Remarks on the Role of Landslide Inventories in the Statistical Methods Used for the Landslide Susceptibility Assessment

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Abstract

In this work, the role of different landslide inventories in susceptibility assessment was evaluated using a non linear regression technique, namely the generalized additive model (GAM).The investigation was carried out in three study areas: the Versa catchment (Oltrepò Pavese, Southern Lombardy, Italy), the Vernazza catchment (Cinque Terre, Eastern Liguria, Italy) and the Pogliaschina catchment (Vara Valley, Eastern Liguria, Italy). Two landslide inventories related to the 2009 and 2013 rainfall events were taken into account in the Versa catchment, whereas two landslide inventories (referred to the same 2011 rainfall event) which differ for methods of detection and criteria adopted for the landslide mapping were considered in the Vernazza and Pogliaschina catchments. The predictive performance of GAM for each landslide inventory was evaluated. The results related to different inventories were compared. The results show that the predictive capability of the model and the landslide susceptibility are significantly influenced by the type of landslide inventory. Thus, the work highlights that a standard criterion for preparing inventories should be adopted in order to produce landslide susceptibility assessment as reliable as possible.

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Introduction

Landslide susceptibility assessment and mapping is a powerful tool to represent coherent information about the spatial distribution of landslides in terms of initiation areas, on the basis of a set of relevant environmental characteristics. Among the procedures available for landslide susceptibility assessment, the statistical methods are widely used (Corominas et al. 2014; Hungr 2016).

The main data layers required for assessing landslide susceptibility are landslide inventories, predisposing and triggering factors (Van Westen et al. 2008; Corominas et al. 2014; Hungr 2016). Landslide inventory is the most important among them, as it gives insight to the location of past landslide occurrences, as well as their failure mechanisms (Corominas et al. 2014).

A wide range of techniques are used to obtain landslide inventories, depending on the purpose of the inventory, the extent of the study area, the scale, the methods used for the detection and the classification, and the skills and experience of the investigators (Guzzetti et al. 2006, 2012; van Westen et al. 2006).

Specifically, landslide inventory maps can be produced using conventional methods (field surveys) and innovative techniques that can be grouped into two main categories: (i) analysis of surface morphology, exploiting digital elevation models (DEMs), (ii) interpretation and analysis of satellite images (Guzzetti et al. 2006, 2012; Mondini et al. 2011).

Based on the type of mapping, landslide inventory maps can be classified as archive or geomorphological inventories (Guzzetti et al. 2000). The archive inventories are based on information of landslides obtained from the literature (Salvati et al. 2009), whereas the geomorphological inventories can be classified as historical, event, seasonal or multi-temporal inventories (Guzzetti et al. 2012). Historical inventories show the cumulative effects of many landslide events over a long period of time. The age of the landslides is not differentiated but given in relative terms, such as recent, old or very old (Galli et al. 2008; Guzzetti et al. 2012). Event inventories show landslide phenomena caused by a single trigger. Seasonal ones represent landsides triggered by single or multiple events during a single season, or few seasons (Fiorucci et al. 2011). Multi-temporal inventories group landslides triggered by multiple events over longer periods (years to decades; Galli et al. 2008).

In addition, the landslides inventories differ also for the classification system used to define the different landslide types. The two most prominent English-language landslide classifications are by Hutchinson (Hutchinson 1968, 1988; Skempton and Hutchinson 1969) and Varnes (Varnes 1958, 1978; Cruden and Varnes 1996). The two systems are generally similar but treat landslide types somewhat different.

Hutchinson's classification emphasizes the results of movement, whereas Varnes' method emphasizes the conditions of slope failure, basing both on the type of movement and the involved material (Lu and Godt 2013). Hungr et al. (2001) updated Hutchinson's (1968, 1988) classification of "debris movements of flow-like form" to further categorize the broad range of flows and conserve long-used terms. Post-failure movement is emphasized and the classification of "landslides of the flow type" is based on the origin, character, and moisture condition of materials (Lu and Godt 2013). Otherwise, Hungr et al. (2014), revised several aspects of the well-known classification of landslides developed by Varnes (1978) modifying the definition of landslide-forming materials, to provide compatibility with accepted geotechnical and geological terminology of rocks and soils.

Thus, despite the clear relevance of landslide inventory maps, the standard criteria for their elaboration remain poorly defined (Guzzetti et al. 2012; van Westen et al. 2006, 2008). The lack of standard criteria limits the credibility and usefulness of landslide maps and the evaluation of their quality, with adverse effects on the derivative products and analyses, such as erosion studies, landscape modeling, susceptibility and hazard assessments, risk evaluations (Guzzetti et al. 2006).

