TITLE: Exploiting Maximum Entropy method and ASTER data for assessing debris flow and debris slide susceptibility for the Giampilieri catchment (north-eastern Sicily, Italy).

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Abstract

This study aims at evaluating the performance of the Maximum Entropy method in assessing landslide susceptibility, exploiting topographic and multispectral remote sensing predictors. We selected the catchment of the Giampilieri stream, which is located in the north-eastern sector of Sicily (southern Italy), as test site. On 1/10/2009, a storm rainfall triggered in this area hundreds of debris flow/avalanche phenomena causing extensive economical damage and loss of life. Within this area a presence-only-based statistical method was applied to obtain susceptibility models capable of distinguish future activation sites of debris flow and debris slide, which where the main source failure mechanisms for flow or avalanche type propagation. The set of predictors used in this experiment comprised primary and secondary topographic attributes, derived by processing a high resolution digital elevation model, CORINE land cover data and a set of vegetation and mineral indices obtained by processing multispectral ASTER images. All the selected data sources are dated before the disaster. A spatially random partition technique was adopted for validation, generating fifty replicates for each of the two considered movement typologies in order to assess accuracy, precision and reliability of the models. The debris slide and debris flow susceptibility models produced

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high performances with the first type being the best fitted. The evaluation of the probability estimates around the mean value for each mapped pixel shows an inverted relation, with the most robust models corresponding to the debris flows. With respect to the role of each predictor within the modelling phase, debris flows appeared to be primarily controlled by topographic attributes whilst the debris slides were better explained by remotely sensed derived indices, particularly by the occurrence of previous wildfires across the slope. The overall excellent performances of the two models suggest promising perspectives for the application of presence-only methods and remote sensing derived predictors.

Keywords: Landslide susceptibility, Triggering mechanism prediction, ASTER, Maxent.

1. Introduction

Landslide susceptibility expresses the likelihood of a landslide occurring in an area conditional to its geomorphological characteristics (Guzzetti et al., 1999), differing from landslide hazard as it does not directly include any evaluation both of the expected magnitude and time recurrence. Thus, for each of the mapping units in which the study area is partitioned, a landslide susceptibility map spatially depicts the probability for a landslide occurrence, calculated by applying a predictive function to a set of physical-environmental variables, which are assumed to express the landslide controlling factors. The predictive function can be heuristically defined or stochastically derived, based on a calibration procedure.

In this contribution three main topics are addressed in the framework of landslide susceptibility assessment: i) integration of DEM derived topographic and remotely sensed attributes; ii) adoption of a presence-only statistical method and iii) distinction of different shallow landslide activation mechanisms.

First, we hypothesised the remotely derived information on the superficial soil characteristics to be dependent on the properties of the shallow regolith layer. Thus, satellite derived data were included in susceptibility models as independent proxy variables for the local properties of the weathered layer.

Several of the most recent contributions in landslide susceptibility studies have focussed on including remote sensing technology to improve the final prediction (Aman et al., 2014; Bai et al. 2013; Elkadiri et al., 2014; Günther et al., 2014; Miller, 2013; Mondini and Chang, 2014; Reichenbach et al., 2014; Youssef et al., 2014). The majority of the community introduces vegetation indices among the predictors or uses satellite imagery to derive digital elevation models (DEMs), and subsequently calculates topographic attributes (Huang et al., 2007; Oh et al., 2012; Pradhan et al., 2010) to be used as causative factors. However, higher resolution DEMs are typically derived from airborne LIDAR (Light detection and ranging; Petschko et al., 2015).

We propose to exploit the spectral capabilities and spatial coverage of Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite images, in order to calculate spatially distributed vegetation and mineral indices (Rowan and Mars, 2003; Yamaguchi and Naito, 2003; Rowan et al., 2003; Mars and Rowan, 2010; Pour et al., 2011; Mulder et al., 2011; Bachofer et al., 2015a) to be included, together with DEM-derived topographic covariates and CORINE land cover data, into the set of predictors for landslide susceptibility purposes.

The second important topic here addressed is the method upon which the final models are built. Common practises involve the use of stochastic and/or data mining methods relying on presence/absence techniques (e.g., Eker et al., 2014; Ermini et al., 2005; Pourghasemi et al., 2013; Lombardo et al., 2014) for calibrating the predictive model. In this research we decided to pursue a presence-only approach, which has recently been introduced within the landslide scientific community (Convertino et al., 2013; Davis et Sims, 2013; Park, 2014) by applying the Maximum Entropy (MaxEnt) algorithm (Elith et al., 2011; Phillips et al., 2004 and 2006; Phillips and Dudík, 2008), which does not rely on the contribution of negative (no-landslide or absence) cases for calibration.

The third subject we investigated is the recognition and distinction of different landslide activation mechanisms, reported as a key step in various researches (Deng and Shi, 2014; Gruber and Mergili, 2013; Guadagno et al., 2005; Hungr, 2007; Strîmbu, 2011). We sought to stochastically ascertain the differences in the triggering phase between the debris flows and debris slides by using MaxEnt and an integrated set of predictors expressing geomorphometric features as well as vegetation and mineral indices derived from satellite imagery.

