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GIS-Multicriteria Analysis Using AHP to Evaluate the Landslide Risk in Road Lifelines

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Abstract: The present paper proposes a new methodology to characterize the landslide susceptibility of the Reggio Calabria metropolitan area. For this purpose, various factors were used, such as land use, slope, rainfall, elevation, lithology, distance from roads and rivers, and thanks to the use of GIS devices and the AHP method, the landslide risk was defined for the whole territory. The values obtained were classified into four categories: low, moderate, high, and very high. They were then exported into the GIS environment to produce a landslide susceptibility map. The study carried out demonstrates the fragility of the Calabrian territory. From the results obtained, in fact, 66% of the metropolitan territory of Reggio Calabria appears to have a medium–high landslide risk.

Keywords: landslide risk; natural phenomena; Reggio Calabria; GIS; AHP method

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1. Introduction

Landslides are natural phenomena as well as man-made disasters that frequently lead to loss of human life and property, as well as causing serious damage to natural resources throughout the world. These occurs because of different associated natural hazards or anthropogenic activities. Natural phenomena include meteorological changes, such as intense rainfall, prolonged rainfall, or snowmelt and again earthquakes or volcanic eruptions. Human disturbances instead include land use alteration, deforestation, carrying out excavations, changes in the slope profile, and infrastructure constructions [1].

The effects associated with the occurrence of landslides include injuries, loss of human life, significant damage to natural resources and infrastructure, such as roads, bridges, and communication lines. To limit this, the realization of the landslide susceptibility map is fundamental to identify possible preventive measures and the planning of evacuation strategies to avoid significant damage and victims. Moreover, landslide susceptibility, hazard and risk maps are of great help to planners for selecting suitable areas to implement development schemes in any area [2,3].

Despite tremendous progress in science and technology, landslides considerably affect the socio-economic conditions of all regions of the globe. The susceptibility to landslides can be defined as the probability of the spatial occurrence of a landslide event based on the relationships between the occurrence distribution and a set of predisposing factors in a given area, such as geo-environmental thematic variables [4]. Landslides cannot be completely prevented but an accurate prediction of the landslide-susceptible areas is of particular importance since this can lead to saving natural resources as well as human lives.

Landslides occur and are controlled by one or more conditioning factors, such as topography, slope, failure mechanism, intensity of rainfall, land cover, geological formation, strength of rocks, and many more [5–7].

The landslide susceptibility assessment can be tricky because of the difficult evaluation of both the spatial and temporal distribution of past events for large areas, mainly due to the limitations and gaps of historical records and geographic information [8].

Many different types of landslide risk assessment zonation techniques have been developed over the last decades. These methods can typically be labeled as being either qualitative or quantitative procedures, also called direct and indirect methods [9–11].

The qualitative approaches are inventory-based and knowledge-driven methods such as distribution analysis or inventory [12], geomorphic mapping [13], and map integration models [14]. They yield direct and countable results but are limited by data availability. By contrast, the qualitative approach is less complex, but the subjective estimation of experts renders its degree of confidence and the accuracy of its results questionable [15].

Direct mapping has the purpose of determining the degree of landslide susceptibility based on a qualitative approach and provides an estimate of "where" landslides are expected.

In this approach, the experience, knowledge of the ground boundary conditions, and the evaluation of pre-existing terrain maps are taken into consideration. Precisely for these reasons, direct methods present results that are subjective since they are linked to the experience and knowledge of the personnel and present many difficulties in transcribing the phenomena due to the occurrence of particular environmental changes in certain areas [16]. This methodology usually uses factors characteristic of the locations where landslides have occurred in the past, together with an assessment of the areas with a potential to experience land sliding in the future, but with no assessment of the landslide's occurrence frequency.

The reliability of landslide-susceptibility maps mainly depends on the scale of work, the quality of the data and the analysis methodology.

On the other hand, indirect mapping is based on quantitative models, such as statistical and deterministic ones, which aim to find numerical correlations between the various factors that favor the occurrence of landslides and their distribution on the earth's surface and based on information obtained from the interrelation between landslide conditioning factors and the landslide distribution. For large areas, statistical methods are the most widely used [17]. The statistical methods include bivariate statistical analysis [18], logistic regression [19–21], multivariate regression [22,23]; multivariate adaptive regression spline [24], statistical index [25,26], analytical hierarchy process analytical hierarchy process [27,28], weight of evidence [29,30], and evidential belief function [31,32].

In recent times, quantitative approaches have been widely used for landslide susceptibility and hazard evaluation. However, it is mostly very difficult to include temporal probability in this analysis of large areas, due to the heterogeneity of subsoil conditions, the numerous conditioning factors, and the absence of a complete historical record of the events that can determine the occurrence of landslides (for example precipitation, earthquakes, and landslides themselves).

Furthermore, these models, however, show a high sensitivity of the results to the quality and accuracy of the thematic data and the specificity of some sensitive factors that could end up not being taken into consideration.

Landslide susceptibility and hazard assessments often use multi-criteria decision analysis (MCDA) techniques since in most cases, the types and format of data that are available are qualitative and quantitative, thereby requiring a semi-quantitative method that incorporates both types of data [33].

The semi-quantitative landslide assessment methods can be considered an effective expert's tool for weighting and ranking the chosen factors, which represent the main causes for landslide susceptibility of the study area, in an objectively optimal and simple way.

Some qualitative methods become semi-quantitative by incorporating ranking and weighting [34,35], as is the case of the analytic hierarchy process (AHP), a multi-objective and multi-criteria decision-making methodology which has been widely applied for the solution of decision problems [36].

This method is based on the analytical hierarchy of involved factors and the comparison between the various pairs of them in order to enable the assignment of a relevant ratio for each factor. Thanks to this method, it is therefore possible to estimate the weight of each factor considered, through the linear correlation of each factor with respect to the others. The ability to correlate different factors has made this method a valuable tool for many researchers in compiling landslide susceptibility maps, which are obtained by correlating and comparing a large number of factors [37].

The management of a large number of factors to be correlated and estimated for the definition of landslide susceptibility is therefore carried out, in most cases, through the use of the geographical information system (GIS) [35].

The increasing popularity of GIS and its ease of use over the last decades has led many studies to use indirect susceptibility mapping approaches.

GIS, which uses data-integration techniques, is a very suitable tool for landslide susceptibility mapping. In fact, with the increasing availability of high-resolution spatial data sets, GIS, remote sensing, and computers with large and fast processing capacity, it has becoming possible to partially automate the evaluation of landslide hazard and susceptibility mapping process and thus minimize fieldwork.

The reliability of these maps depends mostly on the applied methodology as well as on the available data used for the hazard risk estimation. Moreover, GIS is an excellent and useful tool for mapping the susceptibility of an area prone to landslide manifestation.

This study focused on producing a landslide susceptibility map of the Reggio Calabria metropolitan area (Italy) by combining GIS techniques and the AHP method.

The main objectives of the present work can be synthesized to create a landslide susceptibility map for the province of Reggio Calabria, using the GIS software by means of the weighted combination of various factors, such as the slope, lithology, elevation, rainfall, land use, distance of the road and river. From the obtained map, it is possible to evaluate the landslide susceptibility in the areas that are particularly relevant because of the connections between the internal urban areas and the main towns and services located along the coasts and to analyze the degree of landslide risk of the connecting infrastructures (lifelines). This method could be used in other areas of the Calabria Region for the realization of the landslide susceptibility map in order to be able to use the maps obtained to plan the safety of the slopes or, in particular, identify the main road infrastructures more at landslides risk, comparing the results obtained with the various inventories of landslides that occurred in the past.

