Automatically detecting avalanches with machine learning in optical SPOT6/7 satellite imagery

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Safety related applications like avalanche warning or risk management depend on timely information about avalanche occurrence. Knowledge on the locations and sizes of avalanches releasing is crucial for the responsible decision-makers. Such information is still collected today in a non-systematic way by observes in the field, for example from ski resort patrols or community avalanche services. Consequently, the existing avalanche mapping is, in particular in situations with high avalanche danger, strongly biased towards accessible terrain in proximity to (winter sport) infrastructure.

Recently, remote sensing has been shown to be capable of partly filling this gap, providing spatially continuous information on avalanche occurrences over large regions. In previous work we applied optical SPOT 6/7 satellite imagery to manually map two avalanche periods over a large part of the swiss Alps (2018: 12’500 and 2019: 9’500 km^2). Subsequently, we investigated the reliability of this mapping and proved its suitability by identifying almost ¾ of all occurred avalanches (larger size 1) from SPOT 6/7 imagery. Therefore, optical SPOT data is an excellent source for continuous avalanche mapping, currently restricted by the time intensive manual mapping. To speed up this process we now propose a fully convolutional neural network (CNN) called AvaNet. AvaNet is based on a Deeplabv3+ architecture adapted to specifically learn how avalanches look like by explicitly including height information from a digital terrain model (DTM) for example. Relying on the manually mapped 24’737 avalanches for training, validation and testing, AvaNet achieves an F1 score of 62.5% when thresholding the probabilities from the network predictions at 0.5. In this study we present the results from our network in more detail, including different model variations and results of predictions on data from a third avalanche period we did not train on.

The ability to automate the mapping and therefor quickly identify avalanches from satellite imagery is an important step forward in regularly acquiring spatially continuous avalanche occurrence data. This enables the provision of essential information for the complementation of avalanche databases, making Alpine regions safer.