The study area selected for this research corresponds to the Giampilieri catchment (north-eastern Sicily, Italy) where, on 1/10/2009, a multiple-landslides event was triggered by a storm rainfall. On that occasion, hundreds of landslides, primarily consisting of debris flow/avalanche, activated as debris slide or debris flow from the head and intermediate sectors of the slopes, and propagated downhill as channelled or unchannelled flows (debris flows or debris avalanches, according to Hungr et al., 2014).

2. Study area: geological and geomorphological settings

The catchment of the Giampilieri stream is located in the eastern side of the Peloritani Thrust Belt (Fig. 1) with a spatial extent of 10.6 km², including also two secondary hydrographic units located close to the outlet. The linear distance between the ridge and the outlet is approximately 6.5 km, with an elevation ranging from 1050 m to the sea level. Consequently, the topography is rough and marked by steep slopes overlooking the village of Giampilieri.

The Peloritani Thrust Belt consists of seven Alpine units in a stack, whose geometrical order from the bottom to the top can be followed in the field from south to north (Messina et al., 2004). Three of these units, namely the Mandanici Unit, the Mela Unit and the Aspromonte Unit outcrop in the sector where the study catchment is located and encompass medium to high metamorphic rocks: i) phyllites; ii) paragneiss and micaschists; iii) gneiss and paragneiss, respectively. The area has undergone several tectonic phases dating from the Hercynian age (Bonardi et al., 2003; Vitale and Ciarcia, 2013) up to the most recent Quaternary uplift (Catalano and De Guidi, 2003; Catalano et al., 2003; Di Stefano et al., 2012).

On the first of October 2009, hundreds of landslides were triggered in the Giampilieri catchment, primarily involving the shallow weathered layer of the aforementioned rocks and mobilising in the crown area a less than one meter thick regolithic layer. According to some published papers (Aronica et al., 2012; Peres and Cancelliere, 2014; Penna et al., 2014; Schilirò et al., 2015) the regolithic layer is characterised on average by a Unit Weight of 20-25 kNm⁻³, a porosity of near 35%, a permeability of $2 \times 10^{-5} \text{ m s}^{-1}$, a cohesion ranging from 0 to 6 kPa and an internal friction angle of 35 degrees.

The trigger of this multiple-landslides phenomenon was an extreme climatic event that discharged approximately 250 mm of rain in a time-window of eight hours over a very limited area centred on the catchment of Giampilieri. This precipitation overloaded the slopes whose soils had already been saturated by two close minor events dated back two (75 mm) and one week (190 mm) before the 1st October 2009.

The 2009 event has been the study case of a number of papers dealing with either hydrologic, physical or stochastic modelling for shallow landslide susceptibility assessment (e.g., Aronica et al., 2012; Lombardo et al., 2014; Peres and Cancelliere, 2014; Cama et al., 2015; Lombardo et al., 2015; Schilirò et al., 2015, Cama et al., 2016), as well as of specific studies focused on mapping techniques (Ardizzone et al., 2012; Mondini et al., 2011; Ciampalini et al., 2015), rainfall thresholds (Gariano et al., 2015), land-use change effect (Reichenbach et al., 2014) or tectonic control (Goswami et al., 2011; De Guidi and Scudero, 2013).

3. Methodology and used data

3.1 Maximum Entropy

In a contribution entitled: “Information Theory and Statistical Mechanics”, Jaynes (1957) defined the probability distribution obtained from maximum entropy as the least biased possible estimate on a given information. In other words, when applying predictive algorithms, the best model should coincide with the one that has Maximum Entropy. Several developments have subsequently been proposed to this algorithm and its potential application in different areas of science. Among these, Philips et al. (2004, 2006) presented an integrated approach of maximum entropy and GIS technologies for species distribution modelling where the application of this algorithm maximises the entropy in a geographic space. In the present contribution, we exploit the MaxEnt approach to predict the spatial distribution of landslides, with a similar assumption to that described in Convertino et al. (2013).

Merow et al. (2013) illustrate the MaxEnt model architecture as requiring presence only (PO) data and a set of predictors distributed across a regularly gridded space. In analogy to the aforementioned article but in a landslide susceptibility framework, the algorithm initially estimates the density of landslide occurrences within the landscape and generates landslide relative occurrence rates (ROR; Fithian and Hastie, 2013) per each cell. This quantity can be seen as the ratio between probability density of covariates across locations within the considered geographic space where the landslide is present and the probability density of covariates across the entire geographic space, thus obtaining insights on the relative proneness to fail of a given cell compared to another. According to the Maximum entropy

principle, a similarity criterion needs to be fulfilled between the final model and prior expectations. The latter represents a uniform distribution (Merow et al., 2013) in the geographic space, implying that each square mapping unit has the same likelihood of including a landslide. The final model is then selected by constraining the moments of the prediction to the empirical moments of the data (Phillips and Dudík, 2008) and bounding the sum of the probabilities up to 1. Ultimately, MaxEnt predicts the probability of landslide presence using a transformation of the ROR by calculating the logarithm of the raw output, this being called logistic output (Phillips and Dudík, 2008).

