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Landslide susceptibility assessment in complex geological settings: sensitivity to geological information and insights on its parameterization

Abstract The literature about landslide susceptibility mapping is rich of works focusing on improving or comparing the algorithms used for the modeling, but to our knowledge, a sensitivity analysis on the use of geological information has never been performed, and a standard method to input geological maps into susceptibility assessments has never been established. This point is crucial, especially when working on wide and complex areas, in which a detailed geological map needs to be reclassified according to more general criteria. In a study area in Italy, we tested different configurations of a random forest–based landslide susceptibility model, accounting for geological information with the use of lithologic, chronologic, structural, paleogeographic, and genetic units. Different susceptibility maps were obtained, and a validation procedure based on AUC (area under receiver-operator characteristic curve) and OOBE (out of bag error) allowed us to get to some conclusions that could be of help for in future landslide susceptibility assessments. Different parameters can be derived from a detailed geological map by aggregating the mapped elements into broader units, and the results of the susceptibility assessment are very sensitive to these geology-derived parameters; thus, it is of paramount importance to understand properly the nature and the meaning of the information provided by geology-related maps before using them in susceptibility assessment. Regarding the model configurations making use of only one parameter, the best results were obtained using the genetic approach, while lithology, which is commonly used in the current literature, was ranked only second. However, in our case study, the best prediction was obtained when all the geological parameters were used together. Geological maps provide a very complex and multifaceted information; in wide and complex area, this information cannot be represented by a single parameter: more geology-based parameters can perform better than one, because each of them can account for specific features connected to landslide predisposition.

Keywords Susceptibility · Random forest · Comparison · Sensitivity · Geology · Lithology

Introduction

Landslide susceptibility mapping (LSM henceforth) is a very important activity in landslide hazard assessment, consisting in representing over appropriate spatial units the relative spatial probability of landslide occurrence (Brabb 1984). The overwhelming literature on landslide susceptibility is rich of works presenting applications to case studies from the local to the global scale (Youssef et al. 2016; Pradhan et al. 2019; Yang et al. 2019; Trigila et al. 2013; Günther et al. 2013; Hong et al. 2007) obtained mainly by means of statistical techniques (Reichenbach et al. 2018, and references therein), artificial neural networks (Catani et al. 2005), and machine learning algorithms (Brenning 2005, and references therein; Catani et al. 2013).

Many researchers recently presented new improvements in the techniques (Huang et al. 2017; Shirzadi et al. 2017; Pham et al. 2019) or focused on the comparison between different models (Akgun 2012; Pham et al. 2016; Youssef et al. 2016; Bueechi et al. 2019), thus improving the state of the art with analysis tools capable of an increased effectiveness. Some works also performed a sensitivity analysis to different model settings (resolution, scale, parameters, or methods to use parameters) that can be a reference for future works to design a correct and robust model configuration (Catani et al. 2013; Greco and Sorriso-Valvo 2013).

Surprisingly, it seems that these undoubtedly useful and interesting aspects overshadowed the importance of geology in LSM: to the best of our knowledge, a sensitivity analysis on the use of geological information has never been performed, nor a standard method to input geological maps into susceptibility assessments has ever been established.

Geological maps depict the spatial distribution on the topographic surface of rocks with different ages, natures, and characteristics. The aim is not limited to represent the spatial relationships of different mapped units, but it involves also the conveying of information about the Earth's crust evolution (Butler and Bell 1988). Thus, geological maps are not directly conceived to assist landslide modeling, and sometimes, they can be subdivided into a very large number of mapped elements, some of which are not directly related to slope stability (e.g., different units may be defined based on the appearance/disappearance of a fossil species, even if they have the same lithology and geomechanical characteristics).

In the recent literature, it is possible to identify two main methodologies to use geological information in LSM: (i) preexisting thematic maps about the nature of the bedrock are retrieved and used without further elaborations (Pourghasemi and Kerle 2016; Pradhan et al. 2019; Xiao et al. 2019); (ii) existing detailed digital geological maps undergo a reclassification aimed at reducing the number of classes and at defining a stronger correlation with landsliding. This approach is used especially when working over large or complex areas, where a too detailed geological information needs to be generalized (Bălteanu et al. 2010; Van Den Eeckhaut et al. 2012; Trigila et al. 2013). Usually, the reclassification is performed on a lithological or lithotechnical basis, in search for a stronger correlation with landslide predisposition (Catani et al. 2005; Segoni et al. 2018), and may entail some subjectivity in the choice of classes.

In any case, the lithological information is the most recurrent in LSM literature (Akgun 2012; Youssef et al. 2016): different units are grouped according to the main lithologies encountered. In turn, lithologies are defined based on physical characteristics such as grain size, texture, and constituting minerals, which are clearly connected with slope stability.

Some studies (Catani et al. 2005; Manzo et al. 2013) use a lithotechnical approach that moves from a lithological basis but defines classes according to the typical values (measured, estimated, or supposed) of their shear strength parameters. The advantage of this approach is that a stronger correlation between classification and landsliding should be provided by the focus on the geotechnical parameters. The drawback is that spatially distributed maps of geotechnical properties of surface deposits are usually unavailable, with the exception of some recent studies (e.g., Bicocchi et al. 2019). Other studies use also geological units, which are mainly based on the age of deposition of the units (Van Den Eeckhaut et al. 2012; Xiao et al. 2019) even if in local-scale studies this could also partially or totally reflect lithological aspects (Youssef et al. 2016; Cárdenas and Mera 2016; Pourgashemi and Kerle 2016). Besides, a number of alternate approaches can be found in the recent literature about landslide susceptibility mapping: as instance, Meinhardt et al. (2015) use a broad classification into 5 rock types subdivided by the different genesis (e.g., loose soils and metamorphic, intrusive, extrusive, and sedimentary rocks); Myronidis et al. (2016) make use of units classified based on the geological structure; Camarinha et al. (2014), to study shallow landslide susceptibility in a test site in Brazil, used a rock-type classification based on a complex criterion encompassing geology, lithology, and pedology.

