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Relevance of morphometric predictors and completeness of inventories in earthquake-induced landslide susceptibility

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Abstract— **Landslide susceptibility is the likelihood of landslide occurrence in a specific geographic location. A complicated interaction between various morphometric, climatic, seismic, and anthropogenic variables governs landslide susceptibility. Among these variables, morphometric causative factors are important for the generation of landslide susceptibility maps as they provide the basic information related to the topography. In fact, many morphometric variables are commonly included in landslide susceptibility analyses. Additionally, an accurate landslide inventory is a key input to both train and validate a classification model used to prepare susceptibility maps. The objective of this work is to investigate the significance of the causative factors, in relation to different landslide inventories, and their contribution to landslide susceptibility mapping. To do so, we selected a set of five earthquake-induced landslide inventories, developed independently in the aftermath of the 2015 Gorkha earthquake. We obtained landslide susceptibility maps in the framework of a logistic regression model using slope units as spatial mapping domains. We evaluated the significance of the different independent variables relying on p-values corresponding to the susceptibility maps obtained from each inventory. We examined the performance of susceptibility maps by pairwise comparison between the inventories, finding that the significance of variables is not entirely consistent for all inventories. This implies that preparation or selection of a landslide inventory for earthquake-induced landslide susceptibility is a non-trivial step. The pairwise validation of different maps also shows the robustness of the performance varies upon using different inventories.**

I. Introduction

The disastrous earthquake of a magnitude 7.8 at Gorkha, Nepal, on April 25, 2015 triggered numerous landslides in the central Nepal Himalayas. Many researchers carried out the post-earthquake assessment of landslides by producing inventories and susceptibility maps, however, the relevance of independent variables causing landslides has not been specifically analyzed. The factors contributing to the reliability of susceptibility maps calculated from such inventories are the completeness of inventories, the type of mapping units utilized for zonation, and the sampling balance between the inventories [1-2]. Furthermore, the choice of predictors, specifically the morphometric variables derived from a digital elevation model (DEM), is often made without addressing their significance, with a few exceptions [3].

In this study, we selected five existing landslide inventories mapped in the same region after the Gorkha earthquake event. We checked the relevance of the independent variables, performed accuracy assessment on each landslide susceptibility map and validated using the remaining inventories.

II. Material and Methods

In this work, we used five landslide inventories, for the landslide triggered by the Gorkha Earthquake 2015, prepared independently by [4-8]. The first four inventories are polygon-based and the last is point-based inventory. The study area covers the section of Rasuwa, Nuwkot and Sindhupalchowk districts (Figure 1). Table I shows the descriptive details about the five inventories and slope units used in this work.

Inventories	Landslides	Unstable SUs	Landslide area [km^2]	Landslide area (%)
[4]	1,264	66	10.82	0.74
[5]	1,780	87	9.68	0.66
[6]	1,765	81	14.28	0.98
[7]	359	54	3.68	0.25
[8]	371	63	Point inventory	

Table I. Details about landslide inventories used in this study.

In this work, we performed the following six steps:

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Step 1: Five inventories were chosen so that they cover the most affected areas of the earthquake-triggered landslides in the central Nepal. One of the authors (BP) actively participated in preparing the inventory from Ref. [4].

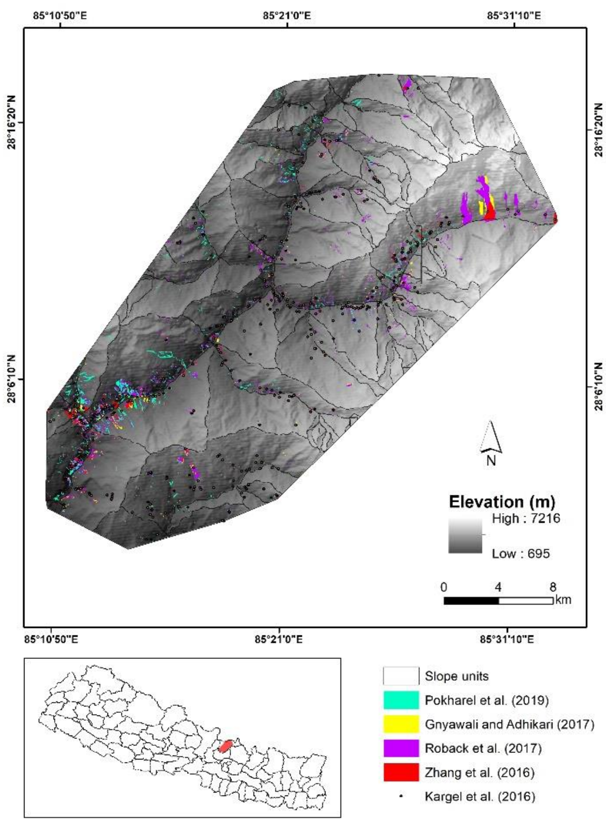

Figure 1. Map of study area. Slope units were delineated in GRASS GIS using the algorithm developed by Ref. [9]. Map is in EPSG:32645 reference system.

