# Application of a fast and efficient algorithm to assess landslide prone areas in sensitive clays. Toward landslide susceptibility assessment, Sweden

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Abstract

This work deals with testing an algorithm used in landslide susceptibility assessment in areas with sensitive clays. The algorithm is based on a procedure which uses soil data and Digital Elevation Models to detect areas prone to landslides and has been applied in Sweden for several years. The algorithm guarantees a faster execution compared to other implementations and an efficient filtering procedure. The adopted computational solution allows using local information on depth to bedrock and several cross-sectional angle thresholds, and therefore opens up new possibilities to improve landslide susceptibility assessment. The overall purpose of our work is to investigate how to optimally use the algorithm in landslide susceptibility assessment and how to obtain the best results from its use. Specifically, we aim at evaluating the effect of filtering, depth to bedrock and local cross-sectional angle thresholds on model performance. The local thresholds were derived by analysing the relationship between landslide scarps and the Quick Clay Susceptibility Index (QCSI). We tested the algorithm in the Göta River valley and several statistics were used to identify the optimal algorithm parameters. The results gave us important insights on how to implement the filtering procedure, the use of depth to bedrock and the derived cross-sectional angle thresholds in landslide susceptibility assessment.

## 1. Introduction

Landslides in sensitive clays are a recognized natural hazard in Canada, Norway, and Sweden. As they may occur in very gentle terrain that judging from external factors only (e.g. the slope steepness) would be considered safe, they are a threat to human lives as well as for transportation corridors. Since landslides in sensitive clays often do not show signs of deformation and displacement before the actual failure (though signs of creep have on some occasions been documented, Demers et al., 1999), landslide hazard or susceptibility maps are essential tools to minimize their impact. In Sweden sensitive clays are classified as quick clays if the sensitivity (defined as the ratio between the shear strength during undrained conditions and its remoulded shear strength) is at least 50 or higher and the fully remoulded shear strength is below 0.4 kPa (Osterman, 1963; Karlsson and Hansbo, 1989).

In the last two decades a large amount of scientific papers dealing with landslide susceptibility assessment have been published, with great focus on the use of statistically and data-driven methods above others (Guzzetti at al., 2006 and references therein). Despite the wide use of statistical methods for landslide susceptibility assessment only few works dealing with landslides in sensitive clays are found in the literature (Erener et al., 2007; LESSLOSS, 2007, Quinn, 2009). An increased interest in mapping landslide susceptibility at a national level has resulted in the Geological Survey of Sweden initiating a project on the matter. Similar efforts have also been made in Austria, Norway, and Italy (Bell at al., 2013; Høst et al., 2013; Trigila et al., 2013).

In Sweden, the methodology to derive stability maps includes a first step which aims at recognizing the soil and slope conditions influencing landslide occurrence (Berggren et al. 1991; Lundström and Andersson, 2007). A typical slope where landslides in sensitive clays occur is characterized by a relatively steep part close to a river or ravine which is backed by flat terrain. The surface slope angle is therefore not representative of the slope conditions in which landslides in sensitive clays occur. Berggren et al. (1991) suggested instead that areas could be classified as susceptible to landslides in sensitive clays based on the ratio dH/dL (the cross-sectional angle), where dH is the difference in height between the point examined and other point below, and dL is the corresponding horizontal distance (i.e., retrogression distance). The idea is that a given lower limit (threshold) for the cross-sectional angle, a worst-case landslide susceptibility map can be generated. A study on landslides of Bergren et al. (1991) found that they all occurred at steeper slopes than 1:10, thus this was suggested as a threshold value. Whereas the calculation of the cross-sectional angle is simple in one dimension it is not trivial in two dimensions as stable ground can act as a physical obstacle influencing the computation.

