Scientific Report

Summary of the research activities of the project PN-III-P4-ID-PCE-2016-0222 within the interval January-December 2018

Note: This report only includes results presented at conferences or submitted for publication. Work in progress is not included.

The following activities were planned for 2018:

Activity 2.1. Field trips

Activity 2.2. Evaluation of the algorithm transferability. Part I

Activity 2.3. Automation of methodology. Part I

Activity 2.4. Development of a semi-automated method for mapping landslides from Digital Elevation Models. Part I

Activity 2.5. Dissemination of the results

Activity 2.6. Project management

Study areas and data

Research is carried out in two distant study areas that are different in geology and land cover and thus they produce landslides with different morphogenetic typology. By using two study areas, we decrease the possibility that our results are site specific and thus increasing the confidence in generalization of our conclusion.

The first study area is located in the Shizuoka Prefecture, in the SE of Honshu Island, Japan (Fig.1) and covers an area of about 125 km2. The scarps in this area are mostly covered by forest. The lithology is dominated by a melange matrix of Late Eocene to Early Miocene accretionary complex with chaotic facies with intrusions of limestone and marble blocks of the same accretionary complex. On the river valley, in the east of the study area, Late Pleistocene to Holocene fan deposits can be found. The existing data consists of a DEM based on the airborne LiDAR (Light Detection and Ranging) at a 5 m spatial resolution, and an inventory of 371 landslide scarps.

The second study area is situated in the Buzău County (Fig.1), Romania, and covers about 800 km2 at the contact between the Romanian Curvature Carpathian Mountains and the Subcarpathian Hills, which are part of the Vrancea seismic region. Cretaceous and Palaeogene flysch (alternations of thick cohesive sandstone with schistose intercalations of marls, clays or bitumen) is specific to the mountainous section, while hills and depressions are built on less cohesive Neogene molasses deposits (a heterogeneous mixture of clays, marls, salt breccias, loose conglomerates, sands and loess-like deposits). Large, dormant (partially relict) landslides prevail in the mountainous flysch sector, while hilly molasse area features very frequent but small landslides. The existing data consist of an optically derived DEM with a spatial resolution of 4 m and an inventory of 663 landslide scarps.

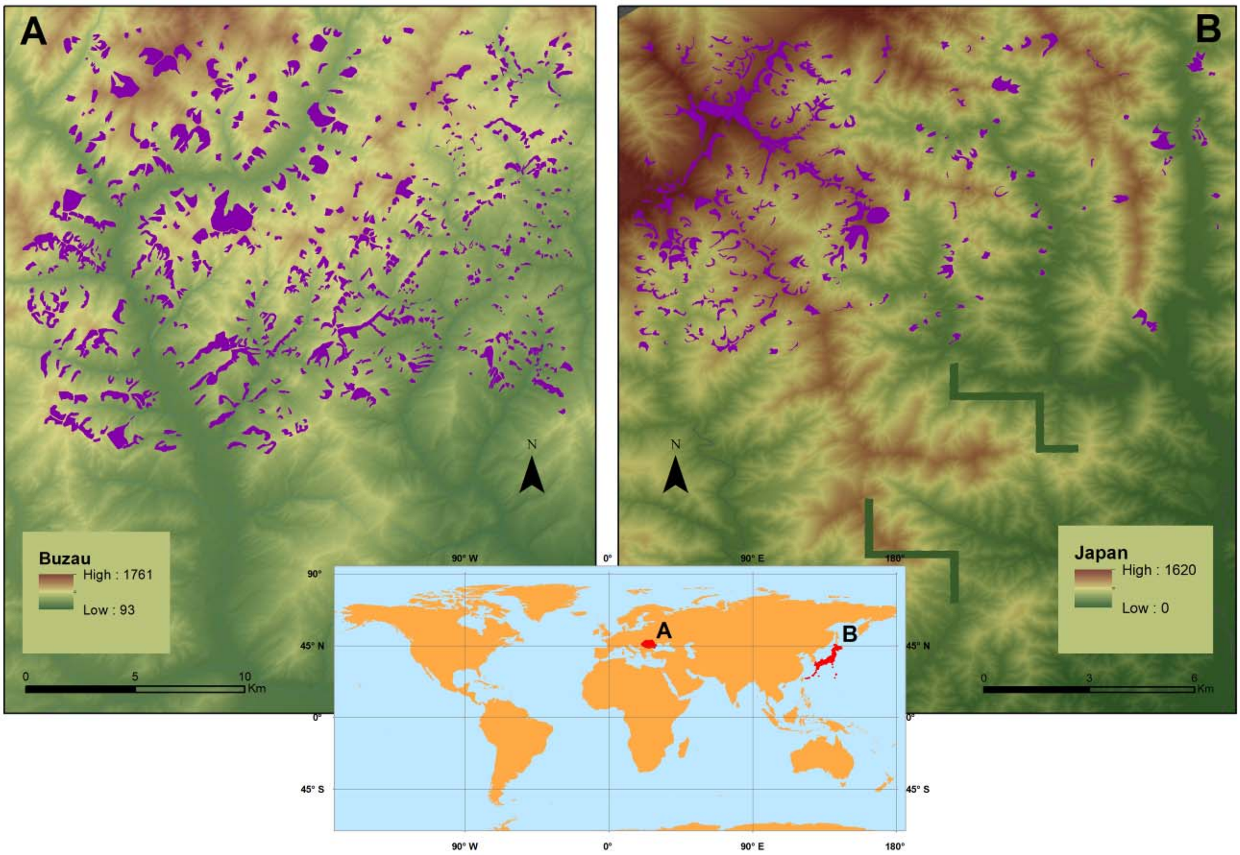

Fig. 1 Landslide scarps inventories and their location

The landslide scarps from the two study areas show significant differences in size (Fig. 2). The average area of the landslide scarp in the Buzau County study site is 8.64 ha and the median size is 4.28 ha, while the mean size of the landslide scarps in the Shizuoka Prefecture study site is 2.35 ha and the median value is 1.44 ha.

