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Estimating the topographic predictability of debris flows

Nele Kristin Meyer [a,b,*], Wolfgang Schwanghart [c], Oliver Korup [c], Bård Romstad [d], Bernd Etzelmüller [b]

[a] International Centre for Geohazards (ICG) c/o NGI, Sognsveien 70, 0855 Oslo, Norway
[b] University of Oslo, Department for Geosciences, Sem Sælands vei 1, 0371 Oslo, Norway
[c] University of Potsdam, Institute of Earth and Environmental Science, Karl-Liebknecht-Str. 24-25, 14476 Potsdam-Golm, Germany
[d] Center for International Climate and Environmental Research (CICERO), Gaustadalléen 21, 0349 Oslo, Norway

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ABSTRACT

The Norwegian traffic network is impacted by about 2000 landslides, avalanches, and debris flows each year that incur high economic losses. Despite the urgent need to mitigate future losses, efforts to locate potential debris flow source areas have been rare at the regional scale. We tackle this research gap by exploring a minimal set of possible topographic predictors of debris flow initiation that we input to a Weights-of-Evidence (WofE) model for mapping the regional susceptibility to debris flows in western Norway. We use an inventory of 429 debris flows that were recorded between 1979 and 2008, and use the terrain variables of slope, total curvature, and contributing area (flow accumulation) to compute the posterior probabilities of local debris flow occurrence. The novelty of our approach is that we quantify the uncertainties in the WofE approach arising from different predictor classification schemes and data input, while estimating model accuracy and predictive performance from independent test data. Our results show that a percentile-based classification scheme excels over a manual classification of the predictor variables because differing abundances in manually defined bins reduce the reliability of the conditional independence tests, a key, and often neglected, prerequisite for the WofE method. The conditional dependence between total curvature and flow accumulation precludes their joint use in the model. Slope gradient has the highest true positive rate (88%), although the fraction of area classified as susceptible is very large (37%). The predictive performance, i.e. the reduction of false positives, is improved when combined with either total curvature or flow accumulation. Bootstrapping shows that the combination of slope and flow accumulation provides more reliable predictions than the combination of slope and total curvature, and helps refining the use of slope–area plots for identifying morphometric fingerprints of debris flow source areas, an approach used outside the field of landslide susceptibility assessments.

1. Introduction

Hillslope mass wasting processes account for up to 14% of the loss of lives due to natural hazards worldwide (Aleotti and Chowdhury, 1999). National costs related to landslides in the U.S., Japan, and the Alpine countries vary between US$ 1 and 5 billion annually (Aleotti and Chowdhury, 1999; Sassa and Canuti, 2008), and yet much of this damage may remain underestimated (Petley, 2012). A large fraction of the world's terrestrial landslide occurrences are concentrated in tectonically active mountain belts, fault zones, and volcanic island arcs (Korup, 2012). Yet mass wasting in mountainous terrain along passive continental margins may also cause substantial problems. The Norwegian traffic network, for example, is impacted by thousands of landslides, avalanches, and debris flows each year that incur annual economic losses of the order of 12 million € (Bråthen et al., 2008; Bjordal and Helle, 2011). Rapid debris flows, i.e. mixtures of unconsolidated sediment and water may travel at speeds >10 m s^{-1} (Hungr et al., 2008), are the most devastating among these mass wasting processes, and cause damage to transport infrastructure of 0.8 million € per year on average (Romstad, 2013). Yet routing traffic arteries through the deeply dissected fjords of western Norway leaves little options such that knowledge about potential debris flow source areas and runout paths is highly desirable.

