The potential of PALSAR RTC elevation data for landform semi-automatic detection and landslide susceptibility modeling

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ABSTRACT
This study demonstrated the potential of methods derived from geomorphometry and regression models to evaluate landslide susceptibility in a study area located in southern Colombia. From a morphometric stance, the first step was to evaluate the quality of DEM sources by comparison to control points obtained by static-mode GPS. The PALSAR_RTC_hi data was selected for having the best accuracy of heights and was used to derive terrain parameters at SAGA software. Then, the Principal Component Analysis selected variables with low collinearity, and we classified twelve landforms using fuzzy k-means algorithm, which was compared to a geomorphological map by using the multinomial logistic regression method in R software. We got a Kappa coincidence index of about 30%. The resulting landslide susceptibility mapping took dependent (a mask with unstable-stable cells from an existing landslide inventory) and independent variables (selected morphometric ones). The binary logistic regression showed the propensity of the area to be adversely affected by landslides. This model’s performance was tested with a ROC curve over a sample, with 20% of landslide database resulting in an Area Under the Curve of 0.55. This result was contrasted with a spatial prediction model of debris flow, explaining the high frequency of avalanches.

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Introduction
Landslides are one of the greatest natural threats to human endeavors, as they often cause human and economic losses, as well as property damage, and elevated costs in infrastructure maintenance (Shahabi, Khezri, Ahmad, & Hashim, 2014). Susceptibility maps are essential to identify the potential loss of areas affected by these geological processes, minimizing its impact (Das, Sahoo, van Westen, Stein, & Hack, 2010).

This study demonstrated the relevance and validity of using statistical and geomorphometric methods to predict landslide susceptibility and the quantitative evaluation of quality on the input variables used in the prediction model. The analysis started on the automatic delineation of the landforms based on the implementation of Digital Elevation Models (DEMs), derived from satellite synthetic aperture radar (SAR) interferometry technology, which allowed to improve spatial resolution, geographical coverage, and, mainly, the quality of the data.

We selected terrain parameters through preprocessing, processing, and characterization of an elevation source (PALSAR_RTC_hi data) at 12.5 m resolution) in a central eastern zone of the department of Cauca, Colombia, located between 76°40′25″ W, 02°14′09″ N, and 76°24′13″ W, 02°36′24″ N, and at a scale of 1:25K. The comparison of 3D coordinates determined that the vertical accuracy of DEM has the potential for obtaining soil parameters at a regional-level scale; 12 landforms were distinguishable from a statistical point of view, with an index of coincidence of 0.28.

Those above allowed the derivation of terrain parameters, the multivariate analysis of them, the fuzzy k-means classification of the landforms and the combination of terrain parameters with a logistic regression approach to obtain a model of prediction of landslide susceptibility. In the first case, we obtained a landform classification accuracy of 28%; in the second, an accuracy of 55%; and a qualitative evaluation of the prediction quality. The results showed the DEMs capability for quantitative analysis of the indicated geomorphological processes.

Theoretical framework
The landslide susceptibility analysis consists of a quantitative assessment of the classification, volume

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1 Dataset: ASF DAAC 2010, ALOS-1 PALSAR_Radiometric_Terrain_Corrected_high_res; Includes Material © JAXA/METI 2007. 10.5067/Z97HFCNKR6VA.