In this context, the aim of this work was to evaluate the importance of the landslide inventory in the landslide susceptibility analysis using a non linear regression technique, namely generalized additive model (GAM, Hastie and Tibshirani 1990). The degree of influence of different landslide inventories on the predictive performance of the model was investigated. The GAM was implemented in three different catchments: the Versa catchment (Oltrepò Pavese, Southern Lombardy, Italy), the Vernazza catchment (Cinque Terre, Eastern Liguria, Italy) and the Pogliaschina catchment (Vara Valley, Eastern Liguria, Italy). The first one was hit by two shallow landslide events (in 2009 and 2013) whereas the other ones, were affected by only one shallow landslide event (in 2011). In this latter case, two different inventories, based on two different detection methodologies, were used.

Study Areas

Versa Catchment

The Versa catchment (Fig. 1a) is located in the Oltrepò Pavese (Southern Lombardy). It is 38 km^2 wide, with altitude ranging between 128 and 662 m a.s.l. The slopes have a low-medium gradient, with values commonly ranging between 15 and 25°. The area is characterized by a bedrock with predominant clayey-marly component, formed of flysch deposits (Ranzano Sandstones, Monte Piano Marls, Val Luretta Formation), representing the Cretaceous to Miocene.

Soil slope covers have a clayey texture and their thickness can reach 3–4 m.

In the Versa catchment, agricultural activities are the most important branch of local economy. Cultivated vineyards represent the most widespread land use class (65%). The areas covered by this land use class are particularly prone to shallow landsliding. Two main events occurred in the last 7 years: 196 shallow landslides were triggered during 27–28 April 2009, whereas 193 shallow landslides were recorded during multiple events of March/April 2013. The shallow landslides recorded were classified according to Cruden and Varnes (1996) classification. Most of them are roto-translational slides evolving into flows, with width/length ratio >1.

Pogliaschina Catchment

The Pogliaschina catchment (Fig. 1b) is located in the Vara Valley (Northern Apennines). It is 25 km² wide, with altitude ranging between 95–100 and 720 m a.s.l. The slopes are characterized by high gradient, since it can reach values higher than 45°. The bedrock is mainly composed of medium and coarse quartz-feldspathic sandstone turbidites

(Macigno Fm.; Tuscan Nappe Unit) and quartz-feldspathic greywacke sandstone-siltstone turbidite (Arenarie di Monte Gottero Fm.; Gottero Unit). The soil slope covers thickness is ranging from 0.5 to 1.5 m.

The area is predominantly covered by woodland, characterized by hard-wood, coniferous and mixed hard-wood and coniferous forests (93% of the whole basin). Vineyards, olive groves and other plantations occupy about 6% of the area (D'Amato Avanzi et al. 2014).

A total of 658 shallow landslides were triggered during the 25 October 2011 event. Also for this inventory, landslides were classified following the Cruden and Varnes (1996) classification. Most of them were classified as complex, translational debris slide-flow, with a width/length ratio equal to 0.03–0.5 (Bartelletti et al. 2015).