The examples above show that a standard method to consider geology in LSM has not been defined, nor a sensitivity analysis to the parameterization of geology has ever been performed (to the best of our knowledge).

In a large and complex area, a detailed geological map could be classified using different approaches. All of them could make sense from a geological point of view and all of them could be put in relation with landslide predisposition. The main objective of this work is to test several of these approaches and to try to answer the following research questions: (i) do the derived susceptibility outputs show noticeable differences? (ii) Which approach performs better? (iii) Can we devise some best practices to handle geological data for future landslide susceptibility assessments?

To pursue this objective, we selected a 3000-km^2 test site in Italy characterized by a very complex geological setting, we classified the mapped geological units according to six different approaches, and we used them as input variables in several tests of a landslide susceptibility model based on the Treebagger random forest algorithm (Breiman 2001; Catani et al. 2013). Afterwards, we compared the results of the tests in terms of AUC (area under receiver-operator characteristic curve) and OOBE (out of bag error). Results were then critically analyzed and discussed, providing new insights on the effectiveness of different parameterization approaches and on the possible use of geological information in landslide susceptibility assessment.

Material and methods

Study area

The study area is located in Northern Tuscany, Italy, and it is a 3100-km^2 territory composed by hills, mountains (up to 2000 m of elevation), and limited alluvial plains (Fig. 1). The geological setting is quite complex (Vai and Martini 2001): the area belongs to the Northern Apennine fold and thrust belt, and since the Tertiary different tectonic units were stacked on each other because of compressive tectonic forces, and since the Upper Tortonian, an extensional tectonic regime dissected the aforementioned units producing a horst and graben structure. Later, in the Pliocene and Quaternary, marine and fluvio-lacustrine basins fostered the sedimentation of terrains, filling the tectonic depressions.

This tectonic evolution has now left the presence of NW-SE trending ridges and a pervasive pattern of faults, thrusts, and folds. Roughly speaking, the area can be divided in two sectors. In the western one, the bedrock is mainly constituted by carbonaceous rocks and metamorphic rocks (mainly metamorphic sandstones and phyllitic schists), giving rise to a sharper relief with higher slope gradients than in the eastern sector, which is characterized by sedimentary rocks (mainly flysch-alternating layers of different lithologies and textures). The mountainsides are mantled by a residual colluvium with a thickness ranging from a few centimeters to a few meters (Mercogliano et al. 2013), which exhibit a marked contrast in geotechnical properties with respect to the bedrock (Tofani et al. 2017).

The area is a significant hotspot of landslides (Battistini et al. 2013) and it is affected by landslides of different typologies (Segoni et al. 2014): rotational and translational slides in the colluvium and complex movements (slides evolving into slow flows) are the most representative, but also, debris flows and rockfalls are present. The typical areal extension of the landslides ranges from 10^2 to 10^6 m^2 and rainfall is the main triggering factor. The area receives an average annual precipitation around 2000 mm/year in the mountains and 1100 mm/year in the plains, with short and intense rainstorms increasing their frequency and severity as a consequence of the recent trends in climate change (Segoni et al. 2015).

Susceptibility assessment

The susceptibility assessment was carried out using an updated version of the software program named Claret (Lagomarsino et al. 2017), which is based on the Treebagger random forest machine learning technique and which automates several passages of the analysis, including random selection of the training/test dataset, evaluation and ranking of the input variables according to their explanatory power, and identification and application of the optimal regression model, model validation.

The random forest is a technique that has been applied to landslide susceptibility only recently (Brenning 2005; Catani et al. 2013); however, it can be considered well-established because its use has been consolidated through many applications in different case studies and because it has often shown better performances when compared with other state-of-the-art methodologies (Trigila et al. 2013; Xiao et al. 2019). In addition, it is very flexible and straightforward to apply, because it can handle at the same time both numerical and categorical variables, it implicitly accounts for mutual dependency between variables, it reduces overfitting, and it does not require particular assumptions on the statistical distribution of the values of the data.

Based on the experience learnt from past sensitivity studies (Catani et al. 2013), the following model configuration was used in this work:

- Training data were sampled randomly in the landslide and in the non-landslide areas;