2. Study Area

The Reggio Calabria metropolitan city, in the Calabria region in the south of Italy, was selected as the study area because the territory is subject to phenomena of hydrogeological and seismic risk; the present study area has suffered from every landslide type.

The territory of Calabria is geologically young and often subject to natural modifications, so hydro-geological disaster (landslides and floods) is one of the risk factors to which Calabria is exposed. This is due, among other conditions, to the physical conformation of the region and the climatic conditions.

Landslides are the most common consequence of the soil instability due to the seismic activity and the hydrogeological problems in Reggio Calabria metropolitan city. Extraordinary conditions, such as earthquakes, and more ordinary meteorological conditions, such as rainfalls, can both induce landslides, rock fall, or debris flow.

The considered study area with 97 cities and towns and with a total population of 530,000 inhabitants is the area of Calabria with the highest population density equal to 165.57 residents/km^2.

The Reggio Calabria metropolitan city covers an area of 3183 km^2, of which 1685 km^2 (52.95%) is represented by hilly terrain, 1.275 km^2 (40.07%) is mountainous and the remaining 223 km^2 (6.97%) are represented by land lowland.

In regions where urban residential areas coincide with mountainous terrains, like in this area, the risk is higher for people, and the economic costs include relocating communities and repairing physical structures.

The Autorità di Bacino of Calabria Region, considering the various mentioned problems, has made available several thematic maps for a complete hydrogeological balance (PAI—Piano di Assetto Idrogeologico, 2001) [38]. These maps, updated in 2016, are accessible through Quantum—GIS, and they describe the landslide hazard and risk areas in the whole region, but they do not give any information about the landslide risk assessment in the strategical infrastructures identified as lifelines [2]. Furthermore, these assessments were carried out without taking into consideration the main connecting and emergency road infrastructures, which, however, play a role particularly relevant during an emergency to allow rapid and efficient access, assistance, and rescue, guaranteeing evacuation and, more in general, maintaining access for all emergency services [2,3].

Therefore, starting from the data provided by the PAI, containing the landslides that have occurred in the past together with an assessment of the areas with a potential to experience land-sliding in the future, and with the integration of factors of particular importance, such as distance from roads and from the rivers, the objective of the present work is to create a landslide susceptibility map for the metropolitan area of Reggio Calabria by means of the weighted combination of various indices using the AHP method.

3. Materials and Method

The first step in every susceptibility assessment consists of collecting all available information and data for the study area, and this stage may be the most important part.

Evaluating the relationship between the landslide occurrence and the conditioning parameters becomes very important for the landslide susceptibility mapping; further analysis of the cause–effect relationships is not always simple, as a landslide is seldom linked to a single cause. So, to produce the landslide susceptibility map in the metropolitan area of Reggio Calabria, a total of 7 inputs were selected for the model, considering the main influencing factors of landslides: the slope, the lithology, the elevation, the rainfall, the land use, the distance of the road, and the river.

In the study carried out, the number of factor classes was increased compared to that of previously published studies, analyzing what was done in the literature by other authors and wanting to obtain a non-homogeneous weight of each class of factor, unlike what was obtained in the previous studies.

3.1. Slope Factor

The slope and the aspect of the slopes play an important role in the occurrence of landslides because they represent the result of the combined influence of many agents. Slope is an important factor in the analysis of landslide; in fact, as the slope increases, the probability of the occurrence of landslide increases because as the slope angle increases, the shear stress of the soil increases.

A digital elevation model (DEM) was utilized using 3D extension of ArcGIS, and the slope angle was extracted from it, using contours with 5 m intervals digitized from topographic sheets and saved as a line layer.

Six slope categories were used as factor classes for the analysis of landslides risk as shown in Table 1.

Table 1. Weight of the individual classes of landslide hazard factors.

	Factor Class	$W_{i,L}$
Slope degree [°]	0–8	0.21
	8.01–18	0.15
	18.01–28	0.13
	28.01–37	0.09
	37.01–47	0.09
	>47	0.33
Land Use	Artificial and waterproof surfaces	0.04
	Arable agricultural areas with sparse vegetation	0.26
	Agroforestry areas with scattered trees and shrubs	0.42
	Wooded areas or areas with important vegetation	0.28
Elevation [m]	<100	0.19
	101–300	0.25
	301–500	0.15
	501–1000	0.27
	>1001	0.13
Rainfall [mm]	0–600	0.02
	600–900	0.19
	900–1200	0.36
	1200–1500	0.25
	<1500	0.18
Lithology	Sedimentary deposits	0.33
	Clays and sandstones	0.21
	Rocks	0.45
River Distance [m]	0–50	0.10
	50.01–100	0.10
	100.01–200	0.18
	200.01–250	0.08
	<250	0.54
Road Distance [m]	0–100	0.10
	101–200	0.08
	201–300	0.07
	301–400	0.06
	401–500	0.06
	>500	0.62

3.2. Lithology Factor

Lithology is a further important parameter with regard to landslide manifestation. It is widely recognized that geology greatly influences the occurrence of landslides because lithological and structural variations often lead to a difference in the strength and permeability of rocks and soils.

For the study area, three factor classes were determined by grouping the different geological formations according to their geological engineering behavior and according to their physical and mechanical characteristics.

Thus, lithology includes three classes as follows: sedimentary deposits, clays and sandstones and rocks.

3.3. Elevation Factor

The altitude does not contribute directly to landslide manifestation, but in relation to the other parameters, such as precipitation, the altitude contributes to landslide manifestation and influences the whole system.

Elevation is useful to classify the local relief and to locate points of maximum and minimum heights within terrains. The elevation is considered the fourth important parameter in the classification of landslide risk. The grid maps of the altitude with cell size 5 × 5 m were produced from the DEM. The separation of the altitude into 5 classes was as follows: <100 m, 101–300 m, 301–500 m, 250–500 m, and >1000 m. The highest density corresponds to the class with an elevation range of 500–1000 m, representing hilly areas.

3.4. Rainfall Factor

As it is well known, precipitation is among the most usual triggering factors for landslide manifestation. For the necessities of this study, the precipitation map was produced, using the annual average precipitation data of the main meteorological stations well distributed in the study area.

This map was separated into 5 classes as shown in Table 1.

3.5. Land Use Factor

The data for the land use in an area are a parameter that seriously affects the slope failures, as slope stability is very sensitive to changes in vegetation. For the necessities of this study, the land use, which reflects the vegetation covering, was classified into 4 categories as follows: artificial and waterproof surfaces, arable agricultural areas with sparse vegetation, agroforestry areas with scattered trees and shrubs, wooded areas, or areas with important vegetation.

3.6. Distance of Road and River Factor

As it is obvious, the artificial and natural parts of the slopes around a road are more sensitive in landslide manifestation. In addition, some lifeline roads have to guarantee effectiveness and efficiency in the immediate aftermath of a natural disaster; in some cases, they have to be maintained also during the event to allow rapid and efficient access and assistance and rescue, guaranteeing evacuation and, more in general, maintaining access for all emergency services. Therefore, the road network was chosen as a principal parameter that consists of the road network of the province of Reggio Calabria, composed of 1850 km of roads.

