Predicting depositional areas of landslides by training multivariate statistical models with four data sets extracted from landslide areas: a case study of rainfall-induced by Ida Hurricane in 2009 on Ilopango Lake, El Salvador.

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INTRODUCTION

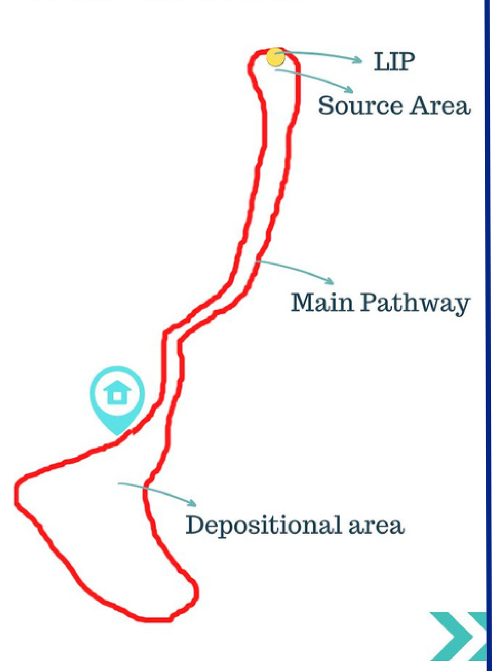
In the literature, prediction of landslide spatial distribution based on a stochastic approach is usually performed by associating the occurrence of past slope failures with the environmental characteristics of their source area or more specifically of their highest point, which is known as Landslide Identification Point (LIP).

In landslide events, most damage occurs in the lowest parts, where houses, farms, and roads are generally located. However, the environmental characteristics of the accumulation zone could be very different from those of the source area.

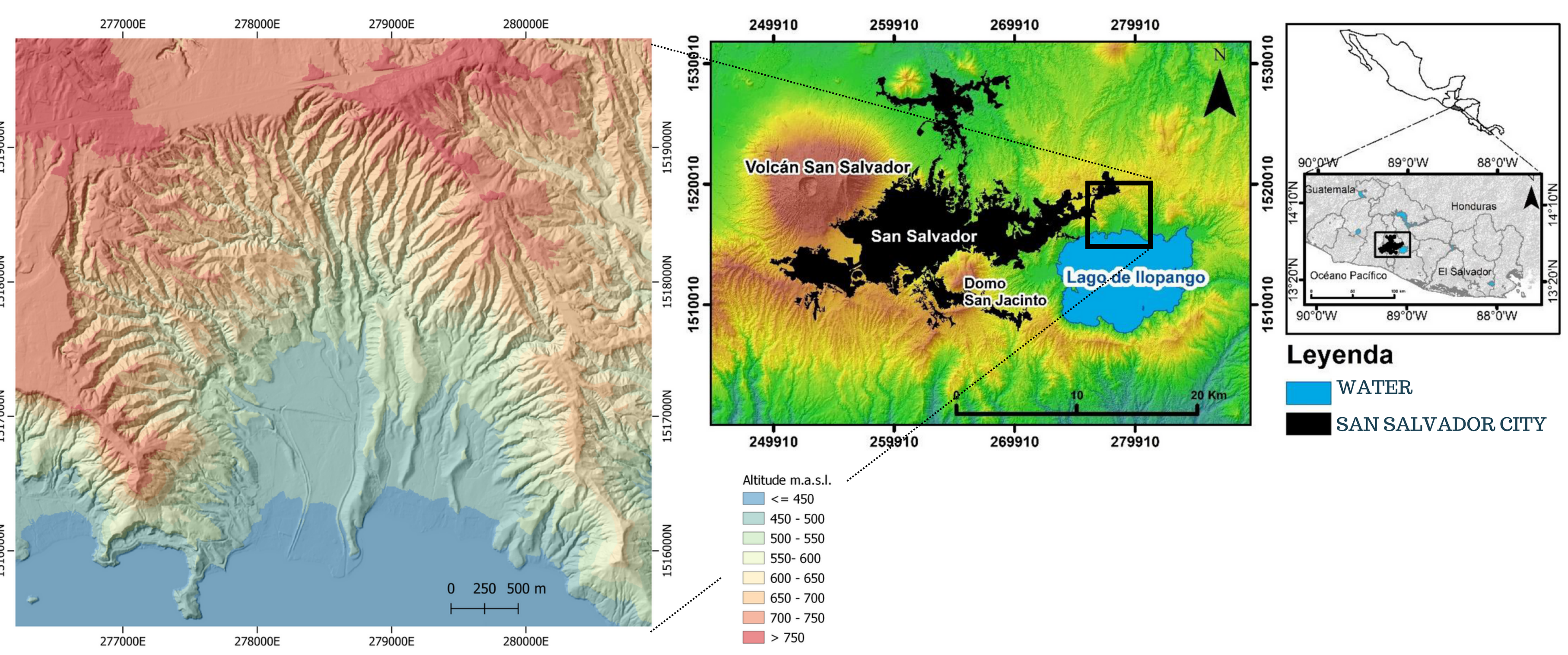
El Salvador is located in the Intertropical Convergence Zone (ITCZ), so it does not present large temperature fluctuations throughout the year, and the temperature depends on the altitude. Nevertheless, during the months between June and November, disturbances can occur that generate low-intensity precipitation producing significant amount of rain, such as the Ida Hurricane in November 2009. During its passage through El Salvador, this hurricane produced torrential rainfalls that caused many flooding and landslides and as result a significant loss of life and property.