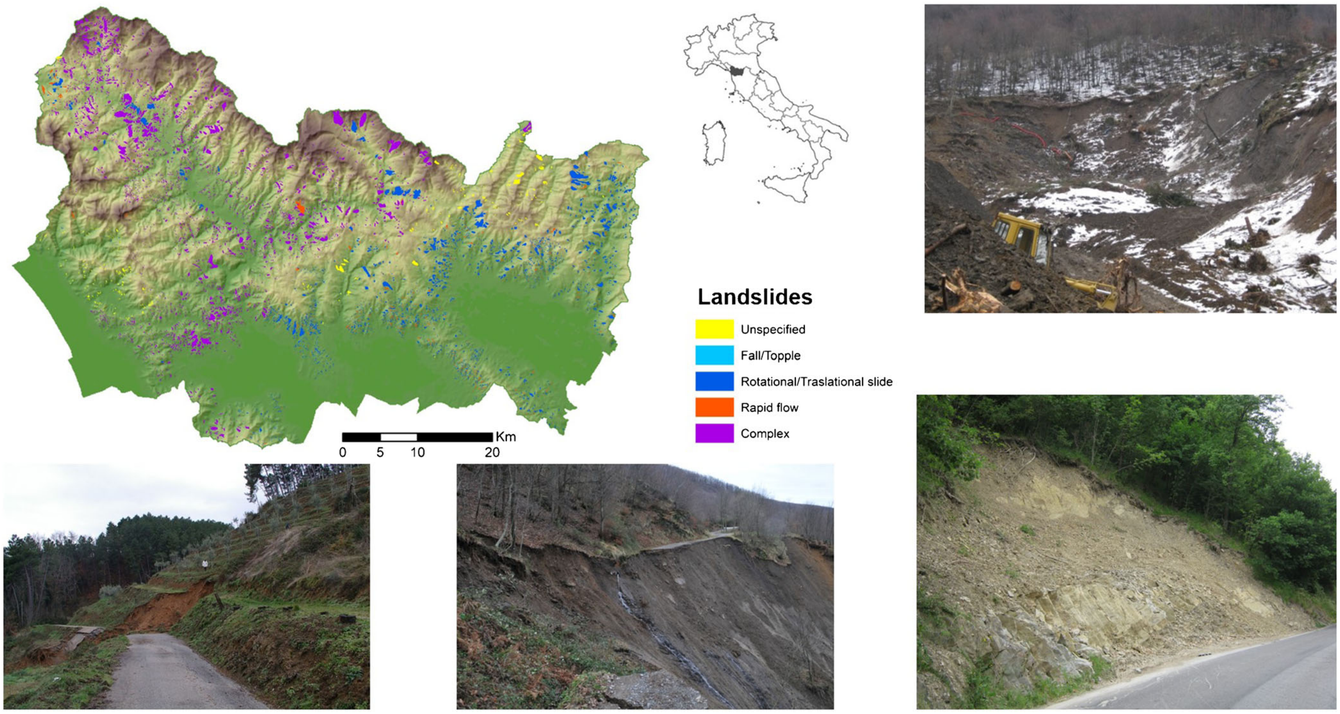

Fig. 1 Study area and landslides

- In the sampled data, landslide conditions and no-landslide conditions are balanced 50–50% to guarantee a balanced prediction;
- The sampled dataset was randomly split into a training (70%) and a test (30%) subset, in which landslide and no-landslide conditions are still equally balanced.
- We performed a regression using a 200-tree forest structure, and for each analysis, the model was run 20 times to get more robust conclusions.

The dependent variable used in susceptibility assessments is represented by landslide and no-landslide conditions. To train and validate the susceptibility model, we used an excerpt of the Italian national inventory of landslides (IFFI) at 1:10,000 scale, which is the most complete catalogue of landslides available in Italy (Trigila et al. 2010), as recently updated by means of radar satellite interferometry technique (Rosi et al. 2018). However, before preparing the landside dataset for the susceptibility model, some preliminary considerations on the mapped landslide typologies are needed. In the study area, the inventory includes 3452 slides, 3294 complex movements, 16 falls, 540 rapid flows, and 522 landslides of unspecified typology. According to the general knowledge of the characteristics of the IFFI inventory in the Tuscany Apennines, and according to some previous studies (Trigila et al. 2013; Segoni et al. 2016), unspecified movements and complex movements were aggregated with the "slides" typology for the following reasons. In the study area, complex movements are typically represented by compound slides evolving into slow flows: since the triggering mechanism and predisposing factors are the same, the susceptibility assessment can consider both slides and complex movements together. Another argument supporting this decision is that in the inventory, the difference among these two categories in small, thus the category in which a landslide is classified may vary according to the subjective interpretation of the surveyors, which were different from province to province. About landslides with unspecified movements, this is a shortcoming of the classification in the IFFI inventory and it can be easily resolved observing the geometrical features of the polygons and the analogy with the dominant landslide typology of the area: these landslides can be also grouped together with slides and complex movements (Catani et al. 2016; Segoni et al. 2016). Our analyses do not account for rockfalls and debris flows, because their number in the study area is limited and their spatial distribution is confined only to some spots. These shortcomings prevent form having a good sample for a rigorous susceptibility analysis regarding falls and debris flows. Moreover, since the triggering mechanism and predisposing factors of rockfalls and debris flows may be very different from those characterizing slides, these typologies could not be grouped with slides in the same susceptibility analysis. As a consequence, only the mapped landsides that can be associated with the "slides" typology of movement were extracted from the IFFI database and used in the susceptibility assessment.

Concerning the independent variables, there is no consensus on the number of parameters to use in a susceptibility assessment: many studies have been published that make use of a high number of parameters (Lee and Pradhan 2007; Nefeslioglu et al. 2011; Segoni et al. 2015; Xiao et al. 2019) and many that use only a few (Hong et al. 2007; Akgun 2012; Manzo et al. 2013). In this study, we decided to use a very basic and reduced set of parameters, because the objective is to explore the sensitivity to geology and to focus the discussion on the impact of this parameter. Using too many parameters is not useful to this purpose; rather, it could cast a shadow on the effect of geology. Consequently, 7 parameters have been selected that are broadly used in literature and that resulted in a high predictive power in other susceptibility assessment performed in this study area (Segoni et al. 2016): elevation, slope gradient, land cover, flow accumulation, aspect, planar curvature, geology.

All morphologic and hydrologic parameters (elevation, slope gradient, flow accumulation, aspect, and planar curvature) were derived by a digital elevation model with 10-m spatial resolution. Land cover was derived by the 1:50,000 Corine Land Cover maps, adopting a site-specific reclassification into 9 classes (urban areas, crops, grasslands, heterogenic rural areas, broad-leaved forests; conifer forests; shrubs; bare rocks; humid areas) already used in previous landslide susceptibility works carried out in the same test site (Segoni et al. 2016; Segoni et al. 2018). Concerning geology, its use as an explanatory variable is more complex and it is explained in detail in the following section.

