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The influence of forest cover on landslide occurrence explored with spatio-temporal information

Elmar M. Schmaltz*, Stefan Steger, Thomas Glade

ENGAGE – Geomorphological Systems and Risk Research, Faculty of Earth Sciences, Geography and Astronomy, University of Vienna, Austria

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ABSTRACT

Multi-temporal landslide inventories in widely forested landscapes are scarce and further studies are required to face the challenges of producing reliable inventories in woodland areas. An elaboration of valuable empirical relationships between shallow landslides and forest cover based on recent remote sensing data alone is often hampered due to constant land cover changes, differing ages of landslides within a landslide inventory and the fact that usage of different data sets for mapping might lead to various systematic mapping biases. Within this study, we attempted to overcome these difficulties in order to explore the effect of forest cover on shallow landslide occurrences. Thus, forest dynamics were examined on the basis of 9 orthophoto series from 1950s to 2015, distinguishing 3 forest classes, based on the wood type. These classes were furthermore distinguished in 12 subclasses, considering stand density and age. A multi-temporal landslide inventory was compiled for the same period based on the aerial photography, 2 airborne LiDAR imageries, 8 field surveys and archive data. We derived topographical parameters (slope, topographical positioning index and convergency index) from the digital elevation model for areal correction and accounting for topographical confounders within a logistic regression model. Empirical relationships were assessed by means of (a) areal changes of forests and logged areas, (b) spatio-temporal distribution of shallow translational landslides, (c) frequency ratios and (d) logistic regression analysis. The findings revealed that forests increased by 16.2% from 1950s to 2015. 311 landslides of 351 in total that where mapped in total could be assigned to the observed time series and were considered for our analyses. Frequency ratios and odds ratios indicated a stabilising effect of all forest classes on landslide occurrences. Odds ratios observed for the models based on aggregated data sets (3 forest classes) indicated provided evidence that forest was constantly estimated to be less prone to slope failure than their non-forested counterparts. The chances for forest classes to be affected by shallow landslides were estimated to be considerably lower whenever topographic predictors were as well included in the model. A detailed inspection of the statistical results suggests that the obtained empirical relationships should be interpreted with care. Challenges in the mapping procedures of forests and landslides, implications of the applied methods and potential pitfalls are discussed.

1. Introduction

A reliable representation of past landslide occurrences is of major importance to analyse associated geomorphic processes (e.g. sediment fluxes and connectivity analyses), the spatial distribution of past landslides or the magnitude-frequency relationships (Hovius et al., 1997; Glade, 1998; Brardinoni and Church, 2004; Petschko et al., 2016). Furthermore, high quality landslide inventories are also of upmost importance to calibrate and validate statistical landslide susceptibility and hazard models as well as to evaluate the performance of physically-based slope stability models (Guzzetti et al., 1999, 2008; Van Den Eeckhaut et al., 2006, 2010; Blahut et al., 2010; Petschko et al., 2013). Event-based landslide inventories portray the location of slope failures that were triggered by one single event like a rainstorm or earthquake (Glade, 1998; Malamud et al., 2004; Bai et al., 2010; Bell et al., 2012). Whereas, historical landslide inventories draw a picture of many landslide events over several time series (Glade, 2001; Malamud et al., 2004; Petschko et al., 2016). The expression multi-temporal landslide inventory relates to an (historical) landslide data set, where a specific date or time-span can be assigned to each landslide (Malamud et al., 2004; Guzzetti et al., 2012; Schlögel et al., 2015). Those multi-temporal data sets are regularly created by interpreting multiple sequences of remote sensing data sets. Landslide inventories can be compiled using a variety of techniques (e.g. aerial photo interpretation,

* Corresponding author at: Office B508, Neues Institutsgebäude (NIG), Universitätsstraße 7, 1010 Vienna, Austria.
E-mail address: elmar.schmaltz@univie.ac.at (E.M. Schmaltz).