For this reason, the aim of the project is to unravel if models build with only the LIP are capable to predict the landslide area, particularly the lowest part, and determine what kind of inventory and variables are useful to effectively predict landslide areas, using as a case of study a drainage basin located in the northern sector of the Ilopango Caldera, El Salvador. Multivariate Adaptive Regression Splines (MARS) was employed as modeling technique. MARS was calibrated and validated by using ten training and ten test samples. The area under the Receiver Operating Curve (AUC) was used to measure the predictive performance of the MARS repetitions.

Debris Flow

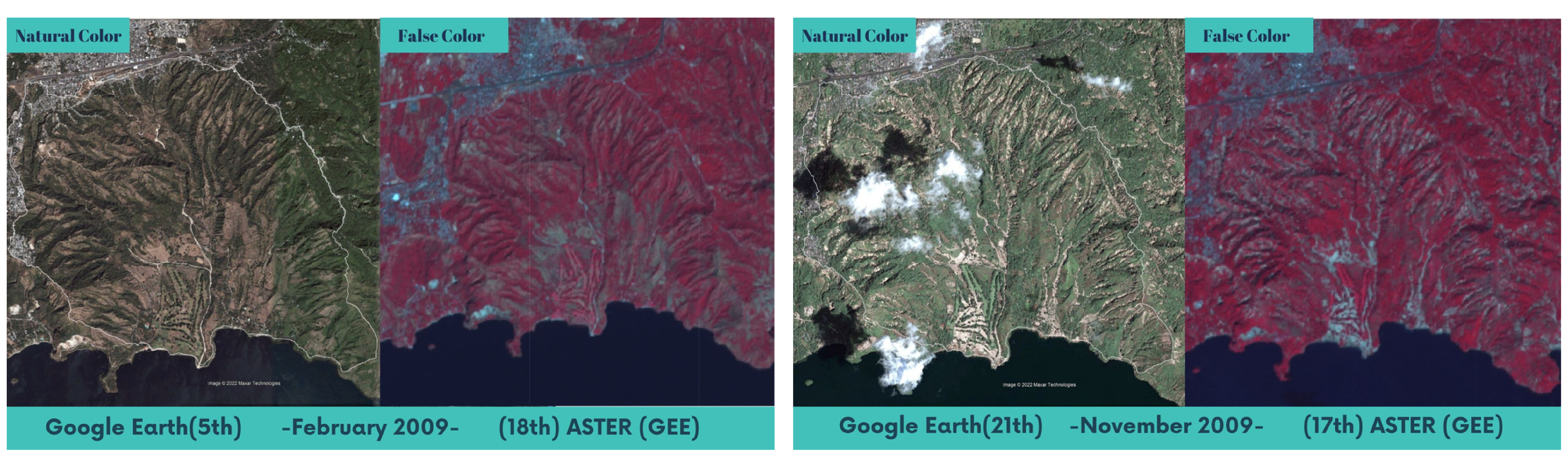


