GIS-Fuzzy Logic Approach for Ecological Restoration Suitability Mapping in Semi-Arid Steppe Ecosystems: A Case Study of Naâma Province, Algeria

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Abstract: This research evaluates the ecological restoration suitability in the northeastern region of Naâma Province, Algeria, a fragile environment undergoing increasing degradation from both climatic stresses and human activities. The study area, including the municipalities of El Biodh and Mecheria, is located in a semi-arid steppe zone, known for its biodiversity and restoration potential. The objective of this study is to produce a spatially explicit map of restoration suitability by integrating fuzzy logic, GIS-based multi-criteria analysis, and environmental variables. A total of 20 indicators (topographic, pedological, climatic, and vegetative) were normalized and combined using fuzzy membership functions. The fuzzy overlay was followed by a defuzzification step using the centroid method to produce a composite suitability map, which was categorized into three classes: suitable, less suitable, and unsuitable. The results showed a heterogeneous spatial distribution, with 47.65% of the landscape classified as unsuitable, 36.08% as less suitable, and only 16.27% as suitable. For model validation, 300 random points were generated, and multiple linear regression was applied to evaluate the influence of each variable group. Climatic variables showed the strongest correlation with suitability ($R = 0.924$, $p < 0.001$), followed by proximity factors ($R = 0.719$, $p < 0.005$), topography ($R = 0.647$, $p < 0.001$), soil properties ($R = 0.521$, $p < 0.001$), and vegetation indices ($R = 0.337$, $p < 0.001$). The study confirms the effectiveness of combining fuzzy logic and GIS for ecological restoration planning and highlights priority areas for intervention within arid and semi-arid landscapes.

Keywords: Ecological restoration, fuzzy membership functions, restoration prioritization, semi-arid land degradation, steppe landscapes, spatial modeling.

Introduction

Ecosystems in arid and semi-arid regions, such as the Algerian steppe, are increasingly exposed to environmental pressures resulting from both anthropogenic activities and climate change (Millennium Ecosystem Assessment, 2005). These pressures lead to a decline in biological productivity, accelerated soil erosion, and progressive vegetation degradation, ultimately affecting biodiversity and ecosystem services (Millennium Ecosystem Assessment, 2005; Lamb et al., 2005). In this context, ecological restoration has emerged as a key strategy to reverse degradation processes, aiming to recover ecosystem functions and enhance ecological resilience (SER, 2004; Aronson et al., 2006). In Algeria, the steppe regions particularly the northeastern part of Naâma Province are characterized by high ecological vulnerability due to overgrazing, unsustainable land use practices, and increasing climatic stress (Hirche et al., 2015). The vegetation in these areas is dominated by steppe formations composed of drought-resistant shrubs, perennial grasses, and halophytic species. Dominant plant families include Asteraceae, Poaceae, Amaranthaceae, Brassicaceae, and Lamiaceae, reflecting adaptation to water scarcity, poor soils, and grazing pressure (Le Houérou, 1995; Quézel and Médail, 2003; Aidoud et al., 2006). These characteristics make the region a relevant model for studying land degradation processes, ecological restoration potential, and vegetation dynamics under semi-arid conditions. The increasing severity of desertification has led to the implementation of several restoration initiatives, particularly reforestation and sand dune stabilization programs. These interventions highlight the ecological, economic, and social importance of combating land degradation (Zair, 2011). Since 1985, the Forest Conservancy has implemented sand dune fixation programs, progressively expanding the treated areas. These actions have primarily relied on biological approaches, notably the plantation of *Tamarix articulata* and *Retama raetam*, which are widely recognized as key species for dune stabilization in arid environments (Greco, 1966). Despite these efforts, the absence of spatially explicit analyses identifying priority areas for intervention remains a major limitation for effective ecological planning. In this context, decision-support tools are essential to improve the targeting and efficiency of restoration strategies. Geographic Information Systems (GIS) combined with fuzzy logic modeling have proven to be powerful approaches for integrating multiple environmental indicators and assessing land suitability (Zadeh, 1965; Malczewski, 2006). These methods allow for multi-criteria spatial analysis while accounting for environmental complexity and uncertainty, there by producing reliable suitability maps for restoration planning (Orta-Salazar et al., 2021; Bortoleto et al., 2016). Accordingly, the objective of this study is to develop a spatially explicit model to evaluate ecological restoration suitability in the study area by integrating topographic, climatic, edaphic, and vegetation indicators using fuzzy logic within a GIS framework. The results are expected to support sustainable land management and guide strategic restoration interventions in vulnerable semi-arid steppe ecosystems.

Materials and Methodology

Study area

The study area covers the municipalities of Mecheria and El Biodh, located in the northeastern part of Naâma Province (western Algeria), within the High Plateaus region. This area belongs to the semi-arid steppe zone. It is characterized by extensive rangelands and plays an important role in pastoral activities. Geographically, Mecheria is located at approximately 33°33′N and 0°17′W, while El Biodh is situated near 33°37′N and 0°00′E. The climate is classified as semi-arid cold (BSk) according to the Köppen classification, with strong seasonal contrasts. Annual precipitation ranges between 250 and 300 mm, mainly occurring during winter and spring. Summers are generally hot and dry, whereas winters are cold and frequently associated with frost events. This area was selected due to its high vulnerability to land degradation, its representativeness of semi-arid steppe ecosystems, and the presence of ongoing ecological restoration initiatives. These characteristics make it a suitable case study for assessing restoration suitability and supporting spatial decision-making (Figure 1).

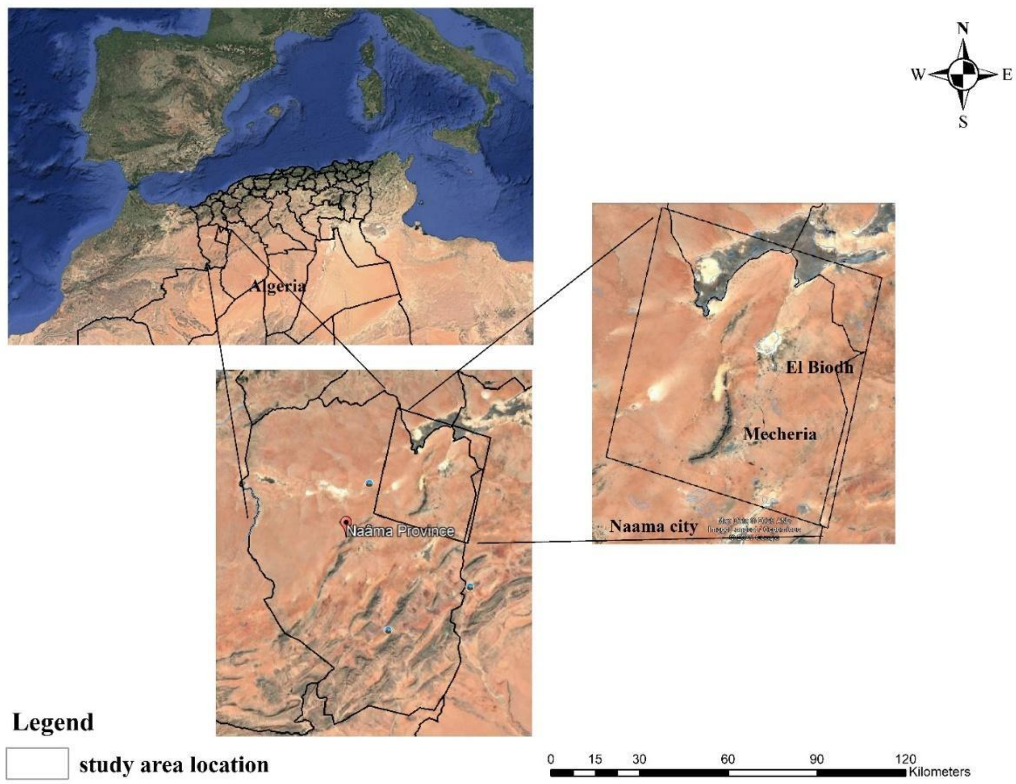

Figure 1. Study area location

Data sets, data preprocessing

The first step involved acquiring satellite imagery of the study area from the USGS Earth Explorer platform. The imagery was sourced from the Landsat 9 satellite (Scene ID: LC09_L2SP_197037_20240828_20240829_02_T1), with a spatial resolution of 30m. The acquisition date in August was selected due to minimal cloud cover during the summer period (cloud cover < 1%), which ensured clearer imagery for analysis. The imagery belongs to the Collection 2 Level-2 surface reflectance product (OLI). These products are distributed as scaled integers, improving data storage and transfer while delivering atmospherically corrected surface reflectance. The reflectance values were derived using the following equation:

