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RESEARCH ARTICLE

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Modeling climatic, terrain and soil factors using AHP in GIS for grapevines suitability assessment

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Abstract

The study carried out in Matera, Italy, used multi-criteria decision-making techniques and geographic information systems to identify optimal area management for sustainable grape production. Terrain parameters such as temperature, pH, humidity, soil texture, slope, altitude, nutrients and precipitation were considered. ArcGIS maps were created, and the northwest part of the field was identified as a favorable area. Fuzzy maps were generated, and measurements were taken in each area to determine optimal land management. The results revealed that 51% of the area was very highly suitable for agricultural activities, and 49% was considered high suitable. Receiver operating characteristic (ROC) analysis of the AHP results demonstrated a high level of accuracy, as indicated by the area under the curve (AUC). The produced maps indicated a similar trend of increasing zone management priorities for physico-chemicals as depth fluctuate. Additionally, results showed that remote sensing indices were the most important variables to predict physico-chemicals zone management. The study also highlighted that the majority of the area supported plant growth due to favorable temperature and humidity conditions, with only a small portion in the northwest showing less favorable results. By identifying management zones, the study aimed to protect crops, better use of irrigation water and improve yields. This study highlights the potential of integrating satellite remote sensing, GIS technology and AHP as a valuable tool for agricultural land use planners and policy makers in identifying optimal locations for managing grape production.

KEYWORDS
AHP model, Ffuzzy, GIS, land suitability, remote sensing, zone management

1 | INTRODUCTION

Matera, in the Basilicata region of Italy, is known for its diverse agricultural production and the economic benefits of tourism. With population growth and land depletion, efficient land use practices are crucial. Climate change, which causes the depletion of soil and water resources, makes it difficult to meet nutritional needs (Usigbe et al., 2023). Climate change poses considerable challenges to agriculture globally (Abbass et al., 2022; Mukhopadhyay et al., 2021) and this susceptibility has drawn increased attention in the literature (Chen & Gong, 2021; Cillis et al., 2018; Kogo et al., 2021; Malhi et al., 2021; Wiebe et al., 2019). Rising temperatures, changes in precipitation and extreme weather events negatively affect production (Agnolucci et al., 2020), with developing countries experiencing significant yield declines and income inequality (Anderson et al., 2020), particularly in the Mediterranean Sea region.

Agriculture is a key economic and social sector, aiming to achieve sustainable production and improve productivity levels (Denora et al., 2023). However, rapid population growth and urban development make it difficult to expand cultivated land (Silva et al., 2023). Precision agriculture, an innovative approach, uses intelligent systems to improve resource use efficiency in uniform agricultural regions (D'Antonio et al., 2015; Fiorentino et al., 2023). However, Italy faces obstacles due to the slow pace of business reorganization. Land suitability assessment involves the assessment of environmental suitability, climate-related indicators and the land itself (AbdelRahman et al., 2018; Arab et al., 2022; Elaaraj et al., 2022; Kılıç et al., 2024; Saraswat et al., 2023). Land suitability studies often use qualitative terms and vague concepts, making it difficult to categorize land into suitability classes and area management (Jones et al., 2012; Mugiyo et al., 2021). Tercan et al., (2022) highlighted the importance of assessing the suitability of land for agricultural purposes and creating commodity-based assessment indices/models to establish sustainable and effective agricultural policies and achieve the self-sufficiency in agricultural production. Geographic information systems (GIS) can help by facilitating the application of fuzzy models and creating land suitability and area management maps (AbdelRahman et al., 2018; AbdelRahman & Metwaly, 2023; Saraswat et al., 2023).

Analytical Hierarchy Process (AHP) is a widely used technique for multi-criteria analysis, facilitating complex decision-making processes (Saaty, 1990; Saaty, 2008). Assessment and analysis of land suitability for agricultural activities are essential tasks in land management (Kumar et al., 2020). One example is the study by (Özkan et al., 2020) who used spatial fuzzy multi-criteria decision analysis within a semi-arid terrestrial ecosystem to assess agricultural land potential at a regional scale. This research was conducted using GIS techniques to improve the accuracy and efficiency of site suitability analysis. Despite extensive research into the nutritional benefits and economic potential of grapevine, there is a significant lack of knowledge about its suitability for crops. This study uses GIS and AHP to assess the suitability of Italian croplands for wine grapes production.

Geographic information systems and AHP are crucial in land suitability research, improving the accuracy of assessments (Ali et al., 2023; Mokarram et al., 2020). A hierarchical model was developed to solve complex land management problems. Studies have used GIS and AHP to assess soil suitability, enabling smallholder farmers to make informed decisions regarding land allocation (Gebre et al., 2021; Radmehr et al., 2022). Integrating multi-criteria decision-making and GIS could improve efficiency and accuracy (Dedeoğlu & Dengiz, 2019). Studies have shown high accuracy in generating land suitability maps, considering soil and meteorological parameters (Arab & Ahamed, 2024; Berhane et al., 2020; El Baroudy, 2016; Malczewski, 2006; Zhang et al., 2015). Overall, GIS and AHP can improve land management decisions (AbdelRahman et al., 2022; Mokarram et al., 2020).

Pilevar et al., (2020), Tashayo et al., (2020) and Ramamurthy et al. (2020) carried out studies on the suitability of land for cultivation in semi-arid regions with saline and calcareous soils. They used fuzzy sets, AHP and GIS datasets to assess the potential. The study revealed favorable conditions for growing cereals of good, average and moderately good quality. The integration of fuzzy sets, AHP and GIS methods enables accurate land use planning and agricultural management.

Soil zone management is crucial to improving agricultural production by identifying land suitable for specific crops. This technique is particularly important in Europe due to the intensive use of land for food and feed, fodder and industrial raw materials (Zema et al., 2022). Studies have shown great interest in managing cropping areas and modeling crop suitability for various climate change scenarios (AbdelRahman et al., 2022; AbdelRahman & Metwaly, 2023).

Agricultural production is crucial for human survival and development, particularly in the context of climate change and diminishing agricultural land. Italy faces a double threat: growing food demand and land degradation. Land suitability analysis (LSA) may be the most effective way to address these challenges (Duc et al., 2019; Massano et al., 2023). Grapevine, a diffused crop in Italy, is characterized by high nutritional value and antioxidant properties. Analytical Hierarchy Process is used to assess the suitability of land for growing grapevine on a national scale. This study aims to fill this gap by leveraging GIS and AHP to assess cultivable land for grapevine production.

Geographic information systems has significantly improved agricultural development planning and site suitability studies, particularly in areas sensitive to climate fluctuations (Januar et al., 2023). Weighted Linear Combination (WLC) approach is used to prioritize areas of land suitable for cultivation (Singha & Swain, 2016).

The hypotheses of the present study are based on the use of models in the production of strategic agricultural products, considering both qualitative and quantitative factors. These factors include expert and scientific knowledge, which are assessed using the AHP. Criteria were chosen encompassing physical, chemical, ecological, climatic and topographical aspects that impact cultivation in the region. Furthermore, by combining AHP with GIS capabilities, there is strong potential for integrating various types of data to assess and categorize the suitability of areas. This study aims to assess the suitability of grapevine for the current climate using GIS-based analyses, provide valuable information on production areas and suitable crops for farmers, and contribute to existing knowledge on impacts of climate change on agricultural systems in mountainous regions (Aliani et al., 2017; Kouli et al., 2014; Malczewski, 2000; Yin et al., 2020; Zarin et al., 2021). As climate change has a significant impact on global weather patterns, understanding its relative effects on certain species becomes crucial to ensure long-term agricultural sustainability. Therefore, this study aims to: (i) delineate homogeneous areas within the vineyard using a multiparametric approach and GIS-based analyses, (ii) contribute to existing knowledge on the impacts of climate change on agricultural systems in the Mediterranean environment. The aim of this investigation was therefore to use "GIS" and "multi-criteria decision-making" techniques to identify optimal locations for delimiting zone management. A remarkable advancement of this current research, compared to previous studies, lies in the identification of areas that contribute significantly to crop yield loss in the study region. This knowledge will facilitate the development of an improved management strategy to maximize yield.

2 | MATERIAL AND METHODS

2.1 | Study area description

2.1.1 | Location

The study area is located in the southern Italy, more precisely in the "Vincenzo Petito Farm" located in Miglionico, in the Basilicata region. The experimental field, whose coordinates are Lat 40.584470° Long 16.552841°, is dedicated to the cultivation of wine grapes in a vineyard of approximately 10 hectares. Figure 1 gives an overview of the entire vineyard, highlighting the presence of seven subplots where different cultivars such as "Greco di Tufo", "Chardonnay", "Merlot", "Cabernet Sauvignon", "Aglianico", 'Sauvignon Blank', and 'Primitivo' are present. To ensure good irrigation, the vineyard is equipped with a system capable of managing different quantities of water. Currently, a uniform irrigation rate is applied.

The vineyard growing season extends from April to November, while the harvest takes place between October and November,-depending on the weather conditions at the time. The vineyard is managed according to conventional practices. On April 15, 2024, the first fertilization was carried out along the plant rows, using 200 kg/ha^{-1} of fertilizer. This fertilizer is composed of 12% total nitrogen (N), 7% ammoniacal nitrogen (N), 5% nitrate nitrogen (N), 8% soluble phosphorus anhydride (P_2O_5) in citrate. neutral ammonium and water, 6.4% soluble phosphorus anhydride (P_2O_5). in water, 16% water-soluble potassium oxide (K_2O), 3% total magnesium oxide (MgO) and 2.4% magnesium oxide (MgO).

