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Comparison of Logistic Regression and Random Forests techniques for shallow landslide susceptibility assessment in Giampilieri (NE Sicily, Italy)

Alessandro Trigila [a,b,*], Carla Iadanza [a], Carlo Esposito [b], Gabriele Scarascia-Mugnozza [b]

[a] ISPRA — Italian National Institute for Environmental Protection and Research, Geological Survey of Italy, Via Vitaliano Brancati 48, 00144 Roma, Italy
[b] Sapienza University of Rome, Department of Earth Sciences, Piazzale Aldo Moro 5, 00185 Roma, Italy

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ABSTRACT

The aim of this work is to define reliable susceptibility models for shallow landslides using Logistic Regression and Random Forests multivariate statistical techniques. The study area, located in North-East Sicily, was hit on October 1st 2009 by a severe rainstorm (225 mm of cumulative rainfall in 7 h) which caused flash floods and more than 1000 landslides. Several small villages, such as Giampilieri, were hit with 31 fatalities, 6 missing persons and damage to buildings and transportation infrastructures. Landslides, mainly types such as earth and debris translational slides evolving into debris flows, were triggered on steep slopes and involved *colluvium* and regolith materials which cover the underlying metamorphic bedrock. The work has been carried out with the following steps: i) realization of a detailed event landslide inventory map through field surveys coupled with observation of high resolution aerial colour orthophoto; ii) identification of landslide source areas; iii) data preparation of landslide controlling factors and descriptive statistics based on a bivariate method (Frequency Ratio) to get an initial overview on existing relationships between causative factors and shallow landslide source areas; iv) choice of criteria for the selection and sizing of the mapping unit; v) implementation of 5 multivariate statistical susceptibility models based on Logistic Regression and Random Forests techniques and focused on landslide source areas; vi) evaluation of the influence of sample size and type of sampling on results and performance of the models; vii) evaluation of the predictive capabilities of the models using ROC curve, AUC and contingency tables; viii) comparison of model results and obtained susceptibility maps; and ix) analysis of temporal variation of landslide susceptibility related to input parameter changes. Models based on Logistic Regression and Random Forests have demonstrated excellent predictive capabilities. Land use and wildfire variables were found to have a strong control on the occurrence of very rapid shallow landslides.

1. Introduction

Italy is with almost 500,000 recorded landslides one of the European countries most affected by landslides (Van Den Eeckhaut and Hervás, 2012; Spizzichino et al., 2013). The country shows a very high exposure to landslide hazard, because of its geological and morphological characteristics: in fact 75% of the country is mountainous-hilly. Landslides are frequent geohazards and, after earthquakes, cause the greatest number of casualties and damage to urban areas, infrastructures, environmental, historical and cultural heritage (Iadanza et al., 2009, 2013; Salvati et al., 2010; Trigila et al., 2010, 2015). In particular shallow landslides, with rapid or extremely rapid movement, caused the most damage both in terms of loss of human lives and economic damage in recent years (Trigila and Iadanza, 2012).

Landslide susceptibility assessment is the first step towards estimation of landslide hazard and risk. The term hazard describes the probability of occurrence of a potentially destructive phenomenon with a given magnitude in a given period of time and in a given area (Varnes, 1984). It is often difficult to determine because of the lack of information concerning dates of occurrence and consequently return period of landslides. Because of these limitations, the analysis of the susceptibility or spatial hazard is the most commonly performed, allowing the identification of zones with high probability of landslide occurrence. Landslide susceptibility models are based on a fundamental axiom: "the past and present are keys to the future" (Varnes, 1984), i.e., areas where landslides have occurred in the past most likely will be affected by landslides in the future. Moreover areas with environmental conditions (e.g., lithology, morphology) similar to those already affected by landslides are more prone to landslides (Varnes, 1984).

The approaches proposed in the literature for landslide susceptibility analysis can be qualitative or quantitative and are classified into heuristic, statistical and deterministic (Corominas et al., 2014). Heuristic methods are direct approaches, where an expert geomorphologist

* Corresponding author at: ISPRA — Italian National Institute for Environmental Protection and Research, Geological Survey of Italy, Via Vitaliano Brancati 48, 00144 Roma, Italy.
E-mail address: alessandro.trigila@isprambiente.it (A. Trigila).

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evaluates landslide susceptibility directly in the field, or indirect approaches in which, on the basis of expert judgement, a weight is assigned to each parameter considered significant for the landslide occurrence. Recently, a semi-quantitative heuristic approach has been used for Pan-European landslide susceptibility assessment (Günther et al., 2014). Deterministic methods (physically based methods) involve the physical modelling of landslides (Soeters and Van Westen, 1996; Crosta and Frattini, 2003), and are thus generally site-specific (slope scale). Statistical methods (data-driven methods), such as Logistic Regression, Discriminant Analysis, Random Forests, Neural Networks (Baeza and Corominas, 2001; Catani et al., 2005; Ermini et al., 2005; Falaschi et al., 2009; Rossi et al., 2010; Trigila et al., 2012) are usually adopted at the basin scale and allow you to determine the contribution of various factors to instability. Quantitative methods for susceptibility assessment are objective and reproducible. Statistical methods, however, are strongly dependent on the accuracy of the input data (Van Westen et al., 2008) which may also lead to significant errors in the final results. In particular, a complete and accurate landslide inventory is necessary for model training and validation. The application of statistical methods requires the use of Geographic Information Systems (GIS) for the production of landslide susceptibility maps over large areas. Considering that different types of landslides are generally influenced by different predisposing factors, it is appropriate to define distinct susceptibility models for each type of movement.

The evaluation of the results predicted by the model is an essential task for landslide susceptibility assessment. Without a proper evaluation and/or validation, models and obtained maps would have a poor scientific value (Chung and Fabbri, 2003). The performance of the model is determined by comparing the predicted values with the observed ones. Therefore the model must be trained and tested with two separate samples of data, operating a spatial or temporal subdivision of the input data. In recent years, several methods have been adopted to evaluate the uncertainties, the robustness and the predictive capability of the models, such as the Success rate curve and Prediction rate curve, contingency tables, the ROC curve and AUC (Chung and Fabbri, 2003; Brenning, 2005; Carrara et al., 2008; Frattini et al., 2010). A few recent research efforts have started to take into account the temporal change of environmental factors, such as land cover, and its influence on the validity of landslide susceptibility maps (Meusburger and Alewell, 2009).

The main purposes of this paper are the development of models for evaluating rapid shallow landslides susceptibility, the comparison between multivariate statistical methods such as Logistic Regression and Random Forests, the analysis of the influence of sampling strategies on model performance and consequently on susceptibility maps. The study area chosen for the implementation of the models is the area of North-Eastern Sicily that was hit by a particularly severe landslide event in 2009.

2. Materials

2.1. Study area

The 25 km^2 large study area is located south of Messina city, in North-Eastern Sicily (Italy). It is highly urbanized with several villages like Giampilieri, Briga, Molino, Altolia and Pezzolo and Scaletta Zanclea. The resident population in the study area is equal to 7247 inhabitants and several transportation infrastructures are located along the coastal strip (Highway A18 Messina–Catania, State Road SS 114 and railway line Messina–Catania).

From the geological data, the area is characterized by metamorphic rocks of Paleozoic age belonging to the tectonic units of the Kabilo–Calabride complex (Lentini et al., 1995). In particular, phyllites, paragneiss, micaschists and locally marbles outcrop extensively. These lithologies have favoured the formation of diffuse heterogeneous debris deposits of loose material (*colluvium*), on top of a weathered bedrock. The thickness of debris varies from 10 cm to 3 m.

Catchments are small (less than 10 km^2), elongated and characterized by steep slopes. The main streams are roughly perpendicular to the shoreline, with a considerable stream gradient (10–15%), low hierarchical order, and flow directly to the sea. The hydrological regime is torrential with poor or no water flow in summer and abundant in autumn and winter. The steep slopes and the small size of the basins lead to a short time of concentration (less than 1 h), an intense erosion and high sediment transport during high intensity rainfall events. The climate regime is Mediterranean/maritime with hot summers and short mild winters and precipitation concentrated in autumn and winter. The mean annual precipitation in the coastal strip is about 800 mm (849.5 mm for the rain gauge of S. Stefano di Briga in the observation period from 1965 to 1994).

Over the centuries the landscape and the morphology has been profoundly modified by humans with the construction of widespread agricultural terraces, now mostly abandoned. The absence of constant maintenance of the dry stone walls and related drainage systems has made the terraced slopes particularly susceptible to landslide occurrence.

The study area was hit on October 1, 2009 by an intense thunderstorm event (high intensity–short duration rainstorm) with 225 mm of rain in 7 h (Basile and Panebianco, 2013). The area had already been affected by heavy antecedent rainfall with a cumulative amount of 300 mm between 15 and 30 September, about 5.5 times higher than the historical monthly average (Basile, 2009; Basile and Panebianco, 2013). Over a thousand landslides occurred, mainly types such as debris flows, debris slide and debris avalanche, according to the Cruden and Varnes (1996) and Hungr et al. (2001) classifications, which caused 31 dead and 6 missing people (Ardizzone et al., 2012) (Fig. 1). Due to the heavy rainfall, the increase in pore water pressure generated by the saturation of the soil caused the slope failures. In terraced areas the hydraulic pressure on the stone walls often resulted in the collapse of the walls with a domino effect on the ones below. The area had been affected in the past by landslide events such as in 1613 and 2000 in Altolia, in 1750, 1805 and 2000 in Molino and in 1791, 1918, 1929, 1932, 2000 and on October 25, 2007 in Giampilieri (Mazziotta, 1919; Chillemi, 1995).

2.2. Landslide inventory

A detailed inventory of the landslides that occurred during the October 1, 2009 event has been prepared by authors at 1:500 scale through the interpretation of high resolution post-event colour orthophotos taken 4–6 days after the event by the Department of Civil Protection, and field surveys in the study area. The shaded relief and the slope angle derived from the 1 × 1 m DEM (LiDAR survey) were particularly useful for the recognition of main scarps, transport

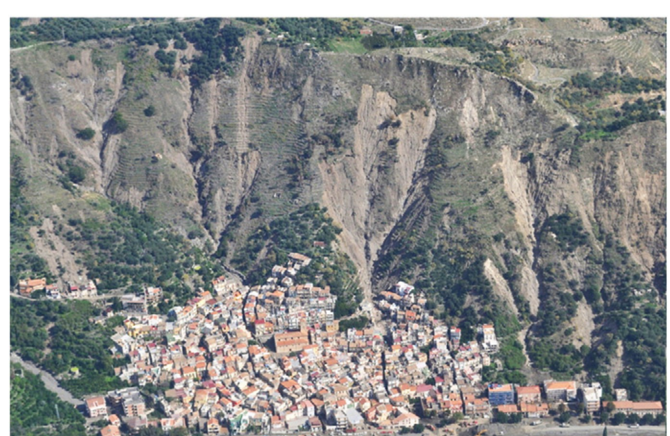


Fig. 1. 1 October 2009 landslide event in the village of Giampilieri.

and accumulation zones, especially in the shadow areas of the orthophotos. 1490 landslide source areas were identified and mapped (Fig. 2). Most of the landslides started as debris slides and evolved into debris flows or debris avalanches, depending on local morphological conditions (channels or open slopes) (Esposito et al., 2012). The opportunity to deal with an event inventory of landslide source areas has offered an unquestionable advantage: all landslides were triggered by the same storm event and thus with very similar conditions of rainfall intensity that differ only in part for the time of activation and for local intensity variations. Then making the assumption that the triggering factor is a constant, we can analyse more strictly the relationship between the observed landslides and the contributing factors.

The surface of the 1490 source areas varies from 8 to 7048 m^2 and covers a total of 0.52 km^2. 5% of the source areas measures less than 26 m^2 and another 5% more than 1254 m^2.

2.3. Controlling factors

The selection of controlling factors to be included as input variables in the models is an essential step in landslide susceptibility assessment. It is also very important to evaluate the quality, resolution, accuracy and temporal change of the input data, considering that they significantly influence the statistical model results.

The explanatory variables used in the present work are: Slope angle, Aspect, Total curvature, Profile curvature, Plan curvature, Flow Accumulation Number, Topographic Wetness Index, Stream Power Index, Distance to stream, Lithology, Land use/land cover, Agricultural terraces and Wildfires. Most of the variables are commonly used in susceptibility analysis, and others have been selected according to the type of landslides (e.g., Flow Accumulation Number) and the characteristics of the study area (e.g., Agricultural terraces and Wildfires).

2.3.1. Slope angle

Slope angle is generally considered one of the main landslide contributing factors; it has been calculated in each cell as the maximum change in elevation over the distance between the cell and its eight neighbours using the Slope function of the ArcGIS Spatial Analyst Toolbox. Slope angle exceeds 33° in 44% of the study area (Fig. 4a).

2.3.2. Aspect

Aspect measures for each cell the downslope direction measured clockwise in degrees from 0° (due north) to 360°; it has been reclassified into 8 classes according to the 8 cardinal directions. Generally, Aspect has implications on the soil water content; in fact north-facing slopes generally have higher humidity and a more abundant vegetation cover, which can lead to greater protection of soil from erosion and shallow landslides (Dai and Lee, 2002). The distribution of Aspect values in the study area is related to NW–SE trend of the main drainage lines (De Guidi and Scudero, 2013) (Fig. 3).

2.3.3. Total, profile and plan curvature

Curvature is a morphometric parameter that represents the spatial variation of the slope gradient. In particular, the plan curvature is the derivative perpendicular to the direction of the maximum slope and allows us to highlight converging (concave curvature) or divergent (convex curvature) water flows (Fig. 4b).

2.3.4. Flow Accumulation Number

This parameter represents the number of upstream cells that flow into each cell of the study area. Due to the large range of values, the parameter is expressed as its logarithm (Catani et al., 2013). Much of the study area is characterized by low values of Log Flow Accumulation, because of the small size of catchments and the low order of streams.