$$Surface\ Reflectance = (DN \times Scale\ Factor) + Offset$$

where:
Scale Factor = 0.0000275
Offset = -0.2

Processing and analysis of reflectance data were performed using ArcGIS 10.8.2 and QGIS. From this data, four key indices were derived: GVMI, SAVI, NDSI, and SVI. These indices were chosen due to their ecological relevance in evaluating land condition and potential for ecological restoration. These indices provided essential information about vegetation health, soil salinity, and the presence of sandy deposits, which are key limiting or favorable factors in the restoration suitability mapping of steppe and semi-arid ecosystems like those in the study region. The combination of SAVI (Soil-Adjusted Vegetation Index) and GVMI (Global Vegetation Moisture Index) was adopted to improve the accuracy and ecological relevance of the vegetation suitability assessment. Each of these indices captures a distinct aspect of vegetation condition. SAVI was used because it incorporates a soil brightness correction factor, making it more reliable in arid and semi-arid environments where bare soil is dominant. Additionally, GVMI was included to assess vegetation water content, providing critical insight into plant moisture stress a key factor in dryland ecosystems that may not be detected by greenness-based indices alone. The integration of these two indices allows for a more comprehensive evaluation of vegetation health and degradation, which is essential for identifying suitable zones for ecological restoration in fragile steppe environments. Below is a detailed description and rationale for the selection of each index (figure.2).

The Soil-Adjusted Vegetation Index (SAVI) was calculated to reduce the influence of soil background reflectance, particularly in areas with sparse vegetation cover. SAVI is expressed by the following formula:

$$SAVI = \frac{(NIR - Red) \times (1 + L)}{(NIR + Red + L)}$$

where NIR corresponds to Band 5, Red to Band 4 of Landsat 9 OLI, and L is a soil brightness correction factor, set to 0.8 (Huete, 1988).

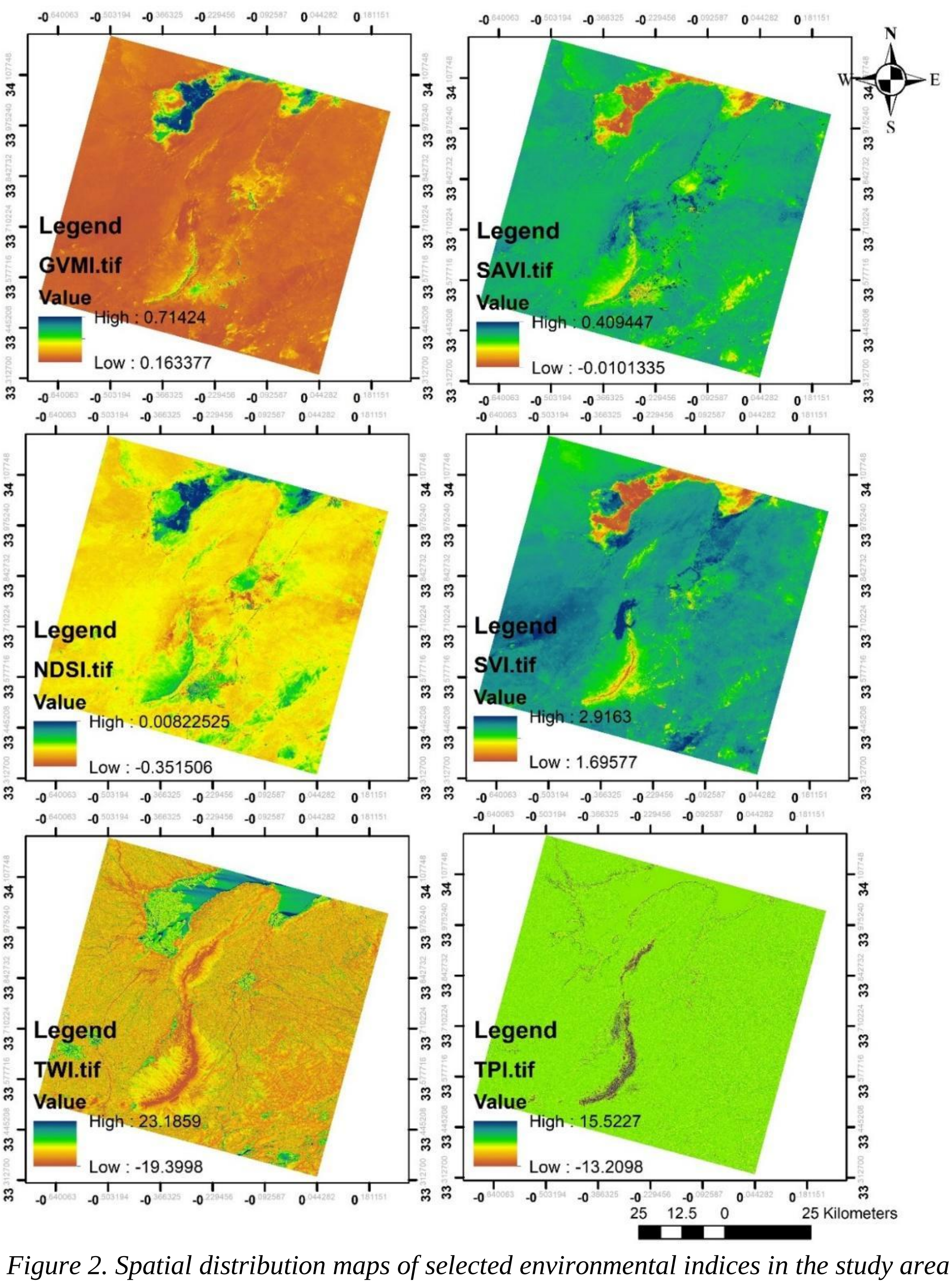

Figure 2. Spatial distribution maps of selected environmental indices in the study area SAVI (Soil-Adjusted Vegetation Index), NDSI (Normalized Difference Salinity Index), TWI (Topographic Wetness Index), TPI (Topographic Position Index), SVI (Sandy Veil Index) and GVMI (The Global Vegetation Moisture Index).

