Journal of Environmental Management 373 (2025) 123672

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Multi-criteria decision analysis for monitoring and evaluating soil erosion risk in forest fire-affected areas

Francesco Vito Ronco [a,b], Annunziata Fiore [a,*], Giovanni Romano [a,**], Giovanni Francesco Ricci [a], Gabriele Nolè [c], Francesco Gentile [a]

[a] Department of Soil, Plant and Food Sciences, University of Bari Aldo Moro, Via Giovanni Amendola, 165/a, Bari, Italy
[b] Apulia Region Civil Protection Department, Via delle Magnolie 6/8, Bari, Modugno, 70026, Italy
[c] CNR IMAA, Tito Scalo, Potenza, 85050, Italy

ARTICLE INFO

Keywords:
Land suitability analysis
Decision support
AHP
Multicriteria evaluation
Ordered weighted averaging
Weighted linear combination

ABSTRACT

Wildfires lead to socio-economic and environmental impacts. These impacts include hydrological instability, which can cause severe damage, especially where infrastructures are present. Post-rehabilitation measures can be useful in reducing or preventing erosion or hydrogeological risks. Decision-makers are called on to prioritize post-fire intervention areas and allocate public funds for this purpose. This work focuses on the assessment of erosion and hydrological risk potential in forested slope areas affected by wildfire using a Multi-Criteria Decision Analysis (MCDA) approach integrated with a GIS environment on a regional scale. Expert perception was considered using the pairwise comparison method as part of the Analytical Hierarchy Process (AHP). This allows expert stakeholders to rank relevant criteria, providing a quantitative metric (weight) for qualitative data. Two MCDA methods are used and compared: Weighted Linear Combination (WLC) and Ordered Weighted Averaging (OWA). Fire frequency, slope (gradient and length), and proximity to infrastructures were found to be the most important factors by the stakeholders. The WLC method provides evidence classified into high and moderate suitability class areas characterized by high values for fire frequency or slope gradient. Conversely, the OWA method, ranging from low to high risks, makes it possible to adapt the method and obtain a range of suitability maps. Novelties of the MCDA-GIS combined methodology adopted in this work are its application on a regional scale and the combination of vulnerability and driving-force factors (namely presence of grey infrastructures, fire frequency). The MCDA-GIS methodology can be suitable for public administrations in that it allows for mapping a regional area more quickly and thus facilitates sector planning.

1. Introduction

The Mediterranean region is highly susceptible to wildfires due to natural and anthropic factors including the high population density, the large number of buildings in interface areas with natural zones, the climatic conditions (such as drought and high temperatures in summer), the abandonment of some rural areas, and the consequent accumulation of fuel, which can contribute to the ignition and spread of fires, especially in summer (Shakesby, 2011; Urbieta et al., 2015; De Girolamo et al., 2022; Zema and Lucas-Borja, 2023). Indeed, as evinced in recent studies (Dupuy et al., 2020; San-Miguel-Ayanz et al., 2022), there is a growing trend in terms of the number of wildfires in European (EU) countries. In 2022 about 900,000 ha of natural areas were affected by forest fires, including 365,000 ha that were part of "Natura 2000" sites (San-Miguel-Ayanz et al., 2023). Moreover, as highlighted by Gomes Da Costa et al. (2020), most of the affected areas (almost 85%) fall within Mediterranean EU countries, such as Italy, Greece, France, and Spain. This scenario could be further exacerbated by the effects of climate change (De Girolamo et al., 2022; Pandey et al., 2023). The technical report produced by the European Commission's Joint Research Centre (JRC) on forest fires in Europe, the Middle East, and North Africa showed that the risk of wildfires in Italy was higher compared to the average value for the reference period (1988–2020) and the number of fires had increased by 9.1% compared to previous years. At regional

* Corresponding author.
** Corresponding author.
E-mail addresses: francesco.ronco@uniba.it, f.ronco@regione.puglia.it (F.V. Ronco), annunziata.fiore@uniba.it (A. Fiore), giovanni.romano@uniba.it (G. Romano), giovanni.ricci@uniba.it (G.F. Ricci), gabriele.nole@imaa.cnr.it (G. Nolè), francesco.gentile@uniba.it (F. Gentile).

https://doi.org/10.1016/j.jenvman.2024.123672
Received 22 May 2024; Received in revised form 22 November 2024; Accepted 7 December 2024
Available online 14 December 2024
0301-4797/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

level, Sicily, Calabria, Sardinia, and Apulia are some of the most affected (San-Miguel-Ayanz et al., 2023).

Wildfires can have severe socio-economic and environmental impacts, such as the loss of ecosystem services (Prichard et al., 2021; Vieira et al., 2023). One of the direct effects is an increase in hydrogeological risk. Indeed, wildfires can alter the vegetation cover and reduce the ability of plants and trees to stabilize the soil, and they can also modify the chemical and physical properties of the soil (Lucas-Borja et al., 2018; Lasaponara et al., 2019; Argentiero et al., 2021; Francos et al., 2023). The excessive heat and the accumulation of ash on soil can give rise to "soil water repellency" phenomena, which contribute to an increase of surface runoff and a decrease of infiltration capacity in the initial periods after the occurrence of a fire, thus increasing susceptibility to sheet or rill erosion processes (Hosseini et al., 2016; Jiménez-Pinilla et al., 2016; Robichaud et al., 2020; De Girolamo et al., 2022; Gonzalez-Romero et al., 2023). The extent of post-fire hydrogeological risk depends on several factors such as fire frequency, rainfall regime, topography (slope), vegetation cover, and fire severity (Vieira et al., 2018; Argentiero et al., 2021).

To reduce hydrogeological risk and protect soils from erosion, some post-rehabilitation measures are needed (Lucas-Borja, 2021; De Girolamo et al., 2022). The European Union (EU), through its new EU forest strategy for 2030 (https://environment.ec.europa.eu/strategy/forest-strategy_en), promotes actions aimed at reducing the risks of wildfires and mitigating their impacts. In particular, ecosystem-friendly management practices can be used to restore damaged forests (Lucas-Borja et al., 2021; San-Miguel-Ayanz et al., 2022). Soil bioengineering techniques are works that combine engineering principles with the use of living plants. These techniques fall into the category of Nature-Based Solutions (NBSs), since they make it possible to control erosion processes and to increase ecosystem functions at the same time (Bischetti et al., 2014; Mickovski et al., 2022; Preti et al., 2022). The Italian law on forest fires (Decree No 353/2000) provides for the use of soil bioengineering intervention, but delegates authorization to the regions. Indeed, within the Regional Plan for Forecasting, Prevention, and Active Control of Forest Fires 2023–2025 (Resolution of the Regional Council No 758/2023), the Apulia Region is promoting soil bioengineering techniques among a range of possible post-fire protection and restoration measures.

From the point of view of decision-makers, such as Regional Forestry Offices or Regional Civil Defense Departments, one of the main issues is to prioritize those areas facing the greatest post-fire hydrogeological or erosion risk so that public funds can be allocated swiftly after a wildfire has occurred (Petratou et al., 2023). Soil erosion models, such as Morgan-Morgan-Finney (Morgan et al., 1984), RUSLE (Renard et al., 1991) or SWAT (Arnold et al., 1998), have often been used for this purpose (Nolè et al., 2020; Lopes et al., 2021; Argentiero et al., 2021; Parente et al., 2022). This approach also makes it possible to quantify the amount of soil erosion and test the impact by applying different mitigation practices (Ricci et al., 2022; De Girolamo et al., 2022). However, one of the limitations is that erosion models might consider only factors related to the amount of sediment produced (such as topography, climate, land use, and land management) (Jaiswal et al., 2015).

Multi-Criteria Decision Analysis (MCDA) is a qualitative approach used with Geographic Information Systems (GIS) software for complex decision-making (Malczewski and Rinner, 2015; Romano et al., 2015; Masoudi et al., 2021). MCDA is often preferred in landscape planning and risk mapping studies because it adds the possibility of considering complex factors (such as the proximity to grey infrastructures and the presence of protected areas), connecting pressure, drivingforces, and effects, and of including the perceptions of experts through the attribution of weights and rankings to the parameters (De Luca et al., 2015; Colapinto et al., 2020; Zhang et al., 2020; Tadesse and Tefera, 2021; Cervelli et al., 2022). For this reason, the MCDA approach has already been successfully applied in various fields, such as the identification of areas in which to implement structural measures to support socio-economic development, the assessment of the demand for ecosystem services, the identification of areas in which to implement particular cultivation systems, and the evaluation of multi-hazard susceptibility areas (Romano et al., 2015; D'Auria et al., 2018; Šiljeg et al., 2024; Zaniboni et al., 2024). With regard to wildfires, the MCDA methodology has usually been used for the identification of vulnerable or fire-prone areas (Rivière et al., 2023; Sivrikaya and Küçük, 2022). Recently, some research works have focused on the prioritization of areas suitable for post-restoration measures after a fire event (Cervelli et al., 2022; Fernandez et al., 2023; Petratou et al., 2023). However, these studies are generally applied to a specific fire event and do not consider factors related to fire occurrence (such as fire frequency), and in this sense further improvements are therefore needed (Cervelli et al., 2022).

Within this framework, this paper focuses on developing a decisional instrument based on the MCDA-GIS combined methodology, linking vulnerability and driving-force factors, such as fire frequency, hydrogeological instability, topography, climate, and the presence of grey infrastructures (such as urban settlements and roads) on a regional scale, to prioritize areas affected by fire in which certain post-rehabilitation measures such as NBSs should be implemented. Specifically, the work aims to (i) identify all the factors related to post-fire hydrogeological or erosion risk, (ii) attribute weights and rankings to parameters, and (iii) map the areas in which post-rehabilitation measures should be implemented.

The work was carried out in the Apulia Region, which is one of the Italian regions with the highest annual average number of fire events. From 2008 to 2021, Apulia ranked sixth nationally in terms of total area affected by fire. More specifically, within this time frame, there were about 120 fires covering areas over 30 ha, with an average of about 150 ha per event and 8.5 events per year (European Forest Fire Information System (EFFIS) database, https://effis.jrc.ec.europa.eu/apps/effis.statistics/estimates).

Two MCDA methods were used and compared to achieve the aim stated above: Weighted Linear Combination (WLC) and Ordered Weighted Averaging (OWA). The approach developed provides useful supporting information for decision-makers in developing strategies for prevention and control of areas affected by wildfire.

2. Materials and methods

2.1. Study area

The Apulia Region extends into the Mediterranean in an NW-SE direction and is the easternmost part of the Italian Peninsula (Fig. 1). The Region's territory has an area of about 19,350 km^2: the lowland area accounts for more than half of the entire area (53.2%), with the remaining part occupied by hills (45.3%) and just over 1% by mountains (Caldara and Pennetta, 1990). The Apulia Region boasts a remarkable abundance of forest and shrublands – set amidst a captivating natural landscape – which are important because of their ecological and environmental value.

The study area focused on the woodlands located within the regional territory of Apulia, in south-eastern Italy (Fig. 1). The National Inventory of Forests and Natural Carbon Sinks (INFC) attributes 191,738 ha of the area to Apulia's forest heritage, broken down as follows:

- 142,349 ha of forest;
- 49,389 ha of other wooded areas (short-tree forests, sparse forests, scrubland, and shrubs).

