHOOD AND ITS COMBINATION WITH AN OPTICAL REMOTE SENSING BASED AVALANCHE DETECTION APPROACH – FIRST ATTEMPTS FOR THE PROVINCE OF SOUTH TYROL (ITALY)

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ABSTRACT: Snow avalanches are potentially dangerous phenomena in many mountainous areas worldwide. Most avalanche related research concentrates on a detailed analysis of single events at local scale. This research focuses at regional scale (i.e., about 7,400 km^2) and aims to (i) delineate the static likelihood of snow avalanche occurrence for South Tyrol, (ii) to detect snow avalanches on the basis of optical remote-sensing data and to (iii) integrate approach (i) and (ii) to achieve a better performing avalanche detection model. In the context of the first activity (i), the methodological framework consists of a statistically based mapping of zones that are prone to avalanche release. The derived avalanche release likelihood model is supposed to be static in time and subsequently coupled with a random walk approach to estimate snow avalanche paths at regional scale. For the second activity (ii) optical remote sensing imagery of the Sentinel-2 Sensor are used to detect avalanches with a change detection approach. Finally, the third activity (iii) involves the combination of the (static) avalanche model (activity i) with the avalanche detection approach (activity ii). First results indicate that the proposed integration of the static statistical avalanche model with a remote sensing based change detection approach has the potential to enhance the data-driven multi-temporal mapping of avalanche occurrence at regional scale.

KEYWORDS: avalanche detection, change detection, generalized additive model, optical remote sensing, Sentinel-2

1. INTRODUCTION

Snow avalanche release depends on the composition of different parameters that can be roughly classified into three main groups: snowpack, weather and terrain. This so called ‘avalanche triangle’ describes the most important indicators for avalanche release: (1) The weather conditions must be suitable to (2) create snowpack instability and (3) the terrain must possess the characteristics necessary for the avalanche to initiate (Fredston and Fesler 1994).

Several previous regional scale studies statistically modelled typical avalanche locations by exploiting historical avalanche inventories and spatial information on predisposing factors (Pistocchi and Notarnicola 2012, Barbolini et al. 2009, Parshad et al. 2017). Other studies focused on the detection of past avalanches on the basis of remote sensing techniques (Larsen et al. 2013, Lato et al. 2012, Eckerstorfer et al. 2016). This contribution presents a first attempt to integrate a static statistically based modelling approach with a bi-temporal remote sensing based change detection procedure. The main objective is to improve the spatio-temporal information on avalanche occurrence at regional scale. From a methodical point of view, the procedure attempts to enhance both, the static statistical avalanche modelling and the dynamic remote sensing based avalanche detection.

2. STUDY AREA AND DATASETS

2.1 South Tyrol, Italy

South Tyrol is the northernmost province of Italy and located in the Eastern Alps. The elevation of this 7400 km² large mountainous region (mean slope 27°) ranges from about 200 m asl to 3900 m asl while the mean annual precipitation varies between 500 and 1500 mm. The combination of a stable snow cover (150 days/year) at elevations higher than 1200 m and the substantial relief energy renders South Tyrol particularly prone to snow avalanche occurrence (Pistocchi and Notarnicola 2012). Up to 2017, more than 2400 avalanches have been registered and mapped by the province

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of South Tyrol to create an area-wide historical avalanche inventory.

2.2 Datasets

The historical avalanche inventory of the province (n = 2491) served as ground-truth data for the statistical model (step i). Topographic predictor variables were directly calculated from a resampled (from 2.5 m to 10 m) Digital Terrain Model (DTM). The spatial information on snow cover probability was derived from MODIS data (Notarnicola et al. 2013) while land cover was adopted from earlier analyses.