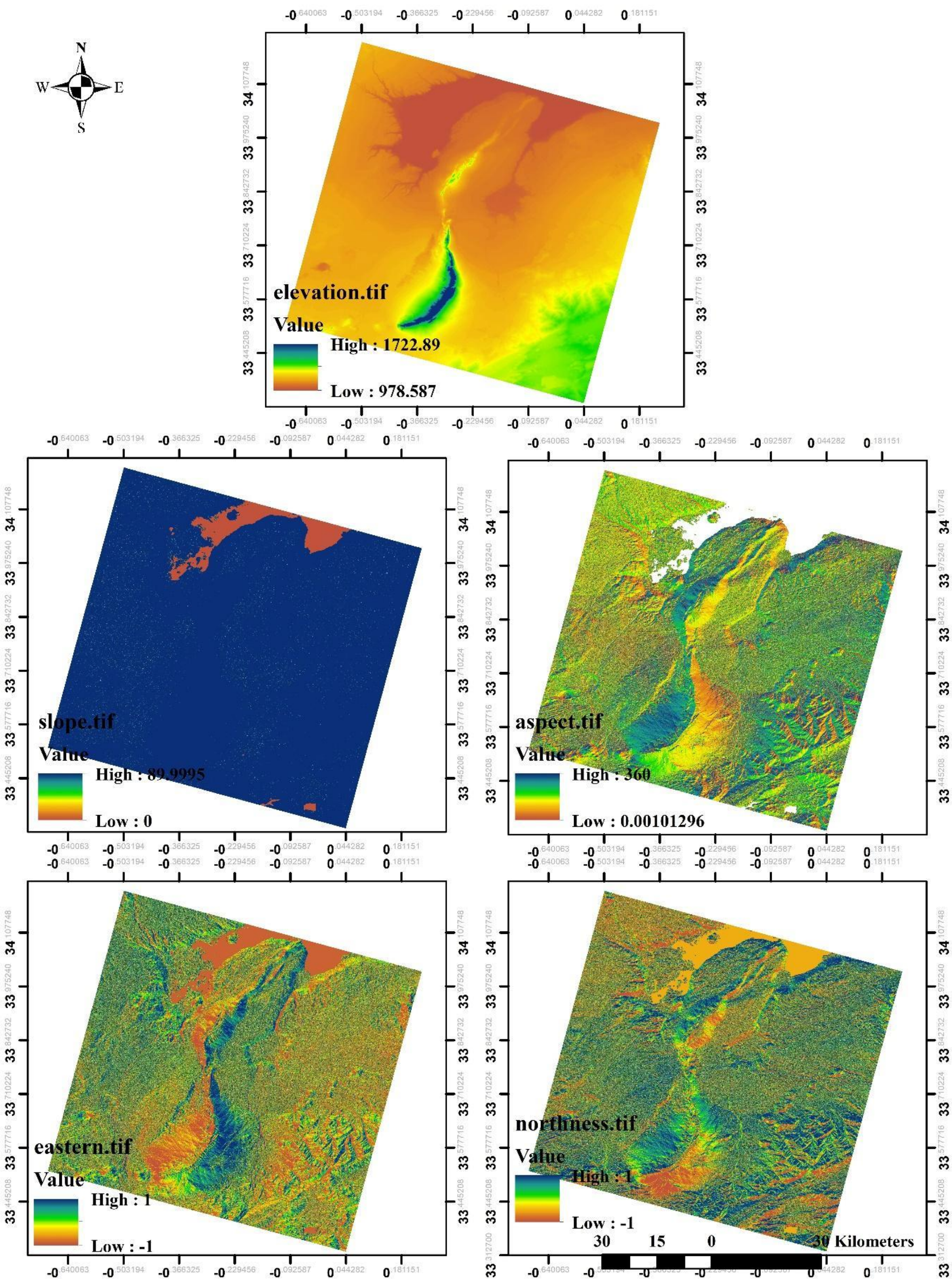

Figure 3. Spatial representation of topographic variables in the study area Elevation, Slope, Aspect, Easterness, and Northness.

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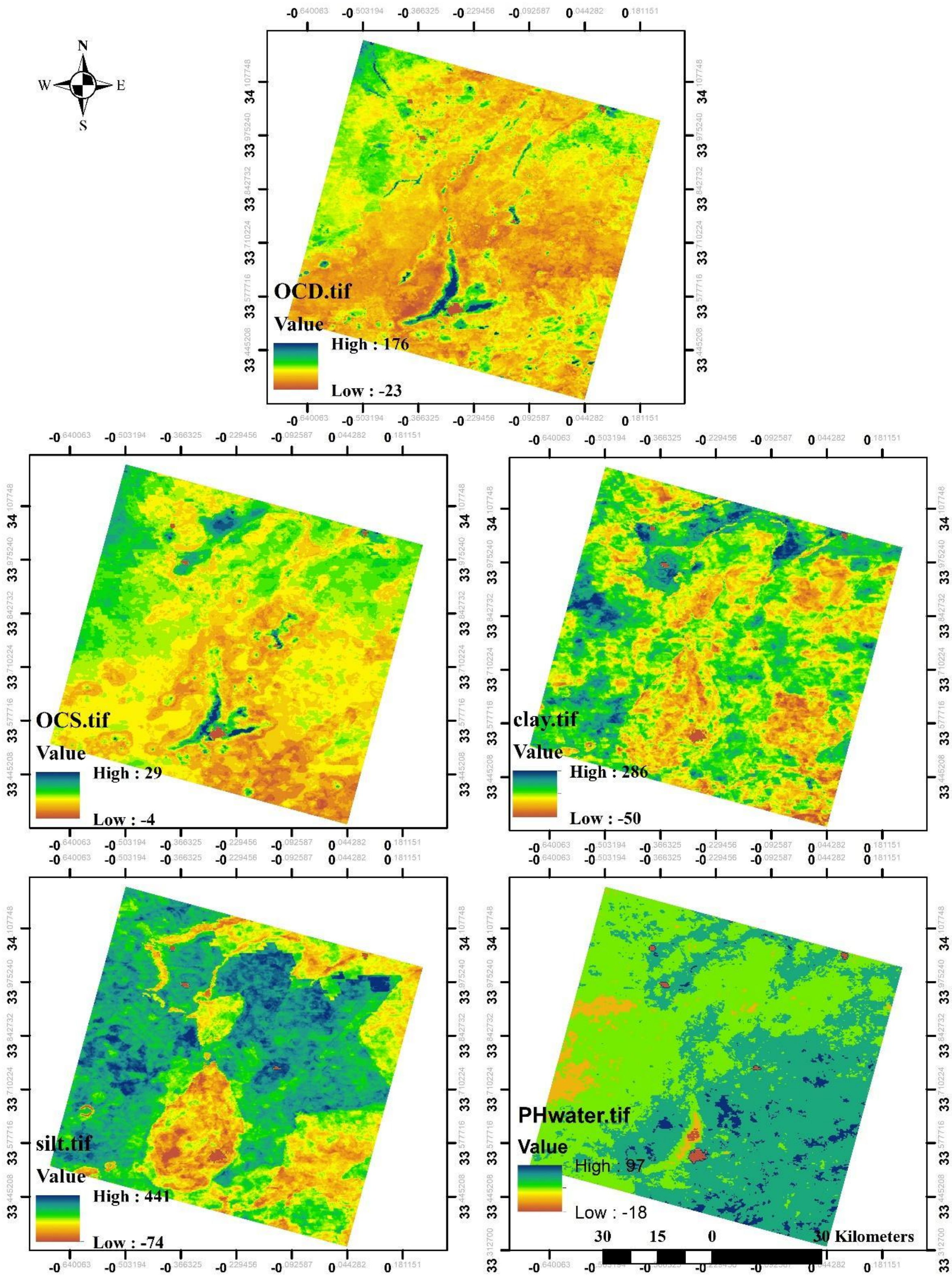

Figure 4. Spatial distribution of selected soil properties in the study area: Organic Carbon Density (OCD), Organic Carbon Stock (OCS), Clay content, Silt content, and Soil pH in water

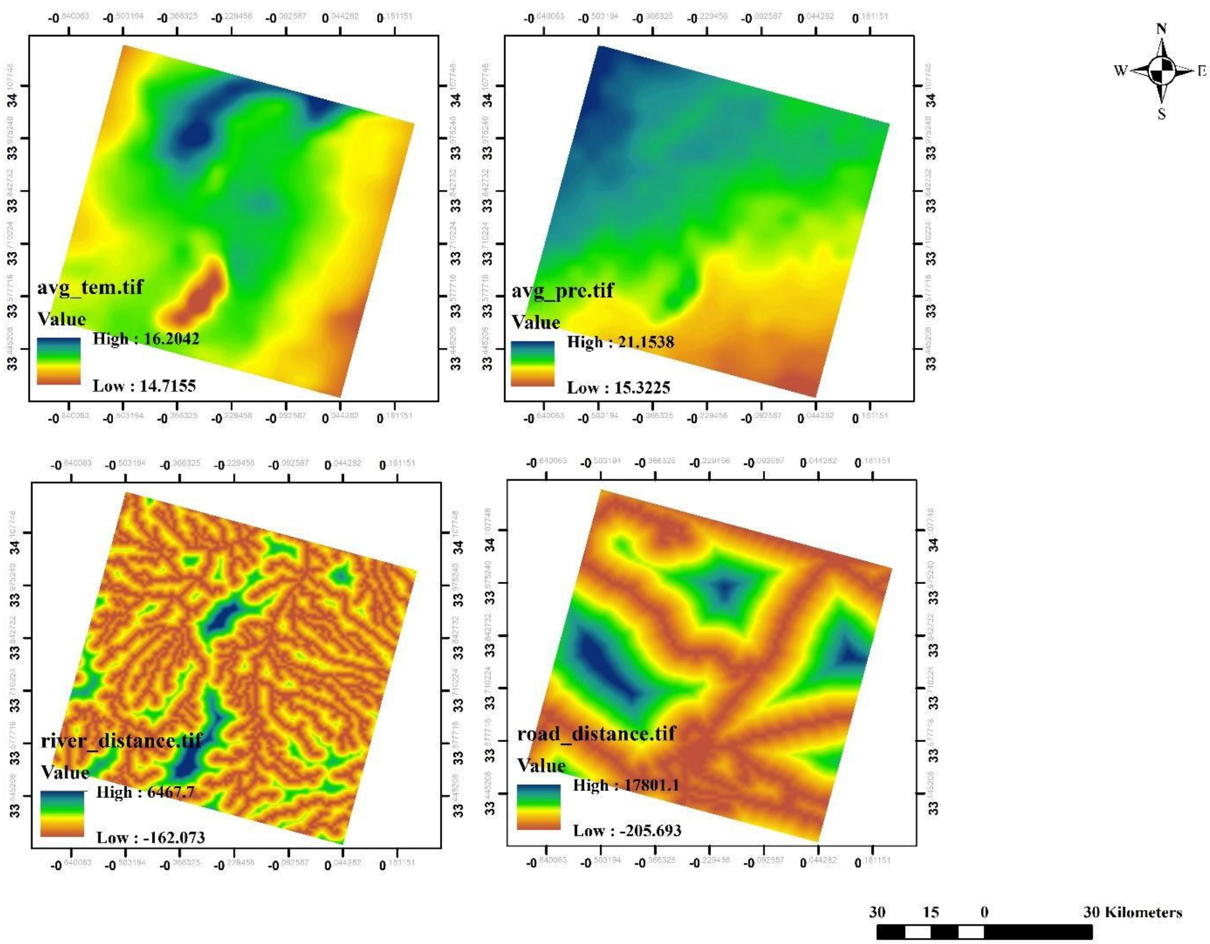

Figure 5. Spatial distribution of key environmental and proximity variables in the study area: Average Monthly Precipitation (2015–2021), Average Monthly Temperature (2015–2021), Distance to Rivers, and Distance to Roads.

