A refinement analysis of the shallow landslides susceptibility at regional scale supported by GIS-aided geo-database

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ABSTRACT

Intense rainfall events often produce a great number of shallow landslides events, which in many cases can hits large areas or an entire regional territory. These slope instabilities cause damage to many roads, buildings, and infrastructures and often human loss. In these conditions, it is useful to refine shallow landslides susceptibility maps at regional scale progressively more reliable and efficacy. To take the highlighted goal it is opportune to promote the use of a circular approach that can considers knowledge (data, methods, models, solutions, etc.) constantly upgraded. To achieve this aims we propose a method that introduces structurally in a possible circular approach (progressive better results with constantly upgraded knowledge) the use of a comprehensive geo-database of shallow landslide events and related implemented through a collection and analysis of numerous sources, including published inventory maps, scientific literature, technical reports and newspapers, integrated by a multi-temporal interpretation of remote sensing images and several field surveys. The method is applied referring to the Calabria region, which is largely affected by this landslide category. The refined geo-database realized includes 22,028 shallow landslides, occurred between 1951 and 2017. The relationship between spatial pattern of the shallow landslides and the analyzed predisposing factors (lithological units, fault density, land use, drainage density, slope gradient, TWI, SPI and LS) showed that the high values of slope gradient, LS factor and drainage density, coupled to low values of TWI, displayed a strong control on the shallow landslide occurrence. The efficacy of the geo-database realization proves their usefulness in order to estimate and validate shallow landslide susceptibility map, which was optimally obtained applied a simple bivariate statistical method. The susceptibility map was classified into five classes and about 26% of the study area falls in high and very high susceptible classes and most of the shallow landslides mapped (76%) occur in the same classes. The AUC value of the prediction rate curve was 0.81, indicating a good prediction capability of the susceptibility map. The interaction between shallow landslide susceptibility map and road network map highlighted that the 20% of the roadways of the region area falls in high and very high...
susceptible areas, whereas was observed that the high (58.4%) and very high (65.6%) susceptibility classes are mainly distributed within cover materials from weathered crystalline rocks. The results obtained in this study indicate that the proposed method can concur to promote a circular approach and support with efficacy a progressive refinement of regional shallow landslide susceptibility map, from 2008 to now, that may be useful tool for national and/or local authorities to manage land use and civil protection planning, and for hazard and risk assessment from regional to slope scale.

**Introduction**

Landslides are one of the most important and widespread geomorphic processes in mountainous and hilly landscapes, representing often a serious hazard in many areas of the World (Brabb 1991; Cendrero and Dramis 1996; Nadim et al. 2006; Gullà et al. 2008; Korup et al. 2010; Conforti et al. 2013; Haque et al. 2016). In the last decades the uncorrected management and planning of territory coupled with to certain human activities (i.e. rapid changes land use driven by intense population pressure and/or urban and agricultural expansion) have given a strong contribute for the increment of landslide risk (Guzzetti 2000; Glade et al. 2005; Beguería 2006; Peduto et al. 2021). In particular, shallow landslides (depth of slip surface ≤ 3 m), which often may rapidly propagate from source areas as earth/debris flows (Campbell 1975; Hungr et al. 2001; Baum et al. 2005; Crozier 2005; Gullà et al. 2008; Sujatha 2020, 2021; Sujatha and Sridhar 2021), causing serious damages to properties and loss of human lives (Govi and Mortara 1981; Brand 1988; Wieczorek et al. 2001; Sorriso-Valvo et al. 2004; Cascini et al. 2008). Shallow landslides occur in areas where climatic condition, weathered rocks, soil characteristics, land use/cover, and morphological features can promote their trigger (Deere and Patton 1971; Bilotta et al. 2005; Beguería 2006; Gullà et al. 2009; Gao and Maro 2010; García-Ruiz et al. 2017; Borrelli et al. 2018). Thus, it is important to recognized, characterized and predict spatio-temporal shallow landslides occurrence affected by complex processes involving different hydrological, morphological and geotechnical properties of the soils (Gullà and Sorbino 1996; Van Asch et al. 1999; Crosta et al. 2003; Gullà, Aceto et al. 2004; Gullà, Mandaglio, and Moraci 2004; Gullà, Mandaglio, Moraci, and Sorriso-Valvo 2004; Gullà, Niceforo et al. 2004; Gullà et al. 2008; D’Amato Avanzi et al. 2009; Mugagga et al. 2012; Cascini et al. 2015; Ciurleo et al. 2017; García-Ruiz et al. 2017). These goals are essential for land management with risk prevention assessment and landslides forecasting aimed to effective early warning systems (Paudel et al. 2007; Fell et al. 2008; Baum and Godt 2010; Rossi et al. 2010). Moreover, accurate information about the landslides occurrence and their interplay with the geo-environmental features can be achieved with effectiveness increasing integrating studies carried out at different scales analysis: regional (small scale > 1:100.000), large area (medium scale 1:100.000–1:25.000) and slope scale (large-detail scales 1:25.000–1:5.000).

Consequently, at regional scale, the realization of landslide inventories and the investigation of their typologies, spatial distribution and time frequency, are useful
and valuable information to understanding landscape evolution and assessing landslide susceptibility, hazard and the risks associated with them (Pelletier et al. 1997; Guzzetti et al. 2003, 2009; Gullà et al. 2008; Hilker et al. 2009; Damm et al. 2010; Rossi et al. 2010; Neuhäuser et al. 2012; Van Den Eeckhaut and Hervás 2012; Hurst et al. 2013; Klose et al. 2014; Tonini et al. 2014; Damm and Klose 2015; Sevgen et al. 2019; Kocaman et al. 2020; Karakas et al. 2021). In particular, shallow landslides susceptibility at regional scale represent a key element to manage land use and civil protection planning and for hazard and risk assessment (Gullà et al. 2008; Regmi et al. 2014; Guo et al. 2015; Gholami et al. 2019).

Despite these destructive impacts of shallow landslides, systematic and updated databases at regional scale are currently lacking, which would allowing archive information on the spatial and temporal distribution of landslides, as well as, developing susceptibility, hazard and risk maps progressively more reliable and efficacy. Therefore, upgrade constantly the knowledge about shallow landslides is useful to support studies, both at regional, large area and slope scales, aimed to define representative sectors, homogeneous large areas and slopes for early warning and for decision making in landslide risk mitigation. Consequently, review of historical sources, newspapers, articles and maps published, and remote sensing images may provide important information for the knowledge of past landslide events, as their spatial and temporal position, intensity and damages caused, and these are useful in building suitable databases (Guzzetti et al. 1994; D’Amato Avanzi et al. 2004; Guzzetti and Tonelli 2004; Gullà et al. 2008; Zèzere et al. 2014; Rosi et al. 2018; Kocaman and Gokceoglu 2019). Landslide databases, at regional, large area and slope scales, can provide useful additional information on other important attributes such as size, cause of triggering (e.g. rainfall, earthquake), damage produced, geotechnical characteristics, interstitial pressures (positive and negative), etc. These data are required to understand landslide phenomena, in terms of triggering and controlling factors, and to model them (Gullà and Sorbino 1996; Gullà, Aceto et al. 2004; Gullà, Mandaglio, and Moraci 2004; Gullà, Mandaglio, Moraci, and Sorriso-Valvo 2004; Gullà, Niceforo et al. 2004; Gullà et al. 2008; Borrelli, Perri et al. 2014; Cascini et al. 2015; Borrelli et al. 2018).

In the period from 1954 to 2015, in Calabria (south Italy), the landslide events have killed 40 and injured 150 people (Petrucci et al. 2009; Gariano et al. 2015; Rago et al. 2017). Calabria region exhibits an extremely high exposure risk for landslides due of its peculiar climatic, geomorphological and geological characteristics and very often to unsustainable land management (Gullà et al. 2009; Conforti, Muto et al. 2014; Borrelli and Gullà 2017). In particular, shallow landslide events are recurrent phenomena in Calabria (Antronico et al. 2004; Sorriso-Valvo et al. 2004; Borrelli, Critelli et al. 2012; Borrelli, Giofrè et al. 2012; Borrelli et al. 2015; Borrelli et al. 2018; Iovine et al. 2014; Cascini et al. 2015; Conforti et al. 2016; Conforti and Buttafuoco 2017; Rago et al. 2017). Furthermore, as showed in Gullà et al. (2008), wide portions of the Calabria are very susceptible to shallow landslides. Despite the small soil volumes involved, the shallow landslides frequently caused considerable economic damages to properties and infrastructures and, in many areas, they also pose a serious threat to the population (Sorriso-Valvo et al. 2004; Gullà et al. 2009).
Referring to Gullà et al. (2008), in this paper we use a method, which promotes a circular approach, that considers upgraded susceptibility models and data, supported structurally by a comprehensive geo-database of shallow landslides and related geo-environmental features. The obtained results can be improved in the future using in a circular approach knowledge constantly upgraded. In particular, the method allows to: (1) analyzing, mapping, compiling and upgrading a geo-database of the shallow landslides, using the landslide events occurred in the Calabria region during the period between 1951 and 2017; (2) assessing the characterization of the spatial pattern of shallow landslides with respect to main geo-environmental factors (e.g. lithology, land-use, slope gradient, drainage density); (3) refining mapping regional shallow landslide susceptibility starting by preceding studies (knowledges) and (4) overlaying of the road network with the susceptibility map for assessing roads exposition to shallow landslide.

**Geographical, geological and geomorphological features**

The Calabria is the southernmost region of the Italian peninsula with a surface area of about 15,076 km\(^2\). It spanning from 40°09’03”N to 37°53’54”N of latitude and
from 15°38′50″E to 17°10′20″E of longitude (Figure 1a). The region is divided administratively into five provinces, named: Catanzaro, Cosenza, Crotone, Vibo Valentia and Reggio Calabria (Figure 1b). The elevation ranges from sea level to 2275 m, with an average value of 523 m.

