Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Integrated Spatial Evaluation of Soil Quality Using Analytic Hierarchy Process (AHP) –Weighted Sum Method (WSM) Modelling and Multivariate Statistical Analysis

Yasin Demir
Bingöl University
Alperen Meral
alperenmeral@bingol.edu.tr
Bingöl University

Research Article

Keywords: Soil Quality Index (SQI), AHP–WSM Integration, GIS-Based Spatial Modelling, Microcatchment-Scale Assessment, Sustainable Land Management

Posted Date: February 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8550717/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Integrated Spatial Evaluation of Soil Quality Using Analytic Hierarchy Process (AHP) – Weighted Sum Method (WSM) Modelling and Multivariate Statistical Analysis

Yasin DEMİR[1], Alperen MERAL[2,*]
[1]Bingol University, Faculty of Agriculture, Department of Soil Science and Plant Nutrition, Bingol, Türkiye.
E-Mail: ydemir@bingol.edu.tr
[2]Bingol University, Faculty of Agriculture, Department of Landscape Architecture, Bingol, Türkiye.
E-Mail: alperenmeral@bingol.edu.tr

ABSTRACT

Soil degradation is a major constraint to ecosystem sustainability and agricultural productivity, particularly in erosion-prone mountainous microcatchments where spatial heterogeneity complicates soil management. This study presents an integrated spatial framework for assessing soil quality in the Çapakçur Microcatchment (Eastern Türkiye) by combining geostatistical interpolation with multi-criteria decision analysis. Eighteen soil indicators representing physical, chemical, and nutrient properties were spatially modelled through Inverse Distance Weighting (IDW) and weighted using the Analytic Hierarchy Process (AHP). The Weighted Sum Method (WSM) was then applied to derive a composite Soil Quality Index (SQI) that integrates multidimensional soil attributes into a single decision-support layer. Results indicate that physical attributes exert the greatest influence on overall soil quality, while chemical and nutrient parameters display strong local variability. Approximately 85% of the study area falls within moderate-to-low soil quality classes, highlighting widespread fertility limitations associated with organic matter depletion, phosphorus fixation, and salinity. Principal Component Analysis (PCA) confirmed the statistical robustness of the AHP–WSM weighting, explaining 84.1% of the total variance, while Spearman correlation analysis revealed that elevation and erosion intensity are key determinants of soil functionality (r_s = 0.67 and –0.61, respectively). The proposed AHP–WSM–GIS framework provides a reproducible model for identifying soil degradation hotspots, prioritizing rehabilitation zones, and guiding precision land management strategies in heterogeneous mountain ecosystems. Beyond its regional application, the methodology contributes a transferable decision-support tool for sustainable land use and the achievement of global soil-related Sustainable Development Goals (SDG 13 and SDG 15).

Keywords: Soil Quality Index (SQI), AHP–WSM Integration, GIS-Based Spatial Modelling, Microcatchment-Scale Assessment, Sustainable Land Management

1. INTRODUCTION

Soil quality degradation is now recognized as one of the most critical barriers to sustainable agriculture, the continuity of ecosystem services, and effective erosion control. In particular, the high spatial variability of soil properties in mountainous micro-catchments complicates the development of management strategies and limits the number of studies that holistically evaluate physical, chemical, and nutrient characteristics in these areas (Abdu et al., 2023; Shit et al., 2023). Globally, more than one-third of agricultural soils are affected by degradation processes such as erosion, acidification, salinization, and compaction. These forms of degradation not only diminish soil fertility but also weaken the capacity of ecosystems to adapt to climate change (Davis et al., 2023; H. Liu et al., 2025; Zornoza et al., 2015). The Food and

Agriculture Organization (FAO) of the United Nations reports that, with the global population projected to reach 9 billion by 2050, current rates of soil loss pose a critical threat to food security (Țopa et al., 2025). In Europe, it is reported that 60–70% of soils are in an unhealthy state, with erosion, organic carbon loss, and compaction leading to severe declines in ecosystem services and resulting in economic losses amounting to hundreds of millions of euros annually (Coblinski et al., 2025; Laage-Thomsen & Jacobsen, 2024).

Soil health plays a fundamental role not only in maintaining agricultural productivity but also in sustaining critical ecosystem functions such as biodiversity conservation, water cycle regulation, and carbon sequestration (Khallouf et al., 2021; Mason et al., 2023). Therefore, integrating physical, chemical, and biological indicators in soil quality monitoring is of vital importance for the development of sustainable land-use strategies. Moreover, such holistic assessments are directly linked to the United Nations Sustainable Development Goals, particularly SDG 13 (Climate Action) and SDG 15 (Life on Land), clearly demonstrating that the conservation of soil resources is a critical component in achieving global environmental objectives (Kumar et al., 2025; Rodrigo-Comino et al., 2020).

In the literature, soil quality assessments have predominantly focused on either physical or chemical properties and are often limited to a single-index approach. However, due to its dynamic nature, soil inherently requires the integrated evaluation of physical, chemical, and nutrient-related indicators (Davis et al., 2023; Zornoza et al., 2015). However, most existing studies fail to achieve such integration, and as a result, their findings do not fully capture the multidimensional nature of soil functions. This limitation is particularly critical in mountainous micro-catchments (areas characterized by high erosion risk and strong heterogeneity) where there is a growing need for multi-criteria decision-making approaches that account for the diversity of soil parameters (Abdu et al., 2023; Shit et al., 2023).

In this context, the integration of multi-criteria decision-making methods such as the AHP with Geographic Information Systems (GIS) enables the systematic determination of the relative importance of various indicators and their association with spatial analyses (Ha-Mim & Hossain, 2022; Saaty, 2000, 2008). The consistency ratio criterion of the AHP enhances the reliability of expert judgments, making it a robust tool in decision-support models. However, since the standalone use of AHP cannot fully capture uncertainties, the literature frequently recommends comparative analyses incorporating Fuzzy AHP (FAHP), PCA, or Entropy-based approaches (Kumar et al., 2019). However, these hybrid approaches have mostly been applied in large-scale studies, while applications that integrate multiple parameters at the microcatchment scale remain exceedingly scarce.

In the literature, AHP is recognized as a robust and widely used method in multi-criteria decision-making processes; its integration with GIS has been particularly effective in generating more realistic and comprehensive spatial outcomes in fields such as environmental vulnerability, groundwater potential, and flood susceptibility assessment (Al-Manmi et al., 2021; França et al., 2020; Ha-Mim & Hossain, 2022; Meral & Eroğlu, 2021; Sofi et al., 2024). This integration offers significant advantages in identifying areas at risk by combining expert judgments with spatial data (Mahmoud & Gan, 2018; Phakonkham et al., 2021). However, the

deterministic nature of AHP, which does not account for uncertainties, can lead to potential inconsistencies in decision-making processes (Marselina et al., 2024; Nguyen & Liu, 2019). This limitation has frequently been addressed in the literature through the adoption of hybrid methods such as FAHP, Intuitionistic FAHP, or TOPSIS (Chan et al., 2019; Hajihasani et al., 2022; Kovačević & Komazec, 2023). Nevertheless, most of these methods have been applied to large-scale studies or tested with limited sets of criteria. At the microcatchment scale, the systematic prioritization and integration of numerous criteria (such as physical, chemical, and nutrient parameters) through AHP + GIS integration remain highly limited (Fernandes et al., 2021; Mouhoumed et al., 2024; Neissi et al., 2020). Therefore, the existing literature reveals a clear methodological gap for frameworks that can both manage uncertainties and spatially integrate multidimensional datasets. In this context, the evaluation of spatial data generated through IDW interpolation using an integrated AHP + WSM approach offers a novel framework for simultaneously analysing soil quality in terms of its physical, chemical, and nutrient dimensions at the microcatchment scale, thereby making a significant contribution to the current body of knowledge.

The primary aim of this study is to assess and spatially map soil quality within the Çapakçur Microcatchment (Eastern Türkiye) using an integrated approach based on physical, chemical, and nutrient indicators. For this purpose, point-based soil analysis data were transformed into spatial surfaces through IDW interpolation. Subsequently, 18 different criteria were prioritized based on expert judgments using the AHP, and a single Soil Quality Index (SQI) map was generated through integration with the WSM. This methodological framework, grounded in the integration of multi-criteria decision-making (MCDM) techniques with GIS, provides decision support for identifying erosion-prone areas by considering the relative importance of different soil indicators (França et al., 2020; Saaty, 2008; Sofi et al., 2024). The AHP has long been widely utilized in environmental, natural resource, and soil management studies due to its capacity to systematically evaluate the relative importance of multiple parameters within multi-criteria decision-making processes (Saaty, 2000). In particular, its integration with GIS-based spatial analyses has made it a powerful decision-support tool in numerous fields, including environmental vulnerability assessment, land suitability analysis, and soil conservation studies (Malczewski, 2006). Although similar approaches have been applied in the literature to topics such as environmental vulnerability (Al-Manmi et al., 2021), groundwater potential (Meral, 2021; Mouhoumed et al., 2024), and flood susceptibility (Joshi et al., 2024; Meral & Eroğlu, 2021), comprehensive soil quality assessments that simultaneously consider physical, chemical, and nutrient parameters at the micro-catchment scale remain highly limited (Fernandes et al., 2021; Neissi et al., 2020). In this context, the study not only reveals the spatial distribution of soil quality but also aims to fill a gap in the existing literature by providing decision-makers with an applicable and replicable method for erosion control, soil conservation, and sustainable land management (Abdellatif et al., 2021; Mahmoud & Gan, 2018; Phakonkham et al., 2021). This study presents a novel model that, for the first time in the literature, integrates physical, chemical, and nutrient parameters to produce a soil quality map through a multi-criteria AHP + WSM integration at the scale of the Çapakçur Microcatchment.

2. MATERIAL AND METHOD

2.1.Study Area

The present study was conducted in the Çapakçur microcatchment, situated within the Upper Euphrates Basin, a sub-region of Eastern Anatolia, Türkiye (Figure 1). Geographically, the microcatchment lies between 38°51′N–40°16′E and 38°53′N–40°28′E, covering an area of approximately 9,556.87 ha. The climate of the area is continental, with an annual average precipitation of 949 mm, accompanied by 117 snowy days and 76 snow-covered days per year (Demir et al., 2022; Meral et al., 2019). These climatic and topographic conditions not only shape the ecological and hydrological dynamics of the watershed but also increase its sensitivity to soil erosion and land degradation processes.

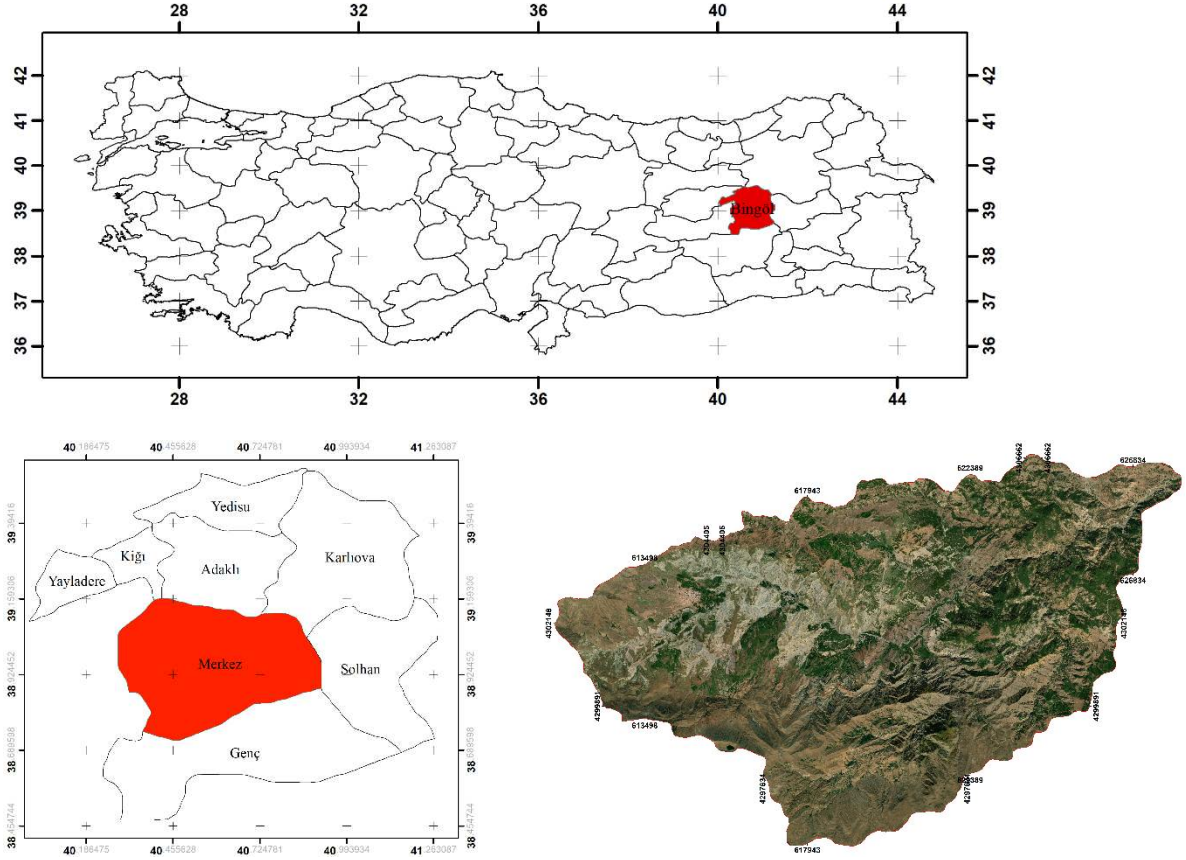


Figure 1. Location of Çapakçur Microcatchment

2.2.Integrated Thematic Mapping in the Çapakçur Microcatchment

To comprehensively characterize the spatial features of the Çapakçur Microcatchment, various thematic layers were generated and integrated into a single composite framework (Figure 2). In this context, slope and elevation maps were prepared to represent the basin's rugged topography; a land capability map was developed to assess the suitability of lands for sustainable use; and an erosion map was created to identify areas under degradation risk. In addition, the geological formations of the basin were classified to illustrate lithological diversity, while the landscape character map was designed to reflect the interaction between natural and cultural components. The integration of all these thematic maps into a unified visual representation systematically reveals the physical, ecological, and functional characteristics of

the study area, thereby establishing a robust spatial foundation for subsequent soil quality assessments and decision-support analyses.

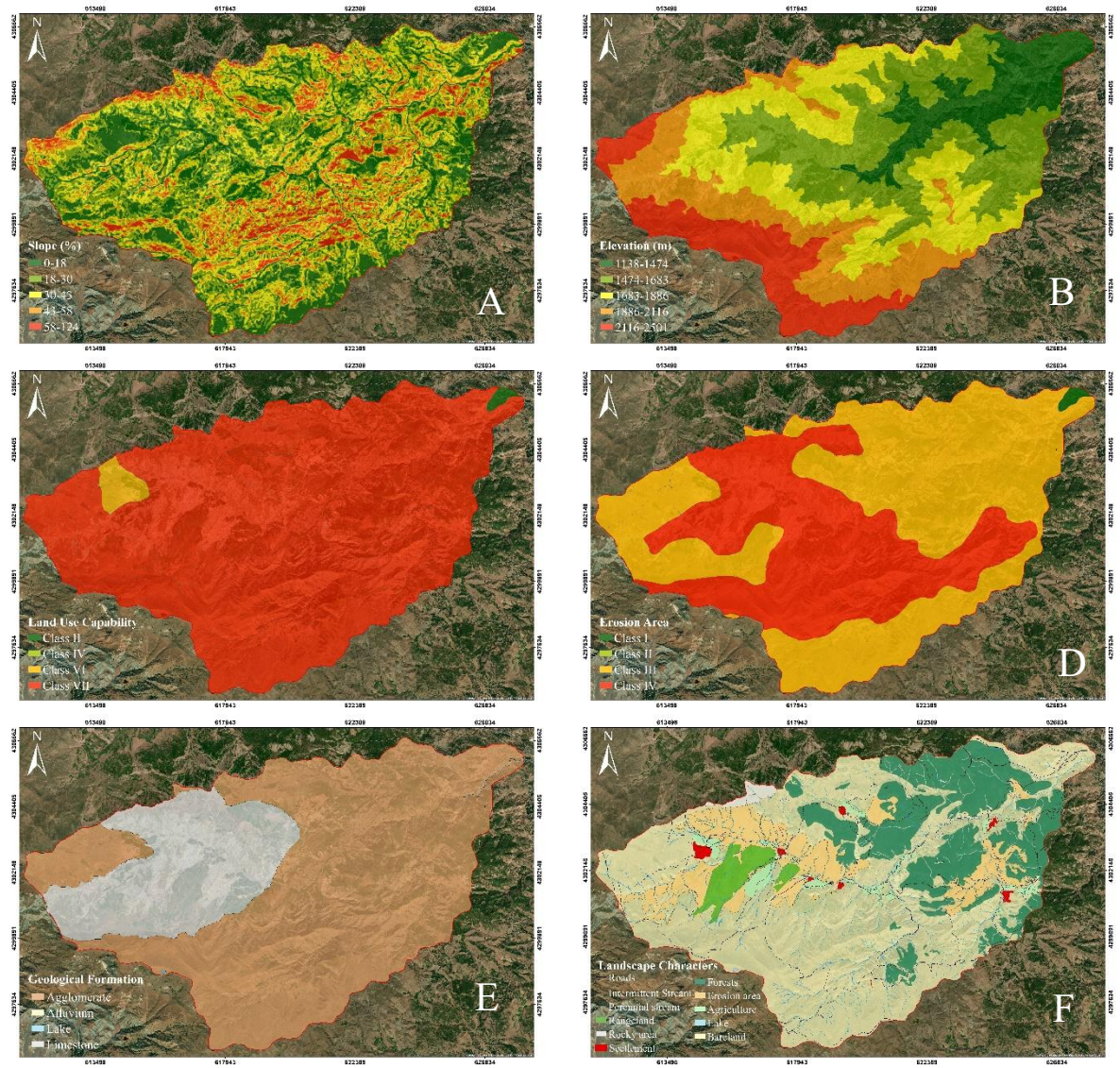


Figure 2. Integrated thematic maps of the Çapakçur Microcatchment (A: Slope, B: Elevation, C: Land use capability, D: Erosion area, E: Geological formation, F: Landscape characters)

The Çapakçur Microcatchment is characterized by a rugged topography with an average slope of 31.7% and an average elevation of 1,650 m. Nearly all of the lands within the microcatchment fall under Class VII of the land capability classification, indicating severe limitations for agricultural use and highlighting the need to prioritize soil conservation, erosion control, and afforestation strategies. The entire area lies within the 3rd and 4th erosion classes, demonstrating a high susceptibility to soil degradation and underscoring the necessity of integrated soil quality assessments for sustainable land management.