The Normalized Difference Salinity Index (NDSI) was calculated using the red and near-infrared bands. The Normalized Difference Salinity Index is an indicator of soil salinity. Values of NDSI approaching +1 are associated with high soil salinity (Nguyen et al., 2020; Konukcu et al., 2006). Studies reveal that the Red and NIR bands, which are used to calculate NDSI, are the most sensitive to the soil's ions that cause salinity (Rengasamy et al., 2003). It is calculated according to the formula:

$$NDSI = \frac{Red + NIR}{Red - NIR}$$

where Red refers to Band 4 and NIR to Band 5 of Landsat 9 OLI imagery. This index was used to highlight salt-affected soils, which tend to reflect more in the red region than in the near-infrared, resulting in positive index values. Conversely, vegetated areas reflect more strongly in the NIR band, producing negative index values, thereby allowing a clear distinction between salinity and vegetation (adapted from NDVI principles; Rouse et al., 1974).

The Global Vegetation Moisture Index (GVMI) was calculated to estimate vegetation water content and detect moisture stress, particularly in arid and semi-arid environments. GVMI is computed using the near-infrared and shortwave infrared bands according to the following formula:

$$GVMI = \frac{(NIR + 0.1) - (SWIR1 + 0.02)}{(NIR + 0.1) + (SWIR1 + 0.02)}$$

Where NIR corresponds to Band 5 and SWIR1 to Band 6 of Landsat 9 OLI imagery. The small constants (0.1 and 0.02) are added to stabilize the index in low-reflectance areas and enhance its sensitivity to vegetation moisture variations (Ceccato et al., 2002). GVMI values tend to be higher for moist and healthy vegetation and lower for dry or stressed vegetation.

The Sandy Veil Index (SVI) was developed by Abdellaoui and Rougab (1997) and modified by Abdellaoui and Marmi (2010) to obtain an index of the following form:

$$SVI = \frac{(Blue + u \times Red + v \times NIR)}{1 + Blue}$$

where: NIR corresponds to Band 5, Red to Band 4, and Blue to Band 2 of Landsat 9 OLI imagery. Constants u and v are 1.5 and 2.5, respectively (Abdellaoui and Marmi, 2010).

Soil Properties

Soil properties were a critical component in evaluating land suitability for ecological restoration. We obtained data from the SoilGrids platform at a depth of 0–5 cm and a spatial resolution of 250 meters, which is considered suitable for regional-scale ecological analysis (Hengl et al., 2017). The selected soil parameters included clay content (%), silt content (%), organic carbon stock (Mg/ha), organic carbon density (g/cm^3), and soil pH (in H_2O) (Figure 4). These variables are widely recognized for their influence on soil texture, structure, water retention, nutrient availability, and microbial activity all of which are essential for supporting plant growth and long-term ecosystem stability (Brady and Weil, 2016; Lal, 2004). Balanced clay and silt contents, for instance, improve water retention and root penetration (Amami et al., 2021). Organic carbon stock was included as an indicator of soil fertility and biological productivity, which is critical for sustaining vegetation in degraded environments (Post and Kwon, 2000). All soil layers were resampled to a 30m spatial resolution using the bilinear interpolation method in ArcGIS 10.8.2. This step was essential for maintaining spatial alignment and analytical precision across all input layers.

Topographic Factors

Topographic data were derived from a Digital Elevation Model (DEM) obtained via the OpenTopography platform, which provides high-resolution global elevation datasets suitable for terrain analysis and ecological modeling (Gesch et al., 2002; Leempoel et al., 2015). To ensure spatial consistency with other environmental variables used in the suitability analysis, the DEM was resampled to a 30m spatial resolution using bilinear interpolation in ArcGIS 10.8.2.

Following resampling, hydrological sinks were filled using the "Fill Sinks" (Yang et al., 2003) algorithm available in QGIS through the SAGA GIS toolbox (Conrad et al., 2015), ensuring topographic continuity and suitability for hydrologically derived terrain analysis. The corrected DEM was then used to generate a set of topographic variables in SAGA GIS, which were included as key environmental indicators in the restoration suitability model:

- Slope: representing terrain steepness, influences water runoff, erosion potential, and soil formation processes.
- Aspect: indicating the compass direction of slopes, affects microclimatic factors such as solar radiation, evapotranspiration, and vegetation growth (Figure 3).
- Topographic Position Index (TPI): used to distinguish between landform types such as ridges, valleys, and plains, which are important in identifying landscape positions suitable for restoration.
- Topographic Wetness Index (TWI): (Figure 2) calculated based on upslope contributing area and slope, estimates the potential for surface moisture accumulation and soil saturation, key factors for vegetation establishment (Beven and Kirkby, 1979).
- Northness and Eastness: trigonometric transformations of the aspect layer, quantify slope orientation towards cardinal directions and are crucial in modeling vegetation responses to sun exposure and wind direction (Moore et al., 1993) (Figure 3).

Climatic Data

Climatic variables were obtained from the WorldClim version 2.1 dataset, which provides high-resolution gridded climate surfaces based on historical weather observations (Fick and Hijmans, 2017). For this study, monthly precipitation, monthly minimum temperature, and monthly maximum temperature were acquired for the period spanning 2015 to 2021 at a spatial resolution of 2.5 arc-minutes (~21 km² per pixel). Each climatic variable consisted of 12 raster layers per year, representing monthly values. Across the seven-year period, a total of 84 rasters (12 months * 7 years) were obtained for each variable. To derive stable climatic inputs for the suitability analysis, the raster layers were summed and divided by 84, yielding multi-year monthly averages for precipitation, minimum temperature, and maximum temperature (Figure 5). These processed layers were subsequently resampled to a 30m resolution using bilinear interpolation in ArcGIS 10.8.2 to ensure spatial alignment with other environmental datasets. The selected climatic parameters are crucial for assessing ecological restoration potential, as precipitation determines water availability, while temperature extremes influence plant physiological tolerance, germination success, and species distribution, particularly in arid and semi-arid environments.

Proximity and Infrastructure

Proximity to infrastructure and hydrological features is a critical factor in determining the suitability of sites for ecological restoration, particularly in arid and semi-arid regions where accessibility and water availability strongly influence project feasibility and sustainability. Spatial data related to roads and rivers were obtained from the following sources:

- Road network data were downloaded from BBBike Extract Service, which provides custom OpenStreetMap (OSM) extracts in various GIS formats.
- River and drainage data were sourced from HydroSHEDS, a reliable global database of hydrological features based on high-resolution DEMs (Lehner et al., 2008).
- The vector data were converted to raster format and processed in ArcGIS 10.8.2 using the Euclidean Distance tool to generate continuous distance surfaces (Figure 5). These included:
- Distance to roads: representing accessibility for field interventions, equipment transport, and future monitoring.
- Distance to rivers: reflecting the proximity to potential natural water sources crucial for the success of vegetation restoration and soil recovery in water-limited environments.
- All proximity rasters were resampled to a 30m spatial resolution using bilinear resampling to ensure alignment with other environmental layers used in the suitability model. These layers helped to identify areas that are both accessible and environmentally favorable for restoration interventions.

Methodology

Following data collection and preprocessing, the suitability analysis was conducted by grouping the selected variables into five main categories representing key environmental factors influencing ecological restoration in semi-arid steppe ecosystems.