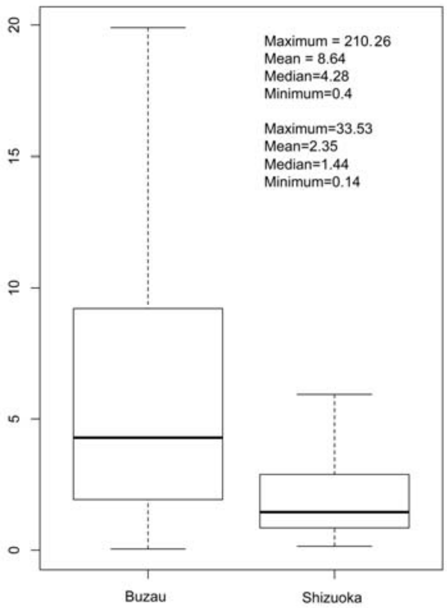

Fig. 2 The area of landslide scarps in the two study sites. Boxplots represent 25-75% of values, whiskers represent 10-90% of values and the line within the box represents the median. Extreme values were omitted.

Activity 2.1. Field trips

We organized a fieltrip in the Romanian study area, in the interval May 13-16. Participants: all team members (Lucian Drăguţ, Flavius Sîrbu şi George Popescu), the volunteer students (Larisa Paulescu şi Silviu Benea) and two collaborators (Prof. Takashi Oguchi, from the University of Tokyo and Dr. Mihai Micu, from the Institute of Geography, Romanian Academy). The modelling results were checked and evaluated as satisfactory. Therefore, publication plans were discussed.

Activity 2.2. Evaluation of the algorithm transferability. Part I

Land-surface variables

We have chosen only predictors that can be extracted from a DEM and ignored predictors like land cover and lithology, which are known to hold an important influence on landslides but fall outside the scope of the study. Furthermore, these land-surface variables (LSVs) had to satisfy two additional conditions: they can be extracted using a moving windows of variable size, and their influence on landslide scarps have a clear geomorphological explanation. Thus, LSVs like total catchment area or hillshade were not considered.

The LSVs were derived from the available DEMs using the RSAGA package that implements the algorithms of SAGA - System for Automated Geoscientific Analyses into the R software as follows:

- Elevation, as expressed by the DEM values, is regularly used as a predictor in modeling of landslides
- Mean curvature
- Plan curvature, is calculated perpendicular to the direction of flow and is generally used to describe the divergence or convergence of flow
- Profile curvature, is calculated on the direction of flow and is generally used to characterize erosion/deposition potential of a slope
- Slope gradient, is the most used predictor in landslide modeling
- The topographic positioning index (TPI), gives an estimate of the slope position of landslides and was found to have a scale dependency
- The topographic roughness index (TRI), measures the unevenness of a terrain by calculating the difference in elevation between a cell and the average of the surrounding cells, in a given window size
- Terrain surface texture (TST), emphasizing fine differences in elevation of different pixels, was derived with the method proposed by Iwahashi and Pike (2007).

The values of these LSVs were associated with one randomly sampled point per scarp, as well as an equivalent number of randomly sampled non-scarp points.

Scaling of LSVs

For scaling of LSVs we propose a methodology that can i) analyze the degree of fitting between each predictors and the modeled variable (presence of landslide scarps), ii) adapt different study areas or scenarios, and iii) easily integrate into a (semi)automated modeling approach (Fig. 3).

At first, each LSV was re-scaled to successively broader representations of topography with focal mean statistics in increasing windows, starting from 3×3 (Dragut et al. 2009). This was done using the RSAGA package by applying a simple smooth filter, in a square, with radius r = (ws - 1)/2, where ws is the size of a moving window (e.g. for a 3×3 moving window, r = (3 - 1)/2 = 1).

