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Landslide Susceptibility Mapping at National Scale: A First Attempt for Austria

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Abstract

Numerous publications that addressing landslide susceptibility were published over the past decades, also due to an increasing demand of spatial information regarding potentially endangered areas. However, studies that provide an overview on landslide susceptibility at national scale are still scarce. This research presents a first attempt to generate a national scale landslide susceptibility map for Austria based on statistical techniques. Binary logistic regression has been applied to delineate susceptible areas using three different predictor sets. The initial predictor set relates to topographic variables only (model A), and was gradually expanded with the factors geology (model B) and land cover (model C). The Area Under the Receiver Operating Characteristic Curve (AUROC) was used to validate the predictions by means of a k-fold cross-validation. The obtained acceptable prediction performances (mean AUROC of model A: 0.76, B: 0.81 and C: 0.82) suggest a relatively high predictive performance of all models. However, during this study, several limitations of the conducted analysis (e.g. limited landslide data, bias propagation, overoptimistic performance estimates) became evident. The main drawbacks and further steps towards a more reliable representation of landslide susceptibility at national scale are discussed.

Keywords

Landslide susceptibility • National scale • Logistic regression • Validation • Austria

Introduction

Landslides are one of the most important geomorphological processes in mountainous regions worldwide. Those phenomena are regularly considered as natural, but are frequently modified by human activities. The manifold occurrence of these events during the past decades and its negative effects on the human lives motivated a substantial increase of research that addresses landslides and their consequences all around the globe (Wu et al. 2015).

Landslide susceptibility is defined as the tendency of a specific area to be affected by a certain type of landslides in the future (Brabb 1984; Glade and Crozier 2005; Fell et al. 2008; Guzzetti et al. 2005). Landslide susceptibility maps are also considered as an important and useful tool for

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territorial land cover planning and disaster management to reduce negative influences on human lives and infrastructure (Cascini et al. 2005; Fell et al. 2008; Bell et al. 2013).

Despite the huge amount of studies addressing landslide susceptibility at regional scales, publications dealing with this kind of assessment at national scale are comparably rare. Examples of such assessments can be found in Bălteanu et al. (2010), Graff et al. (2012), Ferentinou and Chalkias (2013), Günther et al. (2012, 2014), Liu et al. (2013), Sabatakakis et al. (2012), Van Den Eeckhaut et al. (2012), Trigila et al. (2013) and Gaprindashvili and Van Westen (2015), among others.

The quality of landslide susceptibility models is known to be highly dependent on the quality of input data, such as the landslide inventory (Guzzetti et al. 2012; Petschko et al. 2014; Steger et al. 2015) and the terrain attributes (predictors) (Van Westen et al. 2008; Carrara et al. 1999).

This publication is an attempt to delineate landslide susceptibility for the Austrian territory based on statistical techniques. We present the first results and subsequently discuss some challenges that were recognized during our analysis. We also propose future research steps that are expected to further enhance the quality of our model.

Study Area

Austria covers an area of 83,858 km^2, has approximatively 8.5 million inhabitants and is located in the center of the European continent (Statistik Austria 2014) (Fig. 1a). The territory contains a high portion of hill and mountainous areas. The eastern parts of Austria is generally flatter and characterized by a high portion of alluvial plains of the Danube river basin. The elevation ranges from around 110 meters on the eastern part, to almost 4000 m in parts of the southwest region.

Due to the geomorphic and socio-economic setting of Austria, landslides pose a serious threat for private properties, public spaces as well as critical infrastructure (Schweigl and Hervas 2009; Petschko et al. 2013).

Apart from the morphometric settings, Van Westen et al. (2008) demonstrated that factors such as lithology, tectonic structure and land cover are also considered as relevant predisposing factors for landslide occurrence.

