Influence of DEM and Soil Property Uncertainty on an Infinite Slope Stability Model

M. Ulmer[1], P. Molnar[2] and R. Purves[3]

[1]WSL Institute for Snow and Avalanche Research SLF
Flueelastrasse 11
7260 Davos Platz
Switzerland
Telephone: +41 81 417 0243
Fax: +41 81 417 0110
Email: ulmer@slf.ch

[2]Institute of Environmental Engineering, Swiss Federal Institute of Technology Zurich
Wolfgang-Pauli-Str. 15
8093 Zurich
Switzerland
Telephone: +41 44 633 2958
Email: peter.molnar@ifu.baug.ethz.ch

[3]Department of Geography, University of Zurich
Winterthurerstrasse 190
8057 Zurich
Switzerland
Telephone: +41 44 635 6531
Fax: +41 44 635 6848
Email: ross.purves@geo.uzh.ch

1. Introduction

Landslides pose a worldwide threat to humans, infrastructure and agricultural land, with around 1800 people dying in landslides annually (Alexander, 1995). GIS-based slope stability models are widely used to identify areas prone to landsliding, however the predictions of these models, and indeed any models, are susceptible to a range of uncertainties, including that resulting from uncertainty or error in input data and error propagation within models (Heuvelink, 1998). Furthermore, model evaluation typically explores either a single set of parameters, or extremes in individual parameters through sensitivity analysis (e.g. soil parameters (Guzzetti, 2005)), but neglects a holistic characterisation of the nature and form of uncertainty of parameters on model results.

In this paper, we illustrate the importance of digital elevation model (DEM) uncertainty in landslide modelling, and compare it with the uncertainty in other model parameters. We also explore the relation between DEM resolution and prediction performance and methods to evaluate model results using ground truth. The analysis is based on a standard slope stability model using the 'infinite slope approximation', similar to SINMAP (Pack et al., 2005). The model produces a spatially distributed factor of safety (FS) which is the ratio of stabilizing and destabilizing forces on a hillslope. The model is best suited to shallow rainfall-triggered landslides and in our study incorporates two parameters derived from a DEM: slope gradient and the topographic wetness index. Soil properties are represented by four parameters: soil thickness, cohesion, hydraulic conductivity and friction angle. The analysis focuses on a research area in the region of Napf, Switzerland, where a storm in July 2002 led to widespread landsliding (Rickli and Bucher, 2002).

2. Materials and Methods

Modelling was carried out using two DEMs: a LIDAR-derived DEM at a 2 m resolution (DTM-AV produced by Swisstopo) and a DEM of 25m resolution (DHM25 produced by Swisstopo). Soil properties were from a combination of the small-scale Digital Soil Map of Switzerland (BFS, 2000), and more detailed point measurements of soil thickness and friction angle within the study area (Rickli and Bucher, 2002). Finally, high-resolution (20cm) post-event orthophotos were used to locate the initiation zones of 29 landslides which occurred during the July 2002 event and to digitise areas of forest/ non-forest.

Since the aim of the study was to explore the influence of uncertainty in input parameters on slope stability, we first characterised these uncertainties before carrying out Monte Carlo Simulations (MCS) to explore the influence of uncertainty across the study area. DEM uncertainty depended on two surface properties - slope angle through the geometric relation between the LIDAR instrument and the surface, and forest coverage which results in lower densities of raw LIDAR data points under the canopy. Uncertainty in elevation was simulated from normal distributions, with a mean of 0 and the standard deviation dependent on slope angle and forest coverage, with an average of 0.5 m, in accordance with the information given by the DEM producer (Swisstopo, 2005). Furthermore, process convolution (Oksanen and Sarjakoski, 2005) was applied to the uncertainty field added to the DEM to generate spatial autocorrelation in this field. The range of this spatial autocorrelation was difficult to estimate, since no information on this subject is given by the DEM producer, nor could any sensible statement concerning this issue with respect to LIDAR-produced DEMs be found in the literature. The simulation was therefore carried out with two ranges representing optimistic and pessimistic assumptions about DEM quality: 80m and 8m respectively. A larger range implies a more strongly spatially autocorrelated uncertainty field, and thus a smoother variation in the uncertainty in space. Assumptions on variation in soil properties were based on measurements (soil depth and friction angle) and a combination of values from the Digital Soil Map of Switzerland and considerations by the authors of SINMAP (Pack et al., 2005) (hydraulic conductivity and cohesion). Soil depth was assumed to be normally distributed, with a mean of 0.8 m and a standard deviation of 0.27 m. Values for the other three parameters were drawn from a uniform distribution, with rather small ranges to account for the limited information on possible values of these parameters

