



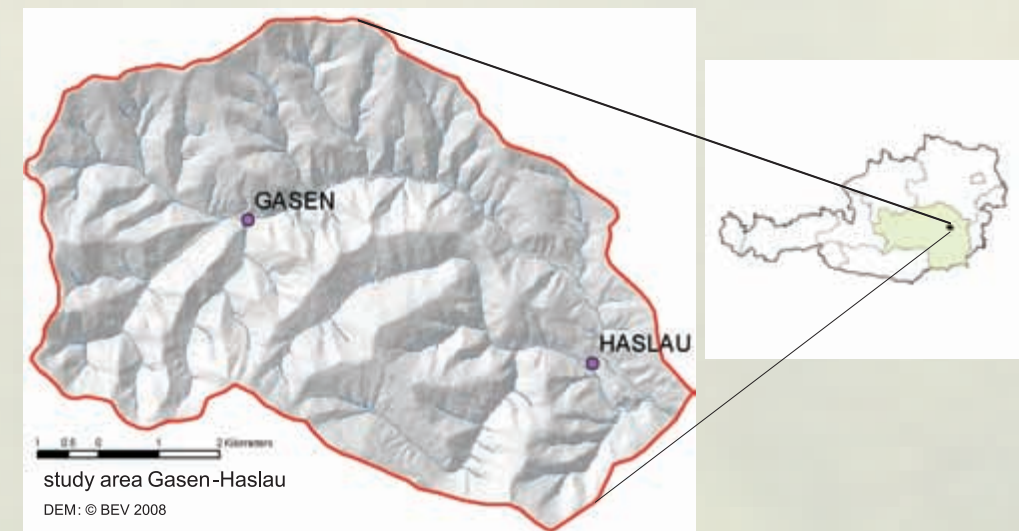
LANDSLIDE SUSCEPTIBILITY MAPPING BY MEANS OF ARTIFICIAL NEURAL NETWORKS PERFORMED FOR THE REGION GASEN-HASLAU (EASTERN STYRIA, AUSTRIA)

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Introduction

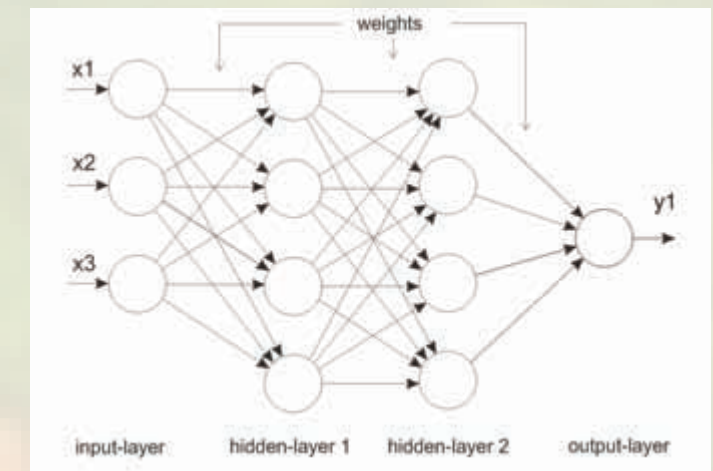
The study area is located in the eastern foothills of Fischbacher Alps in Styria and covers an area of 60 km². The geology is mainly composed of phyllitic mica schist and phyllites, but blackschists, carbonates and orthogneiss can also be found. The elevation ranges from 600 to 1.500 m.

In August 2005, prolonged rainfall (about 200 mm in 48 hrs) with a relatively low intensity (about 15 mm per hour) triggered more than 600 landslides in the region of Gasen-Haslau, Eastern Styria, Austria. By means of Artificial Neural Networks a landslide susceptibility map was generated using 368 landslide points of this event. The main focus of this study is to analyse the capability of this method to assess landslide-prone areas and in particular when using general available data. Furthermore, it should be analysed how much the performance of the Neural Network is affected by a reduction in landslide data for the input model, since the number of mapped landslides available for modelling is quite low in many cases.