Forested areas in Apulia have increased in ten years from 179,040 to 191,738 ha (a total increase of 12,698 ha and an average annual increase of 1482 ha), and the woodland coefficient in the region has increased from 9.25% to 9.90% of the total area. If only the area

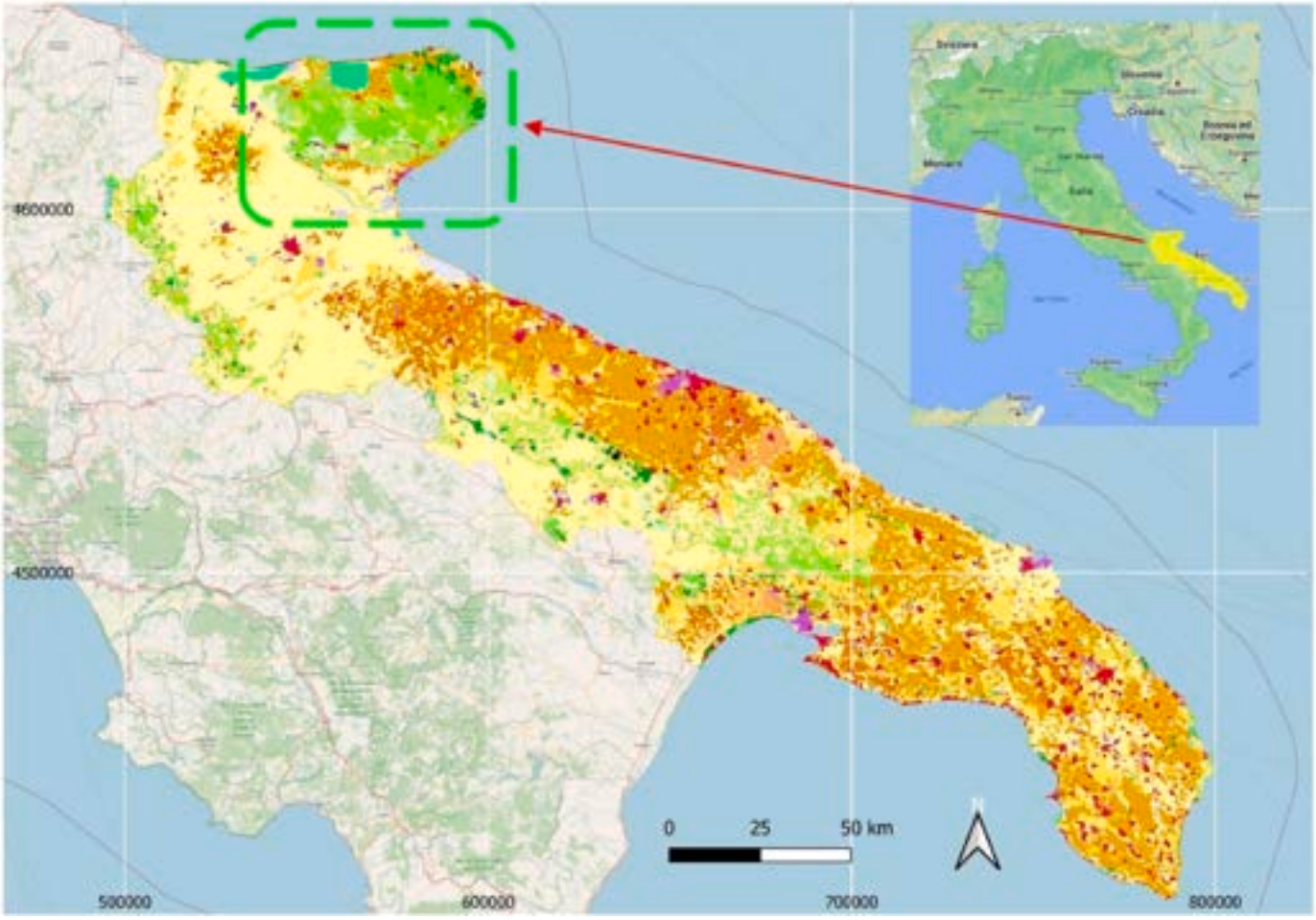

Fig. 1. Geographical position of the woodlands in the Apulia Region based on Corine Land Cover 2012 with its color legend.

classified as "forest" is considered, the index fell from a value of 7.53%–7.35%.

The average and maximum altitudes are 442 m above sea level and 1098 m above sea level, respectively. Slope ranges between 0 and 70.9°, with an average of approximately 11.7°, while the slope aspect is generally in a S-SE direction. The maximum and average values for slope length are 1770.57 m and 40.35 m, respectively. The region experiences a characteristic Mediterranean climate, which is typically mild with limited rainfall in winter, and hot and dry in summer.

Forested and semi-natural areas were identified using the Corine Land Cover 2012 inventory provided by the European Environment Agency (EEA2018 – European Environment Agency). This inventory (Supplementary Fig. S1) provides detailed thematic information on land cover across Europe. The selected land cover types are summarized in Table 1, based on the description provided by Copernicus Corine Land Cover (image collection: "COPERNICUS/CORINE/V20/100m").

2.2. Methodological approach

MCDA based on GIS provides rapid and effective explanations for complex spatial problems (Jaiswal et al., 2002; Carmel et al., 2009). Mathematical equations, economic theories, and information tools are used on computer devices (Taherdoost and Madanchian, 2023) to analyze the scores and weights across different evaluation criteria to

Table 1
Forested and semi-natural areas.

Value	Description
244	Agricultural areas > Heterogeneous agricultural areas > Agro-forestry areas
311	Forest and semi-natural areas > Forests > Broad-leaved forest
312	Forest and semi-natural areas > Forests > Coniferous forest
313	Forest and semi-natural areas > Forests > Mixed forest
321	Forest and semi-natural areas > Scrub and/or herbaceous vegetation as. > Natural grasslands
323	Forest and semi-natural area > Scrub and/or herbaceous vegetation as > Sclerophyllous vegetation
334	Forest and semi-natural areas > Open spaces with little or no vegetation > Burnt areas
421	Wetlands > Inland wetlands > Inland marshes

support decision-makers (Ju et al., 2023).

The methodology adopted in this work to build the MCDA-GIS decisional instrument is summarized in Fig. 2. The first phase consisted in the selection of the factors considered important for the aim of the study, namely to prioritize the areas subject to post-fire hydrogeological or erosion risk. To ensure that the model can be used for preventive purposes before a forest fire occurs and not for a specific fire event, factors related to burned surfaces or fire severity were replaced with factors related to vulnerability and driving force (such as fire frequency, hydrogeological hazard, and proximity to built-up and mobility areas). Moreover, slope, slope length, and Universal Soil Loss Equation (USLE) R and K factors were also included in the MCDA-GIS model. All the input layers were then delimitated in line with the boundaries of the selected study area. To better analyze the distribution of the criteria, each input layer was fuzzy linear-standardized. The next step was the application of the Analytical Hierarchy Process (AHP) through the use of a pairwise comparison matrix to determine the criteria weights (Saaty, 1977, 1980). Subsequently, using QGIS (a free and open-source professional GIS application, https://www.qgis.org/), the two MCDA procedures – WLC and OWA – were applied. In the case of OWA, two different rankings were assigned so as to consider both low and high levels of risk. Finally, the suitability maps related to both the WLC and the OWA (low and high risk) methods were created.

WLC is an aggregation method that preserves the variability of both continuous and discrete criteria characterized by a full trade-off between factors and average risk (Yousefi et al., 2018).

Both WLC and OWA procedures necessitate a standardization of factors to a common numerical range and a subsequent combination of those factors through weighted averaging. This is possible with the fuzzy operation, which can be useful in modeling transitional changes in class membership in an image (Eastman, 2003) and standardizing spatial criteria through a continuous process (Alkaradaghi et al., 2019; Barzehkar et al., 2019). Fuzzy logic is used to resolve the uncertainty and imprecision contributed by decision-making (Kharat et al., 2016; Khastagir, 2018). A simple scaling procedure, based on the theory of fuzzy sets (Eastman, 2006) with a linear membership function (Eastman, 2003), was used for this study. WLC exhibits a full trade-off and average risk, positioned precisely midway between the "AND" and "OR" overlay operations (Supplementary Fig. S2). This means it does not lean towards extreme risk aversion or extreme risk-taking (Romano et al., 2015).

The suitability of every unit territorial element is mapped by the following equation (1):

$$WLC = \sum_{i=1}^{n} w_i x_i \bullet \prod_{j=1}^{m} c_j \quad (1)$$

where w_i = weight of factor i; x_i = standardized value of factor i; c_j = constraints; n = total number of factors; m = total number of constraints.

With the WLC method, a correct risk analysis is not always achieved, as there is the possibility that a limiting factor might be hidden by the high values of the other criteria (Romano et al., 2015). Furthermore, this method positions itself exactly in the middle of a hypothetical risk range, considering neither risk aversion nor risk propensity (Drobne and Lisec, 2009).

The OWA method introduced by Yager (1988) is a parameterized model that, unlike WLC, allows a continuous adjustment of both the level of risk assumption and the compromise among the criteria, obtaining complete control of the degree of trade-off between the criteria involved and the degree of risk (Ferretti and Pomarico, 2013), which delimits the decision strategy triangle (Supplementary Fig. S2).

The OWA method utilizes two sets of weights: criterion importance weights and order weights. Criterion importance weights determine the relative significance of each criterion in the decision-making process. Order weights allow for the adjustment of the degree of emphasis placed on different criteria. By modifying the order weights in OWA, it becomes possible to create a broad spectrum of decision support maps. These maps can encompass various combination methods, including WLC and Boolean overlay ("AND", "OR") (Jiang and Eastman, 2000). This flexibility empowers decision-makers with a diverse range of options and enables the application of different decision strategies based on their specific needs and preferences.

The OWA combination operator is defined using the following expression (2):

$$OWA = \sum_{i=1}^{n} \left(\frac{u_i v_i}{\sum_{i=1}^{n} w_i x_i} \right) z_{ij} \quad (2)$$

where u_i is the reordered ith factor weight (w_i); vi is the ith element of a set of order weights such that $v_i \in [0,1]$ and Σ $(i = 1, n)$ $v_i = 1$; $z_{1j} \geq z_{2j} \geq \ldots \geq z_{nj}$ is obtained by reordering the criterion values x_{1j}, x_{2j}, x_{nj}.

In this case, the order weights provide a low level of trade-off and position the analysis on a continuum from minimum risk-averse (AND-OWA low-risk) to maximum risk-taking (OR-OWA high-risk) (Malczewski et al., 2003).

