## Proceedings of 7<sup>th</sup> Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria

# Compilation of a geo-hazard map for slope instabilities and landslides along the German railway infrastructure

Andreas Knobloch<sup>a</sup>\*, Enrico Kallmeier<sup>a</sup>, Markus Forbriger<sup>b</sup>, Carina Herrmann<sup>b</sup>, Eckhard Roll<sup>b</sup>, Jens Kirsten<sup>c</sup>, Christoph Brendel<sup>d</sup>, Stephanie Hänsel<sup>d</sup>

<sup>a</sup>Beak Consultants GmbH, Am St. Niclas Schacht 13, 09599 Freiberg, Germany
<sup>b</sup>Federal Railway Authority, Heinemannstraße 6, 53175 Bonn, Germany
<sup>c</sup>Federal Highway Research Institute, Brüderstraße 53, 51427 Bergisch Gladbach, Germany
<sup>d</sup>Deutscher Wetterdienst, Frankfurter Str. 135, 63067 Offenbach am Main, Germany

#### Abstract

In Germany and Europe infrastructure managers are already undertaking massive efforts to reduce the risks and effects of mass movements on railway infrastructure. Supporting these efforts and adding the future perspective, we present the results of ongoing project developing a nationwide landslide susceptibility map along the German railway network.

Mechanisms and parameter-interactions that trigger mass movements are complex and related to local conditions regarding, e.g. geology, topography, land use, and climate. In a first step, open source geodata sets, e.g. digital elevation models, geological maps, and digital landscape models were combined within two parallel approaches (i) geotechnical knowledge based, and (ii) artificial neural network (ANN), compared to each other and verified with documented landslide events. To access the future landslide geo-hazard potential along railways under the influence of climate change, the most promising landslide susceptibility map will be enhanced by integrating climate scenario data. Additionally, the resolution of the input datasets will be improved, systematically.

The results obtained within this project will be integrated into the risk assessment tool that will be developed parallel within the BMVI Network of Experts and finally provide decision support to users across the railway sector.

Keywords: mass movements; landslides, climate change; natural hazards; Germany

<sup>\*</sup> Corresponding author. Tel.: +49-3731-781359; fax: +49-3731-781352. *E-mail address:* andreas.knobloch@beak.de

## 1. Introduction

Transport infrastructure in Germany is already affected by climate change as well as natural hazards (Rotter et al. 2011). This is expected to become even more prominent with continued warming of the Earth's surface. Within topic 1 "Adapting transport and infrastructure to climate change and extreme weather events" of the Network of Experts – funded by the German Federal Ministry of Transport and Digital Infrastructure (BMVI) – different departmental research institutes and their partners are working together towards the objective of making transport infrastructure in Germany more resilient.

In Germany, the development of geo-hazard maps is within the sovereignty of State Geological Services (SGD) (Ad-hoc-Arbeitsgruppe Geologie (2016). Therefore, the processing status and the methods used are different. For a general perspective and the comparability of the potential endangerment by mass movements a uniform methodical approach is needed. Therefore, the BMVI Network of Experts pursues an intermodal approach. The project presented here forms the basis for the following work steps within the Network of Experts. The objective of the project is to create a geo-hazard map for slope instabilities and landslides along the German railway system based on a Germany-wide engineering-geological model, which shall consider related geological, morphological and land use information.

## 2. Methodology

The mechanism and the interaction of the controlling parameters are usually complex and strongly determined by local conditions. In order to obtain the best possible result, two different approaches were tested and applied. The general modelling approach is shown in Fig. 1. Firstly, geotechnical expertise was applied in a knowledge-driven approach (decision tree approach, e.g. Krauter et al. 2012) by combining a classification scheme with additional modifiers. Secondly, self-learning artificial neural networks (ANN) were used in a data-driven approach. ANN are capable to model non-linear relationships and have shown their applicability in the field of geoscience, especially for the prediction of geo-hazards (Barth et al. (2014); Roscher et al. (2014); Kallmeier et al. (2016)) and mineral deposits (Barth et al. (2015); Hielscher et al. (2016); Metelka et al. (2015); Noack et al. (2014)).