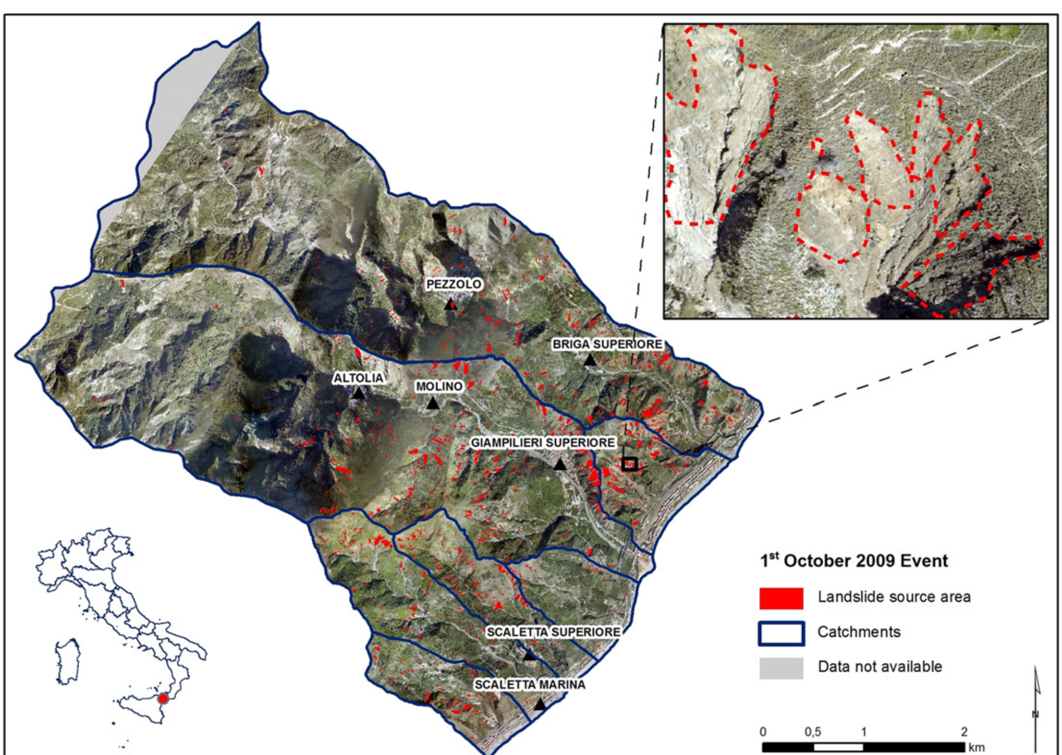


Fig. 2. Inventory of the landslide source areas (1 October 2009 event) mapped by the author on the high-resolution post-event orthophotos and a detail of the landslide source areas in the S. Giovanni basin.

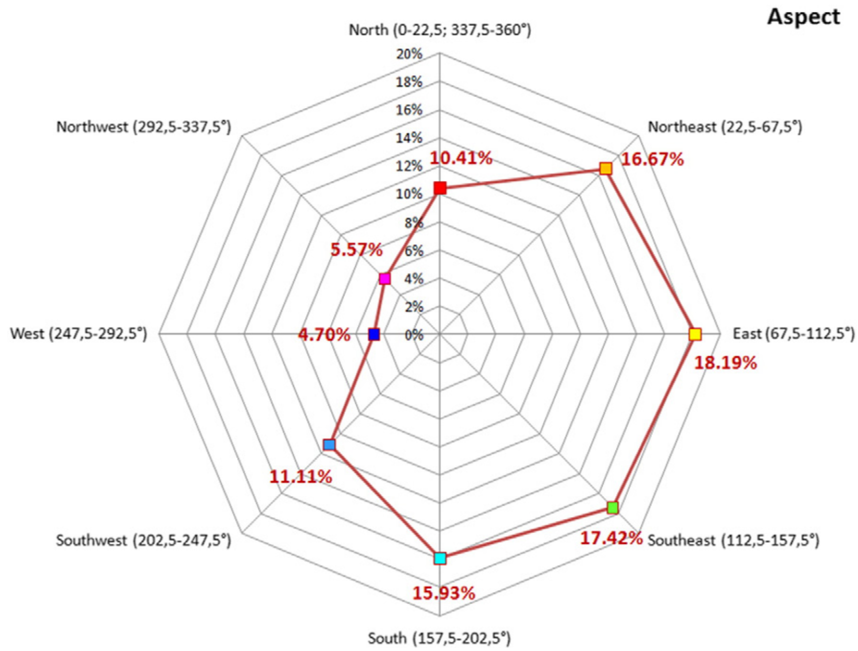


Fig. 3. Distribution of Aspect classes in the study area.

2.3.5. Topographic Wetness Index (TWI)

The Topographic Wetness Index, commonly used to characterize the spatial distribution of soil moisture/saturation, is defined as

$$\mathrm{TWI} = \ln \frac{(FlowAcc + 1) \times CellArea}{\tan(Slope)}.$$

2.3.6. Stream Power Index (SPI)

This parameter, indicative of the erosive power of streams, is calculated as

$$\mathrm{SPI} = \ln((FlowAcc + 1) \times CellArea \times \tan Slope).$$

2.3.7. Distance to stream

This parameter has been introduced to evaluate the role of runoff and the influence of toe erosion by stream on landslide triggering (Devkota et al., 2013). It has been calculated using the Euclidean Distance ArcGIS Tool that gives the distance in metres from each raster cell of the studied area to the closest stream segment.

2.3.8. Lithology

Lithology influences the geo-mechanical characteristics of terrains (Costanzo et al., 2012; Catani et al., 2013). The parameter has been obtained by the reclassification of the Geological Map of Italy at the scale of 1:50,000 CARG Project-Sheet 601 Messina–Reggio Calabria (APAT, 2008). The paragneiss and micaschists are the dominant lithologies in the study area (68%), followed by the phyllites and metasandstones with 16.5%, the marbles with 6.5% and the alluvial deposits with 5.5%. The other lithologies, including calcarenites outcropping in the upper part of the slope behind Giampilieri, are present in small percentages (Fig. 4c). Lithology together with other variables used in the models, such as slope angle, curvature, upslope contributing area and land cover, can provide indirectly the thickness of debris/colluvial deposits (Catani et al., 2010), that is not available for the study area.

2.3.9. Land use/land cover

Land use/land cover is widely considered as a particularly important factor for shallow landslide susceptibility. The vegetation protects slopes against soil erosion, surface runoff and shallow landslides. In fact roots reinforce the soil increasing soil shear strength. Thus, vegetation plays an important hydrological role, causing absorptive and evaporative losses (Greenway, 1987). The velocity of water flow along a slope with a dense vegetation cover is about 1/4 of water flow along the same slope without vegetation in the same rainfall conditions and, therefore, the erosive action, which varies with the square of velocity, may decrease to 1/16 (Bazzoffi et al., 2013). Regarding the land-use data to be included in the models, two different information layers have been analysed and compared: the Corine Land Cover 2006 (European Environment Agency, 2007) database and the Map of the Nature of Sicily Region, realized between 2005 and 2008 by ISPRA and Department of Land and Environment of Sicily Region, which maps habitats according to the European Corine Biotopes classification system (ISPRA, 2009). The quality analysis carried out by comparison between the two land-use layers and high-resolution colour orthophotos highlighted that the CLC 2006 is not suitable for the purposes of this paper, because of the not sufficiently detailed mapping and the absence of several classes of Land use (e.g., urban fabric of villages of Altolia, Molino, Pezzolo and Briga) since the minimum mapping unit is 25 ha. The Map of the Nature instead, although being focused on the representation of habitats and not strictly Land use, has a high detail (minimum mapping unit: 1 ha) and can be conveniently used for the purposes of the present work. The Map of the Nature has been reclassified into 6 classes. The study area is characterized by the presence of forests, scrubland and bushes in the upper part of the basin, while permanent crops (olive groves, citrus orchards and vineyards) prevail in the middle and lower portions. Pastures and natural grassland are common in the study area and often resulted in a significant reduction of vegetation cover and intense erosion (Fig. 4d).

2.3.10. Agricultural terraces (state of maintenance)

The Agricultural terraces have been identified and mapped using high-resolution orthophotos, the shaded relief, the slope and the profile curvature derived from the 1×1 m DEM. They have been classified from imagery according to the state of maintenance: 'Maintained', 'Abandoned', 'Afforested/colonized by forest terraces', and 'Not terraced'. Not terraced and afforested/colonized by forest terraces prevail in the upper part of the main river basins. The terraces are abandoned in almost 55% of the study area (Fig. 4e).

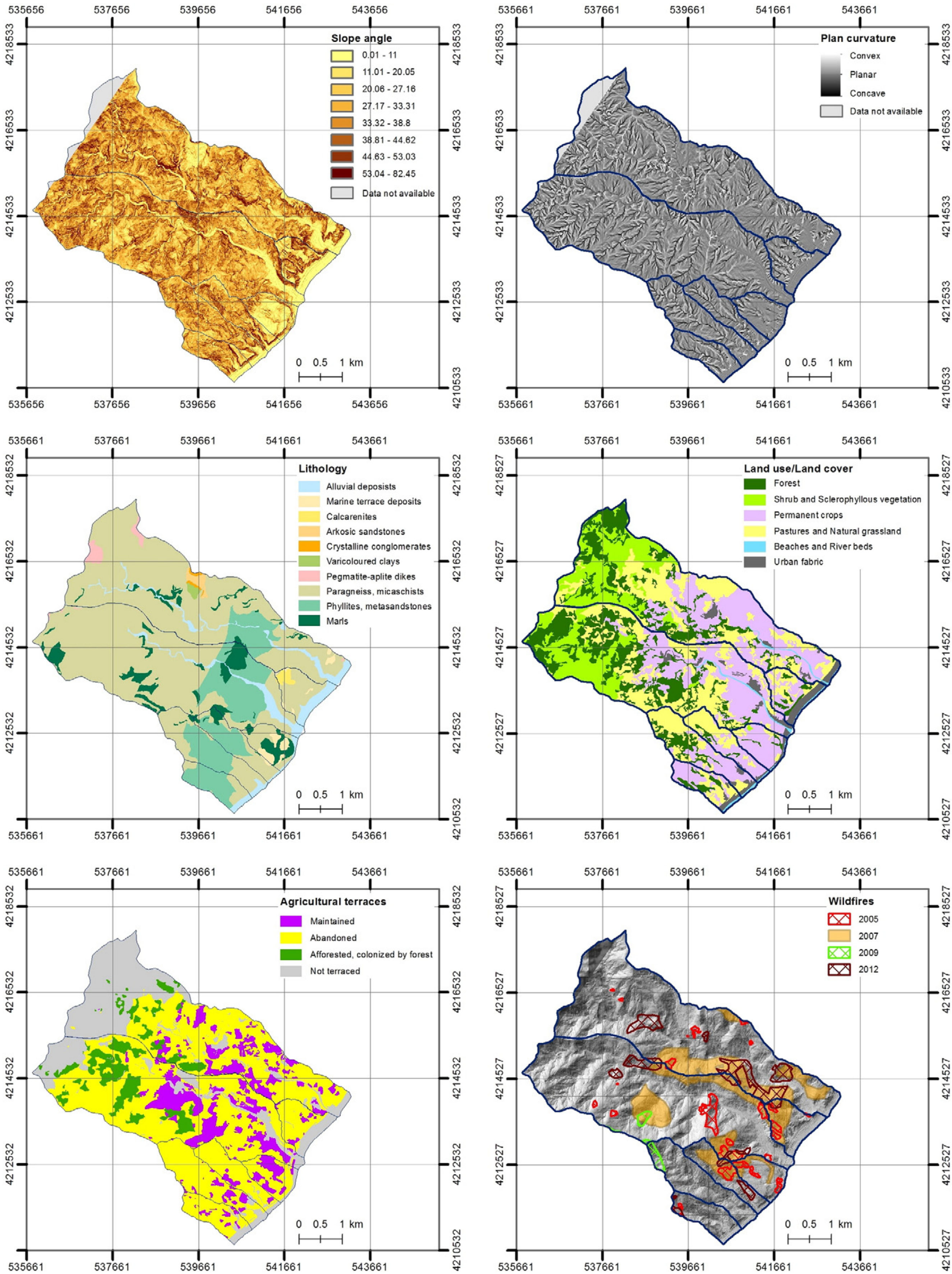


Fig. 4. a) Slope angle in the study area; b) Plan curvature; c) Lithology; d) Land use/land cover; e) Agricultural terraces; f) Wildfires.

2.3.11. Wildfires

Wildfires reduce the vegetation cover, change the soil structure and may have significant effects on hydrological and geomorphological processes resulting in increased runoff, sheet erosion, rill and gully erosion, and increased susceptibility to debris-flows initiation (Rupert et al., 2008). The soil losses, due to splash erosion and runoff erosion are from 10 times to 100 times higher in burned areas (Shakesby and Doerr, 2006). The most critical period for the absence or reduced vegetation cover is in the first months after the wildfire until the vegetative recovery and may continue up to two years and beyond (Garcia-Ruiz et al., 2013), depending on the wildfire type (surface or crown), severity, biomass characteristics, climate regime and also in the case of repeated fire events (Parise and Cannon, 2012). The studied area was largely affected by repeated wildfires (2005, 2007, 2009, 2012). The data sources are the Forestry Department of the Sicilian Region and the Registry of burned areas of the Messina Municipality in 2007, 2009 and 2012. The areas affected by wildfire in 2005 have been mapped by photo interpretation of 2006 colour orthophotos (Geoportal of the Italian Ministry of Environment). The 2007 wildfire was the most extensive and affected 16% of the area, while the 2009 fire involved the study area only marginally. We have classified wildfires into three categories: 'Wildfire', 'Repeated Wildfires' and 'No Wildfire'. The class 'Wildfire' covers an area of 4.145 km^2 (16.43% of the study area), 'Repeated wildfires' 0. 441 km^2 and 'No wildfire' 20.645 km^2 (Fig. 4f).

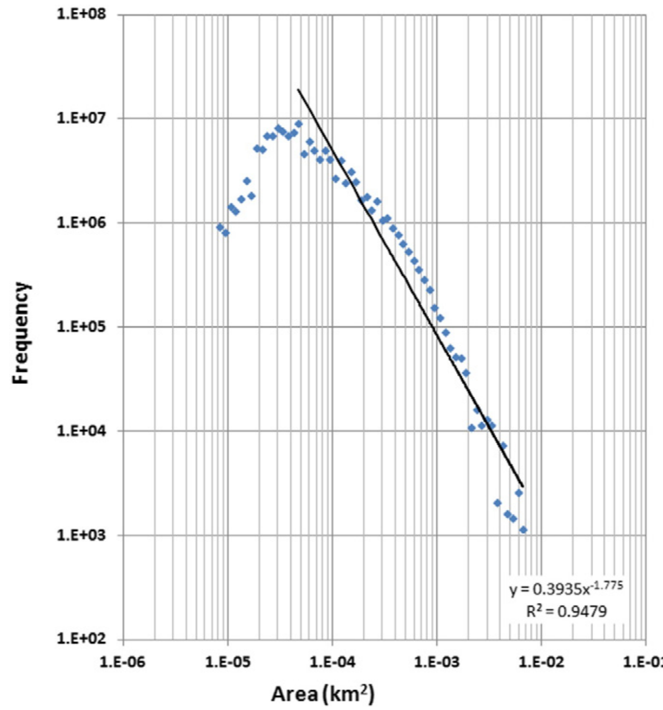


Fig. 5. Frequency–area distribution of detachment zones in the study area.