STUDY AREA



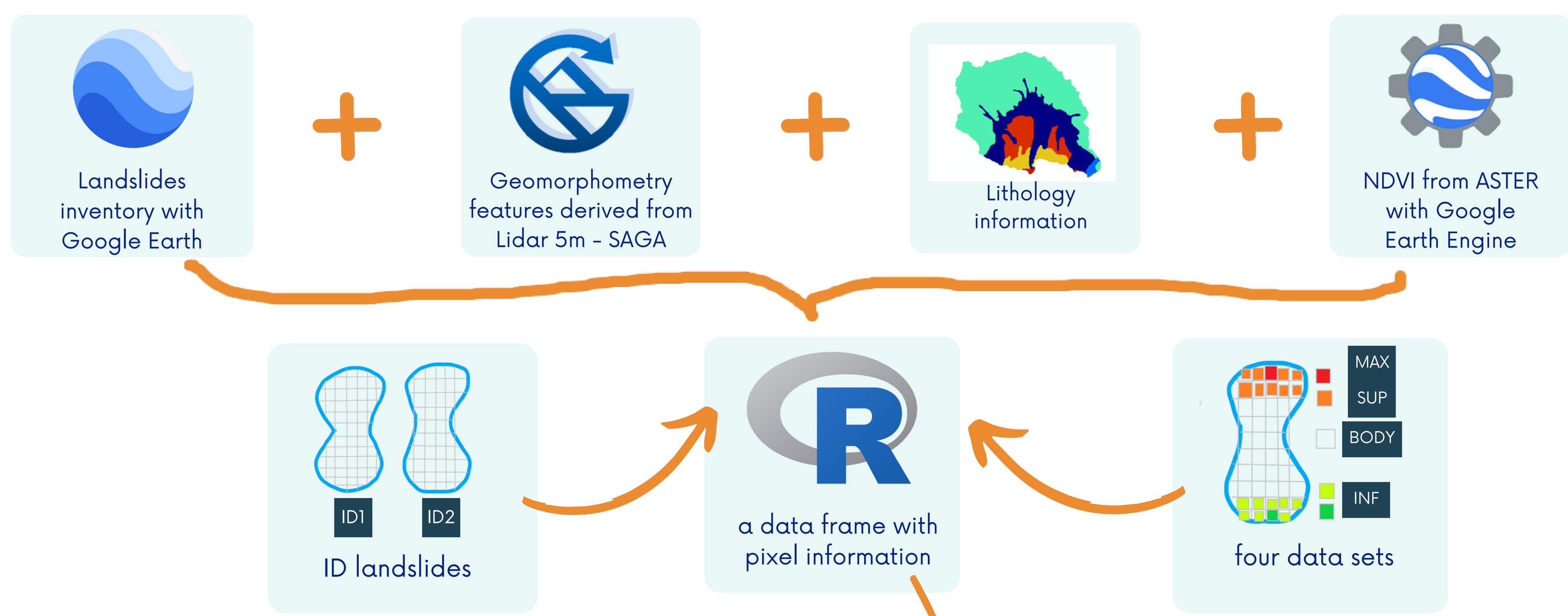
The basin located at northern part of Ilopango Caldera - Area: 11 km2

BEFORE **AFTER**



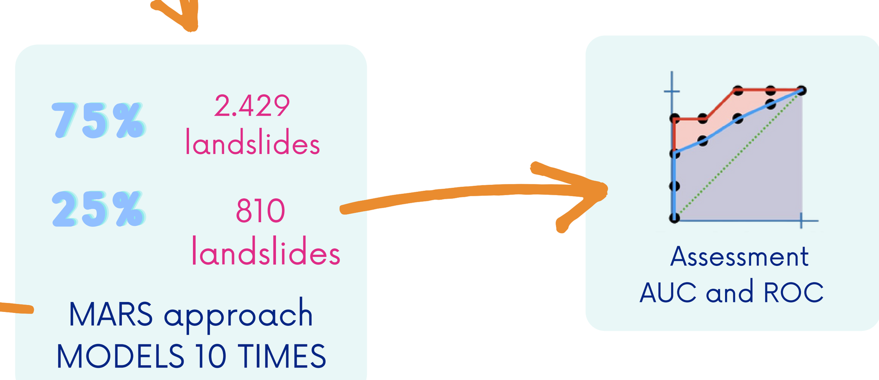
Images from Google Earth and Aster of the land area before and after Ida Hurricane 2009

METHODOLOGY



The most important predictors selected by MARS when applied to the four data sets are:

- 01 Slope Length Factor (LSF)
- 02 Normalized Difference Vegetation Index (NDVI)
- 03 Terrain Ruggedness Index (TRI)
- 04 Lithology (Piroclastic rocks)
- 05 Topographic Position Index (TPI)
- 06 Aspect NE and NW



RESULTS

These tables report the AUC values achieved by MARS models trained and validated with the four datasets.