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and spatial distribution of slope instabilities to determine the potential occurrence of these geological processes in a given area (Barbieri & Cambuli, 2009). According to Gruber, Huggel, and Pike (2009), landslide susceptibility methods assume that a landslide is more likely to occur under causative factors, which are similar to those that caused past landslides. From a quantitative perspective, two approaches can be adopted for its implementation: the first one is deterministic and consists of the dynamic modeling, with mathematical methods, of the physical mechanisms that control slope failure. It is a highly localized approach because of the requirements for detailed data and relies on expert knowledge. Some reports with this approach can be found in Amoroso, Totani, and Totani (2011), Riquelme, Cano, Tomás, and Abellán (2016), Saade, Abou-Jaoude, and Wartman (2016) and Rogers and Chung (2017). The second approach depends on measuring the relevance of causative factors by establishing correlations between previous landslides and geo-environmental variables to predict areas of landslide initiation with a similar combination of factors from local to regional scales (Baeza, Lantada, & Amorim, 2016; Vorpahl, Elesineer, Märker, & Schröder, 2012). This is achieved through techniques such as: discriminant analysis, multivariate statistics, frequency ratios, information value method and logistic regression methods (Mahalingam, Olsen, & O’Banion, 2016). This approach has the advantage of removing the bias from expert judgment, as well as expressing the variability located in the data set (Das, Stein, Kerle, & Dadhwal, 2012).

In studies about landslides, the logistic regression (LR) model incorporates the occurrence of landslides as a discrete and dichotomic variable, and the geo-environmental factors which influence it as explanatory ones (Das et al., 2010). The response variable is the inventory map of landslides over a road section represented in a binary way, while the explanatory variables are the geo-environmental factors that influence landslides: slope, aspect, lithology, units of terrain, land use, soils, geological structures (lineament density), weathering, and drainage density (Martha, van Westen, Kerle, Jetten, & Vinod Kumar, 2013).

The purpose of LR in the case of mapping landslide susceptibility is to describe the relationships between the presence or absence of landslides (dependent variable) and the set of independent parameters such as slope, land use, and lithology. The evaluation of the model can be developed in consideration to another dataset in the same area, or it can be tested in adjacent areas with similar geo-environmental conditions, to find its reliability (Shahabi et al., 2014).

Since the morphological signature of a landslide is an attribute that contributes to its computational delineation, it is important to define the geometric and topological characteristics of the landforms regarding elevation changes in a local neighborhood (Evans, 2012). Morphological signatures can be obtained through the automatic detection of constitutive objects (attributes) of the terrain (Pike, Evans, & Hengl, 2009), as well as descriptive measures (Wilson, 2012). The accuracy of this delimitation depends mostly on the supervised and unsupervised classification of DEM (Anders, Smith, Seijmonsbergen, & Bouten, 2011). Differences between these two segmentation methods can be found in Zhang, Fritts, and Goldman (2008); the quantitative and objective evaluation are the characteristics of unsupervised methods.

The input data used for the analysis and geomorphometric classification of the terrain elements, and for the susceptibility prediction, came from radar technology and are retrievable from sources such as SRTM (Elkhrachy, 2016; Jacobsen, 2004), ALOS PALSAR (Richards, 2009), TanDEM-X (Prashad, 2014), and the Advanced Spaceborne Thermal Emission and Reflectance Radiometer Global Digital Elevation Model (ASTER G-DEM) (Toutin, 2008; Wilson, 2012), among others. These data are stored in a DEM, which is a rectangular arrangement of points in Cartesian space with assigned elevation values that describe the surface of the terrain. For the pre-processing of this information, we evaluated the quality of SRTM3 (3 arc-second resolution), SRTM1 (1 arc-second resolution), ASTER GDEM, PALSAR_RTC_hi data by comparison to a reference DEM derived from topo-map at the scale of 1:25K and GPS-static surveying. The PALSAR_RTC_hi data were finally chosen due to its better accuracy.

The algorithms, based on geomorphometric parameters, allow a differentiation of cells as follows: pits (all the higher neighbors), peaks (all the lower neighbors), channels (neighbors on the two higher opposite sides), ridges (neighbours on the two lower opposite sides), passes (neighbours on the two higher opposite sides and over the lower orthogonal side), and plain (undefined curvature defining different forms) (Pike et al., 2009). The potentiality of this approach was studied by Wood (1996), who demonstrated how these methods could be applied to extract and classify geomorphological objects through a scale hierarchy by inserting them within the calculation of raster windows of variable dimensions.