Buffer zones were created around road lifelines at distances of 100, 200, 300, 400 and 500 m.

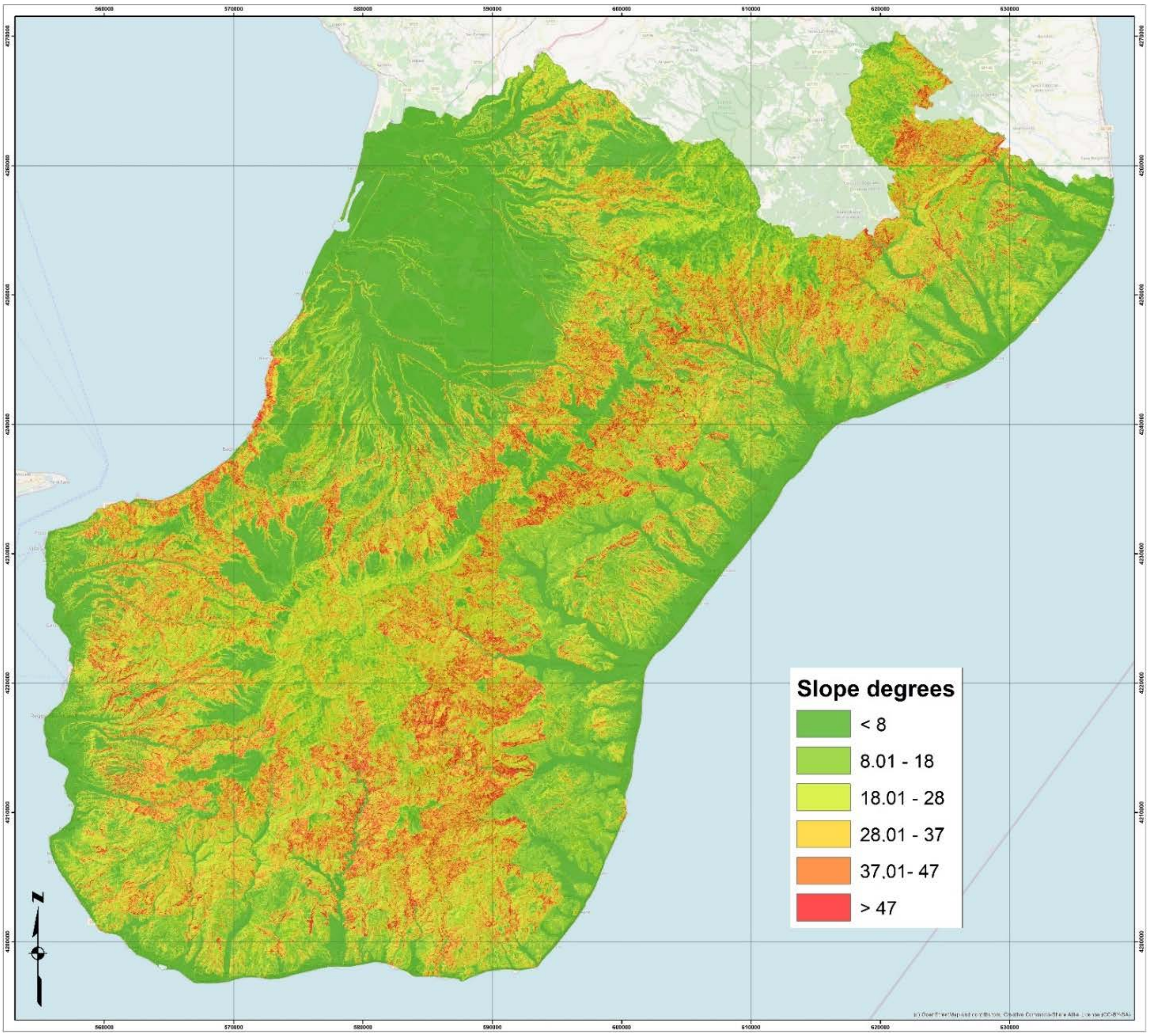
Similar to the road network, the hydrographic network was digitized and saved as line layers in the GIS database, using the topographic sheets as a data source, and buffer zones were created around the bed of the rivers and the streams of the area, at distances of 50, 100, 200, and 250 m. These distances of river are measured from the river's bed boundaries from both sides.

Each factor was characterized in classes whose weight ($\mathbf{W_{i,L}}$) was determined on the basis of the portion of the territory occupied by the class of the factor in the entire metropolitan area of Reggio Calabria (Table 1).

This method was used to identify the amount of territory that the factor class occupies to then be put into relation with the weights of the same calculated with other methods ($\mathbf{W_{i,PAI}}$, $\mathbf{W_{i,AHP}}$) and to be able to determine the degree of landslide susceptibility.

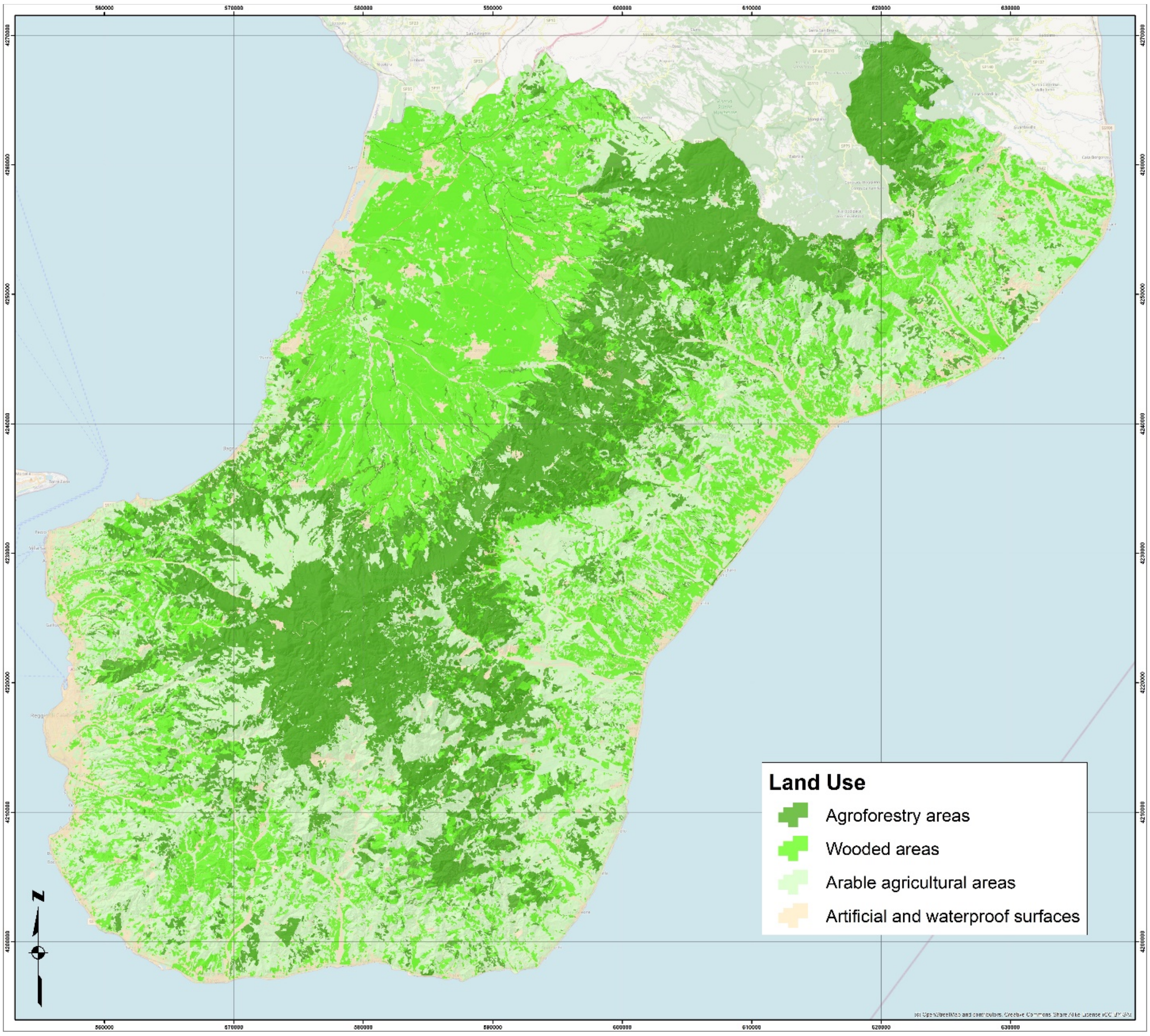
The analysis was carried out by means of GIS devices, which allow to easily analyze a considerable amount of data and to convert the map pixels into data sets.