3. Methods

3.1. Choice of mapping unit

The choice of mapping unit is a crucial step in landslide susceptibility assessment. The mapping unit may consist of regular grid cells, unique condition units — UCU (Carrara et al., 1995; Vergari et al., 2011) or slope units (Carrara et al., 1991, 1995; Guzzetti et al., 1999). The latter, being of larger size, describe the average terrain conditions and are suitable to identify/predict the location of landslides including source, transport and accumulation areas. The raster cells represent best the local conditions and can be favourably used for the study of the source areas (Van Den Eeckhaut et al., 2009). In the present work the regular grid cell has been used. Although it has not a physical or geomorphological meaning, it allows, if appropriately sized, the representation of the morphological characteristics of the area, such as agricultural terraces, scarps and channels that influence the triggering of shallow landslides. In order to choose the optimal size of the grid cell, the following analyses and processing have been carried out by comparing 1 × 1 m, 2 × 2 m, 4 × 4 m, 8 × 8 m and 20 × 20 m cells: a) estimate of the more frequent size of source areas through the frequency–area statistics; b) analysis of the optimal number of grid cells to describe the source areas; c) comparison of the distribution of the slope angle, derived from digital elevation models with different resolution.

Frequency–area statistics have been used to analyse the distribution of the size of source areas and to identify the most frequent area in the inventory. The use of this method is based on the assumption that landslides, like other natural hazards, have a cumulative distribution of the frequency of the landslide area that is described by a power law distribution valid over intervals of several orders of magnitude (Malamud et al., 2004). The estimation of the frequency–area distribution has been determined by the logarithmic binning method (Hovius et al., 1997; Guzzetti et al., 2002; Trigila et al., 2010). The most frequent area is equal to 47 m^2 (Fig. 5).

With regard to point b), the 1 × 1 and 2 × 2 m grid cells are able to represent all detachment zones, 7 source areas are not represented with the 4 × 4 m resolution, 168 (11%) with the 8 × 8 m and 801 (54%) with the 20 × 20 m (Table 1).

Concerning point c), it is essential to have a high-resolution digital elevation model, because the morphometric parameters generally play an important role in landslide susceptibility analysis. In fact the raster resolution determines a different distribution of the slope angle in the study area and in the detachment zones (Van Westen et al., 2008; Fressard et al., 2014). In the study area the original 1 × 1 m DEM (LiDAR) and the resampled DEMs at different resolutions: 2 × 2 m, 4 × 4 m, 8 × 8 m, 20 × 20 m have been compared (Figs. 6,7). The resampling has been obtained determining the mean value of the cells from the 1 × 1 m DEM that fall within the new cell's spatial extent. The shaded relief derived from LiDAR 1 × 1 m is the closest representation of the real surface topography, allowing the recognition of roads, agricultural terraces, stream channels, landslide scarps, etc. The 4 × 4 m resolution still allows us to appreciate these morphological elements, which are mostly lost using 8 × 8 m and 20 × 20 m resolutions. Decreasing the resolution of digital elevation model, we observe a smoothing of the surface with a decrease in the frequency of highest values of slope angle both within the study area and within the detachment zones (Table 2). 1 × 1 and 2 × 2 m resolutions, while better representing the real morphological conditions, are too fine not respecting the axiom of maximizing internal homogeneity and heterogeneity with respect to adjacent cells. On the basis of the above considerations, the 4 × 4 m grid cell (16 m^2) is the best compromise and has been chosen as mapping unit. The study area consists of a total of 1,543,412 cells. The morphological and hydrological explanatory variables have been then derived from the 4 × 4 m resampled DEM; the categorical variables in vector format have been rasterized using 4 × 4 m grid cells.

3.2. Training and test areas

Before the application, it is necessary that the statistical model is trained and tested with two separate samples of data, obtained by a spatial or temporal subdivision of the input data. It is therefore necessary to identify a training area to calibrate the model and a test area in order to assess the predictive capabilities. Alternatively, knowing the date of activation of landslides, it is necessary to divide temporally the dataset: the model is trained with past landslides that occurred prior to a fixed date and tested on conventionally-defined "future" landslides that occurred after that date (Chung and Fabbri, 2003).

In the present work the study area has been divided into a training area, composed of Briga and S. Giovanni river basins (10.403 km^2, 42%

Table 1
Number of cells that represent source areas using different resolution grid cells.

Grid cells	No. of cells per source area				Total no. of cells of source areas	Total no. of represented source areas
	Min	Max	Mean	Median		
1 × 1 m	9	7048	348	156	518,708	1490
2 × 2 m	2	1760	87	39	129,655	1490
4 × 4 m	0	443	22	10	32,477	1483
8 × 8 m	0	110	6	3	8117	1322
20 × 20 m	0	18	2	1	1284	689

of the study area), and in a test area consisting of the Giampilieri river basin and the remaining 4 smaller catchments (14.325 km^2, 58%).

3.3. Bivariate method: Frequency Ratio

A first evaluation of the relationship between source areas and controlling factors has been performed by determining the Frequency Ratio (FR_i) for each parameter (Lee and Min, 2001). This bivariate statistical method consists in comparing the spatial distribution of landslides with predisposing factors, taken individually, in the study area.

The Frequency Ratio (FR_i) assesses the relative importance of each class with respect to landsliding:

$$FR_i = \frac{b}{a} = \frac{\frac{landslide\_cells_i}{landslide\_cells_{tot}}}{\frac{no\_landslide\_cells_i}{no\_landslide\_cells_{tot}}}.$$

Subscript i indicates the i-th class for each variable considered.

This method requires the reclassification into classes of continuous variables, such as the slope angle and other parameters derived from the DEM. It is important to note that the obtained values of FR_i are influenced both by the number of classes and by the thresholds between classes, while in the multivariate statistical models implemented in the present work, continuous variables are used as they are, avoiding to introduce an element of subjectivity. The Jenks Natural Breaks algorithm has been used for the determination of the threshold values between classes of continuous variables in order to minimize the variance within each class and maximize the differences between classes. A FR_i close to 1 indicates an absence of correlation between the i-th class of the parameter under investigation and landslide source areas; an index greater than 1 indicates a direct correlation with source areas, which is more significant as the value of FR_i increases; a value less than 1 indicates an inverse correlation with landslides, namely that the class is directly correlated with stable areas.

The Frequency Ratio method has been used widely to produce susceptibility maps (Süzen and Doyuran, 2004; Gorsevski et al., 2006; Lee et al., 2007; Yilmaz, 2009; Floris et al., 2011) by calculating the Landslide Susceptibility Index (LSI) for each cell of the investigated area. LSI is equal to the sum of the FR_i of all the input parameters.

$$LSI = \sum FR_i$$

In the present work, we have used the Frequency Ratio method both for the descriptive statistics and to produce a susceptibility map.

3.4. Multivariate analysis and sampling strategies

In multivariate statistical models it is necessary to sample all the considered variables on points located in landslide areas and in stable areas. The sampling strategy affects the results of the susceptibility map (Yilmaz, 2010; Petschko et al., 2014). The number of points must be large enough to cover the variability of categorical and continuous parameters in the study area but not too large to avoid spatial autocorrelation of the input parameters that violates the assumption of independence of observations (Van Den Eeckhaut et al., 2006, 2010). It is well known that the greater is the number of the input variables the greater must be the size of the sample required to represent statistically all possible combinations and to discriminate one from the other. The model may have poor predictive capability if the sample used for training is not sufficiently representative of the independent variables. In recent studies it was found that the greater the number of sampling points the greater the predictive ability of the Random Forests technique (Catani et al., 2013). The literature suggests different values of the ratio between points in landslide area and points in stable areas ranging generally from 1:1 to 1:10 (Heckmann et al., 2014).

In the present work two methods of sampling points have been compared: Method 1) multiple points for each source area, on a 4 × 4 m regular grid; Method 2) one point for each source area in the centroid of the cell (4 × 4 m grid) located at the highest altitude. This point was chosen because it generally represents the zone where the movement started, except for retrogressive landslides triggered by stream erosion at the foot of the slope. The first method provides the maximum number of points that can be sampled in the detachment zones (full sample); the second one the minimum number of points. In Method 1 the sampling of multiple points in each source area implies that the number of points in each area varies as a function of its size, with a greater number of points in larger areas. This criterion can be justified by the assumption that the combinations of control factors of larger source areas lead to increased landslide susceptibility. Moreover considering the detail of the scale of analysis, a single point may not be representative of the variability of controlling factors in source areas.

Regarding sampling in stable areas, in both cases a number of points comparable with that of the points in the landslide source areas has been generated (41% points in source areas and 59% in stable areas). The points have been generated randomly with a minimum distance of 4 m between points and at a distance greater than 15 m from the source areas, in order to avoid sampling border zones similar to source areas in terms of controlling factors.

In Method 1 the training sample is made of 12,446 points in source areas and 17,914 in stable areas (Table 3). In Method 2, 639 points in source areas and 887 in stable areas have been sampled for model training.

3.5. Logistic Regression

Logistic Regression (LR) is one of the most widely used methods for landslide susceptibility assessment (Ayalew and Yamagishi, 2005; Lee and Sambath, 2006; Van Den Eeckhaut et al., 2006; Nefeslioglu et al., 2008; Bai et al., 2010). Logistic Regression is a particular type of multivariate regression which is used to study the relationship between a dichotomous response variable coded as 0/1 (absence/presence of landslides) and a set of explanatory variables $x_1 \ldots x_n$, both categorical and numerical (Hosmer and Lemeshow, 2000).

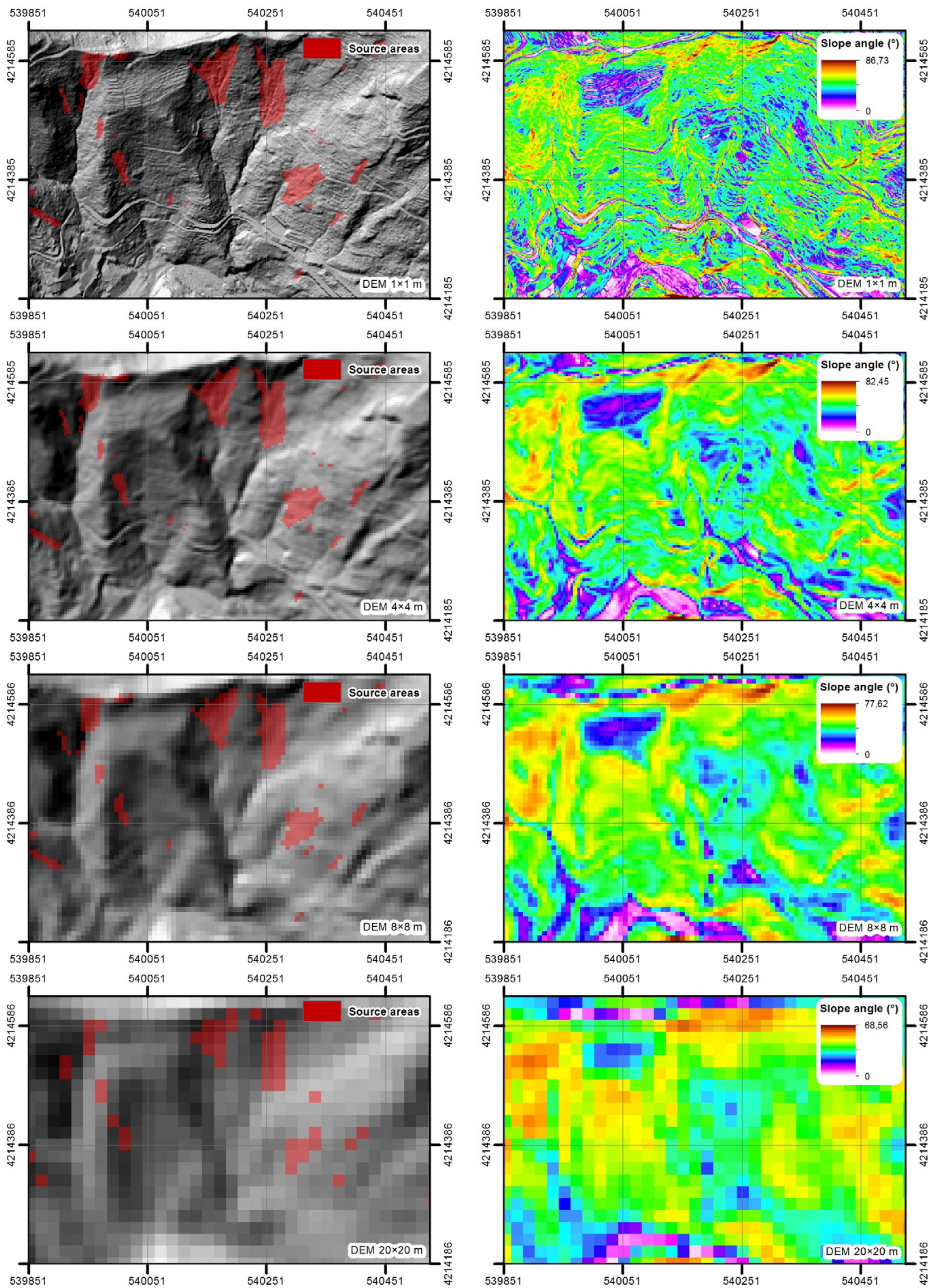


Fig. 6. Digital terrain models at different resolution in a portion of the study area, representation of source areas and slope angle.

