ASSESSING THE ELEVATION DATA EFFECT ON SHALLOW LANDSLIDES SUSCEPTIBILITY MAPPING

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Abstract

The Serra do Mar is a mountain range that extends for approximately 1.500km along the southeastern brazilian coast, with steep slope and high annual rainfall totals concentrated in the summer. These attributes make this one the most susceptible region to shallow landslides in the country and these processes may represent a risk for society if occurring in occupied areas. Therefore, susceptibility maps depicting the spatial probability of occurrence of shallow landslides can be an important tool for land use planning and risk mitigation. These maps can be derived from terrain attributes extracted from Digital Elevation Models (DEMs). However, DEMs can be produced using a variety of technologies, implying in difference in relief representation in each product. The objective of this study was to evaluate the efficiency of two Digital Terrain Models (DTMs) for the production of susceptibility maps using the Information Value (IV) bivariate statistical method. Two DTMs were used: the TanDEM-DTM and a DTM obtained from topographic data (1:10.000) interpolated with Topo to Raster algorithm, both with 12m resolution. DTM influence on the susceptibility model was evaluated in three steps. In the first step, a set of descriptive statistics of the DTMs elevation values were computed. A slope angle map was derived from each DTM and histograms were produced. Then, an elevation difference map between the DTMs was obtained to identify the main areas with discrepant values. In the second step, five morphometric parameters were computed (slope angle; slope aspect; contribution area; plan/profile curvature; and contribution area) and the IV values were calculated using a training subset extracted from a landslide inventory. The model fit and model predictive performance were evaluated using as criterion the area under the Receiver Operating Characteristics curve (AUC_{ROC}). Finally, in the third step the maps were classified in five susceptibility classes for the evaluation of differences in the spatial patterns of susceptibility, with homonymous classes between the maps having the same area. Results show significant differences in the slope angle maps, with larger areas depicted as >30º in the Topo to Raster DTM. The elevation values are significantly different (up to approximately 64m) in some areas, mainly in the valley bottoms and interfluves. The susceptibility model generated with TanDEM-DTM has higher model fit and predictive performance than the model obtained from Topo to Raster DTM. The final susceptibility maps showed significant differences in their susceptibility pattern, demonstrating the influence of elevation data. However, we conclude that these differences cannot be entirely attributed to the influence of elevation data since uncertainties associated with the random partition of the landslide inventory were not evaluated.

1 INTRODUCTION

Shallow landslides are the most frequent mass movements in the Serra do Mar region, a mountain range that extends for approximately 1.500km along the southeastern coast of Brazil, with steep slopes and high annual rainfall total (1750mm to 2000mm). These processes can cause human and economic losses, making landslide susceptibility maps a useful tool in guiding land use. These maps identify the spatial probability of occurrence of a landslide of a given type based on terrain characteristics, without considering the frequency of the process (Corominas *et al.*, 2014).

The methods for assessing landslide can be subdivided into qualitative and quantitative. Qualitative methods represent susceptibility through descriptive scales, wheras quantitative ones aim to determine the probability of occurrence of the process. Among quantitative methods, statistical analyses (bivariate and multivariate) are considered the standard approach for regional scale susceptibility assessments (Corominas *et al.*, 2014).

In recent years, the use of Digital Elevation Models (DEMs) in landslide susceptibility assessments has grown (Martins *et al.*, 2017; Vieira *et al.*, 2018) due to the accuracy of the data and speed provided by these products (Grohmann *et al.*, 2008). DEMs can be generated using different technologies, implying in variations in how each DEM depicts the terrain and therefore in morphological and susceptibility analyses. In Brazil, the use of DEMs obtained from topographic maps is common, as this type of data is often the best available for free or at low cost.

Thus, the objective of this study was to evaluate the efficiency of two of those models (which represent exclusive terrain data and henceforth will be referred as Digital Terrain Models – DTMs) for the production of landslide susceptibility maps using a statistical method

2 STUDY AREA

The Gurutuba river basin (4.5 km²) (municipality of Itaoca) is located in the Serra do Mar south of the state of São Paulo (Figure 1). Between 13th and 14th January 2014, intense rainfall (200mm/2h) was recorded, concentrated in the headwaters, triggering hundreds of shallow landslides (Figure 2). A debris flow was also triggered, reaching the urban center of Itaoca causing human losses and severe damage to infrastructure (Gramani and Arduin, 2015).