Vernazza Catchment

The Vernazza catchment (Fig. 1c) is located along the Tyrrhenian side of the Northern Apennines. It is 5.7 km² wide with altitude ranging between the sea level and 815 m a.s.l. and characterized by slopes with high gradient, up to more than 35°.
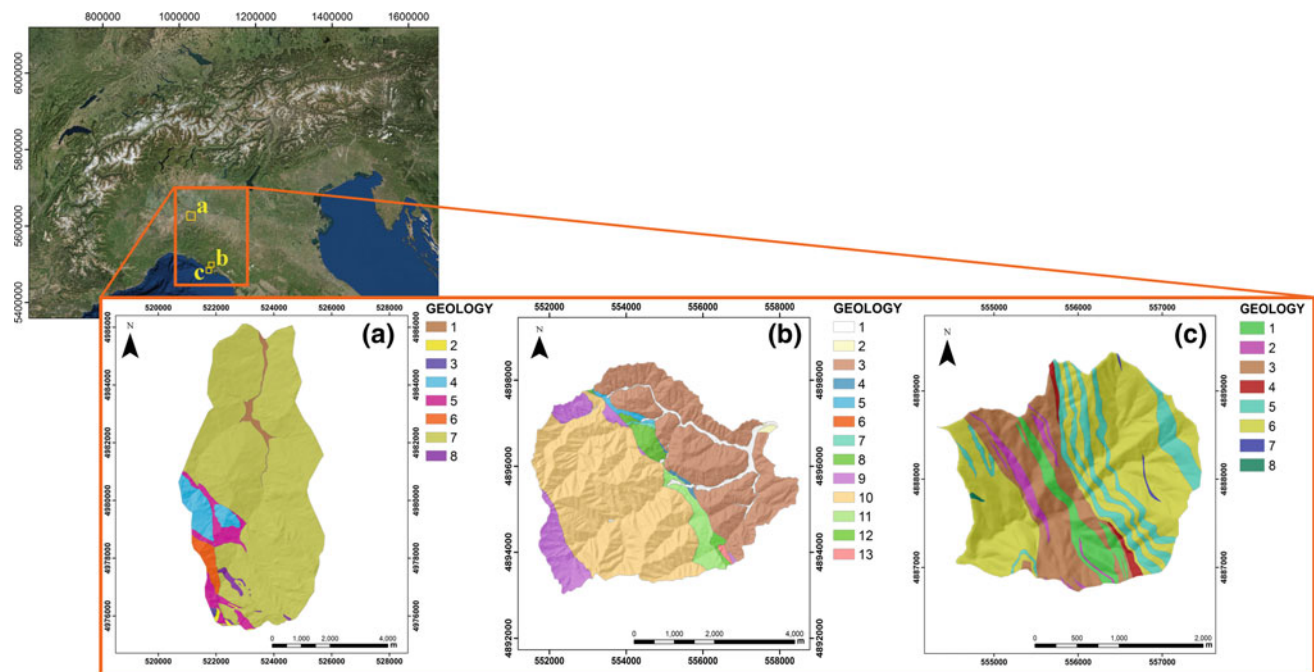
Fig. 1 Geological maps of the study areas: **a** Versa catchment: (1) Alluvial deposits; (2) Ranzano sandstones; (3) Ranzano sandstones (arenaceous *facies*); (4) Ranzano sandstones (marly *facies*); (5) Monte Piano marls; (6) Val Luretta Fm. (arenaceous *facies*); (7) Val Luretta Fm. (calcareous *facies*); (8) Varicolori clays; **b** Pogliaschina catchment: (1) Alluvial deposits (current); (2) Alluvial deposits (recent); (3) Monte Gottero sandstones; (4) Val Lavagna Fm.; (5) Argille a Palombini Fm.; (6) Diaspri di Monte Alpe; (7) Gabbri Fm.; (8) Serpentiniti Fm.; (9) Canetolo clays and limestones; (10) Macigno Fm.; (11) Scaglia Toscana Fm.; (12) Maiolica Fm.; (13) Diaspri Fm.; **c** Vernazza catchment: (1) Ponte Bratica sandstones; (2) Groppo del Vescovo limestones; (3) Canetolo clays and limestones; (4) T. Pignone marls; (5) Macigno Fm.; (6) Macigno Fm. (sandstones *lithofacies*); (7) Macigno Fm. (silty-pelitic *lithofacies*); (8) Macigno Fm. (silty-marly *lithofacies*)

The bedrock is mainly composed of a sandstone-claystone flysch and a pelitic complex. Two types of land use prevail in this basin: terraced areas and woods, occupying 49 and 51% of the whole basin, respectively. Despite the high percentage of terraced areas, only a small part is still cultivated (Cevasco et al. 2014). Due to reworking of debris covers for terracing, the soil thickness is greater on agricultural terraces (up to 2.5 m) than on woodlands (up to 1.5 m).

Several rainfall-induced landslides were triggered on 25 October 2011. A total of 473 landslides were mapped, through the classifications of Cruden and Varnes (1996) and Hungr et al. (2001). Most of them were classified as debris avalanches (Cevasco et al. 2014).

Materials and Method

Statistical Method

The methodology applied for the shallow landslide susceptibility assessment is based on the application of a multiple nonlinear regression model based on GAM.

The GAM represents a semi-parametric extension of the generalized linear model (GLM). Its basic assumption is to replace the linear function used in a GLM with an empirically fitted smooth function, in order to find the more likely functional form to fit the data (Brenning 2008; Goetz et al. 2011). Specifically, it uses a link function to establish the relationship between the mean μ of the response variables (in our work the probability of landslide occurrence) and a sum of a set of smooth functions of independent variables, as shown in Eq. 1 (Jia et al. 2008):

$$g(\mu) = \sum_{i=1}^{n} f_i(x_i) \qquad (1)$$

where g is the link function (logistic in our work) and the f_i are smooth function (typically splines), each depending on a single explanatory variable x_i chosen in a set of n variables $x_1 \ldots x_n$. GAM allows the combination of linear and nonlinear smoothing functions and the application of different modelling policies according to the characteristics of the explanatory variables.