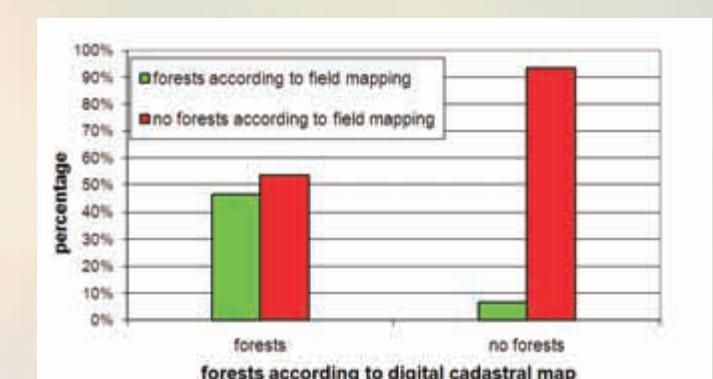
Artificial Neural Networks

Artificial Neural Networks (ANN) are very suitable for non-linear and complex connections. A network consists of nodes (which contain activation functions) and connections between them (which contain weights). The network is fed by input data (geo-parameters) and minimizes step-by-step the error between measured output (mapped landslides) and calculated output (susceptibility map) by optimizing the weights.



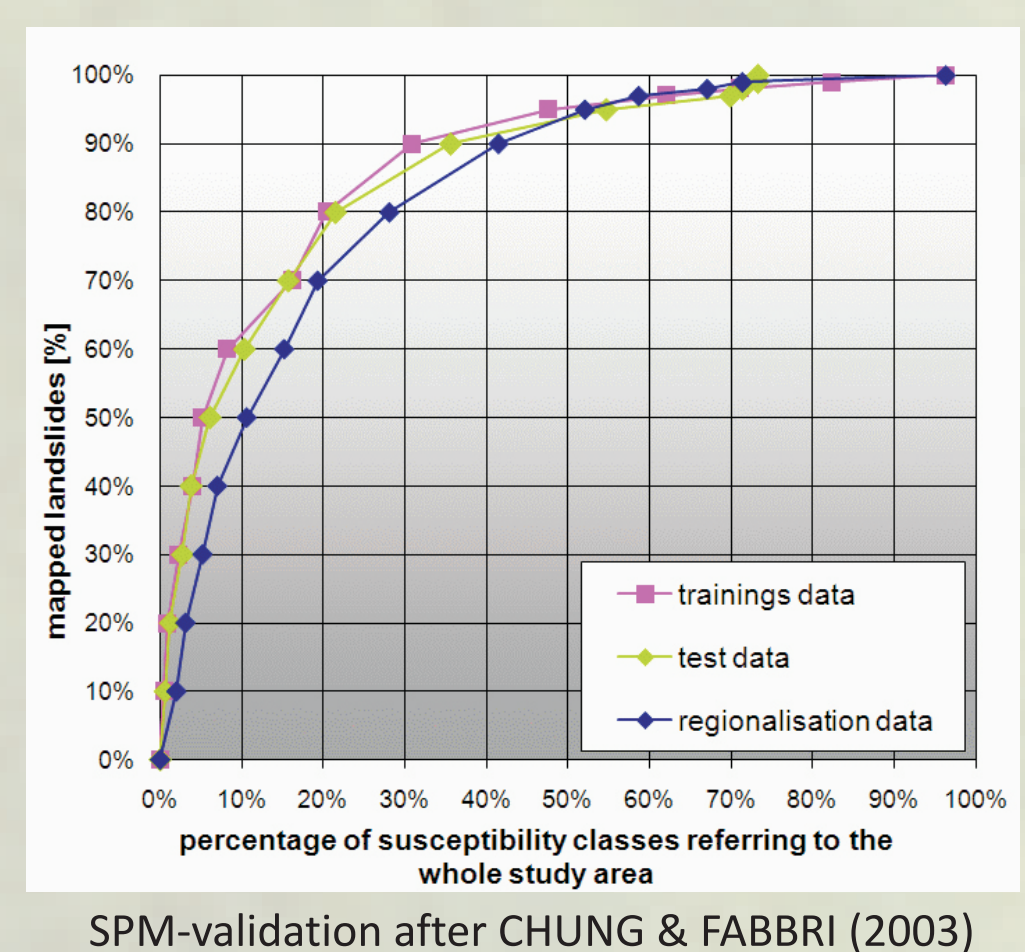
Database and its Inaccuracies

The landslide database used for the Neural Network contained 368 spontaneous landslides (soil slips and earth flows), which occurred during the event of August 2005. Landslides caused by channel erosion were excluded. Several parameters derived by the 50 m DEM, as well as the parameters geology, streets and forests, served as input data. It turned out that the general available forest- and street parameters of the used digital cadastral map did not correspond to the field mapping results in many cases. To test the effect of this less accurate general available data on the model results, the regionalisation data set was created, which contained this data.