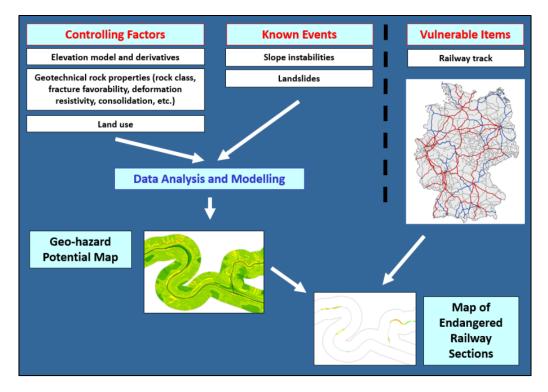


Fig. 1. Overview of general data analysis and modelling approach for the compilation of a nationwide geo-hazard potential map and a map of endangered railway sections

## 2.1. Data Collection

The following base data, partly free, was available within the frame of the project:

- tracks of the German railway network,
- geological overview map 1:200,000 (GÜK200),
- digital landscape model 1:250,000 (DLM250),
- digital terrain model with a raster cell size of 25 m or 10 m (DGM25 and DGM10),
- data from the cadastre of observed geo-hazards from the DB Netz AG and the Saxon State Office of Environment, Agriculture and Geology (LfULG).

## 2.2. Data Preparation

All available data were combined into a unified dataset throughout Germany and stored with a uniform reference system (ETRS89 UTM32N). The following project-relevant model input data were derived from the above-mentioned base data:

- geotechnical properties of the rocks (non-cohesive/cohesive/mixed-grained, unconsolidated/consolidated, fracture-favourable/non-fracture-favourable, deformation-resistant/non-deformation-resistant, with divisional surfaces parallel to layering/without divisional surfaces parallel to layering, etc.),
- properties of the hillsides/slopes (slope angle, horizontal and vertical curvature),
- characteristics of the catchment areas (flow accumulation),
- land use (density of vegetation cover, degree of soil sealing).

## 2.3. Calculation of Geo-hazard Potential

In general, the geo-hazard potential was calculated within a buffer area of 1 km on both sides of the railway track.

Methodically, algorithm and decision trees were applied in a knowledge-driven, first approach for the entire German investigation area (see section 2.3.1). On the other hand, a data-driven, second approach using multivariate statistics and artificial neural networks (ANN) was applied only for the areas of the Free State of Saxony due to the limited availability of the required training data (see section 2.3.2).

## 2.3.1. Approach 1: Calculation using Algorithms/Decision Trees

The geo-hazard potential for slope instabilities and landslides was mapped based on geotechnical expert knowledge in the first step by combining slope angle classification and geo-technical rock classification. For this purpose, a comprehensive classification schema (decision tree) was created, as shown in Table 1. It consists of a classification of the rocks from the GÜK200 and the subsequent overlay and intersection with the slope angle classification based on the DGM20.

According to the classification schema, all areas were initially classified into five principal geo-hazard potential classes:

- Geo-hazard potential class 2: no geo-hazard potential,
- Geo-hazard potential class 5: low geo-hazard potential,
- Geo-hazard potential class 8: moderate geo-hazard potential,
- Geo-hazard potential class 11: high geo-hazard potential,
- Geo-hazard potential class 14: very high geo-hazard potential.

The initial classification result was further refined by including additional controlling parameters. In order to evaluate and weight these factors, modifiers for the land use based on the DLM250, for the rock deformation sensitivity, the degree of rock fracturing and the presence of divisional surfaces in the rock based on the GÜK200, as well as for the flow accumulation based on the DGM20 were determined. These modifiers were combined by an algorithm (see Fig. 2) that is based on expert knowledge (fuzzy logic) and which allows the final down-grade or upgrade of the initial geo-hazard potential classes by one class down (-1) or up (+1).