The adopted procedure is composed of several steps:

1. A dataset consisting of all the landslide pixels and of the same number of randomly selected non landslide pixels was created.
2. This dataset was subdivided into 2 subsets: the training and the test sets. The training set, representing 2/3 of the dataset, was used to build the GAM fitting the samples, whereas the test dataset, including 1/3 of the dataset, was used to estimate the model accuracy.
3. The process of training and test sets random selection was repeated in a 100-fold bootstrap procedure, aimed to identify the most frequent predictors variables. The parameters that are present more than 80% of the time in the bootstrap extractions were identified as the most influential in the shallow landslide occurrence and therefore were chosen to build the model for the landslide occurrence prediction.
4. The predictive accuracy was evaluated through a repeated holdout method for regression with a binary response, slightly modified with respect to the standard procedure (Maindonald and Braun 2010). The accuracy of the 100 different iterations was calculated in all training and test sets. The results were averaged to yield an overall accuracy and then compared.
5. Another measure of the predictive performance of the model was the receiver operating characteristic (ROC) curve (Hosmer and Lemeshow 2000). In particular, the area under the ROC curve (AUROC) was computed to evaluate the model ability to discriminate landslide and non-landslide location. Specifically, the mean value of the 100 AUROC samples obtained from the 100-fold bootstrap procedure was calculated, as well as the bootstrap 95% confidence intervals of AUROC.
6. The shallow landslide susceptibility maps were extracted by extending the prediction of the model to all the study areas. The resulting probability maps obtained by the GAM fit procedure were classified into 4 susceptibility levels (from low to high). Their range values were chosen adopting an equal interval of 0.25.
7. In the last step, to investigate the reliability of landslide probability associated to each pixel, the 95% bootstrap confidence intervals of landslide probability were computed.

Explanatory Variables

For the GAM application, 12 predisposing factors were selected as explanatory variables. Nine of them, representing morphological and hydrological parameters, were extracted by 10 m-resolution, through a set of tools implemented in SAGA GIS. These are: slope angle (SL), slope aspect (ASP), planform curvature (PLA), profile curvature (PRO), catchment area (CA), catchment slope (CS), topographic wetness index (TWI), topographic position index (TPI), terrain ruggedness index (TRI). SL, ASP, PLA and PRO were based on local polynomial approximations, according to Zevenbergen and Thorne (1987). ASP was transformed into

categorical variables in order to avoid the misclassification of flat areas as "No Data" areas. CA and CS were derived using the multiple-flow-direction algorithm (Quinn et al. 1991). CA was transformed into its natural logarithm in order to reduce skewness (Brenning et al. 2015)

In addition to these, geology (GEO), land use (LU) and the Euclidean distance from the road network (RD) were introduced as predictive variables. GEO influences the geotechnical and hydraulic properties of the soil slope cover, while LU controls the effects of vegetation on slope stability. RD highlights the anthropogenic modification of the hillslope profile or drainage system. GEO and LU were obtained by means of GIS analyses consulting specific thematic maps. GEO was carried out considering the different geological formations as reported on the available geological maps.

Response Variables: Landslide Inventories

In the Versa catchment, two different landslide inventories (2009 and 2013) were considered. The 2009 inventory was realized by means of post-event colour aerial photographs (17 May 2009) at resolution of 0.15 m (photo scale of 1:12,000), obtained by aero-photogrammetric survey performed by a private company (Ditta Rossi s.r.l.) The 2013 landslide inventory was carried out using Pleiades satellite images; Pleiades triplet, available through evaluation program organized by AIRBUS Defence & Space, were used in stereo analyst environment.

Both landslide inventories were also completed adding information derived from field surveys and warning by public authority. They were introduced in GAM as single seasonal events (Inventory 2009, Inventory 2013) and then as combination of them, in order to analyse the multi-temporal landslide inventory.

In the Pogliaschina and Vernazza catchments, different inventories based on two methodologies of preparation and referred to the same rainfall event (25 October 2011) were considered.

In the Pogliaschina catchment case, the difference between the two available landslide inventories consists in the instruments and detection method used to map the shallow landslides. The first inventory (Inventory detection 1) was obtained by means of the analysis of post-event aerial photos and digital georeferenced orthophotos (both provided by Liguria Regional Administration). The aerial photos belonged to BLOM C.G.R.S 28 October 2011 flight, whereas the orthophotos were taken by the Air Service of Remote Sensing and Monitoring of Civil Protection of Friuli Venezia Giulia Regional Administration on 28 November 2011. The Inventory detection 1 is composed by 271 landslides. The second landslide inventory (Inventory detection

2) was prepared through the combined use of aerial photographs, digital georeferenced orthophotos (both provided by Liguria Regional Administration) and detailed field surveys. In this case, the inventory consists of 521 landslides.