In the present analyses, the initial prevalence or probability of presence at ordinary occurrence points was set to 0.5 in accordance to Guillera-Arroita et al. (2014). Moreover, the maximum number of iteration before stopping the model building was set to 500; however, a convergence threshold was applied to interrupt the training phase when the drop in log loss per iteration fell below a value of 0.00001.

3.2 Landslide recognition

A few days after the disaster (from 2nd to 5th October) and one month later two field surveys were carried out with the primary objective of correctly classifying the fresh landforms produced by landslides (Fig. 2). The field recognition was then supported by orthophoto interpretation for the systematic mapping and digitisation of the inventory. In particular, the Regional Department of Territory and Environment (ARTA; www.sitr.regione.sicilia.it) provided pre-event orthophotos whilst post-event orthophotos were accessed through the Google EarthTM coverage of the area. Exploiting both the sources pre- and post- event images, two landslide inventories were derived whose intersection allowed us to extract those phenomena uniquely related to the 2009 disaster.

On the whole, the recognised landslides were classified as debris flows or debris avalanches, depending on the interpreted characteristics of the propagation phase; the former being channelized and reaching the drainage network, the latter spreading into the slopes, without producing any linear track (Hungr, 2007; Hungr et al., 2001). Besides, with specific reference to the dynamic of the activation of the movements, based on the features of the scarp or source areas, pure flows and slides were discriminated. The final inventory contained 1121 mass movements of debris flows/debris avalanches types, 824 of these triggered as pure debris flows whilst 297 triggered as debris slides (Hungr et al., 2014). As the target of the susceptibility modelling was the potential new activation, we differentiated between the mapped landslides uniquely according to the triggering movement.

3.3 ASTER data and derived vegetation and mineral indices

The ASTER sensor includes three subsystems with three bands in the visible-near infrared (VNIR; 0.52 – 0.86nm), six bands in the shortwave infrared (SWIR; 1.6 – 2.43nm) and five bands in the thermal infrared (TIR; 8.125 – 11.65nm) wavelength regions. The ground resolution of the VNIR bands is 15 m, 30 m for SWIR and 90 m for TIR (Fujisada, 1995). The ASTER L1B scene was acquired at the 21th July 2007 (09:59 UTC), before the Giampilieri disaster. Prior to further analyses, the SWIR bands of the L1B data, which suffer from cross-detector leakage (Iwasaki et al., 2002) were corrected using the software developed by the Earth Remote Sensing Data Applications Centre (ERSDAC, Japan). Radiometric correction was conducted, following Berk et al. (2008) and Richter and Schlaepfer (2014). The ASTER scene was co-registered with sub-pixel accuracy to a Landsat 7 ETM+ (L1T) panchromatic scene with 15m ground resolution (2000-09-22), in order to increase positional accuracy (Gao et al., 2009; Behling et al., 2014).

After the pre-processing, several multispectral indices were derived from the ASTER VNIR/SWIR bands (Tab 1). The proposed indices are mostly simple band ratios, which are sensitive to surfaces and their reflection and absorption properties for certain spectral wavelength. Distinct wavelengths emphasize the presence or absence of a particular surface cover, or indicate a change of surface cover (Rowan and Mars, 2003; Mulder et al., 2011). The indices are a result of an extensive literature review. The names of the indices indicate their specific purpose in the respective scientific publication. Nevertheless, they can be applied to other surface materials. Vegetation indices were also included: i) Stabilised Vegetation Index (STVI, Ninomiya 2003); ii) Normalized Difference Vegetation Index (NDVI, Rouse et al. 1974); iii) Burn Index (Hudak et al. 2004).

With regards to the mineral indices computed from the ASTER scene, several indices belonging to i) silicates, ii) carbonate-mafic, and iii) iron groups, were obtained to approximate the local shallow soil. Even though not all proposed indices may detect particular minerals or may prove relevance in the specific settings of the study area, we expect some of them to emphasise changes in the mineral composition of the study area. In fact, the aim of this study is not to distinguish between the different mineral compositions in the catchment, but rather to detect spatial trends, which help to explain the variability of landslide occurrences. For example, knowing from field activities that phyllite outcrops in the area were exposed to numerous failures, the authors expected clay-related indices to positively contribute to the overall modelling performance.