Geological information

The basic information on geology is a 1:10,000 scale digital geological map produced and made available by the Tuscany Region. In the study area, it encompasses 194 lithostratigraphic units. Such a detailed information cannot be used in a landslide susceptibility assessment based on statistical machine learning algorithms: the number of classes is too high and some of the classes have a limited spatial extension, thus posing problems for an adequate model calibration. This is a common issue in landslide susceptibility assessments over large areas, and it is commonly solved by grouping the available units into broader classes (Bălteanu et al. 2010; Van Den Eeckhaut et al. 2012; Manzo et al. 2013). In this study, the lithostratigraphic units were grouped into classes following six different approaches. Each approach uses a specific criterion related to a single geological characteristic; therefore, two geological units may be grouped in the same class according to a criterion and may be separated into different classes according to another criterion. All partitioning approaches make sense from the standpoint of geological reasoning, and some functional links can be found to relate them to landslide predisposition (even if their actual connection to landslide susceptibility is to be objectively and quantitatively assessed in the following sections):

•Lithologic approach—Geological units were classified according to their prevailing lithology. This is probably the criterion that has been more widely used in LSM and has years of literature relating different lithologies to different degrees of landslide susceptibility (Fig. 2a).

•Genetic approach—Geological units were grouped into five broad classes according to the genetic process that gave them birth: magmatic rocks, metamorphic rocks, clastic rocks, organogenic rocks, soils (Fig. 2b).

•Detailed structural approach (Fig. 2c)—The Apennine chain has a very complex structure, and geologists have subdivided it into several structural units according to their evolution and response to tectonic forcing. In the study area, 10 different structural units outcrop, and they were used in this criterion. To our knowledge, a similar approach has never been used in LSM. However, it is worth being tested, as it could relate to landslide susceptibility since each structural unit through geological times was subject to a particular tectonic stress-strain history, including uplifting, folding, faulting, displacement, and thrusting. All these processes may be responsible of weakening the bedrock and predisposing it to instabilities.

•Broader structural approach (5 classes)—The same as before, but a broader classification was performed, grouping together similar units to obtain a number of classes (five) comparable with the one used for all the other criteria (Fig. 2d).

•Paleogeographic approach (Fig. 2e)—The Apennine has been traditionally subdivided also in paleogeographic units, according mainly to the paleogeographic environment where rocks were originally formed. We therefore used the main paleogeographic units outcropping in the test area (all recent deposits were grouped together). To our knowledge, a similar approach has never been used in LSM. We decided to test it because rocks with similar lithologies could have different mineralogical or textural characteristics according to the environment of deposition, thus potentially providing a slightly different predisposition to landsliding.

•Chronological approach (Fig. 2f)—In this case, the geological units were grouped according to the age of deposition. This criterion has been already used in the LSM literature, even if quite rarely; however it could be regarded as a potential predisposing factor because broadly speaking, the older a geological unit, the higher the degree of weathering and the exposition to tectonic stress, and this can be linked to the reduction in its strength parameters.

Description of the tests

All data were imported in a GIS, where 15,500 random points were generated (50% inside landslide polygons, 50% outside landslide polygons) and used to sample the values of dependent and independent variables; 70% of them were used to train the model and 30% were used for test. The random forest model was run several times, varying the configuration used to account for the geologic information: a base test in which no information on geology was used, one test for each of the classification criteria described in the previous section (six tests), an additional test using all of them together.

The used model has an internal test procedure that allows for an objective evaluation of the predictive capacity of each variable used and of the model itself. Two parameters have been considered:

- AUC (area under ROC curve)—this parameter estimates the predictive effectiveness of the regression performed. The near the AUC value is to 1, the better the regression approximates the experimental data as an expression of reality. It can be used to quantitatively compare different model configurations in terms of their prediction effectiveness.
- OOBE (out of bag error)—this parameter is an estimate of the relative error that would be committed if the variable to whom it is referred were not used in the regression. During each test, it is automatically calculated for all independent variables and allows quantitative assessment of their explanatory power. OOBE can be used to rank the variables according to their importance.