The collection of descriptive statistics tables of the acquired parameters allows performing a bivariate analysis to establish the amount of similar information that each parameter had, and thus to establish the pertinence of the DEM. Recent developments for the identification of terrain forms include the use of automatic fuzzy classification algorithms to detect the distribution of terrain shapes. The use of land-surface parameters with fuzzy k-means classification (Arrell, Fisher, Tate, & Bastin, 2007) to delineate landform classes must begin with a correlation analysis (PCA) to confirm that candidate entries are not highly related to others.
Methodology

The flow diagram shown in Figure 1 presents the stages of the applied methodology for delineating the landforms and the propensity of the terrain to landslides. The overall stages were landform detection and landslide susceptibility prediction. Landform detection consisted of pre-processing and classification. Pre-processing focused on the evaluation of the DEMs quality, the algorithms of geomorphometry implemented in the libraries of the SAGA software (Conrad et al., 2015) and the PCA (Campo, Pardo, Cesar, Torres, & Sadinle, 2017) for the selection of independent morphometric variables. Classification stage used the fuzzy k-means classification (Venables & Ripley, 2002) as the unsupervised method for the identification of landform classes and the multinomial logistic regression method for the validation of the landform classification model. The construction of the prediction model of landslide susceptibility corresponds to the errors theory and the generalized linear models (Vorpahl et al., 2012), such as logistic regression (LR). The Modified Single Flow Direction model (Pike et al., 2009) allows modeling the maximum potential flood area of a landslide event, starting from an initialization point and analyzing the path of the most pronounced descending slope.

Study area

The study area is located on the south west of Colombia (Figure 2) between the coordinates 2°24′10.86″ north and 76°34′25.44″ west, and 2°26′50.91″ north and 76°31′44.76″ west, with an extension of 25 square kilometers. The zone is crossed by a primary road network and contains several watercourses, some of the tributaries of the Molino river. The zone is characterized by moderate relief with ellipsoidal elevations from 1837 m to 2327 m above sea level (a.s.l).

Results and discussion

Quality of the DEM

The accuracy of the PALSAR_RTC_hi data was evaluated by comparing the heights to control points obtained with a sub-metric accuracy GPS, VRMS of 0.33 m from differential GPS method. We obtained an ellipsoid height accuracy of 5.77 m, lower than the vertical accuracy of 12.5 m for a topographical sheet at a scale of 1:25K in Colombia, using the Demanal module of the BLUH software and according to the Jacobsen methodology (Jacobsen, 2004).
Table 1 shows the DEMs quality evaluation from the three arcsec-SRTM, one arcsec SRTM, and ASTER-GDEM as well as PALSAR_RTC_hi data sources. GPS control points over the road network of the study area were the comparison pattern. As a result of relative accuracy analysis, we selected PALSAR_RTC_hi data because of its smaller error of heights and better spatial resolution. For absolute accuracy analysis of DEMs, we compared PALSAR_RTC_hi data against a topo-map DEM at 30 m resolution, obtained by interpolation with the spline method (Mitáš & Mitášová, 1988) from level curves at 1:25K scale, gave an average quadratic error of about 40 m, a difference explained in the vertical reference datum (ellipsoidal vs. geoidal) (Federal Geographic Data Committee, 2008) (Figure 3). Finally, we derived another DEM by Kriging interpolation, the best method for the generation of DEMs (Chaplot et al., 2006). It was done by adjusting a semi-variogram model of the type “Bessel” to the PALSAR_RTC_hi data elevations with parameters (nugget = 10 m, partial sill = 85 m, and range = 884 m). The ratio nugget/sill about 10% indicated a strong spatial correlation of height DEM, according to Kravchenko (2003) (Figure 4).