The climate of Calabria is typical Mediterranean (Csa, sensu Köppen et al. 1936), characterized by warm, dry summers and cold, wet winters, but it is possible to recognize several areas with different climatic peculiarities, depending on the position with respect to coast and the orographic elements. The average annual precipitation ranges from 600 mm to more than 2000 mm moving from the coastal zone mouth to the internal and mountainous areas, with a mean regional value of about 1150 mm (Versace et al. 1989; Terranova and Iaquinta 2011). Yearly rainfall distribution exhibits a peak from October to March when more than 70% of total annual precipitation occurs, with negligible monthly values from June to September (Terranova and Iaquinta 2011).

From a geological point of view, the Calabria belongs to the Calabrian-Peloritan Arc (CPA), which includes the whole Calabria and the north-eastern sector of Sicily (Figure 1c). The overall architecture of the Arc is made up of a series of basement nappes and ophiolite-bearing tectonic units that are considered to be a remnant of the Cretaceous-Paleogene Europe-verging Eo-alpine chain involved, during the Neogene, in the building of the Apennines orogenic belt (Amodio Morelli et al. 1976; Gueguen et al. 1998; Guerrera et al. 2005).
During the Late Pliocene–Early Quaternary period, the Calabrian Arc has been fragmented by several normal fault segments, both longitudinally (from NE–SW to NNW–SSE) and transversally (from E–W to WNW–ESE) (Ghisetti and Vezzani 1981; Monaco and Tortorici 2000; Van Dijk et al. 2000; Tortorici et al. 2002; Tripodi et al. 2018). These structures caused the dislocation of the Arc into topographic highs (Coastal Range, Sila Massif, Capo Vaticano Promontory, Aspromonte–Serre Massif) bounded by sedimentary basins (Crati, Catanzaro, Crotone and Mesima) where continental and marine sediments settled (Figure 1b).

The Calabrian Arc has been divided into two sectors (Tortorici 1982), a northern and southern, respectively, characterized by a different structural setting and by different geodynamic evolution. The two sectors are separated by a strike-slip tectonic line (i.e. Catanzaro Line) that runs along the Catanzaro basin (Boccaletti et al. 1984; Tortorici et al. 1995; Tansi et al. 2007; Tripodi et al. 2018).

The northern sector, which includes the Coastal Chain and the Sila Massif, is constituted by a pile of nappes made up of granitoid rocks and by high- and low-grade metamorphic and ophiolitic rocks (Figure 2a). These crystalline nappes are overthrusted during the Miocene on the Apennine Carbonate Units, which consists of carbonate platform sequences of passive continental margin (Bonardi et al. 1982). Marine and continental deposits, dating back to the Early Tortonian–Early Pliocene and to the Middle–Upper Pliocene–Pleistocene, are laid transgressively on these different basement units (Van Dijk et al. 2000).

The southern sector of the CPA (Serre Massif, Aspromonte Massif and Capo Vaticano Promontory) is characterized by a pile of crystalline nappes, unaffected by Alpine metamorphism, including metamorphic and plutonic rocks, and related Mesozoic–Cenozoic sedimentary sequences of arenaceous–conglomeratic and arenaceous–pelitic turbidites and varicoloured clays, marls, limestones and sandstones with chaotic structure (Amodio Morelli et al. 1976; Tortorici 1982). In addition, Neogene transgressive sediments are overlapped, in discontinuity to the crystalline–metamorphic rocks.

Due to the complex tectonic history of the Calabrian Arc, outcropping lithologies show different levels of fragmentation and deformation; in particular, the crystalline–metamorphic rocks are pervasively fractured (i.e. cross-cut by a complex fracture pattern related to regional and local-scale faults and fault zones developed during ancient and recent tectonic phases) and affected by intense and deep weathering processes, which produced a disintegration of the rock masses and a thick saprolite horizons, with depths up to 100 m (Cascini et al. 1992; Le Pera and Sorriso-Valvo 2000; Calcaterra and Parise 2010; Borrelli, Critelli et al. 2012; Borrelli, Perri et al. 2014; Borrelli et al. 2016; Biondino et al. 2018; Ietto et al. 2018).

Holocene cover terrains, that unconformably lie on the substrate lithologies, widely crop out at the top of the paleosurfaces in the summit surfaces of Catena Costiera, Sila Massif, Serre Massif, Capo Vaticano Promontory and Aspromonte Massif (i.e. residual soils), or along the slope or topographic lows (i.e. colluvial deposits or detrital deposits), with the maximum thicknesses in the morphological hollows. The valleys are mostly characterized by sedimentation (e.g. alluvial deposits and alluvial fans), with local alternating erosional processes.
From a geomorphological viewpoint, the Calabria contain a great variety of morphologic and topographic contexts; it is characterized by a prevalence of hills and mountains, compared to lowlands (Figure 2b). The mountains (Pollino Massif, Coastal Chain, Sila Massif, Serre Massif and Aspromonte Massif) are characterized by relics of summit paleosurfaces, with pecks higher than 1500 m. These flat or gently-sloping reliefs are bounded by steep slopes and cut by deep and narrow valleys marked by landslide phenomena (Sorriso-Valvo 1993; Calcaterra and Parise 2010; Lucà et al. 2011; Molin et al. 2012; Antronico et al. 2017; Conforti and Ietto 2020).

In many places, the massifs are characterized by rugged profiles, high energy of relief and many steep and straight fault scarps, hundreds of metres tall, where selective erosion – commonly associated with contrasts between lithotypes with differential resistance to erosion – have been observed. In particular, Aspromonte Massif, as consequence of intense uplift is characterized by rugged relief with jagged peaks, serrated ridges, and by an intense dissection of the drainage network (Sorriso-Valvo 1993; Robustelli 2019). In addition, triangular and trapezoidal facets associated with high-angle normal faults can be observed along the fronts of the main mountain ranges of the region (Coastal Range, Sila Massif Serre and Aspromonte Massifs), abruptly separating the mountains from the valley floors and/or coastal plain (Tortorici et al. 1995).

The hilly sectors are mainly developed on sedimentary rocks of different composition and erodibility, where selective erosion has given alternatively way to steep slopes cut on hard rocks in contrast with typically rounded and gentler landscape characterized by pelitic, and more erodible lithologies.

The gently-rolling landscapes, in many zones, have been deeply incised by river network; moreover, the slopes where clayey and marly lithologies outcrop are frequently affected by badland (calanchi) landforms, especially in the Ionian side (Sorriso-Valvo et al. 1992; Pulice et al. 2009, 2013).

Then, as a result of its peculiar geological framework, tectonic history, geomorphological features and climatic characteristics, the Calabria region is very prone to mass movement development. Particularly, in the past decades, severe rainfall events struck the Calabria, triggering landslides, both deep-seated and shallow, and intense water erosion processes, causing serious damages and often fatalities (Sorriso-Valvo et al. 2004; Calcaterra and Parise 2005; Iovine et al. 2006; Gullà et al. 2008, 2009, 2017; Gullà, Aceto et al. 2018; Gullà, Calcaterra et al. 2018; Petrucci et al. 2009; Antronico et al. 2013; Borrelli, Antronico et al. 2014; Borrelli et al. 2015; Borrelli and Gullà 2017; Rago et al. 2017; Conforti and Ietto 2019).

**Method and materials**

In this paper we consider as general reference a circular approach that assumes two pillars: (i) at each scale analysis (small, medium and detail) data, methods, results and solutions are used following a circular path; (ii) the knowledge obtained at a given scale analysis is used to nourish the knowledge at other scales and to improve their efficacy (Figure 3). The proposed method, using of a comprehensive geo-database of shallow landslide (SL) events, is in general declinable at more scale analysis (small scale, medium scale, detailed scale) in any geo-environmental setting with the aims to
improve the knowledges and the risk managements linked to SLs. Following the circular approach, the workflow is powered by SL events data and knowledge acquired from studies at different scale of analysis (Figure 4), derived from both different scales and different sources (e.g. previous shallow landslide inventory maps, technical reports, newspapers, previous catalogues, etc.). In particular, we consider the SLs occurred in Calabria over the past seventy years to evaluate the susceptibility at regional scale and, following hazard and risk, to identify and implement increasingly effective risk management strategies (adaptation, mitigation and risk reduction).

The work was carried out in several phases, which allowed construction of a geospatial database for SLs, including SL inventory and several thematic data, and susceptibility zonation of the SLs, within Calabria region.

In the Phase 1 all the available data related to SLs and geo-environmental features, such as topographical parameters, hydrological, soils, geological and environmental factors derived from different datasets and from direct and indirect surveys, were collected.
In the Phase 2 the collect data were homogenized, integrated, elaborated, and stored in a GIS-aided database. The geospatial database consists of different thematic layers (Figure 4) and was developed using ArcGIS ver. 10.2. The core data are a SL inventory, a digital terrain model (DTM), a lithological map, a fault map, a land use/cover map, as well as drainage and road network maps.

Figure 4. Flowchart of the method proposed for implementing a geo-database for the analysis of shallow landslides at regional scale (small scale).
In the Phase 3 was carried out the characterization of the spatial pattern of SLs with respect to some geological, geomorphological and environmental features (e.g. lithology, faults, slope gradient, drainage network, land use/cover).

In the Phase 4, the susceptibility zonation map of the SLs was elaborate using a GIS-based statistical approach.

Finally, as example application, a first evaluation of the road’s exposition to SLs at regional scale was performed by means intersection between SL susceptibility map and road network map.