2.1.2 | Soil characterization

The surface horizons of the soil have a moderately fine texture composed of sand, silt and clay. According to soil taxonomy, the soil belongs to the fine-textured particle size class and is classified as mollic soil (Antonella et al., 2017; Cassi & Scopa, 2024). These soils are characterized by undulating surfaces ranging from subflat to moderately steep, with limited gully formation. The primary materials consist of clayey and clayey-silty marine deposits, mainly from the Pliocene (blue-gray marly clays), sometimes covered by thin alluvial clayey-silty deposits. These marine deposits are composed of marly clays, sometimes silty, compact, with conchoidal or sub-conchoidal fractures, and with an average calcium carbonate content of around 20%. In some cases, fine sandy or sandy-silty intercalations are present. The different forms of instability of these terrains have a significant impact on

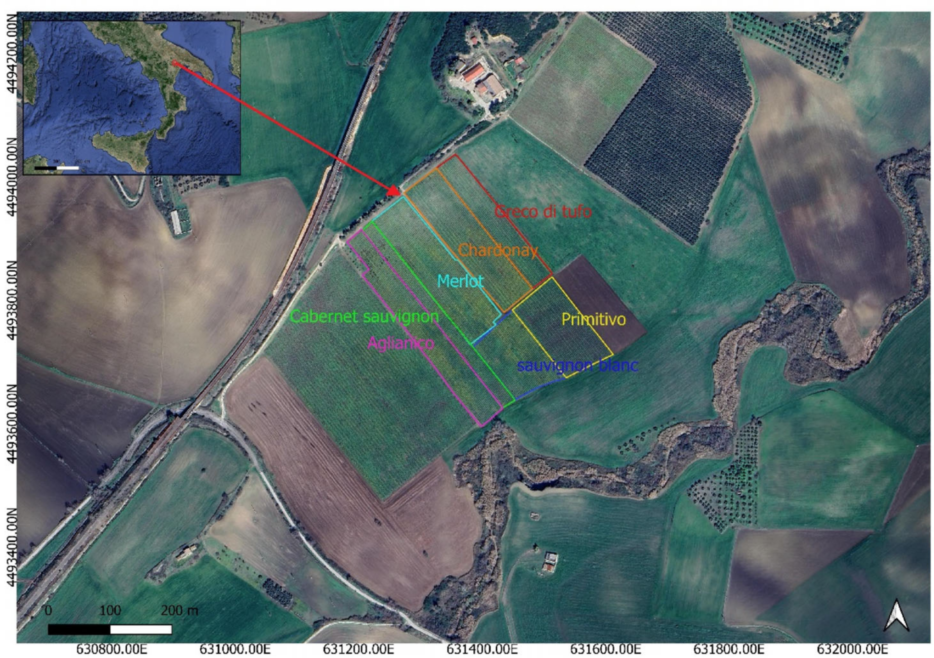

FIGURE 1 Study field. The plots associated with different vineyard cultivars are highlighted with different colors: 'Greco di Tufo' (Red), 'Chardonnay'(Orange), 'Merlot' (Cyan), 'Cabernet Sauvignon'(Green), 'Aglianico' (Magenta), 'Sauvignon Blank'(Blue) and 'Primitivo'(Yellow).

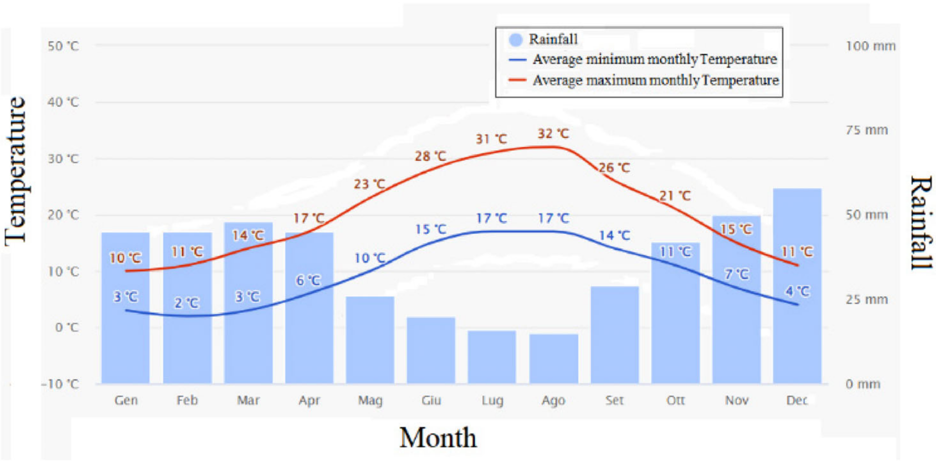

FIGURE 2 Climate data of the study field.

the morphology of the slopes. Slopes with gently undulating shapes and low to moderate slopes are susceptible to erosion by laminar flows, small furrows, mudflows and soliflows. In addition, more serious phenomena such as landslides due to runoff can also occur in these areas.

2.1.3 | Climate characterization

Figure 2 represents the graphical representation of the average monthly minimum and maximum air temperature as well as rainfall data collected by the Miglionico meteorological station (ALSIA) over the last two decades. Precipitation is mainly concentrated during the autumn and winter seasons, with December being the wettest month, receiving 58 mm of precipitation. On the other hand, August has the lowest precipitation, with only 15 mm. The annual average precipitation is estimated at 439 mm, spread over 102 rainy days. In terms of temperature, the highest monthly average is recorded in August, reaching 32 °C, while the lowest average temperature occurs in January, at 2 °C.

The analysis of thermo-pluviometric data using the Bagnouls and Gaussen diagram shows that there is a period of significant water deficit during the months of July and August, with a partial impact on the months of May, June and September. Furthermore, the analysis of soil climate carried out by Billaux (1978) in 1978, considering soils with an average water capacity (AWC) of 100, 150 and 200 mm, reveals a xeric soil moisture regime (Billaux, 1978). The temperature regime of soils indicates a thermal characteristic. Therefore, the climate of this region is characterized by a water deficit and high solar radiation during the summer months and an excess of water during the winter period.

2.1.4 | Growing conditions for selected grapevine species

The analyzed data were collected in the study field. Overall, grapevines was selected for modeling as a 30 reflection of its significance and the need to understand and address the challenges posed by climate change to ensure the sustainability of regional production. The highly suitable level indicates the optimal conditions for the grapevines specie to grow. After gathering criteria from various sources, the reclassification criteria were calculated. To identify the optimal location for growing grapevines, 10 factors were considered: temperature, pH, humidity, soil texture, slope, altitude, nutrients and precipitation. The slope map was created using the digital elevation model (DEM). Air temperature data was obtained from the nearby weather station, while a set of 10 sensors were used to collect soil temperature and humidity at six different depths.

2.2 | Criteria for zone management and suitability analysis

2.2.1 | Temperature

Climate change affects wine production, affecting the yield, composition and quality of grapevines. Current wine regions are primarily located in mid-latitudes, but 90% of traditional regions could disappear by the end of the century due to excessive drought and heatwaves. Warmer temperatures could increase suitability for other regions and encourage the emergence of new wine regions. Existing producers can adapt by changing planting materials, training systems and vineyard management, but this may not be enough to maintain economically viable wine production.

Grapevines thrive in a warm, cool climate between 68 and 77 °F (20 and 25 °C), which allows them to fully ripen and retain their acidity and flavor. Grapevines require 8 to 10 h of sunlight per day to ripen properly, as insufficient sunlight results in insufficient sugar production and poor-quality of the grapes.

2.2.2 | Soil requirements

It is essential that the soil drains well and maintains a pH between 6.0 and 7.0. Poorly drained soils can lead to root rot and other complications that can impact the health of the vines. Additionally, extreme soil acidity or alkalinity can lead to nutrient deficiencies in vines, ultimately negatively affecting the production. To ensure the thriving growth of grapevines and high-quality production, it is crucial to create an optimal environment by providing sufficient sunlight, warm days, cool nights, and well-drained soil with neutral pH in the vineyard. Soil moisture content plays a vital role in grapevine root growth. It is necessary to have less moisture in the soil to ensure optimal conditions for the roots. Excessive soil moisture can negatively impact grapevines roots and lead to various problems. When it comes to growing grapevines, different soil types may be suitable. However, it is crucial that the soil is well drained to avoid waterlogging, which can encourage bacterial rot. Loamy soil is often considered ideal for growing grapevines due to its positive impact on other soil qualities, such as bulk density, hydraulic conductivity and water holding capacity. The presence of nutrients in the soil is also crucial for the growth of grapevines. These nutrients are closely linked to increased microbial activity, adequate nutrient supply to the soil, and the effectiveness of nitrogen fertilizers. Soils with higher clay content tend to perform poorly compared to loamy soils in terms of their ability to retain moisture and nutrients, as well as support favorable microbial activity. Therefore, soils ranging from sandy loam to clay loam are considered suitable for growing grapevines (Arab et al., 2022; Badr et al., 2018; Naulleau et al., 2020; Uyan et al., 2023).

2.3 | Data preparation and inputs

This study used various raster layers as parameters for grapevines suitability modeling, based on the growing conditions described in Table S1 (Arab & Ahamed, 2022). The selected parameters included annual mean temperature, annual precipitation accumulation (mm), humidity (percentage), soil type (FAO soil classification), soil depth (cm), and slope (degrees). These parameters were chosen because of their importance in understanding environmental factors that impact growth and grapevines suitability. Annual average temperature and annual precipitation data were obtained for current conditions. Soil type and depth were derived from the Harmonized World Soil Database (HWSD) Food and Agriculture (FAO) soil classification version 1.2. Elevation data with 30 s resolution were acquired from the Shuttle Radar Topography 30 Mission (SRTM) and used to calculate slope in degrees. Finally, the Land Use/Land Cover (LULC) map was downloaded from ESRI.

2.4 | Suitability analysis using weighted linear combination

This research used the WLC method to develop a suitability map for grapevines, considering growing condition levels in ArcMap. The importance of each environmental parameter was determined by assigning weights, with all parameters receiving a weight of 0.5 to 2.0. Subsequently, the weighted environmental parameters were classified into four distinct suitability classes based on the growth conditions of each species: highly suitable, moderately suitable, less suitable, and unsuitable. These categories were assigned values of 4, 3, 2 and 1 respectively. The reclassified parameters were then combined using the Raster Calculator spatial analysis tool in ArcMap. The resulting result showed values ranging from 1 to 4, with higher values indicating greater suitability in the area. Finally, the integrated result was refined by confining all appropriate areas to their respective management zones on the reclassified map.