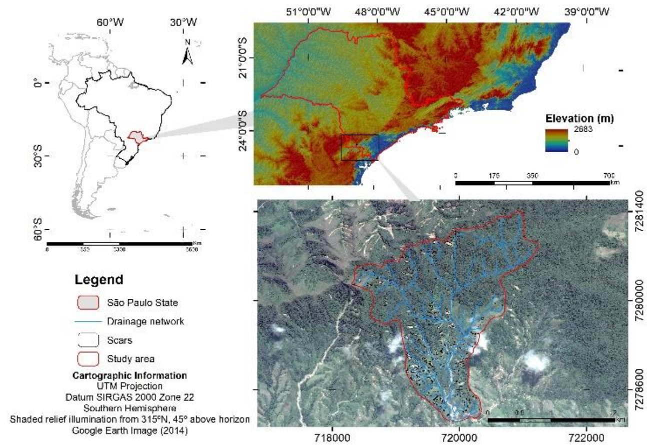

Figure 1: Study area location in São Paulo State (A) and Gurutuba basin after the 2014 event (B).

Figure 2: Shallow landslides triggered in the 2014 event in the municipality of Itaoca Photo by Gramani, M. (2014).

3 DATA AND METHODS

3.1 Digital Terrain Models (DTMs)

Two DTMs generated by different procedures were used: the first one was the *TanDEM-DTM* (*WorldDEM-DTM*) (12m resolution), a DTM produced by the German Aerospace Center (*Deutsches Zentrum für Luft und Raumfahrt*) in cooperation with *Airbus Defence and Space.* This product was generated with data from X band synthetic aperture radars and has vertical and horizontal accuracy < 10m (Krieger *et al.*, 2013). *WorldDEM-DTM* has filtered information to match the radar response of the terrain only.

The second DTM was interpolated from topographic data (1:10.000) using the *Topo to*

Raster algorithm (Hutchinson, 1988), which aims to ensure the drainage network connectivity (Hutchinson, 1988). In this work, the *Topo to Raster DTM* was generated using the drainage network (including intermittent channels), contour lines (10m) and point elevation data. The characteristic drainage network enforcement of this algorithm was performed.

3.2 Information Value method and input data

The bivariate statistical method applied is the Information Value (Yin and Yan, 1988), already used in other works aimed to map areas susceptible to landslides (Bateira, 2015; Zêzere *et al.*, 2017; Dias *et al.*, 2018). The Information Value (IV) of a class *j* of a parameter *i* is defined by Equation 1:

$$IV_{ij} = \ln (Si/Ni) \;/\; (S/N) \qquad (1)$$

where: Si is the number of mapping units with landslides in the class *j* of parameter *i*; Ni is the total number of mapping units in class *j* of parameter *i*; S is the total number of mapping units affected by landslides; and N is the total number of mapping units in the study area.

If IV_{jj} assumes a positive value, the presence of class *j* favors slope instability. Conversely, if IV_{pi} assumes a negative value, the presence of class *j* is favorable to slope stability. In the case of the absence of scars in class *j*, Equation 1 cannot be applied. In these cases, the weight of class *j* was set to the closest negative value inferior to the minimum IV_{ij} computed among all classes of all parameters.

For the susceptibility analysis, it was considered a landslide inventory produced by visual interpretation of *Google Earth* 2014 imagery and field work (Carou *et al.,* 2017). This inventory contains 336 scars (average area = 429.5m²), with total area affected by landslides equal to 3.27% of the basin. The landslide inventory was randomly partitioned in two subsets with equal number of scars (168). The training subset was used compute IV_{ij} values and to evaluate model fit and the test subset was used to evaluate model predictive performance, both as defined by Reichenbach *et al.* (2018).

Five geomorphometric parameters were considered in the susceptibility analysis: slope angle; slope aspect; slope curvature (plan/profile); contribution area; and Topographic Wetness Index (TWI). The reduced number of parameters was an option to minimize uncertainties associated with input data and also to make the analysis of DTM influence on the Information Value model more straightforward.

3.3 Evaluation of DTMs influence on the Information Value model

Evaluation of the DTM influence on the susceptibility model was performed in three steps. In the first step, a set of descriptive statistics (minimum, maximum, average, median and standard deviation) were computed for each DTM. Histogram for slope angle maps derived from each product and a map of elevation difference between the DTMs were calculated. These first steps was performed to evaluate similarities between the two products.

In the second step, the Information Value of each class of each parameter was computed and the final susceptibility map was obtained. Model fit and model predictive performance were quantified using the Area Under the Receiver Operating Characteristics curve (AUC_{ROC}), a general measure of model quality (Bradley, 1997; Fawcett, 2006).

Finally, in the third step the final susceptibility maps were classified in five classes using an area criterion. Homonymous classes between the maps have the same area, allowing a first assessment of the spatial pattern of susceptibility depicted by each map. The susceptibility was classified as follows: Very High (10% of the area); High (20% of the area); Moderate (20% of the area); Low (20% of the area; and Very Low (30% of the area).