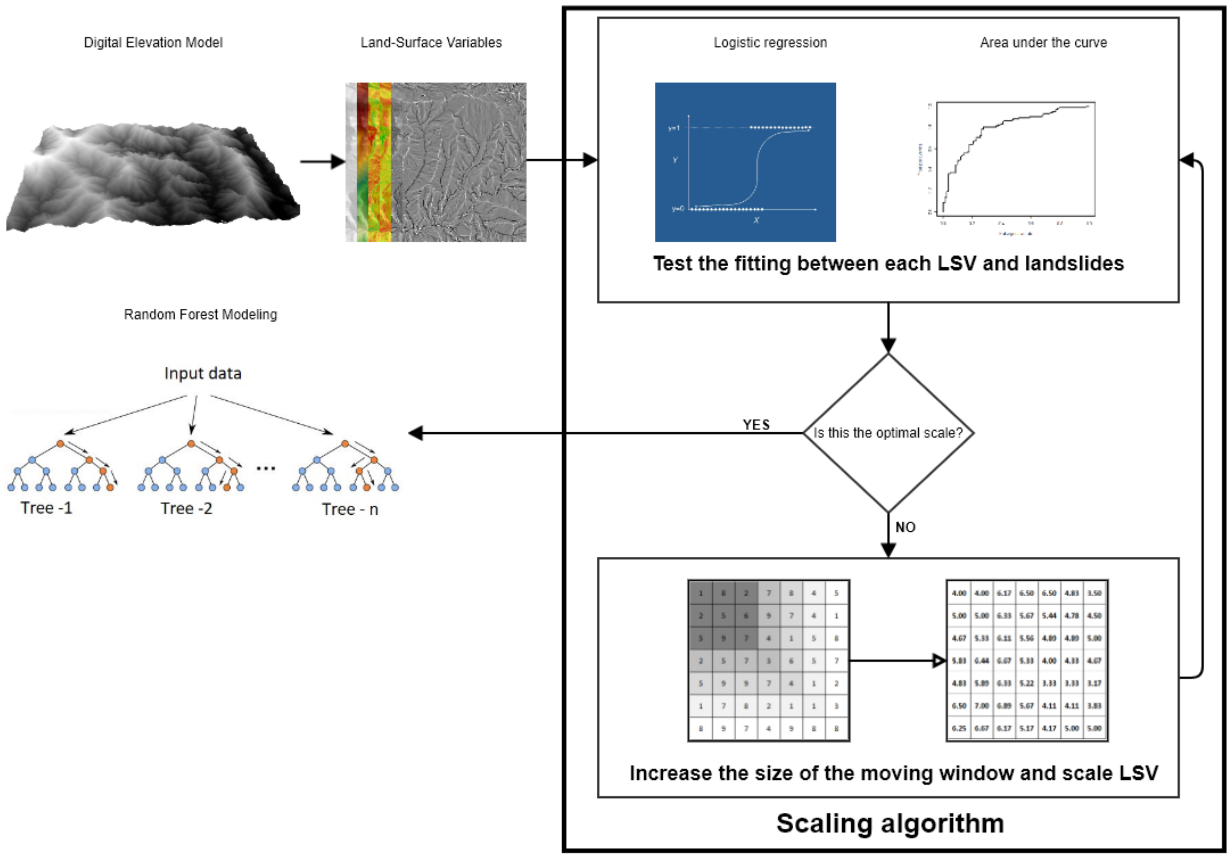

Fig. 3 Experimental Work flow.

For each LSV, the best scale was evaluated in an iterative process, by fitting a simple binary logistic regression, where each scale of the LSV is, in turn, the predictor variable and the scarp presence/absence is the predicted variable. The process continues as long as the result of the logistic regression improves, and it stops when the scale that best describes the presence/absence of scarps is found.

The logistic regression is a generalized linear model used for binary response variables (e.g. presence/absence data) that models the probability of a positive outcome based on predictors, or explanatory variables. It is the most common method used for modeling landslide susceptibility and it is also one of the most often used statistical methods in presence/absence modeling of geomorphological processes or landforms.

The performance of each model was evaluated using the AUC (area under the curve) metric. The AUC is obtained by plotting all possible sensitivity (true positive) rates against 1-sensitivity (false positive) rates, and returns values between 0.5 (no discrimination between presence/absence) and 1 (perfect discrimination between presence/absence). The AUC values and graphs are computed using the ROCR package.

Prediction of landslide scarps

In order to assess the impact of scaling the predictors in modeling, two models were produced and compared: one that used the scaled predictors as input data, while the other used the default LSVs (derived in a 3×3 moving window, without further smoothing). The latter was considered the baseline in evaluation of the scaling performance.

The employed modeling technique is random forest. RF is a robust, easy to use, and computationally efficient classification algorithm with a high level of accuracy. It produces a number of classifications, based on a binary decision algorithm, called decision trees and uses all of them, with a majority voting, to form the best prediction model. Thus each classification is assigned to a certain class (presence or absence) if the majority of decision trees do so. Furthermore, it is possible to obtain the results as probabilities of class assignment for a certain sample by evaluating the strength of the majority of decision trees. RF has several characteristics linked with the input data that are useful for our purposes: I) there is no need for the input data to have a specific distribution, ii) it is not sensible to outliers in the input data, iii) it can use a great number of predictor variables, and iv) it is not sensitive to collinearity in the predictor variables (Catani et al. 2013).

The modeling was performed using the package "randomForest" in the R software, with the settings ntree (number of trees) = 501 and mtry (number of candidate variables) = 3. The ntree value was set in a "trial and error" method in which the model was run with a high number of trees and the results were plotted against the OOB (out of bag error). The ntree value at which the curve flattened was selected as the appropriate one for modeling because a further increase in ntree would not improve the model. The mtry value was obtained by the standard formula, $\sqrt{p}$, where p is the number of variables.

Another output of an RF model is the ranking of predictor importance in creating the model, the so called variable importance (VI). There are many ways for this but we used the simplest method, based on the decrease in mean accuracy. The OOB is calculated using all the predictors and then, in turn, omitting one predictor. The differences between the two OOB values are averaged for all the decision trees and are normalized using the standard deviation of the differences. The predictors that are found to reduce the OOB when used, are regarded as the most important.

In order to account for the random part in RF, the models were run for 25 times and the results were averaged between. The results were evaluated using AUC.

Results

LSVs calibrated to scale predicted better the scarp presence/absence in five out of eight cases for the Shizuoka study area, and in six out of eight cases for the Buzau study area (Fig. 4). Elevation and profile curvature display the best prediction of the landslide scarps at their default scale in both areas, while plan curvature shows the best prediction at the default scale for Shizuoka, and at a 17 x 17 for Buzau. Three predictors (elevation, profile curvature and mean curvature) were found to perform best at the same scale in both study sites (Fig. 4).