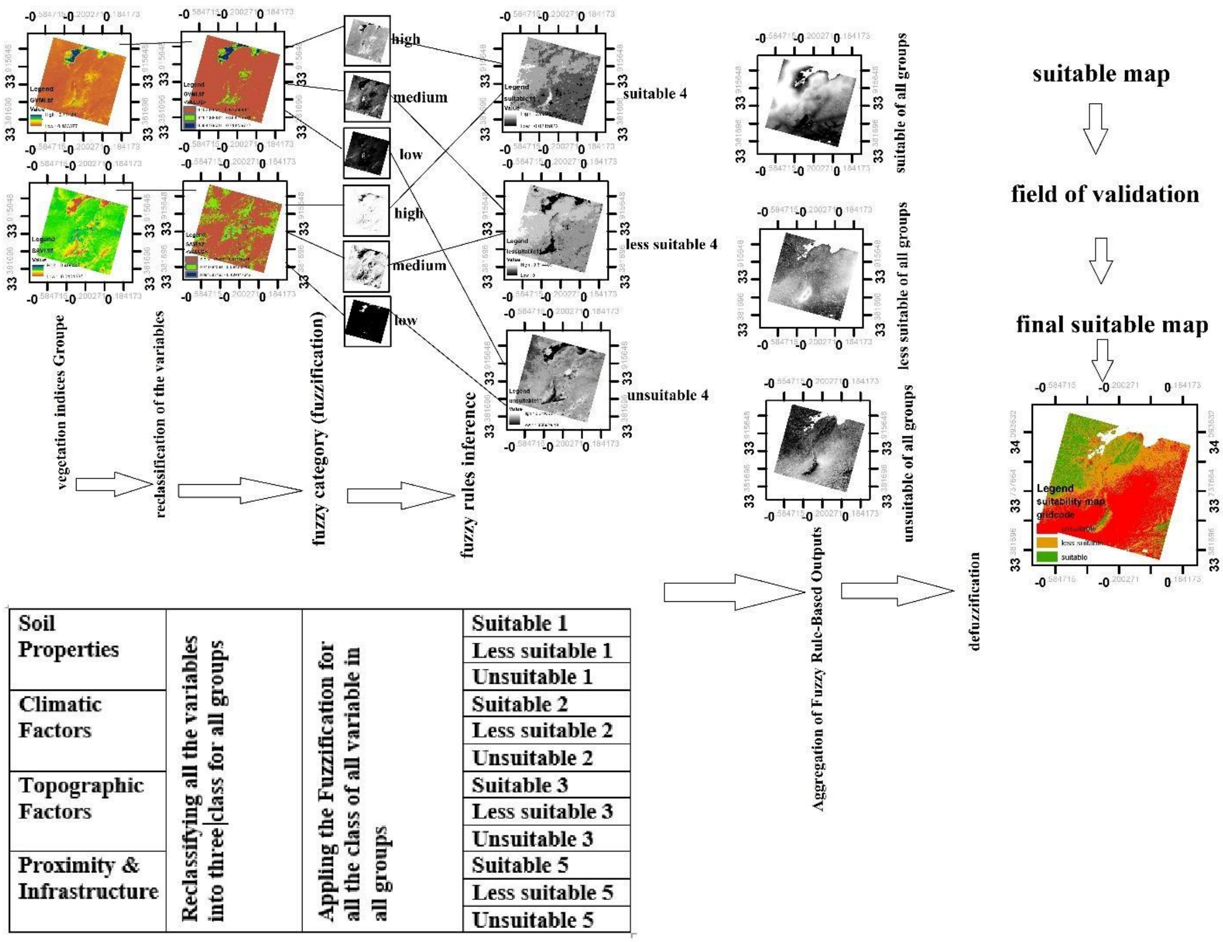

Figure 6. Methodological Framework for Fuzzy Logic-Based Suitability Modeling

Table 1. Environmental variables and their classification thresholds for vegetation cover suitability in the study area.

Group	Variable	Description	Fuzzy Categories	Impact on Plant Suitability	Preferred Condition for Vegetation Growth
Soil Properties	NDSI (Normalized Salinity Index)	Measures soil salinity levels, affecting plant tolerance (Allbed et al., 2014)	Low - Medium - High	High values indicate high salinity, which reduces plant growth (Allbed et al., 2014)	Low NDSI → Suitable for most plants
	SVI (Sandy Veil Index)	Indicates the percentage of sand in soil composition (Abdellaoui and Rougab 1997)	Low - Medium - High	High values indicate sandy soil, which may limit water retention (Abdellaoui and Rougab 1997)	Medium SVI → Balanced soil texture
	Organic Carbon Density (g/cm³)	Represents the amount of organic carbon in soil, indicating fertility (Batjes, 1996)	Low - Medium - High	High organic carbon improves soil fertility (Lal, 2004)	High Organic Carbon → Increases nutrient availability
	Organic Carbon Stock (Mg/ha)	Total carbon stored in soil, supporting plant growth (IPCC, 2006)	Low - Medium - High	More carbon stock supports better plant growth (Batjes, 2011)	High Organic Carbon Stock → Promotes biodiversity

	Clay Content (%)	Percentage of clay in soil affecting drainage and water retention (Brady and Weil, 2017)	Low - Medium - High	High clay retains water but may cause poor drainage (Brady and Weil, 2017)	Medium Clay → Optimal water retention
	Silt Content (%)	Percentage of silt in soil influencing fertility and erosion (Brady and Weil, 2017)	Low - Medium - High	Higher silt improves soil fertility but increases erosion risk (Hillel, 2004)	Medium Silt → Supports plant anchoring
	pH in water	Measures soil acidity or alkalinity, affecting nutrient availability (McKenzie et al., 2004)	Low - Medium - High	Extreme pH levels reduce nutrient availability (Fageria and Baligar, 2008)	Medium pH → Ideal for plant uptake
Climatic Factors	Rainfall (mm)	Annual precipitation amount affecting soil moisture (FAO, 2006)	Low - Medium - High	More rainfall increases water availability (FAO, 2006)	High to Medium Rainfall → Supports plant growth
	Temperature (°C)	Average air temperature influencing evaporation and plant metabolism (Zomer et al., 2008)	Low - Medium - High	Extreme temperatures stress plants, reducing survival (Allen et al., 1998)	Medium Temperature → Optimal for most species
Topographic Factors	TWI (Topographic Wetness Index)	Indicates soil moisture retention potential based on terrain (Beven and Kirkby, 1979)	Low - Medium - High	High TWI means better water retention (Sørensen et al., 2006)	High TWI → Suitable for moisture-loving species
	Elevation (m)	Height above sea level influencing temperature and oxygen levels (Hijmans et al., 2005)	Low - Medium - High	High elevation reduces oxygen and moisture availability (Körner, 2007)	Low to Medium Elevation → Supports plant diversity
	Slope (°)	Measures land inclination affecting stability and erosion (Moore et al., 1991)	Flat - Medium - Steep	Steep slopes increase erosion risk and reduce soil stability (Moore et al., 1991)	Flat to Medium Slope → Reduces runoff, retains moisture
	Aspect (°)	Orientation of a slope relative to the sun, affecting temperature and moisture (Oke, 1987)	Flat - Low (north, east) - medium (east to west) – High (west, north)	North-facing slopes retain more moisture and are cooler, favoring plant growth (McCune and Keon, 2002)	North or East Aspect → Conserves moisture
	TPI (Topographic Position Index)	Identifies terrain position (valley, slope, or peak) (Jenness, 2006)	Valley - Slope - Peak	Valleys retain more moisture, while peaks are drier (Jenness, 2006)	Valley or Slope → Higher water availability
Vegetation Indices	SAVI (Soil-Adjusted Vegetation Index)	Measures vegetation density while minimizing soil background effects (Huete, 1988)	Low - Medium - High	Higher values indicate better vegetation density (Huete, 1988)	High SAVI → More vegetation cover
	GVMI (Global Vegetation Moisture Index)	Indicates canopy water content (Chen et al., 2005)	Low - Medium - High	Low GVMI means vegetation is water-stressed	High GVMI → Indicates healthy vegetation
Proximity and Infrastructure	Distance to Roads (m)	Proximity to human infrastructure affecting land disturbance (Forman and Alexander, 1998)	Near - Medium - Far	Near roads may increase pollution and disturbance (Forman and Alexander, 1998)	Medium to Far Distance → Less human disturbance
	Distance to Rivers (m)	Proximity to water sources influencing soil moisture (Fisher et al., 2018)	Near - Medium - Far	Proximity to water sources improves soil moisture (Huang et al., 2013)	Near to Medium Distance → Better access to water
	Eastern Coordinate	Geographic longitude influencing climate variability (Hutchinson, 2004)	Low - Medium - High	Affects local climate conditions (Barry and Chorley, 2009)	Medium Eastern Coordinate → Balanced climate

Northern Coordinate	Geographic latitude influencing temperature and rainfall (Köppen, 1936)	Low - Medium - High	Affects temperature and rainfall distribution (Barry and Chorley, 2009)	Medium Northern Coordinate → Moderate climate

Vegetation Cover Classification

Vegetation cover was assessed using the Soil-Adjusted Vegetation Index (SAVI) and the Global Vegetation Moisture Index (GVMI). A threshold-based classification was applied to categorize vegetation into three classes: high, medium, and low cover (table 1). High vegetation cover corresponds to dense and healthy vegetation, mainly associated with rehabilitation plantations (*Tamarix articulata* and *Pinus halepensis*) (Kharroubi et al., 2022). Medium vegetation cover represents natural steppe vegetation dominated by scattered shrubs such as *Retama raetam*. Low vegetation cover includes bare or sparsely vegetated areas resulting from aridity or land degradation processes. Threshold values were defined based on expert knowledge and validated through visual interpretation of satellite imagery. This approach has been widely used in vegetation mapping and restoration studies in arid environments (Estoque and Murayama, 2017; El-Gammal et al., 2014; Xie et al., 2010).