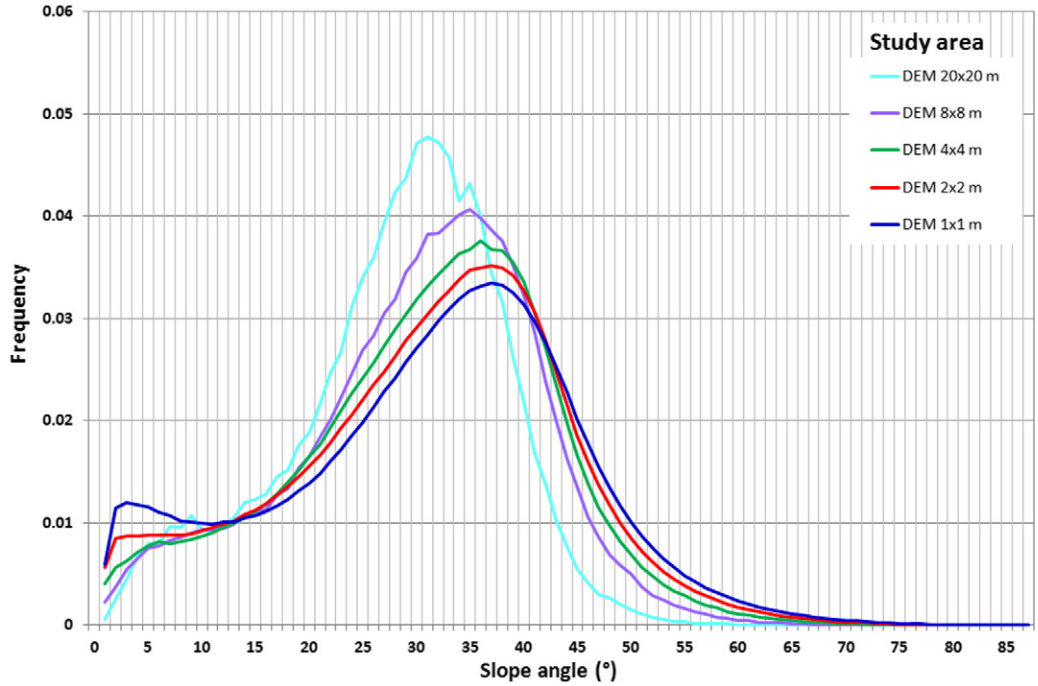


Fig. 7. Comparison of the distribution of slope angle using DEMs at different resolution in the study area.

Table 2
Slope angle statistics using DEMs at different resolution.

Slope angle (°)	1 × 1 m DEM	2 × 2 m DEM	4 × 4 m DEM	8 × 8 m DEM	20 × 20 m DEM
Minimum	0	0	0.01	0.01	0.02
Maximum	86.73	84.94	82.45	77.62	68.56
Mean	30.79	30.62	30.3	29.61	27.58
Standard deviation	13.86	12.91	11.99	11.11	9.77

In landslide susceptibility maps, the model output (between 0 and 1), represents for each grid cell the probability p to belong to a landslide ($Y=1$) (Ayalew and Yamagishi, 2005; Lee and Sambath, 2006):

$$p(Y=1)=\frac{1}{1+e^{-z}}=\frac{1}{1+e^{-(\alpha+\beta_1x_1+\ldots\beta_nx_n)}}=\frac{e^{\alpha+\beta_1x_1+\ldots\beta_nx_n}}{1+e^{\alpha+\beta_1x_1+\ldots\beta_nx_n}}.$$

The odds or likelihood ratio represents the ratio between the probability p that the dependent variable Y is 1 and the probability $1-p$ that the dependent variable Y is 0. The natural logarithm of odds (Logit) is a linear function of the explanatory variables $x_1 \ldots x_n$ and takes values from $-\infty$ to $+\infty$ (Van Den Eeckhaut et al., 2006).

$$Logit(p)=\ \ln\frac{p}{1-p}=\alpha+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n$$

$\beta_1, \beta_2 \ldots \beta_n$ are the coefficients that measure the contribution of the independent variables $x_1 \ldots x_n$ to landslide susceptibility. If the coefficient β is positive, $e^{\beta}>1$ and the factor has a direct correlation with landslides; if β is negative, e^{β} is between 0 and 1.

There are several ways of entering the independent variables in the model; we have used the forward stepwise mode, which starts with the model consisting of only the constant without any variable at step 0 and introducing or removing one variable at each next step. As input data, a matrix with a number of rows equal to the observations (training sample) and a number of columns equal to the explanatory variables plus the dependent variable (1 for points in source areas or 0 for points in stable areas) is provided to the model. In the present study Logistic Regression models have been implemented using the software SPSS ® (IBM). The parameter coefficients have been estimated by maximum likelihood.

3.6. Random Forests

The Random Forests multivariate statistical technique is an implementation of the Bayesian tree or binary classification tree, as it considers an ensemble (forest) of n trees in order to multiply the efficiency and predictive capability (Breiman, 2001; Cutler et al., 2007). The model, implemented with the Matlab® function TreeBagger in regression mode, is suitable to deal with mixed variables, both categorical and numerical. The Random Forests uses the bagging technique (bootstrap aggregation) to select, at each node of the tree, random samples of variables and observations as the training dataset for model calibration. Since the random selection of the training dataset may affect the results of the model, a set of numerous trees helps to ensure the

Table 3
Sampling points in training and test areas according the two sampling methods.

Sampling method in landslide source areas	Training area			Test area		
	No. of point in source areas	No. of point in stable areas [a]	Total no. of points	No. of point in source areas	No. of point in stable areas [a]	Total no. of points
Multiple points on 4 × 4 m regular grid	12,446	17,914	30,360	20,031	29,026	49,057
1 point per source area	639	887	1526	844	1141	1985

[a] Points in stable areas: generated randomly with a minimum distance of 4 m between points and at a distance greater than 15 m from the source areas.

stability of the model. Unselected cases (out of bag) are used to calculate the error of the model (OOBError), equal to the standard deviation error between predicted and observed values, and to establish a ranking of importance of the variables. The relative importance of each predictor variable in the model is measured through the Matlab function OOBPermutedVarDeltaError. For each variable, the function determines the model prediction error if the values of that variable are permuted across the out-of-bag observations. It holds true that the greater is the prediction error, the greater is the importance of the variable.

In the present work, the dependent variable of the Random Forests model, expressed with values between 0 and 1, is represented by the landslide density per mapping unit (4×4 m grid; Section 3.1). Primarily a rasterization (1×1 m grid) of source areas has been performed. Then the landslide density has been calculated as the number of cells of source areas obtained above divided by the mapping unit area (16 m^2). Since the Random Forests technique has a component of randomness at the extraction of independent variables and observations in each node, it is appropriate to preliminarily evaluate the influence of the number of trees and the number of runs on the stability of the model (Catani et al., 2013).

3.7. Model evaluation

The methods most frequently used to evaluate the performance of the models are the Success and Prediction rate curves, the contingency table, the ROC curve and AUC.

The Success and Prediction rate curves have been applied to the Frequency Ratio model. Success rate curve is based on the training subset and gives information on how the model is able to fit observed landslides. Instead Prediction rate curve is calculated with the test subset and provides information about the predictive capabilities of the model (Chung and Fabbri, 2003; Remondo et al., 2003; Melchiorre et al., 2011). Success and Prediction rate curves represent the rank of the landslide susceptibility index in descending order (x-axis) and the cumulative percent of landslide occurrence (y-axis).

The contingency tables display the amount of True Positives (TP), i.e., cells predicted unstable and observed unstable (terrain units with landslides), True Negatives (TN), i.e., cells predicted stable and observed stable (terrain units without landslides), False Positives (FP), i.e., cells predicted unstable but observed stable and False Negatives (FN), i.e., cells predicted stable but observed unstable. This evaluation method is particularly useful if the susceptibility map is intended to be used for planning purposes. Economic costs of misclassification vary considerably depending on the type of error. False Positive misclassification errors determine a limitation in the use of terrain units due to land-use restrictions and therefore a loss of their economic value. False Negative misclassification errors determine higher and not socially acceptable costs in case of casualties and damage to exposed elements (e.g., buildings, infrastructure) (Frattini et al., 2010; Corominas et al., 2014).

The ROC curve (Receiver Operating Characteristics) measures the goodness of the model prediction, plotting, for different susceptibility threshold values, the True Positive rate (*Se*) and the False Positive rate (1-*Sp*). The Area Under Curve (AUC) varies from 0.5 (diagonal line) to 1, with higher values indicating a better predictive capability of the model. AUC values less than 0.7 indicate poor predictive ability, between 0.7 and 0.8 moderate, between 0.8 and 0.9 good and >0.90 are typical of excellent predictive ability of the model (Swets, 1988). However, recent studies showed that models with similar AUC can produce very different susceptibility maps (Trigila et al., 2013).

4. Results and discussion

4.1. Frequency Ratio results

The application of the Frequency Ratio method has produced the FR_i indexes of each class of the 13 control factors (Table 4). The parameters

Table 4
FR_i calculated in the study area for the 13 input parameters.

Factor	FR	Factor	FR
Slope angle		*Topographic Wetness Index*	
0.01–11°	0.0122	0.8668–3.9698	0.9024
11.01–20.05°	0.0640	3.9699–5.1334	0.9576
20.06–27.16°	0.2398	5.1335–6.297	1.0450
27.17–33.31°	0.6660	6.2971–7.7709	1.2196
33.32–38.8°	1.4609	7.771–9.943	1.1551
38.81–44.62°	2.2218	9.9431–13.4338	0.4844
44.63–53.03°	2.3242	13.4339–20.6482	0.0290
53.04–82.45°	1.9372	*Distance to streams*	
Aspect		0–17 m	0.8193
North (0–22.5; 337.5–360°)	0.9527	18–36 m	1.1166
Northeast (22.5–67.5°)	0.8252	37–54 m	1.1611
East (67.5–112.5°)	0.7796	55–73 m	1.1839
Southeast (112.5–157.5)	0.8369	74–93 m	1.0489
South (157.5–202.5)	1.1019	94–112 m	1.0112
Southwest (202.5–247.5)	1.5363	113–132 m	0.7746
West (247.5–292.5)	1.7502	133–155 m	0.6137
Northwest (292.5–337.5)	0.8778	156–185 m	0.5373
Total curvature		186–260 m	0.4813
Concave	1.6136	*Land use/land cover*	
Planar	0.6815	Urban fabric	0.0230
Convex	0.6991	Beaches and river beds	0
Profile curvature		Pastures and natural grassland	1.8477
Concave	1.2868	Shrub and Sclerophyllous vegetation	0.0709
Planar	0.8971	Permanent crops	1.2102
Convex	0.8197	Forest	0.5425
Plan curvature		*Agricultural terraces*	
Concave	1.8320	Not terraced	0.1890
Planar	0.5360	Abandoned	1.5667
Convex	0.7065	Afforested/colonized by forest	0.1022
Log Flow Accumulation		Maintained	0.6783
0–0.2951	0.5048	*Lithology*	
0.2952–0.7719	0.7890	Alluvial deposits	0.0149
0.772–1.2487	1.1512	Marine terrace deposits	0.1882
1.2488–1.8163	1.5435	Calcarenites	0.0944
1.8164–2.6791	1.9125	Crystalline conglomerates	0
2.6792–4.0186	0.8392	Arkosic sandstones	0.1639
4.0187–5.7668	0.0432	Varicoloured clays	0
Stream Power Index		Pegmatite–aplite dikes	0.0551
−5.8648–1.2463	0.0237	Paragneiss and micaschists	0.8905
1.2464–2.7884	0.3948	Marls	0.7846
2.7885–3.9022	0.6603	Phyllites and metasandstones	2.0879
3.9023–5.0159	1.1385	*Wildfires*	
5.016–6.5581	1.7846	No wildfire	0.6778
6.5582–9.1283	2.4368	Wildfire	2.3565
9.1284–15.9823	0.5003	Repeated wildfires	3.9534

with the most significant correlations with the source areas are slope angle, plan curvature, Aspect, SPI, Lithology, Land use/land cover, Agricultural terraces and Wildfire. In particular, slope angle shows a positive correlation in the last 4 classes (33.32°–82.45°) with values of FR_i gradually increasing with slope, except for the last class characterized by very steep slopes and consequently by absence of debris deposits. The first four classes (0°–33.31°) have values less than 1 and therefore an inverse correlation to landsliding. Concerning Aspect, the values of FR_i indicate a positive correlation between source areas and slopes facing to west, southwest and south, confirming the protective effect of vegetation on north facing slopes. Source areas are also strongly correlated with concave plan curvature, due to the presence of water and saturation of soils. The Stream Power Index shows an inverse correlation with the source areas in the first 3 classes, which are representative of flat areas (coastal area) and/or high order streams. The penultimate class, characteristic of areas close to first order streams, presents a good correlation with detachment zones. Regarding Lithology, 'Phyllites and metasandstones', with an index equal to 2.1, is the only class with a direct correlation with landsliding. 'Marbles' and 'Paragneiss and micaschists' have indexes slightly less than 1, while all other classes have very low values of FR_i. 'Crystalline conglomerates' and 'Varicoloured clays', which outcrop in a limited portion of the study area, were not affected by the 2009 event. Regarding the Land use/land cover, the classes 'Pastures and natural grassland' and 'Permanent crops' have a direct correlation with the detachment zones, while 'Shrub and Sclerophyllous vegetation' and 'Forest' are inversely related, as they have a protection effect against soil erosion, runoff and shallow landslides. With regard to Agricultural terraces, the 'Abandoned' terraces, with a value of 1.56 are directly correlated with source areas. 'Maintained' terraces instead have a value of 0.68, indicating a prevalence of stability conditions compared to instability; 'Afforested/colonized by forest' terraces have the lowest value of FR_i, which can be explained by the vegetation protection on the terraces. Lastly, the classes 'Wildfire' and 'Repeated wildfires' have a close correlation with detachment zones, since wildfires that have hit in recent years the study area, have reduced vegetation cover, resulting in an increase of runoff, sheet erosion, rill/gully erosion and debris flows.

The susceptibility map, realized on the basis of the Frequency Ratio indices (Section 3.3) calculated in the training area, shows values of susceptibility between 5.33 and 27.05 (Fig. 8a). To evaluate the performance of the model, the susceptibility map has been divided into 10 equal area susceptibility classes and the Success and Prediction rate curves have been calculated (Fig. 8b). The Success rate curve, calculated on the basis of the training dataset, shows that, in the 10% most susceptible area, the model identifies 53.25% of the observed detachment zones, which rises to 81.95% if we consider the 30% most susceptible area. The Prediction rate curve, built on the test dataset, presents, as expected, lower values than the Success rate curve: respectively 42.69% and 74.53% of the observed landslides. The area under curve is equal to 0.83 for Success rate curve and 0.79 for Predict rate curve. The obtained values show a good predictive ability of the model, given that a random prediction would have predicted only 10% of the landslides in the highest susceptibility class and 30% in the first 3 highest classes.