2.5 | Method

In this research, a decision-making approach known as “fuzzy and AHP” was used to generate land suitability maps. Fuzzy maps were developed for each parameter using linear fuzzy membership functions, assigning values between 0 and 1 based on their significance. Subsequently, a parameter comparison was carried out using the AHP method to create a land suitability/crop zone management map, identifying key areas for crop management. Additionally, maps were produced for various nutrients to identify areas requiring management interventions. A detailed description of both methodologies is provided below. In this investigation, a technique called “fuzzy and AHP” was applied to produce land suitability maps. Fuzzy maps were constructed for individual parameters using linear fuzzy membership functions, with values ranging from 0 to 1 depending on their level of importance (Karaca et al., 2021). Following this, a parameter comparison was carried out using the AHP method to generate a land suitability/crop area management map, highlighting areas of significance for crop management. Additionally, maps were created for different nutrients to identify areas requiring management actions. A full explanation of each method is presented below.

Lands have varying levels of fertility due to a multitude of factors, and achieving good nutrition relies primarily on the balance of essential nutrients required by plants, whether naturally occurring in the soil or supplemented with fertilizers. The closer the balance between these nutrients in terms of quantity and quality corresponds to the optimal threshold for the needs of the plant, the more favorable the yield obtained will be, assuming that all other necessary conditions are met. In cases where a particular nutrient is deficient, its impact on the plant becomes evident, either through observable external manifestations such as a change in leaf color, or indirectly through its influence on agricultural productivity.

2.5.1 | Fuzzy method

Small and large membership function

The Small technique is used to prioritize smaller pixels, leading to improved adhesion to smaller pixels. Conversely, the Large technique is used to highlight pixels with larger values (Figure 1). The mathematical expression of the Small and Large membership functions is described as follows:

(Equation 1: Fuzzy Membership Small)

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f_2}\right)^{f_1}} \tag{1}$$

(Equation 2: Fuzzy Membership Large)

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f_2}\right)^{-f_1}} \tag{2}$$

Tsoukalas and Uhrig (Tsoukalas & Uhrig, 1997) proposed that "f_1" represents the diffusion of the transition from a membership value from 1 to 0, while "f_2 "denotes the threshold point where the membership value reaches .5.

AHP method

The hierarchical analysis process, developed by Saaty in 1980 (Saaty, 1980), is a multi-criteria decision-making method which consists of weighting and prioritizing indicators to select the best option from a set of alternatives. This method reflects natural human behavior and thought processes by breaking complex problems into simpler components and analyzing their interactions. Using pairwise comparisons and scale-based ratings, hierarchical analysis allows decision makers to rank options based on their relative importance. This algebraic and mathematical approach transforms a complex decision-making system into a simple hierarchical structure, allowing experts to collaborate and make informed decisions. The method is based on three key principles: the construction of a hierarchical tree, the establishment of priorities and the logical coherence of judgments. Through this process, decision-makers can effectively evaluate indicators, assign weights and rank options based on their objectives, knowledge and experience.

The process of implementing hierarchical analysis involves several key steps.

First, it is essential to establish a hierarchy and categorize the issue in question. This first step aims to identify the different elements of the decision-making process, such as the decision criteria and the available options.

Subsequently, parallel analyses of these elements are carried out at each level of the hierarchy.

The next step is to determine the relative weights through numerical calculations and evaluate the incompatibility rate of each factor.

Finally, to efficiently rank the different alternatives, the proportional weights are combined.

It should be noted that due to the multitude of input parameters, the number of comparisons has increased significantly. This increase is necessary to ensure the consistency and accuracy of the comparisons made during the hierarchical analysis process.

Based on empirical evidence, it has been shown that the consistency of comparisons is considered satisfactory when the inconsistency rate drops below 0.10; otherwise, adjustments to the comparisons are necessary. The incompatibility rate is determined according to the following procedure: Step 1 consists of multiplying the comparison matrix two by two by the column vector representing the "relative weight" to obtain the weighted vector, which is then called weighted vector total. Step 2 involves calculating the compatibility vector by dividing the total weighted vector inputs by the relative priority vector. The resulting vector is called a compatibility vector.

In the process of using a single vector approach, the preference matrix is considered, which results in the derivation of a distinct vector and its corresponding value by the following equation.

$$a_{11}w_1 + a_{12}w_2 + \ldots + a_{1n}w_n = \lambda.w_1$$

$$a_{21}w_1 + a_{22}w_2 + \ldots + a_{2n}w_n = \lambda.w_2$$

$$a_{11}w_1 + a_{12}w_2 + \ldots + a_{1n}w_n = \lambda.w_n \tag{3}$$

The priority of element i over j, denoted a_{ij}, and the weight of element i, denoted w_i, are important factors in the calculation. Additionally, λ and λ represent constant values, which are the eigenvalues of the matrix. To determine the largest eigenvalue, a suitable estimate of λmax can be obtained by multiplying the vector W by the matrix A. The weight of element i is calculated using the following formula…

$$w_i = \frac{1}{\lambda} \sum a_{ij} w_j \quad i = 1, \ldots, n \tag{4}$$

Step 3 consists of determining the average vector components of the L_{max} compatibility through the acquisition of L_{max}.

In step 4, the compatibility index is calculated following the defined criteria.

$$\mathrm{CI} = (L_{max} - \mathrm{n})/(n-1) \tag{5}$$

where n designates the quantity of criteria in the error.

Calculating the compatibility rate in step 5 involves dividing the adaptation index by a randomly chosen index in order to obtain the adaptation rate, expressed by:

$$\mathrm{CRCI/RI} \tag{6}$$

When making comparisons, compatibility is indicated by a compatibility ratio of 0.1 or less. Subsequently, a map illustrating the suitability of the land for cultivation was produced using the following formula.

$$\text{Land Suitability} = MF1 * W1 + MF2 * W1 + \ldots\ldots\ldots + MFn + Wn \tag{7}$$

The fuzzy map of each variable is denoted by MF, while the weight of each variable is represented by W.

2.5.2 | Data features

The research area used various variables including “slope”, “direction”, “distance between soil samples”, “floor profile”, “average annual rainfall”, “soil texture”, “pH”, “soil salinity”, “total lime” %,” Sulfur;”S.org %,” “total nitrogen‰,” “C/N,” “CEC meq/100 g,” “P_2O_5 ppm available,” “K_2O exchange ppm, ““Exchange Na ppm,” “Exchange Ca ppm”, “Exchange Mg ppm”, “Fe ppm available”, “Cu ppm available”, “Zn ppm available”, “Mn ppm available”, “Soluble B ppm”, “N kg/ha”, “P_2O_5 kg/ha”, “K_2O kg/ha”, “average temperature” and “altitude”. Furthermore, data on soil moisture and temperature were collected from 10 locations for 6 depths on the field These variables were used to prepare the climate maps. The kriging technique was used in two stages. First, it was applied to the various datasets used in the analysis to generate an initial assessment of the parameters involved. Subsequently, in the second stage, kriging was used to create a zoning map using the GIS model generator, incorporating the data obtained from AHP.

The collected data were processed, and zoning maps were created using the “Kriging method” for climate parameters such as average annual precipitation and average temperature. To prepare the slope, direction, plan profile and height from the digital elevation model (DEM) with a resolution of 30 meters, the DEM was downloaded from the “USGS Earth Explorer Portal (http://earthexplorer.usgs.gov/)” and processed in ArcGIS.

To prepare the soil properties, a 1:5000 scale soil map of the research region was generated. Furthermore, a 1:5000 scale topographic map of the research region was used to implement the survey process and create a map of the area.

2.5.3 | Ground data

In this investigation, the crucial land parameters for identifying sites suitable for agricultural production were height, slope and slope direction. The Global Digital Elevation Model (GDEM) was used to evaluate various characteristics, such as elevation, slope aspect, slope and plane curvature, with a resolution of 30 m. Zoning maps for each of these factors are presented in Figure 3. The highest elevations are found in the northern and southern regions of the research area, as illustrated in Figure 3. Approximately 55% of the area is located above 115–120 m, while 45% are located between 120 and 143 m. Furthermore, it has been observed that slopes between 2 and 12 ° are optimal for cultivation (Figure 3).

Land slopes have variable microclimates, influencing erosion and surface runoff. Additionally, clay composition, moisture levels and the presence of essential nutrients such as calcium, magnesium and nitrogen are all influenced by slope. The optimal slope for growing grapevines is less than 15 °. More specifically, a slope of 3° is considered ideal for growing grapevines. Additionally, level slopes are preferred for growing grapevines due to their ability to create humid conditions. Variations in soil moisture play a crucial role in plant growth. Throughout the growing season, soil moisture levels generally decrease at high latitudes, with the rate of decrease varying with altitude. Leaves experience lower temperatures as shrub height increases. Shrub height can have a significant impact on grapevine growing, as temperature and humidity level are key factors. Despite the increase in topographic altitude, most high-altitude terrain is well suited to growing vines and is free from waterlogging. NASA's Shuttle Radar Topography Mission (SRTM), launched in 2019, was used to collect altitude data with a resolution of 30 m.

2.5.4 | Soil data

The study focused on key criteria such as soil structure, pH, and depth, which play a crucial role in crop development and production (Farooq et al., 2022; Xiang et al., 2021). Soil depth is particularly important as it determines the root system of plants, ultimately influencing crop growth and yield (Colombi et al., 2018). In the research area the soil depth varies from 100 to 150 cm. Soil pH level is a critical chemical attribute that influences nutrient availability to plants and regulates various physicochemical properties (Schoenholtz et al., 2000). The pH range in the research region indicates mild alkalinity, with most areas having a neutral pH above 7.6. Another significant factor is soil structure, which influences crop growth and yield. Studies have shown that high clay or sand content in soil can lead to decreased plant growth and yield (Alghamdi et al., 2023). The eastern and southern parts of the region have higher sand content than other areas, while silt is predominant in all sections except for small parts in

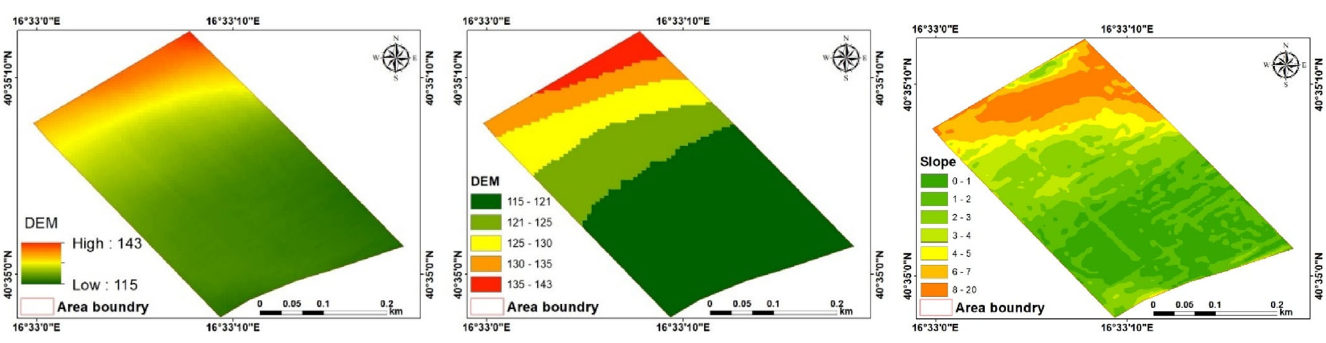

FIGURE 3 DEM and Slope of the study field.

the north, northeast, and southeast. Northern regions have higher clay content than other parts of the study area.