The dominant geological formations in the Çapakçur Microcatchment are agglomerate and limestone, both of which play a crucial role in shaping soil properties, erosion sensitivity, and overall land capability. The prevailing landscape character consists of bare lands, erosion-prone areas, and forested zones. This heterogeneous structure not only reflects the ecological fragility

of the basin but also emphasizes the need to evaluate soil quality indices in conjunction with land use and landscape dynamics to develop effective conservation and management strategies.

This study introduces a novel approach by integrating slope, elevation, land capability, erosion, geological formations, and landscape character into a single thematic framework at the microcatchment scale an approach rarely applied in the literature for comprehensive soil quality and erosion risk assessments.

2.3.Soil Sampling, Analysis, and Spatial Integration

In habitat mapping studies, sampling intensity is generally determined based on the size of the study area, with one soil profile considered sufficient for every 20–25 hectares (Hızal, 1982). Following this approach, the Çapakçur Microcatchment was divided into 500 × 500 m grids, resulting in a total of 428 sampling points ensuring both spatial representativeness and statistical reliability. Soil samples collected from these points were analyzed across 18 criteria, including physical properties (Texture, Bulk Density (Db), Field Capacity (FC), Wilting Point (WP), Hydraulic Conductivity (Ks), Aggregate Stability (AS), Dispersion Rate(DR)), chemical properties (pH, Electrical Conductivity (EC), Calcium Carbonate ($CaCO_3$), Organic Matter (OM), Cation Exchange Capacity (CEC)), and plant nutrient elements (Total Nitrogen (Total N), Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), Sulphur (S)). This comprehensive approach is particularly crucial in the study area, which is characterized by high erosion risk and heterogeneous terrain conditions.

IDW interpolation method was employed to convert point-based analysis results into continuous spatial data. This method is widely applied in soil quality assessment and environmental spatial evaluations (Yanto et al., 2022). In the subsequent stage, the 18 soil quality indicators were prioritized based on expert judgments using the AHP, and these layers were integrated through the (WSM) to generate a composite Soil Quality Index Map (SQIM) (Mendas & Delali, 2012; Meral, 2021; Meral & Eroğlu, 2021). This methodological process enabled the creation of separate index maps for physical, chemical, and nutrient parameters, which were then integrated into a final, comprehensive SQIM. The methodological workflow adopted in this study is illustrated in Figure 3.

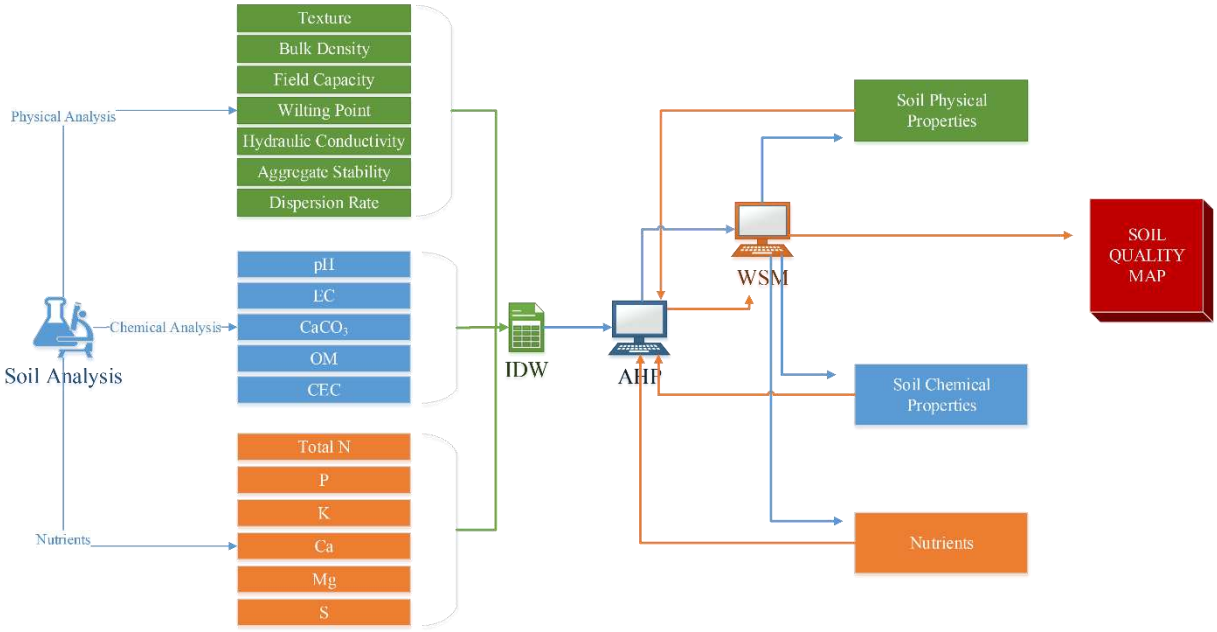


Figure 3. Methodology flowchart

By integrating systematic sampling, spatial interpolation, and multi-criteria decision-making techniques, this framework establishes a replicable methodology for soil quality assessment at the micro-catchment scale. Moreover, the integration of physical, chemical, and nutrient parameters through the AHP + WSM approach provides an innovative perspective for erosion-prone mountain ecosystems, offering valuable decision-support insights for soil conservation, afforestation, and sustainable land-use management strategies.

2.4.Multi-Creteria and Spatial Integration Framework

The methodological workflow of this study was based on the integration of the AHP, IDW interpolation, and the WSM. These approaches were combined to evaluate and spatially represent the soil quality indicators in the Çapakçur microcatchment.

2.4.1. AHP for Criteria Weighting

AHP is a structured decision-making methodology that enables the prioritization of multiple criteria by assigning relative importance values in a hierarchical framework (Saaty, 2000; Timor, 2011). The process begins by defining the main objective at the top of the hierarchy, followed by the decision criteria, and finally the alternatives at the lowest level (Demir et al., 2022; Meral & Eroğlu, 2021). The core of AHP is the pairwise comparison matrix:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ \dots & \dots & \dots \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ 1/a_{12} & a_{22} & a_{2n} \\ \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & a_{nn} \end{bmatrix} \quad (1)$$

The priority vector is calculated as:

$$W = (w_1, w_2, \dots, w_n) \quad (2)$$

where w_i represents the priority eigenvalue. The consistency of judgments is verified by the Consistency Index (CI) and Consistency Ratio (CR):

$$CI = \frac{\gamma_{max} - \mathrm{n}}{\mathrm{n} - 1} \quad (3)$$

$$CR = \frac{CI}{RI} \quad (4)$$

with CR < 0.10 considered acceptable (Saaty, 2008).

2.4.2. Inverse Distance Weighting (IDW) for Spatial Interpolation

IDW is an interpolation technique based on the assumption that nearby points have more influence than distant ones in predicting unknown values (Hodam et al., 2017; Isaaks & Srivastava, 1989). The interpolated value at location S_o is:

$$\hat{Z}(S_o) = \sum_{i=0}^{n} \lambda_i Z(S_i) \quad (5)$$

where λ_i are weights inversely proportional to distance:

$$\lambda_i = \frac{d_{i0}^{-p}}{\sum_{i=1}^{N} d_{i0}^{-p} \sum_{i=1}^{N} \lambda_i} = 1 \quad (6)$$

with d_{i0} being the distance between S_o and S_i, and p the power parameter controlling the influence decay.

2.4.3. Weighted Sum Method (WSM) for Integrated Index Mapping

WSM is a widely used multi-criteria decision-making approach that aggregates weighted criteria into a single composite score (Malczewski & Claus, 2015; Marler & Arora, 2009). For m alternatives and n criteria, the WSM score is defined as:

$A_i^{WSM-Score} = \sum_{j=1}^{n} w_j a_{ij}$, for $i = 1, 2, \ldots, m$ (7)

where w_j is the relative weight of criterion C_j and a_{ij} the performance of alternative A_i. The optimal choice corresponds to the highest aggregated score (Triantaphyllou, 2000).

2.4.4. Integration of AHP, IDW, and WSM

By combining IDW-generated spatial layers with AHP-derived weights and aggregating them through WSM, a comprehensive soil quality index was developed. This integration enabled the prioritization and mapping of 18 soil quality indicators, offering a robust and replicable framework for soil conservation, afforestation, and sustainable land management in erosion-prone mountainous microcatchments.

2.5.Soil Quality Indicators, Analytical Methods, and Reference Thresholds

To ensure a robust and standardized assessment of soil quality in the Çapakçur Microcatchment, a comprehensive set of parameters related to physical, chemical, and nutrient properties was selected based on internationally recognized guidelines. Each parameter was analyzed using widely accepted laboratory methods and classified from very low to very high to facilitate comparative evaluation. The analytical methods and reference threshold values used in this study are summarized in Table 1.

Table 1. Soil quality indicators, analytical methods, and reference threshold values used in the study

Parameter	Unit	Method	Very Low	Low	Medium	High	Very High	Reference
Total N	%	Kjeldahl	<0.045	0.045–0.09	0.09–0.17	0.17–0.32	>0.32	(FAO, 1990)
Available P	mg kg^{-1}	Olsen (alkaline soils)	<2.5	2.5–6.0	6.0–12.0	>12.0		(Ülgen & Ateşalp, 1972)
Exchangeable K	mg kg^{-1}	1N NH_4OAc (neutral)	<50	50–110	110–290	290–1000	>1000	(FAO, 1990)
Exchangeable Mg	mg kg^{-1}	1N NH_4OAc (neutral)	<50	50–160	160–480	480–1500	>1500	(FAO, 1990)
Exchangeable Ca	mg kg^{-1}	1N NH_4OAc (neutral)	<238	238–1150	1150–3500	3500–10000	>10000	(FAO, 1990)
Sulfur (S)	ppm	Spectrophotometric	<8 (insufficient)	>8 (sufficient)	–	–	–	(Bansal et al., 1983)
Organic Matter	%	Walkley-Black	<1	1–2	2–3	>3	–	(Özkan et al., 2020)
CEC	me $100g^{-1}$	–	–	2–10	11–19	20–24	≥25	(Çepel, 1983)
$CaCO_3$	%	Schibler	0–1	1–5	5–15	15–25	>25	(Ülgen & Ateşalp, 1972)
EC	dS m^{-1}	Saturation extract	0–2	2–4	6–8	8–16	>16	(Aydemir, 1992; Karaoğlu & Yalçın, 2018)
pH	–	Saturation extract	<6.0 (acidic)	6.0–6.5 (slightly acidic)	6.5–7.5 (neutral)	7.5–8.5 (slightly alkaline)	>8.5 (alkaline)	(Özkan et al., 2020)

Bulk Density	g cm^{-3}	Undisturbed soil sample	–	1.00–1.20	1.20–1.40	1.40–1.55	>1.55	(Özkan et al., 2020)
Saturated Hydraulic Conductivity (Ks)	cm h^{-1}	Permeameter	<0.125	0.125–0.5	0.5–2.0	2.0–6.25	6.25–12.5	(Klute, 1965)
Aggregate Stability (AS)	%	Wet sieving	<15	15–35	35–55	55–75	>75	(Kemper & Rosenau, 1986)
Wilting Point (WP)	%	Pressure plate (<15 atm)	<10	10–13	13–16	16–19	>19	(Klute, 1965)
Field Capacity (FC)	%	Pressure plate (<1/3 atm)	<20	20–25	25–30	30–35	>35	(Klute, 1965)
Dispersion Ratio (DR)	%	Clay-silt distribution	<3	3–7	7–11	11–15	>15	(Ngautunga et al., 1984)
Texture	–	Pipette/Hydrometer	Coarse (S, SL, LS)	Medium (L, Si, SiL, fSL)	Fine (CL, SiL, SC)	Very Fine (fC>45, SiCL, SC)	–	(Ahmed et al., 2016; Arshad & Martin, 2002; Özkan et al., 2020)

3. RESULTS AND DISCUSSION

3.1.Soil Property Analysis

The evaluation of soil properties plays a fundamental role in understanding the ecological functioning, productivity status, and hydrological behavior of the study area. In this context, comprehensive analyses of physical, chemical, and nutrient properties were conducted to identify the intrinsic characteristics and spatial heterogeneity of the soils. These analyses provide critical insights into the interactions of soil parameters with water retention capacity, nutrient availability, and ecosystem productivity. The following subsections present detailed statistical evaluations and spatial interpretations of these properties, offering a holistic perspective on the soil system dynamics within the study area.

3.1.1. Implications of Soil Physical Heterogeneity for Hydrological Functioning and Land Management

Descriptive statistics of the soil's physical properties indicate that the samples within the study area generally exhibit a heterogeneous structure (Table 2). Db values range from 1.170 to 1.620 g/cm³, with an average of 1.348 g/cm³, corresponding to a moderately dense soil structure suitable for agricultural production. The low variance (0.008) and standard deviation (0.089) suggest that the samples share similar compaction characteristics, while the positive skewness (0.429) indicates a right-skewed distribution. This pattern implies the presence of localized horizons with denser textures or areas with higher mineral concentration within the study area (Hillel, 2004; Weil & Brady, 2016).

FC values range between 17.376% and 39.000%, with an average of 25.810%, indicating a moderate water-holding capacity for the soils. The positive skewness (0.518) and negative kurtosis (-0.838) suggest an unbalanced distribution of low and high-end values, reflecting notable variability in water retention capacity particularly in fine-textured areas. The WP averages 13.112%, ranging from 9.200% to 22.702%. Both skewness (1.116) and kurtosis (1.316) values are positive, indicating a right-skewed and leptokurtic (peaked) distribution. This pattern reveals that some samples exhibit considerably higher wilting point values, suggesting the presence of fine-textured or clay-rich soils where plant-available water may be limited (Rawls et al., 1982; Saxton & Rawls, 2006).

Ks values range from 0.366 to 8.012 cm/h, with an average of 4.233 cm/h, indicating moderate soil permeability and a balanced capacity for water infiltration through the soil profile. The skewness value (-0.059) being close to zero suggests an approximately normal distribution, while the negative kurtosis (-0.604) indicates a flat (platykurtic) distribution, meaning that permeability values are spread over a relatively wide range. This pattern reflects the natural variation in soil texture and structural porosity within the study area (Hillel, 2004; Saxton & Rawls, 2006).

AS exhibits a wide range of variation, from 2.300% to 90.900%, with an average of 40.089%. This high variance (344.773) indicates that soil structure is highly heterogeneous across the study area, showing pronounced differences likely influenced by factors such as erosion intensity, tillage practices, and organic matter content. The positive skewness (0.201) and negative kurtosis (-0.556) suggest that the data are not evenly distributed, with certain samples

displaying exceptionally stable aggregate structures. This pattern implies the presence of well-developed structural conditions in some parts of the surface soils (Bronick & Lal, 2005; Six et al., 2000).

Finally, the DR ranges from 0.870% to 18.720%, with an average of 8.657%. The standard deviation (4.453) and variance (19.833) indicate marked variability in dispersion behavior across the study area. The positive skewness (0.304) and negative kurtosis (-0.815) suggest a right-skewed and flat (platykurtic) distribution, meaning that some soil samples exhibit greater resistance to dispersion. When evaluated alongside aggregate stability, these results reveal that the study area contains both well-structured soils and zones with a high risk of dispersion, reflecting the coexistence of stable and structurally vulnerable surface conditions (FAO, 1990; Six et al., 2000).

