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SCIENCE

Landslide susceptibility of the Prato–Pistoia–Lucca provinces, Tuscany, Italy

Samuele Segoni, Veronica Tofani, Daniela Lagomarsino and Sandro Moretti

Department of Earth Sciences, University of Firenze, Florence, Italy

ABSTRACT

We mapped landslide susceptibility in the provinces of Lucca, Pistoia and Prato (central Italy), a 3103 km² territory that approximately corresponds to the portion of Tuscany principally affected by landslides. We used a methodology based on a treebagger random forest. The input parameters used for the susceptibility assessment are curvature, flow accumulation, topographic wetness index, elevation, profile curvature, planar curvature, slope gradient, aspect, land use and lithology. The map was validated providing satisfactory results (AUC = 0.84). The map classifies the study area into four susceptibility classes that identify areas with different probabilities of being affected by landslides. The [Main Map](#) represents a useful instrument to assist land planning, development of mitigation measures and landslide risk management. Moreover, it could be used in further research addressing quantitative hazard and risk assessment.

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1. Introduction

Landslide susceptibility maps are a graphical representation of the relative probability of the occurrence of landslides in a given area, without taking into consideration the probability of occurrence in time (Brabb, 1984; Varnes, 1984).

On this topic, the scientific literature is extensive and landslide susceptibility maps have been proposed at different scales and using different methodologies (Brenning, 2005; Corominas et al., 2014; Fell et al., 2008; Kanungo, Arora, Sarkar, & Gupta, 2009).

Many studies point out that Italy is very susceptible to landslides: susceptibility maps have been proposed at the national level (Trigila et al., 2013), at regional scale (Catani, Casagli, Ermini, Righini, & Menduni, 2005; Leoni et al., 2009; Manzo, Tofani, Segoni, Battistini, & Catani, 2013; Segoni, Lagomarsino, Fanti, Moretti, & Casagli, 2015b) or at the detail scale (Cervi et al., 2010; Conforti, Pascale, Robustelli, & Sdao, 2014; Mancini, Ceppi, & Ritrovato, 2010; Trigila, Iadanza, Esposito, & Scarascia-Mugnozza, 2015). For Tuscany, the analysis of recent databases (Battistini, Segoni, Manzo, Catani, & Casagli, 2013; Lu, Casagli, Catani, & Tofani, 2012; Lu, Catani, Tofani, & Casagli, 2014; Rosi et al., 2015; Segoni et al., 2015a; Tofani, Dapporto, Vannocci, & Casagli, 2006; Trigila, Iadanza, & Spizzichino, 2010) reveals that the northwestern sector of the region is the most affected by landslides, however, a landslide susceptibility map has never been developed for this portion of Tuscany (which roughly corresponds to the provinces of Lucca, Prato and Pistoia).

The main purpose of this work is to fill this gap and to present a landslide susceptibility [Main Map](#) that could be used for land use planning and as a base for further developments of research related to landslide hazards.

2. Study area

The study area is located in Tuscany (central Italy), and covers 3103 km² (Figure 1(a)). It is dominated by the Apennines fold and thrust mountain belt, which reaches elevations of up to 2000 m. From a geological perspective, the study area is characterized by two different lithological and morphological settings. The eastern sector is dominated by the flyschs of the Macigno formation. Here, slope gradients vary from 0° on the alluvial plains to 55°. The western sector is predominantly comprised of carbonaceous rocks, forming mountainsides that have slope gradients steeper than 60°. In the study area, the bedrock is covered by colluvial soil, which typically reaches a maximum thickness of 5 m.

From a meteorological perspective, the study area is one of the wettest sectors of Tuscany, characterized by a main seasonal peak in autumn and by a dry summer. During the wet season, prolonged rainfalls take place over large sectors of the region. In the summer, convection thunderstorms produce localized rainfall of short duration and higher intensity. The spatial distribution of precipitation is markedly influenced by the topography: the plains are characterized by a mean annual precipitation of around 1100 mm/year, while in the