For the avalanche detection approach, satellite data from the Sentinel-2 Multi Spectral Instrument (MSI) optical sensor was used. Sentinel-2 is acquiring every 3-5 days at mid-latitude. The data are acquired systematically, and they are free of charge. To test the methodical procedure, two images (10 m resolution) related to the western part of the province (i.e. Langtaufers valley) have been analyzed (acquisition on 12/01/18 and 24/01/18) by focusing on the visible (2,3,4) and near-infrared (8) bands (ESA 2013).

3. METHODS

The methodical procedure consists of three main activities: Regional scale statistical mapping of avalanche prone areas (i), avalanche detection using Sentinel-2 optical data and a change vector approach, and (iii) integration of activity (i) and (ii).

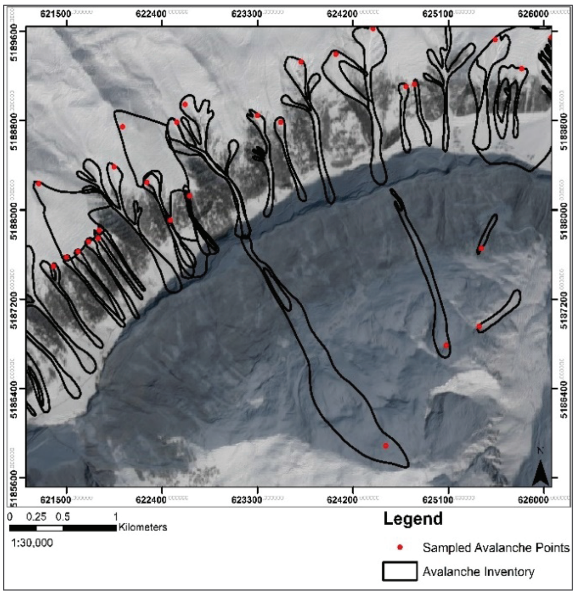

Figure 1: Historical Avalanche Inventory and sampled points on a Sentinel-2 RGB Image (Contains modified Copernicus Sentinel data (2018)/Eurac Research)

The classification approach adopted for activity (i) is based on a binary response variable that relates to past avalanche release zones and avalanche absence locations. Past avalanche release areas were obtained by randomly sampling one point within the upper part of each mapped avalanche polygon (i.e. within the highest 10% of elevation; Fig. 1). Avalanche-absences were represented by a random sample of points located outside known avalanche areas. Historical avalanche presence/absence data is frequently linked with environmental variables that are considered as static in time in order to assess typical predisposing conditions (Pistocchi and Notarnicola 2012). Obviously, the inclusion of dynamic environmental information, such as snowpack or weather, is a challenging task in the case only historical avalanche data is available. Therefore, most regional scale analyses focus on static predisposing factors (e.g. terrain attributes) (Parshad et al. 2017, Maggioni and Gruber 2003, Ghinoi and Chung 2005, Bühler et al. 2013, Barbolini et al 2011). Within this study, frequently adopted variables (i.e. ‘slope’, ‘northness’, ‘elevation’, ‘roughness’, ‘convergence’, ‘land cover’) were used in combination with a snow probability map to elaborate archetypal avalanche release zones (Pistocchi and Notarnicola 2012, Maggioni and Gruber 2003, Ghinoi and Chung 2005). Slope is known as a key predisposing factor for avalanche release. At regional scale, elevation can be considered as a proxy for climatic influences whereas the slope orientation was included to describe the spatially varying effect of radiation. The produced roughness map as well as the land cover map were introduced to represent spatial differences in surface friction (Bühler et al 2013). The convergence index was considered a proxy for recurrent wind and snow accumulation patterns while the snow probability map relates to the general snow availability at regional scale.

Since an initial exploratory data analysis provided evidence of non-linear relationships between the binary response and the chosen predictor variables, a classification algorithm that accounts for non-linearity’s was selected. The Generalized Additive Model (GAM) allowed generating a likelihood map (scores between 0 and 1) that depicts a relative estimate of each pixel to coincide with an avalanche release zone. The resulting avalanche release likelihood map has been validated using model-independent test information via a k-fold cross validation (5 repetitions and 5 folds) and the Area under the Receiver Operating Characteristics curve (AUROC) (Steger et al. 2016).