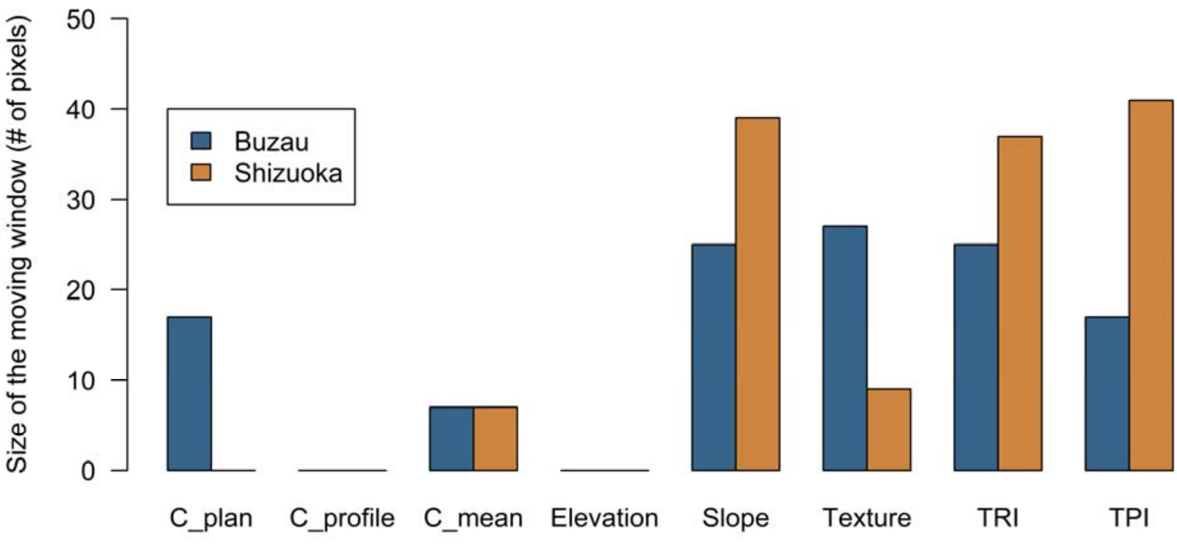

Fig. 4 The size of the moving window at which each LSV predicts best the landslide scarps.

When comparing the performance of the predictors in both study sites, we observe that two predictors (plan curvature and TST) display a higher scale for Buzau, while three others (slope TRI and TPI) show a higher scale for Shizuoka. These results suggest that the relationship between the size of the landslides and the scale of predictors is not straightforward. If such a relationship exists, then it is most probably defined for each individual predictor, and is more complex than a simple linear one. This confirms the findings of Paudel et al. (2016) that there is no universal scale that works for all the LSVs, but rather each LSV performs best at its own scale.

The curvatures, with one exception, perform better at fine scales, while slope, texture, TPI and TRI perform better at broad scales. When scaled, the LSVs increase the prediction power by up to 0.11 (Fig. 5). The most significant increase in the Shizuoka study area is for slope (ΔAUC = 0.10) and TRI (ΔAUC = 0.11). For the Buzau study area, the biggest increase is for mean curvature (ΔAUC = 0.07). The increase in AUC for a scaled LSV compared to the default is greater for the Shizuoka study area, with the exception of mean curvature

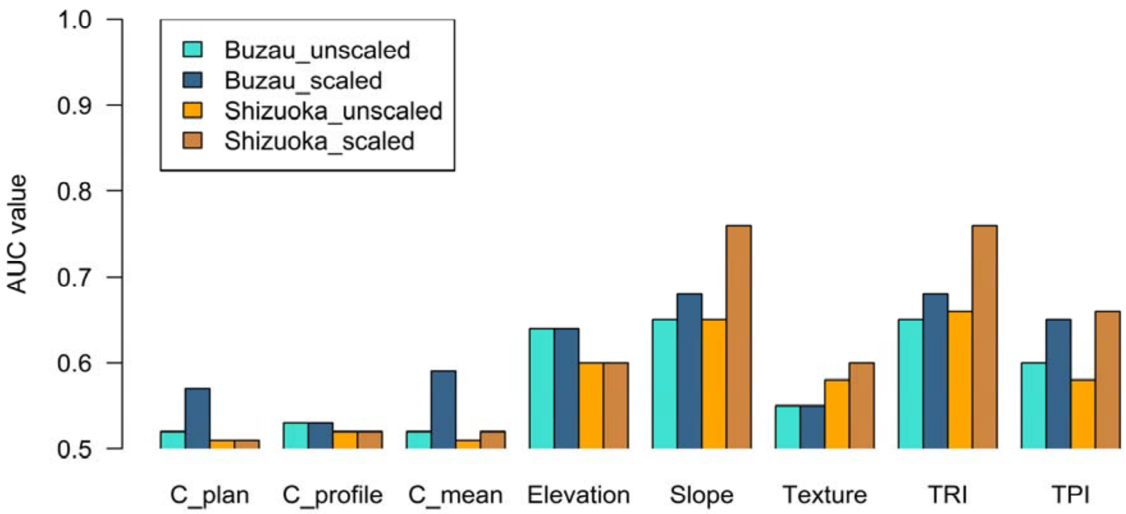

Fig. 5 The AUC results for landslide scarps modeling with individual predictors.