2.5.5 | Model evaluation

Reclassification of criteria

Reclassification was performed either by replacing the existing single value or by grouping the value ranges into a single value to facilitate interpretation of the data in raster format. Five classifications were produced from the raster map for each criterion.

Multi-criteria decision making based on the analytical hierarchy process

Many people have expressed interest in the AHP due to its perceived complex theoretical foundations and its application in various contexts (Jbaihi et al., 2022). Researchers have used AHP in various fields because of its ability to solve decision-making problems by integrating multiple factors. Using AHP, employees can determine the precise weighting of influencing factors to approach optimal solutions in multi-criteria policy dilemmas, thereby moving closer to ideal outcomes. The AHP methodology uses a hierarchical model consisting of strategies, criteria, sub-criteria, and potential solutions to analyze problems (Agyekum et al., 2021). Once the origins of the problem are understood, the hierarchy can be calculated. A pairwise comparison matrix based on a preference scale (Table 1) is generated to assess the relationships between different priorities in the AHP method, with $n(n-1)/2$ comparisons made for each item, where n represents the number of items being compared (Xu et al., 2019).

The AHP technique integrates criteria weights into the problem-solving process through pairwise comparison. Normalizing the pairwise comparison matrix is a crucial step in this process, resulting in a "normalized pairwise comparison matrix." The elements in each column of the matrix are divided by the sum of all columns to create this normalized matrix. The total value of row elements in the resulting matrix is divided by the total number of row components to generate a priority or weight vector. These weights range from 0 to 1, with a cumulative sum of 1. However, consistency issues can arise when making pairwise comparisons using the AHP technique, highlighting the importance of assessing the reliability of the reasoning. Saaty (Saaty, 1989) introduced a consistency ratio to assess the consistency of decisions based on pairwise comparisons. The consistency rate (CR = 0.1) quantifies the number of inconsistent pairwise comparisons, with a threshold for a matrix to be considered consistent. If the consistency rate exceeds the threshold, DM ratings may need to be adjusted. Equation (1) includes the consistency index (CI), the main eigenvalue (m) of the comparison matrix and the random index (RI) depending on the size of the matrix (n) to calculate the coefficient correlation (CR) (Heo et al., 2021).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \frac{\lambda \mathrm{m} - n}{n - 1} \tag{8}$$

Saaty sets an upper limit of "0.10" for this proportion. If the consistency rate of the evaluations falls below 0.10, it is considered that the judgments are sufficiently coherent and the evaluation can take place. Conversely, if the consistency ratio exceeds .10, decisions are considered inconsistent, indicating the need for better solutions. To decrease the consistency rate, one can examine the results and explore alternative approaches (Gerbo et al., 2022). The GIS platform included 10 thematic layers to generate suitability indices for grapes growing areas. This was achieved by employing the weighted superposition method described in the following equation (Tercan & Dengiz, 2022).

$$SI = \sum_{\mathrm{w}=1}^{m} \sum_{1}^{n} Wj \times Xi \tag{9}$$

SI stands for the suitability index for the sites of grapevine cultivation land, m for the total number of themes, n for the total number of classes in a theme, and Xi and Wj for the normalized weights of the i^{th} feature and the j^{th} class of the thematic layer.

Eventually, the weighted overlay based on the percentage weights derived from expert opinions was used to define the vineyards appropriateness classes.

TABLE 1 Scale of preference for the analytical hierarchy process (AHP) pairwise comparison by (Saaty, 1989).

SN	Intensity of importance	Definition	Explanation
1	1	Equal importance	Two activities contribute equally to the objectives
2	3	Weak importance of one over another	Experience and judgment slightly favor one activity over another.
3	5	Essential or strong importance	Experience and judgment strongly favor one activity over another.
4	7	Demonstrated importance	Activity is strongly favored and its dominance demonstrated in practice.
5	9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation.
6	2,4,6,8	Intermediate values between two adjacent judgments	When compromise is needed.
7	Reciprocals	If activity I have one of the above numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	

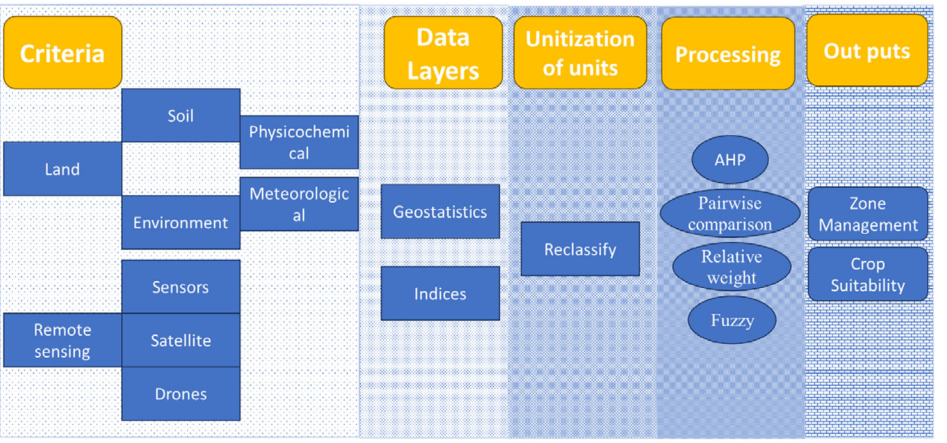

FIGURE 4 Flow chart of the methodology.

$$\text{Weighted Overlay} = \sum_{i=1}^{n} \text{Ci} * W_n \tag{10}$$

where Ci denotes the criterion (*i*) that was reclassified and W_n denotes the number of criteria (*n*) that were weighted.

This research is the first investigation exploring the most advantageous allocation of areas suitable for grapevine cultivation. The use of AHP and GIS was used to create a suitability map, developed using ArcGIS 10.8 software. The spatial data used in this study were obtained from publicly available online sources. The assessment of potential sites for grapevine cultivation was carried out based on eight assessment criteria. A comprehensive evaluation was undertaken to select geospatial analysis model parameters for both sets, as shown in Figure 4.

2.6 | Remote sensing (RS) analyses and sensors

2.6.1 | RS indices

Vegetation indices derived from remote sensing images include the Normalized Difference Vegetation Index (NDVI, (Saaty, 1980)) calculated from an image taken on April 28, 2024, using a multispectral camera mounted on an unmanned aerial vehicle. pilot (UAV) at a spatial resolution of 5 cm. On the other hand, the same index was calculated from a Sentinel2 image (with a spatial resolution of 10 m) obtained on the same date. Additionally, biophysical indices related to vegetation, such as chlorophyll (Cab) and water content (CWC) of vegetation cover, are commonly analyzed using the freely available SNAP software (Weiss & Baret, 2016). The algorithm used for their calculation involves a neural network that examines 8 spectral bands, including the red edge and mid-infrared bands (ESA, 2019; Qiu et al., 2019).

2.6.2 | Filed sensors

The sensor network used in the monitoring system consists of various components. First, there are 10 Decentlab DL-SMTP profilers specifically designed to measure soil moisture and temperature. These profilers are capable of acquiring data at different depths ranging from 10 to 60 cm. Additionally, there is a weather station that measures air temperature, humidity, atmospheric pressure, precipitation and wind. To transmit the collected data, the weather station is equipped with a Raspberry device. In terms of data transmission, the system uses both LoRaWAN and 5G technologies. Each profiler is equipped with a transmitter that communicates with a local gateway via LoRaWAN, which is a long-range wide area network protocol. Data from the profilers is then sent to a server using a 5G SIM card. The data collected can be consulted on a web-gis platform called OD4SA. To provide a visual representation, an example schematic and profilers installed on site are shown in the Figure 5.

3 | RESULTS

The soils data results for 16 soils mixed samples of 30 cm depth, which represent the fertility status of the soils under current cultivation of grapevines. The statistical analyses of these samples are presented as follows in Table 2.

The soil presents a potential fertility status under grapevines cultivation, which indicate the fertilizers use, while these statistics present the homogametic applications of fertilizers doses to soils. This may raise the importance of zoning management of such applications. The high CEC emphasis the capacity of soils to hold the fertilizers and make it available to the plant during a long period while the neutral pH assures the availability of all nutrients under investigations in proper amount to plant in case of proper application of soils. This ensure the importance of determine the zooning managements for fertilizers application and irrigation amounts as it is clear enough that the various in the soils properties is mainly due to the undulation situations of soil slope. As it was evidence that upper parts of soils contain at least 50% stones ≥5–7 cm. while the lower parts of soils contain 7% stones ≤2 cm.

3.1 | AHP results

Resulting Priorities and Decision Matrix presented were used to produce the zoning area for different parameters as shown in Figure 6.

FIGURE 5 Sample scheme of soil moisture sensors network.