The Austrian geological pattern is characterized by the Bohemian Massif in the Northern part, region mainly marked by the Danube basin landscape. The Molasse Zone corresponds to the Alpine foreland and stretches along the whole length of the northern side of the eastern Alps, as well as covering the eastern margin of the Bohemian Massif (Schuster et al. 2013). More to the south and east direction, the Molasse Zone is represented by a hilly landscape. The Helvetic Zone is located more in the middle of Bregenz Forest. To the east, this unit reduces gradually and occurs as repeatedly interrupted bands on the northern edge of the Eastern Alps. In Upper and Lower Austria rocks of the Helvetic units occur as small slices within the Flysch Zone, which is widely known for its considerable predisposition for landslides of the slide-type movement (e.g. Schwenk 1992; Damm and Terhorst 2009; Petschko et al. 2014). The central part of the territory is portrayed by the Austro-Alpine Unit. They form the Northern Calcareous Alps and the Central Eastern Alps. In the south direction, the highest peaks of Austria (Großglockner 3798 m) are located near to the Italian border in the Southern Alpine Unit (Schuster et al. 2013).

Mean annual rainfall ranges from 400 to 600 mm/year in the Eastern part to more than 2000 mm/year in the Southern and Western regions. The localized, highly-intense rainfall events are mainly concentrated during the summer-autumn period and can occur throughout the country.

Landslides are mainly triggered by intense and locally concentrated precipitation events. Most important landslides events of the recent past occurred in August 2005 in Gasen und Haslau, where 780 landslides were reported after a heavy rainfall of 200 mm in 48 h (Schwarz et al. 2009) (Fig. 1c). In June 2009, thousands of landslides were triggered by heavy rainfalls in Feldbach (Hornich and Adelwöhrer 2010). However, localized landslide events occur regularly in all prone regions in Austria.

Data

The nationwide data include a Digital Terrain Model (DTM) available at a 10 m × 10 m pixel resolution. This elevation model was resampled (bilinear interpolation) to the modelling resolution of 100 m × 100 m. Topographic parameters such as topographic position index (TPI), slope gradient, aspect and elevation were derived from this resampled topographical information. The land cover refers to the year 2012 and was obtained from the Copernicus Land Monitoring Services, with a minimum mapping unit of 25 ha. The geological information was provided by the Geological Survey of Austria on a 1:500,000 scale.

Landslide Inventory

The landslide inventory provided by the Geological Survey of Austria is composed from several inventories and historical records and contains 14,519 point features (on average 0.17 landslides/km^2). Those landslides refer in particular to earth slides, based on the Cruden and Varnes (1996) classification (Fig. 1b).

Despite the large amount of landslides, the available inventory data (Fig. 1b) is known to be systematically