The criterion importance weights are established by the AHP. This

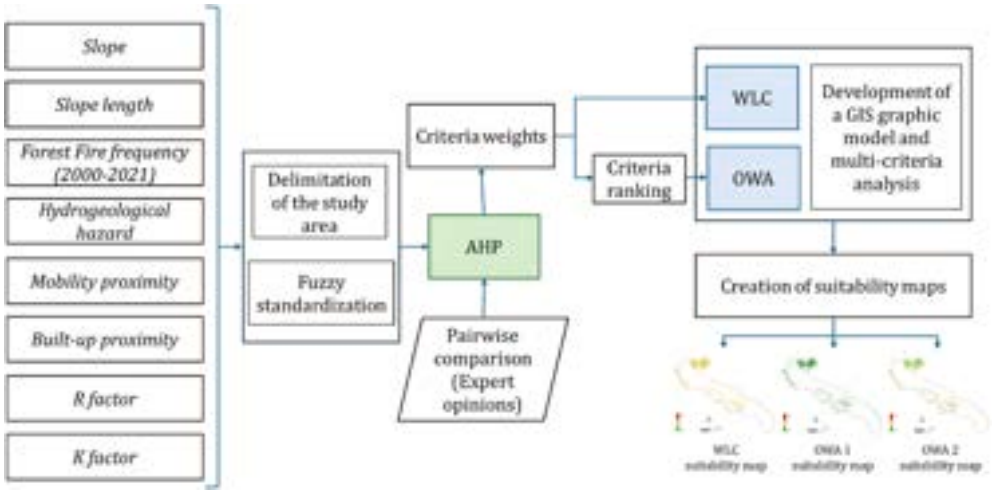

Fig. 2. Flow chart of GIS-based MCDA methods for mapping the surface-erosion potential of forested areas affected by fires, where OWA 1 represents OWA low risk and OWA 2 represents OWA high risk.

approach has been developed by Saaty (1977, 1980) and has been adopted by several researchers for multi-criteria analysis. It provides a hierarchy of decisions by breaking down a complex decision problem into the simplest option. The AHP is a comprehensive approach intended to provide flexibility for taking comparatively appropriate decisions based on subjective judgments of the decision-maker and empirical data (Zarin et al., 2021).

The AHP approach considers pairwise comparisons rather than direct assessment of scores and weights for the criteria, resulting in minor judgmental inconsistencies due to the imperfection of human decisions (Saaty, 1990). One of the advantages of this method is its hierarchical structure, through which the single factors are compared individually, thus reducing bias in the decision-making process (Hodicky et al., 2020).

The criteria identified were compared to each other using a relative importance rating scale, in a pairwise comparison matrix. The weight values were then obtained by calculating the principal eigenvector of the squared reciprocal matrix of pairwise comparisons, followed by normalization of the sum of its components to unity.

To assess the level of consistency in determining the weights and to reduce individual estimation subjectivity, a consistency ratio (CR) index (3) was employed (Gompf et al., 2021; Guillén-Mena et al., 2023). The CR index is based on the principal eigenvalue of the matrix, the order of the matrix, and the average consistency index derived from the comparisons (Boroushaki and Malczewski, 2008).

$$CR = (\lambda_{max} - n) / ((n-1)^* RI) \quad (3)$$

where λ_{max} is the largest or principal eigenvalue of the matrix, n is the number of criteria or factors, and RI is the random index and corresponds to the average of the resulting consistency index depending on the order n. If the calculated CR is less than 0.1, this indicates that the pairwise comparison matrix exhibits acceptable consistency. In such cases, the derived weight values can be considered reliable and can be used for further analysis. However, if the CR is equal to or greater than 0.1, this suggests that the matrix lacks consistency and requires adjustment. This typically involves modifying the values of the elements within the matrix to improve its overall consistency (Chen et al., 2010; Eastman, 2006; Zarin et al., 2021).

The creation of the pairwise comparison matrix for this work required collection input from various stakeholders, considered the most representative in the regional management of post-fire hydrological and erosion risk and planning of mitigation measures, due to their connection with the Apulia Region's forest fire prevention plan (Regional Plan for Forecasting, Prevention, and Active Control of Forest Fires, 2023–2025, Resolution of the Regional Council No 758/2023, www.protezionecivile.puglia.it/): public administrations, Carabinieri forestry officers (Carabinieri Forestali), research centers, and freelancers in the field (agronomists and foresters). Civil defense personnel were selected as public administrators involved in the prevention of environmental disasters and responsible for dealing with local emergency management, along with Carabinieri Forestali. To gather the perspective of experts in environmental fields and earth sciences, researchers from the University of Bari and the National Research Council (CNR) were asked to compile the pairwise comparison matrix. Lastly, expert freelancers in the field contributed to land use planning and the implementation of regeneration works (such as soil bioengineering techniques). The selection of a heterogeneous panel of experts (three from each sector in this work) contributes to reducing bias (Guillén-Mena et al., 2023).

2.3. Dataset and work steps

In this work, the following input layers were used:

- Copernicus CORINE Land Cover (CLC) 2012 inventory, based on www.land.copernicus.eu/en/products/corine-land-cover;
- Digital Terrain Model (DTM) for Apulia, based on www.sit.puglia.it;
- Technical Map of the Apulia Region, based on www.sit.puglia.it;
- European Soil Data Centre (ESDAC) database, based on www.esdac.jrc.ec.europa.eu/;
- Hydrogeological Plan for the Apulia Region, based on www.distrettoappenninomeridionale.it;
- Wildfire Register for the Apulia Region, based on www.protezionecivile.puglia.it/and www.geoportale.incendiboschivi.it/.

All of these tools were downloaded and used to create the datasets used in the MCDA-GIS decisional instrument. The first step involved delimitating the area investigated. The boundary map for multi-criteria evaluation was created using the Copernicus Corine Land Cover (CLC, 2012) dataset. The Copernicus CLC map, imported from the Google Earth Engine data catalog, was employed in cloud computing to capture the woodland areas of the Apulia Region. The core technical parameters of CLC, including a nomenclature consisting of 44 classes, a minimum mapping unit (MMU) of 25 ha, and a minimum mapping width of 100 m, have remained unchanged since its inception.

The second step dealt with the creation of a constraint layer grouping all the unsuitable areas. For the implementation of this process, GIS-based constraint mapping was used to eliminate built-up surfaces.

To identify the most suitable woodland locations for planning targeted interventions aimed at soil erosion control, a comprehensive set of criteria (Table 2) (Wischmeier and Smith, 1978; Moeinaddini et al., 2010; Hosseini et al., 2016) was chosen using information from multiple sources. The criteria that are constant at any location were not considered.

Slope and slope length are critical factors to be considered when assessing soil stability risk and feasibility of land for various purposes. By incorporating slope and slope length as criteria in MCDA, decision-makers can not only determine the compatibility of land with specific land uses but can also avoid unsuitable areas, promote sustainable development, and implement appropriate measures to mitigate erosion, maintain soil productivity, and preserve biodiversity.

The slope and slope length maps were generated from the regional 8 m-resolution Digital Terrain Model (DTM). The slope calculation for each raster cell involved measuring the descent between the cell and its eight surrounding cell neighborhoods. The highest descent value observed among the neighborhood cells was recorded as the slope for the particular cell and was expressed in degrees. The slope length was then calculated, and both the raster layers were linear-standardized to a scale of 0–1.

The importance of infrastructure proximity in multi-criteria evaluation depends on the specific context and objectives of the evaluation, which can vary from project to project. In this work, urban and road proximities were considered in terms of their relative importance in enhancing connectivity between different locations. Furthermore, the infrastructure proximity selected directly affects accessibility. The closer a location is to essential infrastructure such as urban settlements, roads, railways, or utilities, the easier it is for people to reach and utilize the area. Evaluating infrastructure proximity helps identify vulnerabilities and facilitates rapid intervention actions in sites with higher economic opportunities and attractiveness in terms of development and competitiveness. Infrastructure proximity is crucial in assessing resilience and disaster management capabilities. Proximity to evacuation routes, emergency services, and disaster-resistant infrastructure can enhance a location's ability to respond to and recover from natural or man-made disasters. Evaluating infrastructure proximity helps identify vulnerabilities and strengths related to disaster preparedness.

The Technical Map of the Apulia Region (1:5000) provides information, in vector format, about regional mobility and built-up settlements. The road network map derives from the selection of highways, railways, and state, provincial, and municipal roads. In the GIS environment, the vector data were converted into raster format with 8 m spatial resolution, as for the DTM. QGIS software allows for rasterization, calculation of Euclidean distances and proximity, and

Table 2
The evaluation criteria with fuzzy membership shape.

Main criteria	Criteria	Control points				Shape of fuzzy membership
		a	b	c	d	
Physical	Slope	0	72.3	–	–	Monotically increasing
	Slope length	0	1465	–	–	Monotically increasing
Distances from	Roads and railways	4514	0	–	–	Monotically decreasing
	Built-up	2447	0	–	–	Monotically decreasing
Geomorphological	K factor	0.016	0.046	–	–	Discrete
	Hydrogeological class	0	6	–	–	Discrete
Climatic	R factor	671	2497	–	–	Monotically increasing
Anthropic	Forest fire frequency	0	8	–	–	Monotically increasing

standardization with the aim of "Graphical Modeler", a powerful tool that allows users to create and execute custom geospatial workflows in a graphical interface. It provides a visual method for designing, automating, and executing complex geospatial analysis processes by connecting predefined algorithms, tools, and data inputs/outputs.

The map of hydraulic risk was generated starting with the three levels of hydraulic risk (high, medium, and low) mapped by the Hydrogeological Plan for the Apulia Region.

The rain erosivity factor and soil erodibility factor maps were taken from the European Soil Data Centre (ESDAC) database.

Lastly, the Wildfire Register for the Apulia Region provided data on forest fire occurrence. The frequency of forest fires was determined by overlaying fire events from 2000 to 2021.

A workflow was designed by the QGIS Graphical Modeler to wrap the pre-elaboration operations up to the standardization of every criteria layer into a single process. Fig. 3 provides an example of the graphic model used to layer pre-elaboration and standardization for infrastructures. The pre-processing phase can differ depending on the reference factor chosen.

To provide a visual interpretation, in the final step, the range of values from minimum to maximum was grouped into four suitability classes – low, marginal, moderate and high (Charabi and Gastli, 2011). Suitability classes were therefore more clearly identified.

The results were represented both for the whole study area and using an inset, to better highlight the differences between the methodologies. Specifically, the Gargano area was selected as a representative zone to assess the connection between the factors considered and the multi-criteria analysis methods.

3. Results

Regarding the AHP method, the analysis of the expert opinion carried out through the pairwise comparison matrix (Table 3) revealed that wildfire frequency is the main factor influencing post-fire erosion risk, followed by the two slope factors (gradient and length), and proximity to mobility services and built-up areas. K factor, R factor, and hydrological hazards were the factors with the lowest weights (a sample of data collected from one expert from each group can be found in the supplementary material, specifically from Table S1 and Table S5).

The principal eigenvalue (λ_{max}) was computed along with its consistency ratio index (CR), which yielded a value of 0.071. This result, being less than 0.1, indicates a confirmation of both the logical consistency of the judgments provided by the stakeholders and the acceptability of the outcomes.

The unsuitable areas were first grouped in a constraint layer, then the fuzzy criteria were standardized. The type of fuzzy function and the membership function shape are reported in Table 2. To better analyze the distribution of the criteria, the result maps in Fig. 4 show the Gargano inset area, which was selected as representative of the regional forested areas.

A raster-based overlay approach was used with QGIS to perform the MCDA and produce the suitability maps for restoration intervention aimed at territory securing after a fire event. Both the WLC and the OWA methods were used. Specifically, for the WLC method (intermediate level of risk – maximum trade-off), the criteria weights (w_i) were established through the AHP (Table 3) (Saaty, 1977, 1980; Moeinaddini et al., 2010).