For what concerns the Vernazza catchment, two inventories were realized by the use of two different criteria for shallow landslides mapping. In the first inventory (Inventory criterion 1), composed by 364 landslides, among the landslides classified as debris flows (Hungr et al. 2001), a different criterion of mapping was adopted for phenomena occurring on 1st order channels and on 2nd and 3rd order channels, respectively. Regarding the first case, both the source and the sliding areas were mapped. Whereas, with regard to debris flows occurred on 2nd and 3rd order channels, only the source areas were mapped. Moreover, the phenomena (channeled or not) that were interpreted as the result of erosion process caused by surface runoff action were neglected.

In the second inventory (Inventory criterion 2), consisting of 473 shallow landslides, both the source and the sliding areas were mapped for landslides classified as debris flows, irrespective of whether they occurred along 1st, 2nd or 3rd order channels. Moreover, the phenomena interpreted as the result of erosion process due to surface runoff action were considered.

Both in Pogliaschina and Vernazza catchment, the GAM was applied using each single landslide inventory, in order to compare the predictive performance of model introducing different landslide inventories realized following different methods of mapping.

Results

Predictive performances of the GAM by the use of different landslide inventories as response variable are showed in Table 1.

In the Versa catchment, despite the higher value of the AUROC and accuracy reached with the use of the two single seasonal events (Table 1), the use of the Multitemporal inventory allowed to identify the totality of significant predisposing factors for both the analyzed shallow landslide events (Table 1), giving more detailed and representative information of the parameters influencing the landslide susceptibility of the analyzed territory.

In the Pogliaschina catchment, the different methods of detection for the construction of the landslide inventory had no particular influence on the predictive performance of the model, since the results were very similar (Table 1). Instead, the changes were found in the choice of significant parameters.

With the Inventory detection 2, prepared through the combined use of remotely sensed data and field

Table 1 Predictive performance of the GAM and significant explanatory variables chosen by the model according to each landslide inventory used as response variable in the analysis

Study area	Landslide inventory	Significant explanatory variable	Accuracy	Mean AUROC	95% confidence interval of AUROC
Versa catchment	Inventory 2009	SL(s) + CS(s) + ASP + LU	0.72	0.76	0.74–0.77
	Inventory 2013	ASP + LU	0.71	0.76	0.73–0.77
	Multitemporal inventory	SL(s) + ASP + LU + GEO	0.70	0.73	0.72–0.74
Pogliaschina catchment	Inventory detection 1	SL + PLA + ASP + LU + GEO	0.71	0.79	0.78–0.80
	Inventory detection 2	SL(s) + PLA(s) + PRO + CS + ASP + LU + GEO	0.70	0.77	0.77–0.78
Vernazza catchment	Inventory criterion 1	TPI(s) + LU	0.71	0.76	0.75–0.77
	Inventory criterion 2	TPI + ASP + LU + GEO	0.71	0.76	0.75–0.77

SL slope; *CS* catchment slope; *TPI* topographic position index; *PLA* planform curvature; *PRO* profile curvature; *ASP* aspect; *LU* land use; *GEO* geology. The nonlinear explanatory variables are indicated with (s)

investigation, the model has identified, as significant variables, more geomorphological predisposing factors than those selected with the use of the Inventory detection 1. Moreover, with the Inventory detection 2 the model was able to capture the complex geomorphic processes of two geomorphological continuous explanatory variables (SL and PLA), selecting them as nonlinear (s). This failed using inventory 1, since the SL and PLA were selected as linear.

In the Vernazza catchment, both the AUROC value and the accuracy were the same both with Inventory criterion 1 and Inventory criterion 2 (AUROC = 0.76; Accuracy = 0.71), but, the exploitation of the latter allowed, also, to identify more predisposing factors than with the use of the Inventory criterion 1 (Table 1).

In Fig. 2a, b are shown the susceptibility maps and the amplitude of the 95% bootstrap confidence interval of landslide probability. In Table 2 the percentage of the area of each susceptibility class is reported.