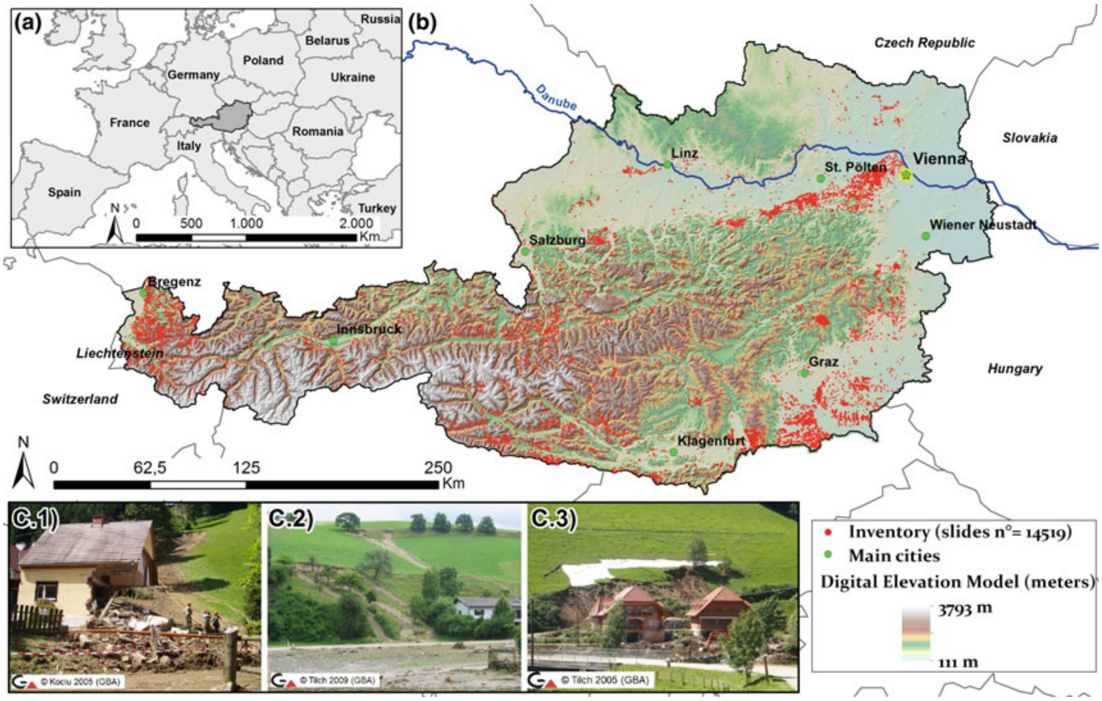

Fig. 1 Austria location in Europe. **a** The digital elevation model for Austria, main cities, and the currently available landslide inventory (n = 14,519). **b** Photographs of exemplary landslides: Gasen, province of Styria, on August 2005 (**c.1**); Klingfurth, province of Lower Austria, on June 2009 (**c.2**); and Haslau, province of Styria, on August 2005 (**c.3**). *Pictures source* Geological Survey of Austria

incomplete. Non-landslide locations were represented by an identical number (n = 14,519) of point observations that were randomly distributed over the entire territory (Goetz et al. 2015; Steger et al. 2016).

Predictors

In total, six widely used landslide predisposing factors (Fig. 2) were selected to model landslide susceptibility at a grid cell resolution of 100 m × 100 m.

Slope angle and elevation were introduced into the model as continuously-scaled variables. The slope orientation was represented by an aspect layer which was classified in four categories, namely north, south, west and east. The relative position of the slope was expressed by the topographic position index (TPI), which was reclassified based on Weiss (2001) (Fig. 2).

The non-topographic predictors include land cover where 44 variables have been reclassified in 8 main categories. Similarly, lithology with originally 65 classes was grouped in 15 classes according to their approximated soil mechanical conditions (Fig. 2).

Methods

The methodological framework of this study is summarized in Fig. 3. The final three models were based on a spatial extent that excluded glaciers, lakes, rivers and their surrounding floodplains.

Modelling

Statistically-based landslide susceptibility models empirically relate past landslide events with associated environmental parameters (e.g. local terrain attributes) (Carrara et al. 1995). The methodology is based on the assumption that future landsliding are likely to evolve under similar conditions that led to past landslides (Brabb 1984).

Landslides susceptibility was modeled using a multiple variable statistical approach, namely logistic regression. This approach is still one of the most applied statistical technique to delineate landslide susceptibility for large areas and is considered to be robust and able to generalize observed relationships (Atkinson and Massari 1998; Brenning 2005;