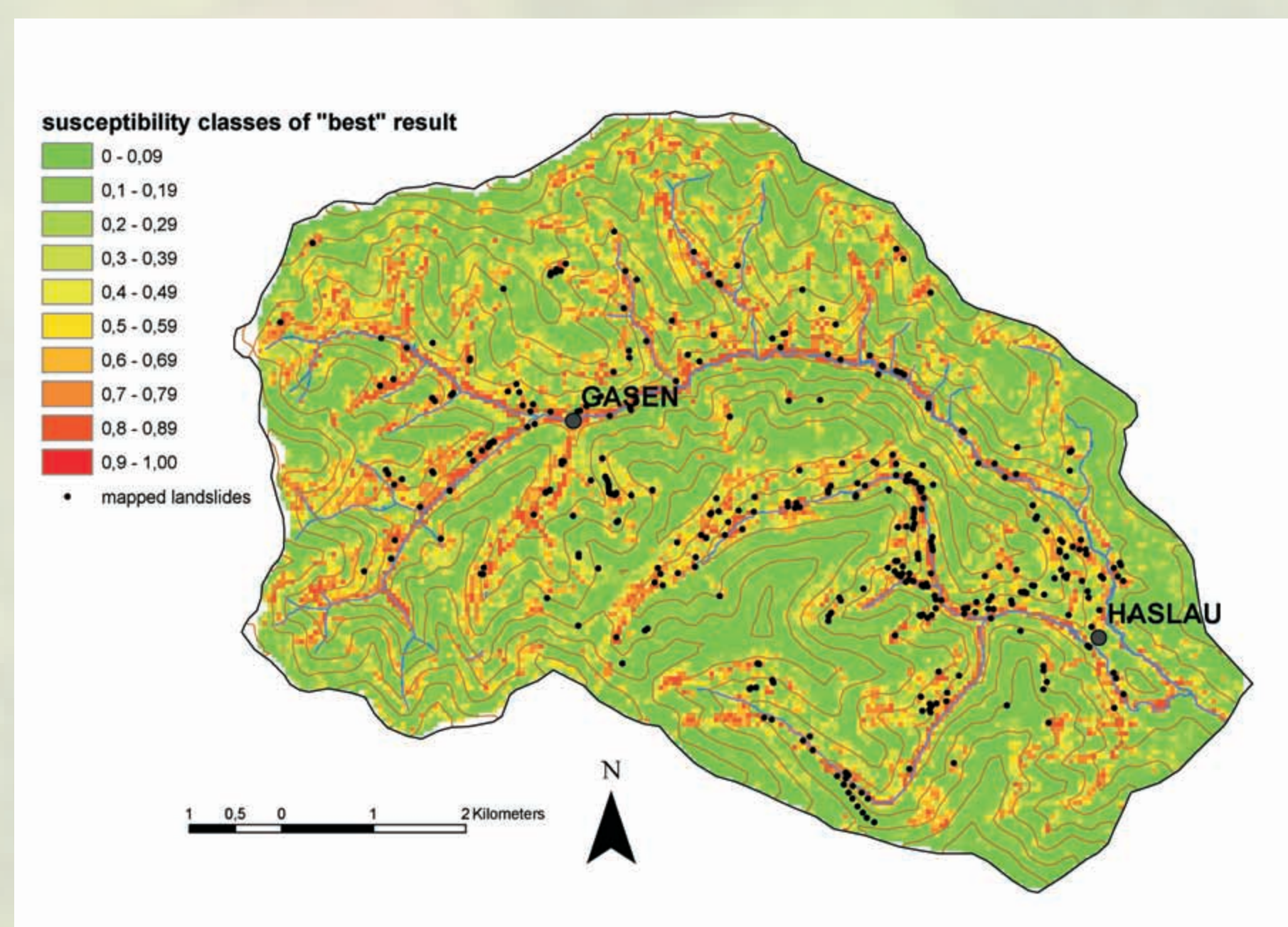


Forests at landslide points: field-mapped and digital cadastral map

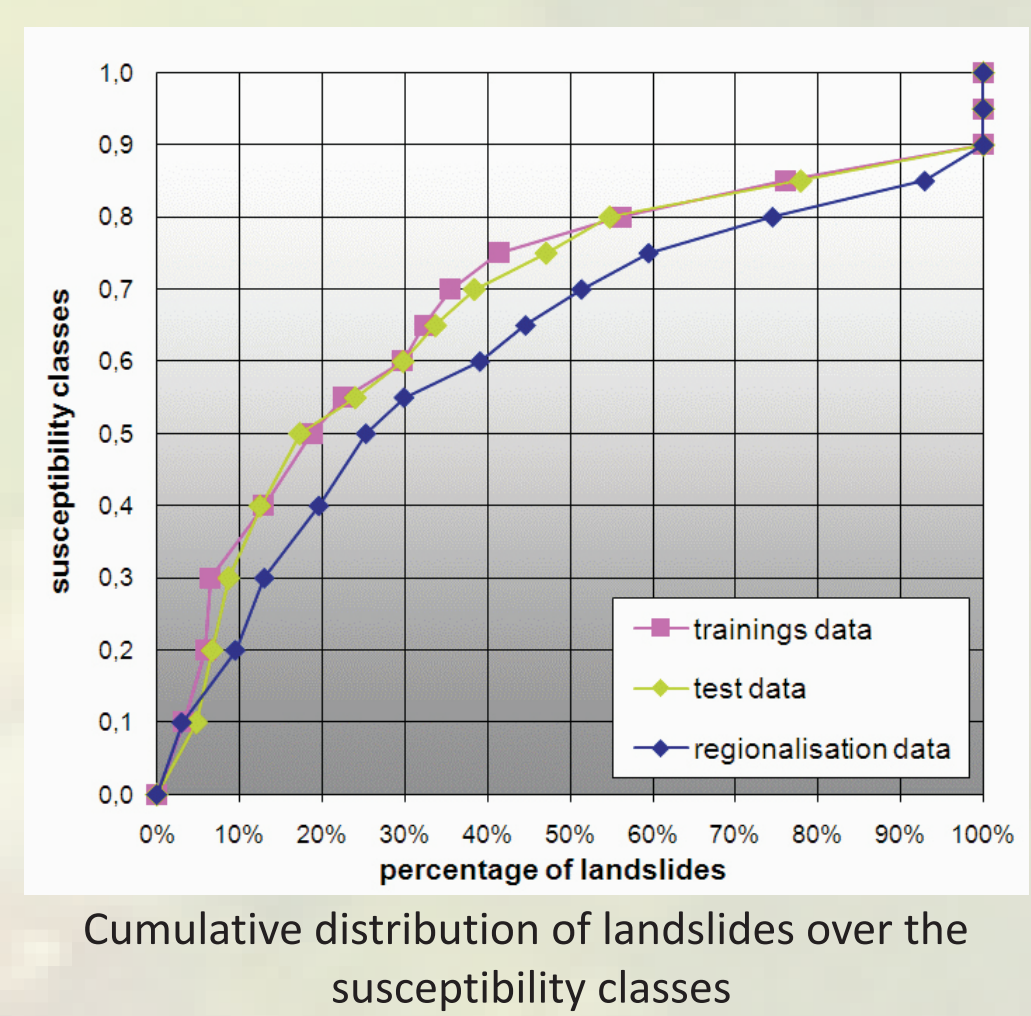
Results and Validation



On the one hand, the “best” result was chosen by the validation of the independent test data; on the other hand, it was also important that only proper variables explaining slope instability were used. The selected “best” result included the variables streets, forest, slope, aspect, profile curvature, curvature classification and flow accumulation. The validation of the test data showed a recognition rate of 82,9 % for the best result. Furthermore, the Spatial Prediction Model Validation after CHUNG & FABBRI (2003) was also performed. Here, the further to the top left the curve is located, the better the result.