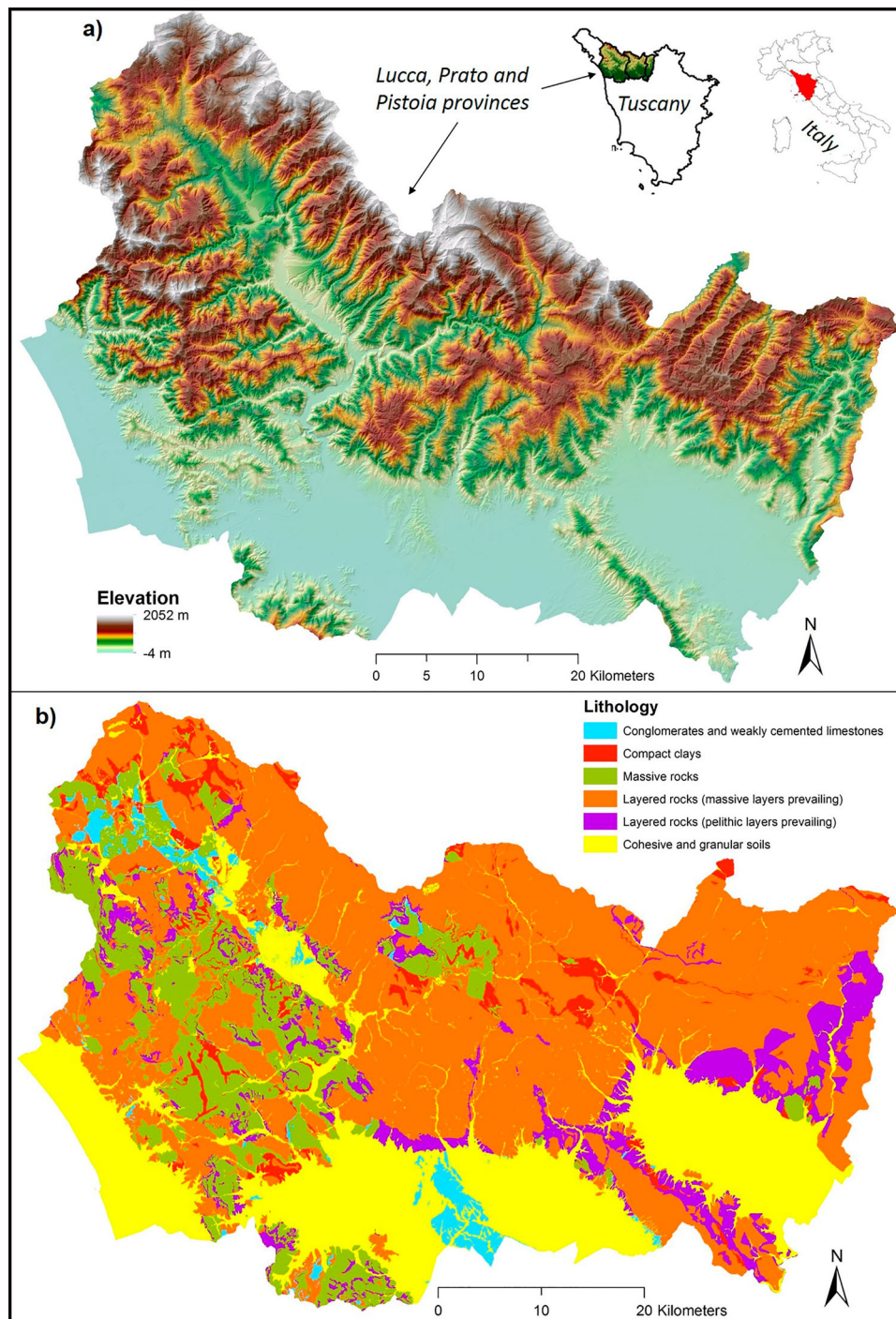


Figure 1. (a) DEM of the study area and (b) main lithological units of the study area.

mountains this values rises up to 2000 mm/year, with occasional annual peaks of 3000 mm.

As a result of the high rainfall rates, the steepness of the slopes and the layered bedrock, landslides pervasively affect the test area: according to the Inventario dei Fenomeni Franosì Italiani (IFFI) database, 5436 landslides are present. Their dimensions range from 10^2 to 10^6 m² and they are almost entirely categorized as rotational/translational slides or as complex movements. As the complex movements are primarily rotational and translational movements evolving into flows, in our susceptibility assessment, we did not make distinctions and we analyzed all landslides

together, since the triggering mechanism is very similar.

The population is mainly concentrated in the valleys, but relevant human settlements and infrastructure are present in the mountainous areas as well and are exposed to landslide hazards (Battistini et al., 2013; Mercogliano et al., 2013; Rosi et al., 2015; Segoni, Rossi, Rosi, Catani, & Casagli, 2014)

3. Methods

To map landslide susceptibility, we used the ‘Random forest’, a machine-learning algorithm for nonparametric

multivariate classification (Breiman, 2001). Although this methodology can be considered relatively new, it has been used in landslide studies through different applications (Brenning, 2005; Catani, Lagomarsino, Segoni, & Tofani, 2013; Pourghasemi & Kerle, 2016; Segoni et al., 2015b; Trigila et al., 2015; Vorpahl, Else-Beer, Märker, & Schröder, 2012; Youssef, Pourghasemi, Pourtaghi, & Al-Katheeri, 2015).

Among its advantages, the random forest technique allows the employment of both categorical and numerical variables, it accounts for interactions and nonlinearities between variables, it allows exploration of a large number of explanatory variables (as it intrinsically emphasizes only those variables of high explanatory power), and no assumption is required about the distribution of the data. Further details on the adopted methodology and on its application to landslide susceptibility mapping can be found in Catani et al. (2013).