In this contribution, we test an algorithm, which is able to quickly and efficiently detect soil and slope conditions (Tryggvason et al., 2015), on real data. The algorithm uses a local visibility operator to calculate the cross-sectional angle, i.e. it checks the elevation of the surrounding cells and lowers them to a value given by the cross-sectional threshold. This procedure is repeated until no further change in elevation is observed. This computational solution allows fast processing times and the use of additional local information on soil depth and cross-sectional angle thresholds. Moreover, the algorithm is endowed with a filtering procedure (not described in the reference), capable to remove areas not prone to landslides. Working with real data, especially high-resolution data, there will be numerous areas that violate the cross-sectional threshold due to noise and/or other real or non-real topographical effects, some of which may only be a few pixels in size. Other unwanted areas identified by the algorithm could be trenches and ditches. Such artefacts most likely do not constitute any real landslide hazard and should be removed in a quick and efficient (preferably automated) procedure (Lindberg et al., 2011). We choose the Göta River valley as a test site. The overall aim of our work is to evaluate the performance of the algorithm on real data, and thereby its usefulness as the main modeling tool to assess landslide susceptibility at national level. We evaluated the results obtained including a depth to bedrock map as input data. We also compared different cross-sectional thresholds with different morphological parameters of landslide scarps to evaluate the rational behind the threshold value of 1:10 suggested by Berggren et al. (1991), that appears to be used as standard in Sweden.

Specifically, we aim at:

1) Analysing the impact of the filtering procedure on the performance of the maps.

2) Comparing the results obtained using information on the depth to bedrock with the results obtained without it.

3) Examining if different morphological parameters are related to the presence of sensitive clays and may support a particular cross-sectional angle threshold.

4) Giving advices on how to use the algorithm and what data to use in the national program for landslide susceptibility assessment.

## 2. Study area and data description

The Göta River valley is located in the Southwestern part of Sweden, connecting Lake Vänern in the north with the Kattegat Sea at the city of Gothenburg in south. Compared to other areas in Sweden, the Göta River valley has a high frequency of landslides (Hågeryd et al., 2007) caused by the presence of quick clays.

In Southwest Sweden the last deglaciation started approximately 14500 years BP and lasted for at least 5000 years producing a series of ice-marginal positions (Lundqvist and Wohlfarth, 2001). During this period deposition of glaciomarine sediments occurred in areas below sea level. Holocene transgression has been documented at about 10000 BP (Svedhage, 1985) and between 9000 BP and 7000 BP (Påsse, 1983). The clay sequences deposited during the last deglaciation are typically found above either bedrock or relatively thin diamicton and sand. The clays can be laminated and interbedded with fine-sand layers in their lowermost portions and the clay-bedrock or clay-sediment contact is abrupt (Stevens, 1990).

In the Göta River valley the deposition of clay sediments began 12000 year BP in salt water when the relative sea level was 125 m above present level. Glaciomarine sediments present different silt content and laminae in the sediment sequences which represent several depositional environments (Stevens, 1990). Coarse material lenses are also common in the sediment sequences due to periods of ice re-advancement, marine transgression and fluvial transportation.

During land uplift, the clay sediments deposited in salt water underwent leaching by fresh water. Leaching is one the factor influencing quick clay formation (Torrance, 1983; Andersson-Sköld et al., 2005; Torrance, 2014) and it has been recognized as a very important factor in quick clay formation in the Göta River valley (Rankka et al., 2004). Quick clays are common in the whole valley and they reach a higher spatial frequency North of Lilla Edet (AA.VV., 2012), where the majority of landslides are localized. The narrow Northern part of the valley is predominantly covered by glacial fine clay while the central part by post glacial silt and glacial/post glacial clay (Fig. 1). In the Southern part of the valley glacial clay sediments are confined to the valley sides in the proximity of the bedrock outcrops whereas postglacial clay sediments cover the main part of the valley floor.

## 3. Methodology

This section describes the methodology used to evaluate the potential usefulness of the algorithm in landslide susceptibility assessment. After presenting the algorithm and the data we describe how we by using the Quick Clay Susceptibility Index (QCSI) as a proxy for clay sensitivity determined QCSI-dependent cross-sectional angle thresholds. We also describe how model performance is influenced by depth to bedrock data, QCSI-dependent cross-sectional angle thresholds, and different filtering parameters.