To take into account different levels of risk that differ from the

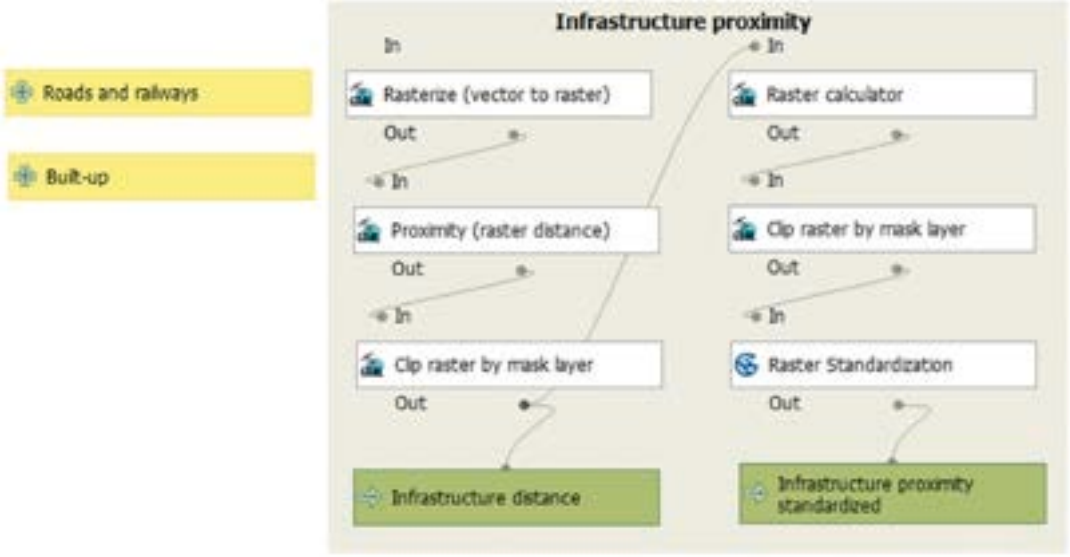

Fig. 3. Flow chart of the method used to create the standardized map of infrastructures.

Table 3
Criteria pairwise comparison matrix. The value corresponds to the mean of the expert responses.

Criteria	Slope gr	Slope lg	Wildfires fr	Mobility prox	Built-up prox	K factor	R factor	Hydr hazard	Weights
Slope gr[a]	1								15.2
Slope lg[a]	1.00	1							15.4
Wildfires fr[a]	3.00	3.00	1						25.0
Mobility prox[a]	0.50	0.50	0.50	1					13.2
Built-up prox[a]	0.50	0.50	0.50	1.00	1				13.2
K factor	0.50	0.50	0.33	0.33	0.33	1			7.0
R factor	0.50	0.33	0.50	0.25	0.25	0.50	1		6.4
Hydr hazard[a]	0.33	0.50	0.33	0.33	0.33	0.50	0.33	1	4.6

[a] Slope gr: Slope gradient; Slope lg: Slope length; Wildfire fr: Wildfire frequency; Mobility prox: Proximity to mobility services, Built-up prox: Proximity to built-up areas; Hydr hazard: Hydrological hazard.

medium level expected by the WLC procedure, two OWA methods were run. The first contemplates a low level of risk and some degree of trade-off (OWA low-risk – some trade-off), while the second contemplates a high level of risk and some degree of trade-off (OWA high-risk – some trade-off).

As reported in Table 4, the order weights were determined and ranked using distinct schemes for the two respective cases.

The categorization into the four suitability classes revealed that the areas classified as minimally, marginally, moderately, and highly suitable make up 0.09%, 96.50%, 3.415%, and 0.001% respectively of the study area (Table 5, Fig. 6).

By applying the OWA method, it is possible to control the level of risk to be presumed in the MCDA and the degree to which factor (trade-off) weights will impact the final map (Drobne and Lisec, 2009), and two suitability maps were therefore generated. The first, characterized by a low level of risk and some degree of trade-off (Fig. 5c), indicates limited suitability across the entire study area, except for some sensitive sites. When land suitability is categorized into distinct levels (Fig. 5d–Table 5, Fig. 6), the transition to the lower level of each class becomes clear. The low suitability class closely corresponded to almost the entire area studied (96.28%). Conversely, only 0.18% (3.82 km^2) of the wooded land was moderately or highly suitable for intervention (Table 5, Fig. 6).

Concerning the hypothesis of high risk and some degree of trade-off, the OWA method produced the maps drawn in Fig. 5e. When land suitability is categorized into distinct classes (Fig. 5f), it is clear that there is an increase from OWA high-risk to WLC for the moderate and high classes from 3.41% to 12.67% and from 0.001% to 1.84% (Fig. 6), respectively. The marginal class falls from 96.50% to 85.48% using the WLC method.

To better express differences between the MCDA performed using both WLC and OWA (low and high risk), results are presented for the Gargano Promontory, an inset representative of the wooded areas in the region (Fig. 7). Generally, regardless of the method considered, the distribution of the areas into the four suitability classes is the same as observed for the whole region (Fig. 5b, d, 5f).

For each MCDA method, it is possible to understand the influence of the weight assigned to each factor and then identified as one of four suitability classes (Fig. 4).

With regard to WLC (Fig. 7a and b), it is possible to observe the influence of the weight assigned to each factor. Indeed, the pixels falling in the moderate and high suitability classes correspond to areas characterized by high values for the factors fire frequency (azure circle), fire frequency and slope gradient (red circle), and slope gradient (blue rectangle).

In the case of OWA with low risk, the suitable sites are influenced by both the weight and the rank of the factors (Fig. 7c and d). The wildfire frequency (dark red circle), and the wildfire frequency, slope length and gradient (blue circle), which were the first three factors in terms of ranking, contributed to generating areas with moderate and high suitability classes (Fig. 7d). Conversely, the low-ranking factors, which were multiplied for lower scores, contributed to making the areas fall into low suitability classes.

Finally, OWA with high risk made it possible to highlight the factors that are low-ranked. Indeed, the areas suitable for intervention in Fig. 7e and f depend on the R factor (arrows) and the hydrological hazard (dark blue rectangles).

4. Discussion

Multi-criteria decision analysis (MCDA) can be successfully applied to land use planning related to environmental issues (Memarbashi et al., 2017; Shuaibu and Kara, 2019; Lombardi and Todella, 2023). This type of methodology allows consideration of multidimensional requirements (Falcone et al., 2016) to evaluate technologies and provide solutions applicable to real decision-making contexts (Lombardi and Todella, 2023). In this study, MCDA was coupled with a GIS tool to define priority areas in which restoration or prevention actions should be implemented after a wildfire event to counteract post-fire erosion processes. The weighted linear combination (WLC) and the ordered weighted averaging (OWA) procedures were used to produce land suitability maps of the Apulia Region study area. To involve decision-makers and experts and to best reflect their objectives and preferences, the analytical hierarchy process (AHP) methodology was employed (Romano et al., 2015; Marques et al., 2021; Masoudi et al., 2021; Guillén-Mena et al., 2023).

Differences in areas that fell under high and moderate suitability classifications, dependent on the characteristics of the MCDA procedures considered, can be highlighted by analyzing the results. The WLC method is based on a medium level of risk and a maximum level of trade-off. The relative weights of the factors are used to define the predominance of a given factor with respect to the others (Romano et al., 2015; Masoudi et al., 2021). This makes it possible to account fully for expert opinion. Indeed, most of the areas falling into high and moderate suitability classes (71.18 km^2) are characterized by high values of fire frequency or slope gradient. On the other hand, as evinced in the literature, the complete offsetting between factors can sometimes mean that WLC is less suitable for spatial planning (Lopes et al., 2021; Kandy et al., 2024). Indeed, in some areas a low score on a factor with a high ranking can be offset by a high score on another (Drobne and Lisec, 2009; Masoudi et al., 2021). The OWA procedure allows the factors involved in the investigations to be weighted according to both the criterion and the order weights. The introduction of the order weights makes it possible to adapt the risk level continuously between “AND” (low risk) and “OR” (high risk) methods and to obtain a wide range of possible suitability maps (Romano et al., 2015; Drobne and Lisec, 2009). In this work, the results for the two extremes (low and high risks) were analyzed. With the OWA low-risk method with some level of trade-off, only 3.82 km^2 fell into high and moderate suitability classes. This reflects the fact that the operator “AND” is very constraining and considers only areas with higher rank orders (Romano et al., 2015; Lopes et al., 2021). Conversely, with the OWA high-risk method with some level of trade-off, the factors undergo a reversal in terms of importance, since the operator “OR” focuses attention on the factors characterized by a low rank (namely hydrological hazard, R factor and K factor) (Jiang and Eastman, 2000; Masoudi et al., 2021), thus increasing the km^2 of the areas that are

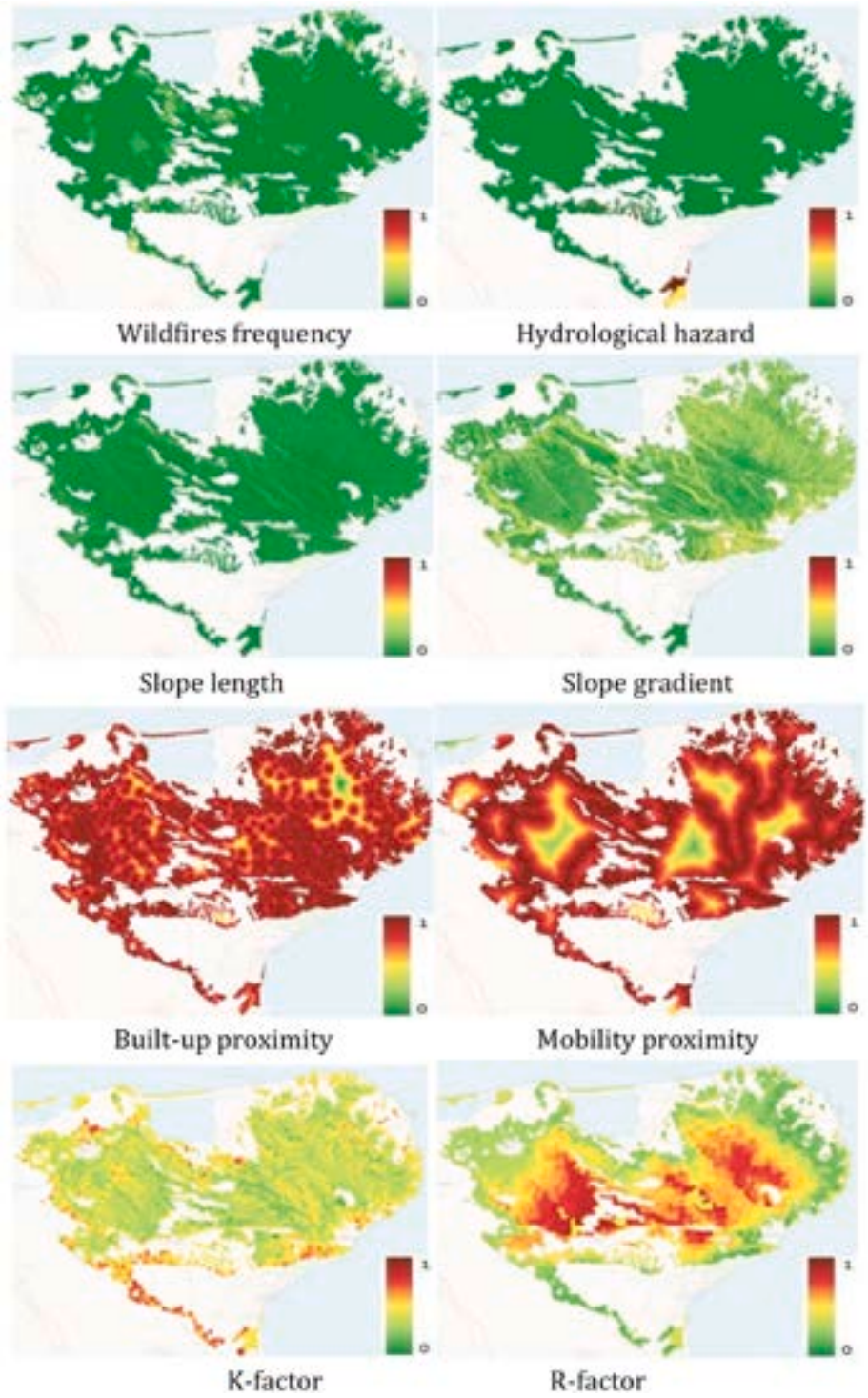

Fig. 4. Fuzzy linear standardization of continuous and discrete criteria for the Gargano area.

identified as falling within high and moderate suitability classes (302.81 km^2). However, giving less order weight to the factors that were considered of paramount importance by the expert stakeholders results in the inclusion of areas located in parts of regional territory characterized by vulnerability in terms of the issue of post-fire erosion but with a low level of risk due to low exposure (for example, because they are far from population centers and transport lines). Other works have also shown an increase in the suitability of the areas when moving from the operator "AND" to the operator "OR" (Romano et al., 2015; Rahman and Szabó, 2022; Rezvani et al., 2022). Considering the data emerging from the results and the general aim of this work – namely to develop a decisional instrument to prioritize areas affected by wildfire and at risk of erosion in which some post-rehabilitation measures should be implemented – a valid solution could be to use the OWA low-risk method and shift the decision-making triangle towards an average risk-taking position and a full trade-off based on the financial resources of the institution itself. In this way, the areas can act as a starting point for the planning analysis, which can, in turn, be reduced or increased depending on the criterion selected. Another valid solution could be coupling the WLC and the OWA procedures, as carried out by Masoudi et al.