Selection of input variables

Inventory of mass movements

Along the road crossing the study area, landslides were located with the GPS in fast static mode, with a maximum error about 5 m, according to Feo,

Table 1. Comparison of the height accuracy of the DEMs used.

| DEM             | Source                        | Data File Name               | Resolution (m) | Error (m) |
|-----------------|-------------------------------|------------------------------|----------------|-----------|
| 3 arcsec-SRTM¹  | CGIAR-CSI                     | Srtm_21_12.zip               | ~90            | 10.89     |
| 1 arcsec-SRTM²  | USGS                          | SRTM1N02W077v1               | ~30            | 10.59     |
| ASTER GDEM V001¹ | NASA Earthdata               | ASTGM.001:2076838685        | ~30            | 19.2      |
| PALSAR_RTC_hi²  | ASF's Data Portal             | ALPSRP230780030              | 12.5           | 5.77      |

¹http://srtm.csi.cgiar.org/
²https://earthexplorer.usgs.gov
³https://asterweb.jpl.nasa.gov/gdem-wist.asp
⁴https://www.asf.alaska.edu/doi/105067/z97fcknsr6va/

Figure 2. Spatial data input in the study area for the terrain modeling.
Martinez, and Muñoz (2016). We found rotational, translational, and falling landslides in 11 sites. These correspond to the binary classification of the dependent variable in the prediction model of landslide susceptibility. Also, we extracted landslide locations from Mass Movement Information System “SIMMA” of Colombian Geological Services (SGC). The 28 events found were separated in 20 events for training.
and eight points for the validation process. In this zone, there were five falls, four rotational and 19 translational slides.

**Automatic delineation of the landforms (un-supervised k-means classification)**

The detailed method for unsupervised classification of landforms using the fuzzy k-means classification method is found in Hengl (2009) and Martínez and Correa (2016). This methodology was applied in the study area where we found, with an Independent PCA, that the variables: vertical depth of the valleys (V-DEPTH), topographic wetness index (TWI), multiresolution index of valley bottom flatness (MRVBF), insolation (INSOLAT), elevation DEM, convergence index (CONVI), and slope (SLOPE), provided non-duplicate information for the design of a landform classification model (Figure 5). The selection of these parameters prevents the multicollinearity effect as it is recommended by Schoch, Blöthe, Hoffmann, and Schrott (2018).

The Valley depth variable allows identifying vertical differences in the relief (Conrad, 2007), while topographic wetness index describes the topographic effect on water accumulation (Wilson & Gallant, 2000). Results derived from the MRVBF allow highlighting valleys located in large areas (Wang & Laffan, 2009). The insolation which exerts a high impact in evaporation of terrain surface and it has strong relationships with topography and the convergence index proposed by Köthe, Gehrt, and Böhner (1996) estimates the convergence and divergence of flow as well as the slope whose values allows to identify the steepest zones in the study area.

The variables above were used like explicative ones for semi-automatic classification of landforms.

We obtained a semi-automatic classification of landforms with the fuzzy k-means classification (Hengl, 2009), an approach implemented in R software (Development Core & Team, 2011). This method assigns an abstract class to each pixel; the class centers were selected in such a way that the sum of the squares was minimal within the groups. The optimal number of classes for the fuzzy clustering was 12, according to Venables and Ripley (2002). The obtained prediction map of the landforms showed well distributed and spatially continuous polygon sizes (Figure 6). The peaks of the hills were enhanced and the transversal section of the terrain, passing through the foot of the slopes and the valleys, with higher relative height.

The terrain surface parameters were used to improve the spatial detail of an official geomorphology map at a scale of 1:100K with the multinomial logistic regression algorithm of the “nnet” package (Venables & Ripley, 2002). This method iteratively adjusts logistic models, for a selected number of classes, to a group of training pixels until the maximum cartographic accuracy is achieved (Hengl, 2009). The comparison of the unsupervised classification model, using the “mda” package of R software, of the landforms against the existing geomorphology map yielded a coincidence index of 0.28.