The results show a significant improvement in the accuracy of the modeling results for both study areas when the predictors have been scaled. The increase is particularly significant in Buzau, where the model improves from AUC = 0.59, which denotes a poor model, to AUC = 0.73, a good model. For Shizuoka, the increase in accuracy is more limited, but is still important, especially considering that the model with default predictors had already shown a good accuracy (Fig. 6).

Our study found out that not all the LSVs have their best fit at the same scale. This can have an impact in the final accuracy of the model, because using each LSV at its appropriate scale not only improves the modeling accuracy (Paudel et al. 2016) but also strongly affects the ranking of predictor importance. Indeed, for the Buzau study area, the ranking changes significantly when the model is constructed with scaled predictors (Fig. 7). For the default model the elevation stands as the most important predictor and is followed by a group of other three predictors with similar importance (TRI, TPI and slope). The curvatures have a lower importance while the texture has a negative importance coefficient. For the scaled model there are two predictors that stand out as being the most important in the model, slope and TPI. It is important to also notice that for the scale model the variable importance graph is more compact showing that all the predictors influence the model, even texture. For the Shizuoka study area, the default model's predictor ranking is quite similar to that of the Buzau default model. The elevation stands as the most important predictor, followed by TRI, slope and TPI, while the curvatures and texture are the list important. For the scaled model there is an even bigger gap between elevation and the other predictors. Notable is the rise in importance of the texture that becomes the second most important predictor, when scaled (Fig. 7)

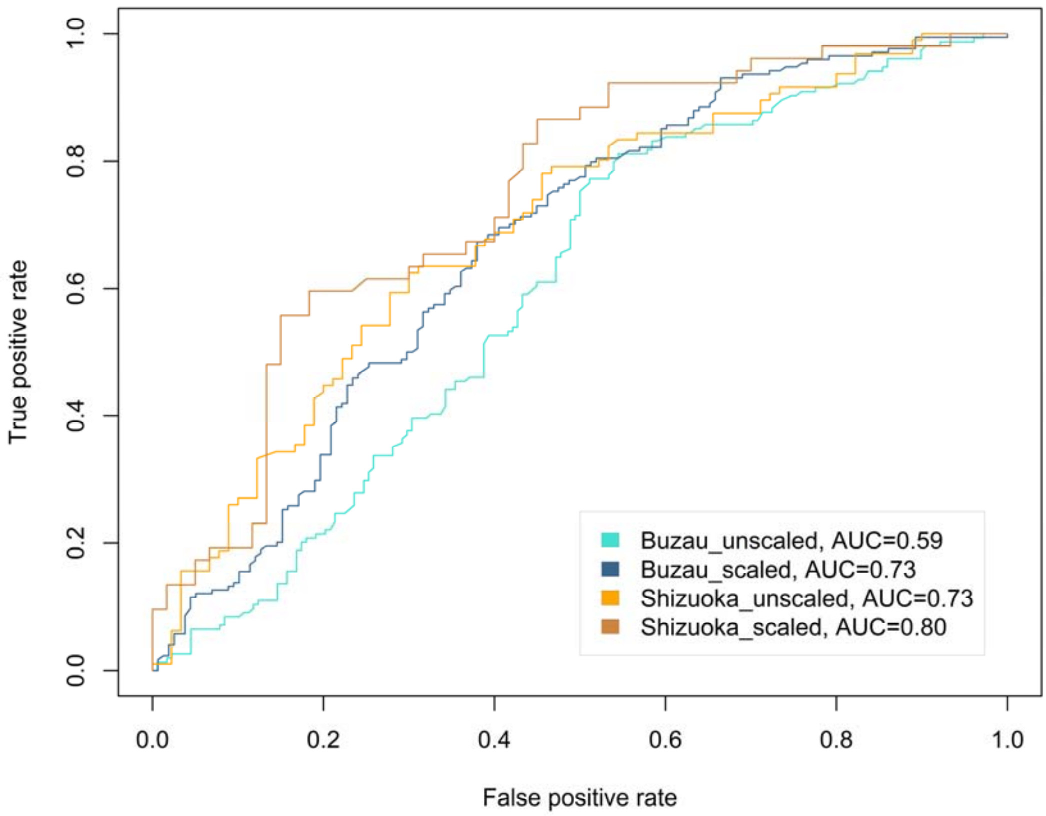

Fig. 6 Model accuracy, measured using the AUC.