### 3.1 Description of the algorithm and of the post-processing filters

The first computer implementation adopted in Sweden to produce landslide susceptibility maps by identifying areas above a specified cross-sectional angle used the visibility operator of ArcGIS (ESRI, Redlands, CA). The visibility operator is able to detect areas above a given altitude angle (our cross-sectional angle threshold). Our algorithm is instead based on a locally limited operator that is applied iteratively.  Rather than searching for surrounding points above a given altitude angle, the operator checks if the central point raises above the given cross-sectional angle to any of the surrounding points (the eight closest points are examined). If the cell is above and is within potentially unstable material, it is lowered to the critical elevation. The procedure is iterated until a global solution (i.e., stable solution) is reached. This local solution allows using several cross-sectional angle thresholds (hypothetically, one for each soil type) and (sparse) information on depth to bedrock, something that is not as straight forward to implement in the classical visibility approach. The bedrock topography may act as a barrier, blocking line of sight, and thus reducing the area affected by a possible landslide. Specifically, the steps executed in the algorithm are the following: the algorithm checks if a cell is within soils that can be affected by landslides; if it is, the algorithm checks if the cross-sectional angle calculated between the cell and its surrounding cells is steeper than the cross-sectional angle threshold; if it is, the elevation of the cell is lowered until the cross-sectional angle calculated between the cell and its surrounding cells equals the cross-sectional angle threshold. If the bedrock surface is reached, the elevation is lowered no further. A global solution is reached when no further change in elevation occurs (Tryggvason et al., 2015).

The raw output of the algorithm, especially when a high resolution DEM is used, shows areas marked as prone to landslides which clearly should not be marked as such – either because they are too small or because they are human artefacts (e.g., ditches). A filtering procedure was therefore introduced in order to automatically remove these areas. The filter is based either on a size criterion or an elevation difference criterion. Specifically, areas are removed if they are smaller than a defined areal threshold or the difference between the highest and the lowest point is below a defined elevation threshold. To avoid that a patchwork of smaller areas that would normally be filtered out are wrongly perceived as a single large potential area due to a network of connecting corridors (e.g. ditches or artifacts in the data), a pre-filter is applied that removes all “thin” areas. The width of the corridors is defined by the pre-filter parameter is referred to as “neck size”. Typically a neck width of a few samples (1-7) successfully divides these areas into smaller areas and makes them susceptible to subsequent filtering. Once the algorithm results are pre-filtered the two other filtering criteria can be successfully applied.

### 3.2 Data description

We used the following map data in our analysis: DEM, soil deposits, depth to bedrock, Quick Clay Susceptibility Index (QCSI), landslide scarps and probability of landslides. The DEM, soil deposit and depth to bedrock maps were used as the input raster data for the algorithm; the QCSI and landslide scarp maps were used to derive QCSI-dependent cross-sectional angle thresholds; the landslide scarp and the probability of landslide maps were used to assess the performance of the model.

The Quick Clay Susceptibility Index (QCSI) represents the probability to find quick clay in a specific area (Persson et al. 2014). In the work of Persson et al. (2014), the QCSI was assessed by a multi-criteria evaluation. Several factors influencing quick clay formation were taken into account: stratigraphy, potential for ground water flux, relative infiltration capacity, and geomorphological conditions for high groundwater flux. The resolution of the QCSI map is 50 m.

We used the NNH (Swedish acronym for “New National Elevation model”) data (Lysell, 2013) as DEM. The NNH data are produced from a point cloud of elevation points acquired by airborne laser scanners. The NNH data are at 2 m resolution.

The soil information was extracted from the soil layer database of the Swedish Geological Survey (SGU), which contains data on soil genesis and grain size. The map is at 1:50 000 scale and it is provided in vector format.