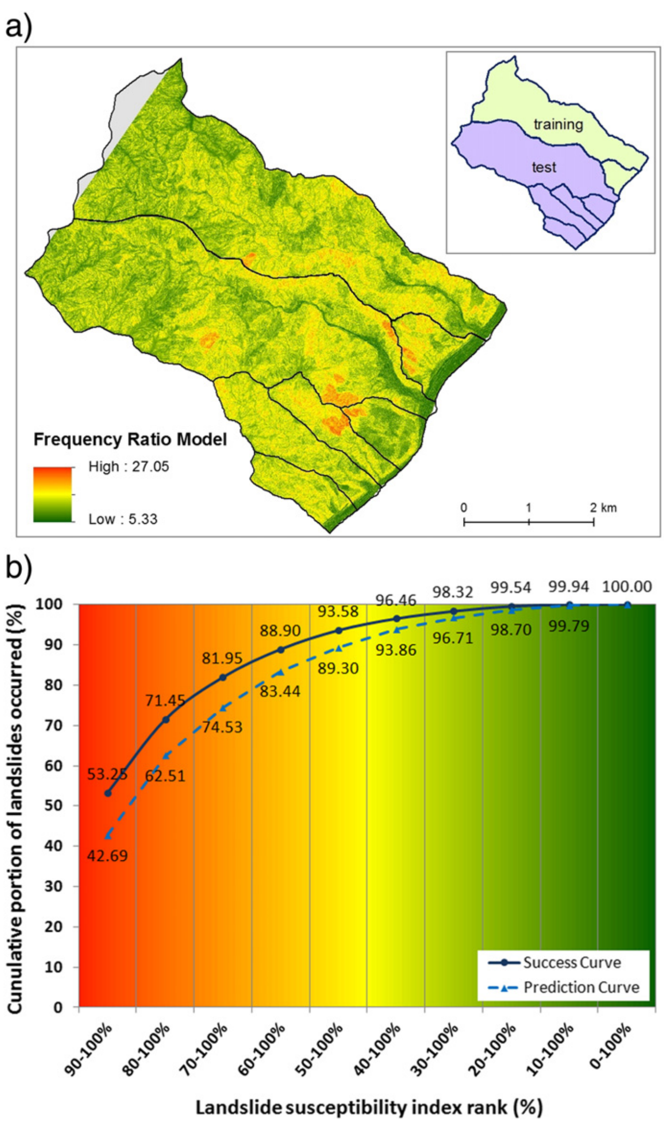


Fig. 8. a) Susceptibility map — Frequency Ratio model; b) model evaluation using Success and Prediction rate curves.

4.2. Logistic Regression results

In the present study three Logistic Regression models have been implemented using the forward stepwise mode (see Section 3.5). The first model (Model 1 LR) uses the 4×4 m regular grid sampling method on source areas, the continuous variables and the categorical variables (Aspect, Lithology, Land use/land cover, Agricultural terraces, Wildfires) transformed into dummies (0/1). This model, calibrated at step 9 using 4 continuous variables and 26 dichotomous variables, correctly classifies 80.8% of points sampled in observed source areas (True Positive) and 83.6% of points outside source area (True Negative) with a cut-off of 0.5.

The model does not converge due to a failure of the likelihood maximization algorithm. This is because three dichotomous variables 'Beaches and river beds', 'Crystalline conglomerates' and 'Varicoloured clays' exhibit quasi-complete separation, i.e., when the dichotomous variable assumes a value of 1 (presence of that class), the dependent variable is always equal to 0 (absence of landslide source areas). These variables occupy an extremely small portion of the study area or have no relation with landslide source areas. However, the Logistic Regression model has been calibrated considering also these variables because their presence leads to a correct estimate of the coefficients of other variables (Allison, 2008). The variables with quasi-complete separation are characterized by extremely high values of regression coefficient and standard error. The values of the coefficient for 'Pastures and natural grassland' and 'Permanent crops' were positive, indicating a direct correlation with landslides while 'Scrub and Sclerophyllous vegetation' has negative coefficient, thus correlated to stable areas. 'Wildfire' and especially 'Repeated wildfire' are strongly correlated with landslides. 'Phyllites and metasandstones' is the lithological class with the highest correlation. 'Afforested/colonized by forest' terraces are related to slope stability while 'Abandoned' ones with instability (Table 5). The susceptibility map has an average value equal to 0.262 over the entire study area, 0.667 in observed source areas and 0.253 in stable areas. The area under the *ROC* curve (AUC) is equal to 0.908 for the training sample, 0.851 for the test sample and 0.854 over the entire study area.

The Model 2 LR has been implemented to overcome the problems of quasi-complete separation observed with dichotomous variables in Model 1 LR, transforming categorical variables into numerical. For this purpose we used the values of FR_i calculated with bivariate statistical analysis, as proposed by Bai et al. (2010). The transformation into numerical variables based on the relative percentage of area affected by landsliding avoids the creation of a high number of dummy variables and allows the consideration of the so called "previous knowledge" of landslide susceptibility (Yilmaz, 2009). The Model 2 LR calibrated at step 9 using 9 independent variables presents the 76.4% of cases correctly classified in source areas and 82.7% in stable areas. The susceptibility map presents a mean value equal to 0.292 over the entire area of the study, 0.685 in source areas and 0.283 in stable areas. The AUC is equal to 0.892 for training sample, 0.861 for test sample and 0.853 for the study area.

The Model 3 LR has been implemented using the training sample consisting of a single point for each source area (Section 3.4) and the categorical variables transformed into numerical using the values of

Table 5
Regression coefficients at step 9 of Model 1 LR.

Step 9 — variables in the equation						
Variable	β	S.E.	Wald	df	Sig.	Exp (β)
Aspect			163.460	7	.000	
North (0–22.5; 337.5–360°)	Reference category					
Northeast (22.5–67.5)	−.453	.068	44.132	1	.000	.636
East (67.5–112.5)	−.507	.067	57.109	1	.000	.603
Southeast (112.5–157.5)	−.095	.068	1.916	1	.166	.910
South (157.5–202.5)	.037	.068	.299	1	.585	1.038
Southwest (202.5–247.5)	−.231	.070	10.932	1	.001	.794
West (247.5–292.5)	−.329	.083	15.872	1	.000	.719
Northwest (292.5–337.5)	−.613	.094	42.124	1	.000	.542
Land use/land cover			1107.629	5	.000	
Urban fabric	Reference category					
Beaches and river beds	−15.389	2087.325	.000	1	.994	.000
Pastures and natural grassland	1.312	.364	12.989	1	.000	3.714
Shrub and Sclerophyllous vegetation	−2.120	.385	30.285	1	.000	.120
Permanent crops	1.591	.364	19.045	1	.000	4.907
Forest	.199	.366	.296	1	.586	1.221
Plan curvature	−.079	.004	511.531	1	.000	.924
Wildfires			1288.411	2	.000	
No wildfire	Reference category					
Wildfire	1.285	.040	1052.069	1	.000	3.615
Repeated wildfires	2.438	.125	380.183	1	.000	11.451
Lithology			564.548	9	.000	
Alluvial deposits	Reference category					
Marine terrace deposits	3.386	.397	72.831	1	.000	29.558
Calcarenites	−.388	.448	.747	1	.388	.679
Crystalline conglomerates	−16.921	3955.106	.000	1	.997	.000
Arkosic sandstones	3.020	.404	55.844	1	.000	20.484
Varicoloured clays	−14.932	3426.437	.000	1	.997	.000
Pegmatite–aplite dikes	1.912	.539	12.572	1	.000	6.767
Paragneiss and micaschists	3.056	.324	89.220	1	.000	21.243
Marls	1.299	.340	14.566	1	.000	3.664
Phyllites and metasandstones	3.514	.327	115.823	1	.000	33.578
Log Flow Accumulation	−6.127	1.050	34.052	1	.000	.002
Slope angle	.009	.018	.222	1	.637	1.009
Stream Power Index	2.776	.456	37.047	1	.000	16.054
Agricultural terraces			899.145	3	.000	
Not terraced	Reference category					
Abandoned	1.261	.061	430.497	1	.000	3.529
Afforested/colonized by forest	−1.458	.157	86.145	1	.000	.233
Maintained	.547	.081	45.020	1	.000	1.728
Constant	−12.877	.670	369.288	1	.000	.000

FR_i. The percentage of cases correctly classified is equal to 81.4% for points in source areas and 86% for points outside detachment zones. The susceptibility map has an average value equal to 0.275 in the study area, 0.669 in source areas and 0.266 in stable areas. The AUC is equal to 0.909 for the training sample, 0.867 for the test sample and 0.849 over the study area.

4.3. Random Forests results

Two susceptibility models with Random Forests technique have been implemented: the first one (Model 4 RF) uses the 4 × 4 m sampling method while the second one (Model RF 5) uses one point for each source area, as was done with the Logistic Regression. The analysis of the variation of the prediction error (OOBError) of the model as a function of the number of trees (Section 3.6) has shown that as the number of trees increases the error decreases and over 170 trees the error becomes stable. For the implementation of the model we used, as the optimal configuration, a forest of 200 trees (Fig. 9).

Regarding the influence of the number of runs on the model results, the values of OOBError calculated for each variable with 1 run have been compared with the corresponding average values of 10 runs. The values

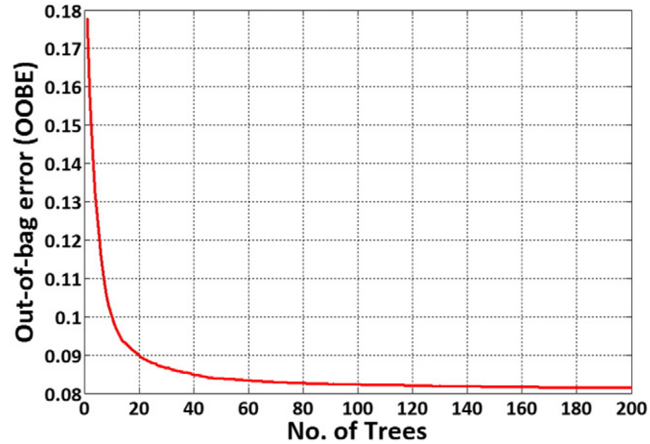


Fig. 9. Out-of-bag error (OOBE) as a function of the number of trees used in the structure of the Random Forests Model 4 RF.

calculated with 1 run are comparable for all variables with the average values of 10 runs, falling within the range of ±2 standard deviations (Table 6).

In order to calibrate the best model, a variable selection procedure has been carried out starting from the full model with all 13 explanatory variables and progressively removing at each step the variable with the lower rank of importance. The aim is to reduce the complexity of the model, eliminating the input parameters not significant for the purposes of prediction. The performance of the models with different numbers of input variables has been evaluated by comparing the values of AUC calculated on test area (Fig. 10). The best model (4 RF) is made up of 12 variables after eliminating the Log Flow Accumulation.

4.4. Model comparison

The comparison of susceptibility maps produced according to the five models (Models 1, 2, 3 LR and Models 4, 5 RF) was carried out through expert judgement, contingency tables, ROC curves and AUC and analysing the frequency distribution, respectively, of source areas and stable areas in susceptibility classes.

From the comparative analysis of susceptibility maps, a remarkable similarity exists among them (Fig. 11). In particular, in the upper part of the two main basins of the study area (Briga and Giampilieri catchments) we observe a low susceptibility due to the presence of forest and shrub and Sclerophyllous vegetation, the absence of burned areas and agricultural terraces. In this upper part only pastures and natural grassland are characterized by medium-to-high values of susceptibility.

Table 6
Comparison of OOBE for each variable using 1 run and 10 runs of Model 4 RF.

	1 run	10 runs		$\frac{OOBE_{1run} - MeanOOBE_{10runs}}{St.Dev.\ OOBE_{10runs}}$
	OOBE	OOBE		
		Mean	St. dev.	
Slope angle	8.3225	8.6703	0.5350	−0.65
Land use/land cover	7.0782	6.3098	0.3261	2.36
Distance to streams	5.9655	6.0144	0.2620	−0.19
Wildfires	5.9515	5.8554	0.2507	0.38
Aspect	5.5958	5.2067	0.2651	1.47
Plan curvature	5.2276	5.3493	0.1999	−0.61
Lithology	3.9464	4.1042	0.1422	−1.11
Agricultural terraces	3.7189	3.6716	0.1431	0.33
Topographic Wetness Index	2.3621	2.3181	0.1529	0.29
Profile curvature	2.1128	2.1476	0.0582	−0.60
Total curvature	2.1054	2.0204	0.0482	1.76
Stream Power Index	1.9444	2.0484	0.1268	−0.82
Log Flow Accumulation	1.8554	1.7510	0.0818	1.28

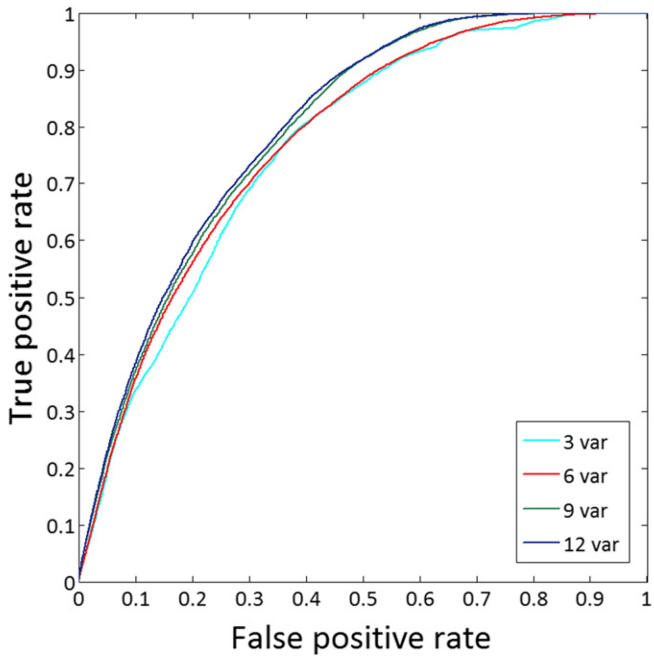


Fig. 10. Comparison of ROC curves of Model 4 RF with 3, 6, 9 and 12 variables.

In the middle and lower parts of the study area, the highest values of susceptibility are strongly correlated with the presence of burned areas, steep slopes, concave plan curvature, pastures or permanent crops. In the coastal strip and in areas with low slope angle a low susceptibility is observed, such as in the Carne Salata catchment.

The differences between Logistic Regression Models 2 and 3 and between Random Forests Models 4 and 5 are due to the different sample size that depends on the sampling method adopted. In particular, the Model 2 (4×4 m regular grid sampling) tends to better classify both low susceptibility zones and high susceptibility zones compared to Model 3 (1 point sampling) (Figs. 12,13). This can be explained by the fact that the Model 2 learns on a number of sampled points twenty times higher that Model 3, better representing the spatial variability and the combinations of the controlling factors. Regarding the comparison between the Random Forests Models 4 and 5, in addition to the consideration mentioned above, a significant underestimation of the susceptibility values of the Model 5 compared to the Model 4 is observed. This is due to the fact that for Model 5 landslide density (input dependent variable) is significantly lower than Model 4 due to the location of the sampling point near the edge of the source area (Section 3.4). Anyway this problem does not affect the Logistic Regression Model 3 because the dependent variable, being dichotomous, always assumes value 1 in the detachment zones.