According to Hengl (2009), this low matching is typical in geo-morphological applications and can be explained because of polygons of the reference map are heterogeneous (Figure 7). The method of training pixels selection (medial axis with “rpoint” method of “spatstat” of R package) assumes that the map has the same quality in all of the study areas.

**Multivariate analysis of morphometric variables to predict landslides**

In the SAGA software (Conrad et al., 2015), the following parameters of the terrain were derived from the PALSAR_RTC_hi data: slope, aspect, curvature, accumulation area, topographic wetness index, convergence

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Figure 5. PCA graph is showing the independent components of the morphometric variables derived by geomorphometry algorithms.
index, depth of the valleys, insolation, and landform. These were derived using geomorphometry algorithms available in the SAGA software (Table 2).

We elaborated a multivariate table with the results of the parameters above. For doing that, we applied the FactoClass package (Campo et al., 2017) of R software (Development Core & Team, 2011), and we obtained a representation of the better variables in the first factorial plane of the PCA method (Figure 8). The classification of the landforms by k-means algorithm showed to be independent of the terrain slope ($r = 0.08$), which is not the case in the landform classification algorithm implemented in the SAGA software, for it is highly correlated with the slope.

Figure 6. The result of the unsupervised classification overlapped on a layer of terrain shading.

Figure 7. Geomorphological map derived of soil map at a scale of 1:100K.
The set of variables decorrelated by PCA: topographic wetness index, convergence index, slope and landforms, the last derived by fuzzy k-means classification, were used as independent variables in a prediction model of landslide susceptibility using the binary logistic regression method. Table 3 shows the LR probability running alternatives in Arc View GIS 3.2 module ArcSDM (Kemp, Bonham-Carter, Raines, & Looney, 2001), which allowed to run the Weight of Evidence (WofE) (Neuhäuser & Terhorst, 2007) and Logistic Regression models. Similar results were obtained using landform derived with SAGA software and k-means algorithm. The best results were achieved with landslide inventory performed along the road network. It can be explained because the most critical events were found over the Molino river watershed and the road axis is parallel to this watercourse.

Figure 9 shows the alternatives with the highest probability. The landslide susceptibility map on the left-side was obtained with a landform derived with algorithms implemented on SAGA software and k-means classification. Both alternatives used the landslide inventory over the road axis. The conclusion is that both alternatives are similar, and being the k-means landform classification more expensive regarding time, a landforms classification with faster methods gave better results.

Equations (1) and (2) show the fitting of data to a logit function.

\[
\text{Logit function } = -8.61 + 0.45M_{\text{TWI}} + 0.95M_{\text{Slope}} + 0.12M_{\text{landformSAGA}} + 0.03M_{\text{CONVI}}
\]

\[
\text{Logit function } = -8.31 + 0.54M_{\text{TWI}} + 1.04M_{\text{Slope}} - 0.13M_{\text{landformK-Means}} - 0.16M_{\text{CONVI}}
\]

Considering the first alternative, which includes the SAGA landform classification and landslide road inventory, it was found that the morphometric parameters more correlated (based on Contrast value) with landslide events are: TWI, SLOPE, TPI, and CONVI. The main contributions of terrain parameters correspond to TWI values between 9.1 and 10.2 or toe slope where there is more water content; SLOPE range 30 to 35° (moderately steep); TPI-based landform classification as streams and mid-slope drainage and CONVI values varying from 90.4 to 109.8 or divergence zones. This model has SLOPE and TWI variables as the highest contrast value, which indicates that they have a high correlation with landslides.