MCS was then carried out to determine the number of simulations necessary to achieve convergence of the MCS results. In our case we tested for convergence by comparing the results of two MCS after 500 iterations and made sure that, in all cases, the difference between broad spatial patterns and global means in simulations appeared qualitatively small enough not to be relevant for the conclusions drawn.

Having explored uncertainty in input parameters, we carried out modelling runs at a variety of resolutions (2, 4, 8 and 25m), where the 4 and 8m DEMs were bilinearly-interpolated from the 2m LIDAR-derived DEM, and the 25m DEM was the standard Swisstopo DEM. The 2 and 4m results factor of safety values were aggregated to a resolution of 8m by retaining only the lowest (least stable) factor of safety.

For the evaluation the initiation zones of 29 visible landslides on the 20cm orthophoto in the study area were digitized as polygons. The mapped slides were all located outside of the forest and consequently, the evaluation reference surface was also limited to open land. The polygons were used to compare model predictions and slide activity. The model prediction for a given landslide was classified as correct if the maximum factor of safety FS inside the slide boundaries was smaller than a chosen threshold. The reasoning behind this rule was that a slide was not considered as having been predicted if only a part of its release area was identified as unstable. Though from a physical viewpoint, one could argue that a single unstable cell is sufficient to trigger a landslide, using only the lowest value inside the slide would favour noisy model results of little practical use.

Finally, the proportion of predicted landslides was combined with the portion of the area classified as unstable to create the Prediction Rate Curve (PRC) (Chung and Fabbri, 2003). The PRC serves as a means to measure prediction performance independently of FS threshold values.

3. Results

Fig. 1 shows an example of the spatial pattern of variability in the factor of safety, where uncertainty was applied to all parameters (soil and topographic). It is clear that uncertainty is higher in flatter areas and areas where the fluvial relief is less pronounced.