The depth to bedrock map is a product of SGU (Daniels and Thunholm, 2014) which is generated by analysing and interpolating soil depth data from three different SGU’s databases: (1) soil depth data indicating the distance between the topographical surface and the bedrock, (2) soil depth data indicating the distance between the topographical surface and a point above the bedrock, and (3) soil depth data indicating an approximately null soil depth. Data type one comes from boreholes and wells that reached the bedrock surface. Data type two comes from boreholes and wells that did not reach the bedrock surface. Both of these two types of data were extracted from the borehole and well databases. Data type three was extracted from several other databases that contain points indicating no soil or very thin soil (e.g., bedrock outcrop, ice striation). The final depth to bedrock map was generated by interpolating to a 50m uniform grid using the inverse weight distance method (Daniels and Thunholm, 2014). Where there is no information, the depth is assumed large, thus it will not influence the results in our modeling.

The landslide scarp map is a product of SGU and it is derived by image interpretation of the NNH data on screen (SGU, 2014). It was converted from a vector map to a raster matching the resolution of the susceptibility map.

The landslide probability map is a product of the Swedish Geotechnical Institute (AA.VV., 2012). The map was produced by calculating the factor of safety along several sections and through a stochastic analysis of the stability calculation's governing variables (Berggren et al., 2011). The landslide probability map shows the probability of landslide divided into 5 classes: negligible probability, low probability, some probability, pronounced probability, and obvious probability (AA.VV., 2012). As the time-dependent factors (e.g., changes in ground water level and pore pressure) only slightly influenced the computation of the landslide probability in Göta Älv, the landslide probability map can be used to assess the performance of our algorithm.

## 3.3 Cross-sectional angle thresholds

The retrogression distance of landslides in sensitive clays, and therefore the cross-sectional angle, has been suggested to be related to the geotechnical parameters of the clays (Mitchell and Markell, 1973) and the retrogression distance has also been found to be correlated with the clay sensitivity (AA.VV., 2012). Since collecting detailed geotechnical data to assess landslide susceptibility is prohibitively expensive at regional scale, we tested an alternative method to derive relationships between cross-sectional angles and geotechnical parameters. Since it has been shown that the QCSI values calculated in Southwest Sweden are correlated with the sensitivity of the clay (Persson at al., 2014), we used the QCSI as proxy for the clay sensitivity. The cross-sectional angles were calculated from the landslide scarp map. First, cross-sectional profiles, representing geometrical conditions before a landslide occurred, were extracted from a sub-sample of the landslide scarps; then the values of the cross-sectional values were calculated. Finally, the relationship between the values of the cross-sectional angles, extracted from the profiles, and the maximum values of QCSI, extracted from the areas enclosed in the landslide scarps, was analysed.

## 3.4 Model evaluation

One way to evaluate the performance of a landslide susceptibility map is to compare it to e.g. a landslide inventory map (i.e., observed data) – if it exists. Two statistical measurements may be used, namely sensitivity and specificity. The sensitivity is the ratio between the correctly classified positive samples (i.e., true positive) and the total positive samples (i.e., landslides), whereas the specificity is the ratio between the correctly classified negative samples (i.e., true negative) and the total negative samples (i.e., stable areas). See Table 1 for details on the computations. While landslides represent observed positive cases the definition of observed negative cases is not as trivial. In the case of frequent and small mass movement events a reasonable estimation of the observed negative cases can be done by randomly extracting samples of areas where landslides have never occurred. In the case of infrequent and relatively big events this approach is not feasible, because of the high likelihood to extract areas not yet identified as unstable. In order to overcome this problem and to obtain reasonable estimations of model performance, we used two maps to validate the models: the landslide scarp map and the probability of landslide map. Several statistical measurements and validation methods were computed to assess model performance.