On the other hand, the second susceptibility model contains the SLOPE (C = 8.49) and LANDFORM K-MEANS (C = 6.3) as the most positive correlation with landslides. TWI values between 9.1 and 10.2,

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Table 2. Methods for deriving morphometric parameters of the terrain.

| #  | Parameter              | Method                        |
|----|------------------------|-------------------------------|
| 1  | Slope, Aspect, Curvature | (Zevenbergen & Thorne, 1987) |
| 2  | Topographic Wetness Index | Standard (Conrad, 2007)       |
| 3  | Index of Convergence   | (Köthe et al., 1996)         |
| 4  | Deepness of the Valleys | (Conrad, 2007)                |
| 5  | Insolation             | (Gallant & Downing, 2003)    |
| 6  | Landforms              | (Hengl, 2009)                |

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Figure 8. The first factorial plane of the PCA with the representation of the morphometric variables of the terrain obtained by geomorphometry algorithms.
SLOPE between 30 and 35°, LANDFORM K-MEANS class of streams and mid-slope drainage and CONVI between 90.4 and 109.8, were the classes more highly related to landslides.

An overall test of conditional independence gave a value of 0.86 and 0.63, respectively, for both models analyzed.

These results showed that morphometric variables, slope, and topographic wetness index are statistically significant variables, and suggest a strong association with the probability of landslide. The typical ROC curve (Beguería, 2006) that measures performance for a binary classifier gave an area under the curve (AUC) of 0.55, which indicates a correct classification rate in the 55% of cases (Figure 10).

The validation of this prediction was based upon the MSF (Modified Single Flow Direction) model (Huggel, Kääb, Haeberli, & Krummenacher, 2003). This method is based on a principle of propagation of the debris flow down the slope, defined as an initialization point. The model defines areas potentially affected by the debris flow by assigning to each cell the relative probability of being affected (Figure 11). The directions of propagation of potential land flow toward the Molino river, on whose afferent area passes the Popayán - Patico route, explains the exposure of some areas of the city in historical events.

### Conclusions

We used algorithms developed within the field of geomorphometry, based on DEM, for the prediction of landslide susceptibility in a study area located in the eastern-center of the department of Cauca, Colombia.

The method of prediction of susceptibility applied was the binary logistic regression model, which considered, as a dependent variable, a map of unstable zones (unit values) and not unstable (null values), and as independent variables, the morphometric parameters derived from the PALSAR_RTC_hi data, which are: slope, convergence index, topographic wetness index, and landforms. The PCA guaranteed the contribution of these parameters to the total variability of the model. This model was validated with the debris flow propagation model, by choosing points of initiation of possible instabilities in the places with a more significant propensity or susceptibility to landslides. This result explains the potential impact over the Molino River to be under potential avalanches due to landslides on its afferent slopes.

The independent factor of the landforms, introduced in the model of landslide prediction, was subjected to an individual modeling by fuzzy k-means classification, using as independent components the following morphometric parameters, also, derived from the PALSAR_RTC_hi data: depth of the valleys,
topographic wetness index, multiresolution index of valley bottom flatness, insolation, elevation DEM, convergence index, and slope. This automatic classification model of landforms was compared to a geomorphology map at a scale of 1:100K by multinomial logistic regression, resulting in a 30% coincidence (kappa index). This low matching is explained at the low detail of the geomorphology map, against which the semi-automatic landform classification was compared. Also, we used the TPI-based landform classification implemented on SAGA GIS software. The conclusion obtained is that both
alternatives gave similar results indicating that the landform classification of SAGA software is more effective than k-means landform classification.

The PALSAR_RTC_hi data were chosen as a source of ellipsoidal elevation data because a quality evaluation of the DEMs: 3 arcsec SRTM, 1 arcsec SRTM 1, ASTER and PALSAR_RTC_hi data, showed that it had the smallest error (~ 6 m) which corresponded to a 1:25K scale according to the Colombian cartographic standard. The PALSAR_RTC_hi data were also compared with a topo-map DEM at 30 m resolution obtained by spline interpolation of level curves at a scale of 1: 25K, which yielded an average quadratic difference of about 40 m which is explained in its vertical datum (average sea level) against the DEM generated with radar technology (ellipsoid of reference).

Disclosure statement
No potential conflict of interest was reported by the authors.

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