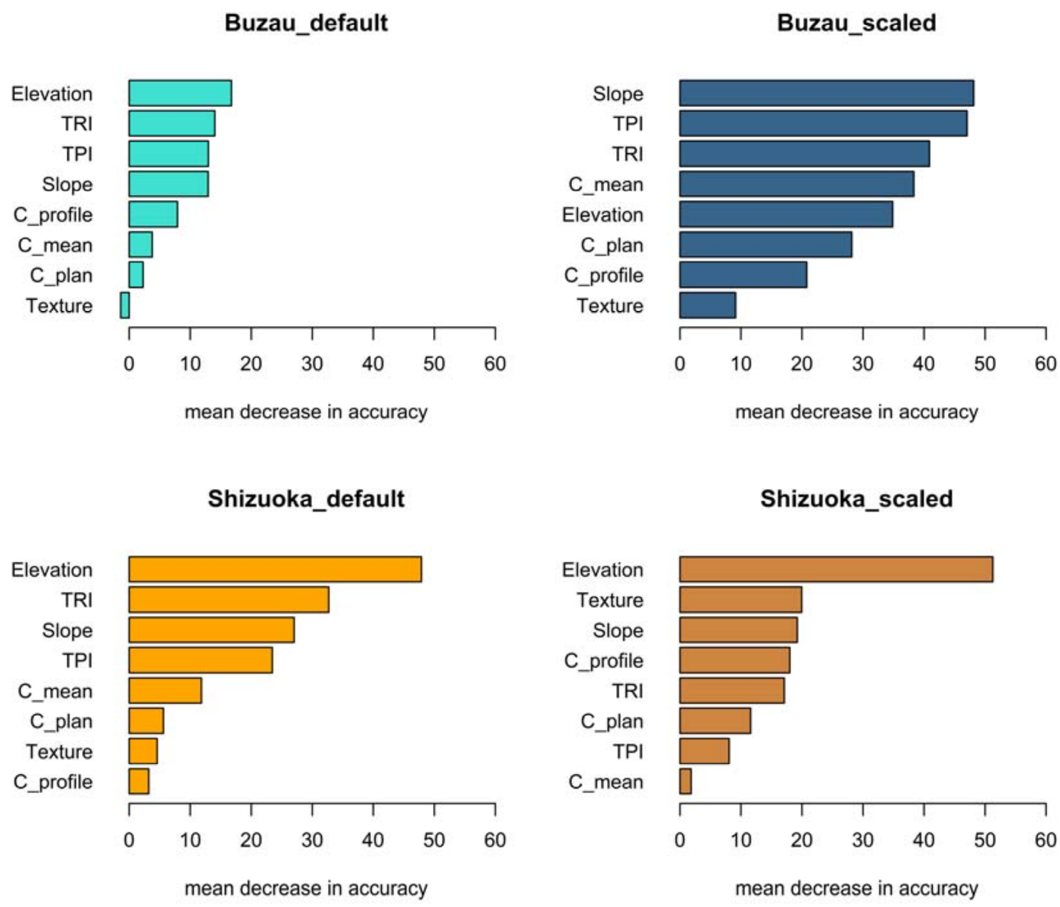

Fig. 7 Variable importance ranking, as resulted from the random forest model.

These findings are supported by similar results presented by Paudel et al. (2016). Also, when testing the effect of DEM resolution on the accuracy of landslide models, Catani et al. (2013) found that using a DEM with a different spatial resolution changes the ranking of variable importance. This is in strong contrast with the vast majority of studies on landslide modeling that use all the LSVs at the same scale. The problem of model accuracy can be, partially, solved by using an algorithm that can have a high number of predictor variables from which it can choose the ones that, actually, improve the model (e.g. RF). But the possibility that some LSVs can be ranked of little or no importance to the model, because they are not used at the proper scale, can have consequences in the geomorphological interpretation of the model.

It is important to note that there are great differences in the ranking of variable importance when computed with RF (Fig. 7) compared with the ranking computed by fitting a logistic regression between the landslide scarps and each individual predictor (Fig. 5). The fact that different modeling approaches produce different variable importance rankings, on the same input data, has also been reported in previous studies (Goetz et al., 2015; Chen et al., 2017), and the analysis into why this happens is beyond the scope of this paper. For our approach it was important only to compare the scaled variable against the unscaled variable for a better fit and that can be better achieved thru the use of a simple regression, since more complex modeling technics, like RF, work best when they use multiple predictors (Catani et al. 2013).

Our results show that, with the exception of profile curvature, all others LSVs have a better fit to the landslide scarps when they were scaled and also that there is no universal scale at which the LSVs should be used but rather that each individual LSV has a particular scale for a particular study area. When we transform the scaling factor, from pixels to square meters, and we compare the results with the average size of the landslides we find that there are significant differences between predictors and between the two study areas (Fig. 8). For the Shizuoka study area there are five LSVs (Plan curvature, Profile curvature, Mean curvature, Texture, Elevation) that are not scaled or scaled to represent an area less than 0.25ha (50×50m) and there are only three variables that are scaled broadly, while in the Buzau study area there are three LSVs (Profile curvature, Mean curvature, Elevation) that are scaled to finer sizes and five that are scaled broadly.