Suitability Classification Approach

All environmental variables were reclassified into three suitability levels (low, medium, and high) to ensure comparability and integration within the suitability analysis. The Jenks natural breaks method (Jenks, 1967) was applied to each variable to define class thresholds based on data distribution (table 1). This method minimizes within-class variance and maximizes differences between classes, making it suitable for heterogeneous environmental data. The classification was applied to variables related to soil properties, climatic conditions, topography, and proximity factors.

Fuzzy Logic Integration

Fuzzification

Following variable reclassification, fuzzy logic was applied to transform discrete suitability classes into continuous values ranging from 0 to 1, allowing a gradual representation of spatial suitability and accounting for uncertainty in environmental data (Zadeh, 1965). A Gaussian membership function was used to compute membership values for each variable. The parameters of the function (mean m and standard deviation σ) were calculated separately for each class (low, medium, and high) based on the distribution of raster values (Table 2), where the mean represents the central tendency and the standard deviation controls the spread. The resulting membership functions were applied to each pixel to generate continuous fuzzy layers, producing smooth transitions between suitability levels. These fuzzy layers were then integrated within the multi-criteria analysis framework to derive the final ecological restoration suitability map through fuzzy inference.

$$\mu(x) = Exp\left(-\frac{(x-m)^2}{2\sigma^2}\right)$$

where:
$\mu(x)$ = the membership degree of x in the fuzzy set
x = the input value
m = the mean (or center) of the Gaussian curve
σ = the standard deviation, which controls the width of the bell curve
Exp = the exponential function

Table 2. Descriptive statistics (mean, standard deviation) and fuzzy classification parameters for environmental variables used in suitability mapping.

Group	Variable	Fuzzy categories	Min	Max	Mean	Std	Group	Variable	Fuzzy categories	Min	Max	Mean	Std
Soil properties	NDSI	Low	-0.35	-0.06	-0.21	0.21	Topographic factors	TWI	Low	-19.4	-10.43	-14.92	6.34
		Medium	-0.06	-0.05	-0.06	0.007			Medium	-10.43	-6.84	-8.64	2.54
		High	-0.05	0.01	-0.02	0.04			High	-6.84	23.19	8.18	21.23
	SVI	Low	1.7	2.54	2.12	0.59		Elevation	Low	978.58	1098.26	1038.42	84.63
		Medium	2.54	2.64	2.59	0.071			Medium	1098.26	1276.31	1187.29	125.9
		High	2.64	2.92	2.78	0.2			High	1276.31	1722.9	1499.61	315.79
	OCD	Low	-23	45.67	11.34	48.56		Slope	Flat	0	27.18	13.59	19.22
		Medium	45.67	93.28	69.48	33.67			Medium	27.18	72.71	49.95	32.19
		High	93.28	176	134.64	58.49			Steep	72.71	90	81.36	12.23
	OCS	Low	-4	5.96	0.98	7.043		Aspect	Low	0	90	45	63.64
		Medium	5.96	13.99	9.98	5.68			Medium	90	270	180	127.28
		High	13.99	29	21.5	10.6			High	270	360	315	63.64
	Clay	Low	-50	109.44	29.72	112.7		TPI	Valley	-13.2	0.18	-6.51	9.46
		Medium	109.44	218.8	164.12	77.31			Slop	0.18	0.64	0.41	0.33
		High	218.8	286	252.4	47.52			Peak	0.64	15.52	8.08	10.52
	Silt	Low	-74	164.31	45.16	168.51	Climatic factors	Rainfall	Low	15.32	17.59	16.46	1.61
		Medium	164.31	335.98	250.15	121.39			Medium	17.59	19	18.3	1
		High	335.98	441	388.49	74.26			High	19	21.15	20.08	1.52
	Ph water	Low	-18	19.88	0.94	26.79		Temperature	Low	14.72	15.41	15.07	0.49
		Medium	19.88	59.57	39.73	28.07			Medium	15.41	15.67	15.54	0.18
		High	59.57	97	78.29	26.47			High	15.67	16.2	15.94	0.37
Proximity and infrastructure	Distance to road	Near	-205.69	3960.59	1877.45	2946.005	Vegetation indices	SAVI	Low	-0.01	0.07	0.03	0.057
		Medium	3960.59	9256.71	6608.65	3744.92			Medium	0.07	0.08	0.075	0.007
		Far	9256.71	17801.12	13528.92	6041.81			High	0.08	0.41	0.25	0.23
	Distance to river	Near	-162.07	1059.88	448.91	864.05		GVMI	Low	0.163	0.227	-0.02	0.045
		Medium	1059.88	2619.83	1839.86	1103.051			Medium	0.227	0.301	0.05	0.052
		Far	2619.83	6467.7	4543.77	2720.86			High	0.301	0.714	0.30	0.292
		Low	-1	-0.41	-0.71	0.42							

	Eastern	Medium	-0.41	0.36	-0.03	0.54							
		High	0.36	1	0.68	0.45							
	Northness	Low	-1	-0.34	-0.67	0.47	-	-	-	-	-	-	-
		Medium	-0.34	0.44	0.05	0.55			-	-	-	-	-
		High	0.44	1	0.72	0.4			-	-	-	-	-

Fuzzy Rules Inference

Fuzzy rule inference was used to integrate the fuzzified environmental variables and derive restoration suitability. It is based on if–then logic that links input variables to output suitability classes (low, medium, and high), allowing decision-making under uncertainty (Mamdani and Assilian, 1975; Zadeh, 1973). In this study, the fuzzy overlay approach was applied to combine all fuzzy raster layers into a single continuous suitability surface. This procedure integrates the membership values of all criteria to generate the final suitability map.

GROUP ONE Soil Properties

- Low NDSI AND low SVI AND high OCD AND high OCS AND medium clay AND medium silt AND medium pH water THEN suitable
- Medium NDSI AND medium SVI AND medium OCD AND medium OCS AND low clay AND low silte AND low pH water THEN less suitable
- High NDSI AND high SVI AND low OCD AND low OCS AND high clay AND high silt AND high phwater THEN unsuitable

GROUP TOW Climatic Factors

- high rainfall AND medium temperature THEN suitable
- medium rainfall AND low temperature THEN less suitable
- low rainfall AND high temperature THEN unsuitable

GROUP THREE Topographic Factors

- High TWI AND low elevation AND low slop AND low aspect (north, east) AND valley TPI THEN suitable
- Medium TWI AND medium elevation AND medium slop AND medium aspect (east to west) AND slope TPI THEN less suitable
- Low TWI AND high elevation AND high slope AND high aspect (west, north) AND peak TPI THEN unsuitable

GROUP FOUR Vegetation Indices

- high SAVI AND high GVMI THEN suitable
- medium SAVI AND medium GVMI THEN less suitable
- low SAVI AND low GVMI THEN unsuitable

GROUP FIVE Proximity and Infrastructure

- Far road distance AND near river distance AND medium eastern coordinate AND medium northness coordinate THEN suitable
- medium road distance AND medium river distance AND low eastern coordinate AND low northness coordinate THEN less suitable
- near road distance AND far river distance AND high eastern coordinate AND high northness coordinate THEN unsuitable

Aggregation of Fuzzy Rule-Based Outputs

Following fuzzy rule inference, the resulting outputs representing suitability classes (Suitable, Less Suitable, and Unsuitable) were aggregated to prepare for the final analysis. Each thematic group (soil properties, climatic factors, topographic factors, vegetation indices, and proximity factors) generated fuzzy rasters corresponding to the three suitability levels. These outputs were integrated using a fuzzy overlay approach with the SUM operator, which computes the cumulative membership values for each pixel across layers within the same class. This process produced three aggregated rasters representing the spatial distribution of Suitable, Less Suitable, and Unsuitable areas, respectively. These layers were used as input for the final defuzzification step.