to predict the BODY area

	MEAN_BODY	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	SD
auc_testBODY_BODY	0.82	0.82	0.81	0.81	0.82	0.81	0.82	0.82	0.81	0.83	0.82	0.0018
auc_testBODY_INF	0.78	0.78	0.77	0.78	0.78	0.78	0.79	0.79	0.77	0.78	0.78	0.0020
auc_testBODY_MAX	0.75	0.75	0.74	0.74	0.75	0.75	0.74	0.75	0.75	0.75	0.74	0.0013
auc_testBODY_SUP	0.76	0.76	0.75	0.75	0.75	0.75	0.75	0.76	0.77	0.76	0.76	0.0019

to predict the INF area

	MEAN_INF	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	SD
auc_testINF_BODY	0.84	0.85	0.84	0.84	0.83	0.83	0.85	0.84	0.83	0.83	0.85	0.0024
auc_testINF_INF	0.88	0.89	0.88	0.88	0.88	0.87	0.89	0.88	0.87	0.88	0.88	0.0018
auc_testINF_MAX	0.61	0.61	0.61	0.59	0.61	0.61	0.64	0.64	0.59	0.58	0.65	0.0066
auc_testINF_SUP	0.63	0.63	0.63	0.62	0.64	0.64	0.65	0.65	0.63	0.62	0.63	0.0034

to predict the MAX area

	MEAN_MAX	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	SD
auc_testMAX_BODY	0.74	0.75	0.74	0.76	0.74	0.76	0.71	0.73	0.75	0.74	0.77	0.0047
auc_testMAX_INF	0.62	0.61	0.62	0.63	0.62	0.64	0.59	0.61	0.63	0.62	0.64	0.0043
auc_testMAX_MAX	0.82	0.81	0.82	0.83	0.83	0.84	0.81	0.81	0.81	0.82	0.83	0.0034
auc_testMAX_SUP	0.82	0.82	0.82	0.83	0.83	0.84	0.81	0.81	0.81	0.82	0.84	0.0030

to predict the SUP area

	MEAN_SUP	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	SD
auc_testSUP_BODY	0.76	0.77	0.76	0.75	0.76	0.78	0.76	0.77	0.75	0.76	0.77	0.0027
auc_testSUP_INF	0.65	0.66	0.65	0.64	0.65	0.67	0.65	0.66	0.64	0.64	0.64	0.0028
auc_testSUP_MAX	0.83	0.81	0.83	0.81	0.83	0.84	0.85	0.84	0.81	0.83	0.83	0.0047
auc_testSUP_SUP	0.83	0.82	0.82	0.81	0.84	0.84	0.84	0.83	0.81	0.82	0.83	0.0037

The INF model achieves the highest AUC values, allowing us to accurately predict the entire landslide area as well as the landslide deposition zone.

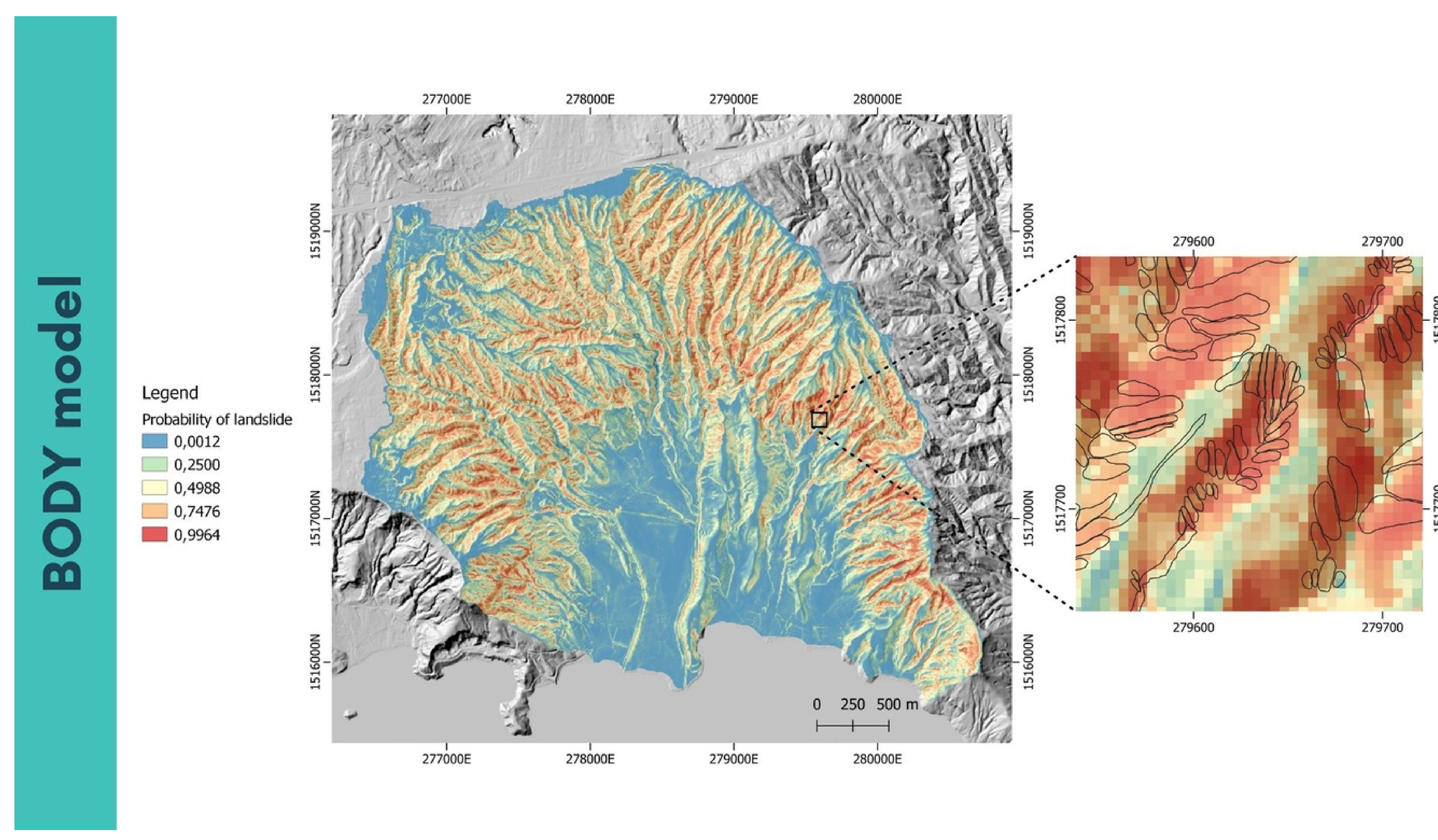
On the other hand, models trained on MAX and SUP data sets obtain excellent (i.e. AUC > 0.8) prediction of source areas whereas fail to predict depositional areas. Similarly, validation of the INF model reveals a poor ability to predict the landslide source areas.