3.4 Topographic attributes and land cover

Both the two sources of data for topographic and land cover site characterisation were taken from before-event source layers: a high resolution digital elevation model (2m cell) obtained by a LIDAR coverage dated at 2007 and the 2006 CORINE land cover (Tab.2 and 3). The DEM-derived attributes were obtained by using SAGA GIS (Conrad, 2006) tools, calculating thirteen covariates, namely: i) Aspect (Zevenbergen and Thorne, 1987); ii) Slope steepness (Zevenbergen and Thorne, 1987); iii) Relative Slope position (Kleber, 1997); iv) Plan Curvature (Heerdegen and Beran, 1982); v) Profile Curvature (Heerdegen and Beran, 1982); vi) Mass Balance Index (Möller et al., 2012); vii) LS Factor (Desmet and Govers, 1996); viii) Topographic Wetness Index (Beven and Kirkby, 1979); ix) Convergence Index (Köthe and Lehmeier, 1993); x) Landform Classification (Guisan et al., 1999) with 20-100 m search radii; xi) Stream Power Index (Moore et al., 1991); xii) SPISLO (Lombardo et al., 2014); xiii) TWISLO (Lombardo et al., 2014). Slope steepness is a proxy for the shear strength on the failure surface and, together with aspect, controls the strata attitude on the slopes. The LS factor is adopted in the USLE (Universal Soil Loss Equation) model for sediment transport-capacity index (Wischmeier and Smith, 1978; Renard et al., 1997) and together with Convergence and Mass Balance Index allows the model to test for interaction between landslides and water erosion on the slopes. The topographic curvatures control divergence and convergence, both of surface runoff and shallow gravitational stresses (Ohlmacher 2007). SPI and TWI are two largely adopted topographic secondary attributes (Wilson and Gallant, 2000), which are based on the specific catchment area (A_s) of each cell and its slope gradient (β): the stream power index ($SPI = \ln(A_s \times \tan \beta)$) indicates the erosive power of flowing water, whilst the topographic wetness index ($TWI = \ln(A_s / \tan \beta)$) is a proxy for the thickness of the soil saturation zone. SPISLO and TWISLO respectively correspond to SPI and TWI divided by their standard deviations, computed in a neighbourhood of one cell; these composite variables (Lombardo et al., 2014) more effectively discriminate the SPI and TWI values on the slopes, strongly smoothing their values on the stream valleys. Relative Slope position and Landform Classification express the morphological characteristics of a cell: slope position or distance from the river and morphological setting. Land use classes mapped through the CORINE 2006 map were also considered as proxy variables expressing the anthropic control on the environment and specific vegetation cover.

3.5 Datasets

A susceptibility model has to produce a probability estimation of unstable conditions (landslide presence) for each of the mapping units in which the mapped area is partitioned. The choice of the type of mapping unit (Carrara et al., 1995; Hansen, 1984; Luckman et al., 1999; van Westen et al., 1993, 1997) is a key factor in landslide susceptibility studies.

According to the resolution obtained for the recorded wavelengths in ASTER data, in the present contribution we structured the predictive model with a 15m square grid cell. As a result, the geographic space coinciding with the catchment of Giampilieri was partitioned into 47084, 15m-side, squared cells whose values of the whole set of predictors were calculated.

To set the status (stable/unstable) of the outcome, we extracted a landslide identification point (LIP) from each landslide polygon, corresponding to the highest 2m pixel along the crown. We then classified as unstable all those cells hosting a LIP, under the hypothesis that, for such shallow and narrow failure surfaces, a 15m area would be large enough to “reflect” in the predictors domain those pre-event conditions which lead to the 2009 activations. Besides, it is worth to mention that the conditions for landslide activation are to be searched also into cells which are actually located outside the failure zone (typically uphill from crowns; Rotigliano et al., 2011). The use of LIPs has been verified as an effective tool in assessing landslide susceptibility in previous applications to the Messina 2009 event (Lombardo et al., 2014; Cama et al., 2015; Lombardo et al., 2015, Cama et al. 2016). The final inventory consisted of 824 and 297 flow and slide LIPs, respectively.

Figure 3 shows the normalised univariate distribution of the predictors in the sites of the LIPs for the two types of mass movements, compared to that of the whole catchment of the Giampilieri stream. Differences for each independent variable can be ascertained among the distributions of debris flows (red line), debris slides (blue line) and the catchment itself (green line) suggesting a potential role for some of predictors (e.g., BURN_I or TWI). At the same time, variables with an almost coincident shape for the three curves are also observed (e.g., Mass_BI or SPISLO).

3.6 Validation

The validation of a predictive model has to furnish a quantitative estimation of its goodness of fit, prediction skill, robustness and geomorphological adequacy (Guzzetti et al., 2006). A widely adopted strategy for validating the predictive models using a coeval landslide inventory is to randomly partitioning it into a training and a test subset, the first used for calibration, the second for real validation. Once a model is obtained, one can cross its predicted probabilities with presence/absence of training and test events, in order to calculate metrics for fitting and prediction skill, respectively. In particular, the results of validation can be analysed in the space of Receiver Operating Characteristic (ROC) plots, reporting the varying-threshold True Positive (TP) Vs. False Positive (FP) trade-off performance, which can be expressed by the Area Under Curve (AUC) metric. It must be noted that, differently from presence-absence approaches, for the case of a presence-only method such as MaxEnt, the ROC AUC test performs the task of distinguishing presence from random, rather than presence from absence (Wiley et al., 2003; Phillips et al., 2006). Thus, AUC values can be interpreted as the probability that, when a site with a landslide present and a site with the landslide absent are drawn at random, the former will have a higher predicted value than the latter (Parolo et al., 2008). Following this approach, the sample of pseudo-negative instances are chosen uniformly at random in the area, making it possible, together with the positive instances, to define a ROC curve (Phillips et al. 2006). In analogy to the classification of the AUC test results described by Hosmer and Lemeshow (2000) for presence-absence cases, Araujo and Guisan (2006) proposed a set of threshold in order to define the performances of a model as a function of the AUC obtained by adopting MaxEnt as modelling tool, these being: 0.50-0.60 = insufficient; 0.6-0.7 = poor; 0.7-0.8 = average; 0.8-0.9 = good; 0.9-1 = excellent.