Table 1. Source data used to create the shallow landslides database for the Calabria region.

| Source data          | References                                  | Period/Rainfall event                      | Number of landslides | Contribution to inventory (%) |
|----------------------|---------------------------------------------|--------------------------------------------|----------------------|------------------------------|
| Scientific papers    | (Gullà et al. 2008)                        | Rainfall events 1951 and 1953              | 7977                 | 36.2                         |
|                      | (Conforti and Ietto 2020)                  | From 1990 to 2018                          | 1358                 | 6.2                          |
|                      | (Borrelli et al. 2018)                    | From 2001 to 2011                          | 750                  | 3.4                          |
|                      | (Conforti et al. 2016)                    | From 1998 to 2014                          | 266                  | 1.2                          |
|                      | (Rago et al. 2013)                        | From 2000 to 2012                          | 210                  | 1.0                          |
|                      | (Conforti and Critelli 2012)               | From 1991 to 2004                          | 127                  | 0.6                          |
|                      | (Conforti, Robustelli et al. 2012)        | From 1991 to 2004                          | 72                   | 0.3                          |
|                      | (Conforti and Ietto 2019)                 | From 1998 to 2011                          | 59                   | 0.3                          |
|                      | (Borrelli, Gioffrè et al. 2012)           | Rainfall event, winter 2000                | 33                   | 0.1                          |
|                      | (Conforti, Filomena et al. 2012)          | From 1991 to 2011                          | 29                   | 0.1                          |
| Inventory map        | (Borrelli et al. 2015)                    | From 2008 to 2010                          | 3399                 | 15.4                         |
|                      | (Sorriso-Valvo et al. 2004)               | Rainfall event, september 2000             | 2084                 | 9.5                          |
|                      | (Borrelli, Critelli et al. 2012)          | From 2000 to 2006                          | 616                  | 2.8                          |
|                      | (Lucà et al. 2011)                       | From 1990 to 2004                          | 423                  | 1.9                          |
|                      | (Rago et al. 2017)                       | Rainfall event 30 October–01 November 2015| 133                  | 0.6                          |
|                      | (Iovine and Merenda 1996)                 | Rainfall event 1972–73                     | 117                  | 0.5                          |
|                      | (Tansi et al. 2016)                      | From 2008 to 2012                          | 85                   | 0.4                          |
|                      | (Biondino et al. 2018)                   | From 2014 to 2017                          | 92                   | 0.4                          |
| Catalogues           | Calabria Basin Authorities               | From 2000 to 2016                          | 934                  | 4.2                          |
| PhD thesis           | (Conforti 2009)                           | From 2000 to 2008                          | 95                   | 0.4                          |
| Degree thesis        | (Vigliarolo 2009)                         | From 2000 to 2006                          | 418                  | 1.9                          |
| Thecnical reports    | Cosenza province                         | Rainfall event winter 2009–2010            | 55                   | 0.2                          |
|                      | Calabria region                           | Rainfall event winter 2009–2010            | 153                  | 0.7                          |
|                      | Calabria region                           | Rainfall event winter 2008–2009            | 371                  | 1.7                          |
|                      | CNR-IRPI (Cosenza)                        | Rainfall events, september 2000 and winter 2008–2009 | 418 | 1.9 |
| Newspapers           | Regional newspapers                      | Rainfall events, winter 2010–2011 and 2013 | 64                   | 0.3                          |
| Photo interpretation and field survey | Orthophotos dated 2008, Google Earth satellite images dated, 2010, 2011, 2014, 2015 and 2016. | From 2008 to 2017 | 1690 | 7.7 |
| Total shallow landslide cataloged | From 1951 to 2017 | | 22,028 | 100 |
**Shallow landslides data**

The methodology process used to collection and storage the data of SLs is summarized in Figure 4. In order to build the SL geo-database, it is necessary to assemble available several data sources (Phase 1). The information included in the database is obtained from previous inventory maps, both in digital- and in paper-based, and scientific papers relating to the Calabria region, as shown in Table 1. Existing inventory maps are mainly SL-event inventories, relating to a single trigger event (Malamud et al. 2004), and secondly are historical SL inventories, which represents the sum of numerous landslide events, and/or geomorphological maps (Guzzetti et al. 2012). Moreover, important information were also gathered from technical reports, PhD thesis, newspapers, and previous catalogues, compiled by regional and local authorities, in the case of the Calabria region the landslides inventory of Regional Basin Authorities (Piano di Assetto Idrogeologico – Law 267/98) adopted in 2001 and updated in 2016 (http://geoportale.regione.calabria.it/opendata). The geo-database includes also information regarding specific geo-hydrological events, generally referred in reports that contain detailed information related to landslides that affected residential areas and road networks in many places of the region.

To complete and integrate the spatial database, a visual interpretation of colour orthophotos, dating to July 2008 (1:10.000 scale), and Google Earth satellite images dated, May 2010, April 2011, July 2014, August 2015 and June 2016, were used. In addition, several geomorphological field surveys, were carried out from 2012 to 2017, to integrate and validate the data obtained by interpretation of the orthophotos and satellite images.

Each source data differs in level of detail; in fact, data coming from different projects, created at different times and spatial scales were pre-processed. In particular, digitalization of all the paper-based maps in vector layers, all the data collected were georeferenced with the same reference system, using the WGS 84 projection datum and the Universal Transversal Mercator as coordinate system, and homogenized. All the SLs recorded within the geo-database were mapped as points, which representing the centre of the source area. According to the classification of Cruden and Varnes (1996) and Hungr et al. (2001), were classified as SLs if they are less than 3.0 m deep and that involve soils, debris and/or weathered terrains which moving by sliding, flowing and complex movement (Borrelli et al. 2018).

In the Phase 2, the data collected and elaborated allowed to generate a multi-temporal SLs inventory database for the Calabria region from 1951 to 2017 (Figure 5). The final product is the construction of a vector layer, with a series of fields in the attribute table that enclose, for each SL, information including the ID (landslide identifier), location (coordinates, province and municipality), source of data, type of movement and data of SL events, where available.

**Geo-environmental data**

The database, also, include a set of geo-environmental factors (Figure 4) such as topographical features, lithology, tectonics, etc. These factors influencing the spatial distribution of landslides, as extensively explained in literature (Dai et al. 2001; Glade
et al. 2005; Yalcin 2008; Pradhan and Lee 2010a; Dou et al. 2015; Youssef et al. 2016; Reichenbach et al. 2018; Gholami et al. 2019). Nevertheless, there is no clear agreement with respect to the precise reasons for their choice, because the landslides occurrence is influenced by the complex interaction of geological, topographic, hydrological, and environmental factors. Thus, according to a literature review (Glade et al. 2005; Lee and Pradhan 2006; Regmi et al. 2014; Conforti, Pascale et al. 2014; Dehnavi et al. 2015; Zini et al. 2015; Tien Bui et al. 2016; Reichenbach et al. 2018; Conforti and Ietto 2020), coupled with the results of field surveys and remote-sensing images—interpretation, the our study considers the following landslide predisposing factors: lithological units, fault density, land use, and a series of morphometric parameters as slope gradient, topographic wetness index (TWI), stream power index (SPI), slope length factor (LS), and drainage density. In particular, for determine the spatial relation between the geo-environmental features and shallow landslide distribution and for assessing shallow landslide susceptibility of the Calabria region, all these thematic layers were transformed into raster format with a 20 × 20 m pixel resolution that corresponds to the DTM resolution.

Slope instability is directly related to the lithologies, their weathering conditions and, consequently, at the interaction on infiltration rates that play an important role as a SL predisposing factors (Saha et al. 2002; Calcacerra and Parise 2010; Iovine et

Figure 5. (a) Shallow landslide inventory map of Calabria region. Examples of shallow landslides occurring in the region: (b) earth flows; (c) debris flows; (d) debris slide.
Figure 6. Geo-environmental factors: (a) Lithological map (Legend: 1) alluvial deposits, 2) gravel and sand deposits, 3) sandstone rocks, 4) conglomerate rocks, 5) clay and marl rocks, 6) evaporitic rocks, 7) flyschoid rocks, 8) low-grade metamorphic rocks, 9) middle-high-grade metamorphic rocks, 10) intrusive rocks, 11) carbonate rocks); (b) Fault density map; (c) Land use map (Legend: 1) artificial and/or urban areas, 2) beaches and dunes, 3) sparsely vegetated areas, 4) arable lands, 5) vineyard areas, 6) fruit trees and olive groves, 7) heterogeneous agricultural areas, 8) pasture areas, 9) scrub and/or herbaceous areas, 10) forest areas); (d) Drainage density map.
al. 2014; Cascini et al. 2015; Ciurleo et al. 2017; Borrelli et al. 2018). The map of the lithological units was obtained using the Geological Map of the Calabria region at scale 1:25,000. Lithotypes are grouped into following eleven lithological classes, based on main lithotechnical features: alluvial deposits, gravel and sand deposits, sandstone rocks, conglomerate rocks, clay and marl rocks, evaporitic rocks, flyschoid rocks, low-grade metamorphic rocks, middle-high-grade metamorphic rocks, intrusive rocks, and carbonate rocks (limestones and dolomites) (Figure 6a).

The fault lineaments are also considered an important factor influencing landslides distribution, because their cause an intense fracturing, alteration and, consequently, a high permeability of the rocks (Parise et al. 1997; Saha et al. 2002; Yilmaz 2009; Borrelli and Gullà 2017; Conforti and Ietto 2020). For the case study the fault lines were derived from the Geological Map of Calabria region, ITHACA Catalogue (ITALy HAzards from CApable faults) (available at http://sgi1.isprambiente.it/geoportal/catalog/main/home.page), and successively the fault density map was elaborated. The fault density map was created by through kernel density algorithm with a search area of 1 Km², using ArcGIS 10.2 software (Conforti and Ietto 2020). The values of fault density map were reclassified into five classes by means of the natural-breaks method (Jenks 1989), as show in Figure 6b.