The liability and accuracy of the collected data also influence the success of the applied methodology. For this reason, raster images were used with an accuracy of a pixel equal to 5 m. The images obtained are shown in Figure 1.



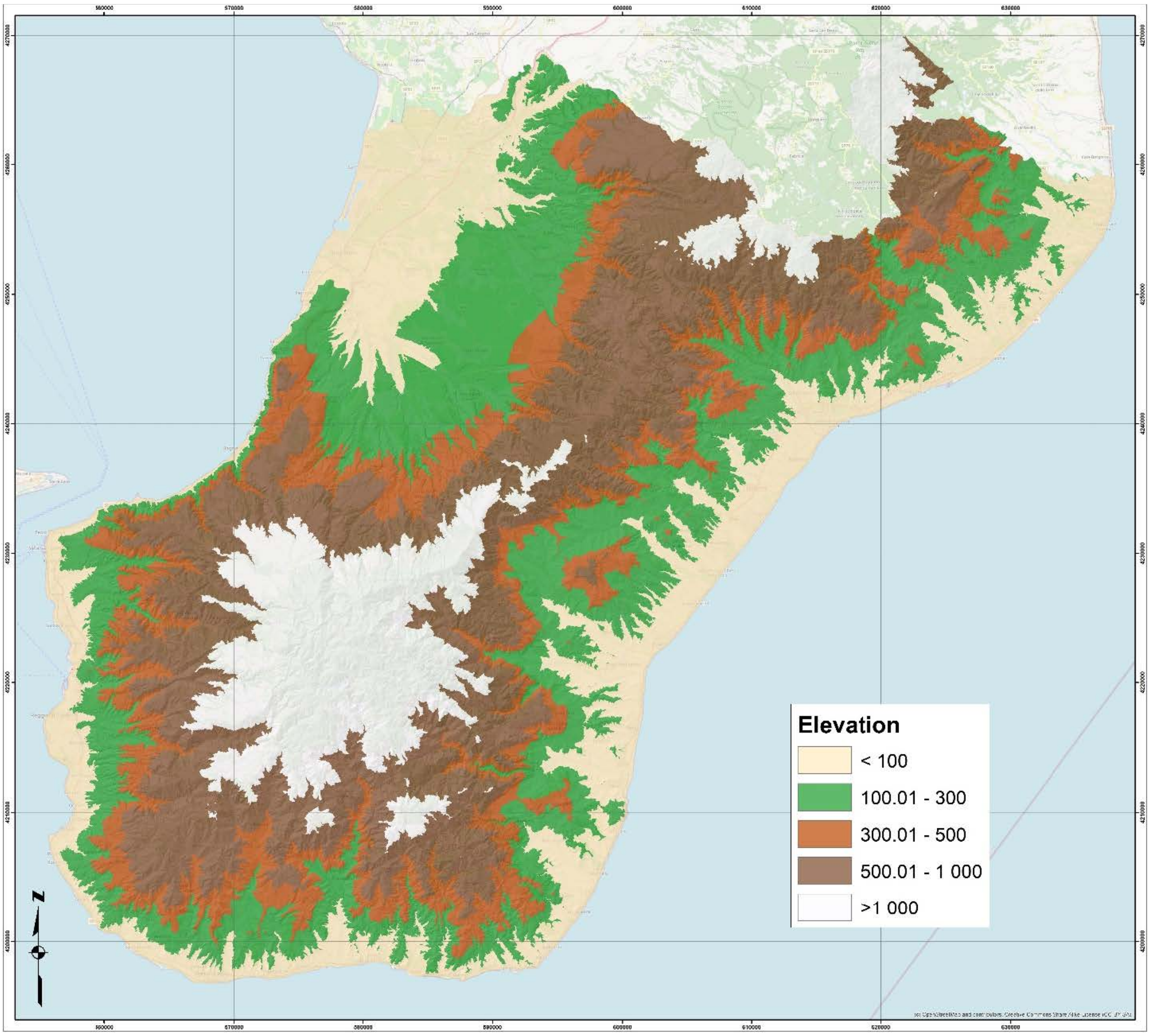
(**a**)

Figure 1. *Cont*.



(**b**)

Figure 1. *Cont.*



(**c**)