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mapping from high resolution airborne laser scanning data, field surveys) or by collecting already existing data sources (Rib and Liang, 1978; Reichenbach et al., 1998; Guzzetti et al., 1999; Ardizzone et al., 2002; Galli et al., 2008; Bell et al., 2012; Santangelo et al., 2015). Literature reveals that the selection of a specific mapping approach is regularly dependent on the scope of the study, data availability and financial and human resources (e.g. time per person for mapping, knowledge of the mapper) (Guzzetti et al., 2012; Petschko et al., 2016). Most of the empirical landslide studies demonstrate that each mapping technique has its benefits and pitfalls (Van Den Eeckhaut et al., 2005; Guzzetti et al., 2012; Schlögel et al., 2015; Steger et al., 2016a). The explanatory power of a landslide inventory and its derived empirical relationships are highly reliant on the completeness and accuracy of landslide information (Guzzetti et al., 1999; Petschko et al., 2013; Steger et al., 2016a, 2016b). In this regard, the inventory should also represent a 'truthful' distribution of the landslides for all different land covers that are existent in an area.

This paper attempts to explore empirically the impact of several types of forest coverages (i.e. differentiated according wood type, stand density and age) on spatio-temporal landslide occurrences. In this regard, we aimed to perform the following procedures:

- Generation of multi-temporal information on the spatial distribution of deciduous, conifer and mixed forest stands, based on orthophotos (OPs) and field surveys.
- Detection of shallow landslide features (scarp area, deposited material) and compilation of a multi-temporal landslide inventory based on field surveys, OPs, airborne laser scanning (ALS) and archive data.
- Elaboration of empirical relations between shallow landslides and forest cover in order to gain insights into the relationship between forest stands and landslide occurrences, by interpreting information obtained by different statistical techniques (i.e. bivariate and multi variable classifiers; Yalcin et al., 2011; Budimir et al., 2015).

The completeness of a landslide inventory is frequently related to the land cover distribution of an area (e.g. Brardinoni et al., 2003; Glade, 2003; Malamud et al., 2004; Guzzetti et al., 2012; Bell et al., 2012; Reichenbach et al., 2014; Steger et al., 2016a). Particularly, forests reveal difficulties when mapping landslides based on the vast majority of available remotely sensed data sets (Brardinoni et al., 2003; Bell et al., 2012; Petschko et al., 2016). Especially with aerial photo interpretation (API) the detection of small landslides or landslide features in woodlands might be rather difficult. Thus, landslide inventories that are based on API, are regularly incomplete in forested areas and might underestimate the apparent spatio-temporal landslide activity. The decreased visibility on OPs or overgrow of older landslides by the forest coverage might further hamper the visibility and correct mapping of landslides and their morphometric features (Rickli et al., 2002; Van Den Eeckhaut et al., 2007). In fact, the positional accuracy and completeness of an API-based inventory is known to be strongly dependent on the spatial resolution of the aerial image (Schwab, 1986; Rollerson et al., 2001; Brardinoni et al., 2003). Brardinoni et al. (2003) point out that the portion of visually not detectable landslides in rugged forested areas can sum up to 85% of the total number of landslides. The usage of widely used derivatives of highly resoluted digital terrain models (DTM), as derived from light detection and ranging (LiDAR) point clouds, has shown to increase the level of sophistication in terrain mapping (Petley, 2010). LiDAR facilitated the identification and mapping of landslides, especially in forested areas (Van Den Eeckhaut et al., 2007; Bell, 2007; Anders and Seijmonsbergen, 2008; Petschko et al., 2016). Furthermore, LiDAR-based DTM derivatives can relieve an identification and delimitation of landslide areas and features even in dense forests (Van den Eeckhaut et al., 2012; Chen et al., 2014). Those data sets are based on filtered point clouds that ideally relate to the bare ground surface alone without any vegetation (Kraus and Pfeifer, 1998; Pfeifer et al., 2004; Pfeifer and Mandlburger, 2008; Hollaus et al., 2009). The contribution of forests to slope stability cannot be ignored (Sidle and Ochiai, 2006; Ghestem et al., 2011) and thus a consideration of shallow landslides in forested areas is demanded when compiling a landslide inventory. Hence, we attempt to combine information from OPs, LiDAR-DTMs, field surveys and archive data to identify shallow landslides and thus to reduce the systematical error of the landslide inventory. However, a combination of the mentioned techniques does not guarantee a proper compilation of a multi-temporal landslide data set and a residual uncertainty of the inventory completeness always remains.