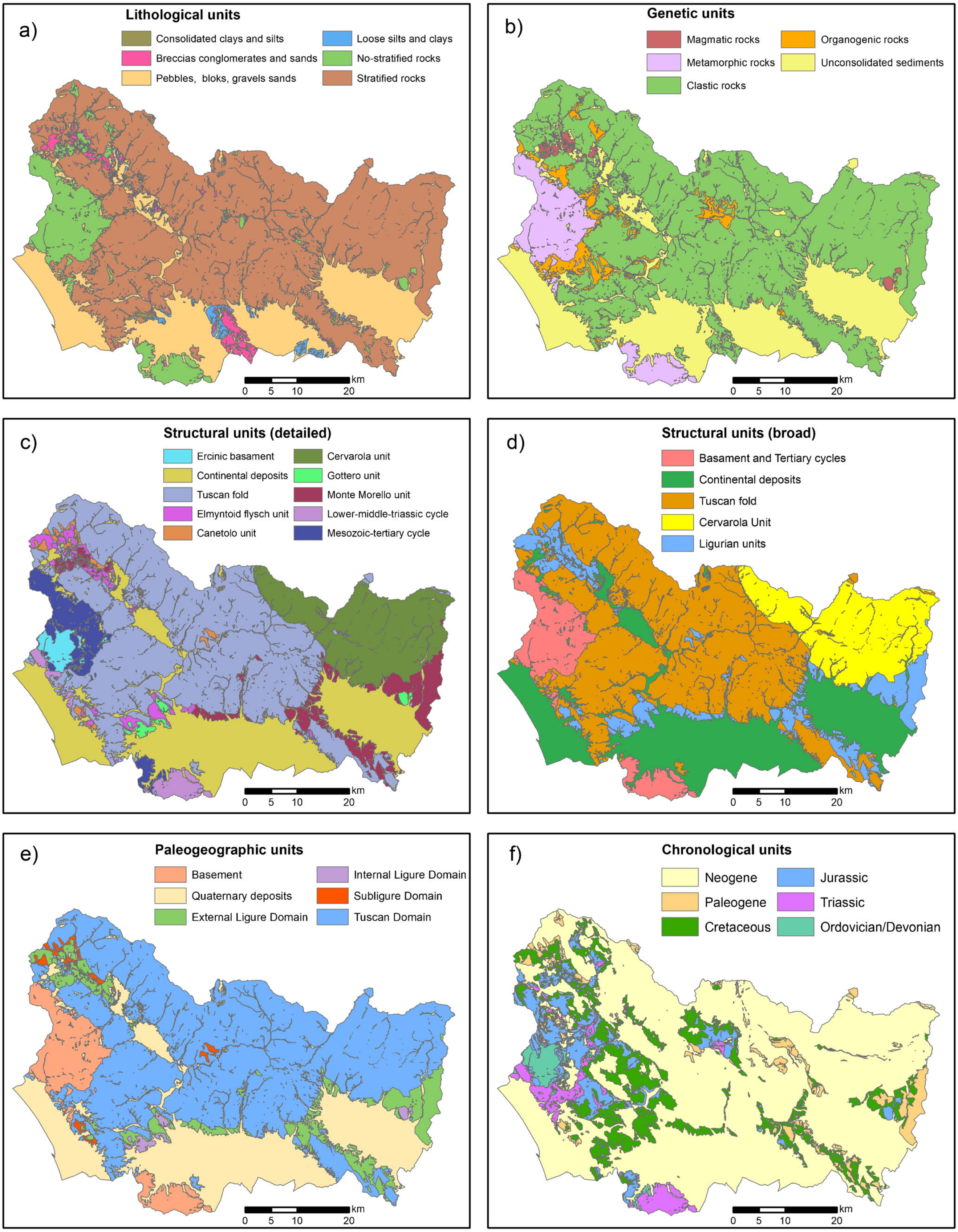

Fig. 2 Reclassification of the geological map according to six different criteria: lithological (a), genetic (b), detailed structural (c), structural (d), paleaogeographic (e), chronological (f)

While AUC allows for a comparison among different model configurations, OOBE allows for a comparison among the variables used in a specific configuration. These parameters are calculated for each model configuration after running and averaging 20 times, to get stable results and to account for the inherent chaotic nature of the random forest algorithm.

In addition, a preliminary run of the model was performed adding to the full configuration a random control variable. This variable was obtained by applying a random value (from 1 to 5) in each pixel of the study area, thus simulating a completely random reclassification of the spatial units used in the susceptibility assessment. The objective of this test is evaluating if the random reclassification outperforms some of the other approaches used. In case it happens, an approach with a predictive effectiveness lower than random values would be deemed inappropriate and discarded. As shown in Fig. 3, all variables had an OOB higher than random variable; therefore, all of them were used in the tests as potentially suitable predictors.

Results

Figure 3 shows the susceptibility maps obtained with the eight configurations that were tested. Susceptibility values range from 0 to about 0.70, and different spatial distributions of the values can be observed with a visual inspection. During the tests, the accuracy of these maps was assessed to understand which one is the most reliable. The results of the validation are summarized in Table 1, which shows the mean and the maximum AUC values obtained with the 20 runs of each configuration. AUC can be used to estimate the forecasting effectiveness of each configuration and thus to rank them accordingly.

From Table 1, it can be seen that the worst performance is obtained with the configuration that neglects geological information (base configuration) and that all the reclassification criteria used in the tests, when used singularly, provide an amelioration with respect to the base configuration. Among these, the best forecasting effectiveness is obtained when the geological units are aggregated following a genetic approach (mean AUC 0.700, maximum AUC 0.724). However, the configuration that includes in the modeling of all six reclassification criteria is by far the most effective, with mean and maximum AUC of 0.752 and 0.774, respectively. Further insights on these outcomes are provided in the "Discussion" section. The ranking of the configurations is identical in case mean AUC or max AUC is taken into account, thus demonstrating the stability of the results obtained in the tests. It is worth remembering that the objective of the present work is not only to produce a susceptibility map of the area but to also provide a sensitivity analysis of the susceptibility model with respect to the geological information. The AUC values are lower than the one obtained in past works on the same test site (Segoni et al. 2016), because a model configuration using a limited number of parameters is used here, to better focus the sensitivity analysis on the impact of geology.

Table 1 Ranking of the model configurations according to their effectiveness (assessed by the AUC values)

Test	Mean AUC	Max AUC
BASE configuration (no geology)	0.606	0.630
BASE + chronological units	0.635	0.656
BASE + structural (detailed)	0.640	0.652
BASE + paleogeographic units	0.648	0.665
BASE + structural units (broad)	0.657	0.676
BASE + lithologic units	0.661	0.682
BASE + genetic units	0.700	0.724
Full configuration (base + all criteria)	0.752	0.774

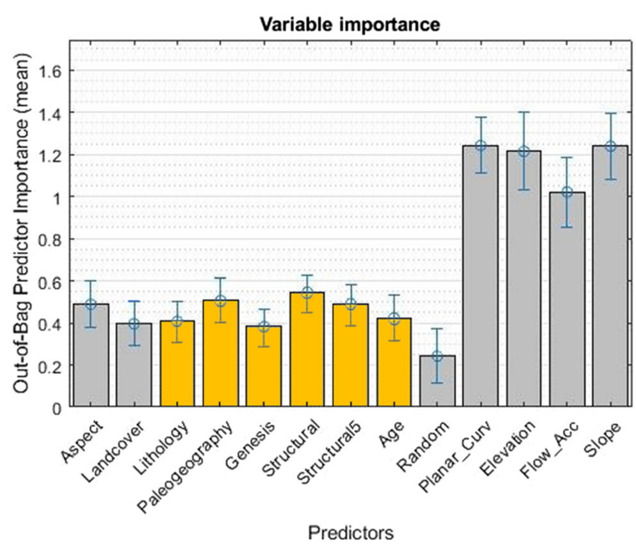

Fig. 3 Estimation of the relative importance of the predictors, including a control random variable. Predictors with geological significance are highlighted in orange

In Fig. 4, the importance of each variable inside each configuration is assessed by means of the OOBE. It can be seen that for the geological parameters, the importance is always relatively high (OOBE around 1.40 and geological variables ranked among the first ones), except when chronological units (and, to a lesser extent, lithologic units) are taken into account.