Step 2. A slope unit (SU) map over the study area was available for this study. The SU map was based on the algorithm developed in Ref. [9] and generalized to account for large areas in Ref. [10].

Step 3. We calculated 9 morphometric variables (raster maps) from the Cartosat-I DEM, and collected three dynamic parameters from the United States Geological Survey (USGS) Shake Maps published after the earthquake event [11] as independent variables responsible for the landslides.

Step 4. We characterized each SU with presence or absence of landslides and with descriptive statistics (mean and standard deviation) of independent variables [2,12,13], except for landforms classes, for which we used the dominant class in each SU. We selected the DEM derivatives as independent variables (Table II), following Ref. [1], who performed a similar analysis. The selected variables have a rather straightforward interpretation in terms of their effect on landslides.

Type	Independent variables	GRASS GIS module/Reference
Dynamic	PGA	[11]
Dynamic	PGV	[11]
Dynamic	MMI	[11]
Static	Slope	r.slope.aspect
Static	Topographic Wetness Index (TWI)	r.topidx [14]
Static	Vector Ruggedness Measure (VRM)	r.vector.ruggedness [15]
Static	Local relief	r.neighbors [16]
Static	Landform classes	r.geomorphon [16]
Static	Plan curvature	r.slope.aspect
Static	Profile curvature	r.slope.aspect

Table II. List of independent variables as studied in [1] and adopted in this work. We also show the specific method used to calculate descriptive statistics by specifying GRASS GIS modules.

Step 5. We chose the smallest number among the stable and unstable SUs (40, in the inventory from [5]) among the five different inventories to generate the training datasets. We randomly selected 75% of both stable and unstable SUs for each landslide inventory dataset, for a total of 60 SUs. We iterated this process for 20 times for each dataset and run the glm() function (generalized linear model, within the R language) to train the logistic regression (LR) – a widely used method in landslide susceptibility modelling. Then, we obtained descriptive statistics and run a χ-square test to calculate the p-values for all independent variables in 20 runs.

Step 6. We prepared boxplots showing the distributions of p-values associated to each inventory, stemming from the 20 runs. We checked the accuracy of the landslide susceptibility maps using area under curve (AUC), and validated the accuracy of the susceptibility map obtained from each inventory, on the slope units not used in the training step, selected from the same inventory and for the remaining for maps. The validation test corresponds to 20 runs as well, from which we calculated mean and standard deviation of AUC for each train/validation pair.