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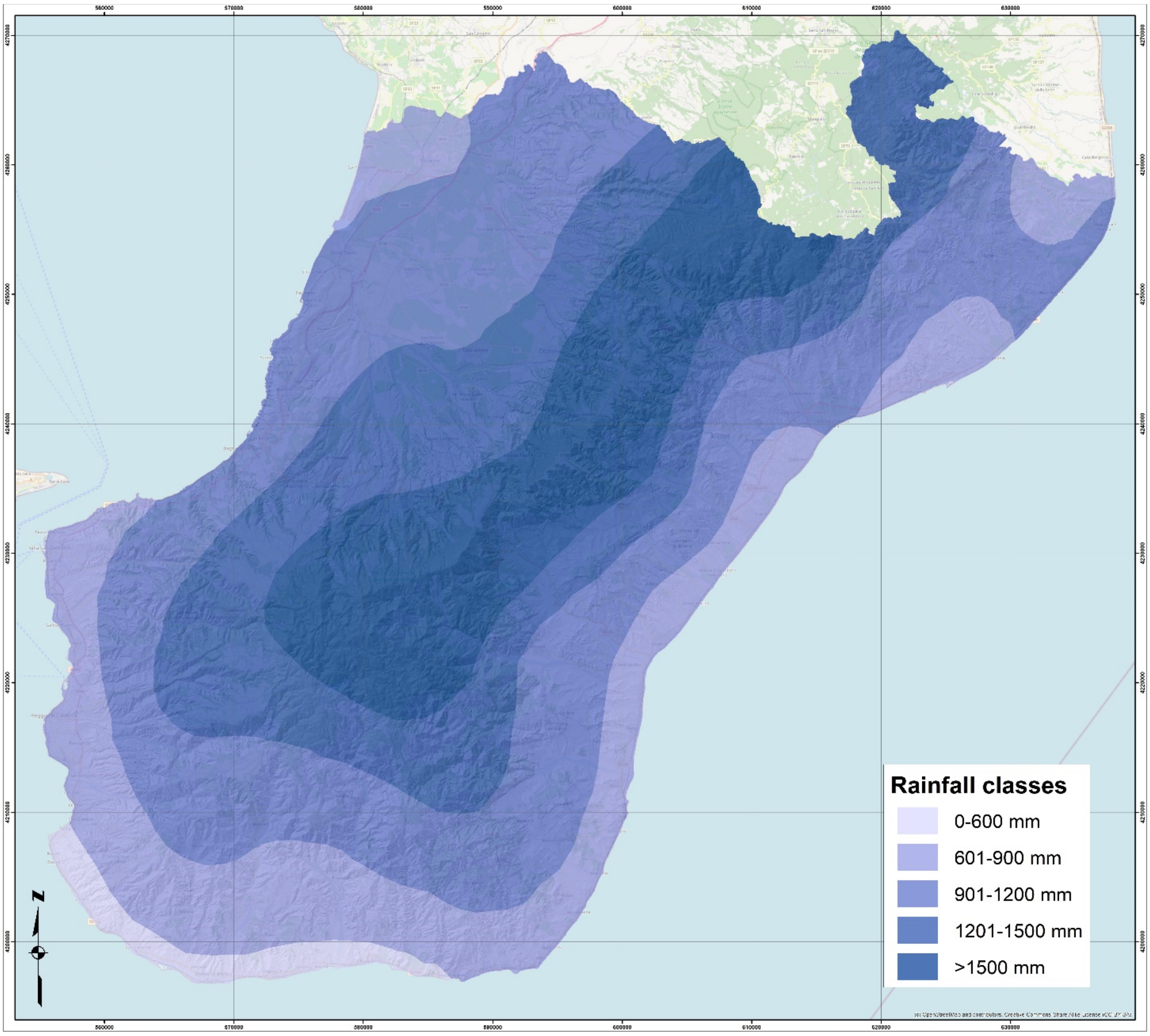

(**d**)

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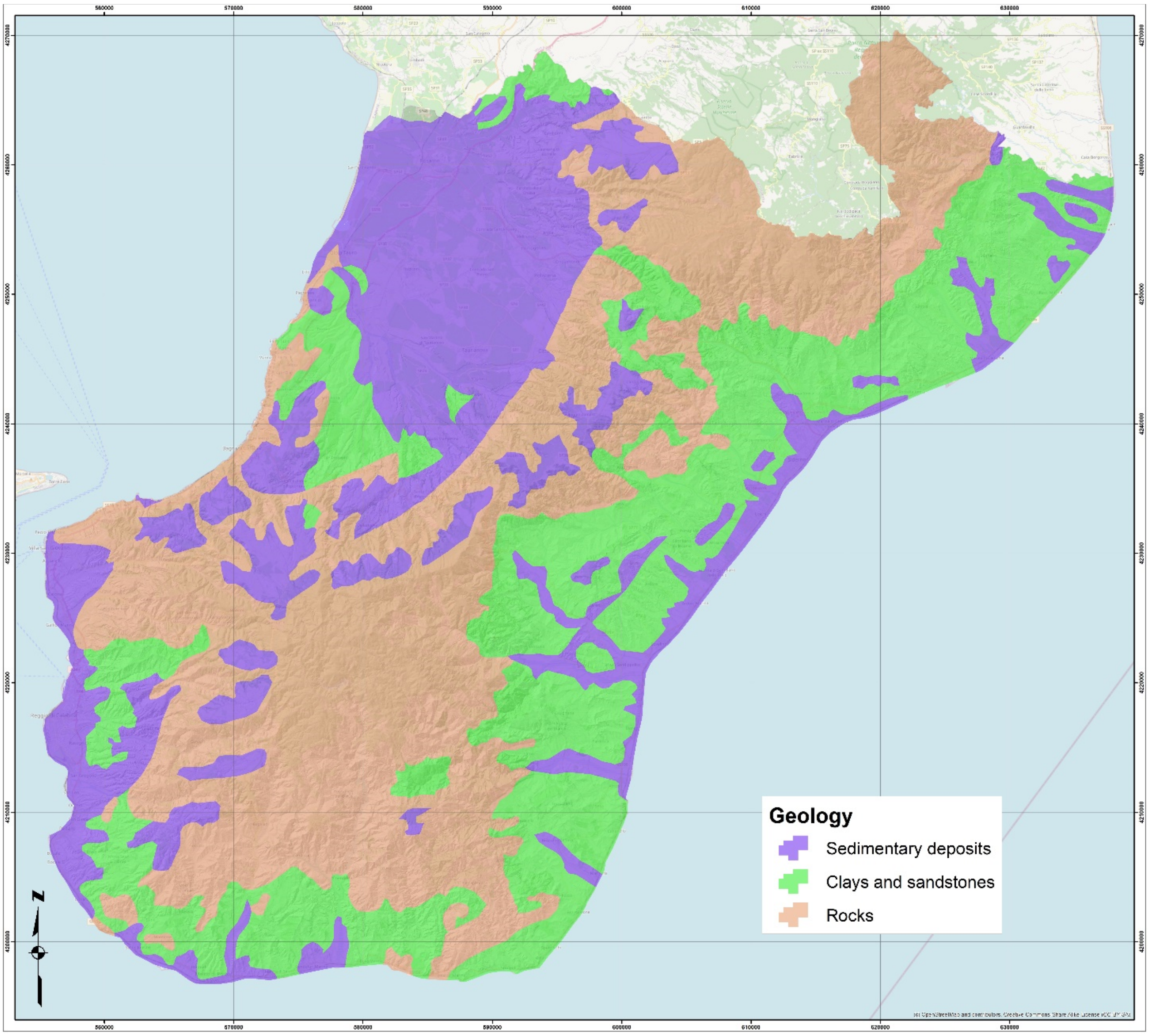
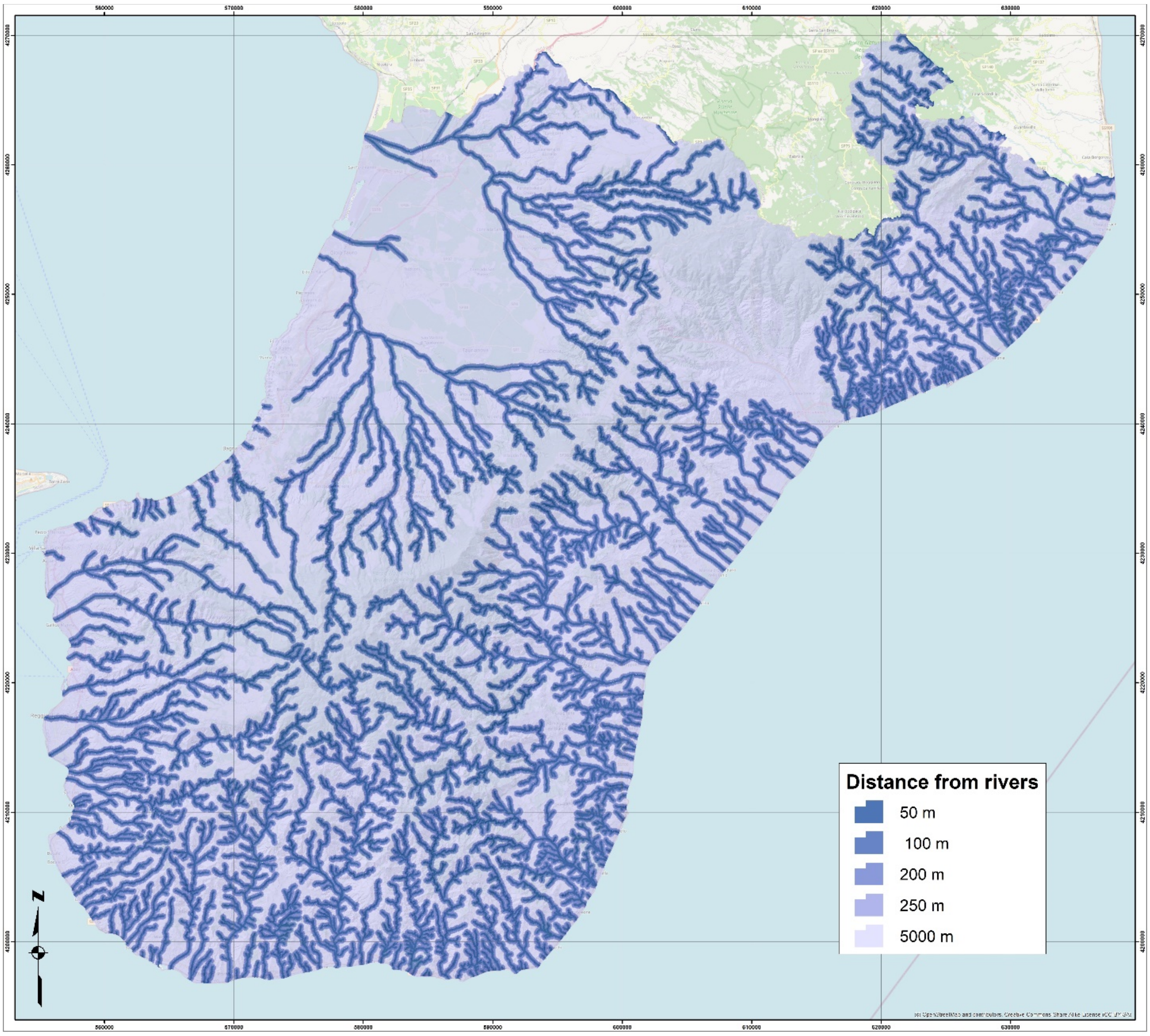