Discussion

The examination of the AUC values obtained in our tests (Table 1) reveals that geology is very important in landslide susceptibility assessment: the model configuration that does not encompass any geological information is by far the one providing the worst prediction. This result was expected; what we consider more important is to discuss the sensitivity of a landslide susceptibility model to the different approaches that can be used to parameterize the geological information. A geological classification based only on the age of formation of the units is the worst performing one in our case of study, but, still, it does provide an improvement over the basic version of the model. In a few words, none of the six configurations tested is completely unrelated to landslides. This highlights an important operational and technical consideration: when working on areas with limited geological information, a susceptibility assessment may still gain from the inclusion of geological mapping among the preparatory factors, whatever its accuracy, scale, or mapped units. Of course, this does not mean that geological information could be entered in the modeling carelessly; on the contrary, our tests show that the approach used to define the geologic units may have a deep impact in the spatial

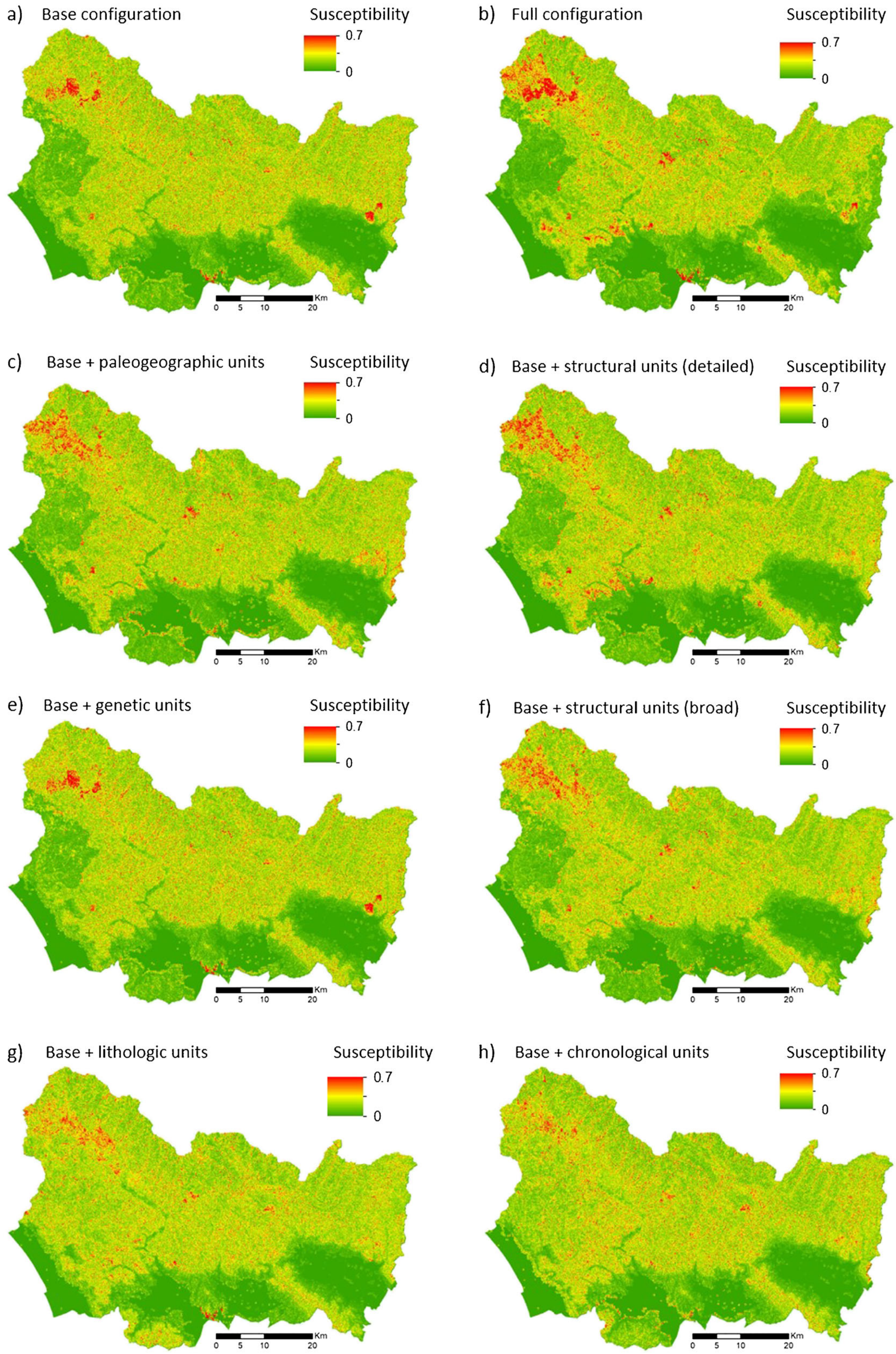

Fig. 4 Susceptibility maps obtained with the different configurations tested: base configuration (a), full configuration using all geological information (b), using paleogeographic units (c), using detailed structural units (d), using genetic units (e), using broad structural units (f), using lithological units (g), using chronological units (h)