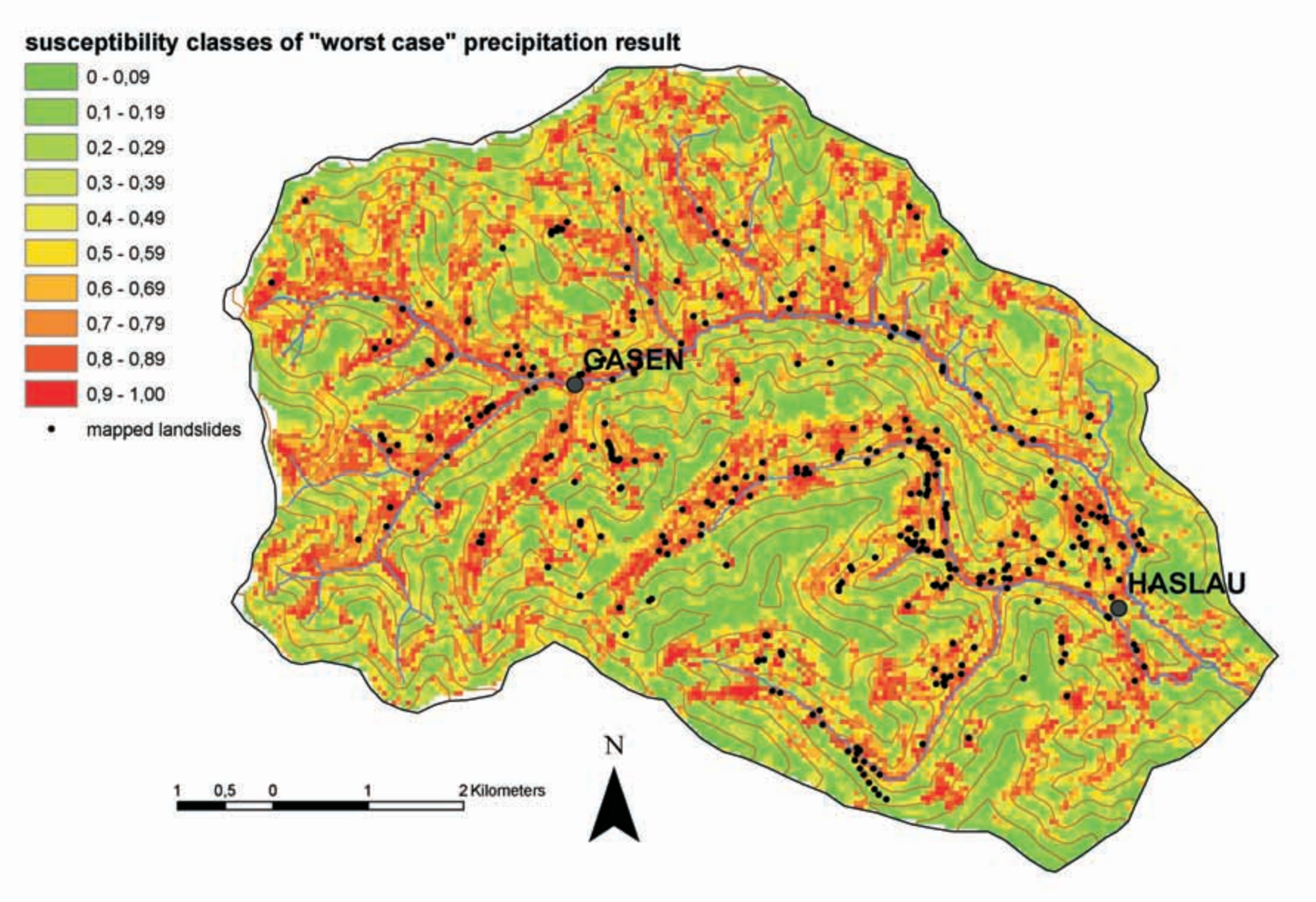


The curve of the independent test data set (= prediction rate curve) and the training data set (= success rate curve) indicate a good performance of the “best” result. Moreover, the curves of the training- and test-dataset are situated close together, so we can assume that the network also has a good capability to generalise. The plot of the regionalisation dataset is located below the two other curves, indicating that the general available land-use map is less suitable for the regionalisation, but still satisfactory. Finally, the cumulative distribution of landslides over the susceptibility classes also revealed the same aspects.