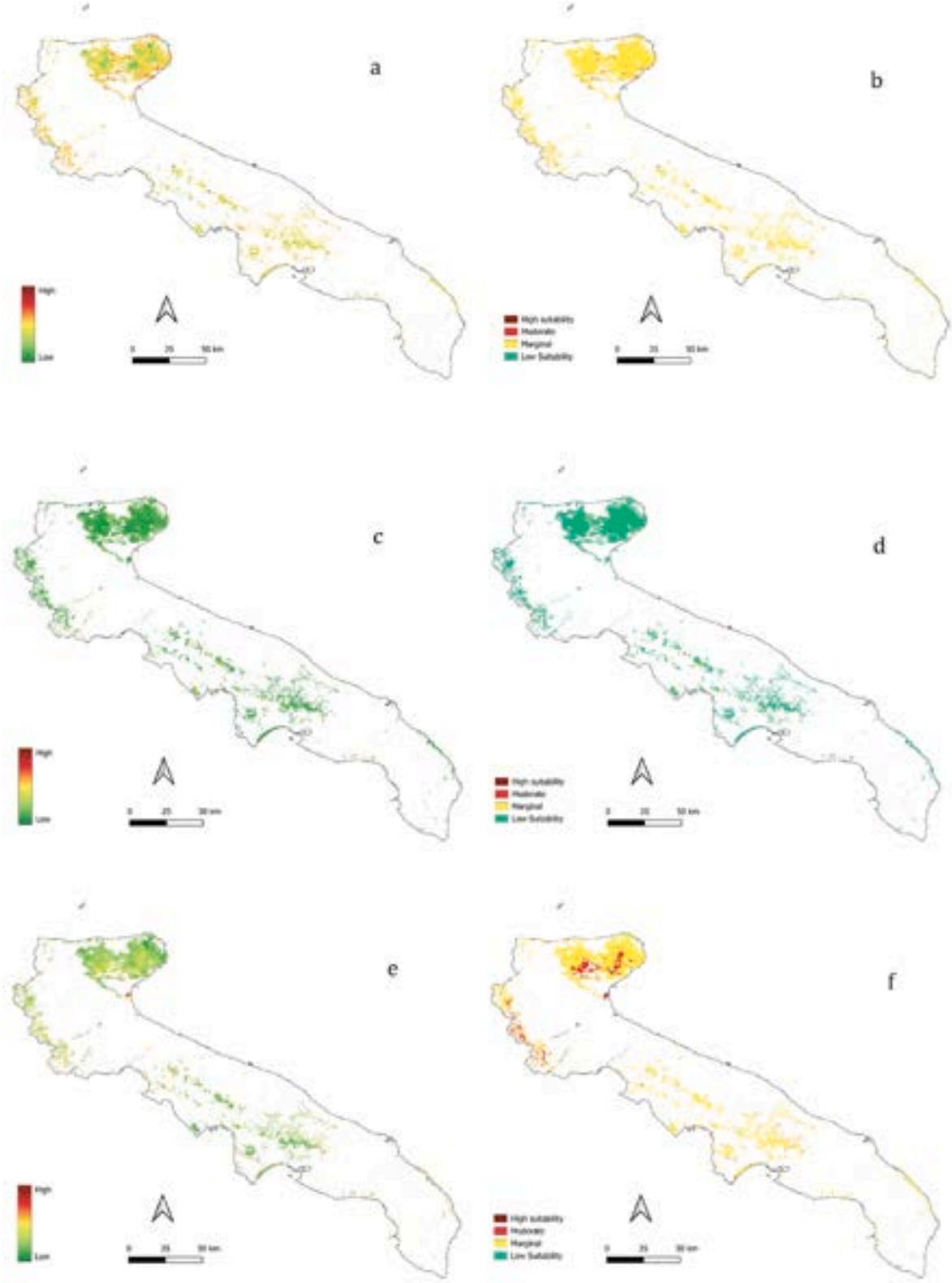

Fig. 5. Spatial distribution of land suitability (a, c, e) and land suitability classes (b, d, f) for territorial securing interventions obtained using the WLC method (a, b), the OWA method for a low level of risk and some trade-off (c, d), and the OWA method for a high level of risk and some trade-off (e, f).

(2021).

The AHP, used in both the WLC and the OWA procedures, is known for its flexibility and ease of application (De Brito and Evers, 2016). The pairwise comparisons make it possible to establish the weight of the factors by comparing each one with the others, limiting subjectivity in decision-making (Vaidya and Kumar, 2006; Guarini et al., 2018; Masoudi et al., 2021). In our work, after a literature analysis, eight factors were selected as those that most influenced the risks derived from post-fire erosion. Among these, fire frequency, slope (gradient and length), and proximity to built-up areas and mobility services were the

Table 4
Determination and classification of weights by performing the OWA method.

OWA - Low level of risk, some tradeoff								
Order weights:	0.5	0.25	0.125	0.048	0.048	0.016	0.008	0.004
Rank:	1st	2nd	3rd	4th	5th	6th	7th	8th
OWA - High level of risk, some tradeoff								
Order weights	0.004	0.008	0.016	0.048	0.048	0.125	0.25	0.5
Rank:	1st	2nd	3rd	4th	5th	6th	7th	8th

The WLC suitability map (Fig. 5a) illustrates the appropriateness values for each territorial unit of 8 m (pixel) on a scale ranging from minimum (dark green) to maximum (dark brown). Values drawn closer to dark green indicate less of a need for intervention, while values nearing red and dark brown represent higher suitability for land restoration.

Table 5
Quantification of areas of different suitability from natural engineering interventions distinguished by classes according to the WLC and OWA methods.

Procedure	Suitability classes	km^2
WLC	Low	1.86
	Marginal	2013.42
	Moderate	71.17
	High	0.01
OWA low risk some tradeoff	Low	2008.83
	Marginal	73.81
	Moderate	3.55
	High	0.27
OWA high risk some tradeoff	Low	0.24
	Marginal	1783.41
	Moderate	264.35
	High	38.46
	Total	2086.46

most important for the expert stakeholders involved. Indeed, Palmer (2022) found that in most parts of the world, the change in frequency and intensity of wildfire, coupled with the change in rainfall regime, increases the probability of debris flow events. Moreover, fires that occur in proximity to cities, roads, and railroads can cause extensive damage (Efthimiou et al., 2020; Li and Chester, 2023). This highlights the importance of strengthening the social science component of decision-making processes among professional forest managers, decision-makers, forest-dependent communities, and researchers (Muys et al., 2011). A larger group of stakeholders, including other experts (such as forestry companies) or non-experts (such as citizens), could be involved. In the latter case, it would be necessary to explain each question to ensure that its meaning is properly understood (Nordström et al., 2011; Marques et al., 2021).

Apulia is one of the Italian regions with the highest number of forest fires (San-Miguel-Ayanz et al., 2023). In this region, and in the rest of the country, climate change could lead to an increase in the frequency of wildfire events (Dupuy et al., 2020; De Girolamo et al., 2022). Decision-makers are therefore called on to prioritize those areas facing greater post-fire hydrogeological or erosion risk in order to ensure that the allocation of public funds can be evaluated swiftly after a wildfire (Petratou et al., 2023). Nature Based Solutions (NBSs) are natural techniques that can both counteract post-fire erosion and, at the same time, restore ecosystem functions (Bischetti et al., 2014; Mickovski et al., 2022; Preti et al., 2022; Bombino et al., 2024). The methodology applied in this work demonstrated its value in identifying areas subject to post-fire erosion risk throughout the Apulia Region, to provide recommendations on which areas to monitor. The combination of factors representing wildfires, grey infrastructures, and hydrogeological risks can be considered one of the strengths of this study. Specifically, the inclusion of historical data on fire frequency, which is related to the vulnerability of an area to a wildfire (Carmel et al., 2009; Khastagir, 2018), made it possible to avoid the use of a specific fire event and create a suitability map, on a regional scale, which can be used by decision-makers to plan interventions before a fire occurs. Moreover, concerning erosion models, MCDA is easier to use and makes it possible to consider complex factors related not only to the generation of the phenomena but also to the presence of human infrastructures (Zhang et al., 2020; Tadesse and Tefera, 2021; Cervelli et al., 2022). The application of the method could also be useful in highlighting high-risk suitability areas in which program interventions can be implemented before the five-year limit imposed by Italian Law No 353/2000 applies.

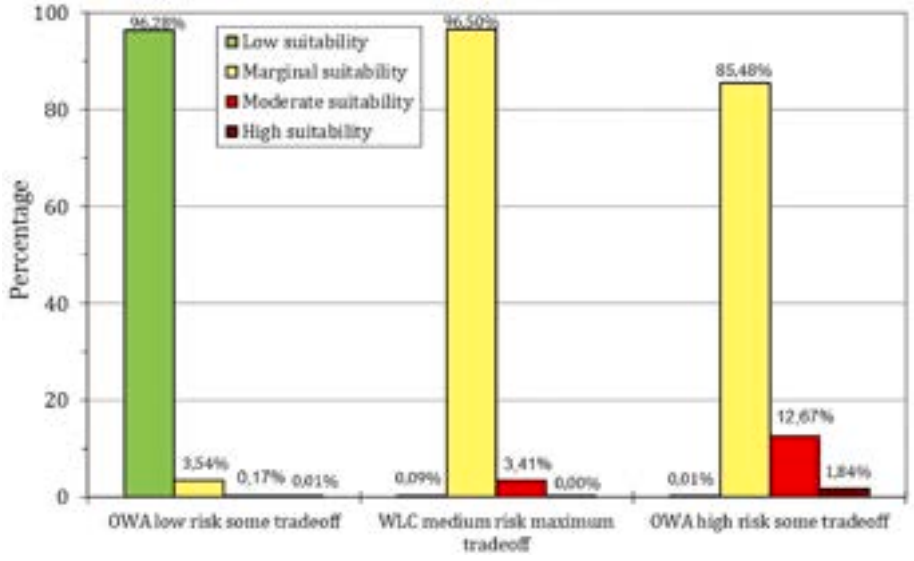

Fig. 6. Distribution of land suitability for increasing levels of risk.