Regarding the comparison between Logistic Regression and Random Forests models, it should be stated that it is not possible to make a rigorous comparison between them, taking into account that the output of the first is the probability of landslide occurrence for each cell, while for the latter is the landslide density. However, plotting the susceptibility values predicted by Model 4 RF (y-axis) and the values predicted by the Model 2 LR (x-axis) for the 49,057 test sample points a good linear correlation is observed ($RF = 0.73 \cdot LR - 0.0024$; $R^2 = 0.85$). It was therefore decided to enter also the Random Forests models in the comparative analysis.

The comparison of the distribution of cells of observed source areas and stable areas in the 10 landslide susceptibility classes (size of 0.1), indicates that the distribution of landslide cells for Model 4 RF and Models LR follow the same increasing trend with the exception of the last susceptibility class (0.9–1) in which the Model 4 RF predicts a lower number of cells (Fig. 12). Regarding the prediction of landslide cells, the Model 2 LR, that uses categorical variables transformed into numerical, is the most performing, because it maximizes the percentage of observed landslide cells in highest susceptibility classes and minimizes it in the lowest classes. However, the LR Model 2 tends to predict a higher number of False Positive in the highest susceptibility classes than the other models (Fig. 13).

For the five models, the contingency tables (Section 3.7) have been calculated with the cut-off equal to 0.5. Compared to other models, the Model 4 RF ensures very high True Negative and low False Positive, maintaining low values of False Negative (Fig. 11).

The performance of the models in terms of AUC (Area Under Curve) resulted in good to high, with the largest AUC, calculated over the entire study area, for Model 4 — Random Forests (Fig. 14, Table 7).

Regarding the importance of the causative factors in landslide susceptibility assessment, comparing the LR forward stepwise procedure and the RF variable selection procedure, four of the five most significant variables (Slope angle, Land use, Wildfires and Plan curvature) are common to both multivariate statistical models.

Finally, the comparison between the susceptibility maps produced with multivariate statistical models (e.g., Logistic Regression — Model 1) and the map produced by the Frequency Ratio method shows that the latter method is not highly selective in the classification of the study area, particularly underestimating the low susceptibility areas (Fig. 15). This limit is due to the fact that the Frequency Ratio map is realized by summing for each cell the weights obtained considering a causative factor at a time. However, the Frequency Ratio method presents a remarkable simplicity of application.

4.5. Influence of temporal change on susceptibility maps

In this work, a preliminary analysis of the temporal change of landslide susceptibility has been also carried out, taking into account that some predisposing factors may change significantly over time as Land use, vegetation cover and local morphological conditions. In the study area the vegetation cover has undergone substantial reductions in recent years mainly because of frequent fires and grazing. However, locally there was also an increase of forests for the recolonization of some abandoned terraces in the upper part of Giampilieri and Briga basins.

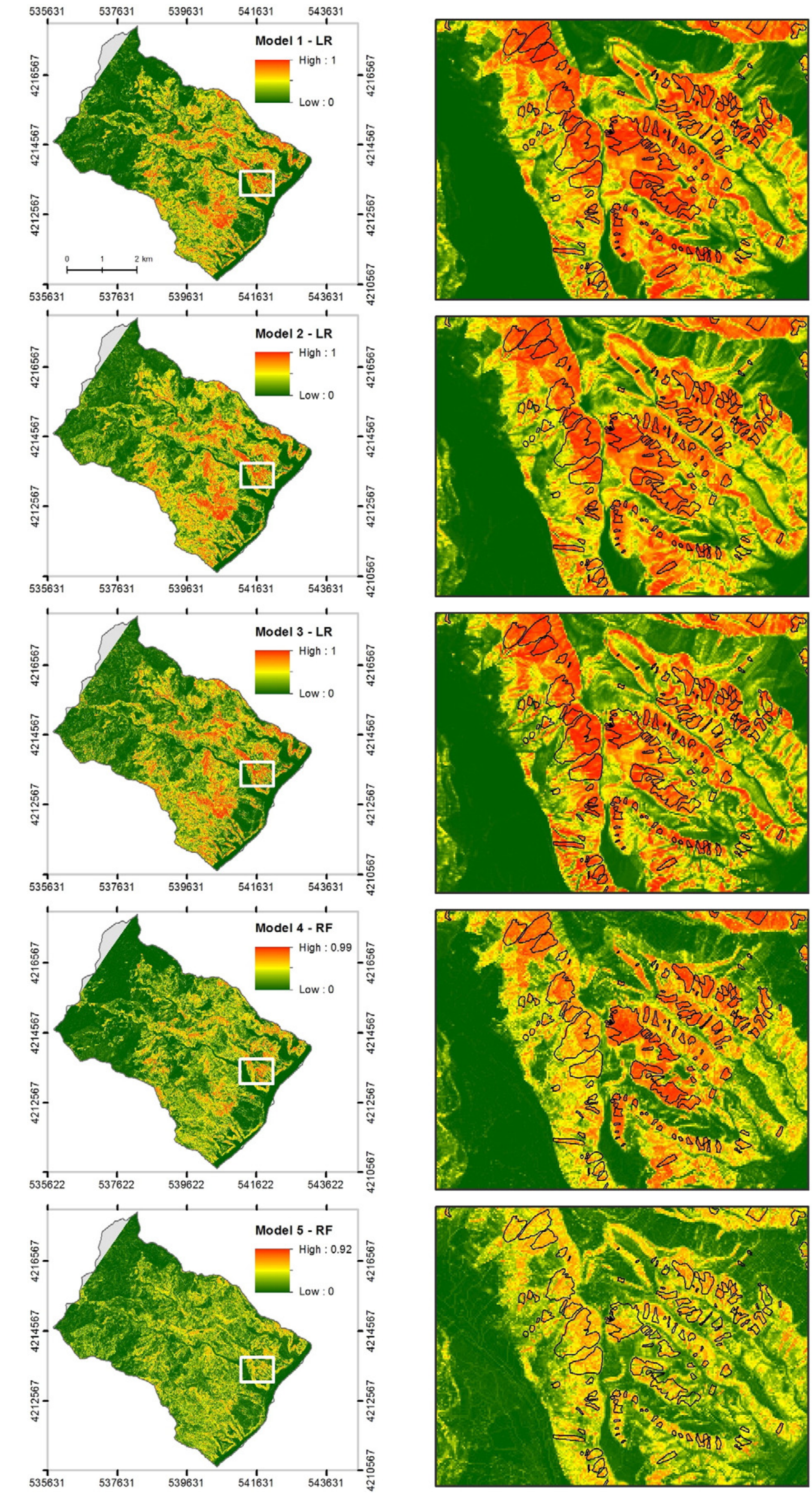
In the susceptibility model (Model 4 RF), in addition to the 2005, 2007 and 2009 wildfires, the 2012 wildfire, which is after the reference scenario (1st October 2009 event), has been also included. The areas burned in 2012 have been classified as “Repeated wildfires” if they were already affected by previous fires or “Wildfire” if they were never burned areas. The comparison of the susceptibility maps of 2009 and 2012 scenarios shows an average increase of 0.095 and a maximum increase of 0.79 in susceptibility values for the areas which have been affected by the fire of 2012 (Fig. 16).

This analysis should be considered partial, not taking into account the following aspects: i) the intensity of fires; ii) the vegetative recovery in areas affected by previous fires (e.g., 2005, 2007); iii) the land-use change in areas affected by 2009 landslides; iv) the variation of morphometric parameters; iv) mitigation measures or reforestation; and v) maintenance operations of agricultural terraces.

5. Conclusions

In the present work we have implemented 5 susceptibility models for rapid shallow landslides by using the multivariate statistical Logistic Regression (LR) and Random Forests (RF) techniques and a bivariate statistical Frequency Ratio method in the area of North-Eastern Sicily affected by the October 1, 2009 landslide event.

The Logistic Regression technique, widely used in the literature in landslide susceptibility assessment, has been confirmed as reliable and high performing in terms of prediction; the Random Forests technique, more innovative and only recently applied to landslide susceptibility, has proved of great performance in terms of minimization of



Mod. 1		Predicted		
		0 - stable	1 - unstable	
Observed	0 - stable	TN 1,184,851 76.77%	FP 326,084 21.13%	No. stable observations 1,510,935
	1 - unstable	FN 8,113 0.53%	TP 24,364 1.58%	No. unstable observations 32,477
		No. stable predictions 1,192,964	No. unstable predictions 350,448	Total No. of observations 1,543,412

Mod. 2		Predicted		
		0 - stable	1 - unstable	
Observed	0 - stable	TN 1,150,118 74.52%	FP 360,817 23.38%	No. stable observations 1,510,935
	1 - unstable	FN 7,293 0.47%	TP 25,184 1.63%	No. unstable observations 32,477
		No. stable predictions 1,157,411	No. unstable predictions 386,001	Total No. of observations 1,543,412

Mod. 3		Predicted		
		0 - stable	1 - unstable	
Observed	0 - stable	TN 1,187,878 76.96%	FP 323,057 20.93%	No. stable observations 1,510,935
	1 - unstable	FN 8,505 0.55%	TP 23,972 1.55%	No. unstable observations 32,477
		No. stable predictions 1,196,383	No. unstable predictions 347,029	Total No. of observations 1,543,412

Mod. 4		Predicted		
		0 - stable	1 - unstable	
Observed	0 - stable	TN 1,321,247 85.61%	FP 189,688 12.29%	No. stable observations 1,510,935
	1 - unstable	FN 10,056 0.65%	TP 22,421 1.45%	No. unstable observations 32,477
		No. stable predictions 1,331,303	No. unstable predictions 212,109	Total No. of observations 1,543,412

Mod. 5		Predicted		
		0 - stable	1 - unstable	
Observed	0 - stable	TN 1,417,886 91.87%	FP 93,049 6.03%	No. stable observations 1,510,935
	1 - unstable	FN 19,079 1.24%	TP 13,398 0.87%	No. unstable observations 32,477
		No. stable predictions 1,436,965	No. unstable predictions 106,447	Total No. of observations 1,543,412

Fig. 11. Comparison of the susceptibility maps produced with the 5 models and the related contingency tables.

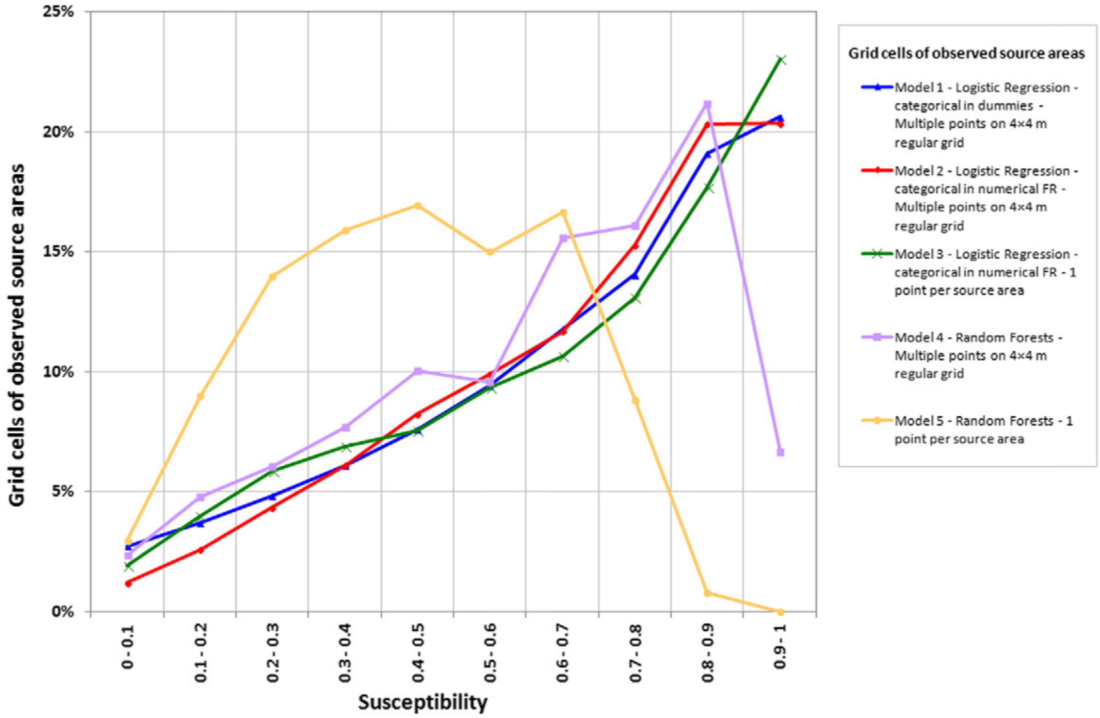


Fig. 12. Distribution of cells of observed source areas in 10 susceptibility classes.

classification errors. The comparison of several models has allowed us to better assess strengths and limits of each method and the statistical reliability of the susceptibility maps produced.

We have also addressed the influence of sampling strategies on the performance of the models and consequently the susceptibility maps, comparing the 4 × 4 m regular grid sampling and the sampling of one point for each source area. The first sampling method better classifies both areas of low and high susceptibility, because it learns on a twenty times higher number of points in the training area, better representing the spatial variability and the combinations of the predisposing factors.

A comparison of the susceptibility maps produced using LR and RF models shows a remarkable similarity between them. In particular, in the upper part of the two main basins of the study area (Briga and Giampilieri catchments) low susceptibility values are related to the presence of forest, shrub and Sclerophyllous vegetation, the absence of burned areas and the absence of agricultural terraces. In this portion

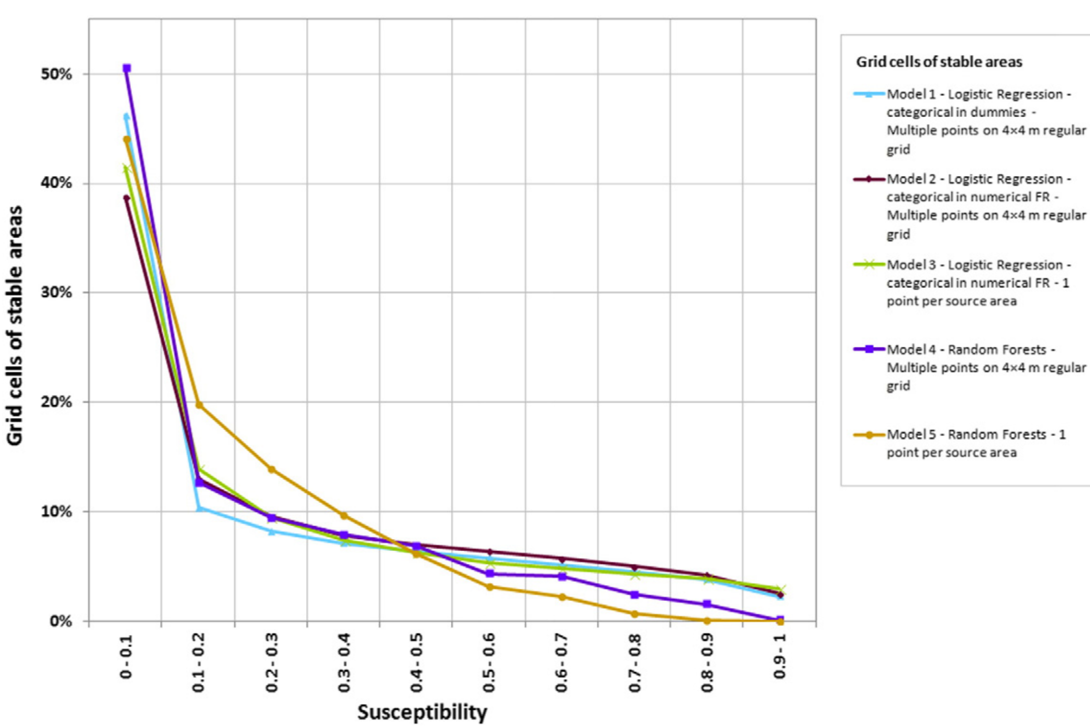


Fig. 13. Distribution of cells of stable areas in 10 susceptibility classes.