In the last calculation step, the calculated apriori/initial geo-hazard potential class and the calculated resulting total modifier from the additional parameters were combined by summation. This resulted in the final geo-hazard potential classes based on approach 1, which were stored in a raster file with values between 1 and 15.

Geo-hazard Potential Class	Slope Angle Classification (DGM20)	Unconsolidated mixed-grained	l Rocks non-cohesive	cohesive	Hard Rocks
15 14 13	14	> 36°		> 30°	> 60°
12 11 10	11	> 30 - 36°	> 36°	> 25 - 30°	> 50 - 60°
9 <b>8</b> 7	8	> 25 - 30°	> 30 - 36°	> 10 - 25°	> 30 - 50°
6 5 4	5	> 10 - 25°	> 25 - 30°	0 - 10°	0 - 30°
3 2 1	2	0 - 10°	0 - 25°		

Table 1. Knowledge-based classification schema (decision tree) of the geo-hazard potential by combining
rock classes, based on the GÜK200, and slope classes, based on the DGM20

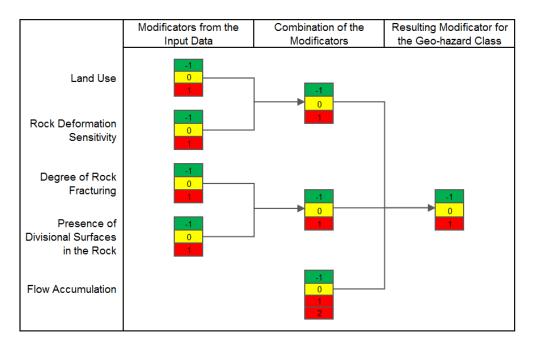


Fig. 2. Flow scheme (algorithm) for calculation of the resulting modification (specification) of the geo-hazard potential classes by combining the modifiers from the different controlling model input data

#### 2.3.2. Approach 2: Calculation using Multivariate Statistics/Artificial Neural Networks (ANN)

In the second model, the geo-hazard potential for slope instabilities and landslides was calculated with artificial neural networks by using the advangeo® Prediction Software. ANN have been described in detail by Hassoun (2003) and Haykins (2008). It is a supervised classification, during which the software caries out an independent (from expert knowledge) weighting and combination of the different influencing parameters (model input data). This model calibration is done by iterative "training" of the ANN, during which the weighting of the parameters is changed until the prediction error at the known locations of observed geo-hazards from the past reaches a minimum.

The final model was created with the following 12 model input data:

- DGM20 negative horizontal curvature,
- DGM20 positive horizontal curvature,
- DGM20 negative vertical curvature,
- DGM20 positive vertical curvature,
- DGM20 flow accumulation,
- DGM20 slope angle,
- DLM250 density of vegetation cover,
- DLM250 degree of soil sealing,
- GÜK200 rock class 1: hard rocks,
- GÜK200 rock fracturing class 1: fracture-favourable,
- GÜK200 rock surface class 2: with divisional surfaces parallel to layering,
- GÜK200 rock deformation sensitivity class 2: distinctive deformation sensitivity.

The prediction result of the artificial neural network within advangeo® is a raster file with a continuous value between 0 (no geo-hazard potential) and 1 (very high geo-hazard potential).

After evaluation of the weighting of the artificial neural network (based on Olden et al. (2002, 2004)), it can be stated that mainly the derived parameters from the DGM20 are the most important parameters with the highest weights in the model: vertical and horizontal curvature and slope angle. On the other side, the flow accumulation derived from the DGM20 does have the lowest influence on the model result out of all used model input data.

## 2.4. Identification the Endangered Railway Sections

In principle, areas in the vicinity of locations with a high geo-hazard potential are also relevant when it comes down to the evaluation of the endangerment of the railway tracks itself. Therefore, in the next processing step, the areas with the highest calculated geo-hazard potential classes (according to calculation with approach 1: geo-hazard potential classes  $\geq 10$ ) or the highest geo-hazard potential (according to calculation with approach 2: geo-hazard potential  $\geq 0.75$ ) were buffered at different distances (0 m = immediate endangerment, 50 m, 100 m and 200 m). After intersection of these buffers with the railway tracks, it was possible to highlight railway sections, where geo-hazards can occur directly at or nearby the railway track (see Fig. 3).