(e)

Figure 1. *Cont.*



(f)

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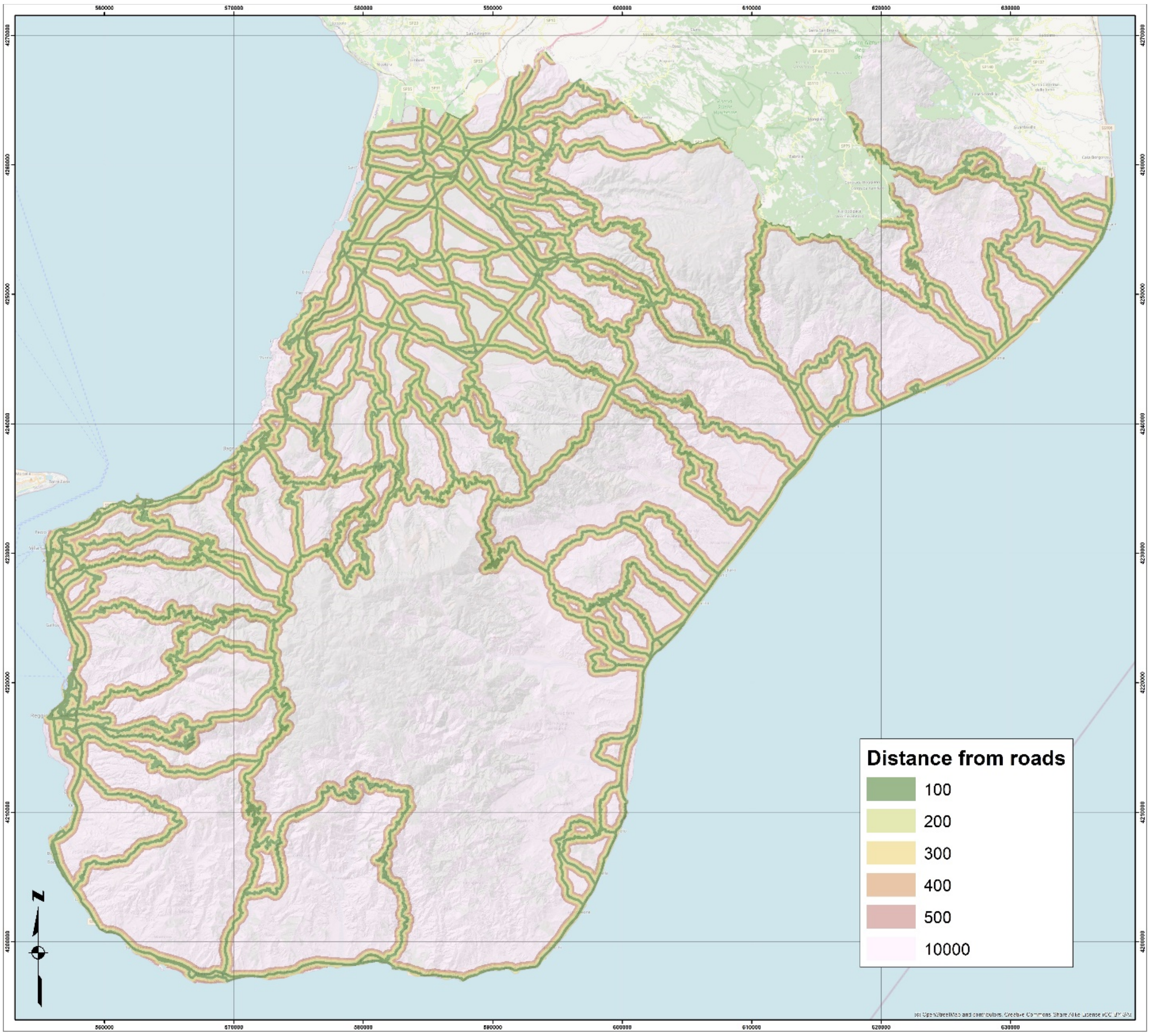
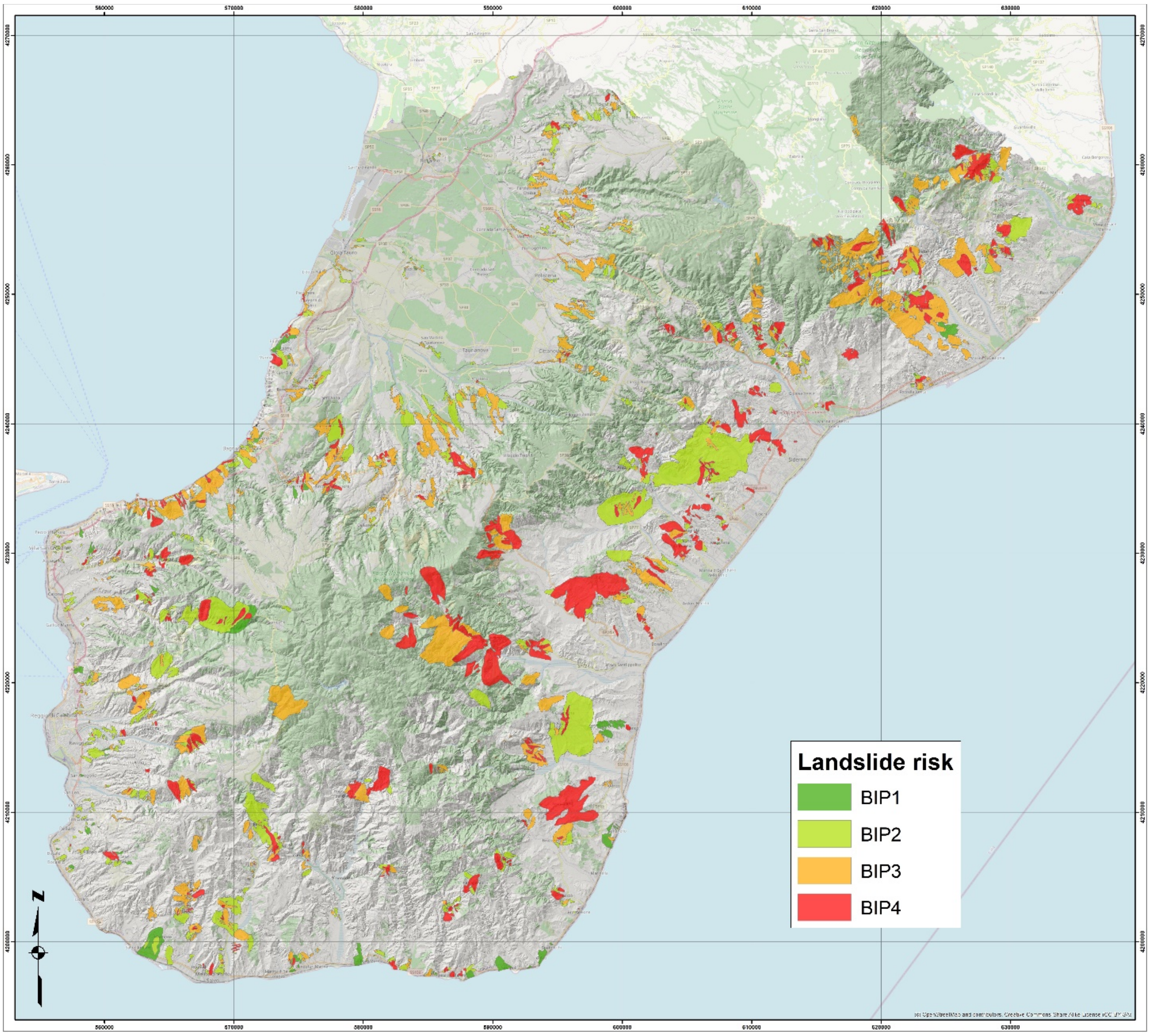