At the same time, for measuring both the precision and the accuracy of a model we need to replicate the assessment so that mean and dispersion values of the produced probability estimations can be analysed for significance. Besides, as the predictive models are based on the regression of a set of covariates, the validation of a landslide susceptibility model cannot be said to be complete if no adequacy analysis is performed, the latter consisting in estimating the geomorphological soundness of the model in terms of the role assumed by the single predictors. Jack-knife tests have been used for estimating the contribution of each single variable to the whole performance of the models, for example by comparing the performance of single *i*-variable model, with that obtained by using all but the *i*-variable model. The loss in the ROC-AUCs caused by a variable suppression indicates, together with

the ROC-AUC of the single variable model, the importance that a variable assumes in the whole modelling procedure. It is important to note that no evaluation of possible interaction effects between variables has been done prior to the analyses. However, jack-knife tests allow to recognise single variable effects with respect to the whole, thus enabling interpretation of analogous variable behaviours as a function of the overall predictive performance. Another way to ascertain the contribution of a covariate is through the Predictor Importance (Vorpahl et al., 2012; Tziritis and Lombardo, 2016), which is a model parameter expressing the role of a predictor with respect to the overall performance, by normalising its contribution with respect to that of the maximum contributor. Furthermore, in order to describe the role that is assumed by the single predictors, response curves (Lombardo et al., 2015; Maerker et al., 2011) should also be taken into account. A response curve depicts the partial dependency of the modelling output, expressed as landslide occurrence probability (i.e., the landslide susceptibility), with respect to the variation of a single independent variable. The response curves enable an immediate geomorphological reading of the whole model, allowing the interpreter to evaluate the geomorphological coherence between the estimated role of the predictors and the expert geomorphological models explaining the mapped slope failures.

Finally, by implementing the model building and validation procedures on a multi-folds routine, the reliability of the model, in terms of inner structure (selected variables, predictor importance and role), predictive performances (goodness of fit and prediction skill) and precision in the estimated probabilities for each cell, can be also assessed.

In the present research, 50 replicates of the 75/25 splitting procedures allowed to estimate precision and accuracy for the performance metrics and the predictor contributions. Besides, exploiting the fifty replicates, we could compute mean values and standard deviations for the probability estimates of each cell, which were reported in susceptibility and error maps, as well as variable-response plots, in which position and dispersion of the model dependence have been plotted in the domain of each predictor.

4. Results

Figure 4 shows the results of the validation of the obtained debris slide and debris flow susceptibility models. The fitting of the two suites of fifty models proved to be excellent (Araujo and Guisan, 2006) on average for the debris slide (0.91), whilst being slightly lower for the debris flow (0.85). With regard to the prediction skill, the performances converged to a good fit (Araujo and Guisan, 2006), with average test ROC-AUC values of 0.8. Nevertheless, the standard deviation for test ROC-AUCs reached 0.013 for debris flow and 0.021 for debris slide, attesting for stable prediction throughout the modelling procedure for both the triggering mechanisms. Analysing the shape of the corresponding ROC-curves (Fig. 5), it is evident the shift between training and test performances, at the same time highlighting a strong stability through the replicates in the first case and a greater variability in the second one, particularly for debris slides. Figure 6 shows the true positive rate for the two failure mechanisms with the debris slide class reaching 70.07% on average with respect to the 68.14% for the debris flows.

By computing the mean values of the fifty estimates of landslide occurrence probability, susceptibility maps were obtained. The two susceptibility maps show (Fig. 7) a common non-susceptible region located approximately at the catchment ridge, whilst the central and the lower sectors depict different susceptibilities between the two landslide typologies. Some differences between the debris flow and debris slide susceptibility maps are evident at a first glance, with the latter being characterised by high probability values only on the northern flank of the catchment. The debris flow susceptibility maps show a similar pattern; however, some highly susceptible areas were also produced for the southern sector.

By intersecting, the mean probabilities of each cell with the corresponding dispersions, the latter being measured by a two standard deviations interval, the model error plots were drawn. Figure 8 shows that the greatest robustness was obtained for the stable conditions (low susceptibility) with a strong density of points on the left tails of the plots. Conversely, the central sector (intermediate susceptibility) was characterised by the strongest variations with the debris slide class having on average twice the standard deviation of debris flows. The right sides of the error plots indicate that the models are also consistent in predicting highly susceptible cells, with almost no cases with a probability higher than 0.9, for the two typologies.