In the Versa catchment, the shallow landslide susceptibility distribution (Fig. 2a; Table 2) is completely different considering the two seasonal inventories (Inventory 2009 and Inventory 2013). Instead, the use of the Multitemporal inventory allowed to obtain a shallow landslide susceptibility map representative of both the events, giving a more reliable description of the susceptibility of the analysed territory. The reliability of the landslide probability is indicated by the amplitude of the 95% bootstrap confidence intervals of landslide probability, shown in Fig. 2b. Effectively, it was possible to notice that the lowest variability was observed exactly using the Multitemporal inventory.

In the Pogliaschina catchment, the percentage of susceptibility distribution in each class was very similar in both the cases (Table 2). However, looking at their spatial

distribution (Fig. 2a), the localization of the highest values of susceptibility was different. The uncertainty of the landslide probability was low with the use of both the landslide inventories, even if, few parts of the catchment (1–2%) were also characterized by high variability of bootstrap confidence intervals amplitude, reaching values equal to 1 (Fig. 2b).

In the Vernazza catchment, there was little difference in the percentage of the area of each susceptibility class by the exploitation of the two different landslide inventories (Table 2). Also the reliability of landslide probability was characterized by low variability in both cases (Fig. 2b). However, in the comparison of the shallow landslide susceptibility maps (Fig. 2a) it was observed a completely different spatial distribution of susceptibility, especially in the upper part of the catchment. In particular, with the use of the Inventory criterion 2, the medium-high susceptibility was mainly identified in correspondence of channels. Instead, considering the Inventory criterion 1, the same areas were characterized by medium-low susceptibility.

Conclusions

The role of the landslide inventories in the landslide susceptibility analysis was investigated. In particular, a non linear regression technique, namely the GAM, was used to test if the method of detection and mapping of landslide inventories, also considering seasonal or multitemporal events, can influence the predictive performance of a statistical model and the corresponding landslide susceptibility map. Concerning the analysis performed in the Versa catchment, it was noted that the use of inventories of single events tends not to consider the overall characteristics of the
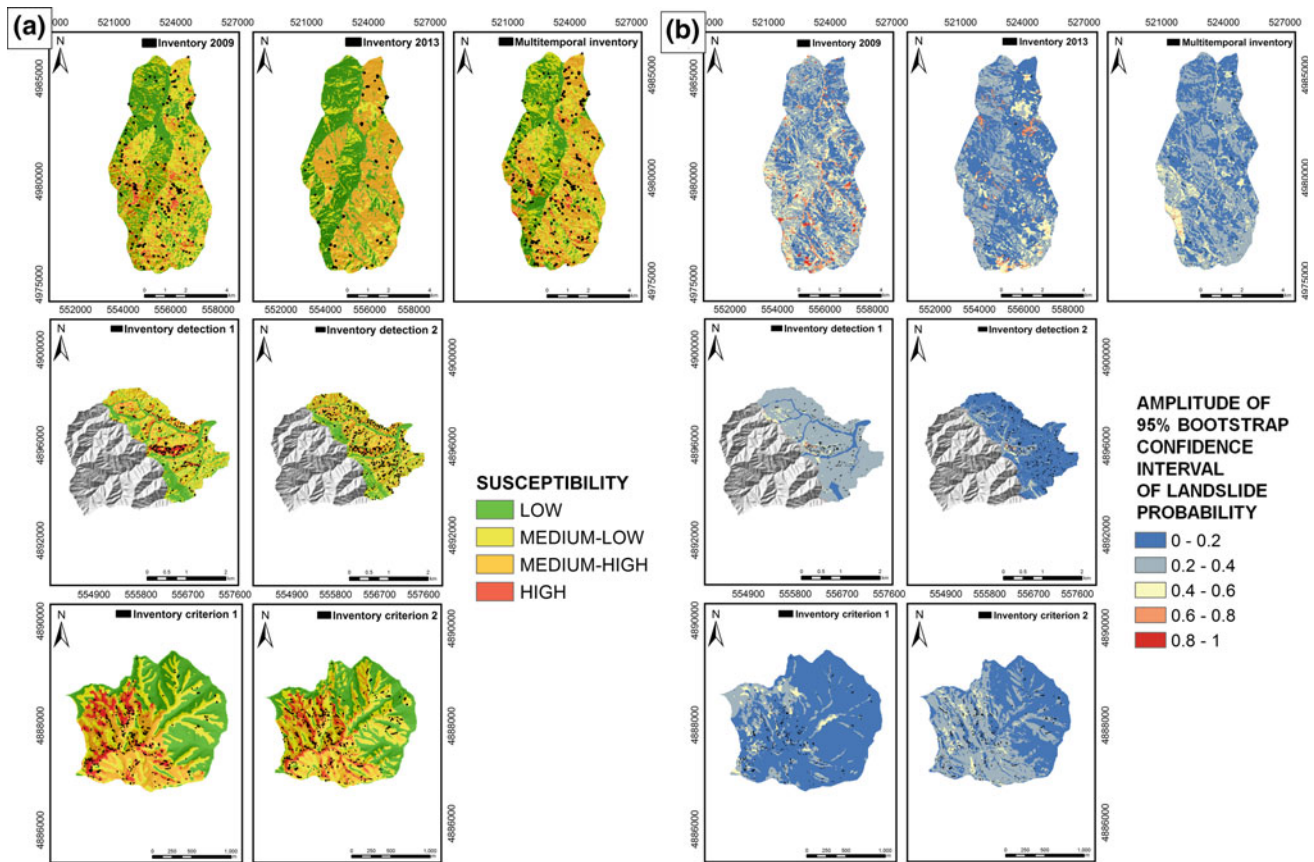
Fig. 2 **a** Shallow landslide susceptibility maps extracted by the use of each different landslide inventory; **b** maps of the amplitude of the 95% of bootstrap confidence interval of landslide probability. *Upper* Versa catchment; *Middle* Pogliaschina catchment; *Bottom* Vernazza catchment