distribution of susceptibility values and in the effectiveness of the modeling. Therefore, during the data collection phase, the investigators should be aware of the geological meaning of the units defined in their maps. In our case study, the best outcomes are obtained when using genetic units, which reclassified the original lithostratigraphic units into broad classes according to the processes leading to the formation of rocks and soils. The most widely used lithologic approach is ranked only as the second-best approach, with performance indicators close to those obtained by the broad structural approach. The distinction between the detailed and the broad structural approaches deserves attention in our opinion. All the criteria used in this work have a very similar number of classes (5 or 6); this characteristic ensures that the sensitivity analysis is not influenced by different degrees of detail in the classification schemes pursued. The only exception is the structural criterion, in which originally, 10 classes were present, and which was reclassified into 5 classes (broad structural criterion) to be consistent with the other criteria. However, we kept in a separate configuration also the detailed structural criterion (based on 10 classes), to test how the degree of detail in the classification affects the results. The use of broader structural units provides better results than using the detailed ones (higher AUC and OOBE values) (Fig. 5); this result can have two interpretations: either the regression model performs a better regression with a "simple" and more generic level of classification, or in the detailed classification, some units are defined that are scarcely significant in describing the predisposition to landsliding.

One of the most significant outcomes of this work is that the validation results show that the susceptibility map with the highest forecasting effectiveness is obtained when all the geological classification schemes are used together: the AUC is markedly higher than the AUCs obtained with any other model configurations relying on a single geological parameter. We explain this outcome observing that geological information may be faceted and very difficult to encompass into susceptibility models, because there are many features related to geology that may influence the spatial distribution of landslides; therefore, more features related to geology should be taken into account with different classification schemes; conversely, if only one approach is used, only a partial information is entered into the modeling. For instance, most of the works found in the literature use a lithological classification, with a strong supporting reason: landslide activity is clearly related to the shear strength parameters of the hillslope material, and broadly speaking, different lithologies have different ranges of strength parameters values. However, one may argue that two different units with the same prevailing lithology may have very different weathering degree and thus different mechanical characteristics: from this point of view, the age of the formation could also be related to landslide susceptibility. However, our tests showed that a chronological classification alone is of little use (it is the worst aggregation criterion among all the tested ones), probably because in similar ages very different rocks or terrains could have been formed. This corroborates the hypothesis that the joint use of lithological and chronological information in the parameterization of geology should not be regarded as a redundant information. Rather, the two information are complimentary. The same example could be extended to other classification approaches: geological units with the same lithology could have been originated in very different depositional environment, e.g. clays could have been formed in lacustrine or sea environment, providing slightly different responses to the geomorphological processes acting on the hillslopes. The same applies for structural units that could differentiate similar rocks, even if formed in similar geologic times, according to their different tectonic histories. Following this reasoning, different assumptions could be considered not mutually exclusive and could be used jointly, to better encompass the complex geological characteristics of a given test site. The separation of different characteristics of geological units into different independent variables may also have the additional advantage of providing the statistical engine with an orderly set of data to classify from, avoiding complex, multi-component variables. The drawback is that different parameters related to geology would be used in the modeling at the same time, thus bringing problems of collinearity and interdependence among the variables. However, it should be noted that many advanced machine learning algorithms (such as the random forest) are widely credited for not being negatively influenced in similar cases. In addition, we observe that in the international literature, the use of more than one parameter describing morphology is widely accepted (and the same can be said for hydrology). Moreover, also, the use of morphological or hydrological variables that are strongly correlated is a common practice, e.g., topographic wetness index and drainage area, or stream power index and slope gradient, or different definitions of curvature, may be used simultaneously.

This work explores only a few approaches (namely, six) to parameterize the geological information and proposes a procedure to select the optimal ones. Of course, in other study areas, other approaches could be defined according to the test site characteristics and to the information available. In addition, it should be stressed that even when using the same approaches used here, different results could be obtained in other locations. Thus, we recommend implementing the susceptibility assessment with a forward selection of parameters: using this technique, the pejorative or redundant parameters would be automatically identified and filtered off.

The examination of the results in terms of OOBE provided interpretations consistent with the findings in the earlier discussion (Fig. 5). Considering OOBE to rank the importance of the variables used inside each model configuration, it can be observed that geology is one of the most important parameters, generally the 2nd or 3rd among 7 parameters. It is important to highlight some exceptions: when geology is the 1st parameter, the configuration provides the highest AUC (configuration based on genetic units), thus confirming that when geology is parameterized for the best, its explanatory power is fully exploited by the regression algorithm to get to optimal results. Conversely, when the importance of geology is lower (4th rank), a reduction in the model performance can be observed (as in the case of the use of chronological units). This highlights the importance of a correct parameterization of the geological information to get a reliable susceptibility assessment.

When coming to observe the OOBE values in the configuration using all geological classification schemes together, the values and the ranking of the geological variables may seem exceptionally low. This is not in contrast with the conclusion that this is the best model configuration: the geological information provided to the model is more complete than in other configurations, thus providing the highest AUC value, the low OOBE values of geological