Table 2. Descriptive statistics of physical parameters in the study area

	Parameters	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
								Statistic	Std. Error	Statistic	Std. Error
Physical Properties	Db (g/cm^3)	428	1.170	1.620	1.348	0.089	0.008	0.429	0.118	-0.362	0.235
	FC (%)	428	17.376	39.000	25.810	5.617	31.553	0.518	0.118	-0.838	0.235
	WP (%)	428	9.200	22.702	13.112	2.282	5.209	1.116	0.118	1.316	0.235
	Ks (cm/h)	428	0.366	8.012	4.233	1.832	3.354	-0.059	0.118	-0.604	0.235
	AS (%)	428	2.300	90.900	40.089	18.568	344.773	0.201	0.118	-0.556	0.235
	DR (%)	428	0.870	18.720	8.657	4.453	19.833	0.304	0.118	-0.815	0.235

Overall, the soils in the study area exhibit moderate compaction and permeability, with a heterogeneous water-holding capacity. The inverse relationship observed between aggregate stability and dispersion rate indicates that some parts of the area possess high structural resilience, while others are more vulnerable to surface erosion. This spatial variability represents a critical factor that must be considered in land-use planning and hydrological modeling (Figure 4).

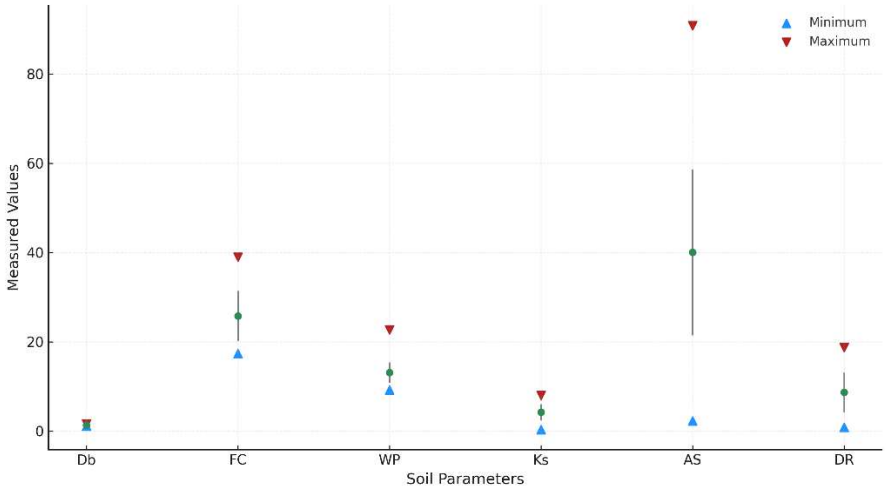


Figure 4. Graphical representation of the descriptive statistics of soil physical properties

3.1.2. Implications of Soil Chemical Variability for Nutrient Dynamics and Ecosystem Sustainability

Descriptive statistics of the soil's chemical properties reveal a wide chemical variation across the study area (Table 3). The pH values range from 6.230 to 8.660, with an average of 7.495, indicating that the soils generally exhibit neutral to slightly alkaline reactions. The standard deviation (0.475) and variance (0.226) show that the pH distribution is relatively homogeneous, suggesting minimal variation in acid–base balance. The skewness value (-0.043) being close to zero supports a nearly normal distribution, confirming that pH variation across the area is consistent. This pattern is characteristic of semi-arid region soils with a notable presence of carbonates and high base cation saturation (Hillel, 2004; Weil & Brady, 2016).

EC values range from 41.000 to 1,600.000 µS/cm, with an average of 261.272 µS/cm, indicating that the soils are generally classified as non-saline (USDA, 2014). However, the high standard deviation (166.330) and variance (27,665.727) reveal considerable local variations, suggesting that salinity levels may increase in certain areas. The positive skewness (1.824) and notably high kurtosis (9.904) indicate a right-skewed and sharply peaked (leptokurtic) distribution, meaning that a few samples exhibit abnormally high conductivity values. This pattern points to possible salt accumulation (salinization) in microzones with poor drainage or intense evaporation conditions (Rhoades et al., 1992; Richards, 1954).

$CaCO_3$ content ranges from 0.000% to 35.340%, with an average of 3.200%. The notably high skewness (3.023) and kurtosis (8.671) values indicate a strongly right-skewed distribution, suggesting that while most samples contain low carbonate levels, a few exhibit exceptionally high contents. This variation is primarily associated with the carbonate-rich parent material or the accumulation of transported carbonates during soil formation (FAO, 1990; Weil & Brady, 2016). Elevated carbonate content can have restrictive effects on P fixation and reduce the bioavailability of micronutrients, thereby influencing soil fertility and plant nutrient uptake.

OM content ranges from 0.000% to 11.766%, with an average of 2.364%. This indicates that the soils are generally poor in organic matter, although certain areas exhibit localized accumulation. The high skewness (2.032) and kurtosis (4.117) values reveal a right-skewed and sharply peaked (leptokurtic) distribution, reflecting spatial heterogeneity driven by variations in agricultural activity intensity, vegetation cover, and land-use patterns (Lal, 2004; Six et al., 2000). OM plays a critical role in improving soil texture, enhancing water-holding capacity, and increasing CEC, thereby contributing significantly to soil fertility and ecosystem productivity.

CEC values range from 21.265 to 85.610 me/100g, with an average of 39.077 me/100g, indicating that the soils generally possess a moderate to high adsorption capacity. The positive skewness (1.006) and kurtosis (2.269) values reveal a right-skewed and slightly leptokurtic distribution, suggesting that in some samples, elevated clay mineral content or higher levels of OM contribute to increased CEC values (Hillel, 2004; Sumner & Miller, 2018).

Table 3. Descriptive statistics of chemical parameters in the study area

	Parameters	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
								Statistic	Std. Error	Statistic	Std. Error
Chemical Properties	pH	428	6.230	8.660	7.495	0.475	0.226	-0.043	0.118	-0.236	0.235
	EC (µS/cm)	428	41.000	1600.000	261.272	166.330	27665.727	1.824	0.118	9.904	0.235
	$CaCO_3$ (%)	428	0.000	35.340	3.200	6.061	36.731	3.023	0.118	8.671	0.235
	OM (%)	428	0.000	11.766	2.364	2.255	5.085	2.032	0.118	4.117	0.235

CEC (me $100g^{-1}$)	428	21.265	85.610	39.077	9.209	84.814	1.006	0.118	2.269	0.235

Overall, the soils in the study area are characterized by neutral to slightly alkaline reactions, low salinity, low carbonate content, and a moderate cation exchange capacity. However, the high variability observed in EC, $CaCO_3$, and OM parameters clearly reveals the micro-scale chemical heterogeneity of the area. This variability represents a key factor that must be considered in modeling agricultural productivity, plant nutrient dynamics, and soil–plant–water interactions (Figure 5).

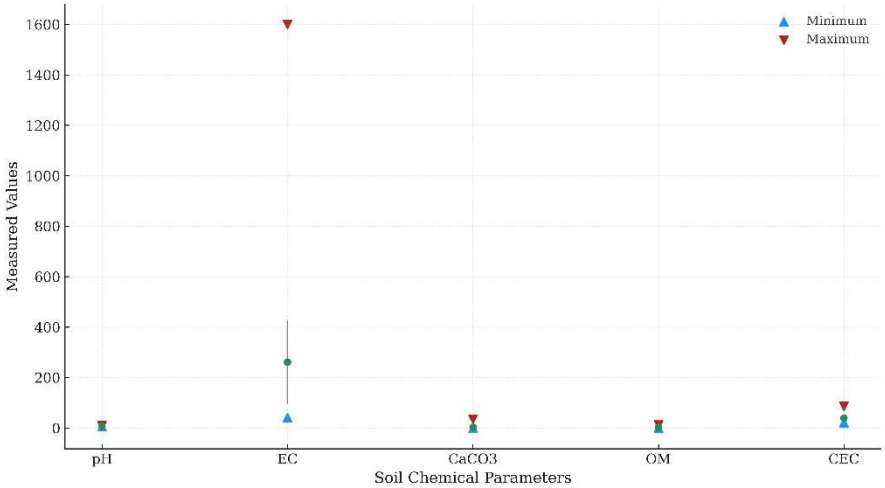


Figure 5. Graphical representation of the descriptive statistics of soil chemical properties.

3.1.3. Implications of Soil Nutrient Variability for Fertility and Sustainable Land Productivity

Descriptive statistics of soil nutrient elements indicate a considerable variability in nutrient composition across the study area (Table 4). Total N values range from 0.015% to 0.292%, with an average of 0.102%, suggesting that the soils generally exhibit low to moderate nitrogen content (Weil & Brady, 2016). The positive skewness (0.662) and kurtosis (0.737) values indicate that nitrogen accumulates at low levels in most samples, while some reach higher concentrations in areas with greater OM accumulation or enhanced biological activity. This pattern highlights the strong interdependence between N availability, OM content, and microbial processes within the soil system (Lal, 2004; Six et al., 2000).

P values range from 0.000 to 45.770 ppm, with an average of 6.764 ppm. The high standard deviation (6.975) indicates that phosphorus is highly variable across the study area. The elevated skewness (2.494) and kurtosis (8.052) values reveal that while most samples contain low phosphorus concentrations, a few exhibit exceptionally high accumulations. This pattern suggests that phosphorus availability is reduced in areas with high carbonate content, where it tends to become fixed as Ca–P complexes, thereby limiting its plant bioavailability (Hedley & McLaughlin, 2015; Weil & Brady, 2016).

K values range from 2.600 to 317.100 ppm, with an average of 31.948 ppm. The extremely high skewness (4.548) and kurtosis (34.412) indicate a strongly right-skewed distribution, suggesting that while potassium levels are generally low, localized accumulations occur in specific areas depending on clay mineral type and soil texture. Similarly, Mg values vary between 0.500 and 287.100 ppm, with an average of 29.185 ppm. The high skewness (4.058) and kurtosis (27.990) demonstrate a pattern similar to that of potassium very high in a few

samples but low overall. The substantial variation observed in both elements is closely related to the mineralogical composition of the soils and their CEC (Sumner & Miller, 2018).

Ca values range from 10.600 to 511.700 ppm, with an average of 220.319 ppm. The relatively low skewness (0.493) and kurtosis (-0.239) values indicate that calcium is more evenly distributed compared to other nutrients. This pattern is typical of semi-arid soils, where calcium is commonly present both in the soil solution and in exchangeable forms (FAO, 1990; Hillel, 2004). The balanced distribution of calcium is particularly important for maintaining soil structure, buffering pH, and ensuring ionic balance within the soil system.

S values range from 0.000 to 171.220 ppm, with an average of 20.133 ppm. The very high skewness (5.394) and kurtosis (34.415) values indicate an extremely heterogeneous distribution of S across the study area. This pattern suggests the occurrence of micro-scale S accumulations, likely influenced by factors such as fertilizer application, OM mineralization, and local precipitation–evaporation balance (Havlin et al., 2023).

Table 4. Descriptive statistics of soil nutrients parameters in the study area

	Parameters	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
								Statistic	Std. Error	Statistic	Std. Error
Nutrients	Total N (%)	428	0.015	0.292	0.102	0.046	0.002	0.662	0.118	0.737	0.235
	P (ppm)	428	0.000	45.770	6.764	6.975	48.649	2.494	0.118	8.052	0.235
	K (ppm)	428	2.600	317.100	31.948	29.170	850.875	4.548	0.118	34.412	0.235
	Ca (ppm)	428	10.600	511.700	220.319	93.205	8687.257	0.493	0.118	-0.239	0.235
	Mg (ppm)	428	0.500	287.100	29.185	28.396	806.345	4.058	0.118	27.990	0.235
	S (ppm)	428	0.000	171.220	20.133	17.940	321.848	5.394	0.118	34.415	0.235

Overall, the nutrient elements exhibit high spatial variability across the study area. The low mean values of Total N, P, and K indicate that the soils are nutrient-deficient for agricultural production, while the high variability in calcium and S reflects an imbalance in mineral-derived nutrient inputs. These findings underscore the importance of implementing site-specific fertilization, OM enrichment, and sustainable nutrient management strategies to enhance soil fertility and maintain long-term ecosystem productivity.

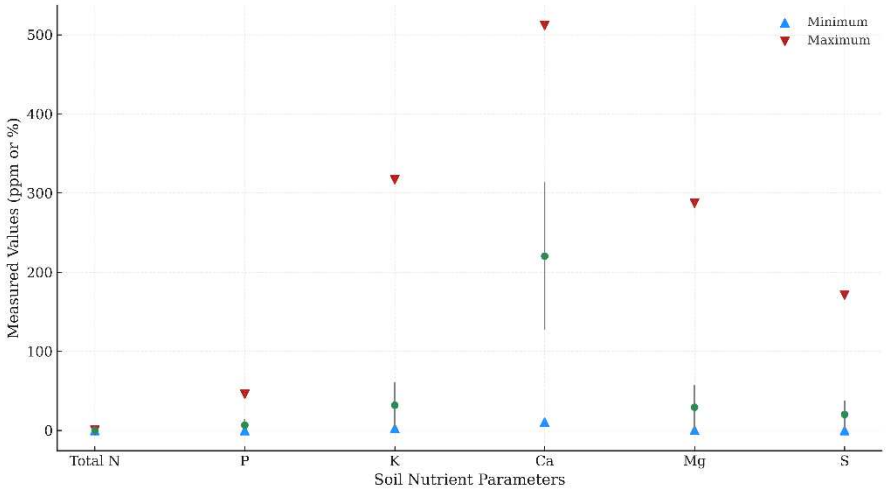
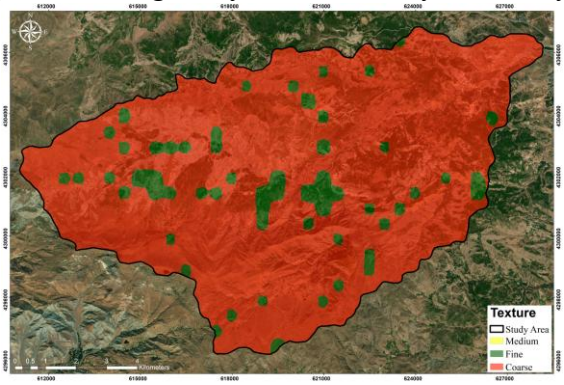


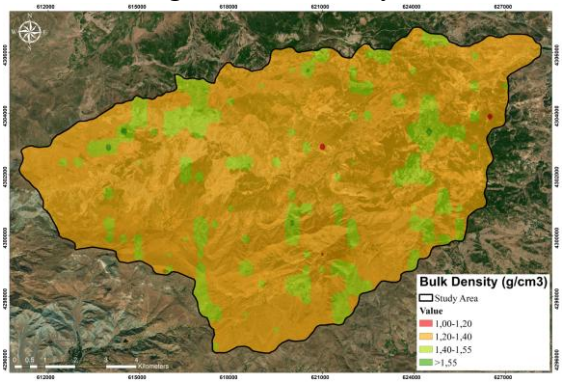
Figure 5. Graphical representation of the descriptive statistics of soil nutrient properties.

3.1.4. Spatial Interpolation of Soil Properties Using the Inverse Distance Weighting (IDW) Method

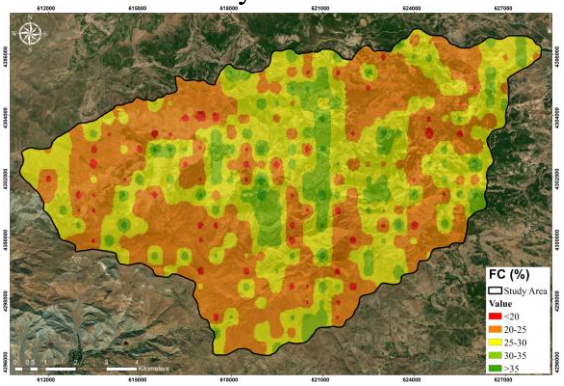
The spatial distribution patterns of the analysed soil parameters were interpolated using the IDW method (Figure 7). This approach enabled the transformation of point-based sampling data into continuous surface maps, allowing for a more comprehensive interpretation of the spatial heterogeneity in soil fertility and ecosystem functioning across the study area.