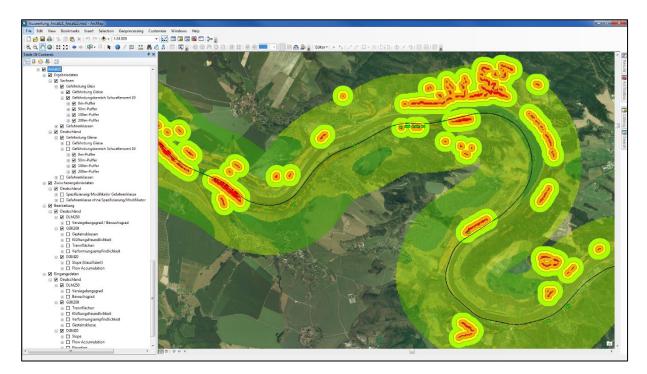


Fig. 3. GIS tool for visualization, analysis and interpretation of the model input data and the model results. Here: Map with points from the geo-hazard cadastre (in green) with buffered areas around the geo-hazard potential class greater than or equal to 10 according to approach 1 and, in transparency, the overall calculation results according to approach 1 and aerial images in the background

## 3. Results

#### 3.1. Geo-hazard Map for Germany

Based on the modelling results from approach 1 (knowledge-driven), a geo-hazard map for entire Germany was compiled at a scale of 1:1,000,000 in format A0. A simplified presentation of the map, which shows the potentially endangered railway sections throughout Germany, can be found in the Fig. 4.

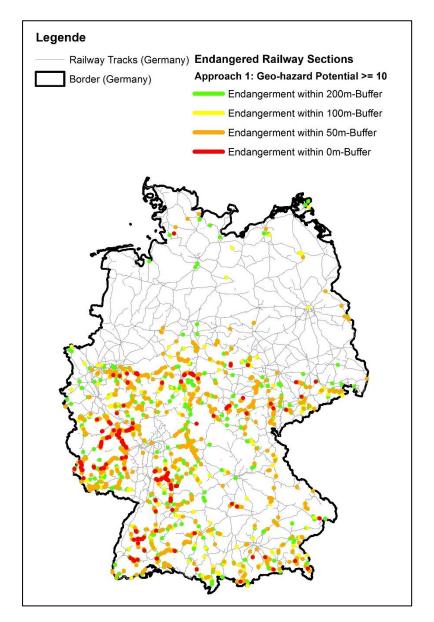


Fig. 4. Germany-wide map showing railway sections that are located directly at or within a buffer of 50, 100 or 200 m away from an area with a calculated geo-hazard potential class of greater or equal 10 based on calculations with approach 1

#### 3.2. Geo-hazard Map for Free State of Saxony and comparison of applied approaches

In order to compare the calculation results from approach 1 (knowledge-driven) and approach 2 (data-driven), a geo-hazard map for the entire Free State of Saxony was created at a scale of 1:500,000 in format A0. For this purpose, two separate maps were plotted on the map itself – each with a separate presentation of the modelling results throughout Saxony for each of the two approaches. A simplified illustration of the two parts of the map is shown in Fig. 5 and Fig. 6. In General, the second approach does highlight more railway track kilometres as potentially endangered by slope instabilities and landslides.

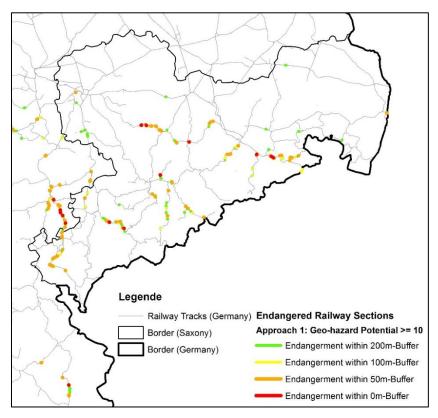


Fig. 5. Saxony-wide map showing railway sections that are located directly at or with-in a buffer of 50, 100 or 200 m away from an area with a calculated geo-hazard potential class of greater or equal 10 based on calculations with approach 1