The degree of agreement between the model results and the observed landslide scarps was evaluated using threshold-based sensitivity curves and prediction rate curves. Threshold-based sensitivity curves show the model's ability to correctly classify landslides if each individual landslide is considered as one sample. This assumption means the sensitivity is dependent on whether a single scarp is considered correctly classified (e.g., when 50% of the landslide scarp is correctly classified, where 50% is a sensitivity threshold). The threshold based sensitivity curves show the sensitivity (i.e. percentage of correctly classified landslide scarps) versus the sensitivity threshold (i.e. percentage of pixels correctly classified in each single scarp). The higher the sensitivity at each sensitivity threshold, the higher the model performance. Prediction rate curves show the sensitivity against the percentage of area classified as prone to landslides. Because the analysis is performed on raster data the sensitivity of the prediction rate curve is computed as the ratio between the number of pixels correctly classified and the total number of pixels with observed landslides. Each single pixel is therefore considered as one sample regardless which landslide it belongs to. The aim of the prediction rate curves, as introduced by Chung and Fabbri (2003), is to assess the performance of the entire susceptibility map. The assumption behind the prediction rate curves is that the higher the number of correctly classified landslides and the lower the area classified as susceptible to landslides, the better the performance. The susceptibility is often represented by a continuous range (e.g., [0, 1]). The prediction rate curves are computed by first sorting the susceptibility level in descending order and then dividing the new rank by the total number of pixels of the study area. The obtained values range from 0 to 1 and represent the portion of the study area classified as susceptible. Those values are finally put in bins with intervals of equal size and the percentage of landslides is computed in each bin. Since our algorithm has a dichotomous output (i.e., not prone, prone to landslides), it is not possible to calculate the prediction rate curve for each single map, therefore we used the concept of the prediction rate curve to evaluate the performance of a set of maps (e.g., filtered maps). We computed the prediction rate curves by plotting the sensitivity data and total area classified as unstable data from several maps in one graph. This means that one single point of the prediction rate curve represents the performance of one map.

The second type of validation was executed by comparing the model results with the probability of landslide map. The original five classes of the probability of landslide map were condensed into two classes: stable (negligible probability and low probability classes) and unstable (some probability, pronounced probability, and obvious probability). The Gilbert skill score (Gilbert, 1884 and Schaefer, 1990) and the Heidke skill score (Heidke, 1926) were computed for each map. The Gilbert skill score measures correctly classified positive samples after removing true positives due to random chance (implying that a compensation is made for the number of used samples and the number of not correctly classified samples, see Table 1). The Heidke skill score measure correctly predicted samples (both positive and negative) after removing samples which are correctly classified due to random chance (see Table 1 for the details).

## 4. Analysis and Results

After introducing how the QCSI-dependent cross-sectional angle thresholds were derived and how the data were treated, we present the results of the model, with special focus on the influence of the depth to bedrock, the filter procedure, and the cross-sectional angle thresholds on the model performance.

### 4.1 Relationship between cross-sectional angle and QCSI

In order to perform the analysis the QCSI map was converted from a 50 m pixel resolution to a 2 m pixel resolution and the landslide scarp map was converted from a vector to a raster with a 2 m pixel size. Our idea was to automatically extract cross section angle values (dH/dl) for each landslide scarp and to analyse the relationship between these and the QCSI values. The dH value represents the height of the slope before the landslide event and dL value represents the maximum retrogression distance. As it was not possible to automatically extract the dH values from all the landslides, a subset of 71 scarps was manually selected from the database. Also, as a value for dH before the landslide is not available, we have to assume that the landslide has not completely altered the topography, and an estimate was done to the side of the landslide were the slope appeared representative. For each of the scarps in the subset a point A on the scarp at the maximum distance (i.e., the maximum retrogression distance) from the scarp outlet was automatically selected by point-to-point comparison. The difference in elevation, dH, was calculated between the point A and the base of the previously identified slope. For each scarp the maximum value of QCSI was extracted from the area enclosed in the scarp. The reason for the maximum was chosen, and not some sort of mean, is simply the assumption that the point (or area) with highest QCSI (the weakest material) likely represent the starting point of the landslide – or at least the area influencing the development of the landslide. The relationship between the maximum QCSI value and the cross sectional angle in Fig. 2 was then analysed. Even if a clear mathematical relationship between the cross-sectional angle and the QCSI cannot be extracted from Fig. 2, we could still identify an upper limit of the cross sectional angle dependent on the QCSI. A similar relationship was found by comparing the cross-sectional angle values with the sensitivity of the clays (AA.VV., 2012), demonstrating that our approach is reasonable.