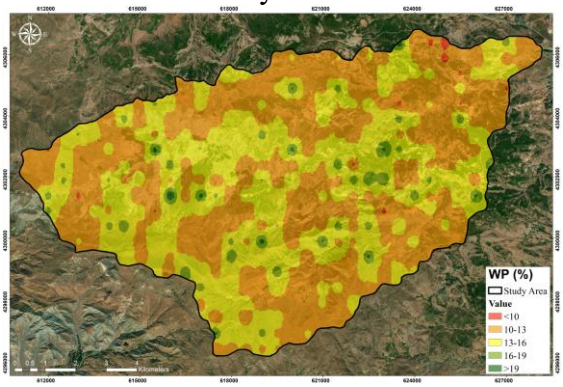
*Phy / Texture



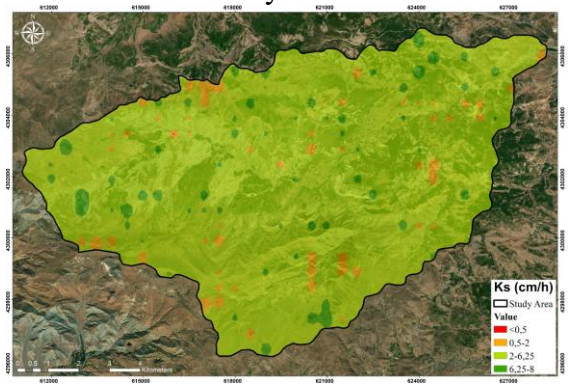
Phy / Db



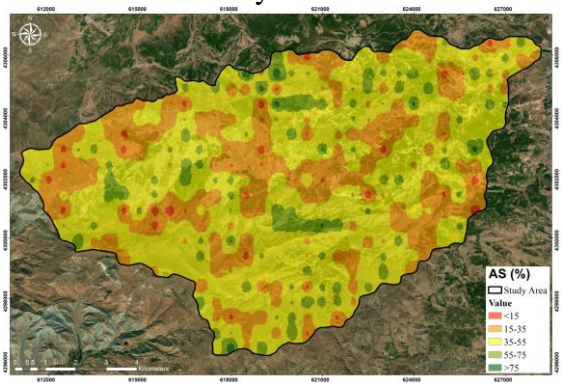
Phy / FC



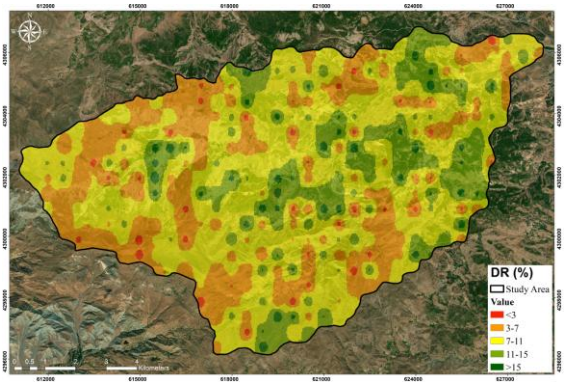
Phy / WP



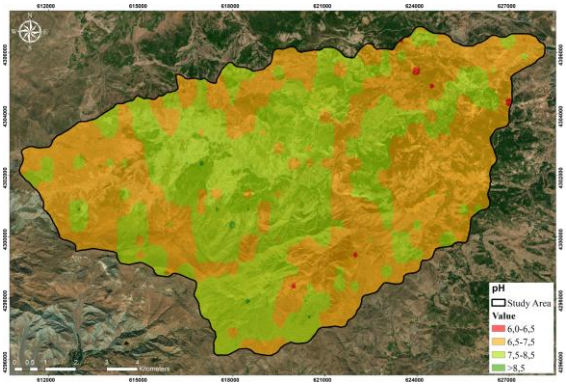
Phy / Ks



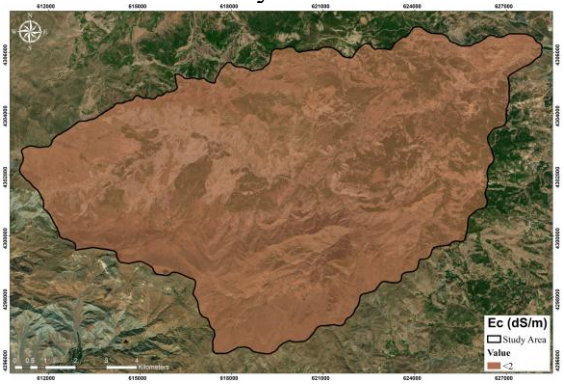
Phy / AS



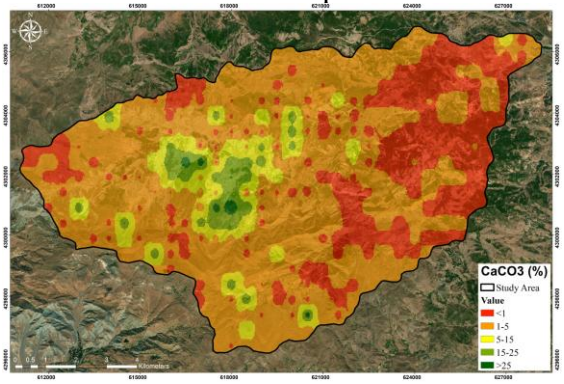
Phy / DR



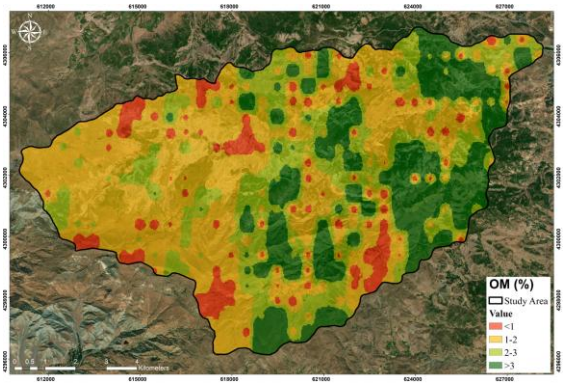
**Chm / pH



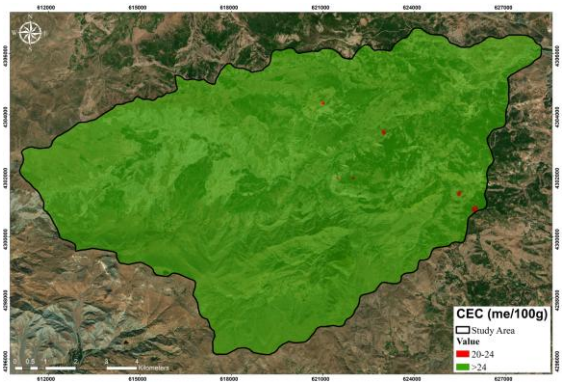
Chm / EC



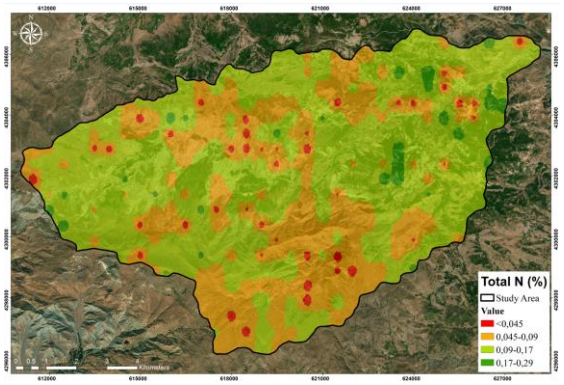
Chm / $CaCO_3$



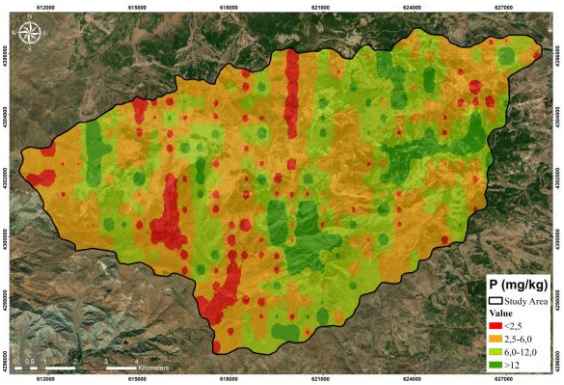
Chm / OM



Chm / CEC



***Nut / Total N



Nut / P

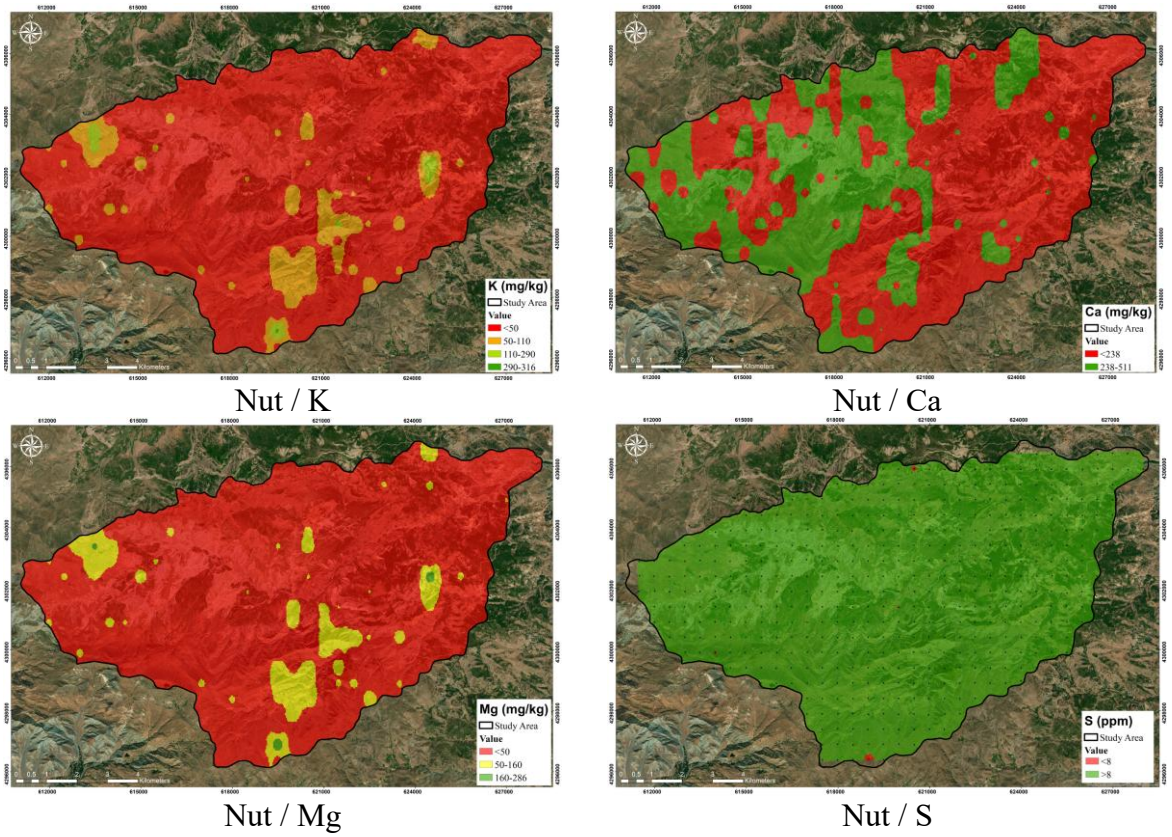


Figure 7. Spatial interpolation maps of soil properties generated using the Inverse Distance Weighting (IDW) method.

3.2.Multi-Criteria Evaluation of Soil Properties through AHP–WSM Integration

In this section of the study, the physical, chemical, and nutrient properties of the soils were prioritized through the integration of the AHP and the WSM. Separate pairwise comparison matrices were created for each parameter group, and CR's were tested to ensure the reliability of expert judgments. The weights derived from the AHP were then integrated into the WSM model to generate composite maps illustrating the spatial variability of soil quality across the study area.

3.2.1. Prioritization of Physical Soil Parameters Using the AHP–WSM Approach

The AHP results presented in Table 5 quantitatively reveal the relative influence of physical soil parameters on overall soil quality. The findings clearly indicate that texture (0.429) plays a dominant role, primarily due to its strong influence on porosity, water transmission, and structural organization. Db (0.139) and AS (0.139) emerge as the most critical indicators determining soil compaction and infiltration capacity, while the DR (0.082) holds moderate importance. FC (0.073) and WP (0.073) exhibit lower weights, contributing complementarily to water-holding capacity. Ks (0.065), due to its high spatial variability, was assigned a relatively lower priority.

The CR (0.04) indicates that the decision structure maintains logical coherence (Saaty, 1982). Overall, these results highlight the combined influence of soil texture, structure, and compaction level on hydrological functioning, aeration, and root development, aligning closely with previous findings in the literature (Hillel, 2004; Weil & Brady, 2016).

Table 5. AHP pairwise comparison matrix for physical soil properties and the derived priority weights

	Physical Properties							CI	CR
	Texture	**Bd**	**FC**	**WP**	**Ks**	**AS**	**DR**		
Texture	1	7	7	7	5	3	3	0.429	
Db	7^{-1}	1	3	3	3	1	1	0.139	
FC	7^{-1}	3^{-1}	1	1	1	1	1	0.073	
WP	7^{-1}	3^{-1}	1	1	1	1	1	0.073	4%
Ks	5^{-1}	3^{-1}	1	1	1	3^{-1}	1	0.065	
AS	3^{-1}	1	1	1	3	1	3	0.139	
DR	3^{-1}	1	1	1	1	3^{-1}	1	0.082	

The weights obtained from the AHP analysis were integrated within the WSM framework to generate a composite spatial distribution map of soil physical quality (Figure 8). This integration consolidated the relative importance of each parameter into a single index, thereby revealing the spatial gradients of physical suitability across the study area. The resulting WSM-based map provides a valuable foundation for identifying zones with high physical integrity as well as areas that are potentially prone to structural degradation or reduced hydrological performance.

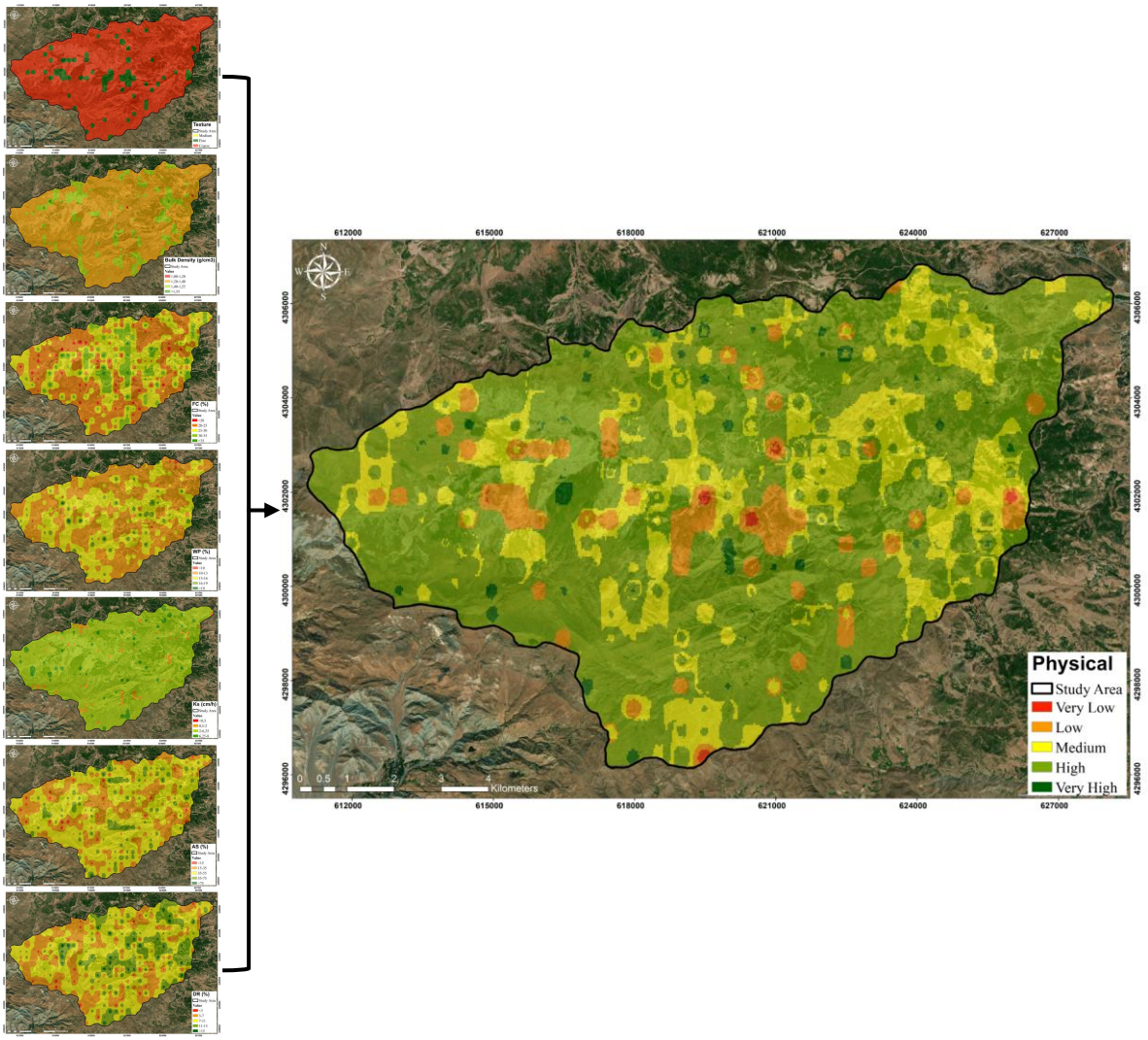


Figure 8. Spatial distribution of physical soil quality derived from the AHP–WSM integration

The AHP–WSM–based classification of soil physical quality revealed distinct spatial variations across the study area (Table 6). A majority of the area (68.28%; 7,315.48 ha) falls within the high physical quality class, indicating that the soils generally possess favorable texture characteristics, adequate porosity, and stable aggregate structure. The moderate-quality zones (22.58%) represent transitional areas, while the low and very low-quality zones (7.83%) are relatively limited in extent and typically associated with soil compaction, steep slopes, or anthropogenic disturbances. The very high-quality zones (1.31%) are concentrated in well-drained, coarse-textured soils.