In order to obtain an integrated view of the susceptible sites in the study area, jointly representing the two susceptibility maps, a probability threshold of 0.5 was assumed to discriminate between stable and unstable predicted conditions. As a consequence, selective (slide or flow) and joint (slide and flow) unstable pixels were produced (Fig. 9). It is clear how, un-selective unstable cases ($P > 0.5$ both for flow and slide activation mechanisms) are twice than the selective cases (only flow or only slides). In general, the spatial distribution of the combined susceptibility shows spatially discriminated domains, with very few sectors where the four cases strictly are interconnected.

With respect to the role of the primary covariates within the models, clear differences arose between slides and flows when analysing the jack-knife tests (Fig. 10). The debris flow activation models showed a stronger control (Fig. 10a, 10c) from topographic attributes with Slope, Steepness and Relative Slope Position being constantly the most important covariates together with the Burn Index. Conversely, the debris slide models were primarily controlled (Fig. 10b, 10d) by Burn Index and the NDVI together with Aspect.

By exploiting the predictor importance, we can sum the effect of different groups of variable, so to obtain a more comprehensive view of all the geo-environmental causes of landslide activation. In particular, we cumulated the predictor importance of the covariates, grouped into three primary sets, namely topographic, mineralogical and vegetational (Fig. 11). The categorical LClass and Use were assigned to the topographic and vegetational set, respectively. Both the two clusters of debris slide and debris flow models mark the influence of mineralogical indices less than 20%; however, the former cluster is much closer to the 60% topographic influence, whilst the latter cluster is located next to the 60% vegetation influence.

Among those covariates that play a fundamental role in the final models, the interpretation of the response curves (Fig. 12) suggests that the Slope has a positive influence for both the landslide typologies, being greater for the debris flows, which are represented with a steeper curve. With regard to the NDVI both landslide typologies were positively correlated up to a value of approximately 0.4; within this range the NDVI expresses low vegetation density whilst from this threshold onward the trend turns negative according to an increase in local greenness. The Burn Index expresses presence of fire from a minimum value of zero coinciding with natural conditions up to its maximum value, which represents presence of ashes in the topsoil. The Burn index may also indicate the presence or absence of minerals like kaolinite, muscovite, illite and phengite, which cause absorption changes in band 6 in

relation to band 5 (Cudahy 2012). The Burn Index response curve shows a positive correlation with both landslide initiation types in the range between 0.5 and 0.7, where the maximum influence is reached and burned conditions are present. From 0.7 onward the relationship becomes anticorrelated for both the landslide triggers. The response curves of the Relative Slope Position show an increasing trend from the minimum of zero, coinciding with the river network, to the maximum value of 0.8, corresponding to the local ridges where the curves reach the asymptotes. The response curve related to the Kaolin Group shows a positive correlation inside the narrow window between 0.8 and 0.9, whilst the remaining domain shows an anticorrelated trend to landslide occurrences. A similar trend is shown in the TWI response curve, with the debris slides activation zone being negatively correlated in the interval between 0 and 4 and the debris flow curve being flatter and almost constantly beneath the 0.4 probability threshold, with the exception of the range between 3 and 4 where values overcome the 0.5 probability. The CORINE 2006 land use shows a broad agreement between the two landslide typologies, with Use9 (Grassland) and Use10 (Olive groves) contributing to landslide prone conditions. Use11 (Erosion scars, badlands, rock outcrops) and Use12 (Shrubland) show a peculiar relationship being positively correlated to debris slide occurrences only and the latter marking the opposite role. The remaining uses, namely Use1 (Continuous fabric), Use2 (Sparsely vegetated areas), Use4 (Mixed groves), Use5 (Coniferous) and Use7 (Non-irrigated arable land) are anticorrelated to both the failure mechanisms.

5. Discussion

The high prediction skill and precision obtained for the two susceptibility models, which have been validated through multi-fold procedures, attest for their robustness and the correctness of the adopted model building strategy. It is worth noting that despite presence-only methods do not exploit the absence information, in the present work, the Maximum Entropy effectively discriminated the two landslide triggering mechanisms. The performances which were observed for this research, are in fact similar to those obtained by adopting different presence/absence statistical techniques (Lombardo et al., 2014; Lombardo et al., 2015).

Regarding the ASTER derived predictors, the results highlighted the Burn Index as the most important predictor among all the adopted covariates for both landslide types. The ASTER scene was acquired on the 21th July 2007 so that the Burn Index was able to capture the effect of several wildfires that burned throughout June and July 2007 affecting the study area (<http://www.comune.messina.it/il-comune/ufficio-urbanistica/catasto-incendi/catasto-incendi->

eventi-2007). Recent studies (Cannon et al., 2008; Cannon and DeGraffe, 2009; Jackson and Roering, 2009; Martin, 2007; Ren et al., 2011) have confirmed the important role of burned vegetation to new landslide activations as a consequence of the increase of piping effect (Leslie et al., 2014) where roots and rootlets were present in the soil column, as well as of the shallow planar water-repellence effect (DeBano, 2000, 2003; MacDonald and Huffman, 2004; McNabb et al., 1989; Robichaud, 1996, 2000). The combined action of piping, roughness reduction and impermeabilization phenomena can differently affect the activation of debris flows and debris slides influencing their initiation.