Land use is also an important factor for SL occurrences. Vegetated areas tend to reduce the action of rain thereby decreasing soil erosion due both raindrop energy dissipated by the dense aboveground biomass and of anchorage provided of the tree roots to terrain that, consequently, its less prone to SLs (D’Amato Avanzi et al. 2004; Saha et al. 2005; Vijith et al. 2014, García-Ruiz et al. 2017). For the aims of this paper the land use map can be obtained by the updated (2012) Corine Land Cover map of Italy (scale 1:100,000), downloaded from website of ISPRA (http://www.sinanet.isprambiente.it/it/sia-ispra/download-mais/corine-land-cover). Land use categories are: artificial and/or urban areas, beaches and dunes, sparsely vegetated areas, arable lands, vineyards, fruit trees and olive groves, heterogeneous agricultural areas, pasture areas, scrub and/or herbaceous areas, forest areas (Figure 6c).

In order to examine the influence of streams on the SLs occurrence the drainage density map is elaborated using the stream network data. For the Calabria territory was used the data available on the website of the Centro Cartografico della Regione Calabria (http://geoportale.regione.calabria.it/opendata). The drainage density, defined by the total length of stream network per unit area (1 km² in this study), was performed by means the line density analysis tool in ArcGIS 10.2 software (Moglen et al. 1998). The resulting map was reclassified into five classes using natural-breaks algorithm as: 0–2.1, 2.1–3.8, 3.8–5.3, 5.3–7.1, 7.1–13.7 km/km² (Figure 6d).

A set of morphometric factors (Wilson and Gallant 2000) such as slope gradient, TWI, SPI and LS is derived from a DTM. Before to calculate the morphometric parameters, the DTM was hydrologically corrected to eliminate the sinks using the algorithm proposed by Planchon and Darboux (2002). For the Calabria region the DTM was downloaded from website of ISPRA (http://www.sinanet.isprambiente.it/it/sia-ispra/download-mais/dem20), with a resolution of 20 m and using the system for automated geoscientific analyses (SAGA) software.
Figure 7. Topographic factors: (a) Slope gradient map; (b) Topographic wetness index (TWI) map; (c) Stream power index (SPI) map; (d) Slope length factor (LS) map.
All morphometric factors have continuous values, which were transformed into classes for the comparison with SL distribution. The size of the classes of each morphometric factor was chosen according to the Jenks natural breaks classification method (Jenks 1989), to define the best value distribution between the classes.

Slope gradient is considered as the major SL-related factor, which is frequently used for the analysis of the landslide susceptibility (e.g. Yalcin et al. 2011; Pourghasemi et al. 2012; Wang et al. 2013). For the case studied the slope map was classified into five categories namely: 0–7°, 7–15°, 15–24°, 24–34°, 34–84° (Figure 7a).

Regarding the TWI factor, it is an indicator of the spatial distribution of soil moisture because groundwater flow often follows the surface topography. This parameter is considered as an important topographic factor within the runoff model that influences the occurrence of SLs (Pourghasemi et al. 2012). According to Moore et al. (1991), the TWI is calculated using equation following:

$$TWI = \ln\left(\frac{As}{\tan \beta}\right)$$  \hspace{1cm} (1)

where $As$ is the specific catchment area (m) and $\beta$ is the slope angle (degs.). Also the values of TWI factor were classified in five classes (2–5, 5–7, 7–9, 9–12, 12–24) for the Calabria region (Figure 7b).

The SPI factor reflects the erosive capacity of flowing water and consequently play a key role to controlling slope-erosion processes, because erosive power of running water directly influences slope toe erosion and river incision (Moore et al. 1991). The SPI parameter is calculated as:

$$SPI = As \times \tan \beta$$  \hspace{1cm} (2)

where $As$ is the specific catchment area in metres and $\beta$ is the slope angle (degs.). The spatial pattern of the SPI factor for the studied territory is shown in the map of Figure 7c, and its values have been classified in four classes following: 0–30, 30–80, 80–200 and 200–400.

The LS factor, which is functions slope length (L) and the slope steepness (S), is used to evaluate the effect of topography on soil erosion in the RUSLE equation (Renard et al. 1997). This morphometric factor greatly controls the surface runoff speed and its considered a sediment transport capacity index, which can be influence the SL occurrence (Zini et al. 2015). There are different approaches found in literature for determining the LS factor in a grid-based DEM. One of them is based on the upslope contributing area of each cell, which can be calculated with the equations described by Moore and Burch (1986):

$$LS = \left(\frac{fa \times \text{cellsize}^{0.4}}{22.13}\right) \times \left(\frac{\sin \beta}{0.0896}\right)^{1.3}$$  \hspace{1cm} (3)

where $fa$ is flow accumulation and is derived from the DTM and $\beta$ is the slope angle (degs.). For the Calabria territory the values of LS factor, as showed in Figure 7d, were classified in the follow five classes: 0–3, 3–6, 6–10, 10–15 and 15–111.
For exploring the role of each selected geo-environmental factor on the occurrence of the SLs, a spatial analysis among SLs inventory with each predisposing factor map (lithology, fault density, land use, drainage density, slope gradient, TWI, SPI and LS) is performed (Phase 3 in Figure 4), using zonal statistic function in the ArcGIS spatial analysis toolbox. Histogram graphs are used as an exploratory tool for assessing

**Spatial analysis between shallow landslides and geo-environmental factors**

Figure 8. Macro-groups of lithological units prone to forming different types of cover materials. Legend: 1) cover materials from coarse-grained sedimentary rocks (CGR); 2) cover materials from fine-grained sedimentary rocks (FGR); 3) cover materials from weathered crystalline rocks (WCR); 4) cover materials from carbonate rocks (CR).
distribution of SLs among these geo-environmental factors. The comparison of the number of SLs with the geo-environmental factors allowed to determine the landslide frequency for each class of the geo-environmental factor, which is calculated as the number of landslides per square kilometre. The landslide frequency values indicate which classes of each predisposing factor, and, as consequence, which portions of the region are more frequently associated with the presence of SLs.

For the Calabria region, using the lithological map (Figure 6a), four lithological macro-groups prone to forming different cover materials were mapped (Figure 8) and the effect of the latter on the SLs distribution were evaluated. The map of the cover materials was prepared by means a grouping of the above-mentioned lithological units (Figure 6a) which, due to weathering processes, have the predisposition to develop different types covers (cover materials from coarse-grained sedimentary rocks – CGR, cover materials from fine-grained sedimentary rocks – FGR, cover materials from weathered crystalline rocks – WCR, and cover materials from carbonate rocks – CR) (Figure 8).

**Modelling of regional shallow landslide susceptibility**

In the Phase 4 the key steps for mapping the SL susceptibility are following: (1) application of a GIS-based bivariate statistical method, (2) validation of the susceptibility map and (3) evaluation of the relative importance of the predisposing factors used for the susceptibility model.

**Bivariate statistical method**

Landslide susceptibility can be assessed using different methods (heuristic, statistical, and deterministic) (Fell et al. 2008). In this study, a regional SL susceptibility pattern is created using a GIS-based bivariate statistical method, named frequency ratio (FR) (Regmi et al. 2010; Pradhan and Lee 2010b; Yalcin et al. 2011; Sujatha et al. 2013; Persichillo et al. 2017). The FR method is one of the most widely used approaches to evaluate the landslide susceptibility at regional scale (Mohammady et al. 2012; Guo et al. 2015; Li et al. 2017), which is based on the bivariate spatial correlations between dependent (shallow landslides inventory) and a set of independent variables (e.g. lithology map, slope gradient map, SPI map, etc). The assumption behind the FR is that future landslides will occur under similar geo-environmental conditions as historical landslides (Guzzetti et al. 1999). To estimate the FR value, the ratio of probability of a landslide occurrence to a non-occurrence for each class of the selected predisposing factors (lithology, fault density, land use, drainage density, slope gradient, TWI, SPI and LS) is computed as follow (Pradhan and Lee 2010b):

$$FR = \frac{N_{pix}(LX_{i,j})}{\sum_{i=1}^{m}N_{pix}(LX_{i,j})} \div \frac{N_{pix}(X_{i,j})}{\sum_{j=1}^{n}N_{pix}(X_{i,j})}$$

(4)

where FR is the frequency ratio of class i of variable j, $N_{pix}(LX_{i,j})$ is the number of pixels with SLs within class i of variable j, $N_{pix}(X_{i,j})$ is the number of pixels within variable $X_{j}$, m is the number of classes in variable $X_{i}$, and n is the number of
variables in the study area. The greater the ratio above unity, the stronger the relationship between landslide occurrence and the given factor’s class attribute. A value of FR greater than 1 means a higher correlation or significant influence of a particular class of a predisposing factor on SL occurrence, on the contrary a value lower than 1 means a weak correlation, whereas a value of unity means that the factor’s class variable does not discernably influence landslide occurrence (Lee and Min 2001; Lee and Pradhan 2006). Subsequently, each predisposing factor map is then reclassified on the basis of the calculated FR values. Finally, the landslide susceptibility index (LSI) is computed for each pixel through map algebra procedures performed in GIS environment, summing all predisposing factors reclassified using the equation (5).

\[
LSI = \sum_{j=1}^{n} FR
\]  

The inferred range of the LSI values is subdivided into five susceptibility classes (very low, low, moderate, high and very high) and the SL susceptibility map of the Calabria region was performed. The natural-breaks technique is selected to perform the reclassification of LSI due its capability of reducing the variance within classes and maximizing the variance between classes (Jenks 1989).

The susceptibility analysis was performed with a pixel-based approach and the software ESRI ArcGIS 10.2, associated with Microsoft Excel 2010 were used to conduct data processing and modelling process.