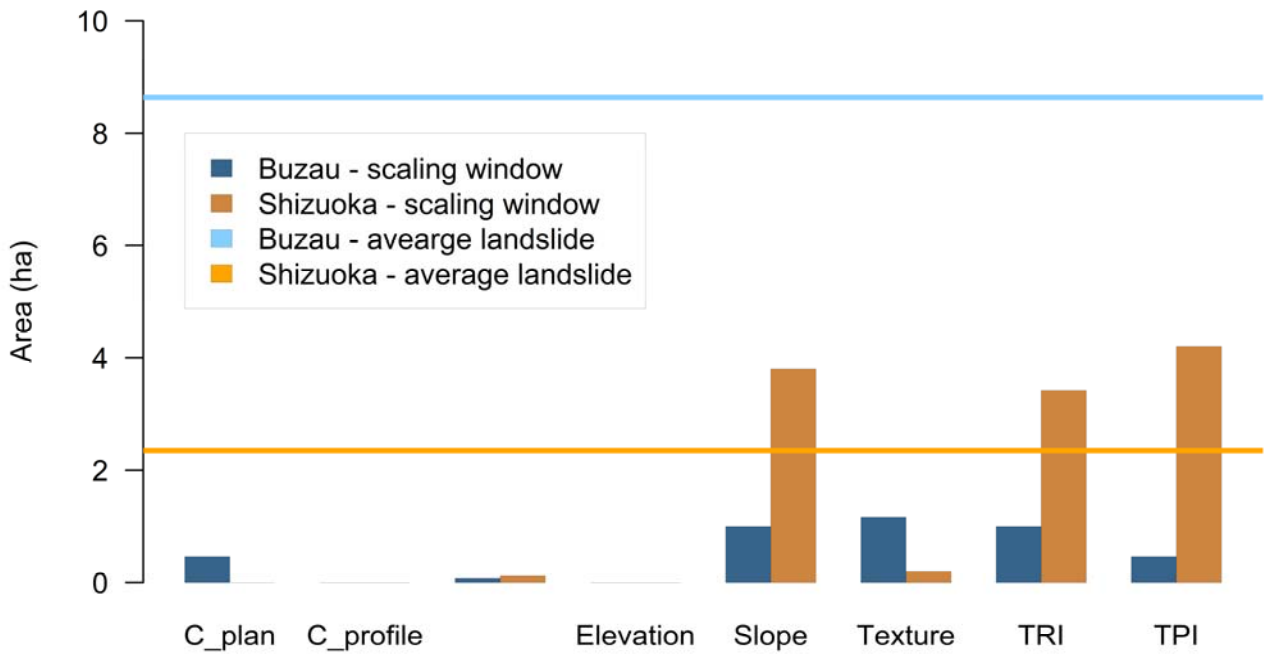

Fig. 8 A comparisons between the area that scaled variables represent (bars) and the average area of landslides (horizontal lines).

All the LSVs that are up-scaled seem to improve the modeling accuracy due to a better representation of topography through elimination of local noise (micro-topography) (Fig. 9). Furthermore, the area that they are scaled to seems to fit to the range of spatial resolutions at which other studies have found to be the most appropriate to model landslides. Thus when studying the effects of DEM resolution on the landslide modeling, DEMs with spatial resolutions ranging from 2 to 500 m have been investigated and the conclusion was that the best results were obtained using DEMs with a spatial resolution of 10 m (Arnone et al. 2016; Schlögel et al. 2018; Wang et al. 2017), 20 m (Sulaiman et al. 2017) and even 50 m (Catani et al. 2013). This results suggest that greater consideration should be given to the choice of DEMs, and their spatial resolution, when modeling landslides. Also the fact that the lowest pixel size (i.e. highest spatial resolution) is not always the best option, is becoming even more important with the increasing availability and use of high and very high resolution DEMs.

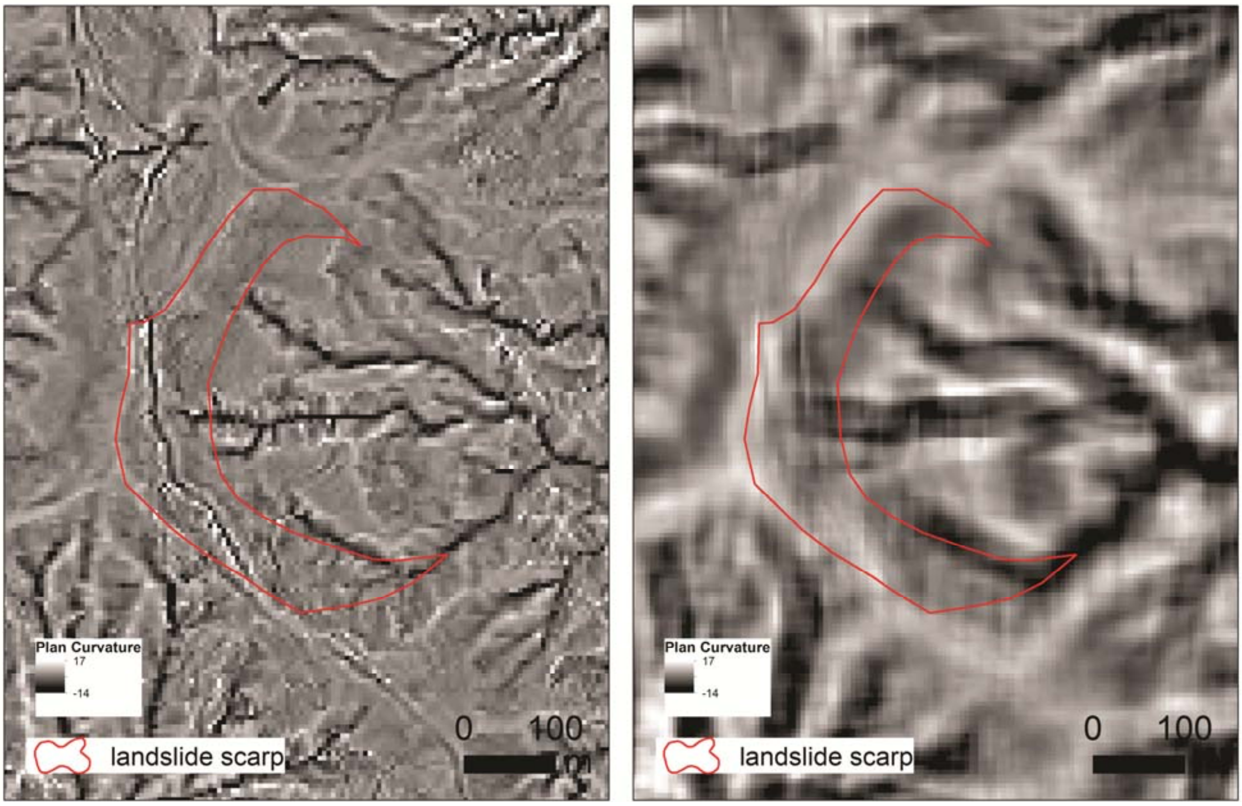

Fig. 9 An example of a scaled predictor in relation to a landslide scarp. Left image: plan curvature at the default scale. Right image: plan curvature scaled in a 9×9 window. Note a north-south trench inside the landslide scarp on the left image that is filtered out on the right image.