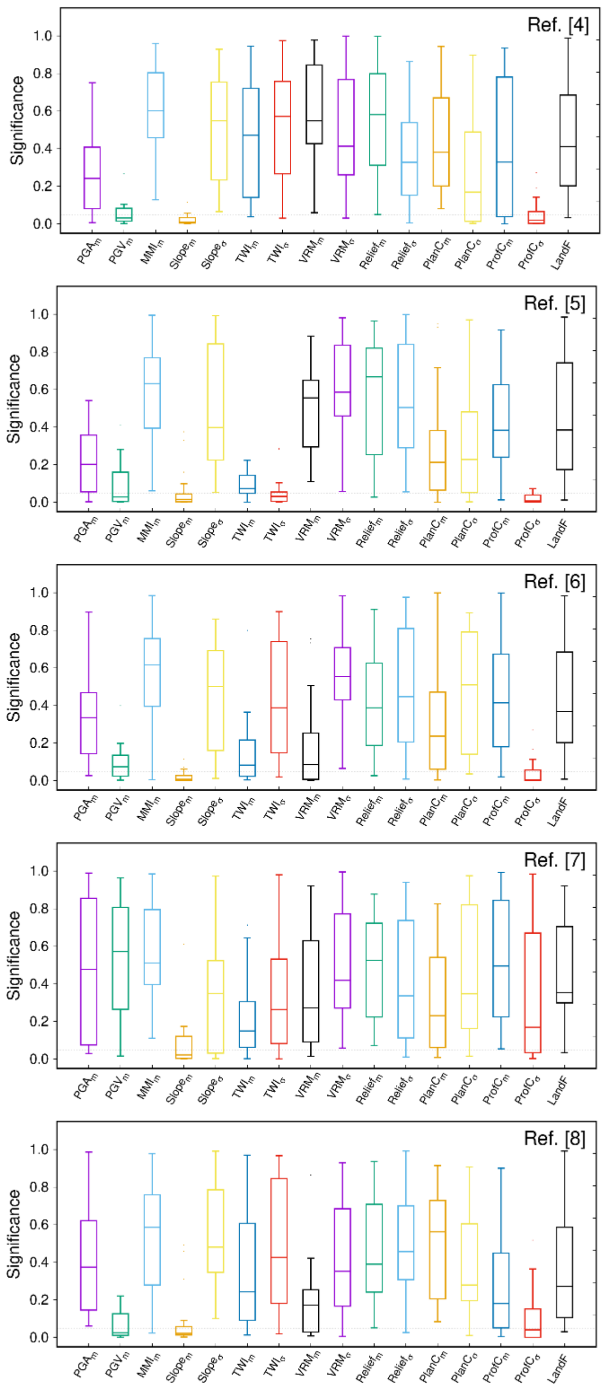

Figure 2. Distributions of the significance (p-value) of the different variables in the logistic regression, obtained from 20 runs of the susceptibility model for each inventory, with different random selections of the training dataset. The horizontal dashed line represents the 0.05 significance threshold.

Inventories	Significant predictors
Ref. [4]	PGV (mean), Slope (mean), Profile curvature (mean)
Ref. [5]	PGV (mean), Slope (mean), TWI (S.D) Profile curvature (S.D)
Ref. [6]	Slope (mean), Profile curvature (S.D)
Ref. [7]	Slope (mean)
Ref. [8]	PGV (mean), Slope (mean), Profile curvature (S.D)

Table III. Significance factors obtained for each inventory (p-value <0.05).

III. Results and Conclusions

Figure 2 shows boxplots of the distribution of p-values of each variable and for each landslide inventory dataset. Table III shows the variables for which the p-value was always smaller than 0.05, in all the 20 randomized runs of the LR. Although all inventories covered the same area, some inconsistency exists in the relevance of the predictors, which may be due to the different number and location of the landslides in the different inventories. In addition, for the same aerial extent, the number of stable and unstable slope units (i.e. of slope units containing no landslide or at least one landslide) differs for different inventories, which ultimately influences the content of landslide susceptibility maps. The morphometric variable that stood significant for all the inventories is slope (mean). Profile curvature (standard deviation) is invariably very significant for four inventories, while its significance was substantially smaller for the one from Ref. [7]. This implies that slope morphometry influences the spatial occurrence of landslide triggered by the Gorkha Earthquake 2015. We stress that the inventory from Ref. [7] contains the smaller number of landslides, which seems to produce a noticeable difference. Table IV lists the results for pairwise validation of the inventories in 20 runs for each. Performance was higher for each map if the validation data

Trained by	Validated by				
	[4]	**[5]**	**[6]**	**[7]**	**[8]**
[4]	**0.68±0.06**	0.71±0.06	0.68±0.05	0.58±0.06	0.68±0.06
[5]	0.63±0.06	**0.74±0.08**	0.71±0.06	0.53±0.07	0.65±0.06
[6]	0.63±0.06	0.73±0.07	**0.71±0.07**	0.57±0.07	0.69±0.04
[7]	0.58±0.07	0.59±0.08	0.62±0.07	**0.60±0.08**	0.61±0.07
[8]	0.70±0.07	0.70±0.08	0.70±0.07	0.62±0.07	**0.69±0.07**

Table IV. Pairwise validation between five inventories. The table shows mean ± standard deviation for AUC of testing/validating dataset.

was from the same inventory, which is expected. The testing sample of the inventory from Ref. [7] had lower performance. The inventories [4], and [8] had same relevant variables (Table III) but the model performances varied.

From our study, we may draw two main conclusions. First, the differences in significant predictors (within LR) creates a difficulty in interpretation and reliability of susceptibility maps. Among morphometric predictors, only mean slope and profile curvature are (almost) always significant – this is a relevant point, being morphometric variables the ones that stay constant across different earthquake events. Second, model performance (within LR) depends upon the number of landslides and/or completeness of the inventory. This is clearly shown by the inventory with smallest number of landslides ([7]) having the weakest performance. We stress that this point could be less relevant where the spatial extent of the study area is larger. Hence, it is necessary to make sure the inventories are representative, i.e. complete enough [17, 18], if one is to use them for landslide susceptibility.

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