**Validation of model**

To evaluate the performance of the model and to check the reliability of the SL susceptibility map, before of the susceptibility analysis, the SL inventory dataset, containing 22,028 SLs, is split into two subsets by means a random partition (Chung and Fabbri 2003). One subset, constitute by 70% of all SLs (SL-training set, 15,420 SLs) is used for applied the SL susceptibility model, and the other subset, remaining 30% (SL-testing set, 6608 SLs), testing datasets, which were not used in the training phase, were used to evaluate the prediction capability of is used to test of the model. The random partition of the two subsets is perform by using create spatially balanced points tool, exists within the Geostatistical Analyst toolbox of the ArcGIS software.

The model validation is based on the concept of the success rate and prediction rate (Chung and Fabbri 2003). The success rate is obtained from the intersection of the SL-training set with the SL susceptibility map, while the prediction rate is obtained comparing latter with the SL-testing set. Subsequently, success rate and prediction rate curves are constructed by plotting the cumulative percentage of SL susceptibility map on the x-axis and the cumulative percentage of SL-training set and SL-testing set on the y-axis, respectively. Success rate curve indicate the goodness of fit of the model, while the prediction rate curve highlights the prediction capability of the susceptibility map. To give a measure of the predictive ability of landslide susceptibility model the area under curve (AUC) is calculated (Chung and Fabbri 2003; Brenning 2005). The AUC value is between 0 and 1; a higher value indicates a higher prediction rate, whereas a value near 0.5 means the prediction is no better than a
random guess (Fawcett 2006; Lee et al. 2008). In particular, when the AUC value in between the range of 0.9–1, the model has excellent performance; if an AUC value in between the range of 0.8–0.9, the model has good performance. If the AUC value between the ranges of 0.7–0.8, the model has fair performance. If the AUC value between the ranges of 0.6–0.7, the model has a poor performance; while, if AUC values are less than 0.6, the model has very poor performance (Lee et al. 2008).

**Selection and relative contribution of the predisposing factors**

The SLs occurrence is influenced from an extensive range of predisposing factors. Therefore, it is important to identify the predisposing factors and their contribute to perform a SL susceptibility map (Irigaray et al. 2007; Romer and Ferentinou 2016). Not all predisposing factors have an equal importance on SL occurrences; thus, the most and least important predisposing factors must be identified and the least effective factors should be removed from modelling, as they can reduce the prediction capability of the susceptibility model. In this study, to investigate the relative importance and identify the contribute of each predisposing factor used in the landslide susceptibility model a jack-knife-based test is applied (Convertino et al. 2013; Tien Bui et al. 2016; Kornejady et al. 2017). In the jack-knife test, the importance of a certain predisposing factor is estimate by excluding in turn each factor by model run constructed using the remaining factors. The accuracy of the models is performed by means the computation of AUC (Convertino et al. 2013; Park 2015). In addition, the prediction patterns of SLs using each predisposing factor alone are also created and for each of them the values of AUC are determined. A comparison between the jack-knife models and a model including all predisposing factors is then performed to identify the factor with the highest gain when used alone and the factor that decreases the gain the most when it is omitted. Then, the Jack-knife test, performed using the SL-training set data, allowed to identification the significance of each factor, their contribution degree and their importance regarding the implementation of the landslide susceptibility model that include all predisposing factors (O’Banion and Olsen 2014; Kornejady et al. 2017). In particular, when the jack-knife test is applied to only one factor the value of AUC provides the absolute importance of the variable to assess the SL susceptibility. Consequently, for the susceptibility analysis only the predisposing factors for which the test showed an AUC greater than 0.5, a standard threshold in establishing the importance of the geo-environmental variables considered, is used (Convertino et al. 2013; Teerarungsigul et al. 2016).

Afterwards, to quantify the relative contribution (RC) of each predisposing factor in the prediction model, the following equation is employed (Park 2015):

\[
RC = \left( \frac{AUC_{\text{all}} - AUC_i}{AUC_{\text{all}}} \right) \times 100
\]

(6)

where AUC_{\text{all}} is the value of AUC computed from the prediction model using all predisposing factors, while AUC_i represent the AUC value when i-th factor is excluded from the computation. Therefore, the higher RC value and the greater the influence of the excluded factor in the susceptibility model (Du et al. 2017).
Results and discussion

Shallow landslides and their relation with geo-environmental variables

The inventory work led to compilation of a geo-database that comprising a total of 22,028 SLs that affected the Calabria region from 1951 to 2017 (Table 1). The spatial distribution of SLs within region was depicted in Figure 5a. Landslide frequency, which is calculated as the number of SLs per square kilometre, is equal to 1.5 across whole Calabria territory. The analysis of SLs distribution respect to the five provinces revealed that Reggio Calabria and Catanzaro were affected by highest occurrence of landslide events, respectively, the 32.4% and 29.1% of all SLs (Table 2), even if the provinces characterized by highest values of landslide frequency (2.7 landslides/km²) were Catanzaro and Vibo Valentia (Table 2).

The results highlight that the SLs significantly control the present-day morphodynamic of the landscape (Figure 5b), and consequently are a great source of sediment delivered to streams (Roda-Boluda et al. 2018; Borrelli et al. 2019; Zhu et al. 2019; Conforti et al. 2021). Along the slopes, the occurrence of SLs was observed either isolated or clustered in groups of several landslides. Rainfall events of short duration with high intensity, or long duration with low intensity are the main triggering factor for the different SL types affecting the study region (Gullà et al. 2008; Borrelli et al. 2015). In many cases these SLs caused serious damage to private and public property, primarily involving lifelines (roads, pipelines, etc.) and buildings, and notwithstanding their limited volumes, such category of landslide phenomena represent a great concern in terms of risk management due to their high-destructive potential (Sorriso-Valvo et al. 2004; Gullà et al. 2009; Borrelli et al. 2015; Conforti et al. 2016; Rago et al. 2017; Conforti and Ietto 2019). Besides, some landslide events have caused victims, injured, and missing people (e.g. the heavy rainstorm event of January 2009 that has trigger many SLs along National Highway A2, caused the road closure and the loss of 3 human lives).

The comparison between SLs inventory and physiographic unit map (Figure 2b) show that about 70% of the SLs occurred in the hilly landscape and more than 28% occurred in the mountain landscape, mainly in correspondence of the Aspromonte and Serre Massif (Table 3). In particular, the spatial distribution shows the highest concentration of mass movements in the Ionian side of the Calabria (Figure 5), which is characterized mainly by a hilly landscape, often highly dissected by V-shaped valleys. In these areas outcropping pelitic lithologies and metamorphic rocks, strongly jointed and weathered, that are more prone to SLs (Antronico et al. 2004; Calcaterra

Table 2. Areal distribution and frequency of shallow landslides in the provinces of the Calabria region.

| Province         | Area (km²) | %    | Shallow landslides | Landslide frequency (Count/km²) |
|------------------|------------|------|--------------------|---------------------------------|
| Catanzaro        | 2389.7     | 15.9 | 6410               | 2.7                            |
| Cosenza          | 6646.9     | 44.1 | 4083               | 0.6                            |
| Crotone          | 1716.9     | 11.4 | 1367               | 0.8                            |
| Reggio Calabria  | 3181.7     | 21.1 | 7136               | 2.2                            |
| Vibo Valentia    | 1141.4     | 7.6  | 3032               | 2.7                            |
| Whole region     | 15076.5    | 100.0| 22,028             | 1.5                            |

G. GULLÀ ET AL.
and Parise 2005; Borrelli et al. 2018; Ietto et al. 2018). A large number of SLs occurred also the south sector of the region, which is characterized by high density of fault lineaments and by a rugged relief with long steep-sided slopes.

According to the classification of Cruden and Varnes (1996), the landslide recognized were mainly referable to complex type, earth and debris rotational or translational slides, rapidly evolved into earth/debris flows and are also known as soil-slip-debris flows (Campbell 1975; Antronico et al. 2004; Calcaterra and Parise 2005; D’Amato Avanzi et al. 2009; Borrelli et al. 2015). Usually, the earth/debris flows were channelled along the drainage lines of first or second order and the material was deposited at the base of the slope, where small fans are locally formed (Figure 9). Additionally, both shallow slides and flows (involving earth or debris), were frequently observed within study area (Figure 5c). Several SLs (mainly of the sliding type) were also mapped both on almost-vertical slopes as terrace escarpments and/or sea cliffs and along the road cuts (Figure 5d).

The analysis of spatial relationship between SLs distribution and the geo-environmental variables selected (lithological units, fault density, land use, drainage density, slope gradient, TWI, SPI, and LS) was performed, by means the comparison among SL inventory map and each predisposing factor map.

Histograms of the percentage of pixels in each variable class and the corresponding percentage of SLs within each variable class are show in the Figures 10 and 11, together with the landslide frequency for each class of the predisposing factors.

The result showed that the spatial pattern of the SLs for the whole region is closely related to the geological and geomorphological framework (Antronico et al. 2004; Gullà et al. 2008; Lucà et al. 2011). The graph in Figure 10a reports the occurrence of SLs for each lithological unit, and shows that intrusive rocks, which are highly tectonized and weathered and mantled by saprolite horizons (Cascini et al. 1992; Le Pera and Sorriso-Valvo 2000; Calcaterra and Parise 2010), and clay and marl rocks are the most prone to SLs, in agreement with researches carry out in several areas of Calabria region (Calcaterra and Parise 2005; Borrelli et al. 2015, 2018; Conforti and Ietto 2020). In these areas were mapped about 40% of the total number of SLs. Instead, the 15% of landslide occurred on slopes carved in the middle-high-grade metamorphic rocks, which are mainly ascribable to gneiss and schists, often covered by remarkable volumes of weathered material (Figure 10a). The landslide frequency, expressed as the ratio between the number of SLs and the area of each lithological unit, shows the highest value (2.92) for the intrusive rocks, while values equal to 2.14 and 2.05, for clay and marl rocks and sandstone rocks, respectively (Figure 10a). Lowest values of landslide frequency were obtained for carbonate rocks (0.38) and alluvial deposits (0.01).