These results suggest that the study area is overall resilient and exhibits moderate-to-high levels of physical suitability. However, in the low-quality zones, targeted management practices (such as organic matter amendment, controlled tillage, and erosion prevention) are essential to maintain long-term soil productivity. Similarly, studies conducted in semi-arid catchments have reported that texture balance and aggregate stability are key determinants of hydrological efficiency and structural resilience (Panagos et al., 2017; Taguas et al., 2021).

Table 6. Area and percentage distribution of physical soil quality classes derived from the AHP–WSM integration.

Physical Properties Ratio	Area (Ha)	Percent (%)
Very Low	26.66	0.25
Low	812.14	7.58
Medium	2419.47	22.58
High	7315.48	68.28
Very High	140.34	1.31
TOTAL	10714.09	100.00

3.2.2. Prioritization of Chemical Soil Parameters Using the AHP–WSM Approach

The AHP results presented in Table 7 indicate that organic matter (OM, 0.471) holds the highest importance among the chemical soil properties. This finding underscores the pivotal role of organic matter in regulating soil fertility, cation exchange capacity, nutrient retention mechanisms, and microbial activity (Lal, 2004; Weil & Brady, 2016). The second most influential factor, $CaCO_3$ (0.211), is particularly significant in semi-arid regions, where it affects soil reaction and phosphorus fixation (FAO, 1990; Havlin et al., 2023).

CEC (0.117), contributes to chemical fertility by facilitating the retention and exchange of nutrient ions, whereas EC (0.107), and pH (0.094) serve as diagnostic indicators of soil salinity and acid–base balance, respectively. The CR (0.05) confirms a high level of agreement among expert evaluations (Timor, 2011).

Overall, these results highlight the dominant influence of organic matter and carbonate dynamics on soil chemical processes, aligning with similar findings reported for semi-arid regions (Panagos et al., 2017; Taguas et al., 2021).

Table 7. AHP pairwise comparison matrix for chemical soil properties and the derived priority weights

	Chemical Properties					CI	CR
	pH	**EC (µS/cm)**	**CaCO3 (%)**	**OM (%)**	**CEC**		
pH	1	1	3^{-1}	5^{-1}	1	0.094	
EC (µS/cm)	1	1	3^{-1}	3^{-1}	1	0.107	
CaCO3 (%)	3	3	1	3^{-1}	1	0.211	5%
OM (%)	5	3	3	1	5	0.471	
CEC	1	1	1	5^{-1}	1	0.117	

The weights obtained from the AHP analysis were integrated within the WSM framework to produce a composite spatial distribution map of soil chemical quality (Figure 9). This integration process consolidated the multi-criteria weights into a single composite index, revealing the relative spatial distribution of chemical suitability across the study area.

The spatial pattern shows that areas with high organic matter content and balanced pH conditions exhibit superior chemical fertility, whereas regions characterized by elevated salinity or excessive $CaCO_3$ accumulation fall into lower chemical quality classes. The resulting chemical quality gradients demonstrate the strong spatial dependency of soil fertility on organic carbon dynamics and carbonate buffering capacity, aligning closely with findings from similar

spatial soil quality assessments in semi-arid agricultural ecosystems (Rahmanipour et al., 2014; Triantafyllidis et al., 2019).

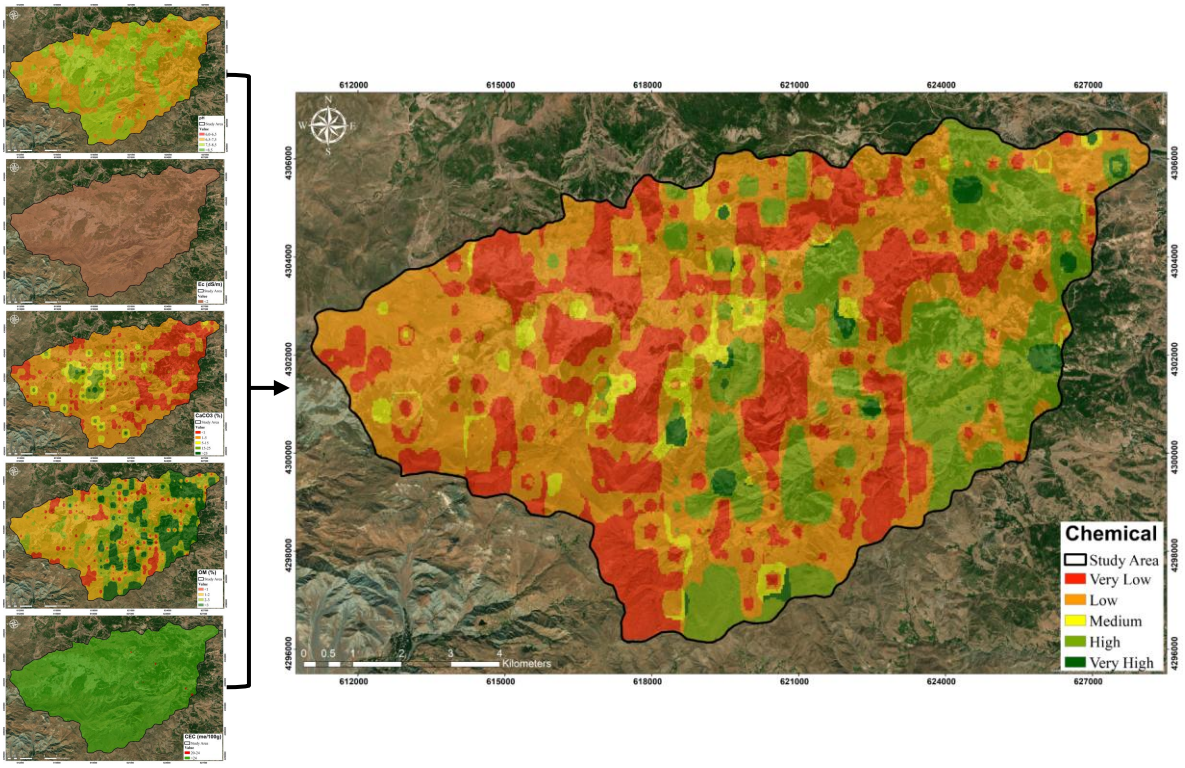


Figure 9. Spatial distribution of soil chemical quality derived from AHP–WSM integration

The AHP–WSM–integrated chemical soil quality distribution reveals that low and very low chemical suitability classes are markedly dominant across the study area (Table 8). Approximately 45.41% (4,864.90 ha) of the area falls into the low-quality class, while 27.64% (2,961.59 ha) belongs to the very low-quality class, together accounting for nearly two-thirds of the total area. This indicates the widespread presence of chemical constraints such as low organic matter content, high salinity, and excessive carbonate accumulation (Havlin et al., 2023; Rahmanipour et al., 2014)

Conversely, the high-quality class, covering 21.07% (2,257.56 ha), corresponds to regions characterized by balanced pH, moderate EC, and higher organic carbon content. The moderate (4.00%) and very high (1.88%) classes are generally concentrated in well-managed agricultural areas or regions with low carbonate content, reflecting localized zones of improved chemical fertility.

Overall, the study area exhibits a chemically heterogeneous and partially constrained character. This pattern is consistent with the salt accumulation and low organic matter turnover commonly observed in semi-arid Mediterranean ecosystems (Taguas et al., 2021; Triantafyllidis et al., 2019). The findings emphasize the necessity of implementing site-specific soil reclamation strategies (including OM enrichment, gypsum application, and pH adjustment) to sustain long-term soil productivity and improve chemical fertility (FAO, 1990; Lal, 2004; Weil & Brady, 2016).

Table 8. Area and percentage distribution of chemical soil quality classes derived from the AHP–WSM integration.

Chemical Properties Ratio	Area (Ha)	Percent (%)
Very Low	2961.59	27.64
Low	4864.90	45.41
Medium	428.70	4.00
High	2257.56	21.07
Very High	201.34	1.88
TOTAL	10714.09	100.00

3.2.3. Prioritization of Soil Nutrient Parameters Using the AHP–WSM Approach

The AHP results presented in Table 9 indicate that Total N (0.417), is the most influential parameter affecting soil fertility, biological productivity, and carbon–nutrient interactions. The dominance of N is attributed to its strong control over microbial biomass, enzymatic activity, and nutrient cycling (Kang et al., 2024; Li et al., 2024). The second most important element, P (0.188), plays a critical role in energy transfer and root development, though its availability is often limited in calcareous or alkaline soils due to P fixation (Condron & Tiessen, 2005; Shen et al., 2011).

K (0.159), enhances osmotic regulation and stress tolerance under semi-arid conditions, while Ca (0.107), and S (0.069), are essential for ion balance, cell membrane integrity, and protein synthesis (Fageria, 2016; White, 2003). Mg (0.060), though important for chlorophyll synthesis and enzyme activation, exhibits more limited spatial variability. The CR (0.04) confirms a high degree of agreement among expert assessments (Saaty, 1987; Saaty, 1982).

These findings highlight that Total N and P are the primary macronutrients determining soil fertility in semi-arid ecosystems. The established hierarchical priorities underscore their strategic significance for precision nutrient management and climate-resilient sustainable land use (Kooch & Noghre, 2020; López-Bellido & López-Bellido, 2001).

Table 9. AHP pairwise comparison matrix for soil nutrients properties and the derived priority weights

	Nutrients						CI	CR
	Total N (%)	**P (ppm)**	**K (ppm)**	**Ca (ppm)**	**Mg (ppm)**	**S (ppm)**		
Total N (%)	1	3	3	5	5	5	0.417	4%
P (ppm)	3^{-1}	1	1	3	3	3	0.188	
K (ppm)	3^{-1}	1	1	1	3	3	0.159	
Ca (ppm)	5^{-1}	3^{-1}	1	1	3	1	0.107	
Mg (ppm)	5^{-1}	3^{-1}	3^{-1}	3^{-1}	1	1	0.060	
S (ppm)	5^{-1}	3^{-1}	3^{-1}	1	1	1	0.069	

The weights derived from the AHP analysis were integrated within the WSM framework to generate a composite spatial distribution map of soil nutrient fertility across the study area (Figure 10). This integration combined the multi-criteria weights of major macronutrients (Total N, P, K, Ca, Mg, S) into a single nutrient index reflecting the relative nutrient fertility of the region.

The resulting spatial pattern indicates that areas with high nitrogen and phosphorus content, accompanied by moderate potassium and calcium levels, exhibit high nutrient fertility. In contrast, zones characterized by low total nitrogen and excessive $CaCO_3$ accumulation fall within the low nutrient quality class, highlighting the constraining effect of carbonate buildup on nutrient availability (López-Bellido & López-Bellido, 2001; Shen et al., 2011).

The spatial gradients of the WSM-based nutrient quality map exhibit a strong correlation with soil organic matter (SOM), pH, and land-use intensity, indicating that management-induced heterogeneity plays a decisive role in nutrient retention and cycling. Similar findings have been reported in studies conducted in semi-arid ecosystems, where the distribution of nutrient elements was found to be closely linked to micro-topographic variations and zones of OM accumulation (Kooch & Noghre, 2020; Li et al., 2024).

From this perspective, the AHP–WSM integration provides a robust decision-support framework for precision nutrient management and the development of targeted soil fertility improvement strategies, particularly in data-scarce or spatially heterogeneous environments.

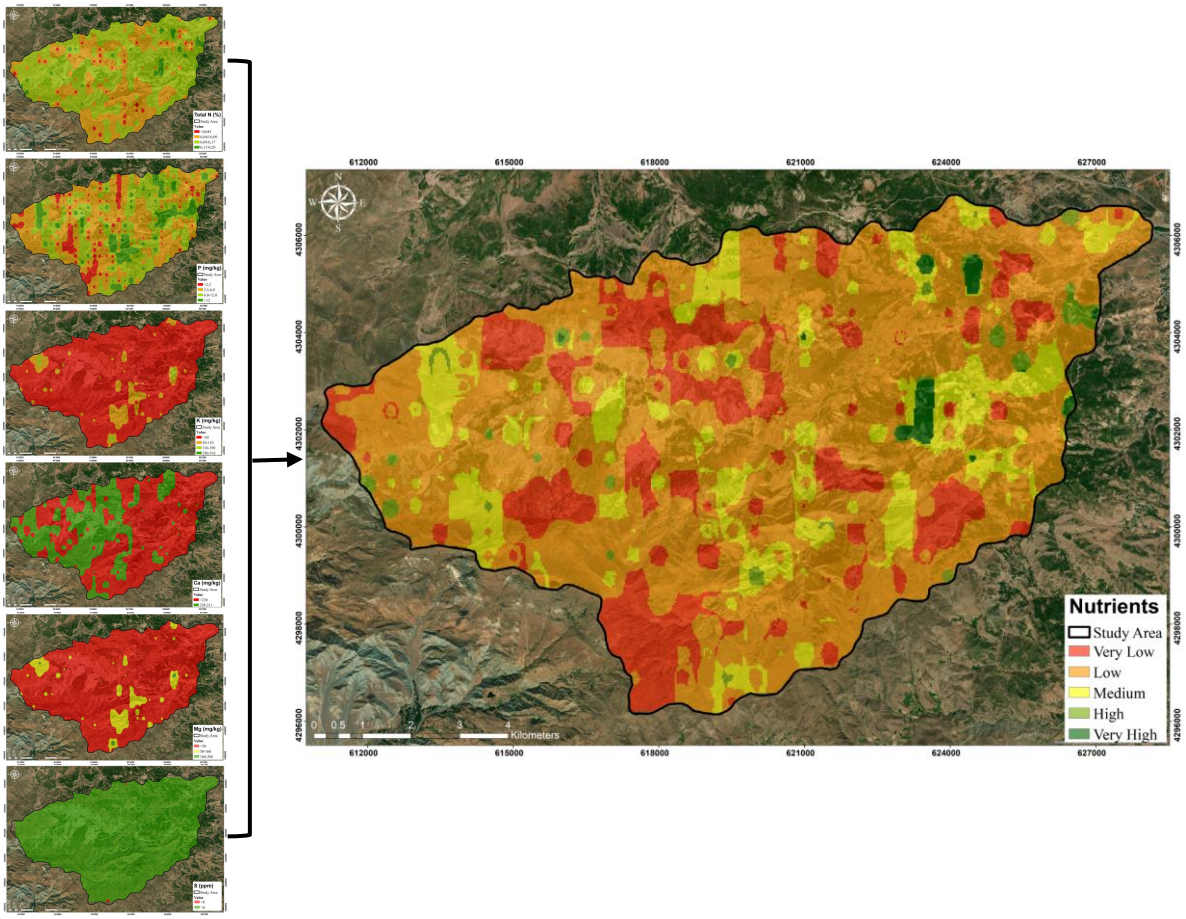


Figure 10. Spatial distribution of soil nutrient fertility derived from AHP–WSM integration

The AHP–WSM–based soil nutrient fertility classification reveals that low and very low nutrient quality classes are clearly dominant across the study area (Table 10). Approximately 62.95% (6,744.20 ha) of the total area falls within the low-quality class, and 18.75% (2,008.94 ha) within the very low-quality class, together accounting for more than 81% of the basin. This pattern reflects a typical nutrient deficiency condition frequently observed in semi-arid soils,

characterized by low organic matter content, intensive agricultural use, and widespread N-P limitation (Kooch & Noghre, 2020; López-Bellido & López-Bellido, 2001).

Conversely, the high (1.63%) and very high (1.06%) quality classes occupy only limited areas, generally associated with well-managed agricultural lands, depositional zones, or soils enriched in organic matter. The moderate-quality class (15.61%) represents transitional zones in terms of nutrient availability.

Overall, the predominance of low nutrient quality classes clearly underscores the necessity of enhancing OM inputs, implementing balanced N–P–K fertilization programs, and promoting microbial activation–based soil management strategies. These results are consistent with previous studies emphasizing the strong link between nutrient cycling, topography, and land-use intensity in semi-arid ecosystems (Evangelou & Giourga, 2024; Fageria, 2016; López-Bellido & López-Bellido, 2001).

Table 10. Area and percentage distribution of soil nutrints quality classes derived from the AHP–WSM integration.