A large toolbox of methods for identifying such areas susceptible to landslides and debris flows has become available (Guzzetti et al., 2006). Susceptibility maps show the spatial propensity or proneness to landslides without quantifying any probability of occurrence, as opposed to hazard maps (Van Westen et al., 2003; Fell et al., 2008). Direct susceptibility mapping of debris flow source areas usually relies on detailed field mapping and is thus restricted to small study areas. For regional-scale studies, indirect and less field-work intensive susceptibility mapping methods use statistical modelling (Van Westen et al., 2003; Guzzetti et al., 2006; Thiery et al., 2007). This approach assumes that the spatial distribution of slope instability is not stochastic but determined by environmental conditions that also control future landslide occurrences (Fabbri et al., 2003; Fabbri and Chung, 2008). Indirect susceptibility mapping uses a set of environmental indicators (= predictor variables) and the spatial distribution of past landslide

* Corresponding author at: International Centre for Geohazards (ICG) c/o NGI, Sognsveien 70, 0855 Oslo, Norway. Tel.: +47 45185079.
E-mail address: nkm@ngi.no (N.K. Meyer).

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events (= response variables) to identify and characterize potentially prone locations via a degree of susceptibility for a given unit area (Guzzetti et al., 2006; Blahut et al., 2010). A special type of bivariate models concerns the concept of process domains delineated in plots of local slope gradient and contributing catchment area, also known as slope–area plots. Such process domains are largely empirical in nature and entail hillslopes, unchannelled valleys, debris flow dominated (or hillslope-controlled) channels, bedrock and alluvial (self-formed) channels (Montgomery and Foufoula-Georgiou, 1993; Montgomery, 1999, 2001; Stock and Dietrich, 2003; Brardinoni et al., 2012; Williams, 2012). The transition from hillslopes to unchannelled or debris flow dominated channels is often characterized by a kink in slope–area plots: Slope increases with drainage area on hillslopes, though decreases at the point of channel or debris flow initiation (Montgomery and Foufoula-Georgiou, 1993; Brardinoni and Hassan, 2006). Debris flow initiation requires steep slopes, accumulation of unconsolidated sediment, and sufficient porewater pressures (Innes, 1983), and these factors can be approximated by the terrain metrics of slope, total curvature, and flow accumulation. Flow accumulation quantifies the upstream contributing area that serves as proxy of accumulated water runoff in humid areas (Blahut et al., 2010; Kappes et al., 2011). Total (or mean) curvature is the average curvature of any two orthogonal normal sections of the terrain surface, describes the overall curvature of the surface, regardless of slope direction (Wilson and Gallant, 2000), and has been used as a proxy for local soil depth or sediment thickness (Montgomery, 1999; Minasny and McBratney, 2001).

Weights-of-Evidence (WofE) is a data-driven statistical bivariate method using a log-linear form of Bayes' theorem to determine the weight (or importance) of evidence (Bonham-Carter, 1994). In several recent studies (Pradhan et al., 2010; Oh and Lee, 2011; Prasannakumar and Vijith, 2012; Quinn et al., 2012; Lee, in press; Regmi et al., in press) WofE is used for regional-scale landslide susceptibility assessments for areas 10^1 to 10^2 km^2 in size, based on landslide inventories with up to several hundreds of entries. The choice of predictor variables is usually based on prior (or a priori) knowledge on the causes of landslides, though often restricted by data availability. The number of predictor variables included in published WofE models differs between studies and ranges from seven to 20 variables (Mathew et al., 2007; Regmi et al., 2010; Xu et al., 2012). Using multiple predictor variables, however, may violate the assumption of conditional independence between these predictors, which is required for an unbiased susceptibility estimate (Thiery et al., 2007). The derivation of unique condition units (UCU) has often allayed this problem (Piacentini et al., 2012). However, such UCUs do not allow quantifying the relative importance of single factors, which is a distinctive advantage of the WofE model (Süzen and Doyuran, 2004).

While the majority of the many hundreds of published landslide susceptibility studies achieve a prediction accuracy of >80% (e.g. Dahal et al., 2007; Regmi et al., 2010; Sterlacchini et al., 2011; Pourghasemi et al., 2013; Prasannakumar and Vijith, 2012), this seeming success is unrelated to the type of model or the number of predictor variables (Korup and Stolle, in press). More complex models with more predictor variables often fail to significantly improve the predictive accuracy obtained by simpler models with a limited number of predictor variables. Sterlacchini et al. (2011) test different WofE models for the same study area and obtain similar predictive performance for all of them despite significant spatial disagreement between the different resulting susceptibility maps. Therefore, susceptibility maps should always be probed for uncertainties related to each susceptibility class.