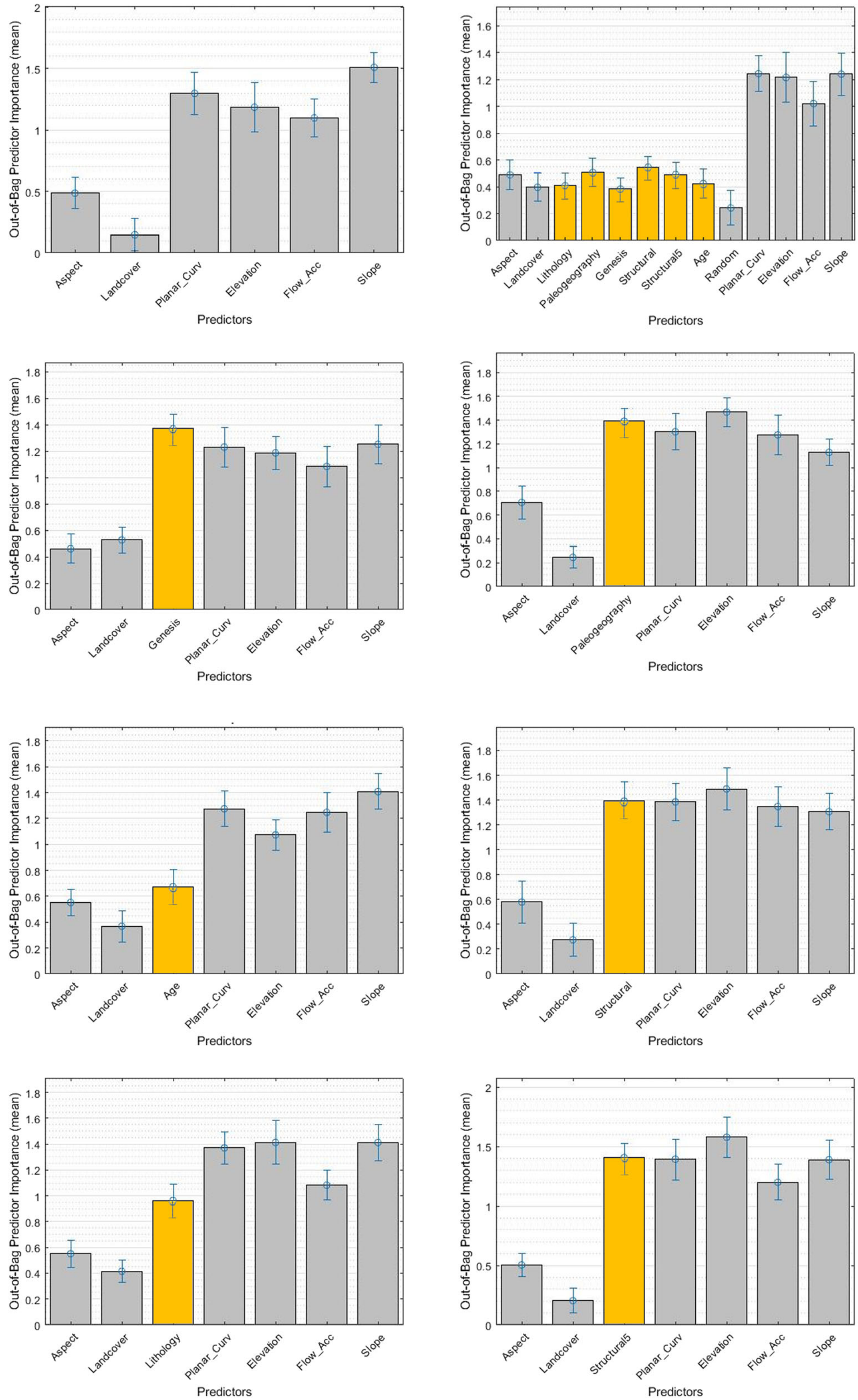

Fig. 5 Out of bag error (OOBE) of the variables used in every test. Predictors with geological significance are highlighted in orange

factors become because the importance of geology is shared among six different factors. If the OOBE values of the geological factors are summed up, a weight of 2.9 is obtained that is similar to the weight obtained summing up the contribution of the factors with a morphological (slope, elevation) and a hydrological (aspect, planar curvature and flow accumulation) meaning (2.7 and 3.0, respectively), thus confirming that the geological information is among the most important ones in a susceptibility assessment and that the task of providing such information can be shared among different parameters.

Conclusion

Since there is no agreement on how geological information should be included in LSM activities, we performed a sensitivity analysis and a series of tests in a study area with a complex geological setting to (i) ascertain the sensitivity of the results to different approaches used to reclassify geological units and (ii) to get some insights on the best approaches to pursue in future susceptibility assessments.

The study area is located in northern Tuscany (Italy) and a regional 1:10000 map, when clipped on the area of interests, encompassing 194 different lithostratigraphic units. Such a detailed information was reclassified into broader units according to six different criteria; all of them somehow are potentially connected with landslide susceptibility: lithology, age, paleogeographic environment of formation, genetic process; tectonic history (according to two different degree of detail).

Using the well-established random forest technique, we performed several landslide susceptibility assessments, varying the approach to use the geological information. The resulting maps were validated, and the different configurations were evaluated with a series of internal tests. The comparison of the results supported the following conclusions:

- Geology is one of the most important parameters in LSM.
- Geological maps provide a very complex and multifaceted information, in wide and complex areas this information cannot be effectively represented by a single parameter.
- Different parameters can be derived from a detailed geological map by aggregating the mapped elements into broader units (in our study: lithologic, chronological, paleogeographic, structural, and genetic units).
- The results of the susceptibility assessment are very sensitive to these geology-derived parameters; thus, it is of paramount importance to understand properly the nature and the meaning of the information provided by geology-related maps before using them in susceptibility assessment.
- Regarding the configurations making use of only one parameter, the best results were obtained using the genetic approach, while lithology, which is commonly used in the current literature, was ranked only second.
- However, in our case of study, the best prediction was obtained when all the geological parameters were used together.
- Different geology-based parameters can perform better than only a geological parameter, because each of them can account for specific settings connected to landslide predisposition. In our case of study, the use of six different geological parameters allowed to account for lithology, tectonic stress, age and environment of formation, and subsequent degree of weathering, thus providing an advanced and complete information to the susceptibility model that, in turn, provided a better prediction.

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