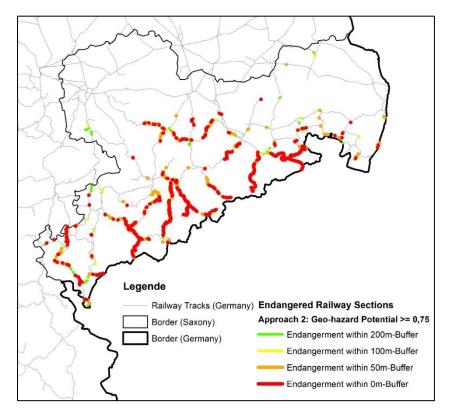


Fig. 6. Saxony-wide map showing railway sections that are located directly at or with-in a buffer of 50, 100 or 200 m away from an area with a calculated geo-hazard potential of greater or equal 0.75 (75 %) based on calculations with approach 2

In order to evaluate the prediction model quality and accuracy of the two different approaches, the calculated geo-hazard potential class (from approach 1) or the calculated geo-hazard potential (from approach 2) were determined at the given points with observed geo-hazards from the past in Saxony, provided by the DB Netz AG and LfULG. The following Fig. 7a provides an overview of the calculated geo-hazard potential classes at these locations, based on the model created with approach 1. A majority of the sites (92 %) was classified with a moderate geo-hazard potential (geo-hazard potential classes 4 - 9).

A significantly higher geo-hazard potential was calculated at the known points from DB Netz AG and LfULG within Saxony based on the application of the artificial neural network model using approach 2. The main portion of the points (67 %) was calculated with a geo-hazard potential of greater than or equal 0.75 (i.e. 75 %). The reason for this is the successful calibration of the prediction model in the course of the training iterations of the artificial neural network. The following Fig. 7b gives an overview of the distribution of the calculated geo-hazards potential at the known geo-hazard locations in Saxony, provided by DB Netz AG and LfULG. For the sake of completeness, it should be noted that the limited database allowed only verification based on the points used in the model. An independent review of the results is necessary for a final assessment. Due to lack of a complete geo hazard cadaster in Germany such an automated calibration of the model was not possible with the model from the first approach.

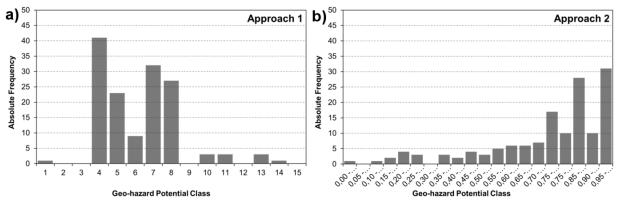


Fig. 7. Histogram of the absolute frequency of the calculated geo-hazard potential classes at the known geo-hazard locations in Saxony based on calculations with a) approach 1 and b) approach 2

#### 4. Conclusion and Outlook

Among the used model input data, only the digital terrain model with a raster cell size of 10 m met the resolution requirements that were necessary for accurate modelling and calculation. On the other side, the geological map at a scale of 1:200,000 and the digital terrain model at a scale of 1:250,000 were not accurate for the intended sharp and precise geo-hazards predictions. Additional information about dip angle and dip direction of the rock units shall be included, too. Therefore, the geological maps at a scale of 1:25,000 (GK25) or the hydrogeological special maps at a scale of 1:50,000 (HyK50) provided by the State Geological Services of Germany shall be used for further investigations.

After the evaluation of data availability, e.g. geo-hazard cadastres, it is recommended to further develop one of the illustrated methodologies of the two approaches 1 and 2. Beside this, future work will focus on the potential effects of climate change on mass movements and how these parameters can be implemented into the existing models.

#### Acknowledgements

The presented research is financed by the German Federal Ministry of Transport and Digital Infrastructure (BMVI) within topic 1 "Adapting transport and infrastructure to climate change and extreme weather events" of the Network of Experts.