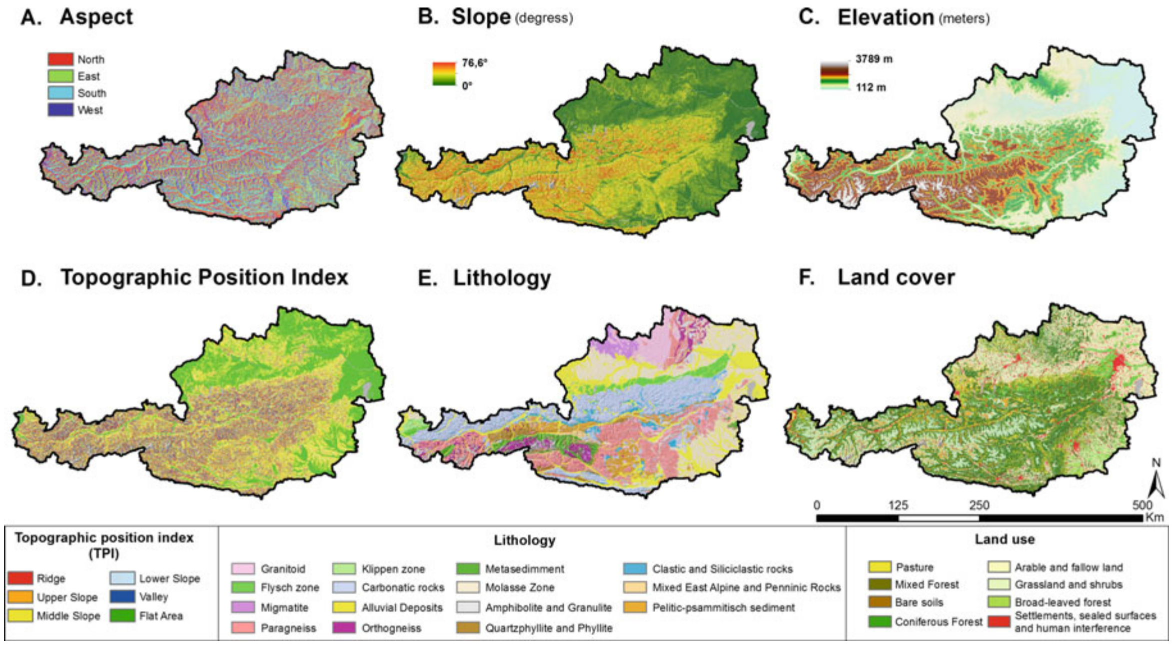

Fig. 2 Predictors used: aspect (*A*); slope (*B*); elevation (*C*); topographic position index (*D*); lithological units (*E*) and land cover classes (*F*)

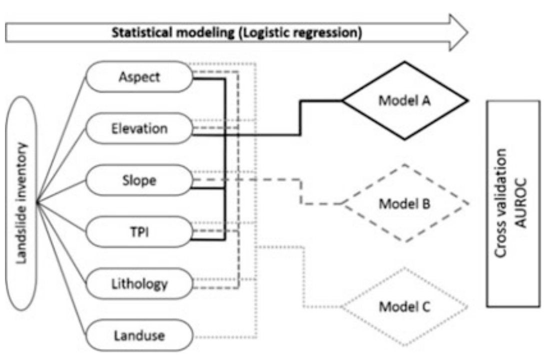

Fig. 3 Methodological scheme of this study

Guzzetti et al. 1999; Van Den Eeckhaut et al. 2012; Van Westen et al. 2008).

Three different predictor sets, leading to different models, have been tested (Fig. 3). The models are:

- Model A: Takes into account only topographic parameters (TPI, Slope, Aspect and Elevation);
- Model B: Apart from the topographic information the lithology information was additionally included (TPI, Slope, Aspect, Elevation and Lithology);
- Model C: Topographic parameters, Lithology and Land cover is included (TPI, Slope, Aspect, Elevation, Lithology and Land cover).

Validation

The model validation was performed using a *k*-fold cross-validation technique (here with 10 folds and 50 repetitions) (Brenning 2012). This technique repeatedly partitions the available data sets into disjoint training and test sets (Brenning 2005). Within each partition, the AUROC was estimated for the independent test sets to finally obtain the model's predictive performance. The AUROC always ranges from 0.5 (random model) to 1 (perfect discrimination between landslides and non-landslides) (Brenning 2005).