Defuzzification

Defuzzification was applied to convert fuzzy membership values into a single crisp output representing the final restoration suitability map. The Centroid method (center of gravity) was used to derive a representative suitability value for each pixel based on the distribution of fuzzy memberships (Mamdani and Assilian, 1975). This process integrated the three aggregated fuzzy layers (Suitable, Less Suitable, and Unsuitable) using a weighted combination approach, assigning relative weights of 3, 2, and 1 respectively. The resulting continuous raster provides a spatially explicit representation of restoration suitability, enabling the identification of priority areas for ecological restoration.

$$CoG = \frac{\Sigma\ \mu(x)\ \times\ W}{\Sigma\ \mu(x)}$$

Where:
$\mu(x)$ = is the fuzzy membership value for each pixel
W = is the weight assigned to each suitability level
$(\sum \mu(x) * W)$ = is the weighted sum across all suitability classes.

Validation of the Suitability Model

The reliability of the fuzzy logic-based suitability model was assessed using Multiple Linear Regression (MLR), which evaluates the relationship between the final suitability scores and key environmental variables (table 3). This method is widely used in spatial modeling to test the explanatory power of predictor variables and validate model consistency (Majeed, 2010; Kumar et al., 2014; Ostovari et al., 2020).

Spatial Sampling and Data Extraction

A systematic sample of 300 points was generated across the study area using a fishnet grid to ensure spatial coverage. Values from the normalized raster layers were extracted at each point and compiled into a dataset for statistical analysis.

Regression Analysis

Multiple Linear Regression was applied with the final suitability map as the dependent variable and the environmental factors as independent variables. This analysis quantifies the contribution of each variable and assesses the degree to which the model reflects underlying ecological relationships. The coefficient of determination (R^2) was used to evaluate the explanatory power of the model and confirm its internal consistency.

Results

Spatial Analysis and Distribution of Suitability Areas.

The final restoration suitability map was produced following the defuzzification process using the Centroid Method (Center of Gravity), which integrated all environmental and spatial variables considered in the study. The resulting map categorizes the study area into three primary suitability levels for restoration: Suitable, Less Suitable, and Unsuitable (Figure 7). The analysis revealed that the Unsuitable category dominates the landscape, covering approximately 2568.34 km^2, which accounts for 47.67% of the total study area (5389.26 km^2). These areas are predominantly situated in the southern and southeastern regions, characterized by steep slopes, arid climatic conditions, and degraded soil properties. The Less Suitable areas comprise 1944.31 km^2 or 36.08% of the total area. These zones serve as transitional areas between suitable and unsuitable conditions, often featuring moderate vegetation cover, limited soil fertility, and average topographic characteristics. In contrast, the Suitable category encompasses only 876.6 km^2, representing 16.27% of the landscape (Figure 8). These areas are primarily concentrated in the northwestern part of the study area, where favorable conditions prevail, such as better soil moisture content, and gentler slopes. These proportions reflect the spatial heterogeneity of ecological restoration potential across the study area. The predominance of unsuitable zones highlights significant environmental constraints and emphasizes the need for carefully targeted restoration interventions. Conversely, the limited extent of suitable areas underscores the importance of prioritizing these zones for immediate and effective ecological rehabilitation.

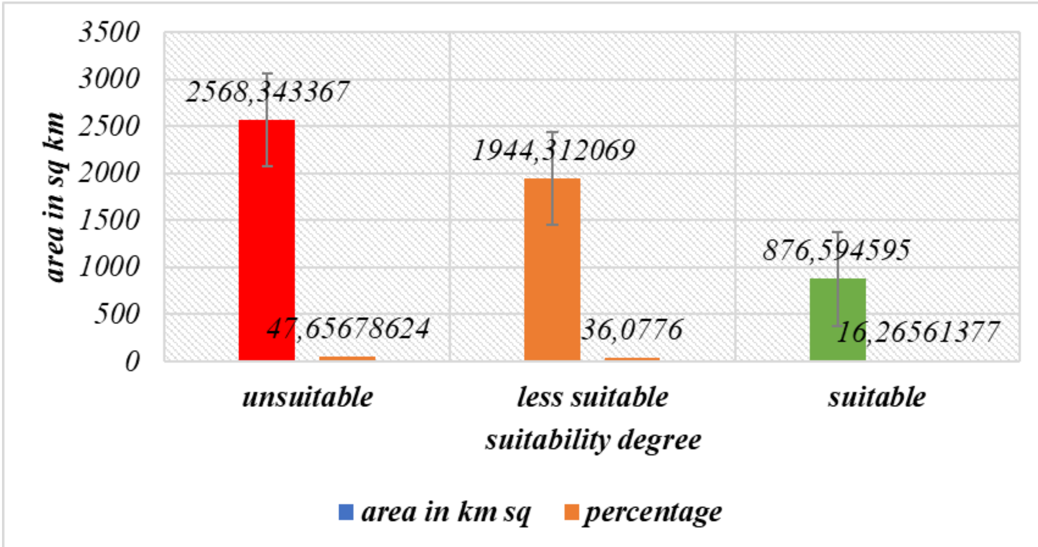

Figure 7. Distribution of restoration suitability classes by area (km²) and percentage in the study area.

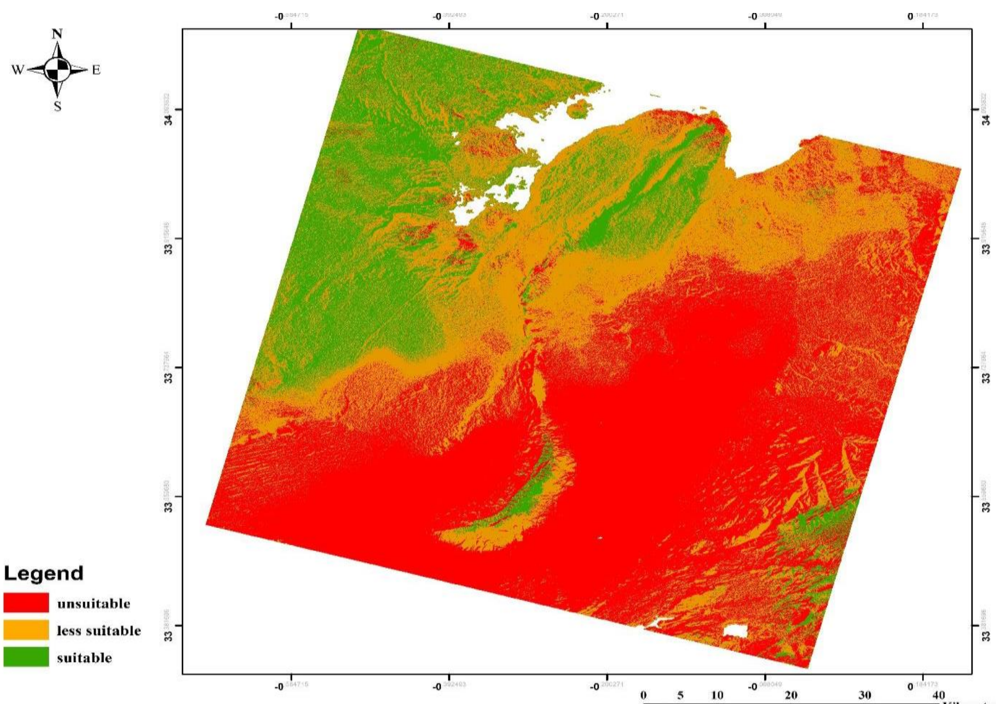

Figure 8. Final restoration suitability map for the study area

Validation of the Fuzzy Logic-Based Land Suitability Model

The fuzzy logic-based land suitability model was validated using multiple regression analyses for each group of variables. This assessed their explanatory power and correlation with the final suitability map. The climatic group demonstrated the highest performance, with a Multiple R of 0.924 and an R2 of 85.3%. This indicates a very strong relationship between climatic variables and restoration suitability. Rainfall emerged as the most significant predictor (Beta = 0.924, P < 0.001), underscoring its critical role in plant establishment and growth within the semi-arid steppe environment. Interestingly, temperature showed no significant effect. The vegetation indices group exhibited a weak to moderate correlation (Multiple R = 0.337; R2 = 11.3%). This suggests that while these indices offer insights into current plant conditions, they are not strong standalone predictors of restoration suitability. SAVI had a significant positive effect (Beta = 0.3, P < 0.001), whereas GVMI showed a significant negative effect (Beta = -0.195, P < 0.001). This negative correlation for GVMI might indicate that areas with lower moisture indices are prioritized for intervention due to degradation.