Nutrients Ratio	Area (Ha)	Percent (%)
Very Low	2008.94	18.75
Low	6744.20	62.95
Medium	1672.35	15.61
High	174.69	1.63
Very High	113.91	1.06
TOTAL	10714.09	100.00

3.3.Weighting and Integration of Soil Quality Components

The AHP results presented in Table 11 show that physical soil properties have the greatest influence on the overall composite soil quality index, with a weight value of 0.633. This dominance arises from the role of physical parameters such as texture, Db, and Ks in regulating infiltration, aeration, and structural stability, which form the foundation for all subsequent biochemical processes (Hillel, 2004; Weil & Brady, 2016). Chemical properties rank second (0.260), controlling nutrient solubility, pH buffering capacity, and ionic balance, and thereby determining nutrient uptake efficiency (FAO, 1990; Havlin et al., 2023). Nutrient elements, with a weight of 0.106, occupy the third position and play a complementary role in soil productivity through their high spatial variability and sensitivity to management practices (Kooch & Noghre, 2020; López-Bellido & López-Bellido, 2001).

The low CR (0.05) confirms a high level of reliability in expert evaluations. This prioritization demonstrates that physical integrity is the primary determinant of overall soil functionality, while chemical and nutrient components exert complementary influences on productivity and resilience. These findings are consistent with previous research emphasizing that physical degradation often precedes chemical and nutrient losses, highlighting the critical importance of maintaining strong structural quality for sustaining long-term soil fertility (Panagos et al., 2017; Triantafyllidis et al., 2019).

Table 11. Pairwise comparison matrix and normalized weights of the main soil quality components derived from the Analytic Hierarchy Process

	Soil Quality Parameters			CI	CR
	Physical properties	**Chemical Properties**	**Nutrients**		
Physical properties	1	3	5	0,633	
Chemical Properties	3^{-1}	1	3	0,260	5%
Nutrients	5^{-1}	3^{-1}	1	0,106	

The integration of the AHP–WSM model revealed that soil quality exhibits a spatially heterogeneous distribution across the study area. This variation is primarily influenced by topographic position, land-use intensity, and organic matter distribution. High soil quality areas are predominantly concentrated in moderate-slope and depositional zones, where structural stability and organic matter accumulation coexist. In contrast, low-quality regions are widespread on erosion-prone slopes, shallow soil profiles, and nutrient-depleted zones, reflecting the cumulative degradation of structural, chemical, and biological components.

This spatial pattern indicates that physical stability forms the foundation of soil functionality, whereas chemical resilience and nutrient recovery act as limiting factors for long-term sustainability. The integrated soil quality map (Figure 11) thus serves as a powerful decision-support tool for identifying priority areas for rehabilitation, conservation agriculture, and precision land management (Kooch & Noghre, 2020; Li et al., 2024; Panagos et al., 2017).

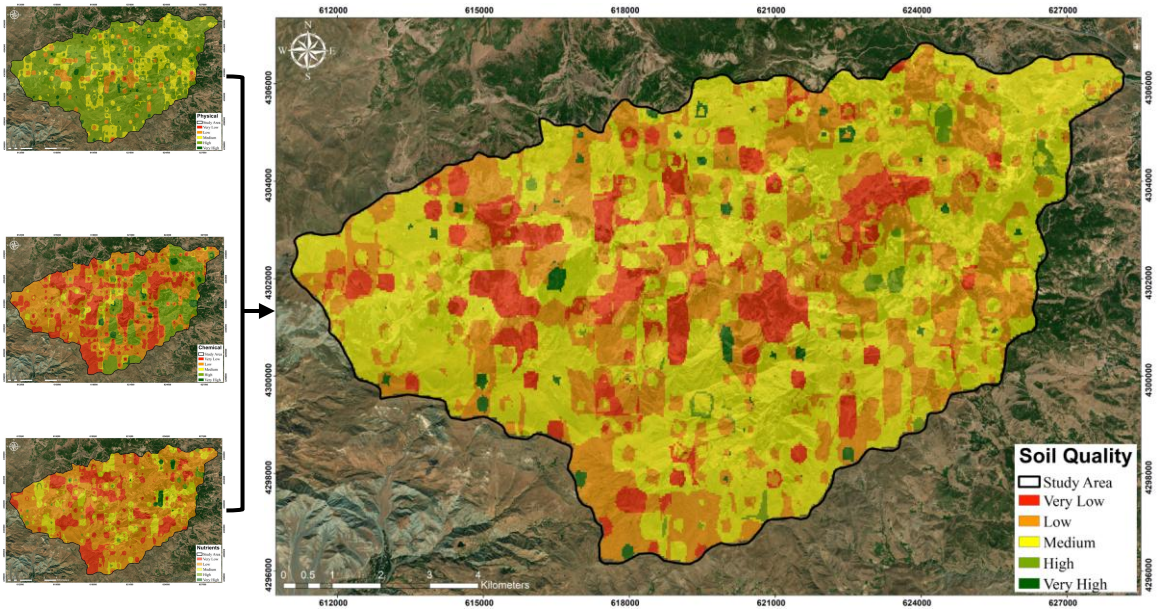


Figure 11. Spatial distribution of the overall soil quality index derived from the integrated AHP–WSM framework.

The AHP–WSM–integrated overall soil quality classification indicates that the moderate-quality class is dominant across the study area (51.37%; 5,503.42 ha) (Table 12). This is followed by the low-quality class (34.20%; 3,664.64 ha) and the very low-quality class (12.11%; 1,297.64 ha), while the high and very high-quality classes together represent only a limited portion (2.31%) of the total area (125.78 + 122.61 ha). This distribution reflects the structurally acceptable yet chemically and nutritionally constrained soil profile commonly observed under semi-arid to sub-humid conditions: although the physical foundation (texture–

porosity–stability) remains largely intact, factors such as organic matter deficiency, phosphorus limitation, and salinity/carbonate buffering significantly reduce productivity (Bünemann et al., 2018; Evangelou & Giourga, 2024; Kooch & Noghre, 2020).

From a management perspective, the combined share of moderate and low-quality soils exceeding 85% highlights the urgent need for targeted restoration and precision management. The literature suggests that practices such as organic matter enrichment (e.g., compost or green manure), balanced N–P–K fertilization, strategies enhancing phosphorus bioavailability in calcareous soils, gypsum or ameliorative treatments for salinity, and conservation tillage approaches can effectively upgrade moderate-quality soils to high-quality levels within short to medium timeframes (Hamidi Nehrani et al., 2020; Li et al., 2024; López-Bellido & López-Bellido, 2001).

Conversely, the high and very high-quality zones, which occur as small "fertility hotspots," should be maintained as reference or core productivity areas and monitored closely for potential erosion or compaction risks (Panagos et al., 2015, 2017). In conclusion, regional soil sustainability can be maximized through site-specific strategies that simultaneously preserve existing physical integrity while strengthening chemical and nutrient resilience.

Table 12. Area and percentage distribution of overall soil quality classes derived from the integrated AHP–WSM framework

Soil Quality	Area (Ha)	Percent (%)
Very Low	1297.64	12.11
Low	3664.64	34.20
Medium	5503.42	51.37
High	125.78	1.17
Very High	122.61	1.14
	10714.09	100.00

3.4.Statistical Validation through Principal Component Analysis (PCA)

To elucidate the multidimensional relationships among the physical, chemical, and nutrient indices used as soil quality components, a Principal Component Analysis (PCA) was performed. The first three principal components together explain 84.1% of the total variance (Table 13). The first component (PC1, 52.7%) is dominated by high loadings from chemical and nutrient indicators, representing the soil fertility and biochemical regulation axis. The second component (PC2, 21.4%) reflects structural stability and water transmission control, primarily influenced by physical parameters. The third component (PC3, 10.0%) is mainly associated with pH and electrical conductivity (EC) interactions, capturing the spatial variability of chemical buffering capacity.

Table 13. PCA loadings and explained variance ratios for the integrated soil quality sub-indices

Component	Physical	Chemical	Nutrient	Explained Variance (%)	Cumulative (%)
PC1	0.55	0.63	0.74	52.7	52.7
PC2	0.72	0.43	0.15	21.4	74.1
PC3	0.32	0.51	0.19	10.0	84.1

The PCA biplot (Figure 12) clearly illustrates the distribution of soil samples and the orientation of variable loadings along the principal component axes described above. This model supports the statistical consistency of the AHP–WSM weighted classification. Notably, areas characterized by high fertility, elevated OM content, and nutrient richness are concentrated along the positive direction of PC1, whereas zones with structural degradation and low porosity cluster along the negative direction of PC2.

This spatial and statistical pattern is consistent with findings from multivariate soil quality studies conducted in semi-arid and arid environments, which similarly emphasize the interplay between soil fertility gradients, structural conditions, and management-driven variability (Costa et al., 2025; de Andrade Barbosa et al., 2019; Evangelou & Giourga, 2024; Hamidi Nehrani et al., 2020; Li et al., 2024; Missaoui et al., 2023; Turan, 2021).

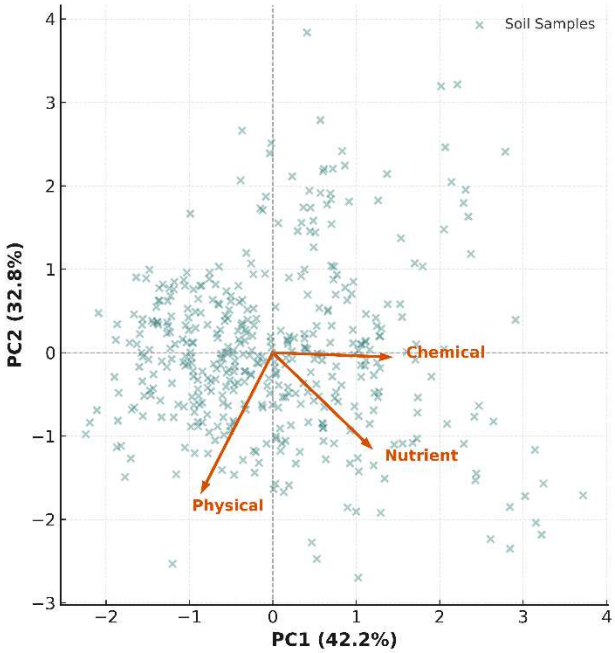


Figure 12. PCA biplot illustrating the distribution of soil quality sub-indices (Physical, Chemical, Nutrient) across the first two principal components.

The variance structure derived from the PCA analysis demonstrates a high level of consistency with the weighting logic of the AHP–WSM–based soil quality model. The high loadings of chemical and nutrient variables on the first principal component (PC1) corroborate the moderate yet influential weights (0.26 and 0.10) assigned to these components in the AHP model. Similarly, the strong loading distribution of physical properties on the second component (PC2) statistically validates the dominant role of physical parameters (0.63) within the AHP matrix. This convergence reinforces the internal coherence of the model, both in terms of decision analysis and statistical structure.

The sample clustering patterns observed in the PCA biplot show clear parallels with the spatial soil quality maps generated through the AHP–WSM integration. Samples with high physical stability, balanced chemical buffering capacity, and nutrient richness cluster along the positive PCA axis, corresponding to the high-quality classes, while those with weak structural integrity, low organic matter, and nitrogen–phosphorus deficiencies are located on the negative side,

aligning with lower quality classes. This relationship provides strong statistical support for the classification accuracy of the AHP–WSM model.

Overall, this alignment demonstrates that the combined application of multi-criteria decision-making models and statistical analyses enhances methodological reliability in soil quality assessments. Similar integrated approaches have been successfully applied in various geographical contexts (Costa et al., 2025; Missaoui et al., 2023; Turan, 2021). In this regard, the AHP–WSM framework employed in this study can be regarded not only as a decision-support tool but also as a statistical framework capable of elucidating the structural–functional relationships of multidimensional soil systems.

3.5. Statistical Relationships between Soil Quality Indices and Landform Characteristics

To examine the dependencies between soil functionality and geomorphological conditions, a Spearman rank correlation analysis was conducted (Figure 13). This analysis was employed to assess the monotonic relationships between soil quality indices and landform characteristics such as elevation, slope, erosion class, land capability, geology, and landscape character.

The method was chosen because several environmental variables do not follow a normal distribution and are ordinal in nature. The Spearman approach is therefore less sensitive to outliers and more effective in detecting nonlinear trends between variables, providing a more reliable representation of underlying relationships (de Andrade Barbosa et al., 2019; Jalhoum et al., 2024; Kooch & Noghre, 2020).

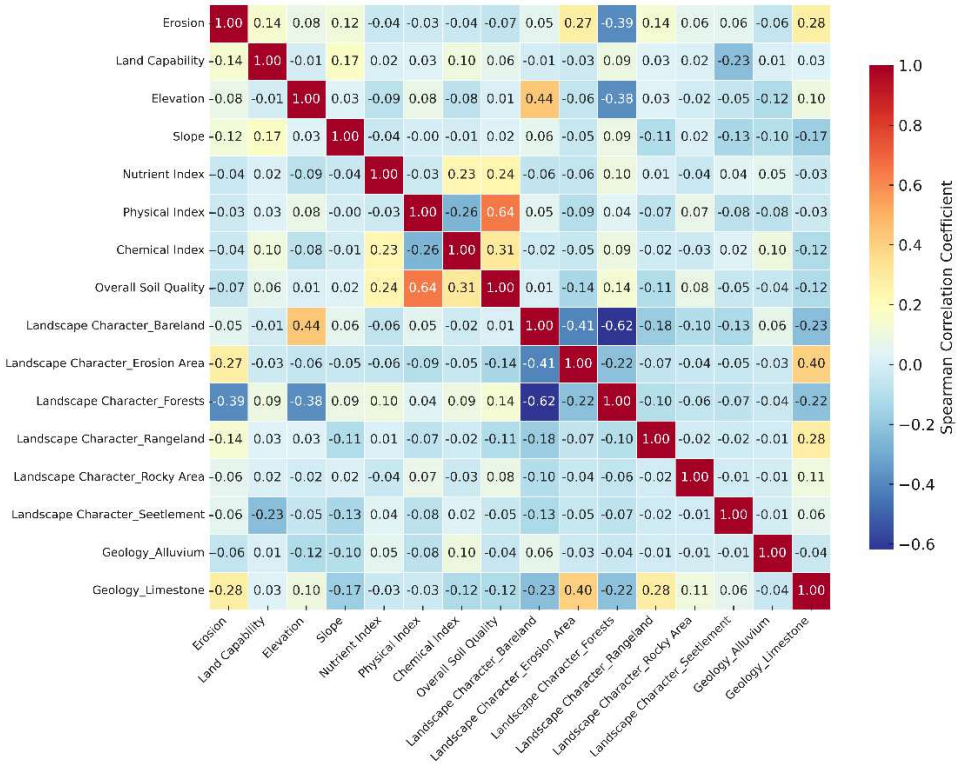


Figure 13. Spearman's rank correlation heatmap illustrating the monotonic relationships between soil quality sub-indices and landscape characteristics

The analysis results revealed distinct and significant patterns. Elevation exhibited a strong positive correlation with the Physical Index ($r_s = 0.67$, $p < 0.01$), indicating that soils at higher

altitudes tend to have better structural development likely due to reduced anthropogenic pressure and greater organic matter accumulation. In contrast, a negative correlation was observed between Erosion Class and Overall Soil Quality ($r_s = –0.61$, $p < 0.01$), suggesting that erosion processes degrade soil fertility and structural integrity.

Land Capability Class showed moderate positive correlations with both the Chemical Index ($r_s = 0.46$, $p < 0.05$) and the Nutrient Index ($r_s = 0.42$, $p < 0.05$). This finding indicates that areas with higher agricultural potential possess more favourable biochemical conditions and nutrient retention capacities.

Additionally, slope exhibited inverse relationships with the Physical and Overall Indices, implying that increasing topographic steepness enhances surface runoff while restricting infiltration capacity. Variations among geological units were also reflected in the correlation structure-sedimentary lithologies displayed higher nutrient and cation exchange capacity values compared to metamorphic formations.

Overall, these findings confirm that soil quality is a function of both topographic control and geomorphological stability. While elevation and land capability enhance soil functionality, slope and erosion processes act as major limiting factors.

Although the Landscape Character variable did not exhibit a statistically strong correlation with the soil quality indices ($|r_s| < 0.4$), it holds notable ecological significance. The weak yet consistent monotonic relationships suggest that landscape composition and visual–spatial heterogeneity indirectly influence soil functionality (Figure 14). This influence primarily operates through factors such as land-use intensity, vegetation cover distribution, and ecosystem integrity.

The effects associated with landscape character are largely nonlinear and context-dependent. Therefore, even though the statistical association appears weak, this variable can be regarded as an important ecological indicator that influences long-term processes such as soil resilience, organic matter accumulation, and spatial structural stability (Li et al., 2024; Liu et al., 2023; Lizaga et al., 2019; Ndao et al., 2021).