(g)

Figure 1. *Cont.*



(**h**)

Figure 1. Topographical parameter maps: (**a**) slope degree; (**b**) land use; (**c**) elevation; (**d**) rainfall; (**e**) geology; (**f**) river distance; (**g**) road distance, (**h**) PAI landslide risk areas.

So, the weight of each class was determined by the examination of the value attained by each factor class in the landslide areas identified by the PAI, with respect to the past landslide events ($\mathbf{W_{i,PAI}}$) that occurred in the territory of the metropolitan area (Table 2). This parameter allows to determine the importance of each individual class based on historical data relating to landslides that occurred in the past.

Table 2. Weight of classes of factor in the landslide areas identified by the PAI.

	Factor Class	$W_{i,L}$	$W_{i,PAI}$
Slope degree [°]	0–8	0.21	0.07
	8.01–18	0.15	0.15
	18.01–28	0.13	0.17
	28.01–37	0.09	0.11
	37.01–47	0.09	0.10
	<47	0.33	0.39
Land Use	Artificial and waterproof surfaces	0.04	0.04
	Arable agricultural areas with sparse vegetation	0.26	0.37
	Agroforestry areas with scattered trees and shrubs	0.42	0.38
	Wooded areas or areas with important vegetation	0.28	0.21
Elevation [m]	<100	0.19	0.10
	101–300	0.25	0.40
	301–500	0.15	0.23
	501–1000	0.27	0.21
	>1001	0.13	0.06
Rainfall [mm]	0–600	0.02	0.02
	600–900	0.19	0.12
	900–1200	0.36	0.46
	1200–1500	0.25	0.29
	<1500	0.18	0.11
Lithology	Sedimentary deposits	0.33	0.26
	Clays and sandstones	0.21	0.34
	Rocks	0.45	0.46
River Distance [m]	0–50	0.10	0.11
	50.01–100	0.10	0.10
	100.01–200	0.18	0.18
	200.01–250	0.08	0.08
	<250	0.54	0.53
Road Distance [m]	0–100	0.10	0.14
	101–200	0.08	0.11
	201–300	0.07	0.09
	301–400	0.06	0.07
	401–500	0.06	0.06
	>500	0.62	0.53

Later using the AHP method, we were able to obtain a relative significance of the relevant factors after the pairwise comparison matrix was constructed.

The pairwise comparison method was developed by Saaty in the context of the analytical hierarchy process. The AHP approach allows assessing the relative weight of multiple elements in an initiative manner [39].

After defining the weight of each factor, with respect to the past landslide events identified by the PAI, its relative weight was calculated with the AHP method. The rating score of relative significance was set from 1 to 9, indicating less important to much more important factors.

The pairwise comparison matrix is shown in Table 3 using a 7 × 7 matrix, where diagonal elements are equal to 1.

The row describes the importance of factor, and the values of each row are compared with each column to define the relative importance to obtain a rating score. For example, the slope is significantly more important than the elevation and therefore assigned the value 8. Conversely, the importance of the elevation with respect to the slope is equal to 1/8.

Table 3. Pairwise comparison matrix.

	Slope	Land Use	Elevation	Rainfall	Lithology	River Distance	Road Distance
Slope degree	1.00	7.00	8.00	2.00	7.00	4.00	9.00
Land Use	0.14	1.00	3.00	0.20	4.00	0.33	5.00
Elevation	0.13	0.33	1.00	0.20	4.00	0.20	8.00
Rainfall	0.50	5.00	5.00	1.00	3.00	3.00	7.00
Lithology	0.14	0.25	0.25	0.33	1.00	0.17	3.00
River Distance	0.25	3.00	5.00	0.33	4.00	1.00	5.00
Road Distance	0.20	0.20	0.13	0.14	0.33	0.20	1.00

After evaluating and confirmed the consistency of the created eigenvector matrix for the AHP method, the weight for each factor using this method was obtained (Table 4).

Table 4. Weight of normalized landslide hazard factors through AHP method.