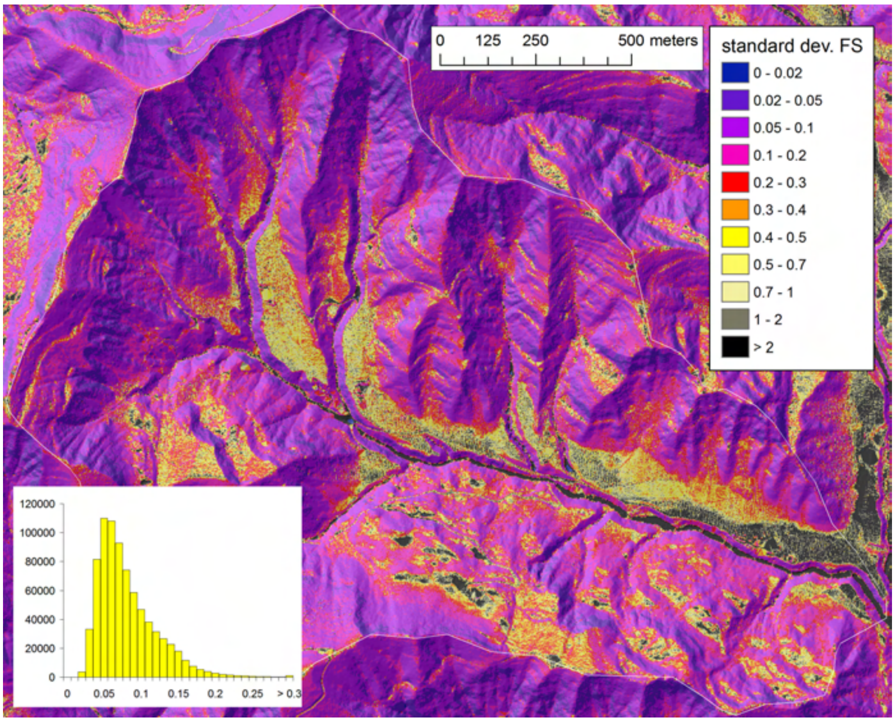

Figure 1. Standard deviation of the factor of safety after 500 Monte Carlo runs. The relevant range of factor of safety values is about 1.5. The histogram shows the distribution of the standard deviations of all cells.

Prediction Rate Curves for 4 resolutions of DEM are shown in Fig. 2. Best performance is achieved when the PRC is furthest removed from the 1:1 line which represents a random model. This means that well-performing models maximise the fraction of cells correctly classified as landslides and at the same time destabilize the smallest area of the basin. The results of the run using the 8m-DEM showed the best performance, while the two finer scale DEMs (2 and 4m) yielded very similar results. The DHM25 did considerably worse, but mainly at the conservative end of the model results. This means that the DHM25 was successful in predicting a certain amount of slides (in this case 70%) while missing a number of events. However to predict all slides correctly at this resolution almost the whole area has to be considered slide-prone. The finer scale DTMs perform better at the conservative (upper) end of the PRC but 40 to 50% of the entire area is still considered unstable before all slides are predicted, in comparison with a total area of 0.2% of the area where slides are actually found.

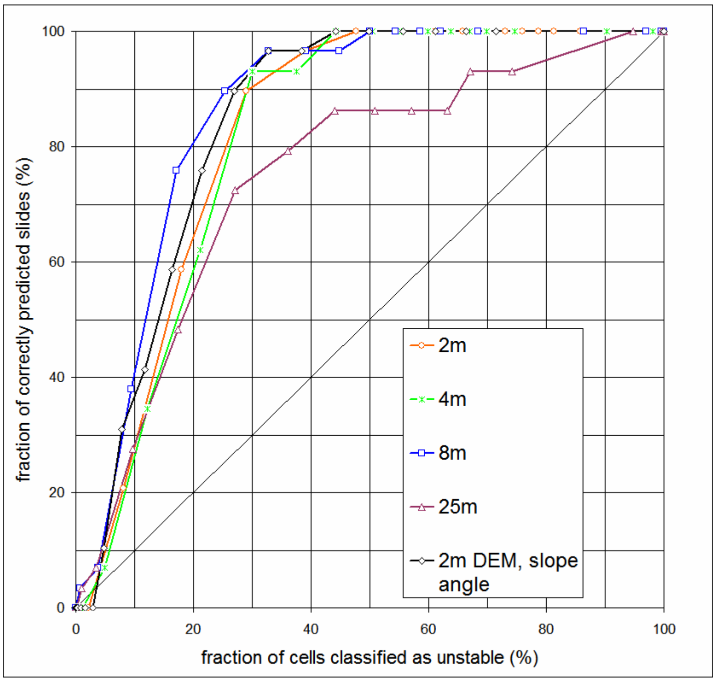

Figure 2. Prediction rate curves of slope stability model results using DEMs with four different resolutions and prediction rate curve of a slope angle map.

The model performance can thus not be seen as very satisfactory. This reflects the remarks of the authors of SINMAP who state that the model's purpose is to produce and map broad stability classes to identify regions where more detailed assessments are warranted (Pack et al., 2005). A further indication that model performance is generally quite poor is the fact that predicting slides simply from the slope inclination map by slopes larger than a threshold yields results that are as good as the slope stability model. The slope map used was derived from the 2m DEM and aggregated to a resolution of 8m using a method equivalent to the slope stability model results. Its results can therefore be compared to those of the slope stability model results also using the 2m DEM. The PRC of the slope map is shown in Fig. 2. We interpret these results to imply that, firstly slope steepness is a primary factor for landslide susceptibility in this area, and secondly, that the wetness of the shallow soils in the study area has a less significant effect on landslide susceptibility, or that the model fails to predict wetness correctly.