4 RESULTS AND DISCUSSION

4.1 Descriptive statistics

DTMs have similar descriptive statistics (Table 1) and similar elevation histograms. The median showed thar the lower elevation values influence the average. Standard deviation values (STD) showed that both DTMs have a similar dispersion of their elevation values

Table 1. DTMs descriptive statistics

DTM	Min	Max	Average.	Median	STD
TanDEM-DTM	274.1	980.0	693.4	774.4	195.0
Topo to Raster	277.6	993.8	693.2	771.4	195.6

Slope angle histograms (Figure 3) have unimodal distributions and peaks between 20º and 30º. The peaks were less pronounced for the slope derived from *TanDEM-DTM* data, which has a lower number of pixels between 20º and 30º. *Topo to Raster* DTM depicts more areas with high slope angles (> 30º), which are considered the most susceptible areas in the Serra do Mar (De Ploey and Cruz, 1979; Dias *et al.*, 2017; Martins *et al.*, 2017).

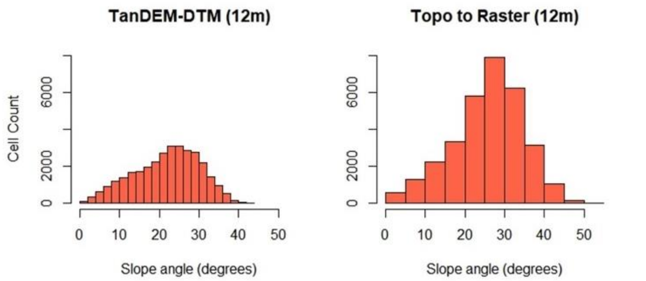

Figure 3: Slope angle histograms derived from *TanDEM-DTM* (left) and *Topo to Raster* (right).

Despite similarities of the descriptive statistics, elevation difference between the DTMs are concentrated in specific areas, ranging up to 63.7m. Largest positive discrepancies are concentrated in the valley bottom and adjacent areas, while the largest negative discrepancies (*Topo to Raster* DTM has a higher elevation value than *TanDEM-DTM*) are located in interfluvial sectors.

These differences may be attributed to the application of hydrological corrections during the interpolation process with *Topo to Raster* method, which uses the input drainage network vector to ensure drainage connectivity.

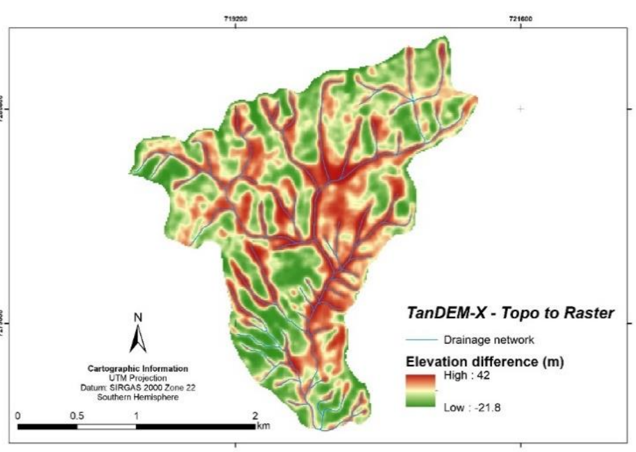

Figure 4: Elevation difference map obtained by subtracting the elevation values from *Topo to Raster* DTM from *TanDEM-DTM*.

4.2 Model fit and model predictive performance assessment

The IV values computed for the input data derived from *TanDEM-DTM* ranged between -5.84 and 2.09, while the model generated with input data derived from *Topo to Raster* DTM had variation between -5.33 and 2.33 (Figure 5). In both susceptibility models, the highest IV were computed for the slope angle class > 36º. A positive IV was also computed for the areas with slope angles between 30º and 36º.

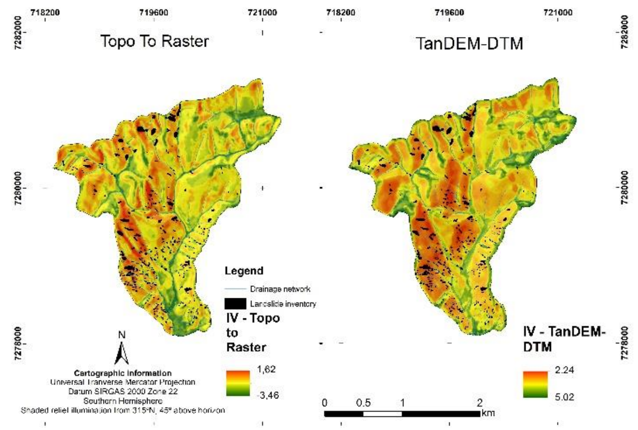

Figure 5: Susceptibility maps generated using the Information Value model and input data derived from *Topo to Raster* DTM (left) and *TanDEM-DTM* (right).