### 4.2 Input filter data and parameters

The DEM was used without further processing, whereas the depth to bedrock map was resampled to 2 m pixel size. The soil map was manipulated to obtain two raster maps: a best case soil class map and the

QCSI-dependent soil map. The best case soil class map was derived by grouping the soil deposits according to the likelihood they contain sensitive clays. The selection of the best case classes was done following a classification scheme used at the SGU. Deposits with high probability to contain sensitive clays, such as clay and silt deposits of glacial or post-glacial origin, are assigned to the best case scenario soil class. Please refer to Table 2 for more details on the subdivision. The resulting map was converted to a raster with 2 m pixel size. The QCSI-dependent class map was obtained by subdividing the best case scenario soil class into 13 subclasses (Table 3) according to the relationship between the cross-sectional angle and the QCSI shown in Fig. 2. For example, Class 1 was assigned to pixels with QCSI lower than 0.195, Class 2 to pixels with QCSI between 0.195 and 0.2, and so on.

In order to identify the optimal filter parameters we selected a test area from the study area and executed multiple runs of the pre-filter, which adjusted the neck size threshold, and two additional filters that adjusted the minimal area considered and the elevation difference criteria. The runs were done using the best case soil class, each of which were executed using no information on the depth to bedrock, while setting the cross-sectional angle thresholds equal to 1:10 (Bergren et al., 1991). Because the neck size is a parameter of the pre-filter aimed at separating different land slide areas, adjustments in the neck size were never tested alone but in combination with one of the other two filters.

The Gilbert skill score, the Heidke skill score, and the two measurements of the prediction rate curves (i.e., sensitivity and total area prone to landslides) were calculated after the filter processing. The Heidke skill score shows that the model performance continuously increases if the neck size increases, whereas it reaches the maximum when the elevation difference threshold is equal to 5 m. (Fig. 3 – a, b). The minimal area threshold does not have any influence on the performance (Fig. 3 - b). The Gilbert skill score (not shown) gave almost identical results as the Heidke skill score. The combination of two prediction rate curve scores (Fig. 4) also shows that the higher the elevation threshold the higher the performance as the sensitivity remains stable while the percentage of area prone to landslide decreases. After taking the results in Figure 3 and Figure 4 into consideration we decided to continue the analysis using two applications of the pre-filter with the neck size equal to five pixels and setting the elevation difference filter parameter equal to 5 m. Small areas were filtered out by setting the minimal area threshold equal to six pixels (i.e., 24 m2). Figure 5 shows the effect of the filtering procedure, which was executed using the optimized parameters, in a subarea of the study area.