Acknowledging these constraints, our strategy of predicting topographic susceptibility to debris flow initiation in western Norway follows a minimalist approach with regard to the number of predictors, which should allow maximum transparency when interpreting our predictions. Numerous susceptibility studies show that slope, total curvature, and flow accumulation are among the most important predictor variables of mass wasting (Lee and Choi, 2004; Dahal et al., 2007; Regmi et al., 2010; Fischer et al., 2012), and we further test this proposal here. We acknowledge that, among others, lithology, precipitation, vegetation cover or human activity, may also influence debris flow initiation (Van Westen et al., 2003). Yet these remain difficult to quantify at high spatial resolution (Fischer et al., 2012). Moreover, Fabbri et al. (2003) and Guinau et al. (2007) found that landslide susceptibility maps based on topographic metrics outperformed maps based on other thematic layers or a combination of both. To quantify the uncertainties arising from previous knowledge about debris flows in our area, we aim at deriving from training data a model with a minimum number of predictor variables. These should be both readily available and sufficiently representative of the physical processes and environmental controls of debris flow initiation. We then quantify model uncertainties arising from different classification schemes and random subsets of observed debris flows, before computing the errors of our prediction on separate test data.

2. Study area and data

Many parts of Norway are exposed to rapid mass movements (Jaedicke et al., 2009), which in parts have been documented in a national database (Skrednett, 2013; Fig. 1). Within this database 710 entries are debris flows reported by the national road and railway authorities, and consulting agencies from 1900 to 2008. Each entry features the timing and approximate coordinates of where debris flows had deposited or blocked a traffic line. We focus on a study area in western Norway, extending from Ålesund in Møre og Romsdal to Notodden in Telemark (close-up in Fig. 1). The Precambrian basement dominates the largest part of the study area. In the southern and central parts, nappes from the Caledonian orogenesis form the bedrock. The lithology is dominated by granites and gneisses (Bøe et al., 2010; Fischer et al., 2012). Topographically the area is characterized by an extensive plateau at elevations between 1200 and 1500 m, which is deeply incised by fjords and U-shaped valleys. The treeline ranges between 600 and 1050 m with a strong west–east gradient, rising with increasing distance from the coast (Rössler et al., 2008). Within our study area 429 debris flows are recorded along the transport routes that closely follow valley bottoms or lower slopes of the steep fjord sidewalls (Fig. 1). Since the source areas of these events are unknown, we checked each reported coordinate, and relocated each event to its point of initiation identified on aerial photographs using 3D visualization (Norkart Virtual Globe, http://www.virtual-globe.info). Initiation points were set by tracking debris flow paths upstream to the deposition site where channels or bare hillslopes were clearly discernible. This manual mapping procedure enabled us to validate each debris flow event, and classify the events into open-slope (38%) and channelized (46%) debris flows. For 16% of the events it was difficult to identify a distinct flow path from the optical imagery since significant land cover changes had occurred after the debris flow occurrence and before the acquisition of the aerial photograph. We selected 263 debris flows (~60%) documented prior to 2005 as training data, and the remaining 166 debris flows (~40%) as testing data. The higher data density of the inventory in recent years results from a reporting bias rather than increasing debris flow activity (Jaedicke et al., 2009).

We used a digital elevation model (DEM) with 10 m grid resolution for extracting three topographic candidate predictors of susceptibility to debris flow initiation. The DEM is derived from 5 m contour lines (FKB-H5) in settled areas, and 20 m contour maps (N50) in remote areas. In settled areas the vertical error is 2 m while in remote areas it is 6 m (Statens Kartverk, 2011). We resampled the DEM to 20 m resolution to reduce a possible resolution bias in remote areas (Fischer et al., 2012), and clipped the DEM to account for documentation gaps of debris flows in remote areas. Lastly, we extracted only those first-order catchment areas draining towards roads or railways, and excluded fjords and lakes (Fig. 1).