	$\mathbf{W_{i,AHP}}$
Slope	0.403
Land Use	0.086
Elevation	0.061
Rainfall	0.242
Geology	0.037
Road distance	0.148
River distance	0.023

The landslides index for each individual pixel was finally obtained by the weighted sum of the weight determined on the basis of the portion of territory occupied by the factor class ($\mathbf{W_{i,L}}$), the weight reached by each factor class in the landslide areas identified by the PAI ($\mathbf{W_{i,PAI}}$), and the weight of the same factor obtained from the AHP method ($\mathbf{W_{i,AHP}}$).

$$\mathbf{LI} = \sum_{i=1}^{n} \mathbf{W_{i,L}} + \mathbf{W_{i,PAI}} + \mathbf{W_{i,AHP}}$$

The values thus obtained for the assessment of susceptibility were classified into five ranges; in particular, values below 0.17 represent the portions of territory with low risk, values between 0.1701 and 0.25 represent the portions of territory with moderate risk, values between 0.2501 and 0.3 represent the portions of territory with high risk, and values greater than 0.301 represent the portions of the territory with very high risk.

The above-mentioned results highlight that 61% of the whole territory of the metropolitan area is affected by a high landslide susceptibility value. In particular, the surface at low risk of landslide is equal to 7% of the entire metropolitan area, at moderate risk is equal to 32%, at high risk is equal to 36%, and at very high risk is equal to 25%.

The values obtained for the assessment of susceptibility were classified into five ranges in such a way that, having identified the lower and higher values in each range considered, the number of pixels with respect to the total was equalized between the various classes. This ensures that each class range has approximately the same number of values in each class and that the change between intervals is fairly consistent [40].

From the obtained map (Figure 2), it is possible to notice that the highly and very highly susceptible zones are the hills, i.e., the areas between the coasts and the central part of the province. These areas are particularly relevant because of the connections within the various internal urban areas and the main towns and services located along the coasts. Further, the landslide susceptibility evaluation procedure adopted resulted to be in agreement with the work performed by the Calabria Region Basin Authority: 80% of the highly and very highly susceptible areas coincide with the landslide areas identified by the PAI maps.

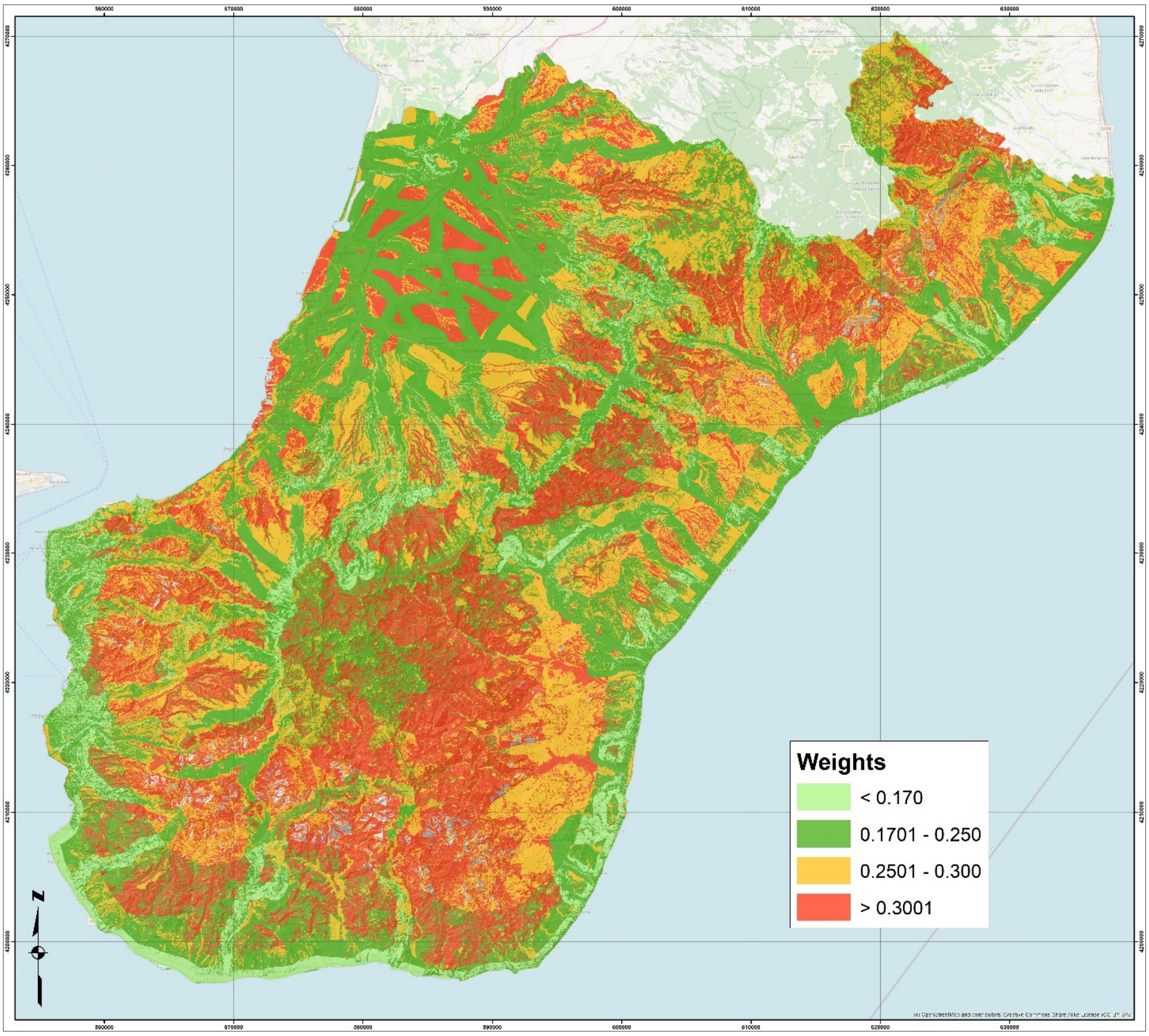


Figure 2. Landslides susceptibility map.

4. Results

The study carried out demonstrates the fragility of the Calabrian territory. From the results obtained, in fact, 38% of the metropolitan territory of Reggio Calabria appears to have a medium landslide risk and 28%, a high landslide risk. The results obtained from the model are congruent with the landslide risk areas identified by the PAI and are more reliable than previous studies [5]. In particular, the model produces an overestimation of only 8% of the areas at risk of medium–high landslide, compared to the areas surveyed by the PAI, thus also managing to determine the risk of landslides in those areas not classified by the PAI due to the absence of exposed elements. These areas, however, are still of fundamental importance, as they are crossed by connecting infrastructures.

This method could be used in other areas of the Calabria Region for the realization of the landslide susceptibility map in order to be able to use the maps obtained to plan the safety of the slopes or, in particular, identify the main road infrastructures on which to carry out work risk mitigation (lifelines). The results of this preliminary analysis can give important information on the relative criticality of the different road sectors, thereby allowing attention and economic budgets to be shifted toward the most critical aspects, where structural and non-structural mitigation measures could be implemented. In such a sense, they supply useful information regarding the intervention priorities and, above all, a scale of inspection surveys and analyses of a structural nature which can find the effective level of susceptibility of the infrastructure, as well as the most opportune mitigation actions for the reduction of risk levels. This latter aspect will be the subject of future studies.

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