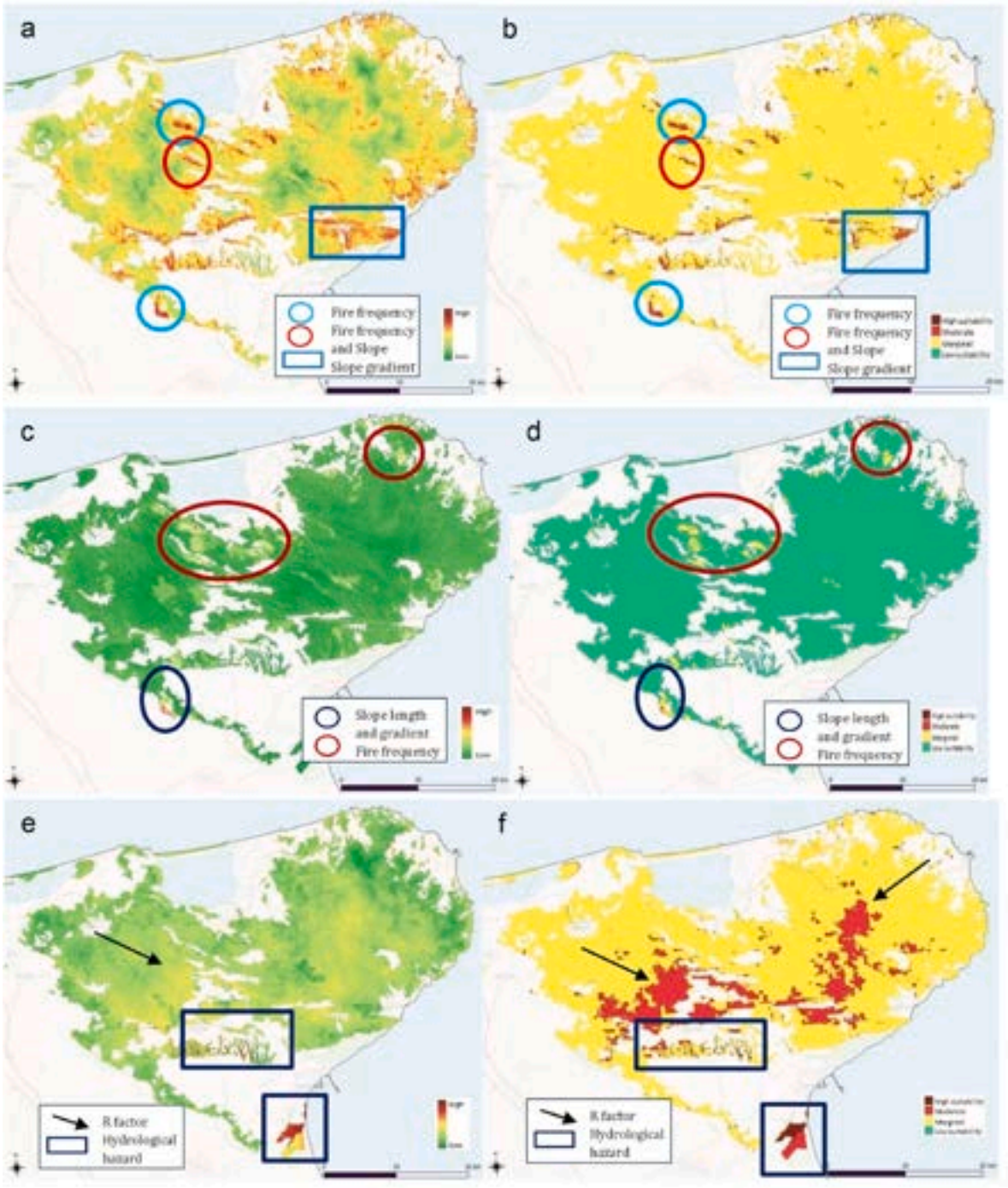

Fig. 7. Spatial distribution of land suitability (a, c, e) for territory-securing interventions and land suitability classes (b, d, f) obtained using WLC (a, b), OWA low-risk (c, d) and OWA high-risk (e, f) methods.

5. Conclusions

This study shows the advantages of the MCDA analysis method for spatial planning. Multi-criteria assessments are resolved by defining criteria, standardizing criteria, determining factor weights, and implementing a multi-criteria assessment. The problem of assigning multiple objectives is solved by standardizing the suitability maps for a single objective and assigning the best-ranked cells to each objective.

The results allowed us to understand the spatial distribution potential for land use, based on the suitability of high-to-low potential areas. According to the maps, areas with high suitability are concentrated in the areas where K factors, forest fire criterion, and hydrogeological risk are most developed.

The use of the AHP to weight the chosen criteria allowed the participation of experts and decision-makers in spatial planning.

Through this study, it is possible to highlight the advantages of using automatic methods for land use planning in the Apulia Region. Through the open-source GIS platform, expert technicians belonging to the public administration were able to implement the study.

The methodological approach implemented in this study makes it possible for fire surveillance and prevention bodies, such as the Region's Civil Protection services, to understand the sensitive areas that could be most exposed to risk as quickly as possible. This narrows the field of regional wooded areas for which it would be necessary to carry out

appropriate field checks to verify the state of post-fire soil erosion hypothesized by the MCDA analysis and, subsequently, plan appropriate interventions. To apply the planning model, the starting data could be compared with the regional areas where fires were recorded in the forest fire prevention season, with verification of the correspondence between the areas susceptible to the problem of post-fire erosion.

Finally, combining the results of this study with the management plan for the area could support sustainable development, improve living standards for residents, and protect the territory and the natural environment.

CRediT authorship contribution statement

Francesco Vito Ronco: Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Annunziata Fiore:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Giovanni Romano:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Giovanni Francesco Ricci:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Conceptualization. **Gabriele Nolè:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Francesco Gentile:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

-The research activity was financed by Civil Protection - Puglia Region program “INTERREG ipa cbc Italia-Albania-Montenegro: Project To Be Ready”.

-Ronco F.V., Fiore A. and Romano G. contributed equally to this work.

-The work of Ricci G.F. was funded by FSE REACT-EU, DM 1062 del August 10, 2021, Ricercatori a Tempo Determinato di tipo A (RTDA), Asse IV - Istruzione e ricerca per il recupero - Azione IV.4 - Dottorati e contratti di ricerca su tematiche dell’innovazione, Azione IV.6 - Contratti di ricerca su tematiche Green.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123672.

Data availability

Data will be made available on request.

References

Alkaradaghi, K., Ali, S.S., Al-Ansari, N., Laue, J., Chabuk, A., 2019. Landfill site selection using MCDM methods and GIS in the sulaimaniyah governorate, Iraq. Sustainability 11 (17), 4530. https://doi.org/10.3390/su11174530.

Argentiero, I., Ricci, G.F., Elia, M., D’Este, M., Giannico, V., Ronco, F.V., Gentile, F., Sanesi, G., 2021. Combining methods to estimate post-fire soil erosion using remote sensing data. Forests 12, 1105. https://doi.org/10.3390/f12081105, 2021.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development 1. JAWRA Journal of the American Water Resources Association 34 (1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x.

Barzehkar, M., Dinan, N.M., Mazaheri, S., Tayebi, R.M., Brodie, G.I., 2019. Landfill site selection using GIS-based multi-criteria evaluation (case study: SaharKhiz Region located in Gilan Province in Iran). SN Appl. Sci. 1, 1082. https://doi.org/10.1007/s42452-019-1109-9.

Bischetti, G.B., Di Fi Dio, M., Florineth, F., 2014. On the origin of soil bioengineering. Landsc. Res. 39 (5), 583–595. https://doi.org/10.1080/01426397.2012.730139.

Bombino, G., D’Agostino, D., Marziliano, P.A., Pérez Cutillas, P., Praticò, S., Proto, A.R., Manti, L.M., Lofaro, G., Zimbone, S.M., 2024. A nature-based approach using felled burnt logs to enhance forest recovery post-fire and reduce erosion phenomena in the mediterranean area. Land 13 (2), 236. https://doi.org/10.3390/land13020236.

Boroushaki, S., Malczewski, J., 2008. Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGIS. Comput. Geosci. 34 (4), 399–410. https://doi.org/10.1016/j.cageo.2007.04.003.

Caldara, M.A., Pennetta, L., 1990. L’evoluzione dell’ambiente olocenico nel basso Tavoliere di Puglia. Bonifica 6, 47–66.

Carmel, Y., Paz, S., Jahashan, F., Shoshany, M., 2009. Assessing fire risk using Monte Carlo simulations of fire spread. For. Ecol. Manag. 257 (1), 370–377. https://doi.org/10.1016/j.foreco.2008.09.039.

Cervelli, E., Pindozzi, S., Allevato, E., Saulino, L., Silvestro, R., Scotto di Perta, E., Saracino, A., 2022. Landscape planning integrated approaches to support post-wildfire restoration in natural protected areas: the vesuvius national park case study. Land 11 (7), 1024. https://doi.org/10.3390/land11071024.

Charabi, Y., Gastli, A., 2011. PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. Renew. Energy 36 (9), 2554–2561. https://doi.org/10.1016/j.renene.2010.10.037.

Chen, Y., Yu, J., Khan, S., 2010. Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environ. Model. Software 25 (12), 1582–1591. https://doi.org/10.1016/j.envsoft.2010.06.001.

Colapinto, C., Jayaraman, R., Ben Abdelaziz, F., La Torre, D., 2020. Environmental sustainability and multifaceted development: multi-criteria decision models with applications. Ann. Oper. Res. 293 (2), 405–432. https://doi.org/10.1007/s10479-019-03403-y.

De Brito, M.M., Evers, M., 2016. Multi-criteria decision-making for flood risk management: a survey of the current state of the art. Nat. Hazards Earth Syst. Sci. 16 (4), 1019–1033. https://doi.org/10.5194/nhess-16-1019-2016.

De Girolamo, A. M., Cerdan, O., Grangeon, T., Ricci, G. F., Vandromme, R., Porto, A. L., 2022. Modelling effects of forest fire and post-fire management in a catchment prone to erosion: Impacts on sediment yield. Catena, 212, 106080. https://doi.org/10.1016/j.catena.2022.106080.

De Luca, A.I., Molari, G., Seddaiu, G., Toscano, A., Bombino, G., Ledda, L., Milani, M., Vittuari, M., 2015. Multidisciplinary and innovative methodologies for sustainable management in agricultural systems. Environmental Engineering & Management Journal 14 (7). https://doi.org/10.30638/eemj.2015.169.

Decree No. 353/2000 https://www.parlamento.it/parlam/leggi/00353l.htm.

Drobne, S., Lisec, A., 2009. Multi-attribute decision analysis in GIS: weighted linear combination and ordered weighted averaging. Informatica 33 (4).

Dupuy, J.L., Fargeon, H., Martin-StPaul, N., Pimont, F., Ruffault, J., Guijarro, M., Hernando, C., Madrigal, J., Fernandes, P., 2020. Climate change impact on future wildfire danger and activity in southern Europe: a review. Ann. For. Sci. 77, 1–24. https://doi.org/10.1007/s13595-020-00933-5.