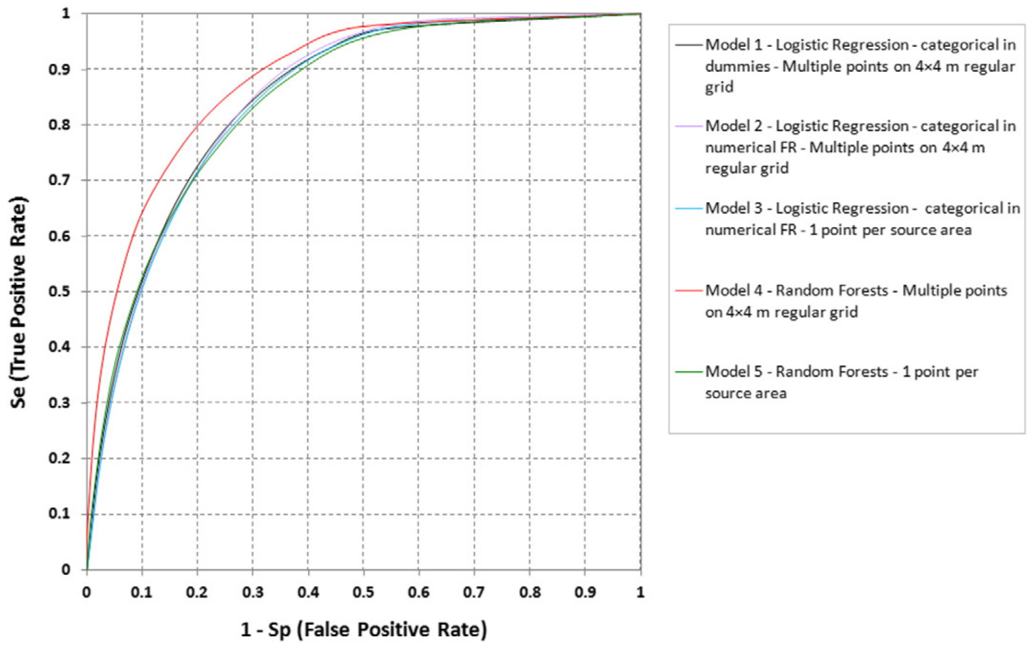


Fig. 14. ROC curves of the 5 models.

Table 7
AUC values of the 5 models.

	AUC training	AUC test	AUC study area
Model 1 — LR — categorical in dummies — multiple points on 4 × 4 m regular grid	0.908	0.851	0.854
Model 2 — LR — categorical in numerical FR — multiple points on 4 × 4 m regular grid	0.892	0.861	0.853
Model 3 — LR — categorical in numerical FR — 1 point per source area	0.909	0.867	0.849
Model 4 — RF — multiple points on 4 × 4 m regular grid	0.953	0.798	0.888
Model 5 — RF — 1 point per source area	0.913	0.772	0.850

of the study area only pastures are characterized by medium to high values of susceptibility. In the middle and lower part of the study area, the highest values of susceptibility are strongly correlated with the presence of burned areas, steep slopes, concave plan curvature, pastures or permanent crops.

The RF model, compared to the LR ones provides higher values of True Negative and lower values of False Positive, still providing low values of False Negative. The performance of the models, in terms of AUC, range from good to high (between 0.89 and 0.95 on the training sample, between 0.77 and 0.87 on the test one and between 0.85 and 0.89 over the entire study area), with the largest AUC for the Random Forests Model with 4 × 4 m regular grid sampling.

The RF technique has proved particularly powerful in dealing with categorical variables; in contrast, the LR technique has encountered some problems related to the quasi-complete separation of some classes of categorical variables transformed into dummies. In this regard we also tested the transformation of categorical variables in numerical, using the Frequency Ratio values.

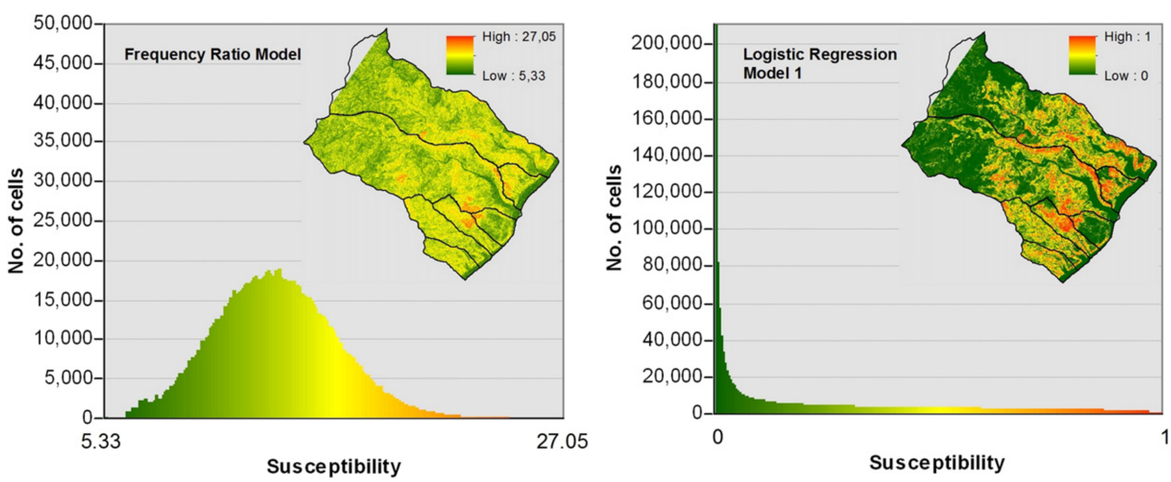


Fig. 15. Comparison of susceptibility maps produced by the Frequency Ratio method and Logistic Regression model.

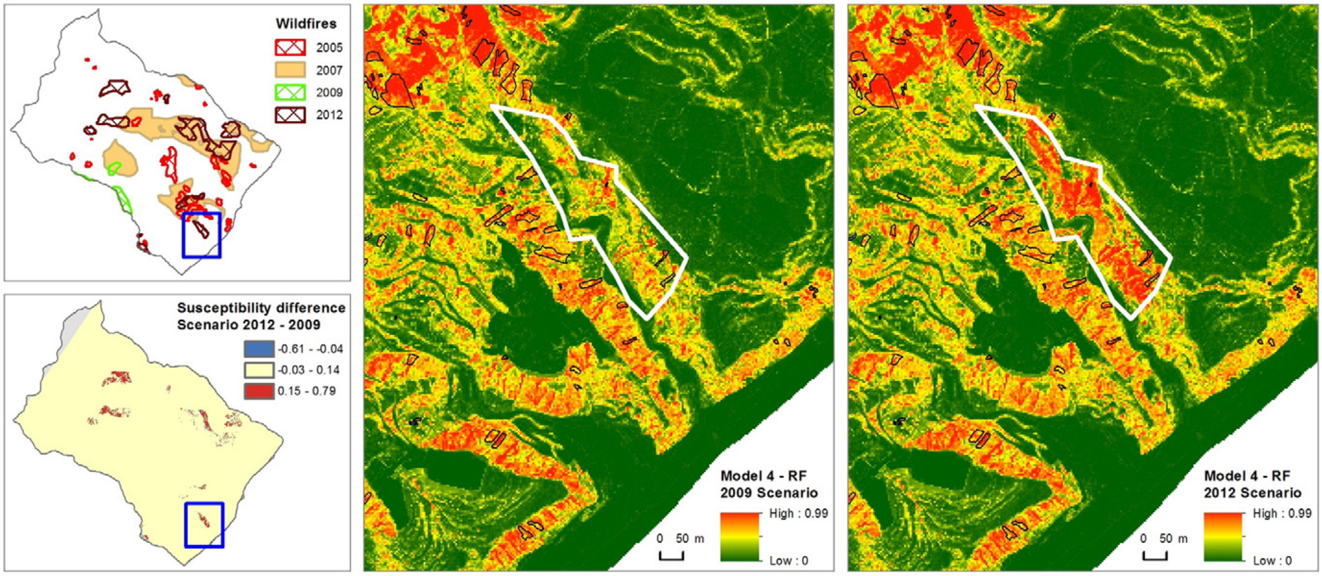


Fig. 16. Temporal change of susceptibility maps — 2009 and 2012 scenarios (Model 4 RF).

Regarding the importance of explanatory variables in landslide susceptibility assessment, comparing the LR forward stepwise procedure of entering variables and the RF variable selection procedure, four of the five most significant variables (Slope angle, Land use, Wildfire and Plan curvature) are common to both multivariate statistical models.

In conclusion, the LR and RF methods are fully comparable in terms of identification of the most significant variables and predictive capabilities. Although the Random Forest technique is better for the minimization of False Positive, the Logistic Regression method, providing as output the probability of landslide occurrence, is more easily applied for risk assessment and land-use planning.

The Frequency Ratio method, although is confirmed valid and easy to apply for the descriptive statistics of predisposing factors, performs poorly for the production of a susceptibility map as it is not highly selective in the classification of the study area, particularly underestimating low susceptibility areas.

Finally the susceptibility maps are not stationary but need to be updated over time, due to temporal changes of the geo-environmental factors. The study showed that new wildfires lead to an increase in the values of the landslide susceptibility map.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.geomorph.2015.06.001.

References

Allison, P.D., 2008. Convergence failures in logistic regression. Proceedings of SAS Global Forum 2008, Statistics and Data Analysis (Paper 360-2008) (11 pp.).

APAT, 2008. Dipartimento Difesa del Suolo/Servizio Geologico d'Italia Carta Geologica d'Italia alla scala 1:50.000, Foglio 601, Messina. Reggio di Calabria, S.EL.CA, Firenze, 2008.

Ardizzone, F., Basile, G., Cardinali, M., Casagli, N., Del Conte, S., Del Ventisette, C., Fiorucci, F., Garfagnoli, F., Gigli, G., Guzzetti, F., Iovine, G., Mondini, A.C., Moretti, S., Panebianco, M., Raspini, F., Reichenbach, P., Rossi, M., Tanteri, L., Terranova, O., 2012. Landslide inventory map for the Briga and the Giampilieri catchments, NE Sicily, Italy. J. Maps 8, 176–180.

Ayalew, L., Yamagishi, H., 2005. The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda–Yahiko Mountains, Central Japan. Geomorphology 65, 15–31.

Baeza, C., Corominas, J., 2001. Assessment of shallow landslide susceptibility by means of multivariate statistical techniques. Earth Surf. Process. Landf. 26, 1251–1263.

Bai, S.B., Wang, J., Lu, G.N., Zhoub, P.G., Houb, S.S., Xub, S.N., 2010. GIS-based logistic regression for landslide susceptibility mapping of the Zhongxian segment in the Three Gorges area, China. Geomorphology 115, 23–31.

Basile, G., 2009. Rapporto sugli eventi meteo che hanno colpito la provincia di Messina il giorno 1 ottobre 2009. Dipartimento Regionale della Protezione Civile, Regione Siciliana (19 pp.).

Basile, G., Panebianco, M., 2013. Experimental alert model for hydrogeological risk: a case study in Sicily. In: Sassa, K., Canuti, P., Margottini, C. (Eds.), Landslide Science and Practice. Early Warning, Instrumentation and Monitoring 2. Springer-Verlag, Berlin Heidelberg, pp. 603–610.

Bazzoffi, P., Ciccarese, L., De Meo, A., Di Leginio, M., Fumanti, F., Guerra, P., Iadanza, C., Munafò, M., Rossi, L., Romano, R., Trigila, A., 2013. Linee guida per la valutazione del dissesto idrogeologico e la sua mitigazione attraverso misure ed interventi in campo agricolo e forestale, Manuali e Linee Guida 85/2013. ISPRA (98 pp.).

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Brenning, A., 2005. Spatial prediction models for landslide hazards: review, comparison and evaluation. Nat. Hazards Earth Syst. Sci. 5, 853–862.

Carrara, A., Cardinali, M., Detti, R., Guzzetti, F., Pasqui, V., Reichenbach, P., 1991. GIS techniques and statistical models in evaluating landslide hazard. Earth Surf. Process. Landf. 16, 427–445.

Carrara, A., Cardinali, M., Guzzetti, F., Reichenbach, P., 1995. GIS technology in mapping landslide hazard. In: Carrara, A., Guzzetti, F. (Eds.), Geographical Information Systems in Assessing Natural Hazards. Kluver Academic Publishers, Netherlands, pp. 135–175.

Carrara, A., Crosta, G., Frattini, P., 2008. Comparing models of debris-flow susceptibility in the alpine environment. Geomorphology 94, 353–378.

Catani, F., Casagli, N., Ermini, L., Righini, G., Menduni, G., 2005. Landslide hazard and risk mapping at catchment scale in the Arno River Basin. Landslides 2, 329–342.

Catani, F., Segoni, S., Falorni, G., 2010. An empirical geomorphology-based approach to the spatial prediction of soil thickness at catchment scale. Water Resour. Res. 46. http://dx.doi.org/10.1029/2008WR007450.

Catani, F., Lagomarsino, D., Segoni, S., Tofani, V., 2013. Landslide susceptibility estimation by random forests technique: sensitivity and scaling issues. Nat. Hazards Earth Syst. Sci. 13, 2815–2831.

Chillemi, F., 1995. I casali di Messina: strutture urbane e patrimonio artistico. EDAS, Messina (472 pp.).