Several studies addressed the spatio-temporal effects of forest dynamics in hillslope reinforcement (Rickli et al., 2002; Sidle and Ochiai, 2006; Rickli and Graf, 2009; Ghestem et al., 2011; Papathoma-Köhle and Glade, 2013). Trees are known to be able to stabilise a hillslope. Coarse tree roots anchor into the underlying soil mantle and give stability to the tree, whereas rooting depth and architecture of the root system mainly depend on species, age, substrate and relief (Ghestem et al., 2011). Moreover, forest stands lower the soil moisture content by soil water assimilation of the roots. Clear-cutting of forested areas has two main destabilising effects. Firstly, the loss of the canopy coverage allows rainwater to infiltrate immediately into the soil and potential unstable layers become (nearly) saturated considerably faster. Secondly, cohesion forces of roots decrease constantly during the following years after clear-cutting which additionally reduces slope stabilisation (Sidle and Ochiai, 2006). Regions, where hillslopes are under agricultural and silvicultural practice, experience a periodical transition of timber harvesting and afforestation activities (Marden and Rowan, 1993). In this regard, we hypothesise that particularly areas that are affected by periodical anthropogenic transformation might show a higher tendency to landslide triggering events (Glade, 2003). These areas should be under a strong focus when creating a multi-temporal landslide inventory for the purpose of exploring potential land cover related effects on landslide occurrence. We expect that the consideration of harvested woodlands or afforested areas can yield both an upgrade of information and an increase of accuracy of a multi-temporal landslide inventory. Therefore, the location of a landslide and the date of its occurrence should be analysed simultaneously with the history of its ambient vegetation coverage conditions.

Based on information on past landslide occurrences, a variety of statistical and machine-learning techniques have been used to model landslide susceptibility. Besides logistic regression analyses (Budimir et al., 2015) and their extensions, such as multivariate adaptive regression splines (MARS) (Felicisimo et al., 2013; Conoscenti et al., 2016), also conditional analysis (Clerici et al., 2006; Yilmaz, 2010) or discriminant analysis (Carrara et al., 1991) are regularly adopted. Machine-learning techniques such as artificial neural networks (Lee et al., 2004; Yilmaz, 2009), classification and regression trees (Catani et al., 2013), maximum entropy (Lombardo et al., 2016) or support vector machines (Ballabio and Sterlacchini, 2011) have as well been utilized to map landslide susceptibility. Frequently observed statistical relationships between recent land coverage and a historic landslide data base might be misleading, especially due to the fact that (i) landslide ages often differ substantially within a historic inventory and (ii) the land cover observed today does regularly not match the land coverage present at the time of landslide initiation (Van Westen et al., 2008; Guzzetti et al., 2012; Petschko et al., 2014; Steger et al., 2016a, 2016b). Especially, in populated areas where mitigation measures, such as land management and afforestation are expected to be of highest value, land cover can usually not be considered as static in time. Thus, in order to explore the effect of forest on landslide occurrence, we believe that it is particularly important to consider temporally and spatially differentiated information for both, landslide initiation and land cover. Therefore, statistical analyses based on bivariate models (i.e. frequency ratios) and multi variable logistic regression (i.e. odds ratios) were conducted for initially all 12 forest subclasses in each time series, and