Differences were ascertained between debris flows and debris slides with a primary control of the topographic predictors on the former whilst the latter appeared to be more controlled by the remote sensing covariates. For the debris slide type, the most relevant predictor proved to be the Aspect; this covariate is usually assumed as a proxy for strata attitude, which for the specific mass movement could have played an important role in the failure mechanism approximating shallow sliding layers. Debris slides appeared to have also been primarily controlled by the presence of burned vegetation through the fifty replicated. This result, coupled with the topographic aspect effect can be interpreted through the shallow presence of planar water repellent layers that could have led to an initial planar movement subsequently evolved into debris avalanches or flows as a function of the geomorphic control. The Burn Index also appeared to strongly affect the debris flows, albeit to a lesser extent. In contrast to debris slides, for this type of mass movement, the important role of burned vegetation can be interpreted as attributed to the piping effect, which combined with other topographic conditions, can give rise to landslide trigger. The most relevant mineral index was the Kaolin Group index, which may be explained by the fact that typical outcrops in the study area comprise metamorphosed clays of phyllite and schist types.

6. Conclusions

Simultaneous widespread landslide activations pose a serious threat to human lives and infrastructures. Urban planners need to integrate reliable landslide susceptibility maps to their schemes in order to minimise the risk and plan the best response to potential disasters. An important subject strongly affecting the final production of landslide susceptibility maps is represented by the acquisition of the data upon which susceptibility models are built. In this contribution, we applied a presence-only method to depict the landslide proneness by integrating two primary sources of predictors, namely DEM- and remote sensing- derived. In

particular, we tested the contribution of multispectral ASTER-derived vegetation and mineral indices in order to support the actual landslide susceptibility modelling procedure.

The results of this research demonstrates how multispectral ASTER data can increase the predictive performance of landslide susceptibility models. Together with morphological covariates, the ASTER-derived predictors showed high predictor importance and well distinguished response curves depending on the triggering mechanism (slide/flow).

The use of multispectral remote sensing data proved to be a very promising perspective for basin/regional scale analysis, especially when the wavelengths between 1.6 – 2.43 nm are covered. Furthermore, field calibration of the data can greatly increase the quality of the data also allowing deeper explanations of the physical relationships between spectral signal and slope stability. Future hyperspectral satellite missions like EnMap and PRISMA will allow even more precise mineral mapping analyses (Pignatti et al 2013, Guanter et al. 2015).

As regards the adopted statistical technique, MaxEnt performed in susceptibility modelling with the same skill and accuracy of frequently adopted presence/absence methods, without requiring complex and time consuming negative multi-extraction routines before the actual analyses (e.g., Costanzo et al. 2014; Lombardo et al., 2014; Conoscenti et al. 2016).

Ultimately, the research has confirmed the correctness in splitting the recognised phenomena, depending on the specific activation mechanisms (slide/flow). In fact, the differences in the predictor importance and response curves demonstrate that the relationships between predictors and dependent change for the two failure typologies. Moreover, conditions potentially leading to both activation mechanisms were detected, together with selective susceptible sites. The LIPs adoption in indicating diagnostic areas able to make the model learn the potential unstable conditions, confirmed to be effective for modelling shallow landslides such as the ones which triggered in the Giampilieri catchment in 2009. In this sense, the sensitivity of the susceptibility models for the two landslide typologies demonstrated the correctness both of the landslide recognition survey and the adoption of the simple landslide identification point for calibration.

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Figure 2. Continuum of processes for plant removal showing possible scenarios for balance of driving forces (flow) and resisting forces (roots). At the left end of the figure (1), driving force exceeds root strength and the plant can be removed without scour of the substrate. At the right end of the figure (3), scour has reduced the resisting force of the roots to zero, and the plant is removed by the force of the flow. In reality plant removal is likely to occur at some point between (1) and (3) at a point (2) along the continuum where scour has reduced the resisting force of the roots to a point where the flow can remove the plant from its substrate.

Figure 3. Map showing the location of the three vegetation study sites in this study.

Figure 4. A) Plant bending apparatus showing reel, telescopic arm, specially-designed mount and camera tripod. B) Close up of load cell during bending test. C) View of the bending test apparatus in action.

Figure 5. Example of the flume set up for a *Phragmites* run, and inset picture showing modified dowels for cottonwood plant runs, with addition of synthetic leaves.

Figure 6. A) Root pulling device used to measure breaking forces of roots and rhizomes and B) Plant-pulling device being used to measure the force required to extract young *Phragmites* stems from a sandbar in the Elm Creek reach along the Platte River, NE.

Figure 7. A) Rootball of reed canarygrass B) 1-year-old cottonwood seedling and C) a Phragmites rhizome

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Figure 8. Plots comparing plant pullout forces with root breaking and stem bending forces.