Chung, C.F., Fabbri, A.G., 2003. Validation of spatial prediction models for landslide hazard mapping. Nat. Hazards 30, 451–472.

Corominas, J., Van Westen, C., Frattini, P., Cascini, L., Malet, J., Fotopoulou, S., Catani, F., Van Den Eeckhaut, M., Mavrouli, O., Agliardi, F., Pitilakis, K., Winter, M.G., Pastor, M., Ferlisi, S., Tofani, V., Hervás, J., Smith, J.T., 2014. Recommendations for the quantitative analysis of landslide risk. Bull. Eng. Geol. Environ. 73, 209–263.

Costanzo, D., Rotigliano, E., Irigaray, C., Jiménez-Perálvarez, J.D., Chacón, J., 2012. Factors selection in landslide susceptibility modelling on large scale following the GIS matrix method: application to the river Beiro basin (Spain). Nat. Hazards Earth Syst. Sci. 12, 327–340.

Crosta, G.B., Frattini, P., 2003. Distributed modelling of shallow landslides triggered by intense rainfall. Nat. Hazards Earth Syst. Sci. 3, 81–93.

Cruden, D.M., Varnes, D.J., 1996. Landslide types and processes. In: Turner, A.K., Schuster, R.L. (Eds.), Landslides Investigation and Mitigation. Special Report 247. Transportation Research Board, Washington, D.C., pp. 36–75.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J.C., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88, 2783–2792.

Dai, F.C., Lee, C.F., 2002. Landslide characteristics and slope instability modelling using GIS, Lantau Island, Hong Kong. Geomorphology 42, 213–228.

De Guidi, G., Scudero, S., 2013. Landslide susceptibility assessment in the peloritani Mts. (Sicily, Italy). Nat. Hazards Earth Syst. Sci. 13, 949–963.

Devkota, K.C., Regmi, A.D., Pourghasemi, H.R., Yoshida, K., Pradhan, B., Ryu, I.C., Dhital, M.R., Althuwaynee, O.F., 2013. Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. Nat. Hazards 65, 135–165.

Ermini, L., Catani, F., Casagli, N., 2005. Artificial neural networks applied to landslide susceptibility assessment. Geomorphology 66, 327–343.

Esposito, C., Scarascia-Mugnozza, G., Trigila, A., Finoia, M.G., 2012. Susceptibility assessment of shallow landslides in the Messina province. In: Eberhardt, E., Froese, C., Turner, A.K., Leroueil, S. (Eds.), Landslides and Engineered Slopes. Protecting Society through Improved Understanding vol. 1. CRC Press, Taylor & Francis, Banff, Alberta, Canada, pp. 825–830.

European Environment Agency, 2007. CLC2006 technical guidelines. EEA Technical Report No 17/2007 (66 pp.).

Falaschi, F., Giacomelli, F., Federici, R., Puccinelli, A., D'Amato Avanzi, G., Pochini, A., Ribolini, A., 2009. Logistic regression versus artificial neural networks: landslide susceptibility evaluation in a sample area of the Serchio River valley, Italy. Nat. Hazards 50, 551–569.

Floris, M., Iafelice, M., Squarzoni, C., Zorzi, L., De Agostini, A., Genevois, R., 2011. Using online databases for landslide susceptibility assessment: an example from the Veneto Region (northeastern Italy). Nat. Hazards Earth Syst. Sci. 11, 1915–1925.

Frattini, P., Crosta, G.B., Carrara, A., 2010. Techniques for evaluating the performance of landslide susceptibility models. Eng. Geol. 111, 62–72.

Fressard, M., Thiery, Y., Maquaire, O., 2014. Which data for quantitative landslide susceptibility mapping at operational scale? Case study of the Pays d'Auge plateau hillslopes (Normandy, France). Nat. Hazards Earth Syst. Sci. 14, 569–588.

Garcia-Ruiz, J.M., Arnaez, J., Gomez-Villar, A., Ortigosa, L., Lana-Renault, N., 2013. Fire-related debris flows in the Iberian Range, Spain. Geomorphology 196, 221–230.

Gorsevski, P.V., Gessler, P.E., Foltz, R.B., Elliot, W.J., 2006. Spatial prediction of landslide hazard using logistic regression and ROC analysis. Trans. GIS 10, 395–415.

Greenway, D.R., 1987. Vegetation and slope stability. In: Anderson, M.F., Richards, K.S. (Eds.), Slope Stability. Wiley and Sons, New York, pp. 187–230.

Günther, A., Van Den Eeckhaut, M., Malet, J.P., Reichenbach, P., Hervás, J., 2014. Climate-physiographically differentiated Pan-European landslide susceptibility assessment using spatial multi-criteria evaluation and transnational landslide information. Geomorphology 224, 69–85.

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, 181–216.

Guzzetti, F., Malamud, B.D., Turcotte, D.L., Reichenbach, P., 2002. Power-law correlations of landslide areas in central Italy. Earth Planet. Sci. Lett. 195, 169–183.

Heckmann, T., Gegg, K., Gegg, A., Becht, M., 2014. Sample size matters: investigating the effect of sample size on a logistic regression susceptibility model for debris flows. Nat. Hazards Earth Syst. Sci. 14, 259–278.

Hosmer, D.W., Lemeshow, S., 2000. Applied Logistic Regression. John Wiley and Sons, Inc., New York (528 pp.).

Hovius, N., Stark, C.P., Allen, P.A., 1997. Sediment flux from a mountain belt derived by landslide mapping. Geology 25, 231–234.

Hungr, O., Evans, S.G., Bovis, M., Hutchinson, J.N., 2001. A review of the classification of landslides of the flow type. Environ. Eng. Geosci. 7, 221–238.

Iadanza, C., Trigila, A., Vittori, E., Serva, L., 2009. Landslides in coastal areas of Italy. In: Violante, C. (Ed.), Geohazard in Rocky Coastal Areas. The Geological Society, London, Special Publications 322, pp. 121–141.

Iadanza, C., Cacace, C., Del Conte, S., Spizzichino, D., Cespa, S., Trigila, A., 2013. Cultural heritage, landslide risk and remote sensing in Italy. In: Sassa, K., Canuti, P., Margottini, C. (Eds.), Landslide Science and Practice. Risk Assessment, Management and Mitigation. vol. 6. Springer-Verlag, Berlin Heidelberg, pp. 491–500.

ISPRA, 2009. Gli habitat in Carta della Natura. Schede descrittive degli habitat per la cartografia alla scala 1:50.000. MLG 49/2009, 335 pp.

Lee, S., Min, K., 2001. Statistical analysis of landslide susceptibility at Yongin, Korea. Environ. Geol. 40, 1095–1113.

Lee, S., Sambath, T., 2006. Landslide susceptibility mapping in the Damrei Romel area, Cambodia using frequency ratio and logistic regression models. Environ. Geol. 50, 847–855.

Lee, S., Ryu, J.H., Kim, I.S., 2007. Landslide susceptibility analysis and its verification using likelihood ratio, logistic regression, and artificial neural network models: case study of Youngin, Korea. Landslide 4, 327–338.

Lentini, F., Carbone, S., Catalano, S., Grasso, M., 1995. Principali lineamenti strutturali della Sicilia nord-orientale. Studi Geologici Camerti, Volume Speciale 1995/2pp. 319–329.

Malamud, B.D., Turcotte, D.L., Guzzetti, F., Reichenbach, P., 2004. Landslide inventories and their statistical properties. Earth Surf. Process. Landf. 29, 687–711.

Mazziotta, F., 1919. Notizie storiche dei villaggi di Messina dalla loro origine fino all'anno 1916. Villaggio Artalia. Archivio storico messinese, Messina vol. 18, pp. 73–116.

Melchiorre, C., Castellanos Abella, E.A., Van Westen, C.J., Matteucci, M., 2011. Evaluation of prediction capability, robustness, and sensitivity in non-linear landslide susceptibility models, Guantánamo, Cuba. Comput. Geosci. 37, 410–425.

Meusburger, K., Alewell, C., 2009. On the influence of temporal change on the validity of landslide susceptibility maps in an alpine catchment, Switzerland. Nat. Hazards Earth Syst. Sci. 9, 1495–1507.

Nefeslioglu, H.A., Gokceoglu, C., Sonmez, H., 2008. An assessment on the use of logistic regression and artificial neural networks with different sampling strategies for the preparation of landslide susceptibility maps. Eng. Geol. 97, 171–191.

Parise, M., Cannon, S.H., 2012. Wildfire impacts on the processes that generate debris flows in burned watersheds. Nat. Hazards 61, 217–227.

Petschko, H., Brenning, A., Bell, R., Goetz, J., Glade, T., 2014. Assessing the quality of landslide susceptibility maps — case study Lower Austria. Nat. Hazards Earth Syst. Sci. 14, 95–118.

Remondo, J., González, A., Díaz De Terán, J.R., Cendrero, A., Fabbri, A., Chung, C.F., 2003. Validation of landslide susceptibility maps; examples and applications from a case study in Northern Spain. Nat. Hazards 30, 437–449.

Rossi, M., Guzzetti, F., Reichenbach, P., Mondini, A.C., Peruccacci, S., 2010. Optimal landslide susceptibility zonation based on multiple forecasts. Geomorphology 114, 129–142.

Rupert, M.G., Cannon, S.H., Gartner, J.E., Michael, J.A., Helsel, D.R., 2008. Using logistic regression to predict the probability of debris flows in areas burned by wildfires, Southern California, 2003–2006. USGS Open File Report-1370 (16 pp.).

Salvati, P., Bianchi, C., Rossi, M., Guzzetti, F., 2010. Societal landslide and flood risk in Italy. Nat. Hazards Earth Syst. Sci. 10, 465–483.

Shakesby, R.A., Doerr, S.H., 2006. Wildfire as a hydrological and geomorphological agent. Earth Sci. Rev. 74, 269–307.

Soeters, R., Van Westen, C.J., 1996. Slope instability recognition, analysis, and zonation. In: Turner, A.K., Schuster, R.L. (Eds.), Landslides Investigation and Mitigation. Special Report 247. Transportation Research Board, Washington, D.C., pp. 129–177.

Spizzichino, D., Margottini, C., Trigila, A., Iadanza, C., 2013. Landslide impacts in Europe: weaknesses and strengths of databases available at European and national scale. In: Sassa, K., Canuti, P., Margottini, C. (Eds.), Landslide Science and Practice. Inventory and Hazard Assessment vol. 1. Springer-Verlag, Berlin Heidelberg, pp. 73–80.

Süzen, M.L., Doyuran, V., 2004. A comparison of the GIS based landslide susceptibility assessment methods: multivariate versus bivariate. Environ. Geol. 45, 665–679.

Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240, 1285–1293.

Trigila, A., Iadanza, C., 2012. The national landslide inventory, landslide events, impacts and mitigation measures in Italy. In: Eberhardt, E., Froese, C., Turner, A.K., Leroueil, S. (Eds.), Landslides and Engineered Slopes. Protecting Society through Improved Understanding vol. 1. CRC Press, Taylor & Francis, Banff, Alberta, Canada, pp. 273–278.

Trigila, A., Iadanza, C., Spizzichino, D., 2010. Quality assessment of the Italian Landslide Inventory using GIS processing. Landslides, Journal of the International Consortium on Landslides 7, pp. 455–470.

Trigila, A., Catani, F., Casagli, N., Crosta, G., Esposito, C., Frattini, P., Iadanza, C., Lagomarsino, D., Lari, S., Scarascia-Mugnozza, G., Segoni, S., Spizzichino, D., Tofani, V., 2012. The landslide susceptibility map of Italy at 1:1 million scale. Geophysical Research Abstracts, European Geosciences Union — General Assembly 2012, Vienna 22–27 April 2012.

Trigila, A., Frattini, P., Casagli, N., Catani, F., Crosta, G., Esposito, C., Iadanza, C., Lagomarsino, D., Lari, S., Scarascia-Mugnozza, G., Segoni, S., Spizzichino, D., Tofani, V., 2013. Landslide susceptibility mapping at national scale: the Italian case study. In: Sassa, K., Canuti, P., Margottini, C. (Eds.), Landslide Science and Practice. Inventory and Hazard Assessment vol. 1. Springer-Verlag, Berlin Heidelberg, pp. 287–296.

Trigila, A., Iadanza, C., Munafò, M., Marinosci, I., 2015. Population exposed to landslide and flood risk in Italy. In: Lollino, G., Manconi, A., Guzzetti, F., Culshaw, M., Bobrowsky, P., Luino, F. (Eds.), Engineering Geology for Society and Territory. Urban Geology, Sustainable Planning and Landscape Exploitation vol. 5. Springer International Publishing, Switzerland.

Van Den Eeckhaut, M., Hervás, J., 2012. State of the art of national landslide databases in Europe and their potential for hazard and risk assessment. Geomorphology 139–140, 545–558.

Van Den Eeckhaut, M., Vanwalleghem, T., Poesen, J., Govers, G., Verstraeten, G., Vandekerckhove, L., 2006. Prediction of landslide susceptibility using rare events logistic regression: a case-study in the Flemish Ardennes (Belgium). Geomorphology 76, 392–410.

Van Den Eeckhaut, M., Reichenbach, P., Guzzetti, F., Rossi, M., Poesen, J., 2009. Combined landslide inventory and susceptibility assessment based on different mapping units: an example from the Flemish Ardennes, Belgium. Nat. Hazards Earth Syst. Sci. 9, 507–521.

Van Den Eeckhaut, M., Marre, A., Poesen, J., 2010. Comparison of two landslide susceptibility assessments in the Champagne-Ardenne region (France). Geomorphology 115, 141–155.

Van Westen, C.J., Castellanos, E., Kuriakose, S.L., 2008. Spatial data for landslide susceptibility, hazards and vulnerability assessment : an overview. Eng. Geol. 102, 112–131.

Varnes, D.J., 1984. Landslide hazard zonation: a review of principles and practice. Commission on Landslides of the IAEG, UNESCONatural Hazards No. 3 (61 pp.).

Vergari, F., Della, Seta M., Del Monte, M., Fredi, P., Lupia Palmieri, E., 2011. Landslide susceptibility assessment in the Upper Orcia Valley (Southern Tuscany, Italy) through conditional analysis: a contribution to the unbiased selection of causal factors. Nat. Hazards Earth Syst. Sci. 11, 1475–1497.

Yilmaz, I., 2009. Landslide susceptibility mapping using frequency ratio, logistic regression, artificial neural networks and their comparison: a case study from Kat landslides (Tokat–Turkey). Comput. Geosci. 35, 1125–1138.

Yilmaz, I., 2010. The effect of the sampling strategies on the landslide susceptibility mapping by conditional probability and artificial neural networks. Environ. Earth Sci. 60, 505–519.