D’Auria, A., De Toro, P., Fierro, N., Montone, E., 2018. Integration between GIS and multi-criteria analysis for ecosystem services assessment: A methodological proposal for the National Park of Cilento, Vallo di Diano and Alburni (Italy). Sustainability 10 (9), 3329. https://doi.org/10.3390/su10093329.

Eastman, R.J., 2003. IDRISI kilimanjaro. In: Guide to GIS and Image Processing. Clark Labs, Clark University.

Eastman, R.J., 2006. IDRISI andes. In: Guide to GIS and Image Processing. Clark Labs, Clark University.

EEA, 2018 – European Environment Agency. Copernicus Land Monitoring Service – High Resolution Layer Forest Product Specifications. Copernicus Project, UE.

Efthimiou, N., Psomiadis, E., Panagos, P., 2020. Fire severity and soil erosion susceptibility mapping using multi-temporal Earth Observation data: the case of Mati fatal wildfire in Eastern Attica, Greece. Catena 187, 104320. https://doi.org/10.1016/j.catena.2019.104320.

Falcone, G., De Luca, A., Stillitano, T., Strano, A., Romeo, G., Gulisano, G., 2016. Assessment of environmental and economic impacts of vine-growing combining life cycle assessment, life cycle costing and multicriterial analysis. Sustainability 8, 793. https://doi.org/10.3390/su8080793, 2016.

Fernandez, J., Maillard, O., Uyuni, G., Guzmán-Rojo, M., Escobar, M., 2023. Multi-criteria prioritization of watersheds for post-fire restoration using GIS tools and Google earth engine: a case study from the department of santa cruz, Bolivia. Water 15 (20), 3545. https://doi.org/10.3390/w15203545.

Ferretti, V., Pomarico, S., 2013. Ecological land suitability analysis through spatial indicators: an application of the Analytic Network Process technique and Ordered Weighted Average approach. Ecol. Indicat. 34, 507–519. https://doi.org/10.1016/j.ecolind.2013.06.005.

Francos, M., Vieira, A., Bento-Gonçalves, A., Úbeda, X., Zema, D.A., Lucas-Borja, M.E., 2023. Effects of wildfire, torrential rainfall and straw mulching on the physicochemical soil properties in a Mediterranean forest. Ecol. Eng. 192, 106987. https://doi.org/10.1016/j.ecoleng.2023.106987.

Gomes Da Costa, H., De Rigo, D., Liberta′, G., Durrant, T., San-Miguel-Ayanz, J., 2020. European Wildfire Danger and Vulnerability under a Changing Climate: towards Integrating Risk Dimensions, EUR 30116 EN. Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/46951,JRC119980. ISBN 978-92-76-16898-0.

Gompf, K., Traverso, M., Hetterich, J., 2021. Using analytical hierarchy process (AHP) to introduce weights to social life cycle assessment of mobility services. Sustainability 13 (3), 1258. https://doi.org/10.3390/su13031258.

Gonzalez-Romero, J., Zema, D.A., Carrà, B.G., Neris, J., Fajardo, A., Plaza-Álvarez, P.A., Moya, D., Peña-Molina, E., de las Heras, J., Lucas-Borja, M.E., 2023. Soil erosion modelling of burned and mulched soils following a Mediterranean forest wildfire. Soil Use Manag. 39 (2), 881–899. https://doi.org/10.1111/sum.12884.

Guarini, M.R., Battisti, F., Chiovitti, A., 2018. A methodology for the selection of multi-criteria decision analysis methods in real estate and land management processes. Sustainability 10 (2), 507. https://doi.org/10.3390/su10020507.

Guillén-Mena, V., Quesada-Molina, F., Astudillo-Cordero, S., Lema, M., Ortiz-Fernández, J., 2023. Lessons learned from a study based on the AHP method for the assessment of sustainability in neighborhoods. MethodsX 11, 102440. https://doi.org/10.1016/j.mex.2023.102440.

Hodicky, J., Özkan, G., Özdemir, H., Stodola, P., Drozd, J., Buck, W., 2020. Analytic hierarchy process (AHP)-based aggregation mechanism for resilience measurement: NATO aggregated resilience decision support model. Entropy 22 (9), 1037. https://doi.org/10.3390/e22091037.

Hosseini, M., Keizer, J.J., Pelayo, O.G., Prats, S.A., Ritsema, C., Geissen, V., 2016. Effect of fire frequency on runoff, soil erosion, and loss of organic matter at the micro-plot scale in north-central Portugal. Geoderma 269, 126–137. https://doi.org/10.1016/j.geoderma.2016.02.004.

Jaiswal, R.K., Mukherjee, S., Raju, K.D., Saxena, R., 2002. Forest fire risk zone mapping from satellite imagery and GIS. Int. J. Appl. Earth Obs. Geoinf. 4 (1), 1–10. https://doi.org/10.1016/S0303-2434(02)00006-5.

Jaiswal, R.K., Ghosh, N.C., Galkate, R.V., Thomas, T., 2015. Multi criteria decision analysis (MCDA) for watershed prioritization. Aquatic procedia 4, 1553–1560. https://doi.org/10.1016/j.aqpro.2015.02.201.

Jiang, H., Eastman, J.R., 2000. Application of fuzzy measures in multi-criteria evaluation in GIS. Int. J. Geogr. Inf. Sci. 14 (2), 173–184. https://doi.org/10.1080/136588100240903.

Jiménez-Pinilla, P., Doerr, S.H., Ahn, S., Lozano, E., Mataix-Solera, J., Jordán, A., Zavala, L.M., Arcenegui, V., 2016. Effects of relative humidity on the water repellency of fire-affected soils. Catena 138, 68–76. https://doi.org/10.1016/j.catena.2015.11.012.

Ju, W., Xing, Z., Wu, J., Kang, Q., 2023. Evaluation of forest fire risk based on multicriteria decision analysis techniques for Changzhou, China. Int. J. Disaster Risk Reduc. 98, 104082. https://doi.org/10.1016/j.ijdrr.2023.104082.

Kandy, D.M., Mörtberg, U., Wretling, V., Kuhlefelt, A., Byström, G., Polatidis, H., Barney, A., Balfors, B., 2024. Spatial multicriteria framework for sustainable wind-farm planning–Accounting for conflicts. Renew. Sustain. Energy Rev. 189, 113856. https://doi.org/10.1016/j.rser.2023.113856Kharat.

Kharat, M.G., Kamble, S.J., Raut, R.D., Kamble, S.S., 2016. Identification and evaluation of landfill site selection criteria using a hybrid Fuzzy Delphi, Fuzzy AHP and DEMATEL based approach. Model. Earth Syst. Environ. 2, 98. https://doi.org/10.1007/s40808-016-0171-1.

Khastagir, A., 2018. Fire frequency analysis for different climatic stations in Victoria, Australia. Nat. Hazards 93 (2), 787–802. https://doi.org/10.1007/s11069-018-3324-x.

Lasaponara, R., Proto, A.M., Aromando, A., Cardettini, G., Varela, V., Danese, M., 2019. On the mapping of burned areas and burn severity using self organizing map and sentinel-2 data. Geosci. Rem. Sens. Lett. IEEE 17 (5), 854–858. https://doi.org/10.1109/LGRS.2019.2934503.

Li, R., Chester, M.V., 2023. Vulnerability of California roadways to post-wildfire debris flows. Environ. Res.: Infrastructure and Sustainability 3 (1), 015003. https://doi.org/10.1088/2634-4505/acb3f5.

Lombardi, P., Todella, E., 2023. Multi-criteria decision analysis to evaluate sustainability and circularity in agricultural waste management. Sustainability 15 (20), 14878. https://doi.org/10.3390/su152014878.

Lopes, A.R., Girona-García, A., Corticeiro, S., Martins, R., Keizer, J.J., Vieira, D.C.S., 2021. What is wrong with post-fire soil erosion modelling? A meta-analysis on current approaches, research gaps, and future directions. Earth Surf. Process. Landforms 46 (1), 205–219. https://doi.org/10.1002/esp.5020.

Lucas-Borja, M.E., 2021. Efficiency of postfire hillslope management strategies: gaps of knowledge. Current Opinion in Environmental Science & Health 21, 100247. https://doi.org/10.1016/j.coesh.2021.100247.

Lucas-Borja, M.E., Calsamiglia, A., Fortesa, J., García-Comendador, J., Guardiola, E.L., García-Orenes, F., Cago, J., Estrany, J., 2018. The role of wildfire on soil quality in abandoned terraces of three Mediterranean micro-catchments. Catena 170, 246–256. https://doi.org/10.1016/j.catena.2018.06.014.

Lucas-Borja, M.E., Delgado-Baquerizo, M., Muñoz-Rojas, M., Plaza-Álvarez, P.A., Gómez-Sanchez, M.E., González-Romero, J., Peña-Molina, E., Moya, D., de las Heras, J., 2021. Changes in ecosystem properties after post-fire management strategies in wildfire-affected Mediterranean forests. J. Appl. Ecol. 58 (4), 836–846. https://doi.org/10.1111/1365-2664.13819.

Malczewski, J., Rinner, C., 2015. Multicriteria Decision Analysis in Geographic Information Science, vol. 1. Springer, New York, pp. 55–77. https://doi.org/10.1007/978-3-540-74757-4.

Malczewski, J., Chapman, T., Flegel, C., Walters, D., Shrubsole, D., Healy, M.A., 2003. GIS–multicriteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. Environ. Plann. 35 (10), 1769–1784. https://doi.org/10.1068/a35156.

Marques, M., Reynolds, K.M., Marto, M., Lakicevic, M., Caldas, C., Murphy, P.J., Borges, J.G., 2021. Multicriteria decision analysis and group decision-making to select stand-level forest management models and support landscape-level collaborative planning. Forests 12 (4), 399. https://doi.org/10.3390/f12040399.

Masoudi, M., Centeri, C., Jakab, G., Nel, L., Mojtahedi, M., 2021. GIS-based multi-criteria and multi-objective evaluation for sustainable land-use planning (case study: qaleh Ganj County, Iran)"landuse planning using mce and mola". Int. J. Environ. Res. 15, 457–474. https://doi.org/10.1007/s41742-021-00326-0.

Memarbashi, E., Azadi, H., Barati, A.A., Mohajeri, F., Passel, S.V., Witlox, F., 2017. Land-use suitability in Northeast Iran: application of AHP-GIS hybrid model. ISPRS Int. J. Geo-Inf. 6 (12), 396. https://doi.org/10.3390/ijgi6120396.

Mickovski, S.B., Gonzalez-Ollauri, A., Henneton, V., 2022. Considerations on the design of shellfish reef against coastal erosion. In: Proceedings of the 2nd Vietnam Symposium on Advances in Offshore Engineering: Sustainable Energy and Marine Planning. Springer, Singapore, pp. 222–229. https://doi.org/10.1007/978-981-16-7735-9_23.

Moeinaddini, M., Khorasani, N., Danehkar, A., Darvishsefat, A.A., 2010. Siting MSW landfill using weighted linear combination and analytical hierarchy process (AHP) methodology in GIS environment (case study: karaj). Waste management 30 (5), 912–920. https://doi.org/10.1016/j.wasman.2010.01.015.

Morgan, R.P.C., Morgan, D.D.V., Finney, H.J., 1984. A predictive model for the assessment of soil erosion risk. J. Agric. Eng. Res. 30, 245–253. https://doi.org/10.1016/S0021-8634(84)80025-6.