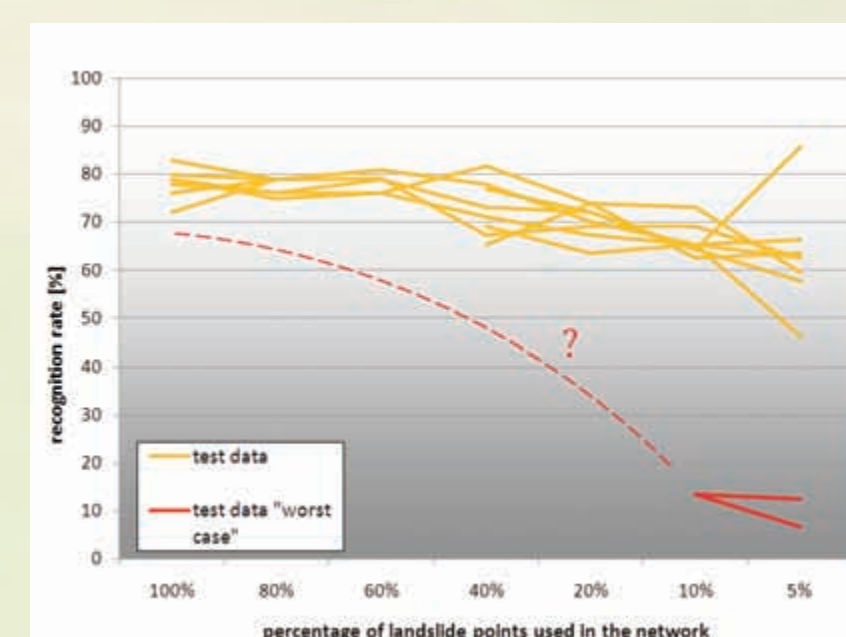
Including Precipitation Data

In order to create a susceptibility map with more general validity (also valid for other, similar precipitation events), the INCA-precipitation data of the August 2005 event were integrated into the model. INCA precipitation data (HAIDEN ET AL. (2007)) are derived from radar data calibrated on station data and are available with a temporal resolution of 15 min and a spatial resolution of 1 km². Hence a “worst case” precipitation map was created by attributing the highest occurring precipitation of the event of August 2005 uniformly to the whole study area (SCHWARZ, L. & TILCH, N. 2008). For this reason, the “worst case” result showed high susceptibility values over a large extent of the study area. Looking at the recognition rate, this result performed better (94,2 %) than the “best” result without precipitation. Looking at the SPM-Validation of CHUNG & FABBRI (2003), both results performed equally. But it has to be pointed out that the precipitation data itself still showed uncertainties.