To train and validate the susceptibility model, we used data from IFFI, the Italian national inventory of landslides at 1:10,000 scale (Trigila et al., 2010). In the IFFI inventory, each landslide is reported as a single polygon, without distinctions between depletion and deposition zones. For this reason, in the study area, where the majority of the mapped phenomena are slow moving landslides, for the modeling we have used the total landslide area: assuming that the transport zone has a limited length, the deposition zone is relatively near to the depletion zone and consequently they have similar geological and geomorphological conditions.

One of the main features of Treebagger algorithm is the possibility of feeding it with a large number of input parameters, regardless of their correlations and mutual influences, because a forward selection of input parameters discards uninfluential or pejorative predictors and gives a proper weight to each parameter (Catani et al., 2013). We therefore fed the machine-learning algorithm with a large number of input parameters: curvature, flow accumulation, topographic wetness index, elevation, profile curvature, planar curvature, slope gradient, aspect, land use and lithology. Morphometric attributes were derived from a digital elevation model (DEM) with 10 m pixel size. Land use was derived from a 1:50,000 scale map, which in the study area was reclassified into nine classes: urban areas, crops, grasslands, heterogenic rural areas, forests (broad-leaved), forests (conifers), shrubs, bare rocks and humid areas. Lithology was derived from a lithological map at 1:100,000 scale, which was reclassified into six classes: conglomerates and weakly cemented limestones; compact clays; massive rocks; layered rocks (pelitic layers prevailing); layered rocks (massive layers prevailing) and cohesive and granular soils (Figure 1(b)).

Although the structural setting is a well-known factor controlling slides and earthflows, it was not possible to directly take it into account in our analysis. This was due to the absence of information sources with a

sufficient degree of homogeneity over the whole study area that could provide structural setting elements to be translated into categorical or numerical variables for the landslide susceptibility assessment. However, it is widely known that the morphology of the Apennine slopes is controlled by slope-scale geological structures and variations in stratigraphy (Pinto et al., 2016); therefore, we can consider that the structural setting of the area is indirectly and implicitly taken into account by the large number of morphometric parameters used in the analysis.

To obtain the input variables for the susceptibility model, the grid for each morphometric or thematic attribute was resampled to a 100 m pixel size and split into two variables: one considering the average value encountered in the 100 × 100 m cell (mean value for numerical attributes and prevailing class for categorical values), the other considering its variability inside the 100 × 100 m cell (standard deviation for numerical attributes and number of classes for categorical values). Several studies have noted that morphometric attributes based on derivatives of elevation landslides are more susceptible to peak values rather than mean values (Catani et al., 2013; Segoni et al., 2015b); for slope gradient and for all kinds of curvature we included an additional resampling criterion based on the maximum value. Consequently, the total number of input parameters used is 23.

Concerning the response variable of the binary classification problem at hand (landslide/no landslide), we used the landslide inventory map to derive a grid (with characteristics identical to the grids of the other input parameters) that accounts for the presence of one or more landslides in each of the 100 × 100 m cells of the grid.

To map landslide susceptibility, we randomly sampled the study area to select 10% of the pixels for training and 10% for testing. Such percentages have been proved to be a good compromise between quality of the results and speed of the calculations (Catani et al., 2013).

The automated procedure of forward selection of input parameters identified the optimal configuration of the susceptibility model encompassing all 23 variables. According to the testing procedure, the variables with the higher predictive power were standard deviation of elevation, mean profile curvature, standard deviation of flow accumulation, mean flow accumulation and mean elevation. Some variables have a very low predictive power (e.g. variability of land cover, variability of aspect), but, still, their use increased the overall predictive power of the model.

The final output of the methodology is a raster with a 100 × 100 m cell size, where each pixel has a percentage value expressing the probability of landslide potential. According to our analysis, the susceptibility values range from 0% to 91%.

Table 1. Classes used to draw the susceptibility map of the Lucca, Prato and Pistoia provinces.

Susceptibility class	Susceptibility values
Null to very low	<6%
Low	$6\% \leq \text{susceptibility} < 10\%$
Moderate	$10\% \leq \text{susceptibility} < 19\%$
High	$\geq 19\%$

To ease the interpretation of the results, the percentage values were reclassified into four susceptibility classes (Table 1). The criterion used to define the four classes is based on the approach proposed by Catani et al. (2005), in which the cumulative density function of the Treebagger output values within mapped landslides (cdfL) was compared to the total cumulative density function (cdfT). According to this approach, a sudden increase in the cdfL curve that is not accompanied by a similar rise in the cdfT curve represents a threshold output value that could be set as a limit between susceptibility classes. The identification of such thresholds can be made easier plotting the difference between the derivatives of the two cdf functions and identifying the main peaks or the sharpest fluctuations of the plot. Further details can be found in Catani et al. (2005).

