

The role of pre-landslide morphology in statistical modelling of landslide-prone areas

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Abstract—The ultimate goal of most statistically-based landslide susceptibility studies is to portray areas that are more or less prone to future slope instability. A number of strategies have been presented to sample the position of the underlying training observations (i.e. landslide locations) within raster-based landslide susceptibility models. Previous research emphasized that the location of past landsliding should preferably be represented by variables that describe the conditions before landslide occurrence (pre-landslide conditions). The assumption behind is that an in-depth description of post-landslide conditions might hamper the identification of susceptible terrain that did not fail yet, but is likely to be affected by future landsliding. In practice, however, data on pre-landslide conditions is rarely available. This contribution outlines the main outcomes of recently published research Ref. [1]. The aim was to elaborate differences between landslide susceptibility models based on post-landslide digital terrain models (DTMs) and their counterparts calibrated with approximated pre-landslide DTM derivatives. In this context, also the associated effects of raster resolution and landslide size were considered. The pairwise model comparisons (post- vs. pre-landslide) showed that the DTM raster resolution and the size of the geomorphic phenomena of interest (i.e. smaller vs. larger landslides) controlled whether and how the modelling results differed. The experiments indicate that commonly available post-landslide DTMs can still reasonably be utilized to derive landslide susceptibility models in case they are resampled to a comparably low resolution (i.e. with respect to landslide size).

I. INTRODUCTION

Almost all published landslide susceptibility models are based on topographic variables derived from (recent) DTMs. Available spatial information on past landsliding frequently refers to a time before the available DTM data was acquired (e.g. geomorphological landslide inventories) [2]. Since landslide phenomena are likely to leave a distinct signature on earth surface topography, the question arises whether statistical models trained with recent post-landslide DTM derivatives (e.g. slope angle, curvature indices, aspect) are appropriate to identify generally

landslide-prone terrain that was not yet affected by slope instability. Intuitively, pre-landslide conditions should be preferred for a statistical spatial landslide prediction task [3–7]. The analysis associated with this contribution [1] investigated differences between grid-based landslide susceptibility models based on post-landslide topographies and their counterparts based on an approximated pre-landslide morphology. It was tested whether the underlying DTM resolution and the size of the landslide phenomena play a critical role on (i) how the models differ (post- vs. pre-landslide models) and on (ii) the (f)utility to consider pre-landslide topography in susceptibility modelling.

II. STUDY AREA AND DATA

The 12 km² large landslide-prone hillslopes of the Dreiklang area (Vorarlberg, Austria, Fig. 1) served as a test site for the experiments [8]. A multi-temporal landslide inventory which consists of 366 polygons (mean size 842 m², median 427 m²) build the basis for the analyses (for more details refer to Ref. [1]). Environmental variables were extracted from a 1:50,000 lithological map, a 1 m airborne Light Detection And Ranging (LiDAR) DTM and multi-temporal land cover information [9].

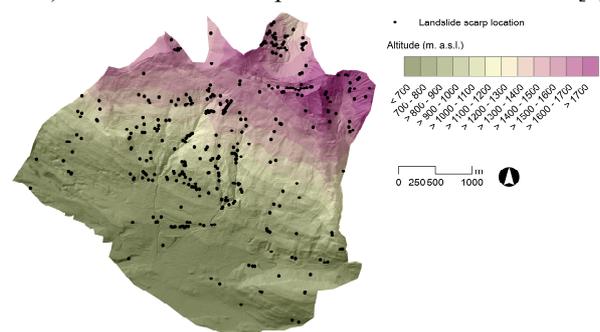


Figure 1. The study area located in Vorarlberg (Austria) and the spatial distribution of the 366 mapped landslide scarp locations.

III. METHODS

The workflow, described in more detail in Ref. [1], comprised A. an initial approximation of pre-landslide topography and a derivation of commonly used topographic variables (different resolutions) and B. a separate statistically-based modelling of landslide susceptibility (post- vs. pre-landslide topography) followed by an in-depth result evaluation.