### Table 3. Areal distribution and frequency of the shallow landslides in the physiographic units.

| Physiographic units       | Area (km²) | %  | Shallow landslides | Count | %  | Landslide frequency (count/km²) |
|---------------------------|------------|----|--------------------|-------|----|---------------------------------|
| Coastal plain             | 738.7      | 4.9|                    | 56    | 0.3| 0.1                             |
| Fluvial plain             | 1387.0     | 9.2|                    | 257   | 1.8| 0.2                             |
| Hilly landscape           | 6874.9     | 45.6|                   | 15311 | 69.5| 2.2                             |
| Mountain landscape        | 6075.8     | 40.3|                   | 6254  | 28.4| 1.1                             |
| Whole region              | 15076.5    | 100|                   | 22028 | 100| 1.5                             |

and Parise 2005; Borrelli et al. 2018; Ietto et al. 2018). A large number of SLs occurred also the south sector of the region, which is characterized by high density of fault lineaments and by a rugged relief with long steep-sided slopes.

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During the field surveys, it was observed that the failure surface of the SLs was commonly located at the soil-bedrock contact (2–3 m deep), sometimes involving portions of weathered bedrock (Calcaterra and Parise 2005; Gullà et al. 2008; Borrelli et al. 2015; Conforti et al. 2016; Conforti and Ietto 2020). Therefore, the results of comparisons between the type of cover materials and SLs distribution showed that more than 42.2% of the total number of SLs fall within the CWR material, while the 30.7% and 23.6% occurred, respectively, in CGR and FGR, and only the 1.5% of the SLs were recognized in the CR (Table 4). Contrary, the highest value of landslide frequency was obtained for the FGC, whereas the lowest was recorded in the CR (Table 4).

It was also observed that several SLs occurred close to the fault zones, which produced weakness area in the rock masses favouring the deep weathering processes, either held responsible of geomorphic instability (Parise et al. 1997; Borrelli et al. 2018). Therefore, the relationship between SLs and fault density was also analyzed. The fault density map, computed on the basis of the cumulative length of fault lineaments per unit area, showed a range of values from 0 to 10.3 km/km², and five fault density classes were defined (Figure 4b). The spatial distribution of fault density showed that the class 0–0.5 km/km², with the 45%, prevails and consequently 39% of the landslides occurred in this class (Figure 10b). The fault density classes of 0.5–1.1 and 1.1–2.5 include the 24 and 29% of the landslides, respectively. The remaining SLs (8%) were mapped in areas characterized by values of fault density more than 2.5 km/km² (Figure 10b). Regarding to landslide frequency, the results showed that the highest values were recorded in the fault density class 3.6–10.3 km/km² while in the fault density class 0.0–0.5 km/km² were observed the lowest value (Figure 10b). Nevertheless, in agreement to previous researches (Gupta 2005; Parise et al. 1997; Conforti and Ietto 2020), can be define that the landslide frequency increases with the growth of fault density values, because the mechanical properties within the fault
zones, which are characterized by cataclastic rocks along the zones of maximum shear, are significantly reduced.

As regards the land use types, is difficult to assess the influence of vegetation on the SLs occurrence, because geological, morphological and soil features of an area can influence the vegetation, as well as the SLs distribution (D’Amato Avanzi et al. 2004). On the ten land use classes recognized within of Calabria region (Figures 6c and 10c), the most dominant classes are forest areas (37%) and heterogeneous agricultural areas (19%). Thus, examination of occurrence of shallow landslides with respect to land use classes reveals that the SLs occurred mainly in these areas (Figure 10c). The discrete percentage of SLs were record in the forest areas can be reasonably related that in these areas several SLs occurring near the secondary drainage network where, due of deep and steep incisions, the woods cover is less thick.

The highest values of landslide frequency were recorded in sparsely vegetated areas (3.38), followed by scrub and/or herbaceous areas (3.18) (Figure 10c).

Figure 10. Percentage of the areal distribution and frequency of shallow landslides for: (a) lithological units (in which 1) alluvial deposits, 2) gravel and sand deposits, 3) sandstone rocks, 4) conglomerate rocks, 5) clay and marl rocks, 6) evaporitic rocks, 7) flyschoid rocks, 8) low-grade metamorphic rocks, 9) middle-high-grade metamorphic rocks, 10) intrusive rocks, 11) carbonate rocks); (b) fault density; (c) land use (in which 1) artificial and/or urban areas, 2) beaches and dunes, 3) sparsely vegetated areas, 4) arable lands, 5) vineyards areas, 6) fruit trees and olive groves, 7) heterogeneous agricultural areas, 8) pasture areas, 9) scrub and/or herbaceous areas, 10) forest areas); (d) drainage density.
The comparison between SL occurrence and drainage density is given in Figure 10d. The latter, points out that more than 66% of the SLs occurred within the areas with drainage density values between 3.8 and 7.1 km/km². In addition, the results showed that the landslides frequency gradually increase with the growth of the drainage density (Figure 10d), which highlight a positive correlation between drainage density and SL occurrence. This relationship could be mainly related to the develop of linear erosion processes at the head of stream as well as by water saturation of the shallower horizons, which are able to predisposing the slopes to trigger of SLs (Mugagga et al. 2012; Conforti et al. 2016; Conforti and Ietto 2020).

![Figure 11. Percentage of the areal distribution and frequency of shallow landslides for: (a) slope gradient; (b) TWI factor; (c) SPI factor; (d) LS factor.](image)

![Table 4. Areal distribution and frequency of the shallow landslides within the macro-groups of lithological units prone to forming different types of cover materials.](image)

| Cover material | Area Km² | % | Shallow landslides Count | % | Landslide frequency Count/km² |
|----------------|----------|---|---------------------------|---|-----------------------------|
| CGR            | 3892.06  | 25.8| 6756                      | 30.7| 1.74                       |
| FGR            | 2770.74  | 18.4| 5176                      | 23.6| 1.87                       |
| WCR            | 5676.11  | 40.2| 9290                      | 42.2| 1.72                       |
| CR             | 876.58   | 5.8 | 332                       | 1.5 | 0.38                       |

CGC = Cover materials from coarse-grained sedimentary rocks; FGC = Cover materials from fine-grained sedimentary rocks; WCR = Cover materials from weathering crystalline rocks; CR = Cover materials from carbonate rocks.
The results for SLs occurrence and slope gradient suggest that the steep slopes are more prone to failure than gentler slopes (Saha et al. 2002; Guillard and Zezere 2012; Park 2015). Slopes with gradients more than 24 degrees represent 23% of the region and contain about 66% of SLs, whereas on slopes with gradients less than 15 degrees, that represent more than 52% of the study area, were recorded less than 12% of landslides archived (Figure 11a). Instead, the landslide frequency increases with the increase of the slope gradient, as expected (Figure 11a). Also, the highest values of landslide frequency were observed in the class 24–34 degree (2.99) and 34–84 degree (6.73).

The graph of the TWI factor (Figure 11b), show that, approximately 87.3% of the study area is characterized by values of TWI ranged from 2 to 9. In contrast, only 8.5% of the landslide occurred in areas with TWI values more than 7, which are characterized by very low landslide frequency (< 0.4 landslides/km²). Therefore, the results highlight that the high values of landslides frequency tended to be negatively correlated with low values of TWI (Pradhan 2013, Conforti, Pascale et al. 2014).

The SPI factor map displays significant variability with values ranging from 0 up to 400, that are subdivided into the following four classes (Figure 11c). The highest values both of the landslide distribution (about 66% of the total landslides) and landslide frequency were achieved in the SPI classes 80–200 and 200–400, with a value of 2.32 and 2.35 landslides/km², respectively (Figure 11c). Therefore, the results displayed a direct relationship of SPI with SLs, where a high frequency of SLs was linked to high values of SPI. SPI is an important factor because the erosive power of water runoff directly influences the linear erosion along the valleys, causing steep slopes on which can be triggered landslides (Zhu et al. 2019).

With respect to LS factor values, which ranging from 0 to 111, clear difference occurs among landslide distribution (Figure 11d). The 85.1% of the total shallow landslides were concentrated on slopes with values of LS varying from 3 to 15 (Figure 11d). Landslide frequency showed that this later increases with the growth of the LS factor, with a maximum value of frequency of 6.03 landslides/km², recorded in the class 15–111 (Figure 11d). Hence, this morphometric factor can be considered very important for shallow landslides generation.

**Shallow landslide susceptibility assessment**

**Predisposing factors**

Using the SL-training set, the frequency ratio method (Eq. 4) was applied to calculate the FR value for each class of the predisposing factors illustrated above (Table 5). Successively, the jack-knife test was applied for the selection of the proper predisposing factors as well as determining their relative importance in the overall shallow landslide susceptibility assessment.