TABLE 2 Descriptive statistics.

	pH	$CaCO_3$ (%)	Sand (%)	Silt (%)	Clay (%)	S. Org %	Total N.	C/N	CEC meq/100 g	P_2O_5 Av. ppm
Valid	16	16	16	16	16	16	16	16	16	16
Missing	40	40	40	40	40	40	40	40	40	40
Mean	7.775	9.2	30.75	33.794	35.456	2.321	1.405	9.213	25.331	57.2
Std. Deviation	0.148	7.5	2.823	4.869	5.901	1.048	0.437	1.932	2.767	43.434
CV	1.904	81.522	9.180	14.408	16.643	45.153	31.103	20.970	10.923	75.934
Minimum	7.6	0	25.5	26.2	25.7	0.88	0.68	7.1	19.8	8.9
Maximum	8	23	36.1	40.1	44.1	3.94	2.06	12.3	30	173.5

	K_2O ex. ppm	Na ex. ppm	Ca ex. ppm	Mg ex. ppm	Av. Fe ppm	Cu ppm	Zn ppm	Mn ppm	Br ppm
Valid	16	16	16	16	16	16	16	16	16
Missing	40	40	40	40	40	40	40	40	40
Mean	593.531	42.619	3885.175	499.913	7.694	4.082	0.788	6.891	0.523
Std. Deviation	140.081	37.101	549.44	154.555	1.432	3.248	0.483	1.546	0.075
CV	23.601	87.053	14.142	30.916	18.612	79.569	61.294	22.435	
Minimum	351.3	11.4	3088.5	316.7	6.01	0.88	0.26	4.73	0.41
Maximum	838.3	118	4612.5	868.7	13.53	13.53	1.98	9.98	0.66

The AHP-based MCDM process was used in this study to efficiently assign optimal weights to criteria that influence various factors. The investigation focused on identifying the most suitable locations for growing grapevines in the research area. It was observed that one criterion had the highest priority weight, while the remaining eligible components had decreasing priority weights. The results of the study revealed a ratio of consistency (CR) of 0.075, which is below the threshold of 0. 10. This CR value means the percentage of weight assigned to the criteria. Among the criteria considered, temperature appeared with the highest weight percentage, while nutrients had the lowest weight percentage.

Figure 7 shows the map of vegetation indices obtained by remote sensing on April 28, 2024. Figure 7a specifically presents NDVI, calculated from the multispectral camera on UAV, on the other hand, Figure 7b illustrates the same index calculated from a Sentinel2 image (spatial resolution 10 m) acquired on the same date, which is quite significant. The practically lower values of the index derived from satellite data can for all intents and purposes be attributed largely to the disparity in spatial resolution, which is actually quite large. In the espalier vineyard, the vegetation does not completely cover the field for the most part, allowing the soil to persist in a subtle way. Nevertheless, both maps show a consistent trend in the NDVI index.

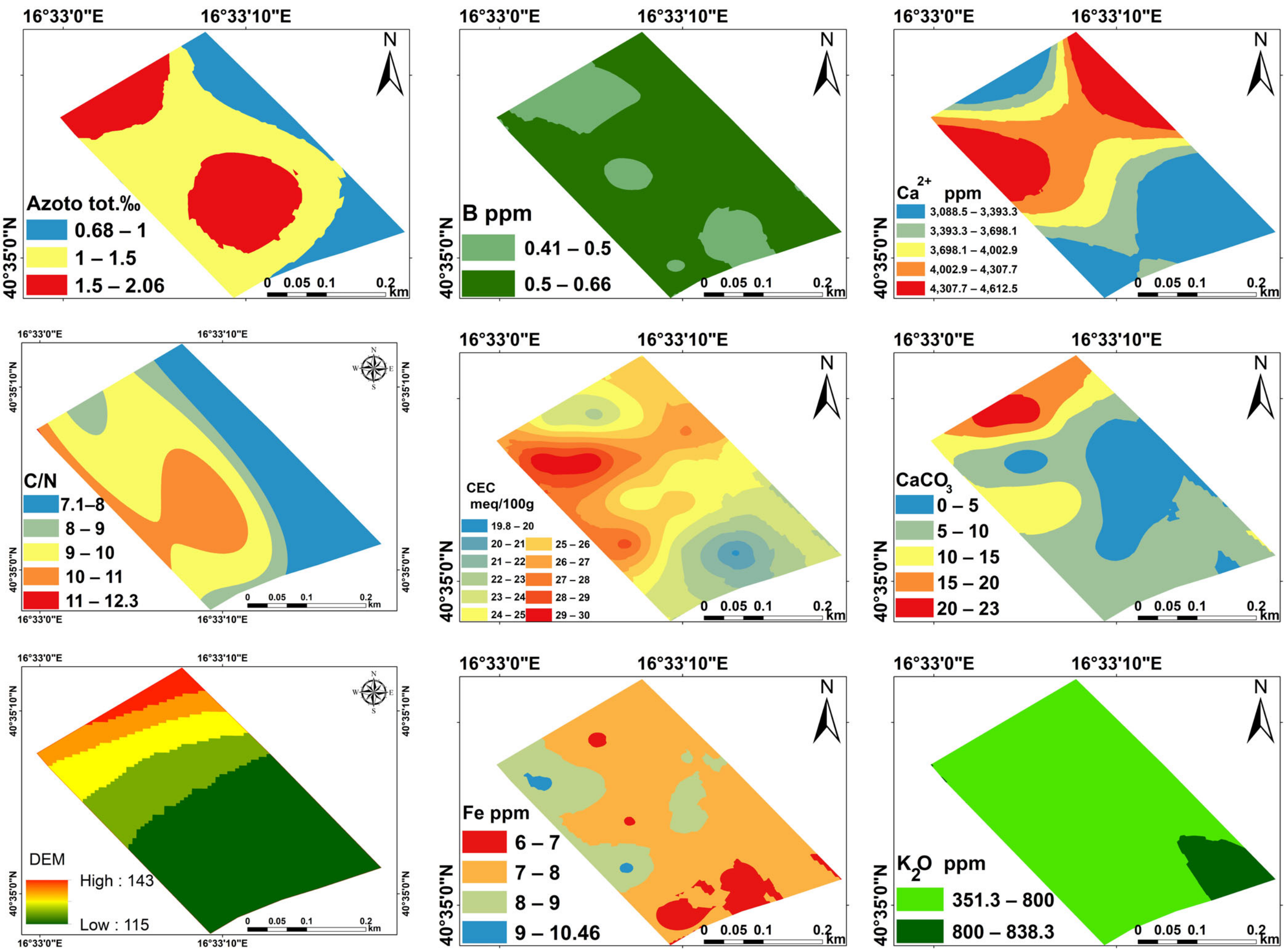

FIGURE 6 Zoning map of each of the input parameters.

Moving on to Figure 7c,d, they present the biophysical indices (Weiss & Baret, 2016) of the vegetation, in particular the chlorophyll (Cab) and water (CWC) content of the vegetation cover actually quite significantly (Qiu et al., 2019; Clevers, 2010). The Cab and CWC indices demonstrate lower values in the central area of the field, which is quite significant.

Figure 8 shows the average daily soil moisture levels at different depths recorded by soil moisture sensors located at the sample points ID shown in Figure 5.

On the other hand, Figure 9 presents the weather conditions observed in March and April 2024. Analyzing the graph, it becomes evident that the precipitation occurred from April 17 to 21, with a notable precipitation episode of 10 mm on the 20 April.

The research uses satellite information and statistical methods to examine readings of climate fluctuations, changes in soil moisture and temperature, and vegetation cover in the study area, covering a period of sensor readings of up to six depths. The results reveal increasing trends in potential evapotranspiration, soil moisture and vegetation cover. These elements collectively explain about 62% of the observed changes in soil properties that affect the plant. This understanding has the potential to improve climate adaptation and environmental rehabilitation strategies.

This study was carried out to determine suitable land areas for sustainable production of grapevines in Italy. It considered 10 parameters and expert opinions. Data was analyzed using ArcGIS maps. The terrain was classified as high and highly suitable, with the north-western part being the most suitable. The study emphasizes the potential of satellite remote sensing, GIS technology and analytical hierarchy process for agricultural land use planning and management.

Altitude does not directly affect the accumulation of soil physicochemicals, but it could modify its spatial distribution by influencing vegetation type and microclimate. Higher altitude led to a decrease in soil temperature, which reduced the rate of soil moisture conversion and transport.

Slope aspect mainly affects soil temperature, humidity and vegetation type by modifying direct solar radiation, leading to differences in higher soil nutrient and water content created favorable conditions for plant growth and microbial activity in lower parts. Higher temperatures on sun-exposed slopes could affect mineralization, leading to nutrients depletion.

Slope position affects the conversion and transport of nutrients downslope by influencing the intensity of soil erosion. slope, affecting the spatial and temporal distribution of nutrients by influencing soil