Results

The appearance of the obtained landslide susceptibility maps differ, especially between the models solely related to topographic parameters (model A) and those models that

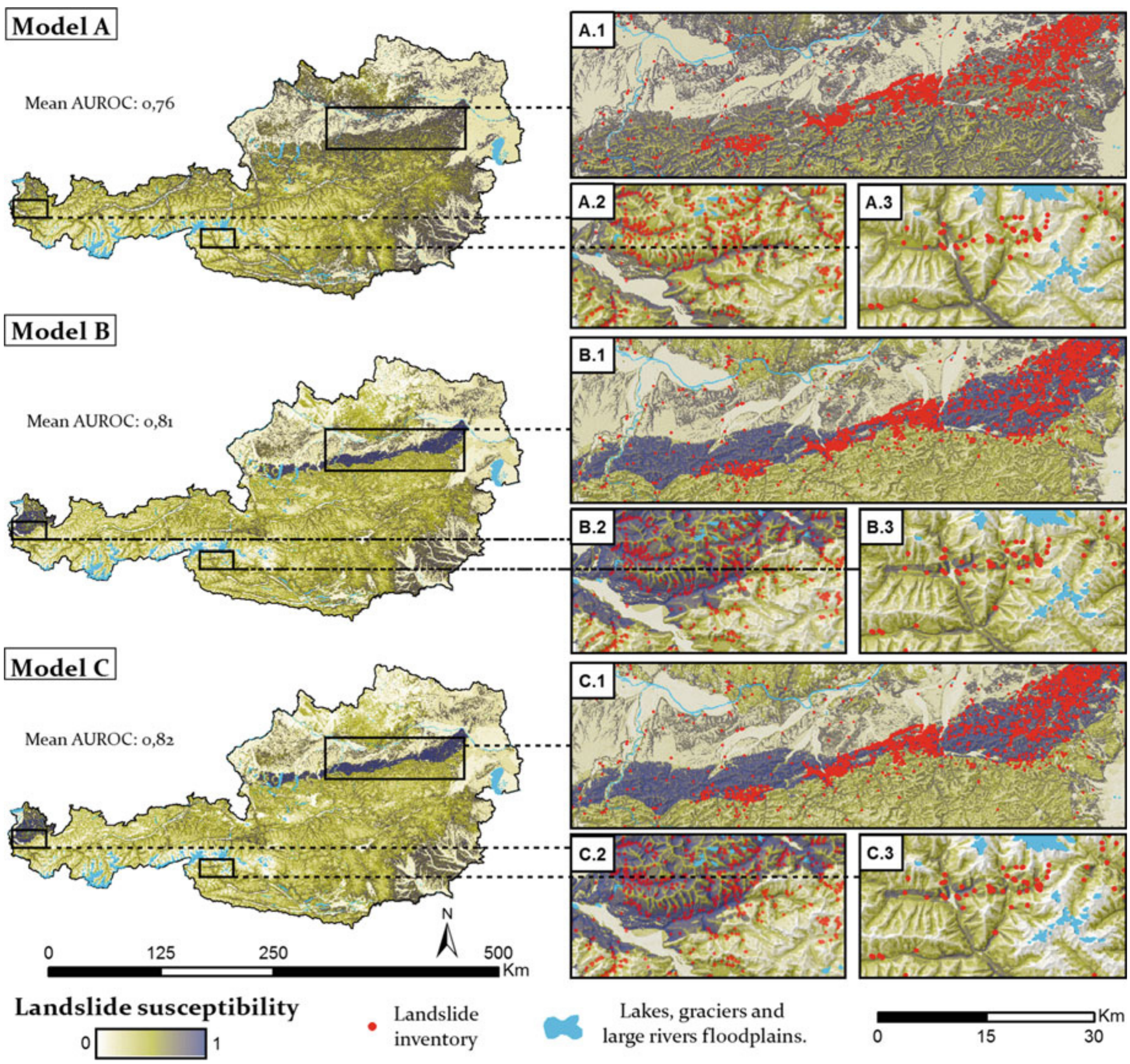

Fig. 4 The final maps calculated from the different datasets (Models *A*, *B* and *C*). Note the sharp transitions between the Flysch Zone (cf. Fig. 2) and its surroundings in *B1*, *B2* and *C1*, *C2*