A. Data preparation

Pre-landslide topography was approximated automatically by (i) deleting mapped landslides areas from the original 1 m DTM and by (ii) refilling the resultant ‘landslide holes’ with interpolated elevation values (TIN interpolation followed by moving window-based smoothing of rasterized values). The newly generated pre-landslide DTM and the original post-landslide DTM were resampled bilinearly to a resolution of 2.5 m, 5 m, 10 m and 25 m to derive frequently used topographic variables: slope, profile slope curvature (i.e. convergence index) and slope orientation (i.e. northness and eastness) (Fig. 2). The effect of landslide size on the modelling results was evaluated by preparing two equally sized response variables (183 landslides each) that contain landslide information on (i) relatively large phenomena (> median landslide polygon size) and (ii) comparably small landslides (< median).

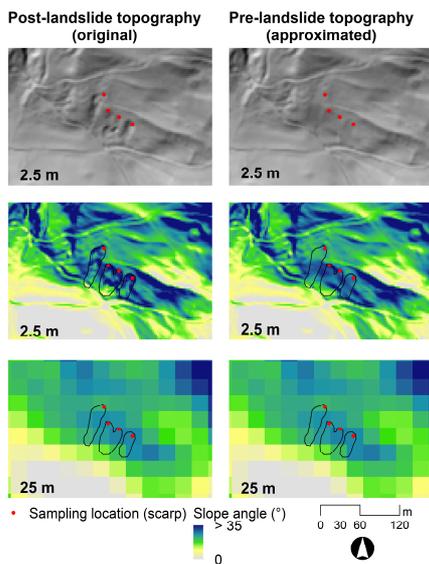


Figure 2. Visual impression of post-landslide topography (left column) and approximated pre-failure topography (right column). The underlying cell size is displayed at the bottom left of each plot.

B. Modelling and model evaluation

Generalized linear (mixed) models were trained separately for data sets associated with different raster resolutions and the two landslide size groups. The (fixed effect) predictor set of the final

models contained the variables slope, convergence index, northness, eastness and lithology. Land cover classes were introduced as a random intercept to ‘average out’ an expected varying completeness of landslide information among land cover units according Ref. [10]. The model evaluations focused on a pairwise comparison of post-landslide models with their pre-landslide equals using different criteria: the discriminatory power of variables (based on the Area Under the Receiver Operating Characteristic, AUROC), predictive performance (based on k-fold cross-validation), the effect size of variables (i.e. odds ratio), variable importance and the spatial pattern of the final maps [1].

IV. RESULT SUMMARY

The evaluations exposed that landslide susceptibility models trained with post-landslide topographic variables can, but must not differ from models that consider an approximated pre-landslide topography. The pairwise comparisons (post-landslide vs. pre-landslide) highlighted that the detail in terrain representation (i.e. raster resolution) as well as the size of mapped landslides controlled whether or not the respective models differed. For instance, differences in the discriminatory power of the variables slope and convergence diminished with a decreasing raster resolution. Most distinct differences were observed for models associated with high resolutions and larger landslides (Fig. 3).