Furthermore, the produced static model also served as an input for the subsequent random walk process path model that allowed identifying likely avalanche paths and deposits. In summary, the three highest deciles, related to the release likelihood map, were introduced separately into the Gravitational Process Path Model (Wichmann 2017) to generate three avalanche path maps. The chosen random walk approach was parameterized according avalanche-specific recommendations given by Wichmann (2007). The final process path model (further referred to as GPPM) was produced by combining the three single (normalized) avalanche path maps using weights that correspond to the associated release likelihood. The GPPM was validated by calculating the AUROC on the basis of avalanche observations that relate to the entire avalanche polygon.

The second activity (ii) is based on Sentinel-2 imagery and relates to a change vector approach in the polar domain, based on Bovolo and Bruzzone (2007). In the context of avalanche detection in this paper, one image X_1 acquired before and one image X_2 acquired after a known avalanche event were selected. Two change images were calculated considering the visible and the infrared bands as follows:

$$C_b = X_2 - X_1 \; where \; b \in \{VIS, IR\}$$

Where C_b describes the change of the two images considering a given band b. The idea of this approach is to calculate two change variables ρ and θ, where ρ shows the intensity and θ the angle of the change when considered in a polar domain:

$$\rho = \sqrt{{C_{VIS}}^2 + {C_{IR}}^2}$$

$$\theta = \tan^{-1}\left({C_{IR}}/{C_{VIS}}\right)$$

By setting a threshold for ρ allows the binary discrimination between “changed pixels” and “non-changed pixels”. The resulting map was then used to mask θ, which consists only of the changed pixels and depicts different angles (“types of change”). Setting a second threshold based on θ aimed to differentiate avalanche-pixels from other phenomena. This approach appeared useful as changes can also concern other phenomena like shadowing effects, snowmelt,fresh snow or miss-registration errors.

The third step (iii) combined both results to improve the avalanche detection method. The GPPM in this case served as a mask to confine the change detection to the likely avalanche affected areas. In comparison to the approach that did not consider the GPPM, the performed masking simplified the avalanche detection as structures not related to avalanches could be filtered. In this case, also the threshold for the differentiation between change and no change could be computed automatically allowing for an automatic computation of vector change maps within the polar domain. The computation of the threshold was done using the Expectation Maximization algorithm (Moon 1996). Based on the distribution of detected changes, the function seeks to find a predefined number of modes. The intersecting x-value of the two modes is the optimal threshold for the differentiation in Bayesian terms.

4. RESULTS

The validation results provided quantitative evidence that the produced release likelihood model exhibits a high ability to “predict” model-independent avalanche release zones at regional scale (mean AUROC: 0.83). The subsequent province-wide GPPM (Fig. 2) still reached an acceptable model performance (AUROC of 0.74).

The second activity (ii) resulted in a vector change map for the selected test site (i.e. Langtaufers Valley). The results of this first trial have been achieved with the manual selection of thresholds for ρ and θ. The resulting change map has been compared with recent point-based avalanche data from 2018. From a regional point of view, these avalanche points were, in most cases, in close proximity and high spatial agreement with the changes marked on the vector change map. Major discrepancies between known avalanche locations and detected avalanche zones were observed within shadowed areas. The integration of activity (i) and (ii) further improved the remote sensing based avalanche detection, particularly in terms of a decreased portion of false alarms (i.e. non-avalanche areas wrongly classified as avalanches) due to the a-priori exclusion (i.e. masking) of non-susceptible areas via the GPPM.