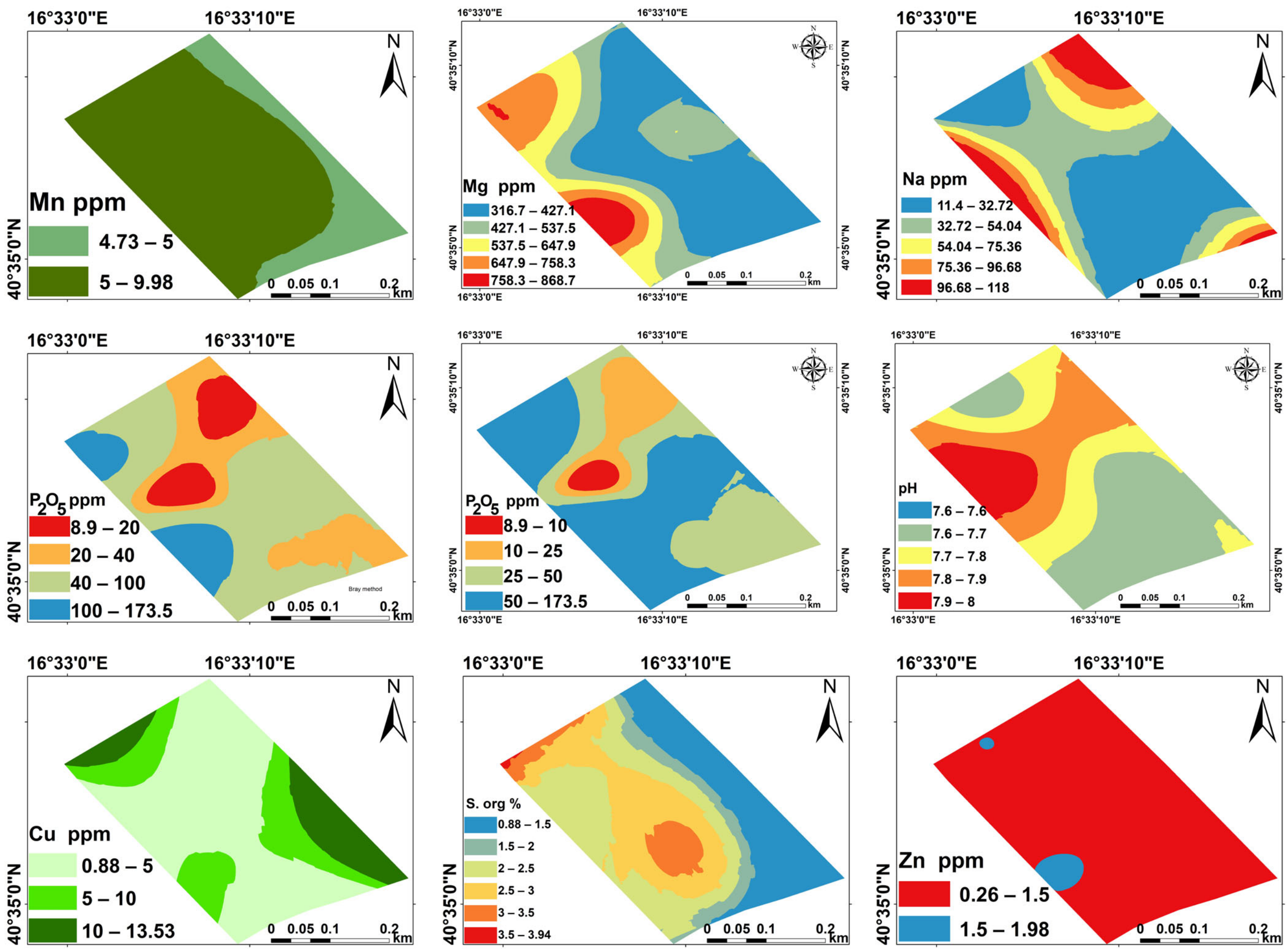

FIGURE 6 (Continued)

particle separation, sediment transport and redistribution, and soil particle deposition processes.

Gradient and slope length are more complex factors affecting the spatial distribution of nutrients in sloping cultivated lands. The steepness of slopes is the main driver of surface runoff and soil erosion, while the length of slopes complicates the erosion process. Higher erosion rates occur in locations with steeper and longer slopes, changing the spatial distribution of nutrients in the area. The study explores the impact of climate FACTOR on grapevines production in Italy, demonstrating the potential for estimating future changes in productivity (Massano et al., 2023).

4 | DISCUSSION

4.1 | Multi-collinearity test

Identifying factors that influence the modeling process is a crucial step because it improves model accuracy by leveraging the interrelationship between independent variables (Alghamdi et al., 2023; Ebiwonjumi et al., 2023). Variance inflation factor (VIF) and tolerance indices are commonly used to resolve collinearity issues. The tolerance, which represents the ratio of independent attributes, is the reciprocal of the VIF value. It indicates the extent of ratio variance inflation and highlights how collinearity introduces inconsistency in ratio evaluation. Tolerance indices (TOL) and influence factor (IF) are used to assess collinearity. According to (Arabameri et al., 2018), the variables are not collinear if the VIF is ≤5 and the TOL is ≤0.1.

The collinearity test was carried out on the effective factors, including the percentage of sand with a tolerance of 0.3 and a VIF of 3.0, the percentage of silt with a tolerance of 0.2 and a VIF of 4.9, the degree of slope with a tolerance of 0.7 and a VIF of 1.9, the temperature in degrees Celsius with a tolerance of 0.2 and a VIF of 4.3, the percentage of clay with a tolerance of 0 .2 and a VIF of 4.6, the electrical conductivity in ds/m with a tolerance of 0.7 and a VIF of 1.3, the pH with a tolerance of 0.8 and a VIF of 1.1, the rainfall in millimeters with a tolerance of 0.5 and a VIF of 2.0, and the aspect of the slope with a tolerance of 0.9 and a VIF of 1.1. (Figure 10).

In this investigation, the final land suitability maps for crop cultivation were developed using a multi-criteria decision-making approach. Initially, fuzzy membership functions were used to establish a fuzzy map for each parameter. The fuzzy map was created based on

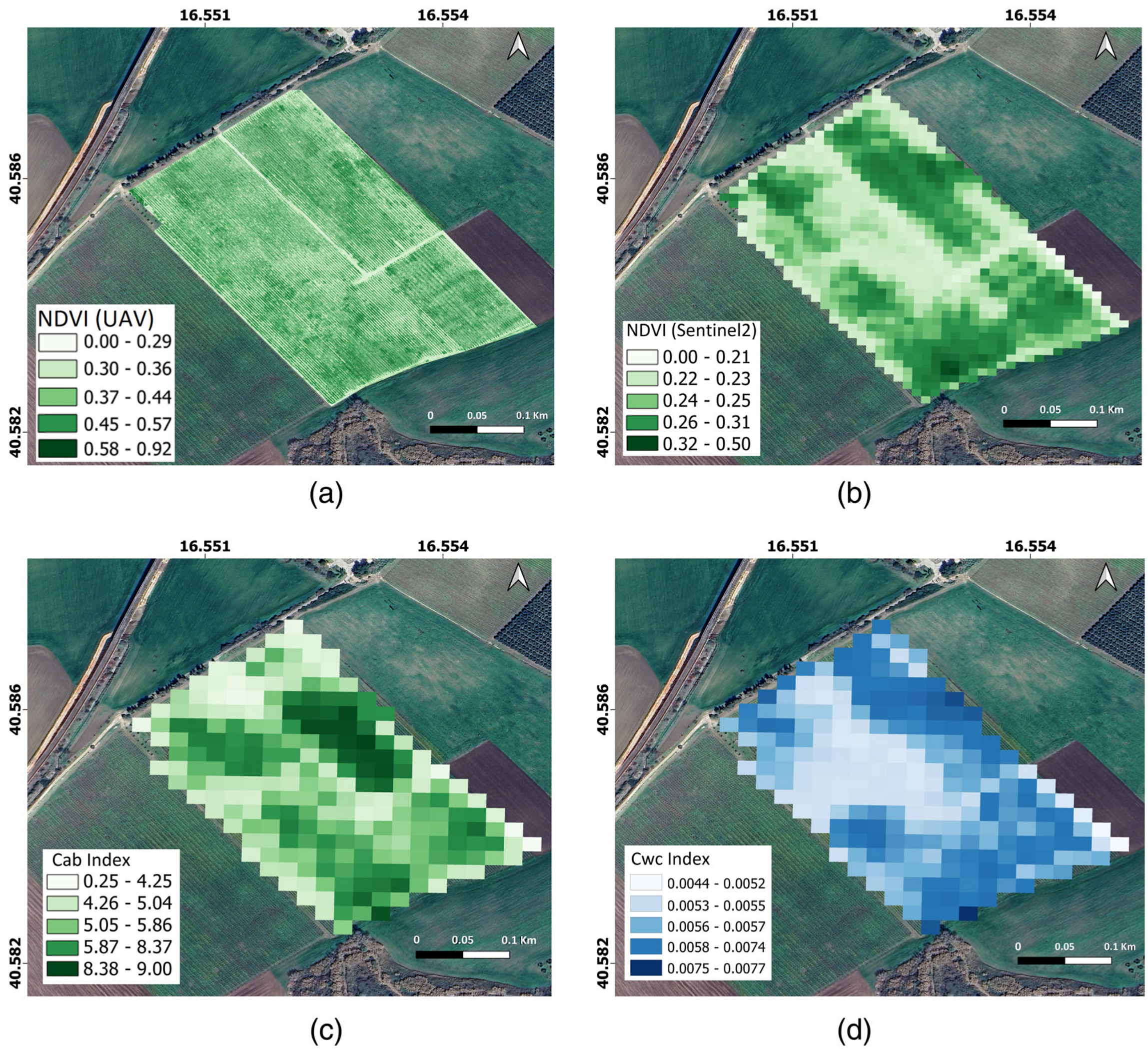

FIGURE 7 Input parameters of remote sensing images acquired on 2024 May the 28. (a) NDVI map from UAV (5 cm spatial resolution); (b) NDVI from Sentinel2 (10 mt spatial resolution); (c) Canopy Chlorophyl Content Index computed from Sentinel2; (d) Canopy Water Content Index computed from Sentinel2.

the optimal values of the parameters and their impact on grapevines performance, as shown in Table 2. The closer the fuzzy numbers are to 1, the more influential the values of each factor are for the grave wine cultivation. Conversely, parameters with negligible effects have values close to zero. Figure 6 displays the fuzzy map prepared for each factor, indicating that areas characterized by a southern slope direction, an altitude ranging from 115 to 143 m, a loamy soil texture, a neutral pH, proximity to water sources water, rain conditions, slope and appropriate temperature. are perfectly suited to grapevines cultivation. These features display values close to 1 in the membership function.

In this research, a "multi-criteria decision-making" approach was used to generate the final land suitability maps for grapevine cultivation. Initially, fuzzy membership functions were used to determine the suitability of each parameter, resulting in the creation of fuzzy maps. These maps considered the optimal values for each parameter and their impact on crop yield, as shown in Table 2. The closer the fuzzy numbers were to 1, the more influential the values of each factor were for the crop. Conversely, the parameters with no effect had values close to zero.

Figure 6 shows the fuzzy maps prepared for each factor. It reveals that the area most suitable for cultivation has certain characteristics, such as a south-facing slope, specific altitude, loamy soil texture, lower NPK content, neutral pH, proximity to water sources. water, precipitation during granular fertilizer applications, lower NPK content. slope and specific degrees of soil moisture and temperature. These characteristics have values close to 1 in the membership function, indicating their high cultural fit.