To get an independent validation, for the pixels not sampled for training or testing of the susceptibility model, the estimated membership class probability was compared with the true class (landslide or no landslide) and receiver–operator curves (ROC curves) were drawn. The area under the ROC curve (AUC) is one of the most widely used a metrics to assess the overall quality of a model.

4. Conclusions

In this work, we present a landslide susceptibility **Main Map** of the provinces of Lucca, Prato and Pistoia, which corresponds to the portion of Tuscany (central Italy) more commonly affected by landslides. The susceptibility map has been validated using the software ClaReT and a ROC curve was automatically produced. The AUC (area under ROC curve) value of 0.84 and a visual comparison (Figure 2) revealed a good agreement of the final result with observations.

The **Main Map** shows that the provinces Prato, Pistoia and Lucca are widely susceptible to landslides; if we exclude the flat valley floors, low and moderate susceptibility areas can be identified in wide portions of the territory. Highly susceptible areas characterize the northwestern sector (high Serchio valley), some mountainsides in the central sector of the area and most of the hillsides close to the main valley floor. According to the map, landslides threaten railways and main roads and most of the towns located in hilly or mountainous territory.

The **Main Map** can be used to identify the areas that are most likely to be affected by landslides in the future, thus representing a useful aid to assist land planning, landslide risk management and the development of mitigation strategies. Moreover, the map could be exploited in future research in two ways: (i) to develop a complete hazard map which, in turn, could be used in a quantitative risk assessment and (ii) following the approach of Segoni et al. (2015b), it could be combined with the regional landslide early warning system based

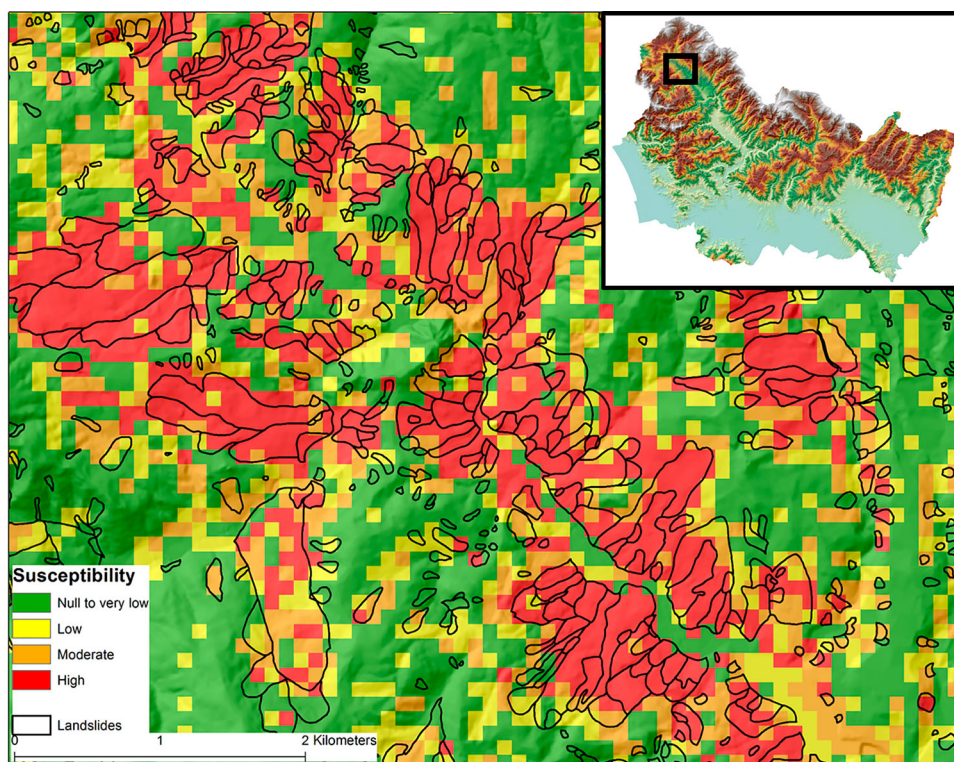


Figure 2. Detail of the susceptibility map and comparison with the inventory of mapped landslides.

on rainfall thresholds (Segoni et al., 2014, 2015a) to improve the effectiveness and the spatial resolution of the forecasting of landslides.

Software

The landslide susceptibility analysis was carried out using the software ClaReT, which uses a random forest implementation based on Matlab (Matworks, version 7.11, treebagger object (RFtb) and methods).

The final output of ClaReT was a table, which was imported in to Esri ArcGIS10.1[®] and converted to a 100 m cell size raster editing and display. The susceptibility raster can be obtained upon request by contacting the corresponding author.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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