4. Implications of Uncertainty for Prediction Performance

The results of the uncertainty analysis and the evaluation were combined to assess the influence of model uncertainty on model performance. The standard deviation of the factor of safety for each cell, as determined by Monte Carlo Simulation, was added as a range to the deterministic factor of safety computed with mean parameters and no

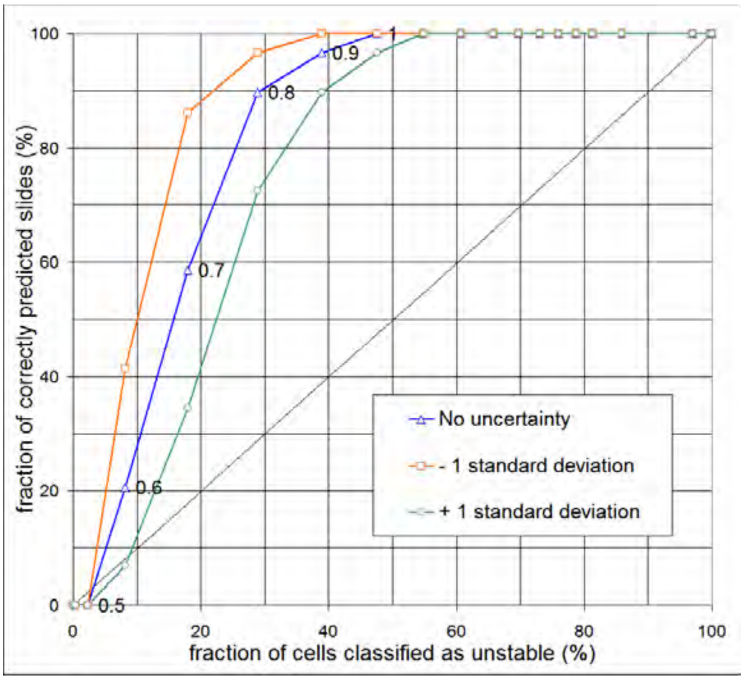

Figure 3. Prediction rate curves of the factor of safety and a range of one standard deviation from the factor of safety. The vertical distance between the curves represents the range of uncertainty. Labels on the graph indicate factor of safety classification thresholds.

uncertainty. The result is shown in the PRC in Fig. 3. The vertical distance between the two PRC incorporating the uncertainty analysis represents the range of uncertainty.