5. DISCUSSION

5.1 *Avalanche Likelihood Mapping*

The combination of different methodical steps and diverse data sources showed promising results, but some challenges as well. The produced regional scale avalanche release likelihood model was

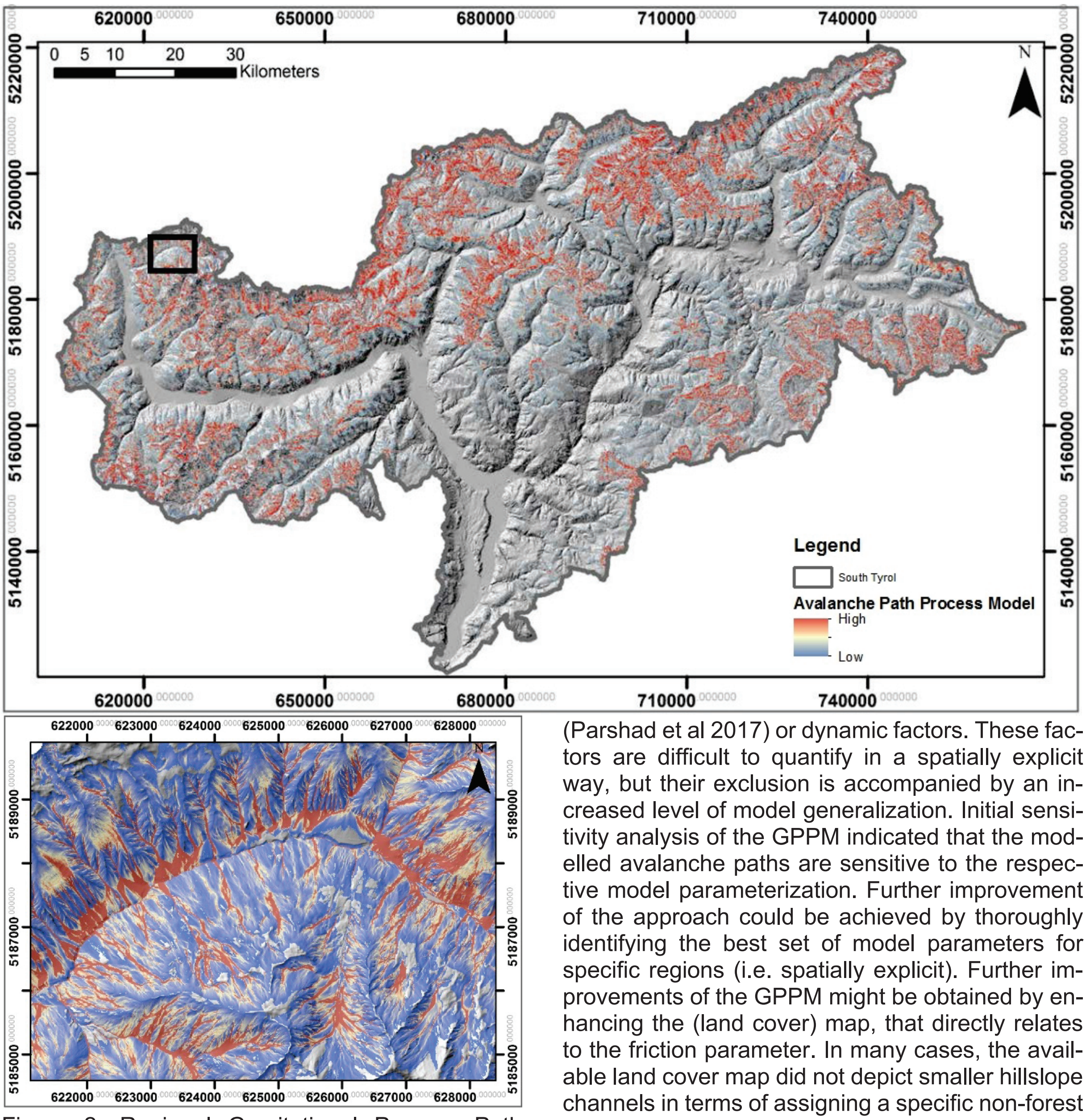

Figure 2: Regional Gravitational Process Path Model with subset of the Langtaufers Valley. The overview map depicts the GPPM generated with a global friction parameter while the excerpt relates to the GPPM obtained without a spatially differentiated friction parameter.