The results of jack-knife test were presented in Figure 12. The red bar illustrates the accuracy of model using all factors (susceptibility prediction model), evaluated by means the calculation of AUC value. The green bars represent the results of the models with one-by-one factor removal, which evaluate the relative impact of each factor in the susceptibility model. Likewise, the blue bars indicate the values of AUC using...
Table 5. Frequency ratio values distribution for each class of the selected landslide predisposing factors.

| Predisposing factors | Area of factor class | Shallow landslides of training set | Frequency ratio (b/a) |
|----------------------|----------------------|-----------------------------------|----------------------|
|                      | km²                  | count (-)                         | % (b)                | (-)       |
| Lithology            |                      |                                   |                      |           |
| 1) Alluvial deposits | 2455.8               | 14                                 | 16.3                 | 0.1       | 0.01     |
| 2) Gravel and sand deposits | 1719.8               | 1773                               | 11.4                 | 11.5      | 1.01     |
| 3) Sandstone rocks   | 1407.8               | 2015                               | 9.3                  | 13.1      | 1.40     |
| 4) Conglomerate rocks | 764.5                | 936                                | 5.1                  | 6.1       | 1.20     |
| 5) Clay and marl rocks | 1714.5               | 2633                               | 11.4                 | 17.1      | 1.50     |
| 6) Evaporitic rocks  | 50.9                 | 51                                 | 0.3                  | 0.3       | 0.98     |
| 7) Flyschoid rocks   | 905.2                | 945                                | 6.0                  | 6.1       | 1.02     |
| 8) Low-grade         | 1171.6               | 522                                | 7.8                  | 3.4       | 0.44     |
|                     |                      |                                    |                      |           |           |
|                     |                      |                                    |                      |           |           |
| Fault density (km/km²) |                    |                                   |                      |           |           |
| 1) 0–0.5            | 6778.9               | 6054                               | 45.0                 | 39.3      | 0.87     |
| 2) 0.5–1.1          | 3454.9               | 3661                               | 22.9                 | 23.7      | 1.04     |
| 3) 1.1–2.5          | 3603.5               | 4197                               | 23.9                 | 27.2      | 1.14     |
| 4) 2.5–3.6          | 872.1                | 1033                               | 5.8                  | 6.7       | 1.16     |
| 5) 3.6–10.3         | 362.8                | 475                                | 2.4                  | 3.1       | 1.28     |
| Land use            |                      |                                    |                      |           |           |
| 1) Artificial and/or urban areas | 467.7               | 376                                | 3.1                  | 2.4       | 0.79     |
| 2) Beaches and dunes, areas | 130.8               | 37                                 | 0.9                  | 0.2       | 0.29     |
| 3) Sparsely vegetated areas | 111.3               | 256                                | 0.7                  | 1.7       | 2.25     |
| 4) Arable lands      | 2137.8               | 1145                               | 14.2                 | 7.4       | 0.52     |
| 5) Vineyard areas    | 31.9                 | 1                                  | 0.2                  | 0.0       | 0.03     |
| 6) Fruit trees and olive groves areas | 2206.5               | 1666                               | 14.7                 | 10.8      | 0.74     |
| 7) Heterogeneous agricultural areas | 2926.4               | 3379                               | 19.4                 | 21.9      | 1.13     |
| 8) Pasture areas     | 74.2                 | 100                                | 0.5                  | 0.6       | 1.32     |
| 9) Scrub and/or herbaceous areas | 1419.2               | 3145                               | 9.4                  | 20.4      | 2.16     |
| Drainage density (km/km²) |                        |                                    |                      |           |           |
| 1) 0–2.1            | 1715.5               | 423                                | 11.4                 | 2.7       | 0.24     |
| 2) 2.1–3.8          | 4260.9               | 2789                               | 28.3                 | 18.1      | 0.64     |
| 3) 3.8–5.3          | 4766.2               | 4520                               | 31.6                 | 29.3      | 0.93     |
| 4) 5.3–7.1          | 3474.6               | 5725                               | 23.1                 | 37.1      | 1.61     |
| 5) 7.1–13.7         | 855.1                | 1963                               | 5.7                  | 12.7      | 2.24     |
| Slope gradient      |                      |                                    |                      |           |           |
| 1) 0–7°            | 3868.1               | 333                                | 25.7                 | 2.2       | 0.08     |
| 2) 7–15°           | 4034.6               | 1480                               | 26.8                 | 9.6       | 0.36     |
| 3) 15–24°          | 3649.0               | 3498                               | 24.2                 | 22.7      | 0.94     |
| 4) 24–34°          | 2444.0               | 5147                               | 16.2                 | 33.4      | 2.06     |
| 5) 34–84°          | 1067.9               | 4962                               | 7.1                  | 32.2      | 4.54     |
| TWI                 |                      |                                    |                      |           |           |
| 1) 2–5            | 2524.1               | 9107                               | 16.7                 | 59.1      | 3.53     |
| 2) 5–7            | 7835.0               | 5004                               | 52.0                 | 32.5      | 0.62     |
| 3) 7–9            | 2805.6               | 930                                | 18.6                 | 6.0       | 0.32     |
| 4) 9–12          | 1331.9               | 282                                | 8.8                  | 1.8       | 0.21     |
| 5) 12–24       | 579.4                | 97                                 | 3.8                  | 0.6       | 0.16     |
| SPI                 |                      |                                    |                      |           |           |
| 1) 0–30          | 5231.6               | 1595                               | 34.7                 | 10.3      | 0.30     |
| 2) 30–80        | 3651.5               | 3775                               | 24.2                 | 24.5      | 1.01     |
| 3) 80–200       | 3005.4               | 4834                               | 20.0                 | 31.3      | 1.57     |
| 4) 200–400     | 3171.1               | 5216                               | 21.1                 | 33.8      | 1.61     |
| LS                 |                      |                                    |                      |           |           |
| 1) 0–3       | 6304.9               | 1087                               | 41.8                 | 7.0       | 0.17     |
| 2) 3–6       | 3914.6               | 2888                               | 26.0                 | 18.7      | 0.72     |
| 3) 6–10     | 3086.1               | 5203                               | 20.5                 | 33.7      | 1.65     |
| 4) 10–15    | 1481.9               | 5030                               | 9.8                  | 32.6      | 3.32     |
| 5) 15–111  | 286.0                | 1212                               | 1.9                  | 7.9       | 4.14     |
each factor alone, which measure the importance of each factor in predicting shallow landslide pattern for the Calabria region.

The models performed using factors one-at-a-time (the blue bars), highlighted that all the geo-environmental variables selected were defined significant for determine the spatial SL occurrence, because their AUC values are greater than 0.5 (Figure 12). In particular, the highest AUC was obtained for LS factor (0.76), followed by slope gradient and TWI factors with an AUC values of 0.74, highlighting that the morphometric features are the most important driver of the shallow landslide distribution in the study area. While, for the land use and fault density were recorded the lowest values of AUC, 0.58 and 0.54, respectively, which shows the medium/low importance of these factors in predicting landslide pattern. Hence, all the eight factors were selected for landslide susceptibility model.

The relative importance of a predisposing factor was estimated by excluding the factor and then calculated the overall accuracy of the model (Lee and Talib 2005). The results displayed that all the predisposing factors have contributed positively to performed the susceptibility model (Figure 12). The graph (green bars) show a decrease of AUC values (i.e. loss of performance) by comparing the prediction model based on all predisposing factors with that when one factor was excluded (Figure 12). The larger the decrement, the greater the influence of the excluded factor (Teerarungsigul et al. 2016; Du et al. 2017). In addition, the analysis of RC of each predisposing factor highlight that each predisposing factor had different contributions to the prediction modelling (Table 6). Therefore, slope gradient, with a RC value of 5.90%, followed by LS (5.18%) and TWI (4.94%) have the greatest influence on susceptibility model, while the fault density with a RC of 3.73%, yielded the lowest importance (Table 6). These findings support the previously results obtained from spatial relationship between SLs distribution and the geo-environmental variables, which showed that the SLs occurrence in the Calabria region is mainly controlled by morphometric factors. In addition, these results are in agree with the studies carried out by others such as Van Den Eeckhaut et al. (2006) and Pradhan and Lee (2010b) where slope gradient was indicated as one of the most important predisposing factors.

Susceptibility map
The SL susceptibility map of the Calabria region was produced by frequency ratio model, using eight predisposing factors (lithological units, fault density, land use, drainage density, slope gradient, TWI, SPI and LS) and the SL-training set, consisting of the 70% of the total shallow landslide inventory. By crossing the SL-training set layer with each predisposing factor map, the FR value was calculated for each factor class (Table 5).

The overall maximum FR values were attributed to class 5 of slope gradient factor (FR= 4.54) and class 5 of LS factor (FR= 4.14), which corresponds both to highest values of slope gradient and LS factor (Table 5). In addition, high values of FR were also found for the class 4 of the SPI and class 5 of drainage density factors (Table 5). These results confirm the good spatial correlation exists between the SLs occurrence and the high values of these morphometric factors (Dai et al. 2001; Gao and Maro
2010; Pourghasemi et al. 2012; Althuwaynee et al. 2014; Gholami et al. 2019). On the contrary, the lowest FR value was obtained to class 5 (vineyards areas) of land use factor \((\text{FR}_5 = 0.03)\). Moreover, FR value was particularly low where carbonate rocks and alluvial deposits crop out \((\text{FR} = 0.28\) and \(\text{FR} = 0.01\), respectively), as well as, low values of FR occurred in areas where slope gradient ranges between \(0^\circ\) and \(15^\circ\) and drainage density ranges from 0 to 3.8 km/km\(^2\) (Table 5). This indicate the low influence on SLs occurrence of these classes.

In order to obtain LSI, all predisposing factors, reclassified on the basis of calculated FR values, were summed by using map algebra tool, implemented in GIS software. The values of LSI obtained have a minimum of 1.93 and a maximum of 21.76, with an average value of 7.99 and a standard deviation of 3.58. The LSI values, computed for each grid points, were classified into five classes (very low, low, moderate, high and very high) using natural breaks method, and the SL susceptibility map of the Calabria region was created (Figure 13a). The percentage of area affected by very low, low, moderate, high and very high susceptibility was summarized in Table 7. Given this classification, about 26% of the study area falls in high to very high susceptibility classes. Most of the SLs of the entire dataset (75.9%) occur in these classes, whereas only 7.5% of the SLs falls within of areas with low and very low susceptibility, and the remaining 16.6% falls into moderate susceptibility class (Table 7).