Finally, using Equation 7, The final map of land suitable for grapevines production was created (Figure 11). As shown in Figure 11, the region's southernmost areas are more suited for growing grapevines. So that the region is in "high, and very high" land suitability classes, respectively.

Our survey results indicate that the use of hierarchical analysis and GIS model approach facilitates the transformation of qualitative data into quantitative data, proving to be a valuable technique for

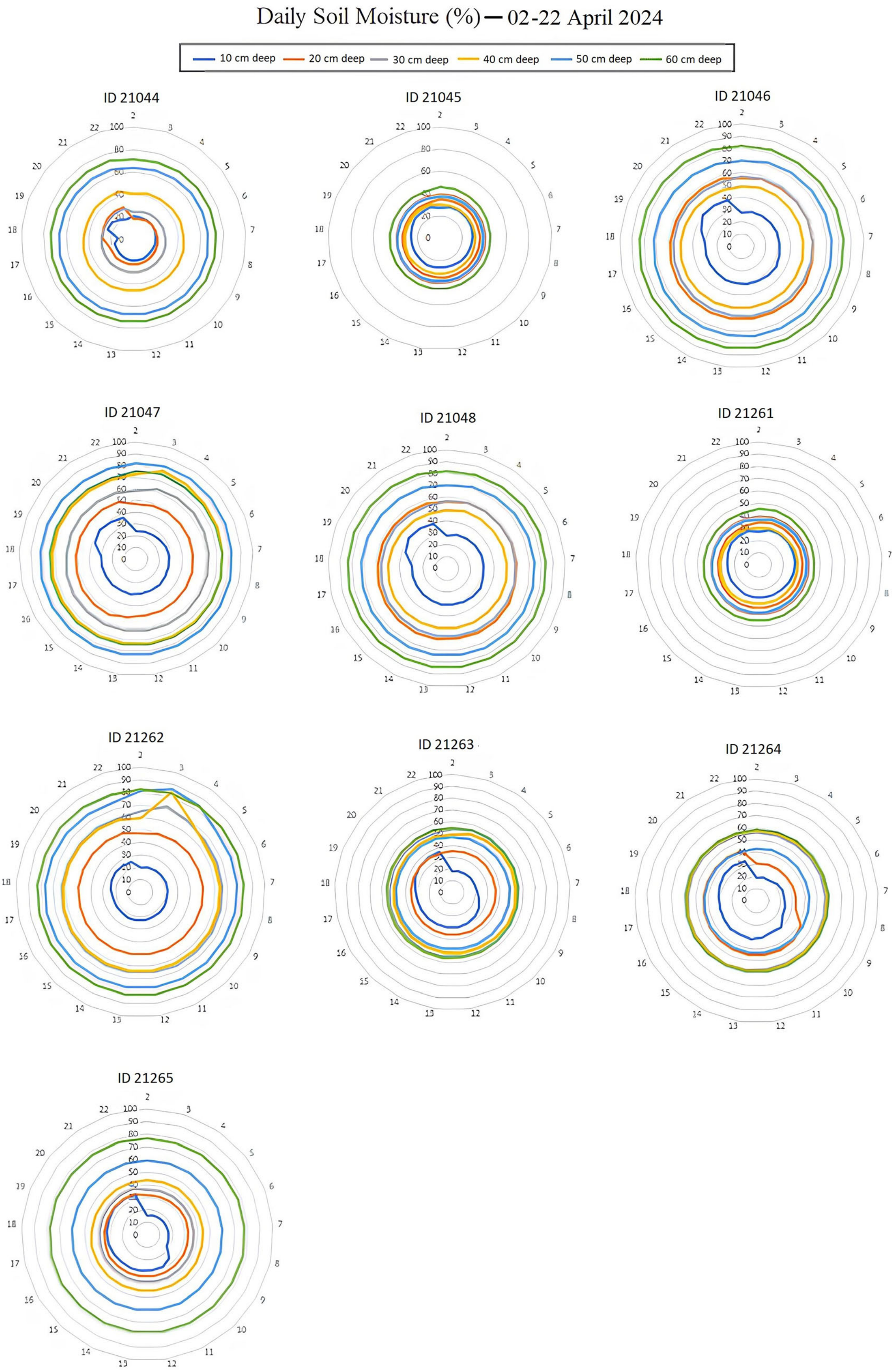

FIGURE 8 Daily average Soil Moisture at 6 different depths from 2024 April the 2nd to the 22nd. The ID number associated to each graph refers to the location of the sensors as shown in Figure 5.

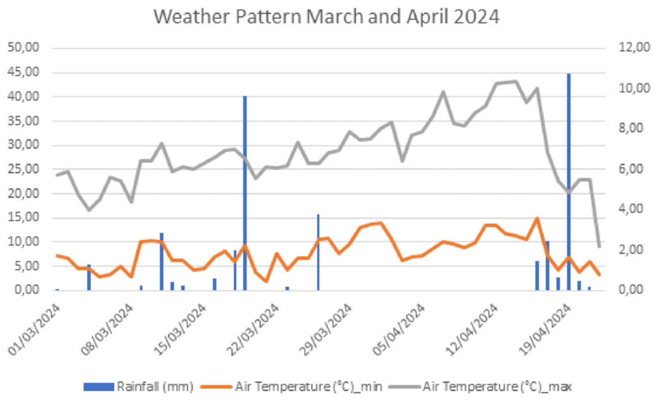

FIGURE 9 Daily Rainfall, minimum and maximum air temperature on 2024 March and April.

assessing land suitability. This research also highlights the effectiveness and flexibility of GIS methodologies in land suitability assessment due to their many advantages over manual techniques in analyzing and mapping geographic data. In addition, the integration of "fuzzy, AHP and GIS" approaches contribute synergistically to the assessment of the suitability of land for cultivation. Previous studies have also shown that the high accuracy of this model can be exploited to identify suitable locations for growing other crops such as wheat and barley (Mokarram et al., 2020).

4.2 | Accuracy of the model

Identification of zoning management and model quality play a crucial role in model validation (Ghosal et al., 2022; Yao et al., n.d.). Therefore, the results obtained during model validation are valuable (Fan et al., 2006). When estimating the model value, it is essential to consider Area Under Curve (AUC) values. The value and accuracy of the model are higher as the AUC approaches 1 (Rawlani & Sovacool, 2011). To validate the results, the model underwent verification. In these circumstances, maps illustrating the suitability and all the characteristics of soil and climatic factors were used to construct the curve. The ROC/AUC results demonstrated the excellent performance of the AHP model. The AUC value and prediction accuracy of the AHP model were determined to be 91% with Std. error of .02. The accuracy assessment revealed that the AHP model was suitable for area modeling and management.

The assessment of land suitability for grapevines and wine production and the identification of environmental constraints in this study relied heavily on the use of Sentinel-2 MSI and GIS information. In order to ensure the sustainability of grapes growing, it is imperative to take into account climatic and topographical conditions, because they play an important role. The SRTM digital elevation datasets prepared by NASA were particularly valuable in this research, as they provided accurate elevation data for the creation of the elevation layer in the study area, thus facilitating the digital terrain mapping. The selection of climate factors in this study was based on previous research findings, serving as a guiding framework. A crucial step in the land suitability assessment process is to determine the weight of each parameter that influences the assessment. Given the varying importance of these criteria, multiple factors contribute to the assessment of land suitability. This study used a multi-criteria decision-making process by integrating AHP with biophysical and remote sensing characteristics. The consistency ratio (CR) for grapes production in this study was found to be less than 0.1, which can be attributed to the adoption of the AHP in conjunction with the weighted superposition model (Zhao & Qu, 2024).

The selected RS indices, shown in Figure 7, were used for the study applications due to their ability to be correlated with various vegetation properties, thereby simplifying the complex process. This is also due to the low-cost generation of image data, which is crucial for their applications. However, the effectiveness of RS indices depends on the quality of the multispectral data and the interpretation of their values, it is not identical to other remote sensing images and cannot be validated using conventional accuracy assessment methods. It is commonly used for local-scale vegetation management and large-scale vegetation monitoring, but its effectiveness depends on reliable sensors and data processing methods. RS Indices Data have their strengths and limitations, and their variability and low repeatability or comparability are also important considerations (de la Iglesia Martinez & Labib, 2022; Huang et al., 2021; Navidi et al., 2023; Stamford et al., 2023; Vanella et al., 2020) therefore, the combination of RS indices with soil data in AHP, is effective for zoning management interpolations.

Compared to the map in Figure 5, along the north-east, south-west diagonal and in the central left area of the field, the sensors pattern shown in Figure 8, generally exhibit a greater value of soil humidity, especially in the deeper layers. The blue area, shown in the water management zones map in Figure 11, is associated with a greater value of soil moisture (about 40%) in the first soil layer (10 cm deep) in correspondence with the rainfall events, although small, which occurred between 17 and 20 April 2020. n 19 April approximately 45 mm of rainfall and lower air temperatures were recorded compared to the previous days (Figure 9). The area that corresponds approximately to the south area of the field shows lower value of soil moisture at superficial and deep layers then the previous case, but the first layer appears more sensitive to water presence then the green area.