Table 2 Percentage of the area of each susceptibility class and the uncertainty of landslide probability (95% bootstrap confidence intervals of landslide probability) according to each landslide inventory used in each investigated area

Study area	Landslide inventory	Susceptibility distribution			
		Low ($0 \leq p \leq 0.25$) (%)	Medium-low ($0.25 \leq p \leq 0.50$) (%)	Medium-high ($0.50 \leq p \leq 0.75$) (%)	High ($0.75 \leq p \leq 1$) (%)
Versa catchment	Inventory 2009	30	36	27	7
	Inventory 2013	40	18	42	0
	Multitemporal inventory	25	36	35	4
Pogliaschina catchment	Inventory detection 1	32	40	22	6
	Inventory detection 2	29	39	26	6
Vernazza catchment	Inventory criterion 1	37	28	27	8
	Inventory criterion 2	34	32	25	9

territory in terms of predisposing factors. In fact, they are better represented by the use of a multitemporal inventory, which is able to provide more detailed and more representative information on the parameters that affect the landslide susceptibility of the territory. In addition, with the use of a multitemporal inventory, the shallow landslide susceptibility assessment improved in terms of degree of reliability of the distribution of susceptibility.

In the Pogliaschina catchment, the different methods of detection used for preparing landslide inventories did not influence the predictive performance of the GAM. On the contrary, they led to a modification of the spatial distribution of the susceptibility, in particular for areas characterized by high value of susceptibility.

In the Vernazza catchment, the use of two landslide inventories, prepared following two different criteria for mapping debris flows, led to change results in terms of spatial distribution of susceptibility. Thus, based on the obtained results, it is evident how a standard criterion for the preparation of landslide inventories is necessary in order to produce susceptibility maps as reliable as possible for purposes of land management.

References

Bartelletti C, D'Amato Avanzi G, Galanti Y, Giannecchini R, Mazzali A (2015) Assessing shallow landslide susceptibility by using the SHALSTAB model in Eastern Liguria (Italy). Rend Online Soc Geol Ital 35:17–20

Brenning A (2008) Statistical geocomputing combining R and SAGA: the example of landslide susceptibility analysis with generalized additive models. In: Böhner J, Blaschke T, Montanarella L (eds) SAGA—Seconds out (=Hamburger Beiträge zur Physischen Geographie und Landschaftsökologie, 19), pp 23–32

Brenning A, Schwinn M, Ruiz-Páez AP, Muenchow J (2015) Landslide susceptibility near highways is increased by one order of magnitude in the Andes of southern Ecuador, Loja province. Nat Hazards Earth Syst Sci Discussion 2:1945–1975

Cevasco A, Pepe G, Brandolini P (2014) The influences of geological and land-use settings on shallow landslides triggered by an intense rainfall event in a coastal terraced environment. Bull Eng Geol Env 73:859–875

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

Cruden DM, Varnes DJ (1996) Landslide types and processes. In: Turner AK, Schuster RL (eds) Landslides: investigation and mitigation, transportation research board special report, 247. National Academy Press, Washington, D.C., pp 36–75

D'Amato Avanzi G, Galanti Y, Giannecchini R, Bartelletti C (2014) Shallow landslides triggered by the 25 October 2011 extreme rainfall in Eastern Liguria (Italy). In: Lollino G, Giordan D, Crosta GB, Corominas J, Azzam R, Wasowski J, Sciarra N (eds) Engineering Geology for Society and Territory, vol 2. Springer International Publishing, Switzerland, pp 515–519