additionally included lithology (model B) and land cover (model C) (Fig. 4). The susceptibility map produced with topographic variables reflected the obtained positive relation between slope angle and landslide occurrence (i.e. positive slope coefficient) as well as a negative relation between elevation (i.e. negative elevation coefficient) and landslide susceptibility. Thus, those susceptibility maps depicted that steeper slopes were more susceptible than flatter slopes and high alpine areas less susceptible than lower-lying regions (Fig. 4A.3; B.3; C.3).

The maps corresponding to the models B and C revealed a concentration of high susceptibility values within specific lithological units. As expected, landslide susceptibility was highest within those lithological units that contained highest landslide densities (e.g. Flysch 1,13 landslides/km^2). This tendencies and corresponding sharp transitions are clearly reflected by the spatial pattern of the final maps (cf. Fig. 4 B1, C1).

The obtained AUROC values provided evidence for an acceptable to high prediction capacity of corresponding models (Fig. 4). The model A revealed a median AUROC of 0.76, while the models B and C performed slightly better from a purely quantitative perspective (0.81 and 0.82 respectively).

Discussion

The conducted analyses proved valuable from a purely quantitative perspective (i.e. high predictive performances). Nevertheless, there remain some issues which need to be addressed. Therefore, we discuss several reasons in the following section on why the obtained susceptibility models do not represent a perfectly reliable representation of landslide susceptibility for Austria.

Input Data

This study provided another example that the quality of a spatial landslides susceptibility models is highly reliant on the quality of the landslide information (Guzzetti et al. 2012; Van den Eackhaut et al. 2012). This research is based on a simple compilation of several already existing landslide inventories of different origin, completeness and qualities. A visual inspection of this inventory clearly shows the systematically incompleteness of the used inventory. A higher completeness is assumed to be in the areas were previous detailed mapping campaigns have been conducted. In contrast, areas were no landslide was mapped can either be (i) non susceptible to landsliding, (ii) subject to data unavailability, or (iii) unmapped landslides in terms of spatial assessments.

This study provides another example and further evidence that a systematic inventory-based incompleteness (i.e. inventory-based bias) may be directly propagated into the final modelling results whenever a specific predictor is able to describe such an inventory-based error (Steger et al. 2016). This was specifically the case by introducing lithology as a predictor. Thus, the observed high susceptibility values within certain lithological units (e.g. Flysch Zone) do not necessarily reflect a plausible relationship and can as well be a product of an over representation of landslide observations in these units. In analogy, lithological units predicted as less susceptible might also be just affected by an under representation of past landslide events.

Similar tendencies (i.e. bias propagation) were expected by additionally introducing land cover as a predictor, since land cover is likely to be related to systematic incompleteness of a landslide inventory (Petschko et al. 2015; Steger et al. 2016). Furthermore, we point out that an inclusion of land cover as a predictor variable might be inappropriate within our analyses, because the applied recent land cover data does presumably not perfectly correspond to the coverage present when the respective landslides were initiated (Petschko et al. 2014).

The model generated with only topographic variables is, despite its lowest predictive performance, assumed to be less affected by such direct bias propagations. However, we also expect distorted relationships present within this model due to confounding factors (Steger et al. 2016). For example, as slope angles are not equally distributed over the entire territory (cf. Fig. 2b), we expect that the obtained relation between landslide occurrence and the predictor slope is more influenced by those inclinations that are present in the areas where the inventory is more complete.