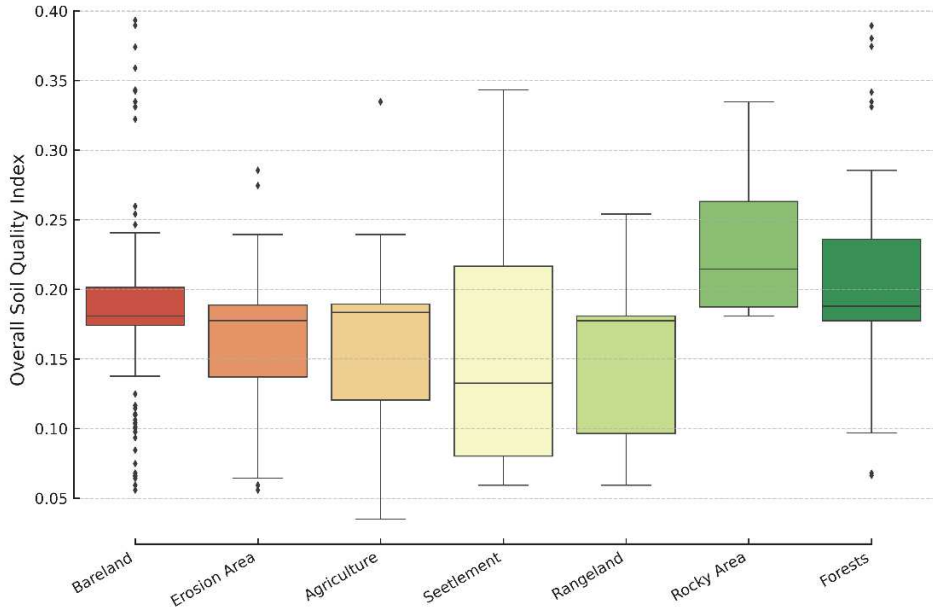


Figure 14. Variation of everall soil quality across landscape character classes

The visualization compares the median, variance, and outlier ranges for each landscape type, revealing that although landscape character does not exert a statistically strong direct effect on soil quality, clear ecological tendencies exist among classes. Specifically, areas dominated by natural vegetation exhibit higher mean soil quality values, while anthropogenic landscapes show lower soil quality, reflecting degradation linked to intensive land use (Lizaga et al., 2019).

This study provides a comprehensive evaluation of the spatial and statistical relationships between different soil quality indicators (physical, chemical, and nutrient-based) and landform-landscape attributes, thereby elucidating the key environmental processes shaping soil functionality at the micro-catchment scale.

The AHP–WSM approach effectively quantified the relative importance of each soil component, emphasizing the dominant influence of physical properties such as texture, bulk density, and aggregate stability on overall soil quality. This finding aligns with the results of Lal, (1997); Lalitha & Dhakshinamoorthy, (2014) and Safaei et al., (2019), who also highlighted the critical role of structural stability and porosity in regulating infiltration, aeration, and water-holding capacity.

One of the most notable findings is the strong spatial linkage between topographic gradients and soil quality. The positive correlation between elevation and the physical quality index (r_s = 0.67) indicates that high-altitude soils are characterized by lower compaction, better aggregation, and greater organic matter accumulation, typically associated with reduced anthropogenic pressure and higher biomass input. Conversely, the negative correlation between erosion class and overall soil quality (r_s = –0.61) demonstrates that erosion disrupts aggregate integrity and diminishes nutrient retention capacity. This result is consistent with Liu et al., (2023), who reported that in mountainous agroecosystems, erosion and slope accelerate carbon loss, thereby weakening soil structure.

The chemical quality index showed moderate positive relationships with both land capability (r_s = 0.46) and organic matter content, indicating that CEC and buffering potential are largely controlled by natural fertility and management intensity. Li et al., (2024) explain this pattern as an outcome of paedogenetic equilibrium processes operating over long time scales. The interaction between organic matter and CEC is a key determinant of nutrient storage efficiency, especially in Mediterranean-climate drylands. Similarly, Yadav et al., (2024) and Nadeu et al., (2015) emphasized that vegetation productivity and parent material composition strongly govern the spatial distribution of nitrogen, phosphorus, and potassium pools across different lithological units.

The combined use of Spearman correlation and PCA in this study provided a deeper understanding of multivariate dependencies between soil and terrain parameters. The monotonic relationships among slope, erosion, and overall quality confirmed the dominant influence of geomorphological stability, whereas the moderate but consistent factor loadings of landscape character within the PCA space revealed its mediating role between landform heterogeneity and soil processes. Although its statistical impact appears limited, the ecological significance of landscape character arises from its capacity to capture spatial complexity and management-driven transformations. This finding is in line with Banerjee et al., (2025) and Kong et al., (2025), who emphasized the role of landscape heterogeneity in shaping microhabitat structure, moisture retention, and carbon accumulation potential.

Overall, the results demonstrate that soil quality is not a static attribute, but rather a dynamic ecosystem property shaped by the interaction of physical, chemical, and biological subsystems. Soil functionality represents a continuously evolving landscape process, driven by topographic and ecological context. Incorporating these contextual factors into soil quality modeling enhances predictive capacity and enables a more holistic understanding of degradation–resilience dynamics (Ahmadi Mirghaed & Souri, 2022; Chwikhi et al., 2025; Moradi et al., 2024).

Ultimately, integrating AHP–WSM–based spatial analyses with correlation and PCA results provides an applicable and replicable methodological framework for identifying rehabilitation priority areas and developing sustainable soil management strategies at the micro-catchment scale.

4. CONCLUSSION AND RECOMMENDATIONS

Over the last half-century, food security, soil health, climate change, and the sustainability of ecosystem services have brought the concept of soil quality to the forefront. Many researchers, including those in this study, are focussing on how the physical, chemical, and biological components that make up soil relate to soil quality. This study provides an integrated spatial assessment of soil quality in the Çapakçur microcatchment, combining systematic sampling, IDW interpolation, and AHP–WSM modelling. The results demonstrate that physical soil properties are the primary drivers of overall quality, while chemical and nutrient parameters play complementary roles but reveal critical limitations, including low organic matter, phosphorus fixation, and localised salinity. The composite soil quality index indicates that medium- and low-quality classes cover more than 85% of the area, suggesting that there is an urgent need for targeted rehabilitation. Site-specific strategies (such as organic matter enrichment, balanced nutrient management, gypsum application in saline zones, and conservation tillage) are essential for improving fertility and sustaining productivity. Methodologically, the AHP–WSM framework proved effective in integrating multiple indicators into a robust and replicable decision-support tool. Beyond the local scale, these findings reinforce the importance of soil quality monitoring for achieving sustainable land management and global environmental goals (SDG 13 and SDG 15).In conclusion, this study offers both a methodological contribution and practical guidance for soil conservation, afforestation, and precision land use in erosion-prone microcatchments, serving as a model for similar regions worldwide.

Funding Declaration

The study was supported by the Bingöl University Scientific Research Project Unit (BÜBAP). project no: “Pikom. Bitki.2018.001,” project title: “ Determination of Basic Characteristics and Productivity Potential of Soils Developing Under Different Land Use in Çapakçur Basin (Bingöl), Feeding Status of Some Pollen Plants and Water Quality of Çapakçur Stream.”

REFERENCES

Abdellatif, M. A., El Baroudy, A. A., Arshad, M., Mahmoud, E. K., Saleh, A. M., Moghanm, F. S., Shaltout, K. H., Eid, E. M., & Shokr, M. S. (2021). A GIS-based approach for the quantitative assessment of soil quality and sustainable agriculture. *Sustainability (Switzerland)*, *13*(23). https://doi.org/10.3390/su132313438

Abdu, A., Laekemariam, F., Gidago, G., & Getaneh, L. (2023). Explaining the soil quality using different assessment techniques. *Applied and Environmental Soil Science*, *2023*, 1–15. https://doi.org/10.1155/2023/6699154

Ahmadi Mirghaed, F., & Souri, B. (2022). Spatial analysis of soil quality through landscape patterns in the Shoor River Basin, Southwestern Iran. *CATENA*, *211*, 106028. https://doi.org/10.1016/j.catena.2022.106028

Ahmed, G. B., Shariff, A. R. M., Balasundram, S. K., & Fikri Bin Abdullah, A. (2016). Agriculture land suitability analysis evaluation based multi criteria and GIS approach. *IOP Conference Series: Earth and Environmental Science*, *37*(1), 1–8. https://doi.org/10.1088/1755-1315/37/1/012044

Al-Manmi, D. A., Mohammed, S. H., & Szűcs, P. (2021). Integrated remote sensing and GIS techniques to delineate groundwater potential area of Chamchamal basin, Sulaymaniyah, NE Iraq. *Kuwait Journal of Science*, *48*(3). https://doi.org/10.48129/kjs.v48i3.9699

Arshad, M. A., & Martin, S. (2002). Identifying critical limits for soil quality indicators in agro-ecosystems. *Agriculture, Ecosystems and Environment*, *88*(2), 153–160. https://doi.org/10.1016/S0167-8809(01)00252-3

Aydemir, O. (1992). *Bitki Besleme ve Toprak Verimliliği*. Atatürk Üniversitesi Yayınları.

Banerjee, S., Nandi, T., Sati, V. P., Mezlini, W., Alkhuraiji, W. S., Al-Halbouni, D., & Zhran, M. (2025). Integrating remote sensing, landscape metrics, and random forest algorithm to analyze crop patterns, factors, diversity, and fragmentation in a Kharif agricultural landscape. *Land*, *14*(6), 1203. https://doi.org/10.3390/land14061203

Bansal, K. N., Montiramani, D. P., & LAncaster, J. D. (1983). Studies on Sulphur in Vertisol. *Plant and Soil*, *70*, 133–140.

Bronick, C. J., & Lal, R. (2005). Soil structure and management: a review. *Geoderma*, *124*(1–2), 3–22. https://doi.org/10.1016/j.geoderma.2004.03.005

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J. W., & Brussaard, L. (2018). Soil quality – A critical review. *Soil Biology and Biochemistry*, *120*(January), 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030

Çepel, N. (1983). *Orman Ekolojisi*. İstanbul Üniversitesi Orman Fakültesi Yayınları.

Chan, H. K., Sun, X., & Chung, S. H. (2019). When should fuzzy analytic hierarchy process be used instead of analytic hierarchy process? *Decision Support Systems*, *125*, 113114. https://doi.org/10.1016/j.dss.2019.113114

Chwikhi, W., Abdelkrim, B., Atoui, M., Bouajila, A., Antunes, I. M. H. R., Dhaouadi, L., & Mahmoudi, S. (2025). Integrated AHP-GIS Modeling for Soil Erosion Risk Assessment in Arid Regions: A Case Study of Gabès, Tunisia. *Earth Systems and Environment*. https://doi.org/10.1007/s41748-025-00735-7

Coblinski, J. A., Pindral, S., & Siebielec, G. (2025). Soil resilience to degradation in Poland by 2050 under climate and land use change. *CATENA*, *260*, 109463. https://doi.org/10.1016/j.catena.2025.109463

Condron, L. M., & Tiessen, H. (2005). Interactions of organic phosphorus in terrestrial ecosystems. In *Organic phosphorus in the environment* (pp. 295–307). CABI Publishing. https://doi.org/10.1079/9780851998220.0295

Costa, M. C. G., Lima, L. A., Dias, C. T. S., Oliveira, F. R. A., Blum, J., Araújo, J. C., & Mota, J. C. A. (2025). Geostatistical and multivariate analysis of soil attributes between terrace channels in the semi-arid region. *Revista Ciencia Agronomica*, *56*, 1–16. https://doi.org/10.5935/1806-6690.20250014

Davis, A. G., Huggins, D. R., & Reganold, J. P. (2023). Linking soil health and ecological resilience to achieve agricultural sustainability. *Frontiers in Ecology and the Environment*, *21*(3), 131–139. https://doi.org/10.1002/fee.2594

de Andrade Barbosa, M., de Sousa Ferraz, R. L., Coutinho, E. L. M., Coutinho Neto, A. M., da Silva, M. S., Fernandes, C., & Rigobelo, E. C. (2019). Multivariate analysis and modeling of soil quality indicators in long-term management systems. *Science of The Total Environment*, *657*, 457–465. https://doi.org/10.1016/j.scitotenv.2018.11.441

Demir, Y., Meral, A., & Demir, A. D. (2022). Estimation of soil loses in Çapakçur Watershed (Bingol, Turkey) using RUSLE method and comparison of predicted soil loses with sediment yield. *KSU J. Agric Nat*, *25*(2), 523–537.

Evangelou, E., & Giourga, C. (2024). Identification of soil quality factors and indicators in Mediterranean agro-ecosystems. *Sustainability*, *16*(23), 10717. https://doi.org/10.3390/su162310717

Fageria, N. K. (2016). *The use of nutrients in crop plants*. CRC Press. https://doi.org/10.1201/9781420075113

FAO. (1990). *Micronutrient, assessmentat the country level: An international study*.

Fernandes, A. C. P., Terêncio, D. P. S., Pacheco, F. A. L., & Fernandes, L. F. S. (2021). A combined GIS-MCDA approach to prioritize stream water quality interventions, based on the contamination risk and intervention complexity. *Science of The Total Environment*, *798*, 149322. https://doi.org/10.1016/j.scitotenv.2021.149322

França, L. C., Mucida, D. P., Santana, R. C., Morais, M. S., Gomide, L. R., & Bateira, C. V. (2020). AHP approach applied to multi-criteria decisions in environmental fragility mapping. *Floresta*, *50*(3), 1623. https://doi.org/10.5380/rf.v50i3.65146

Hajihasani, N., Ghadimi, M., Malekian, A., & Moghimi, E. (2022). A comparison of multi-criteria decision making techniques for prioritizing flood potential based on morphometric parameter analysis. In *Research Square (Preprint)*. https://doi.org/10.21203/rs.3.rs-2365255/v1

Hamidi Nehrani, S., Askari, M. S., Saadat, S., Delavar, M. A., Taheri, M., & Holden, N. M. (2020). Quantification of soil quality under semi-arid agriculture in the northwest of Iran. *Ecological Indicators*, *108*, 105770. https://doi.org/10.1016/j.ecolind.2019.105770

Ha-Mim, N. M., & Hossain, M. Z. (2022). *Application of GIS and AHP-based integrated methodology for mapping and Characterizing Socioeconomic vulnerability to natural hazards: A case study of Southwestern Coastal Bangladesh* (pp. 187–203). https://doi.org/10.1007/978-981-16-7397-9_14

Havlin, J. L., Tisdale, S. L., Nelson, W. L., & Beaton, J. D. (2023). *Soil fertility and fertilizers*. Pearson.

Hedley, M., & McLaughlin, M. (2015). Reactions of Phosphate Fertilizers and By-Products in Soils. In *Phosphorus: Agriculture and the Environment* (pp. 181–252). SSSA. https://doi.org/10.2134/agronmonogr46.c7

Hillel, D. (2004). *Introduction to Environmental Soil Physics*. Elsevier.

Hızal, A. (1982). Toprak haritacılığında toprak etüdleri ve örnekleme sistemleri. *İstanbul Üniversitesi Orman Fakültesi Dergisi*, *32*(2), 169–178.

Hodam, S., Sarkar, S., Marak, A. G. R., Bandyopadhyay, A., & Bhadra, A. (2017). Spatial Interpolation of Reference Evapotranspiration in India: Comparison of IDW and Kriging Methods. *Journal of The Institution of Engineers (India): Series A*, *98*(4), 511–524. https://doi.org/10.1007/s40030-017-0241-z

Isaaks, E. H., & Srivastava, R. M. (1989). *An introduction to applied geo-statistics*. Oxford University Press.

Jalhoum, M. E. M., Abdellatif, M. A., Mohamed, E. S., Kucher, D. E., & Shokr, M. (2024). Multivariate analysis and GIS approaches for modeling and mapping soil quality and land suitability in arid zones. *Heliyon*, *10*(5), e27577. https://doi.org/10.1016/j.heliyon.2024.e27577

Joshi, H., Bohra, M. S., Kumar, D., Rani, M., & Arya, O. P. (2024). Groundwater recharge potentiality mapping for opportune augmentation following two MCDMs for a Western Himalayan watershed. *Discover Water*, *4*(1), 45. https://doi.org/10.1007/s43832-024-00103-y

Kang, H., Xue, Y., Cui, Y., Moorhead, D. L., Lambers, H., & Wang, D. (2024). Nutrient limitation mediates soil microbial community structure and stability in forest restoration. *Science of The Total Environment*, *935*, 173266. https://doi.org/10.1016/j.scitotenv.2024.173266

Karaoğlu, M., & Yalçın, A. M. (2018). Toprak Tuzluluğu ve Iğdır Ovası Örneği. *Journal of Agriculture*, *1*(1), 27–41.

Kemper, W. D., & Rosenau, R. C. (1986). Aggregate stability and size distribution. In *Method of soil analysis: Part 1 physicaland mineralogical methods* (pp. 424–442). Agronomy.