Finally, BODY models perform excellently only when applied to discriminate between landslide bodies and stable slopes.

CONCLUSIONS

- The best model to predict the whole landslide area is INF, although BODY model can also be used.
- BODY and INF models are weak in predicting the highest part of the landslides.
- SUP and MAX models provide a poor prediction of the whole landslide area and especially of the depositional area but are able to discriminate between source areas and stable slopes.
- Finally, if the accurate prediction of landslide depositional areas is needed, calibration of the models should be performed by including in the training samples the lowest portions of the landslides.

BODY model



REFERENCES

- Calderón-Cucunubá L.P. (2018). El uso de la Geomática en la caracterización geométrica y morfológica de la Caldera de Ilopango," República del Salvado". REPOSITORIO NACIONAL CONACYT. http://ninive.uaslp.mx/xmlui/bitstream/handle/i/5686/Tesis_Laura%20Paola%20Calderon%20Cucunuba%20(1).pdf?sequence=1
- Carrara, A., Cardinali, M., Guzzetti, F., & Reichenbach, P. (1995). Gis Technology in Mapping Landslide Hazard. 135–175. https://doi.org/10.1007/978-94-015-8404-3_8
- Guzzetti, F., Carrara, A., Cardinali, M., & Reichenbach, P. (1999). Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. Geomorphology, 31(1–4), 181–216. https://doi.org/10.1016/S0169-555X(99)00078-1
- Hengl, T., & Reuter, H. I. (2008). Geomorphometry: concepts, software, applications (Vol. 33). Developements in Soil Science.
- Hungr, O., Leroueil, S., & Picarelli, L. (2014). The Varnes classification of landslide types, an update. Landslides, 11(2), 167–194. https://doi.org/10.1007/S10346-013-0436-Y/FIGURES/33
- Jackson, R. D., & Huete, A. R. (1991). Interpreting vegetation indices. Preventive Veterinary Medicine, 11(3–4), 185–200. https://doi.org/10.1016/S0167-5877(05)80004-2
- Rotigliano, E., Martinello, · C, Hernandéz, · M A, Agnesi, · v, & Conoscenti, · C. (2019). Predicting the landslides triggered by the 2009 96E/Ida tropical storms in the Ilopango caldera area (El Salvador, CA): optimizing MARS-based model building and validation strategies. Environmental Earth Sciences, 78, 210. https://doi.org/10.1007/s12665-019-8214-3
- Shary, P. A. (1995). Land surface in gravity points classification by a complete system of curvatures. Mathematical Geology 1995 27:3, 27(3), 373–390. https://doi.org/10.1007/BF02084608

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Scan

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