The LSVs that are scaled broadly, to an area of more than 2500 m2 (50×50 m) seem to be less related with the micro topography developed on the landslides and more with the size of the landslides themselves. They are related to the findings of (Claessens et al. 2005) that concluded that there is no universal scale and DEM resolution that should always be used and recommended that the DEM should be adapted to the average size of the landslides.

For the Shizuoka study site, the three LSVs (slope, TRI and TPI) that are scaled broadly represent an area greater than that of the average area of landslides while, the broadly scaled LSVs for the Buzau study site represent an area of approximately three times smaller than that of the average landslide. This can be related to the type and accuracy of the DEMs. The Lidar DEM used for the Shizuoka study site has a higher accuracy than that of the optically derived DEM for the Buzau study site, and the latter has more artefacts resulted from the transformation from a DSM (digital surface model) to a DTM (digital terrain model). But also an even greater uncertainty in interpreting the relation between the area at which the LSVs were scaled and the area of the landslides is the variability in sizes of the landslides from the two study sites and also the variability in sizes within each study site. This is valid especially in the Buzau study site where the difference in area of the smaller landslides, which are the majority, and the bigger landslides is significant and using only the average to express the size is statistically unrepresentative. The complex relation between the scaling factors of different predictors and the sizes of landslides under different conditions should be addressed in future studies.

Activity 2.3. Automation of methodology. Part I

Work in progress. Manuscript in preparation, expected to be submitted by January 2019.

Activity 2.4. Development of a semi-automated method for mapping landslides from Digital Elevation Models. Part I

Automation of landslide mapping included the following actions:

- finalizing the algorithm for selection and scaling of the input data for segmentation;
- exploring the potential of Google Earth Engine to process massive data.

Thus, we have developed a script that can be run using the free software R, which can scale predictors using the methodology presented above. The necessary input data for the tool is a DEM from which the predictors will be extracted and a shapefile containing presence/absence data for the variable that is to be modelled.

Computer Code Availability

Link to code: http://mapslide.projects.uvt.ro/wp-content/uploads/2017/12/Folder-nou.7z (zipp file)

Name of code: Scaling tool for landslide modelling

Developer: Flavius Sirbu, mapslide project (Bd. V. Parvan, no4, Timisoara, Romania; tel: +40727886512; e-mails: flavius.sirbu@gmail.com; flavius.sirbu@e-uvt.ro)

Year first available: 2018

Hardware required: The hardware requirement depends on the size (number of pixels) of the study area

Software required: R studio, SAGA

Program language: R

Program size: <1MB

Details on how to access the source code:

Input data (should be stored in the working directory):

- DEM, in. sgrd format.
- Shapefile, point, with present/absent data on landslides. The first three columns of the shapefile should be: “FID”, “Shape”, “CID”. The last one should be binary, with presence/absence of landslides.

Input settings: The only setting that the script needs is the path of the working directory. However, one additional setting can be easily adjusted, the number of trees for the Random Forest (RF) model. This can be done in line 22 of the code and should be considered, for a re run of the script, after analyzing the first plot produced by the RF model.

Output data:

- In the working directory:
  - 7 land surface variables (LSVs): curvature, plan curvature, profile curvature, texture, slope, TPI and TRI
  - 8 scaled predictors (7LSVs + DEM)
  - 1 .csv table with the best scale for each LSV (and their fit at each scale)
  - A raster in two formats (.tiff and. sgrd) with the modeled landslides based on scaled LSVs
- In R studio environment
  - 2 plots for scaling (radius of the moving window for each LSV and the fit at each scale, radius of the moving windows for each LSV)
  - 3 plots for Random Forest (out of bag error - in order to analyze if the RF model uses the right number of trees, Variable importance plot, The AUC plot)

To run the model:

1. Create a working directory on your hard disk
2. Insert a DEM and a shapefile in this directory, following the instructions from input data)
3. Set the script to work in this directory (line 18)
4. Set the name of the DEM in the script (line 20)
5. Set the name of the shapefile in the scrip (line 21)
6. Run the script

Because processing sequences took between hours and days, we explored the potential of using Google Earth Engine (GEE) for speeding them up. This work was presented at Geomorphometry 2018 by Ovidiu Csillik and Lucian Drăguţ. The extended abstract is available at http://2018.geomorphometry.org/Csilik_Dragut_2018_geomorphometry.pdf.

Activity 2.5. Dissemination of the results

The results obtained so far have been presented in two international and one national conferences. Thus, a PICO talk titled ”The influence of data scaling in modelling landslide scarps” was presented at EGU (Vienna, April 8-13) https://meetingorganizer.copernicus.org/EGU2018/EGU2018-7894.pdf. An oral presentation with the title ”Improving landslide scarp detection by scaling the predictors” was delivered within the Romanian Symposium on Geomorphology (Buzău, 16-20). Two oral presentation were delivered at Geomorphometry 2018 (Boulder, Colorado, August 13-17), namely ”Sensitivity of land-surface variables to scale in identifying landslide scarps” (http://2018.geomorphometry.org/Sirbu_others_2018_geomorphometry.pdf) and „Towards a global geomorphometric atlas using Google Earth Engine” (http://2018.geomorphometry.org/Csilik_Dragut_2018_geomorphometry.pdf).

Activity 2.6. Project management

Not for public release.

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Project manager,

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