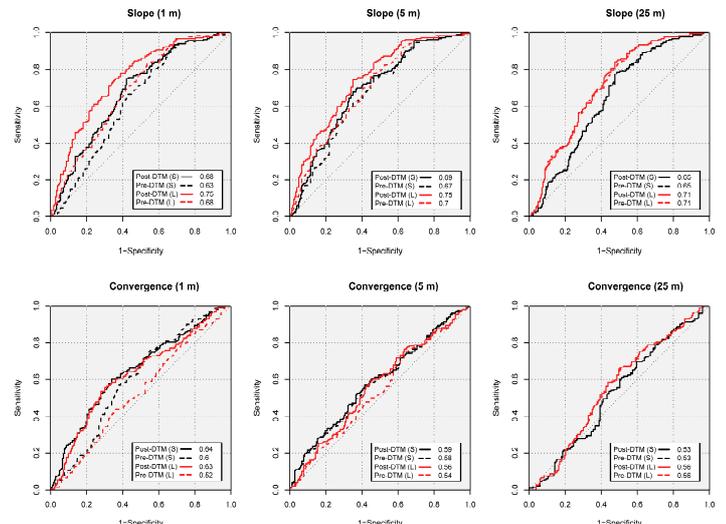


Figure 3. Discriminatory power of the variables slope and convergence based on single-variable logistic regression for different raster resolutions (1 m, 5 m, 25 m) and the two landslide size groups (S: smaller landslides in black, L: larger in red). Confrontations of the AUROCs reveal decreasing differences among the models (post- vs. pre-landslide) with coarser raster resolutions. At higher raster resolutions, larger differences were observed for models based on larger landslides (confront straight and dashed red lines and associated AUROCs).

Similar trends were observed when evaluating the multiple-variable models by means of estimated predictive performances, the effect size of variables and the relative importance of variables: higher similarity of post-landslide and pre-landslide models in case the models were based on lower raster resolutions (e.g. 10 m, 25 m) and smaller landslides. At a spatial resolution of 25 m, differences between the modelling results were negligible. Difference maps of classified landslide susceptibility maps (Fig. 4) visually highlight (i) a considerable portion of dissimilarly classified raster cells for high resolution maps which are based on larger landslides (top right) and (ii) similar predictions for lower resolution maps based on smaller landslides (bottom left).

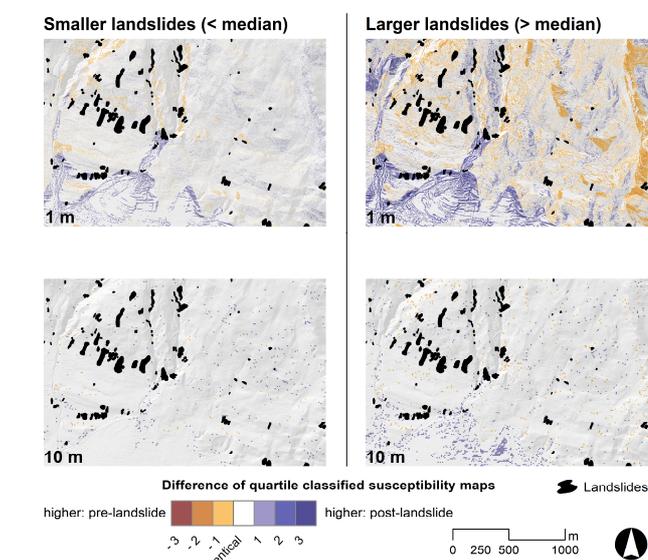


Figure 4. Difference of quartile classified susceptibility maps. The highest (lowest) portion of dissimilarly predicted cells can be observed for maps based on a higher (lower) raster resolution and larger (smaller) landslides. The underlying cell size is displayed at the bottom left of each plot. Note that the expressions “smaller landslides” (left column) and “larger landslides” (right) relate to the training data. Mapped landslides of both size groups are shown in each map.

V. CONCLUSION

The study [1] showed that an undesired too detailed description of landslide morphology within raster-based landslide susceptibility models can not only be minimized by estimating pre-landslide topography, but also by simply resampling a DTM to a lower spatial resolution and by excluding topographic variables that predominantly reflect the geomorphic remnants of past slope failure. For larger deep-seated movements, an approximation of pre-landslide topography or an application of alternative spatial units (e.g. slope-units, [11]) is recommended. Critical decisions in statistical landslide modelling, such as the selection of variables and raster resolution, should not be based on model performance

estimates, but on the ultimate goal of a study: identification of landslide-prone terrain (i.e. emphasis on generalization and the future) or landslide detection (i.e. emphasis on describing the past). DTM derivatives that mainly depict landslide morphology may be of limited use to identify not yet failed susceptible terrain [1]. It is planned to investigate the (f)utility to approximate pre-failure conditions in the context of dynamic physically-based slope stability modelling.

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