These previous paragraphs highlight that the assumed systematic incompleteness of the present inventory considerably affected the quality of the underlying model. Further analysis steps are expected to provide deeper insights into potential limitations of the present landslide information. A subsequent adapted modelling design (e.g. excluding predictors that directly describe a bias, adapted sampling strategy) might further increase the geomorphological plausibility of our modelling results.

An additional aim is to expand the present landslide data set with additional spatial information on past landslide occurrences. Furthermore, we point to the importance of an adapted sampling design, especially for landslide-absences, in order to further minimize the previously mentioned direct bias propagations [a similar strategy was conducted by Van den Eeckhaut et al. (2012)]. Furthermore, an a priori exclusion of areas where landslides are very unlikely to occur in the future (e.g. floodplains) might additionally increase the explanatory power of modelling results.

The predictor set used within this study (aspect, elevation, slope angle, topographic position index, lithology and land cover) consisted of variables that are frequently used within statistical landslide susceptibility models (Van Westen et al. 2008). Several studies showed that the addition or exclusion of predictors affects both, the appearance of landslide susceptibility maps as well as corresponding validation results (Iovine et al. 2014; Carrara et al. 1999; Sabatakakis et al. 2012; Van Westen et al. 2008). This was also observed within this study.

Despite the highlighted drawbacks of this first approximation, some empirical relations obtained within this study still appear plausible from a geomorphic perspective. For instance, although very high slope angles are apparent, steep high alpine areas were predicted as less susceptible than gentle hilly slopes of the alpine foothills. This seems to be realistic, especially because high-alpine areas may regularly exhibit thin soil covers. However, we stress that an inference of geomorphic processes from empirical models produced with highly incomplete data should clearly be avoided (Brenning et al. 2015; Steger et al. 2016). In the future, we aim to test the influence of including additional predisposing factors such as soil cover, others geological features, as well as climatic and hydrological information. We will investigate the consequences of these additional factors on the appearance of the final maps, the modelled relationships, the potential bias propagation and the prediction performances.

Validation

The model previously mentioned as the least affected by an inventory-based bias (model A) had the lowest predictive performance of all models. In contrast, the models B and C, which were observed to strongly reflect the inventory-based incompleteness, showed an apparent higher ability to predict future landslide locations. This observation further contributes to the suspicion that the predictive performance of a statistical landslide susceptibility model is not directly associated with the geomorphic plausibility of modelling results. Overoptimistic performance estimates might be common, whenever a specific predictor (in this case lithology) might be systematically related to an inventory-based incompleteness (Steger et al. 2016).

This study highlights that a well performing statistical susceptibility model (i.e. in terms of predictive performance) is not necessarily a geomorphic plausible one. We further underline the importance of an additional expert-based plausibility check. Despite the modifications suggested within the previous paragraphs we intend to further explore the effects of changing the representation of predictors by changing the respective grid resolution and testing slope-unit based approaches (Alvioli et al. 2016).

Conclusions

As within all types of quantitative analysis, the final results were strongly dependent on the input parameters, like the landslide inventory and predictors used. Despite those limitations, the results are considered as a useful first approximation at a national scale.

Nevertheless, some issues have to be pointed out:

- The quality of landslide data (e.g. completeness and positional accuracy) should further be improved in order to increase the explanatory power of the modelling results.
- Factors such as lithology and the topographic position index (De Reu et al. 2013) should be revised and reclassified for a better representation.
- The addition of new variables, such as precipitation, hydrological information and soil information (e.g. type, depth, etc.) could be valuable, since they are known to influence landslide occurrence significantly.
- A new sampling approach is considered crucial to produce more reliable results. One improvement might be to restrict the random sampling of landslide-absences to those locations where the inventory is considered more complete.
- The application of classification methods that allow to model non-linear relationships (e.g. generalized additive models) might prove to be useful. For instance, we suspect that the association between landslide occurrence and slope angle may be non-linear (i.e. low susceptibilities for very low and very high slope angles).

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