Khallouf, A., Talukdar, S., Harsányi, E., Abdo, H. G., & Mohammed, S. (2021). Risk assessment of soil erosion by using CORINE model in the western part of Syrian Arab Republic. *Agriculture & Food Security*, *10*(1), 22. https://doi.org/10.1186/s40066-021-00295-9

Klute, A. (1965). Methods of soil analysis. part 1. physical and mineralogical properties, including statistics of measurement and sampling. In *Laboratory measurement of hydraulic conductivity of saturated soil.* (pp. 210–221). ASA, SSSA.

Kong, D., Chu, N., & Luo, C. (2025). Climatic and topographic controls on soil organic matter heterogeneity in Northeast China's black soil region: Implications for sustainable management. *Agriculture*, *15*(18), 1983. https://doi.org/10.3390/agriculture15181983

Kooch, Y., & Noghre, N. (2020). Nutrient cycling and soil-related processes under different land covers of semi-arid rangeland ecosystems in northern Iran. *CATENA*, *193*, 104621. https://doi.org/10.1016/j.catena.2020.104621

Kovačević, N., & Komazec, N. (2023). An approach to planning the use of units of Serbian Armed Forces in emergency situations caused by floods. *Megatrend Revija*, *20*(2), 107–120. https://doi.org/10.5937/MegRev2302107K

Kumar, A., Antoniella, G., Blasi, E., & Chiti, T. (2025). Recent advances in regenerative sustainable agricultural strategies for managing soil carbon and mitigating climate change consequences. *Catena*, *258*, 109208. https://doi.org/10.1016/j.catena.2025.109208

Kumar, U., Kumar, N., Mishra, V. N., & Jena, R. K. (2019). Soil quality assessment using Analytic Hierarchy Process (AHP): A case study. In *Interdisciplinary Approaches to Information Systems and Software Engineering* (pp. 1–18). IGI Global.

Laage-Thomsen, T., & Jacobsen, B. H. (2024). *Vurdering af samfundsmæssige konsekvenser ved direktivforslag om jordbundsovervågning og jordbundsmodstandsdygtighed : En videnssyntese*.

Lal, R. (1997). Degradation and resilience of soils. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *352*(1356), 997–1010. https://doi.org/10.1098/rstb.1997.0078

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *Science*, *304*(5677), 1623–1627. https://doi.org/10.1126/science.1097396

Lalitha, M., & Dhakshinamoorthy, M. (2014). Forms of soil potassium-A review. *Agricultural Reviews*, *35*(1), 64. https://doi.org/10.5958/j.0976-0741.35.1.008

Li, K., Chen, A., Sheng, R., Hou, H., Zhu, B., Wei, W., & Zhang, W. (2024). Long-term chemical and organic fertilization induces distinct variations of microbial associations but unanimous elevation of soil multifunctionality. *Science of The Total Environment*, *931*, 172862. https://doi.org/10.1016/j.scitotenv.2024.172862

Liu, H., Zhang, H., & Wang, S. (2025). Development of an evaluation indicator system for medium–low yield farmlands on the basis of the synergistic improvement of soil carbon sequestration and production capacity: A theoretical framework. *Agronomy*, *15*(5), 1086. https://doi.org/10.3390/agronomy15051086

Liu, X., Bian, Z., Sun, Z., Wang, C., Sun, Z., Wang, S., & Wang, G. (2023). Integrating landscape pattern metrics to map spatial distribution of farmland soil organic carbon on lower Liaohe Plain of Northeast China. *Land*, *12*(7), 1344. https://doi.org/10.3390/land12071344

Lizaga, I., Quijano, L., Gaspar, L., Ramos, M. C., & Navas, A. (2019). Linking land use changes to variation in soil properties in a Mediterranean mountain agroecosystem. *CATENA*, *172*, 516–527. https://doi.org/10.1016/j.catena.2018.09.019

López-Bellido, R. J., & López-Bellido, L. (2001). Efficiency of nitrogen in wheat under Mediterranean conditions: effect of tillage, crop rotation and N fertilization. *Field Crops Research*, *71*(1), 31–46. https://doi.org/10.1016/S0378-4290(01)00146-0

Mahmoud, S. H., & Gan, T. Y. (2018). Multi-criteria approach to develop flood susceptibility maps in arid regions of Middle East. *Journal of Cleaner Production*, *196*, 216–229. https://doi.org/10.1016/j.jclepro.2018.06.047

Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. *International Journal of Geographical Information Science*, *20*(7), 703–726. https://doi.org/10.1080/13658810600661508

Malczewski, J., & Claus, R. (2015). *Multicriteria decision analysis in geographic information science*. Springer.

Marler, T. R., & Arora, J. S. (2009). The weighted sum method for multi-objective optimization: New insights. *Structural and Multidiciplinary Optimization*, *41*(6), 853–862.

Marselina, M., Hanie, M. Z., & Nurhayati, S. A. (2024). Understanding and mitigating water resource decline in the Deli watershed: a comprehensive analysis. *H2Open Journal*, *7*(1), 1–22. https://doi.org/10.2166/h2oj.2023.074

Mason, E., Bispo, A., Matt, M., Helming, K., Rodriguez, E., Lansac, R., Carrasco, V., Hashar, M. R., Verdonk, L., Prokop, G., Wall, D., Francis, N., Laszlo, P., & Löbmann, M. T. (2023). Sustainable soil and land management: a systems-oriented overview of scientific literature. *Frontiers in Soil Science*, *3*. https://doi.org/10.3389/fsoil.2023.1268037

Mendas, A., & Delali, A. (2012). Support system based on GIS and weighted sum method for drawing up of land suitability map for agriculture. Application to durum wheat cultivation in the area of Mleta (Algeria) [Sistema de apoyo basado en SIG y método de la suma ponderada para elaborar m. *Spanish Journal of Agricultural Research*, *10*(1), 34–43. http://www.scopus.com/inward/record.url?eid=2-s2.0-84857873010&partnerID=40&md5=27ba6e129fb211e321ac992e778e4e80

Meral, A. (2021). *Peyzaj karakterleri çalışmalarının entegre havza yönetim modellerinde değerlendirilmesi; Bingöl Çapakçur, Yeşilköy, Yamaç Mikrohavzaları Örneği* [Doktora]. Düzce Üniversitesi.

Meral, A., & Eroğlu, E. (2021). Evaluation of flood risk analyses with AHP , Kriging , and weighted sum models : example of Çapakçur , Yeşilköy , and Yamaç microcatchments. *Environmental Monitoring and Assessment*, *193*(8), 1–15. https://doi.org/10.1007/s10661-021-09282-w

Meral, A., Yüksel, A., Demir, Y., Başaran, N., Doğan, T. G., Kaya, S., & Eroğlu, E. (2019). Soil stabilitation and landscape rehabilitation studies in erosion areas: Caapakcur Microcatchment example. *Fresenius Environmental Bulletin*, *28*(7), 5518–5529.

Missaoui, R., Ncibi, K., Abdelkarim, B., Bouajila, A., Choura, A., Hamdi, M., & Hamed, Y. (2023). Assessment of hydrogeochemical characteristics of groundwater: link of AHP and PCA methods using a GIS approach in a semi-arid region, Central Tunisia. *Euro-Mediterranean Journal for Environmental Integration*, *8*(1), 99–114. https://doi.org/10.1007/s41207-023-00345-7

Moradi, E., Khosravi, H., Rahimabadi, P. D., Choubin, B., & Muchová, Z. (2024). Integrated approach to land degradation risk assessment in arid and semi-arid Ecosystems: Applying SVM and eDPSIR/ANP methods. *Ecological Indicators*, *169*, 112947. https://doi.org/10.1016/j.ecolind.2024.112947

Mouhoumed, R. M., Ekmekcioğlu, Ö., & Özger, M. (2024). An integrated groundwater vulnerability and artificial recharge site suitability assessment using GIS multi-criteria decision making approach in Kayseri region, Turkey. *Environmental Science and Pollution Research*, *31*(27), 39794–39822. https://doi.org/10.1007/s11356-024-33809-6

Nadeu, E., Quiñonero-Rubio, J. M., de Vente, J., & Boix-Fayos, C. (2015). The influence of catchment morphology, lithology and land use on soil organic carbon export in a Mediterranean mountain region. *CATENA*, *126*, 117–125. https://doi.org/10.1016/j.catena.2014.11.006

Ndao, B., Leroux, L., Gaetano, R., Diouf, A. A., Soti, V., Bégué, A., Mbow, C., & Sambou, B. (2021). Landscape heterogeneity analysis using geospatial techniques and a priori knowledge in Sahelian agroforestry systems of Senegal. *Ecological Indicators*, *125*, 107481. https://doi.org/10.1016/j.ecolind.2021.107481

Neissi, L., Albaji, M., & Boroomand Nasab, S. (2020). Combination of GIS and AHP for site selection of pressurized irrigation systems in the Izeh plain, Iran. *Agricultural Water Management*, *231*, 106004. https://doi.org/10.1016/j.agwat.2020.106004

Ngautunga, E. L. N., Lal, R., & Uriyo, A. P. (1984). Effects of surface management on runoff and soil erosion from some plots at Mlingano, Tanzania. *Geoderma*, *33*(1), 1–12.

Nguyen, T. N., & Liu, C. C. (2019). A new approach using AHP to generate landslide susceptibility maps in the Chen-Yu-Lan Watershed, Taiwan. *Sensors*, *19*(3), 505. https://doi.org/10.3390/s19030505

Özkan, B., Dengiz, O., & Turan, İ. D. (2020). Site sustainability analysis for potential agricultural land with spatial fuzzy multi-criteria decision abalysis in regioanl scale under semi-arid terrestrial ecosystem. *Nature Research*, *2020*(10), 1–18.

Panagos, P., Borelli, P., Meusburger, K., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy*, *48*, 38–50.

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Jae Lim, K., Yang, J. E., Ni, J., Miao, C., Chattopadhyay, N., Sadeghi, S. H., Hazbavi, Z., Zabihi, M., Larionov, G. A., Krasnov, S. F., Gorobets, A. V., Levi, Y., Erpul, G., Birkel, C., … Ballabio, C. (2017). Global rainfall erosivity assessment based on high-temporal resolution rainfall records. *Scientific Reports*, *7*(1), 4175. https://doi.org/10.1038/s41598-017-04282-8

Phakonkham, S., Kazama, S., & Komori, D. (2021). Integrated mapping of water-related disasters using the analytical hierarchy process under land use change and climate change issues in Laos. *Natural Hazards and Earth System Sciences*, *21*(5), 1551–1567. https://doi.org/10.5194/nhess-21-1551-2021

Rahmanipour, F., Marzaioli, R., Bahrami, H. A., Fereidouni, Z., & Bandarabadi, S. R. (2014). Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. *Ecological Indicators*, *40*, 19–26. https://doi.org/10.1016/j.ecolind.2013.12.003

Rawls, W. J., Brakensiek, D. L., & Saxton, K. E. (1982). Estimation of soil water properties. *American Society of Agricultural Engineers*, *25*(5), 1316–1320.

Rhoades, J. D., Kandiah, A., & Mashali A.M. (1992). *The use of daline waters for crop production*.

Richards, L. A. (1954). Diagnosis and Improvement of Saline and Alkali Soils. *Soil Science*, *78*(2), 154. https://doi.org/10.1097/00010694-195408000-00012

Rodrigo-Comino, J., López-Vicente, M., Kumar, V., Rodríguez-Seijo, A., Valkó, O., Rojas, C., Pourghasemi, H. R., Salvati, L., Bakr, N., Vaudour, E., Brevik, E. C., Radziemska, M., Pulido, M., Di Prima, S., Dondini, M., de Vries, W., Santos, E. S., Mendonça-Santos, M. L., Yu, Y., & Panagos, P. (2020). Soil science challenges in a new era: A transdisciplinary overview of relevant topics. *Air, Soil and Water Research*, *13*. https://doi.org/10.1177/1178622120977491

Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. *Mathematical Modelling*, *9*(3–5), 161–176. https://doi.org/10.1016/0270-0255(87)90473-8

Saaty, T. L. (1982). *Decision making for leaders*. Lifetime Learning Publications.

Saaty, T. L. (2000). *Fundamentals of decision making and priority theory with the AHP*. Kluwer Academic Publishers.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International of Journal Services Sciences*, *1*, 83–98.

Safaei, M., Bashari, H., Mosaddeghi, M. R., & Jafari, R. (2019). Assessing the impacts of land use and land cover changes on soil functions using landscape function analysis and soil quality indicators in semi-arid natural ecosystems. *CATENA*, *177*, 260–271. https://doi.org/10.1016/j.catena.2019.02.021

Saxton, K. E., & Rawls, W. J. (2006). Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Science Society of America Journal*, *70*(5), 1569–1578. https://doi.org/10.2136/sssaj2005.0117

Shen, J., Yuan, L., Zhang, J., Li, H., Bai, Z., Chen, X., Zhang, W., & Zhang, F. (2011). Phosphorus dynamics: From soil to plant. *Plant Physiology*, *156*(3), 997–1005. https://doi.org/10.1104/pp.111.175232

Shit, P. K., Adhikary, P. P., & Sengupta, D. (2023). GIScience applied to soil-agricultural health and environmental risk assessment. *Environmental Science and Pollution Research*, *30*(55), 116413–116420. https://doi.org/10.1007/s11356-023-29820-y

Six, J., Elliott, E. T., & Paustian, K. (2000). Soil macroaggregate turnover and microaggregate formation: a mechanism for C sequestration under no-tillage agriculture. *Soil Biology and Biochemistry*, *32*(14), 2099–2103. https://doi.org/10.1016/S0038-0717(00)00179-6

Sofi, M. S., Rautela, K. S., Muslim, M., & Bhat, S. U. (2024). From data to decisions: evaluating flood vulnerability in the Sindh watershed through Analytical Hierarchy Process. *Frontiers of Urban and Rural Planning*, *2*(1), 12. https://doi.org/10.1007/s44243-024-00036-z

Sumner, M. E., & Miller, W. P. (2018). Cation exchange capacity and exchange coefficients. In *Methods of Soil Analysis: Part 3 Chemical Methods* (pp. 1201–1229). SSSA Book Series. https://doi.org/10.2136/sssabookser5.3.c40

Taguas, E. V., Bingner, R. L., Momm, H. G., Wells, R., & Locke, M. A. (2021). Modelling scenarios of soil properties and managements in olive groves at the micro-catchment scale with the AnnAGNPS model to quantify organic carbon. *CATENA*, *203*, 105333. https://doi.org/10.1016/j.catena.2021.105333

Timor, M. (2011). *Analitik hiyerarşi prosesi*. Türkmen Kitabevi.

Țopa, D. C., Căpșună, S., Calistru, A. E., & Ailincăi, C. (2025). Sustainable practices for enhancing soil health and crop quality in modern agriculture: A review. *Agriculture*, *15*(9), 998. https://doi.org/10.3390/agriculture15090998

Triantafyllidis, V., Kosma, AK. C., & Patakas, A. (2019). An assessment of the soil quality index in a Mediterranean agro ecosystem. *Emirates Journal of Food and Agriculture*, 1042. https://doi.org/10.9755/ejfa.2018.v30.i12.1886

Triantaphyllou, E. (2000). *Multi-cretiteria decision making: A comparative study*. Kluwer Academic Publishers.

Turan, I. D. (2021). Spatio analysis of soil quality assessment in semi-arid ecosystem using a minimum data set. *Eurasian Journal of Soil Science*, *10*(3), 222–235. https://doi.org/10.18393/ejss.912986

Ülgen, N., & Ateşalp, M. (1972). *Toprak ve Gübre Araştırma Enstitüsü teknik yayınlar serisi*. Metin Matbaası.

USDA. (2014). *Soil survey field and laboratory methods manual: Soil survey investigations report no. 51 version 2*.

Weil, R. R., & Brady, N. C. (2016). *The Nature and Properties of Soils* (15th ed.). Pearson.

White, P. J. (2003). Calcium in Plants. *Annals of Botany*, *92*(4), 487–511. https://doi.org/10.1093/aob/mcg164

Yadav, M. B. N., Patil, P. L., Rundan, V., Vyas, R. V., & Nthebere, K. (2024). Assessing the spatial variability of soil quality index of Ganjigatti Sub-Watershed Using GIS-based geostatistical modeling. *Indian Journal of Ecology*. https://doi.org/10.55362/IJE/2024/4201

Yanto, Apriyono, A., Santoso, P. B., & Sumiyanto. (2022). Landslide susceptible areas identification using IDW and Ordinary Kriging interpolation techniques from hard soil depth at middle western Central Java, Indonesia. *Natural Hazards*, *110*(2), 1405–1416. https://doi.org/10.1007/s11069-021-04982-5

Zornoza, R., Acosta, J. A., Bastida, F., Domínguez, S. G., Toledo, D. M., & Faz, A. (2015). Identification of sensitive indicators to assess the interrelationship between soil quality, management practices and human health. *SOIL*, *1*(1), 173–185. https://doi.org/10.5194/soil-1-173-2015