mainly based on static environmental conditions. Even though the model exhibited a comparably high predictive performance, it should be noted that the actual release of snow avalanches also depends on additional factors whose quantification is difficult to achieve. In many cases, avalanches are caused specifically by anthropogenic influences (Parshad et al 2017) or dynamic factors. These factors are difficult to quantify in a spatially explicit way, but their exclusion is accompanied by an increased level of model generalization. Initial sensitivity analysis of the GPPM indicated that the modelled avalanche paths are sensitive to the respective model parameterization. Further improvement of the approach could be achieved by thoroughly identifying the best set of model parameters for specific regions (i.e. spatially explicit). Further improvements of the GPPM might be obtained by enhancing the (land cover) map, that directly relates to the friction parameter. In many cases, the available land cover map did not depict smaller hillslope channels in terms of assigning a specific non-forest class (i.e. many channels very displayed as forests). The unrealistic high friction values within those areas strongly restricted the plausibility of the results (i.e. to short avalanche paths). This problem was tackled by testing GPPMs with and without a spatial friction parameter. The GPPM produced without a spatially explicit friction coefficient was more suitable for our purpose. A consideration of a very detailed land cover map (e.g. at tree-level) is expected to further optimize the results.

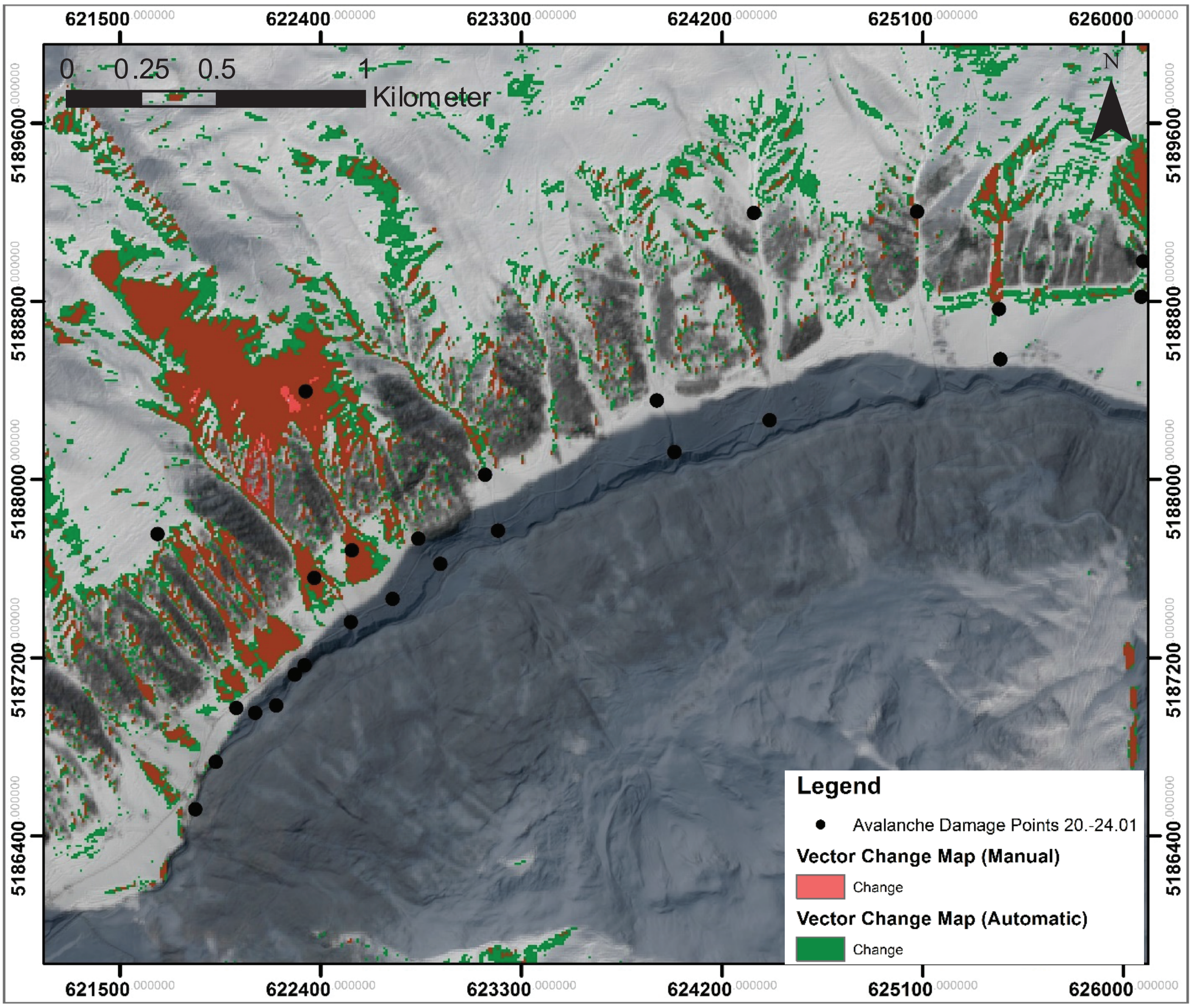

Figure 3: Comparison between the Change Vector Maps with manual and automatic selected thresholds (Contains modified Copernicus Sentinel data (2018)/Eurac Research)

5.2 Avalanche Detection with Optical Remote Sensing

Optical remote sensing data is rarely used for the detection of past snow avalanches (Eckerstorfer et al 2016). Several aspects related to the analysis of optical data in mountain regions limited the performed investigations. For instance, snow cover can change on a daily basis while clouds frequently obstruct the view on the underlying terrain. Even though the temporal resolution of Sentinel-2 improved with the launch of Sentinel-2b, the frequent presence