### 4.3 Influence of depth to bedrock, filter, and cross-sectional angle thresholds on model performance

We verified how the depth to bedrock, the filter procedure, and the QCSI-dependent cross-sectional angle thresholds influence the model performance by executing multiple runs of the algorithm by either including or neglecting to include each in all possible combinations and then assessing model performance. These runs were executed only on the areas reclassified into the best case scenario soil class. The first part of the analysis aimed at studying the effect of the depth to bedrock and of the filter procedure and was executed using the same cross-sectional angle threshold for the whole best case scenario class. Several cross-sectional angle thresholds were used in several algorithm runs in order to assess the effect of depth to bedrock and filtering on a wide range of algorithm outputs. The second part of the analysis was executed in order to assess how the QCSI-dependent cross-sectional angle thresholds influence model performance. The cross-sectional angle threshold was decreased according to the QCSI for each algorithm run (i.e. from 1:1 to 1:22, see table 3). We used the 13 cross-sectional angle thresholds shown in Table 3 for both the first and second part of the analysis, but each respective analysis technique used the threshold values differently. During the first part of the analysis each cross-sectional angle threshold was used for the whole best case scenario soil class. In the second part of the analysis, the best case scenario soil class was subdivided in to 13 soil subclasses (SC) with a corresponding QCSI range and cross-sectional angle threshold (dH/dL). The array of values is presented in Table 3. For ease of explanation, we will denote each row of the array with an index i (where i assumes discrete values from 2 to 13). The algorithm is run for each SC(i). In the first part of the analysis we used each dH/dL(i) for the entire best case scenario soil class, whereas during second part of the analysis (i.e. QCSI-dependent procedure) dH/dL(i) is used for SC from SC(i) to SC(13) and dH/dL(i-1) for SC from SC(2) to SC(i-1). For example, in the first part of the analysis the threshold 1:8 was applied for the entire best case scenario soil class, whereas in the second part of the analysis the threshold 1:8 was applied from subclass 5 to 13 and the threshold 1:5 from subclass 2 to 4.

First, we show the results representing the effect of the depth to bedrock and of the filter procedure. We calculated threshold-based sensitivity curves for each cross-sectional angle threshold in Table 3, but we show only the results for the ratio dH/dL equal to 1:8 and 1:22 (Fig. 6). The curve calculated for the ratio 1:8 shows that the performance of the model deteriorated when the filter was applied (Fig. 6-a), since the curve of the filtered maps lays below the curve of the not filtered maps. This was especially evident for thresholds between 40% and 80%. This result is expected as the curves show only the correctly classified landslides provides no information if the classification of the stable areas has been consequently improved or not. However, the difference between filtered and not filtered maps was annulled when the cross-sectional angle is decreased to 1:22 as shown in Figure 6-b. When taking the total area prone to landslides into consideration, as shown in the prediction rate curves of Figure 7, the curve for the filtered set of maps indicates that the performance is better when the filtering is used. For cross-sectional angle thresholds between 1:8 and 1:13 the filtered maps outperform the maps that have not been filtered. The values of sensitivity are approximately the same, whereas the total area classified as prone to landslides is significantly lower for the filtered maps. The use of the bedrock information does not significantly increase the performance of the filtered maps. The Gilbert skill score and the Heidke skill score (Fig. 8) show higher values (i.e., better model performance) for filtered outputs than for not filtered outputs. The difference in performance between the not filtered and the filtered maps is clear for low values of the cross-sectional angle thresholds, whereas at high values of the cross-sectional angle thresholds the performances are very similar. Similar conclusions can be drawn when comparing the maps obtained by using or neglecting the bedrock information. While the use of depth to bedrock information increases the value of the statistical measurements its inclusion provides a relatively small improvement to model performance when compared to the effects of using the filtering. Worth of note is that improvement in model performance is only evident at low values of the cross sectional angle thresholds for all cases considered. In general, all four sets of maps (i.e., no bedrock/no filter, no bedrock/filter, bedrock/no filter, bedrock/filter) show similar trends in the Gilbert skill score and the Heidke skill score when the cross-sectional angle threshold is decreased: the scores reach their maximum at ratio 1:10 and 1:13 respectively and remain stable even if the thresholds are further decreased. From this we conclude that the inclusion of the filtering procedure has a more significant effect on improving model performance compared to the addition of the depth to bedrock information.