Muys, B., Hynynen, J., Palahi, M., Lexer, M.J., Fabrika, M., Pretzsch, H., Gillet, F., Briceño, E., Nabuurs, G.-J., Kint, V., 2011. Simulation tools for decision support to adaptive forest management in Europe. Forest Systems 3 (4), 86. https://doi.org/10.5424/fs/201019s-9310.

Nolè, G., Santarsiero, V., Lanorte, A., Tucci, B., Capurso, V.A., Ronco, F.V., Murgante, B., 2020. Model of post fire erosion assessment using RUSLE method, GIS tools and ESA Sentinel DATA. Computational Science and Its Applications–ICCSA 2020: 20th International Conference, Cagliari, Italy, July 1–4, 2020, Proceedings, Part V 20, 505–516. https://doi.org/10.1007/978-3-030-58814-4_36. Springer International Publishing.

Nordström, E.M., Eriksson, L.O., Karin, Ö., 2011. Multiple criteria decision analysis with consideration to place-specific values in participatory forest planning. Silva Fenn. 45. https://doi.org/10.14214/sf.116, 2 article id 116.

Palmer, J., 2022. Nature, vol. 601. Springer, 13 January 2022. https://www.nature.com/articles/d41586-022-00028-3&sa=D&source=docs&ust=1715192054670229&usg=AOvVaw0GPo_EF0XuYLD9ZTvylUrZ.

Pandey, P., Huidobro, G., Lopes, L.F., Ganteaume, A., Ascoli, D., Colaco, C., Xanthopoulos, G., Giannaros, T.M., Gazzard, R., Boustras, G., Steelman, T., Charlton, V., Ferguson, E., Kirschner, J., Little, K., Stoof, C., Nikolakis, W., Fernández-Blanco, C.R., Ribotta, C., Lambrechts, H., Fernandez, M., Dossi, S., 2023. A global outlook on increasing wildfire risk: current policy situation and future pathways. Trees, Forests and People 14, 100431. https://doi.org/10.1016/j.tfp.2023.100431.

Parente, J., Girona-García, A., Lopes, A.R., Keizer, J.J., Vieira, D.C.S., 2022. Prediction, validation, and uncertainties of a nation-wide post-fire soil erosion risk assessment in Portugal. Sci. Rep. 12 (1), 2945. https://doi.org/10.1038/s41598-022-07066-x.

Petratou, D., Nunes, J.P., Guimarães, M.H., Prats, S., 2023. Decision-making criteria to shape mulching techniques for fire-prone landscapes. Landsc. Ecol. 1–21. https://doi.org/10.1007/s10980-023-01659-1.

Preti, F., Capobianco, V., Sangalli, P., 2022. Soil and Water Bioengineering (SWB) is and has always been a nature-based solution (NBS): a reasoned comparison of terms and definitions. Ecol. Eng. 181, 106687. https://doi.org/10.1016/j.ecoleng.2022.106687.

Prichard, S.J., Hessburg, P.F., Hagmann, R.K., Povak, N.A., Dobrowski, S.Z., Hurteau, M. D., Kane, V.R., Keane, R.E., Kobziar, L.N., Kolden, C.A., North, M., Parks, S.A., Safford, H.D., Stevens, J.T., Yocom, L.L., Churchill, D.J., Gray, R.W., Huffman, D.W., Lake, F.K., Khatri-Chhetri, P., 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecol. Appl. 31 (8), e02433. https://doi.org/10.1002/eap.2433.

Rahman, M.M., Szabó, G., 2022. Sustainable urban land-use optimization using GIS-based multicriteria decision-making (GIS-MCDM) approach. ISPRS Int. J. Geo-Inf. 11 (5), 313. https://doi.org/10.3390/ijgi11050313.

Renard, K.G., Foster, G.R., Weesies, G.A., Porter, J.P., 1991. RUSLE: revised universal soil loss equation. J. Soil Water Conserv. 46 (1), 30–33.

Resolution of the Council Regional No. 758/2023, https://burp.regione.puglia.it/documents/20135/2242783/DEL_1681_2023.pdf/7f640776-1c0b-0c3b-79cb-06b6e6106e4a?version=1.0&t=1704725060137#:~:text=758%2F2023%3B,%2D%20Con%20Decreto%20P.C.M.

Rezvani, S.M., de Almeida, N.M., Falcao, M.J., Duarte, M., 2022. Enhancing urban resilience evaluation systems through automated rational and consistent decision-making simulations. Sustain. Cities Soc. 78, 103612. https://doi.org/10.1016/j.scs.2021.103612.

Ricci, G.F., D'Ambrosio, E., De Girolamo, A.M., Gentile, F., 2022. Efficiency and feasibility of Best Management Practices to reduce nutrient loads in an agricultural river basin. Agric. Water Manag. 259, 107241. https://doi.org/10.1016/j.agwat.2021.107241.

Rivière, M., Lenglet, J., Noirault, A., Pimont, F., Dupuy, J.L., 2023. Mapping territorial vulnerability to wildfires: a participative multi-criteria analysis. For. Ecol. Manag. 539, 121014. https://doi.org/10.1016/j.foreco.2023.121014.

Robichaud, P.R., Lewis, S.A., Wagenbrenner, J.W., Brown, R.E., Pierson, F.B., 2020. Quantifying long-term post-fire sediment delivery and erosion mitigation effectiveness. Earth Surf. Process. Landforms 45 (3), 771–782. https://doi.org/10.1002/esp.4755.

Romano, G., Dal Sasso, P., Liuzzi, G.T., Gentile, F., 2015. Multi-criteria decision analysis for land suitability mapping in a rural area of Southern Italy. Land Use Pol. 48, 131–143. https://doi.org/10.1016/j.landusepol.2015.05.013.

Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15 (3), 234–281. https://doi.org/10.1016/0022-2496(77)90033-5.

Saaty, T.L., 1980. The Analytic Hierarchy Process. McGraw-Hill; McGraw Hill, New York, NY, USA.
Saaty, T.L., 1990. How to make a decision: the analytic hierarchy process. Eur. J. Oper. Res. 48 (1), 9–26. https://doi.org/10.1016/0377-2217(90)90057-I.
San-Miguel-Ayanz, J., Durrant, T., Boca, R., Maianti, P., Liberta′, G., Artes Vivancos, T., Jacome Felix Oom, D., Branco, A., De Rigo, D., Ferrari, D., Pfeiffer, H., Grecchi, R., Nuijten, D., 2022. Advance Report on Wildfires in Europe, Middle East and North Africa 2021, EUR 31028 EN. Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/039729, 2022, ISBN 978-92-76-49633-5.
San-Miguel-Ayanz, J., Durrant, T., Boca, R., Maianti, P., Liberta′, G., Oom, D., Branco, A., De Rigo, D., Ferrari, D., Roglia, E., Scionti, N., 2023. Advance Report on Forest Fires in Europe, Middle East and North Africa 2022. Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/091540, 2023.
Shakesby, R.A., 2011. Post-wildfire soil erosion in the Mediterranean: review and future research directions. Earth Sci. Rev. 105 (3–4), 71–100. https://doi.org/10.1016/j.earscirev.2011.01.001.
Shuaibu, J.A., Kara, C., 2019. Evaluating suitability for sustainable urban growth of Abuja by using MCE and GIS. International Journal of Advanced and Applied Sciences 6 (7), 68–76. https://doi.org/10.21833/ijaas.2019.07.009.
Šiljeg, A., Šiljeg, S., Milošević, R., Marić, I., Domazetović, F., Panđa, L., 2024. Multi-hazard susceptibility model based on high spatial resolution data—a case study of Sali settlement (Dugi otok, Croatia). Environ. Sci. Pollut. Res. 31 (28), 40732–40747. https://doi.org/10.1007/s11356-023-30506-8.
Sivrikaya, F., Küçük, Ö., 2022. Modeling forest fire risk based on GIS-based analytical hierarchy process and statistical analysis in Mediterranean region. Ecol. Inf. 68, 101537. https://doi.org/10.1016/j.ecoinf.2021.101537.
Tadesse, T.B., Tefera, S.A., 2021. Comparing potential risk of soil erosion using RUSLE and MCDA techniques in Central Ethiopia. Modeling Earth Systems and Environment 7 (3), 1713–1725. https://doi.org/10.1007/s40808-020-00881-z.
Taherdoost, H., Madanchian, M., 2023. Multi-criteria decision making (MCDM) methods and concepts. Encyclopedia 3 (1), 77–87. https://doi.org/10.3390/encyclopedia3010006.
Urbieta, I.R., Zavala, G., Bedia, J., Gutiérrez, J.M., San Miguel-Ayanz, J., Camia, A., Kooley, J.E., Moreno, J.M., 2015. Fire activity as a function of fire–weather seasonal severity and antecedent climate across spatial scales in southern Europe and Pacific western USA. Environ. Res. Lett. 10 (11), 114013. https://doi.org/10.1088/1748-9326/10/11/114013.
Vaidya, O.S., Kumar, S., 2006. Analytic hierarchy process: an overview of applications. Eur. J. Oper. Res. 169 (1), 1–29. https://doi.org/10.1016/j.ejor.2004.04.028.
Vieira, D.C.S., Malvar, M.C., Martins, M.A.S., Serpa, D., Keizer, J.J., 2018. Key factors controlling the post-fire hydrological and erosive response at micro-plot scale in a recently burned Mediterranean forest. Geomorphology 319, 161–173. https://doi.org/10.1016/j.geomorph.2018.07.014.
Vieira, D., Borrelli, P., Jahanianfard, D., Benali, A., Scarpa, S., Panagos, P., 2023. Burned soils in Europe require attention: post fire soil erosion is long lasting. In: EGU General Assembly Conference Abstracts. https://doi.org/10.5194/egusphere-egu23-13341. EGU-13341).
Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall erosion losses. A guide to conservation planning. Agriculture Handbook 537. Washington, DC.
Yager, R.R., 1988. On ordered weighted averaging aggregation operators in multicriteria decisionmaking. IEEE Transactions on systems, Man, and Cybernetics 18 (1), 183–190. https://doi.org/10.1109/21.87068.
Yousefi, H., Hafeznia, H., Yousefi-Sahzabi, A., 2018. Spatial site selection for solar power plants using a gis-based boolean-fuzzy logic model: a case study of Markazi Province, Iran. Energies 11 (7), 1648. https://doi.org/10.3390/en11071648.
Zaniboni, A., Tassinari, P., Torreggiani, D., 2024. GIS-based land suitability analysis for the optimal location of integrated multi-trophic aquaponic systems. Sci. Total Environ. 913, 169790. https://doi.org/10.1016/j.scitotenv.2023.169790.
Zarin, R., Azmat, M., Naqvi, S.R., Saddique, Q., Ullah, S., 2021. Landfill site selection by integrating fuzzy logic, AHP, and WLC method based on multi-criteria decision analysis. Environ. Sci. Pollut. Res. 28, 19726–19741. https://doi.org/10.1007/s11356-020-11975-7.
Zema, D.A., Lucas-Borja, M.E., 2023. Effects of prescribed fire on the post-fire hydrological processes in agro-forest ecosystems: a systematic review and a meta-analysis. Hydrol. Process. 37 (9), e14957. https://doi.org/10.1002/hyp.14957.
Zhang, H., Zhang, J., Zhang, S., Yu, C., Sun, R., Wang, D., Zhu, C., Zhang, J., 2020. Identification of priority areas for soil and water conservation planning based on multi-criteria decision analysis using Choquet Integral. Int. J. Environ. Res. Publ. Health 17 (4), 1331. https://doi.org/10.3390/ijerph17041331.