of cloud cover represents a major challenge. Detectable snow cover changes can be not only related to avalanche occurrence, but quite often also to fresh snowfall or snow melting. The time span for avalanche detection might also be a function of snow characteristics and avalanche magnitude (i.e. larger avalanches might be visible for longer time spans). The “cloud problem”, which reduces the respective frequency of observable snow pixels, could then lead to incomplete avalanche detection. A third issue of optical remote sensing data, especially within mountainous areas, are the shadows. As the sun is not in the nadir at the time of acquisition, the images contain large areas that are shadowed. Our first results provided evidence of a substantially decreased performance of the change detection approach within shadowed areas. To remedy this, a separate application of two classifiers (i.e. shadowed areas and areas without shadows) is expected to be of major benefit.

Furthermore, the initial manual setting of thresholds for ρ and θ was subjective and would further restrict the envisaged automatization. To overcome this issue, the Expectation Maximization (EM) method was applied to detect an optimal binary threshold for the identification of changed and unchanged pixels. The final heuristic evaluation of all results indicated that the integration of steps (i) and (ii) lead to more plausible results, also in terms of well-identifiable avalanche structures and a reduction of noisy areas (Fig. 3). In summary, the automated processing chain showed promising results while future activities will also focus on an automatization to achieve near real time spatial avalanche occurrence information.

6. CONCLUSION

The conduction of studies on snow avalanches on regional scale is a challenge, but offers opportunities as well. The spatial scale limits the options for input data and usually increases the level of generalization of the results. This study showed that the combination of a static regional scale snow avalanche model with a remote sensing based change detection approach has the potential to improve spatio-temporal avalanche detection. Future research will build on this study and aims to further optimize and automatize the performed analysis.

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