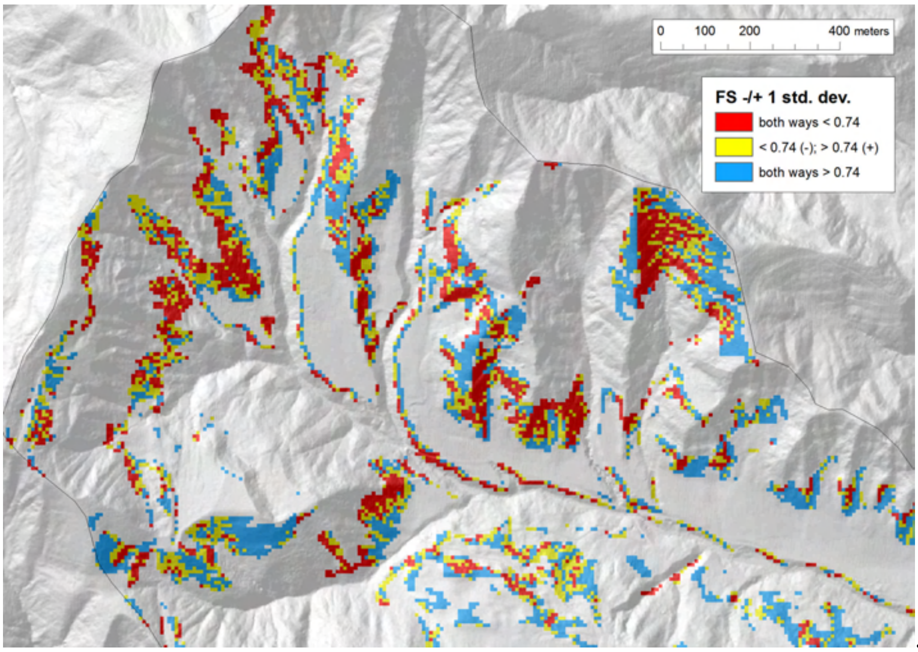

Figure 4: Sensitivity of stability values to uncertainty. Red cells are classified as "unconditionally" unstable (FS < 0.74), blue cells are classified as "unconditionally" stable (FS > 0.74). Yellow cells switch class when one standard deviation is added or subtracted.

To explore sensitivity of slide prediction to uncertainty in soil and DEM parameters, for a given classification threshold (FS = 0.74, at which about 72% of all slides are predicted correctly), cells were grouped in three classes: The first two are those classified as "unconditionally" stable or unstable, respectively, even when a standard deviation is added or subtracted. The third class contains the cells that change from stable to unstable or vice versa when a standard deviation is added or subtracted. These cells represent the areas where the uncertainty affects the prediction performance. They cover 28% of the study areas that is both unforested and steeper than 20° (in other words the areas where slides might occur and where ground truth data were available) (Fig. 4.). This helps to put the MCR results into context, and it demonstrates that model uncertainty affects the results significantly.

An equivalent analysis was made with the instability model based only on slope. The cells switching between unstable and stable when adding uncertainty account in this case for only 9% of the potentially unstable area, as opposed to 28% when using the slope stability model. This suggests that a further advantage of simply using topographic slope as a predictive model in areas where slope dominates landsliding is its increased robustness with respect to uncertainty.

5. Conclusions

Uncertainty of the analysed slope stability model is clearly important, and given the mediocre prediction performance, a simple slope map much less prone to uncertainty might do a better job. Indeed, this study suggests that the main source of uncertainty in this case is not input parameters, but rather the choice of model itself.

In general, when evaluating models of natural hazards, their practical use should be considered, especially as the increasing availability of high resolution DEMs, creates a need to generalise results. In this case high DEM resolution also violates the main assumption behind the slope stability model, i.e. that the slope is "infinite" in that its width is much larger than the soil depth. Another conclusion of this work is that understanding of the spatial structure of soil properties and DEM-error is poor and that to perform uncertainty studies there is a general need for better models of the spatial structure of DEM uncertainty.

References

Alexander DE, 1995: Survey of the field of natural hazards and disaster studies. In: Carrara A and Guzzetti F, (eds), *Geographical information systems in assessing natural hazards,* Kluwer Academic Publisher, Dordrecht, Netherlands, 1-19.

Chung C-JF and Fabbri AG, 2003: Validation of spatial prediction models for landslide hazard mapping. *Natural Hazards,* 30: 835-844.

BFS, 2000: *Digitale Bodeneignungskarte der Schweiz*. Bundesamt für Statistik, Servicestelle Geostat.

Guzzetti F, 2005: *Landslide hazard and risk assessment*. Dissertation, Rheinische Friedrich-Wilhelms-Universität Bonn.

Heuvelink GB, 1998: *Error Propagation in Environmental Modelling with GIS*. Taylor & Francis, London, UK.

Pack RT, Tarboton DG, Goodwin CN and Prasad A, 2005: *SINMAP 2. A Stability Index Approach to Terrain Stability Hazard Mapping, technical description and users guide for version 2.0*. Technical report, Utah State University.

Oksanen J and Sarjakoski T, 2005: Error propagation analysis of DEM-based drainage basin delineation. *International Journal of Remote Sensing*, 26: 3085-3102.

Rickli C and Bucher H, 2002: *Shallow landslides in Napf and Appenzell areas in the 2002 storms*, WSL report for BAFU.

Swisstopo, 2005: *Flyer DTM-AV*. http://www.swisstopo.ch/pub/down/products/digital/height/dtm_av_flyer_de-fr.pdf. Access: 2. 4. 2007.