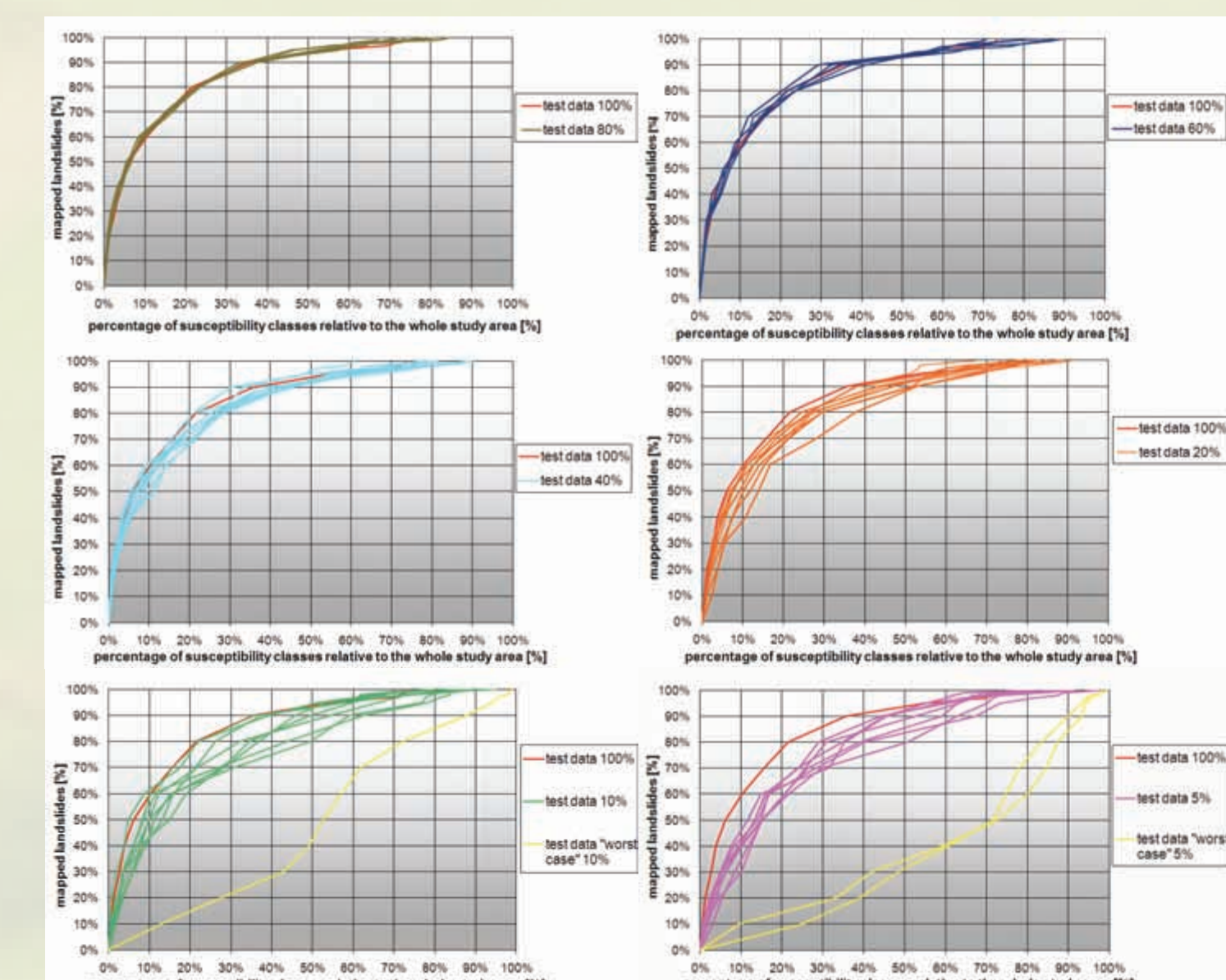


Reduction of Landslide Data

Normally, the number of mapped landslides available for a model setup and the spatial accuracy are much lower than in this study. For this reason, it was investigated how much a reduction in the number of landslides used to create a model affects the results by randomly reducing the number of landslide points from 100% to 80, 60, 40, 20, 10 and 5 % of the total sample. This procedure was repeated several times. For capturing the full possible range, at 10 and 5 % a “worst case” scenario was created by choosing landslide points that are situated in locations which are expected to have a low susceptibility (inside forests etc.). It became apparent that the range in the recognition- and prediction rate curve spreads slowly from the high percentages to the very low percentages (highest range at 5 %). It also turned out that the quality of the results remains nearly the same down to about 30%, while it decreases clearly at 10 and 5% (especially for the “worst case” results). Consequently, 75-150 landslide points of the same data quality as in this study should be sufficient for calculating a susceptibility map with ANN for other similar study areas.



Reduction of landslide data (100 to 5 %): Recognition rate



Reduction of landslide data (100 to 5 %): Prediction rate curves

Conclusions

Employing Artificial Neural Networks produces good results in susceptibility analysis and shows a good capability of generalisation. Limitations occur for the regionalisation of these results over a 50 m grid by using a general available land use map. Precipitation as input data can slightly improve the result and contributes in creating a susceptibility map of more general validity. The analysis of data reduction indicates that by using only about 30 % of the original landslide data, a susceptibility map of nearly the same quality could be generated as when using the total number of samples.

References

- HAIDEN, T., KANN, A., STADLBACHER, K., STEINHEIMER, M., WITTMANN, C. (2007): Integrated Nowcasting through Comprehensive Analysis (INCA) - System overview. ZAMG report
- CHUNG, C.J. & FABBRI, A.G. (2003): Validation of spatial prediction models for landslide hazard mapping, in: Natural Hazards, 30
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