The IV results using data derived from *TanDEM-DTM* presented a better model fit compared to the one derived from *Topo to Raster* DTM (AUC_{ROC} equal to 78.9% and 77.0%, respectively) (Figure 6). As well, the predictive performance of the IVderived from *TanDEM-DTM* was higher (AUC_{ROC} equal to 82.4% and 76.7%, respectively).

It is unusual for the predictive performance to be superior to the model fit, as in the case of the susceptibility model generated with *TanDEM-DTM*. This may be related to uncertainties associated with the random partitioning of the landslide inventory that were not evaluated in this paper. Thus, such differences of predictive performance cannot be entirely attributed to the influence of elevation data on the susceptibility model.

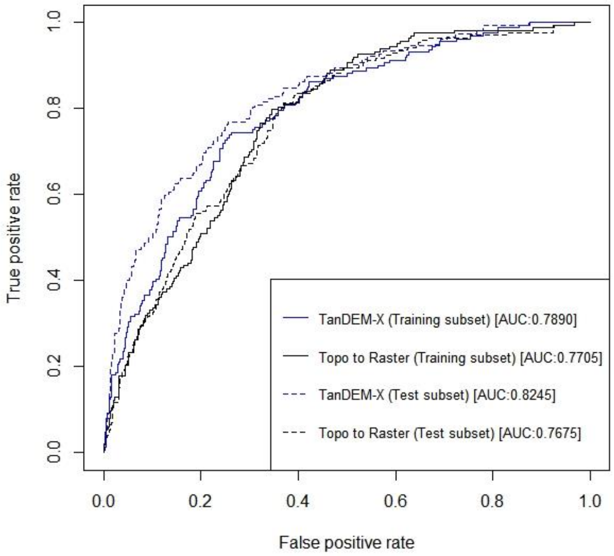

Figure 6: Receiver Operating Characteristics curves and area under the ROC curve for both susceptibility models.

The final classified maps showed significant visual differences in their spatial patterns of susceptibility (Figure 7). The highlighted sector (Figure 7) corresponds to an area where there is a discrepancy in elevations values between DTMs up to 42m (Figure 4), demonstrating the influence of elevation data on the spatial pattern of susceptibility of the final maps.

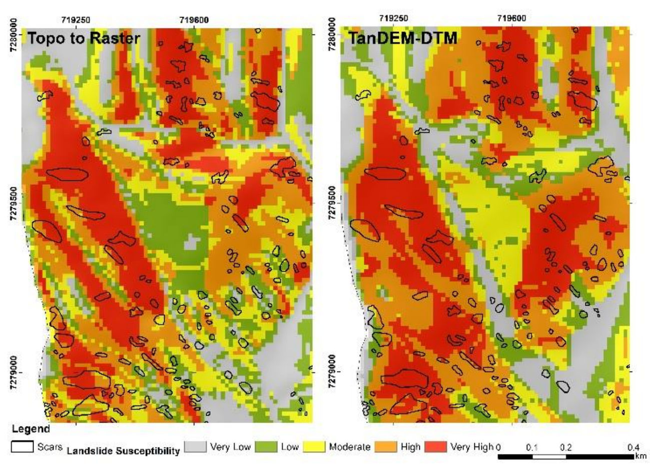

Figure 7: Classified susceptibility maps for *Topo to Raster* DTM (left) and *TanDEM-DTM* (right).

5 CONCLUDING REMARKS

The susceptibility analyses performed with *TanDEM-DTM* and *Topo to Raster* DTM showed similar model fit, with higher predictive performance for the model obtained from input data derived from *TanDEM-DTM*. However, although area under the ROC curve values area similar, the final maps depicted different spatial susceptibility patterns.

These differences cannot be totally linked to differences in the DTMs, since uncertainties associated with the random partitioning of the landslide inventory were not evaluated in this study. However, the differences between the slope angle maps derived from each DTM suggests that the elevation data has strong influence over the spatial susceptibility pattern depicted in maps.

Future works can evaluate the influence of inventory partitioning, aiming to isolate and quantify the influence of elevation data on the spatial susceptibility patterns of the maps generated through statistical analysis. Other datasets can also be included in the analysis (SRTM; ALOS AW3D; etc.).

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