Figure 9. Maximum drag (driving) forces calculated from flume study, and estimated for maximum in-field velocities, compared with patch uprooting resistance, and bending resistance. A) shows results for 1-year-old cottonwood seedlings with stem density of 26 stems per m² and B) shows results for 2-year-old cottonwood seedlings with stem density of 13 stems per m². Drag forces acting on young cottonwood seedlings were calculated to be as high as 156 N at a flow velocity of 1.5 ms⁻¹, and would be sufficient to bend all young (<2 years old) cottonwood seedlings growing on sandbars. In addition, drag forces at 1.5 ms⁻¹ are likely to be capable of removing the weakest one to two-year old seedlings. The estimated drag force acting at this velocity (156 N) is still well below the mean values for patch resistances of one and two year old cottonwood seedlings (249 and 315 N, respectively).

Figure 10. Maximum drag (driving) forces calculated from flume study, and estimated for maximum in-field velocities, compared with patch uprooting resistance, and bending resistance A) shows results reed canarygrass with a stem density of 400 stems per m² and B) shows results for reed canarygrass with a stem density of 800 stems per m².

Figure 11. Maximum drag (driving) forces calculated from flume study, and estimated for maximum in-field velocities, compared with patch uprooting resistance, and bending resistance. Data shown are for *Phragmites* stems with a density of 200 stems per m².

Figure 12. Velocities relating to the ability of drag forces to uproot patches of A) one-year old and B) two-year old cottonwoods during a $227 \text{ m}^3\text{s}^{-1}$ flow event. Dark green areas indicate locations where velocities are so low that no uprooting of cottonwood seedlings would occur. The mid-green patches show where the weakest, most shallow rooted seedlings could be uprooted, with yellow and red velocity zones indicating the locations where velocities are high enough that uprooting is most likely, where these areas occur overlap with in-channel bars.

Tab. 1: Spectral indices derived from ASTER VNIR and SWIR bands, following Bachofer et al. (2015b).

Index and literature reference	Formula	Variable
Alteration/Laterite (Bierwirth, 2002)	$(4/5)$	Alter_I
Burn Index (Hudak et al., 2004)	$(3-5)/(3+6)$	BURN_I
Calcite (Pour et al., 2011)	$(6/8) \cdot (9/8)$	CALC_I
CCE (Rowan and Mars, 2003)	$(7+9)/8$	CCE_I
Clay 1 (Rowan and Mars, 2003)	$(5+7)/6$	Clay1_I
Clay 2 (Bierwirth, 2002)	$(5 \cdot 7)/(6 \cdot 6)$	Clay2_I
Dolomite (Rowan and Mars, 2003)	$(6+8)/7$	Dolomite_I
Kaolinitic (Hewson et al., 2005)	$(7/5)$	Kaolinitic_I
Kaolin Group (Cudahy, 2012)	$(6/5)$	Kaol_G
Kaolinite (Pour and Hashim, 2011)	$(4/5) \cdot (8/6)$	Kaol_I
MgOH Group (Cudahy, 2012)	$(6+9)/(7+8)$	MgOH_G
Muscovite (Hewson et al., 2001)	$(7/6)$	Muscovite_I
NDVI (Rouse et al., 1974)	$(3-2)/(3+2)$	NDVI
OH 1 (Pour and Hashim, 2011)	$(7/6) \cdot (4/6)$	OH1_I
PHI (Hewson et al., 2001)	$(5/6)$	PHI_I
STVI (Ninomiya, 2003)	$(3/2) \cdot (1/2)$	STVI

Tab. 2: Continuous predictors.

Continuous predictors		
Attribute	Variable	Units
Convergence Index	Conv_I	Dimensionless
Slope-Length Factor	LS_Fact	Dimensionless
Mass Balance Index	Mass_BI	Dimensionless
Plan Curvature	Plan_C	1/metres
Profile Curvature	Prof_C	1/metres
Relative Slope Position	RS_Pos	Dimensionless
Slope Steepness	Slope	Radians
Stream Power Index	SPI	Dimensionless
SPISLO	SPISLO	Dimensionless
Topographic Wetness	TWI	Dimensionless
TWISLO	TWISLO	Dimensionless

Tab. 3: Categorical predictors.

Categorical predictors		
Variable	Code	Class
Landform Classification (LClass)	1	V-shape river valleys
	2	Local valley in plains
	3	Upland incised drainages
	4	U-shape valleys
	5	Broad flat areas
	6	Broad open slopes
	7	Flat ridge tops mesa tops
	8	Flat ridge/hilltops within broad valleys
	9	Local ridge in plains
	10	Mountain tops
Land Use (Use)	1	Continuous urban fabric
	2	Sparsely vegetated areas
	4	Mixed groves
	5	Coniferous
	7	Non-irrigated arable land
	9	Grassland
	10	Olive groves
	11	Erosion scars, badlands, rock outcrops
	12	Shrubland
Aspect	1	North
	2	North-East
	3	East
	4	South-East
	5	South
	6	South-West
	7	West
	8	North-West