4.3 | Advantages and disadvantages of this research work

The benefits of this work are based on the use of the earth's ecological capacity, which plays a crucial role in achieving sustainable development and preserving soil and water resources. The effectiveness of this work depends on the use of the ecological potential of the land, which constitutes an essential factor in achieving sustainable development and safeguarding soil and water resources (Seyedmohammadi & Navidi, 2022). The assessment of soil characteristics and land

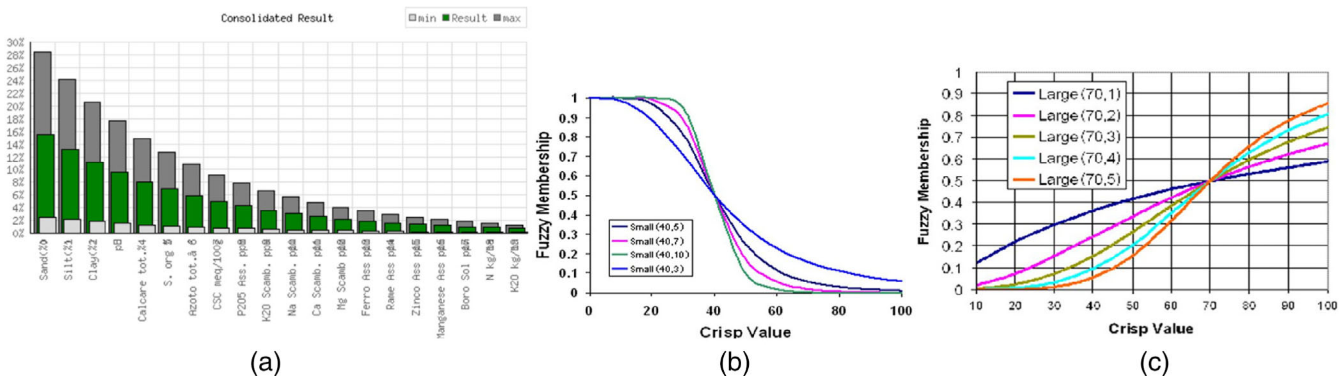

FIGURE 10 (a) Consolidates results, (b) Small and (c) Large membership function.

boundaries is a crucial step in the land suitability assessment process, as it plays an important role in sustainable land management and in mitigating the impacts of land use. land degradation to ensure continued production of agricultural crops (Seyedmohammadi, Sarmadian, Jafarzadeh, Ghorbani, & Shahbazi, 2018). Land suitability assessment can inform decisions on appropriate land uses to maximize crop yield while making best use of them, but without harming the ability of natural resources such as soil to support growth. Fuzzy method was deemed superior in representing land suitability classes due to its enhanced flexibility in capturing various data sources and deriving weightings for meaningful classes, as highlighted by (Navidi et al., 2022; Ngo et al., 2020; Seyedmohammadi et al., 2019; Seyedmohammadi, Sarmadian, Jafarzadeh, & McDowell, 2018). This study combines AHP and the pairwise comparison method, to identify factors influencing suitability. Limitations of the study include its focus on the Basilicata region and its use of fuzzy AHP technique to account for uncertainty and subjectivity. This is in accordance with similar studies of Ngo et al, (Frem et al., 2023).

4.4 | Future work

These assessments provided valuable information to farmers, thereby improving their environmental performance. However, more research is needed to establish strategies for sustainable systems. Additional research is needed to understand consumer perceptions and behaviors toward sustainable practices. Limitations of the study include the assessment of environmental dimensions and the lack of technical data, requiring more specific field investigations to fully assess the sustainability of Italian wine systems (Frem et al., 2023; Yang et al., 2024). The ecosystem influenced by climate, soil and vines, affecting the sensory attributes of the wine. A strong expression of terroir requires varietal precocity adapted to local conditions and vines faced with limiting factors, such as water stress or low nitrogen availability. A multidisciplinary approach is necessary to optimize the expression of the terroir through plant material and vineyard management (van Leeuwen, 2022). Further studies are required on climate change, which causing extreme events and shifting agricultural land use, impacting grapevines cultivation and winemaking (Arias et al., 2022; Baban et al., 2007; Castillo-Diaz et al., 2023; Droulia & Charalampopoulos, 2021; Mattas et al., 2024; Merrill et al., 2020; Naulleau et al., 2020; Payne & Kwofie, 2024; Yang et al., 2023).

5 | CONCLUSIONS

This research aimed to identify optimal plots for sustainable grapevine cultivation in Italy, leveraging the AHP, GIS technology, and satellite remote sensing to evaluate 10 different variables. The study utilized ArcGIS for an in-depth analysis and employed fuzzy logic alongside AHP methods to produce land suitability maps, which showed that the most favorable conditions were predominantly in the northwest region. Lower and certain middle zones also displayed conducive crop growth conditions, with minor irrigation adjustments suggested for higher elevations.

The multi-criteria decision-making approach highlighted in this study proved effective in distinguishing areas suited for different agricultural purposes, emphasizing the importance of precise management to enhance crop yields in semi-arid regions affected by climatic and soil constraints. Additionally, the research pointed out the significant role of topographic factors like slope orientation and steepness in influencing soil nutrient distribution and microclimatic conditions, underscoring the potential of this methodology to be adapted for other regions and contribute to improved agricultural practices globally, particularly with enhanced data contributions from local wine consortia.

The objective of this research was to identify suitable plots of land for the sustainable cultivation of grapevines in Italy. The analysis took into account 10 variables as well as comments from experts in the field. Using ArcGIS mapping tools, the data was thoroughly examined. This investigation highlights the promise of satellite remote sensing, GIS technology, and the analytical hierarchy process in agricultural land use planning and administration. The study results revealed that the "multi-criteria decision-making" approach is a valuable technique for objectively evaluating multiple factors. In this particular study, "fuzzy and AHP methods" were used to create land suitability maps and establish area management for the vineyard. Geographic Information System was used to analyze the geographic data, process the maps and integrate them with the weights assigned to each parameter in the "AHP method".

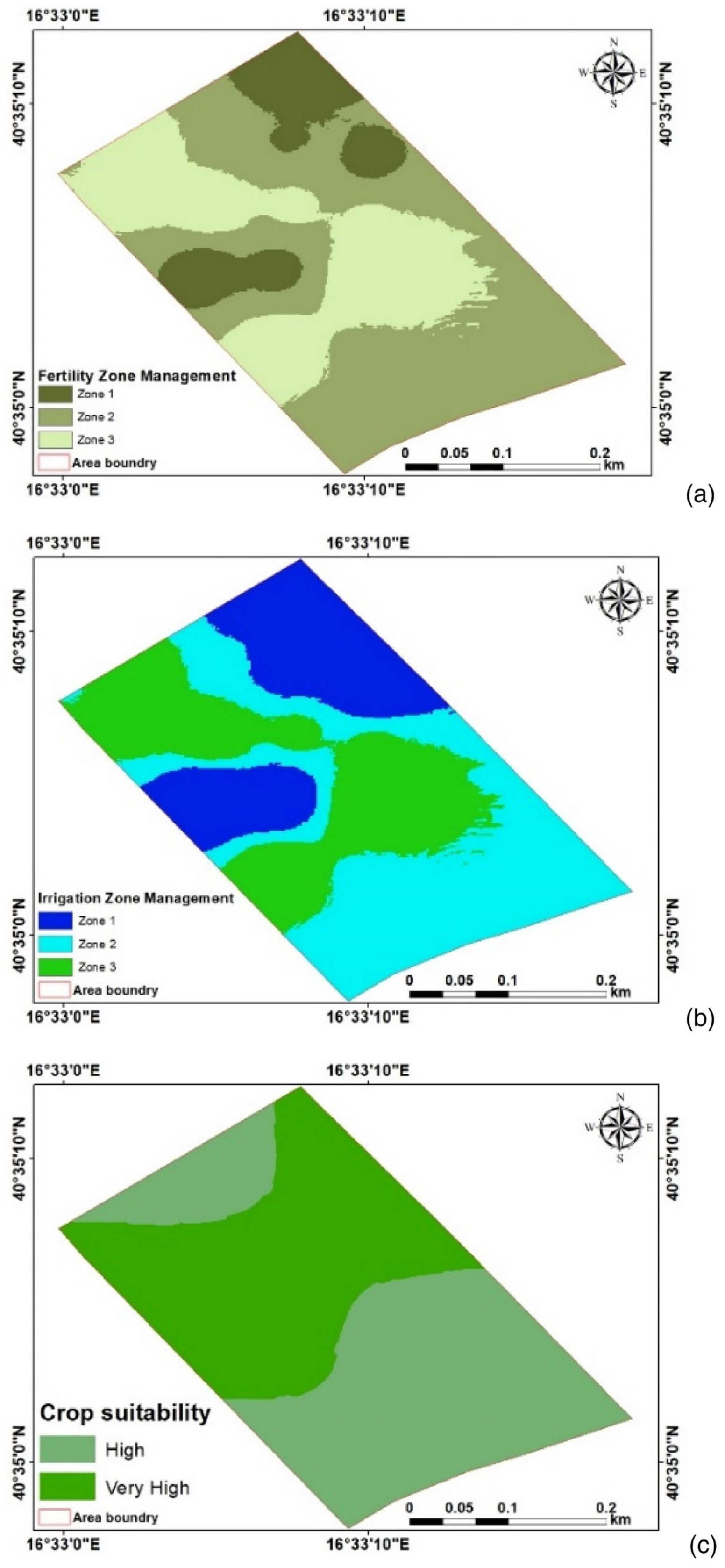

FIGURE 11 (a) and (b) Zone management maps for cultivation using fuzzy-AHP method and (c) Land suitability.

Land suitability maps showed that the study area is classified into "very high" and "high" suitability categories, with the most optimal conditions present in the northwest region. Conversely, the lower zones and a small part of the middle zones have more favorable conditions for crop growth than the remaining zones. Additionally, area management results indicated that most regions possess suitable conditions in terms of temperature and soil moisture for crop growth. Although minor changes to irrigation practices may be necessary in some higher elevation areas, overall, they do not pose a significant threat to the study area. Using the "multi-criteria decision-making" method, it is possible to identify suitable locations for growing different crops based on the results of this study. Furthermore, it is crucial to identify areas that require careful management in order to implement spatial management techniques and improve crop yield in semi-arid regions affected by climate and soil limitations.

Topographic factors, such as elevation, slope orientation, slope position, and slope steepness, significantly influence the spatiotemporal distribution of soil characteristics on slopes. These factors modify regional microclimatic, hydrological, soil erosion processes and ecological conditions, affecting the spatial distribution of physico-chemicals at regional and slope scales in the field. Topographic factors, such as slope steepness, slope aspect, length and position influence the spatial distribution of soil nutrient content. However, determining their impact on nutrient distribution remains a challenge. Statistical methods and models based on these factors are essential for nutrient management in various environmental situations.

The methodology can be applied to other countries and regions, with the participation of the wine consortium improving data quality and knowledge.

AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST STATEMENT

The authors would like to hereby certify that there is no conflict of interest in the data collection, analyses, and interpretation in the writing of the manuscript, and in the decision to publish the results. The authors would also like to declare that the funding of the study has been supported by the authors' institutions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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