Fiorucci F, Cardinali M, Carlà R, Rossi M, Mondini AC, Santurri L, Ardizzone F, Guzzetti F (2011) Seasonal landslides mapping and estimation of landslide mobilization rates using aerial and satellite images. Geomorphology 129(1–2):59–70

Galli M, Ardizzone F, Cardinali M, Guzzetti F, Reichenbach P (2008) Comparing landslide inventory maps. Geomorphology 94:268–289

Goetz JN, Guthrie RH, Brenning A (2011) Integrating physical and empirical landslide susceptibility models using generalized additive models. Geomorphology 129:376–386

Guzzetti F, Cardinali M, Reichenbach P, Carrara A (2000) Comparing landslide maps: a case study in the upper Tiber River Basin, Central Italy. Environ Manage 25(3):247–363

Guzzetti F, Reichenbach P, Ardizzone F, Cardinali M, Galli M (2006) Estimating the quality of landslide susceptibility models. Geomorphology 81:166–184

Guzzetti F, Mondini AC, Cardinali M, Fiorucci F, Santangelo M, Chang KT (2012) Landslide inventory maps: new tools for an old problem. Earth-Sci Rev 112:42–66

Hastie TJ, Tibshirani R (1990) Generalized additive models. Chapman & Hall, London

Hosmer DW, Lemeshow S (2000) Applied logistic regression. Wiley, New York

Hungr O, Evans SG, Bovis M, Hutchinson JN (2001) Review of the classification of landslides of the flow type. Environ Eng Geosci 7:221–238

Hungr O, Leroueil S, Picarelli L (2014) The Varnes classification of landslide types, an update. Landslides 1:167–194

Hungr O (2016) A review of landslide hazard and risk assessment methodology. In: Aversa et al (eds) Landslides and engineered slopes. Experience, theory and practice, pp 3–27

Hutchinson JN (1968) Mass movement. In: Fairbridge RW (ed) Encyclopedia of geomorphology. Reinhold, New York, pp 688–695

Hutchinson JN (1988) General report: morphological and geotechnical parameters of landslides in relation to geology and hydrogeology. In: Bonnard C (ed) Proceedings of the 5th international symposium on landslides. Balkema AA, Rotterdam, pp 3–36

Jenks G (1967) The data model concept in statistical mapping. Int Yearbook Cartography 7:186–190

Jia G, Yuan T, Liu Y, Zhang Y (2008) A static and dynamic factors-coupled forecasting model or regional rainfall-induced landslides: a case study of Shenzhen. Sci China Ser E: Technol Sci 51:164–175

Lu N, Godt JW (2013) Hillslope hydrology and stability. Cambridge University Press, Cambridge

Maindonald J, Braun WJ (2010) Data analysis and graphics using R: an example-based approach. Cambridge series in statistical and probabilistic mathematics, p 552

Mondini AC, Chang KT, Yin HY (2011) Combining multiple change detection indices for mapping landslides triggered by typhoons. Geomorphology 134(3–4):440–451

Quinn P, Beven K, Chevallier P, Planchon O (1991) The prediction of hillslope flow paths for distributed hydrological modelling using digital terrain models. Hydrol Processes. 5:59–79

Salvati P, Balducci V, Bianchi C, Guzzetti F, Tonelli G (2009) A WebGIS for the dissemination of information on historical landslides and floods in Umbria, Italy. GeoInformatica 13: 305–322

Skempton AW, Hutchinson JN (1969) Stability of natural slopes and embankment foundations. In: Proceedings of the 7th international conference on soil mechanics and foundation engineering, Mexico City, pp 291–340

van Westen CJ, van Asch TWJ, Soeters R (2006) Landslide hazard and risk zonation—why is it still so difficult? Bull Eng Geol Environ 65:167–184

van Westen CJ, Castellanos Abella EA, Sekhar LK (2008) Spatial data for landslide susceptibility, hazards and vulnerability assessment: an overview. Eng Geol 102:112–131

Varnes DJ (1958) Landslide types and processes. In: Eckel EB (eds) Landslides and engineering practice, Highway Research Board special report no. 29, pp 20–47

Varnes DJ (1978) Slope movement types and processes. In: Schuster RL, Krizek RJ (eds) Landslide analysis and control, Transportation Research Board special report 176. National Academy of Sciences, National Research Council, Washington, D.C., pp 11–33

Zevenbergen LW, Thorne CR (1987) Quantitative analysis of land surface topography. Earth Surf Proc Land 12:47–56