#### **5. References**

- Ad-hoch-Arbeitsgruppe Geologie (2016): Gefahrenhinweiskarten geogener Naturgefahren in Deutschland ein Leitfaden der Staatlichen Geologischen Dienste (SGD). Geol. Jb. A 164, Hannover.
- Barth, A., Knobloch, A., Noack, S., Schmidt, F. (2014): Neural Network-Based Spatial Modelling of Natural Phenomena and Events. In: Systems and Software Development, Modelling, and Analysis: New Perspectives and Methodologies. IGI-Global. ISBN13: 9781466660984. p. 186-211.
- Barth, A., Knobloch, A., Legler, C., Noack, S. (2015): Nutzung künstlicher neuronaler Netze zur Einschätzung der Rohstoffperspektivität des Erzgebirges. Vortrag auf der Tagung "Bergbau, Rohstoffe und Energie", 2015. TU Freiberg. Abstrakt veröffentlicht in: "Bergbau, Energie und Rohstoffe", 7.- 9.10. 2015, Tagungsband, 388 Seiten, Hrsg: DMV, RDB, Institut für Markscheidewesen und Geodäsie, Institut für Bergbau und Spezialtiefbau der TU Freiberg, ("Wissenschaftliche Schriftenreihe des Markscheidewesens" des DMV).

Hassoun, Mohamad H. (2003): Fundamentals of Artificial Neural Networks. MIT Press, Bradford Book, 2003.

Haykins, S. (2008): Neural Networks and Learning Machines. Pearson, 3rd edition, 2008.

- Hielscher, P., Barth, A. (2016): Auf der Suche nach verdeckten Lagerstätten: 3D-Prognosen mit künstlichen neuronalen Netzen. Presentation at the 22nd Company Symposium of Beak Consultants GmbH, 15.04.2016.
- Kallmeier, E., Barth, A., Boehnke, R. (2016): Temporal and spatial prediction of lignite mining waste rock pile stability by using artificial neural networks. AIMS Aachen International Mining Symposia Mining in Europe, Aachen.
- Krauter, E., Kumerics, C., Feuerbach, J., Lauterbach, M. (2012): Abschätzung der Risiken von Hang- und Böschungsrutschungen durch die Zunahme von Extremwetterereignissen. Berichte der Bundesanstalt für Straßenwesen. Straßenbau. Heft S 75. Bergisch-Gladbach, (http://bast.opus.hbz-nrw.de/volltexte/2012/577/pdf/S75b.pdf).
- Metelka, V., Baratoux, L., Jessel, M., Barth, A., Naba, S. (2015): Regolith landform mapping in western Burkina Faso, using airborne geophysics and remote sensing data in a neural. Research Gate, 2015.
- Noack, S., Knobloch, A., Etzold, S., Barth, A., Kallmeier, E. (2014): Spatial predictive mapping using artificial neural networks. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-2, 2014. ISPRS Technical Commission II Symposium, 6 – 8 October 2014, Toronto, Canada, 2014.
- Olden, J. O., Jackson, D. A. (2002): Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks. In: Ecological Modelling 154 (2002) 135 150, 2002.
- Olden, J. D., Joy, M. K., Death, R. G. (2004): An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. In: Ecological Modelling 178 (2004) 389-397, 2004.
- Roscher, M., Barth, A., Kallmeier, E., Drebenstedt, C., Götz, M. (2014): Aufbau eines integrierten Kippensicherheits- und Bewertungssystems (IKSB). Final report of company Beak Consultants GmbH and TU Bergakademie Freiberg for the company Lausitzer- und Mitteldeutsche Bergbauverwaltungsgesellschaft. Unpublished report, 2014.
- Rotter, M., Hoffmann, E., Welp, M. (2011): Anpassung an den Klimawandel Themenblatt. UBA KomPass (https://www.umweltbundesamt.de/sites/default/files/medien/364/publikationen/kompass\_themenblatt\_verkehr\_2015\_net.pdf).