In the second part of the analysis, we looked at the effect of the QCSI-dependent cross-sectional angle thresholds on model performance. The analysis was done only on the maps which used information on the depth to bedrock and underwent filtering. By looking at the thresholds-based sensitivity curves (Fig. 9), we notice that the models obtained with the QCSI-dependent cross-sectional angle thresholds perform worse than models obtained without the QCSI-dependent cross-sectional angle thresholds (i.e. one cross-sectional angle threshold for the entire best case scenario soil class was used). It was found that differences in model performance decreased if the cross-sectional angle thresholds increased as also shown in the earlier analyses (Fig. 6). When the performance was calculated on the entire map, as in the case of the prediction rate curves, inserting the cross-sectional angle thresholds neither negatively nor positively influenced the model performance. The Gilbert and Heidke skill scores (Fig. 10) show higher values for the maps obtained without QCSI-dependent cross-sectional angle thresholds if the cross-sectional angle threshold is between 1:8 and 1:15.

# 5 Discussion and Conclusions

By using several methods to validate the performance of the model and by running the algorithm with several settings we gained some insight into the usefulness of the algorithm and of the proposed modelling approach. In general, the results of the validation show that the model has very good performance in spite of the relative simple method (i.e. the method only needs two main data sources: a digital elevation model and a map of soil deposits). The filtering procedure, wherein areas deemed not prone to landslides are removed, is a very important step for increasing overall model performance. However, the effect on model performance is not clear for high cross-sectional angles (1:1 through 1:5) which we believe is due to a high frequency of discontinuous areas classified as prone to landslides. Also, it should be noted that since the filter parameters were optimized with a cross-sectional angle threshold of 1:10, they may not be optimal in case of a high frequency of discontinuous areas resulting when the algorithm is run with high cross-sectional angle thresholds. With all of this in mind, the only drawback of the filtering procedure is that it will slightly decrease the detection of the positive sample.

The results show that inserting the inclusion of the depth to bedrock data does not significantly decrease the falsely detected unstable areas and that the increased model performance is not as significant as the increase of model performance obtained after filtering. We believe that there are two reasons for this: 1) the output of the models is very sensitive to changes in the cross-sectional angle thresholds meaning the performance improvements gained from including the depth to bedrock data are hidden until very low angles are considered; 2) the resolution of the depth to bedrock map is 50 m pixel size meaning that it gives only a rough idea of the bedrock surface. We believe that if the analysis were performed with a depth to bedrock map at the same resolution as the DEM the effect of the bedrock data would be more evident, which may be the case if drilling or detailed geophysical investigations are done in an area of particular interest.

Surprisingly, the use of the QCSI-dependent cross-sectional angle thresholds did not improve model performance. Since we found a relationship between the QCSI and the cross sectional angle we expected to obtain better performance by using the QCSI-dependent cross-sectional angle thresholds, especially when the validation was done by comparing the results of the algorithm with the landslide scarp maps. We propose two possible explanations for this: 1) the resolution of the QCSI map allows to establish a relationship between the QCSI values and the cross-sectional angles extracted from the landslide scarps, but it is not high enough to provide optimal results on the resolution used in the performed analysis; 2) the advantage of removing false positive detection via the QCSI-dependent cross-sectional angle thresholds may be more evident in areas with low frequency of landslides.

The results show that the optimal cross-sectional angle thresholds are between 1:8/1:10 and 1:13/1:15, with the maximum performance reached at 1:13 in most of the cases. This suggests that 1:13 should be used as cross-sectional angle threshold in the overview mapping of area prone to landslides.

In order to proceed with the assessment of landslide susceptibility at national level, we recommend:

1) Use our algorithm to perform the analysis as it guarantees a relatively fast execution time, allows inserting local information (e.g., depth to bedrock), and uses an efficient filtering procedure.

2) Use the filtering procedure to automatically remove false detected areas prone to landslides and use statistical measurements to optimize the filtering parameters.

3) Perform the analysis using the currently available depth to bedrock map as it can slightly improve the performance of the maps. However, a map of the depth to bedrock with a higher resolution (< 50 m pixel size) is desirable.

4) Examine the use of the QCSI-dependent cross sectional angle thresholds to a greater extent. Future work could look at other ways to insert the QCSI-dependent cross-sectional angle threshold and evaluate the effect of these thresholds in areas with a lower frequency of landslides.

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