The susceptibility map allowed to delineate some sectors particularly sensitive to SLs, highlighting that the high and very high classes of susceptibility are localized mainly along the eastern reliefs of the Sila, Serre and Aspromonte massifs (Figures 2b and 13a). These sectors are dominated by a rugged landscape, strictly linked to regional uplift (Parise et al. 1997; Calcaterra and Parise 2005, 2010; Molin et al. 2012; Robustelli 2019). However, these sectors of Calabria are frequently affected by rainfall

**Figure 12.** Jack-knife test results for the Calabria region to evaluate the relative importance of predisposing factors used for shallow landslide susceptibility model. The red bar shows the best calibrated model for the predisposing factors all together, the green bars the models excluding the indicated factor and blue bars measure the importance of each factor in predicting the shallow landslide distribution.
events of short duration and high intensity that caused a great number SLs (Versace et al. 1989; Sorriso-Valvo et al. 2004; Gullà et al. 2008; Terranova and Iaquinta 2011; Gullà et al. 2012; Rago et al. 2017).

Most of the areas affected by high and very high susceptibility (about 50% of the study area) are dominated by long steep slopes and deeply fluvial valleys, often fault-controlled, which are frequently carved in the rocks highly fractured and weathered and characterized by high values of LS, SPI and drainage density. Moreover, susceptibility is very high in the areas of the region, where clay and marls deposits mainly outcrop and frequently covered by scrub and herbaceous, as well as on pasture areas. Slopes more prone to SLs are also situated in correspondence of sparsely vegetated areas.

By comparing the spatial distribution of macro-groups of lithological units prone to forming different types of cover materials (CGR, FGR, CWR and CR) with the susceptibility map was observed that the high (58.4%) and very high (65.6%) susceptibility classes are mainly distributed within the WCR (Table 8), which mainly corresponds with areas characterized by steep slopes and high values of fault density.

In summary, following a circular approach we used data related to shallow landslides and geo-environmental features – derived from both different scales (i.e. small, medium and detail scales) and different sources (e.g. previous shallow landslide inventory maps, technical reports, newspapers, previous catalogues, etc.) – homogenized, integrated, elaborated, and stored in a GIS-aided database, for mapping shallow landslides at regional scale (Figure 13a).

**Accuracy analysis**

The accuracy of the SL susceptibility map was carried out using SLs both of SL-training set and SL-testing set by generating the corresponding success rate and prediction rate curves (Figure 13b and c). The success rate curve has an AUC value of 0.83 (Figure 13b), which indicates the good ability of the method and predisposing factors to correctly classified the SL-training set, used for building the model. The AUC value for the prediction rate curve is 0.81 (Figure 13c), highlighted good performance of the susceptibility map (Brenning 2005; Lee et al. 2008). Also, the very similar result of AUC values of both the success rate and prediction rate curve confirms the correctness of sampling procedure of the SL-training set and the SL-testing set.

The susceptibility map correctly classifies as very high and high 76.8% of the SL-training set and shows a slightly lower prediction performance of 73.7% for the SL-

### Table 6. AUC values when each predisposing factor is excluded in the susceptibility model and the relative contribution (RC) value of each factors on landslide susceptibility model with all factors.

| Predisposing factor | Success rate AUC | RC (%) |
|---------------------|------------------|--------|
| Slope gradient      | 0.781            | 5.90   |
| LS factor           | 0.787            | 5.18   |
| TWI factor          | 0.789            | 4.94   |
| Lithology           | 0.791            | 4.58   |
| Land use            | 0.792            | 4.58   |
| Drainage density    | 0.794            | 4.34   |
| SPI factor          | 0.795            | 4.22   |
| Fault density       | 0.799            | 3.73   |
testing set (Table 7). Only the 7.9% of the SL-testing set are attributed to the low and very low susceptibility classes and the remaining 18.4% of the SL of testing set fall in the moderate susceptibility class (Table 7). These finding highlight that the SL pattern generally agrees with the pattern of the high susceptibility classes.

Overall, the validation results suggest a good reliability of the model employed in this study to estimate the spatial probability of the future occurrence of SLs in the Calabria region. Also, the finding obtained may be compared with most other works that used the frequency ratio method for mapping the landslide susceptibility (e.g. Lee and Talib 2005; Pradhan and Lee 2010b; Regmi et al. 2014; Guo et al. 2015; Chen et al. 2016; Gholami et al. 2019).

Finally, landslide density analysis was also performed to validate the SL susceptibility map (Sarkar et al. 2008; Pham et al. 2016). The landslide density is defined as the ratio between the percentages of SLs and the percentages area of each susceptible class; higher susceptible classes should have higher values of landslide density for reliable landslide susceptibility maps (Pham et al. 2016). The results showed that the
landslide density gradually increases from the very low to the very high susceptibility class (Table 7). Therefore, these finding confirm the effectiveness of the susceptibility map.

**Comparison between road network and shallow landslide susceptibility**

The roads constitute one of element highly vulnerable to SLs (Jaiswal et al. 2010; Klose et al. 2014; Borrelli et al. 2015; Donnini et al. 2017). Therefore, a first evaluation of the road’s exposition to SLs at regional scale can be carried out by intersection between SL susceptibility map and road network map. The results of this analysis are summarized in Figure 14 and reveal that the 20% of the road network across areas that fall within the classes of high and very high susceptibility. In addition, the 17% of the roads are affected by moderate susceptibility, while the remaining 63% falls into low and very low susceptibility classes (Figure 14a). The remarkable vulnerability of the road network among to SLs occurrence was confirmed by field investigations carried out after the several rainstorms that affected the Calabria region in the last two decades (Table 1), triggering numerous SLs, which involved many sectors of roadways (Figure 14b and c). The SLs have causing a partial or complete destruction of a road or traffic restriction of certain areas. In addition, these finding also suggests that in main cases the presence of roads can be able to predisposing the slopes to trigger of SLs, especially where are presents cutting slopes at too steep an angle or the use of geomaterials unsuitable for the embankments construction (Gullà et al. 2009; Conforti and Ietto 2019). These results highlight the need to draw the attention of land management experts to the impact of the SLs on infrastructures and structures.

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**Table 7.** Percentage area of the susceptibility classes in the map, percentage of shallow landslides distribution and related landslide density falling among the susceptibility classes.

| Landslide susceptibility index (LSI) | Susceptibility class | Area (%) | Shallow landslides (%) | Landslide density |
|-------------------------------------|---------------------|----------|------------------------|------------------|
| 1.93–5.27                           | Very low            | 24.3     | 0.6                    | 0.02             |
| 5.27–7.84                           | Low                 | 27.2     | 6.7                    | 0.25             |
| 7.84–10.72                          | Moderate            | 22.6     | 15.9                   | 0.74             |
| 10.72–14.45                         | High                | 17.4     | 34.1                   | 1.97             |
| 14.15–21.76                         | Very high           | 8.5      | 42.7                   | 4.88             |

**Table 8.** Areal distribution of shallow landslide susceptibility classes within the macro-groups of lithological units prone to forming different types of cover materials.

| Cover material | Shallow landslide susceptibility classes |
|----------------|------------------------------------------|
|                | Very low | Low | Moderate | High | Very high |
| CGR            | 68.7     | 29.3| 21.3     | 18.9 | 15.2      |
| FGR            | 13.1     | 31.5| 21.7     | 11.9 | 7.4       |
| WCR            | 14.4     | 34.5| 49.5     | 58.4 | 65.6      |
| CR             | 3.8      | 4.6 | 7.5      | 10.8 | 11.8      |

CGR = Cover materials from coarse-grained sedimentary rocks; FGR = Cover materials from fine-grained sedimentary rocks; WCR = Cover materials from weathered crystalline rocks; CR = Cover materials from carbonate rocks.
Figure 14. (a) Shallow landslide susceptibility distribution overlaid on the main road network of the Calabria region; (b) Sector of National Highway A2 that across an area with high landslides susceptibility where the trigger of several shallow landslides, in January 2009, blocking the roadway partially; (c) Shallow landslides involving a portion of a road falling in an area classified as very high susceptibility.
Conclusions

In this paper a comprehensive geospatial database of SLs for the Calabria region (Southern Italy), was implemented. This geo-database comprises an inventory of the SLs and the main geo-environmental factors that predispose the slopes to their trigger. To determine the spatial distribution and the characteristics of each SL were collected and georeferenced existing literature (i.e. published inventory maps, scientific reports), coupled with a multi-temporal interpretation of remote sensing images and several field surveys. A total of 22,028 SLs, occurred between 1951 and 2017, which if continuously update, constitutes the main component of a robust geo-database. The main typologies of SL recognized are complex phenomena, slides, and flows that can involve earth or debris.

The achieved results suggest that the distribution pattern of the SLs and its comparison with the selected geo-environmental factors (lithological units, fault density, land use, drainage density, slope gradient, TWI, SPI and LS) provide valuable information for define the landslide-prone areas of the Calabria region. All the predisposing factors selected had a positive effect on the SL susceptibility model but with different contribute: slope gradient, LS and TWI were found to be the most important factors for the susceptibility model, whereas the fault density yielded the lowest predictive capabilities.

Referring to the areas where can be present cover materials (CGR, FGR, WCR and CR), the SLs distribution showed that the high values of the landslide frequency affected mainly the FGR and secondly the CGR and WCR.

The SL susceptibility map, showed that the zones classified as high and very high susceptibility accounted for 26% of the total area. The AUC value for the success rate curve was equal to 0.83, while for the prediction rate curve was 0.81, indicating a good prediction capability of the susceptibility map. Also, the outcomes demonstrated that the frequency ratio is a statistical method easy to apply and to update as well as provide a high prediction capability for mapping SL prone areas within Calabria region.

In addition, the intersection between SL susceptibility map and road network map highlighted that the 20% of the roadways of the Calabria region are seriously threatened by SLs.

Finally, the geo-database and the SL susceptibility map permit to individuate large areas and slopes where can be carried out or deepening studies at medium and detail scales, aimed to typify shallow landslides and relative remedial works.

Overall, results obtained in this paper can be used both for land use planning and hazard-risk assessment at regional scale and as basic data to assist with more efficacy the road network management, and as reference for planning of new road infrastructure.

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