Table 3. Regression Statistics of Environmental Variables Used in the Model Validation Process

Group variable	Regression			ANOVA		Coefficients	
	Multiple R	R Square	P-value	F	Significance F	Beta	P-value
Climatic Factors	0.924	0.853	0.000	1740.9	0.000		
Rainfall						0.924	0.000
Temperature						0.024	0.289
Vegetation Indices	0.337	0.113	0.000	22.206	0.000		
SAVI						0.3	0.000
GMVI						-0.195	0.000
Soil Properties	0.521	0.272	0.000	75	0.000		
NDSI						0.112	0.000
SVI						0.083	0.003
OCD						0.119	0.000
OCS						0.295	0.000
Clay						0.028	0.298
Silt						0.133	0.000
Ph-Water						-0.247	0.000
Topographic Factors	0.647	0.419	0.000	42.466	0.000		
TWI						-0.183	0.000
Elevation						-0.447	0.000
Slop						0.159	0.000
Aspect						0.166	0.001
TPI						-0.135	0.003
Proximity and infrastructure	0.719	0.516	0.002	78.97	0.000		
Eastern						0.340	0.000
Northen						-0.220	0.000
Road distance						0.485	0.000
River distance						-0.132	0.002

The soil group showed a moderate correlation (Multiple R = 0.521; R^2 = 27.2%). Organic carbon stock (Beta = 0.295, P < 0.001) and pH (Beta = -0.247, P < 0.001) were the most influential soil factors. Other variables such as silt content, organic carbon density, salinity index (NDSI), and sandy veil index (SVI) also had significant effects, while clay content was not significant. The topographic group revealed a moderate to strong correlation (Multiple R = 0.647; R^2 = 41.9%), highlighting the importance of terrain characteristics in determining suitability. Elevation showed a strong negative effect (Beta = -0.447, P < 0.001), while slope (Beta = 0.159, P < 0.001) and aspect (Beta = 0.166, P = 0.001) had positive effects. TWI and

TPI had negative but significant effects, suggesting that valleys and gentle slopes with favorable orientations can enhance restoration potential. Finally, the proximity and infrastructure group presented a strong correlation (Multiple R = 0.719; R^2 = 51.6%). Distance to roads (Beta = 0.485, $P < 0.001$) and eastern coordinates (Beta = 0.340, $P < 0.001$) had positive impacts. Conversely, northern coordinates (Beta = -0.220, $P < 0.001$) and river distance (Beta = -0.132, $P = 0.002$) showed negative effects, underscoring the importance of accessibility and water availability in rehabilitation planning.

Discussion

The findings of this study are consistent with a wide range of research on ecological restoration suitability mapping, particularly those based on multi-criteria decision analysis and spatial modeling approaches. For example, Bortoletto et al. (2016) demonstrated that integrating multiple environmental layers into a composite index improves the reliability of restoration prioritization. In a similar way, the present study integrates heterogeneous environmental variables using a fuzzy logic framework, allowing gradual transitions between suitability classes and better handling of spatial uncertainty. Beyond methodological similarities, the spatial patterns observed in this study are consistent with results reported in other arid and semi-arid ecosystems. In North African drylands, particularly in Algeria, Morocco, and Tunisia, restoration suitability is commonly constrained by strong climatic gradients, soil degradation, and anthropogenic pressure. These conditions often result in fragmented landscapes where only limited zones exhibit high restoration potential. Comparable patterns have been reported in semi-arid steppe systems of the Algerian High Plateaus and Chott Hodna basin, where land degradation and overgrazing significantly reduce ecosystem recovery capacity. These regional similarities confirm that semi-arid steppe ecosystems share common limiting factors across the Mediterranean dryland belt. The role of vegetation indices such as NDVI and SAVI, as highlighted by Questad et al. (2014), is also consistent with our findings, although their explanatory power varies depending on environmental context. In degraded steppe environments, vegetation indices often reflect degradation status rather than driving restoration potential, which explains their relatively lower contribution compared to climatic and topographic variables in our model. This behavior is also reported in other arid ecosystems, where vegetation signals are highly dynamic and strongly influenced by interannual climatic variability. Climate emerged as the dominant controlling factor in the present study, which aligns with broader findings from dryland ecosystem research. In Mediterranean and Sahelian environments, precipitation variability and temperature extremes are consistently identified as the primary drivers of vegetation distribution and restoration feasibility. This reinforces the idea that restoration success in arid zones is fundamentally climate-constrained, particularly under increasing climate change pressure. Topographic and soil factors also played an important role in defining spatial suitability patterns. Similar studies in semi-arid catchments of Morocco and Tunisia have shown that slope, elevation, and soil characteristics strongly influence erosion processes and vegetation establishment. These findings are consistent with the present study, where areas with favorable topographic conditions exhibited higher restoration suitability. Soil constraints, particularly related to fertility and structure, further limit restoration potential, as also reported in Sahelian drylands and North African steppe systems. From a methodological perspective, the use of fuzzy logic provides a significant advantage over traditional binary classification methods by better representing uncertainty in environmental systems. This aligns with Aguirre-Salado et al. (2023), who demonstrated the effectiveness of integrating GIS and MCDA for restoration planning. Unlike deterministic approaches, fuzzy-based models allow continuous variation in suitability, which is particularly relevant in highly heterogeneous landscapes such as semi-arid steppes. In addition, the validation approach adopted in this study is consistent with methodological frameworks proposed by Rahmati et al. (2016) and Pontius et al. (2008), particularly in terms of spatial sampling and statistical evaluation of model performance. These methods ensure that the model output is not only spatially coherent but also statistically robust. The results support the growing consensus that ecological restoration planning in arid and semi-arid regions must integrate multiple biophysical variables within flexible modeling frameworks. The similarities observed with other dryland regions highlight the transferability of GIS–fuzzy logic approaches, while also emphasizing the strong climatic and edaphic constraints that characterize restoration potential in these environments.

Conclusion

This study provides a spatially explicit assessment of ecological restoration suitability in the semi-arid steppe ecosystem of the northeastern region of Naâma Province, Algeria. The area is characterized by high ecological fragility and increasing land degradation driven by climatic stress and anthropogenic pressures. By integrating Geographic Information Systems (GIS), fuzzy logic modeling, and 20 environmental variables, the study successfully generated a detailed suitability map to support ecological restoration planning under environmental uncertainty. The results reveal a highly heterogeneous spatial pattern of restoration potential. Unsuitable areas dominate the landscape (47.65%), followed by moderately suitable zones (36.08%), while only a limited proportion (16.27%) is highly suitable for restoration interventions. These findings highlight the severity of land degradation and the limited natural capacity for ecosystem recovery in the study area, emphasizing the need for targeted and prioritized restoration strategies. Among the evaluated variables, climatic factors emerged as the dominant driver of restoration suitability, particularly precipitation variability, followed by proximity factors, topography, and soil properties. Vegetation indices contributed to describing current land conditions but showed relatively lower explanatory power when compared to climatic and geomorphological variables, confirming that vegetation alone is insufficient to characterize restoration potential in highly degraded dryland systems. The validation results using Multiple Linear Regression further confirmed the internal consistency of the model, with strong statistical relationships observed between suitability scores and environmental drivers, particularly climatic variables ($R = 0.924$, $p < 0.001$). These results are consistent with findings from other semi-arid and arid regions, where climate is widely recognized as the primary limiting factor controlling ecosystem restoration potential. Overall, the integration of fuzzy logic and GIS-based multi-criteria analysis proved to be an effective and flexible approach for handling environmental uncertainty and spatial complexity. Unlike traditional binary classification methods, the fuzzy-based model allows gradual transitions between suitability classes, providing a more realistic representation of landscape variability. From a practical perspective, the results provide valuable guidance for land management and ecological restoration planning. Priority should be given to moderately suitable areas, where restoration efforts are more likely to succeed under current environmental conditions, while highly degraded zones may require long-term intervention strategies. Future research should integrate socio-economic factors and stakeholder participation to further improve decision-making frameworks and ensure more holistic and sustainable restoration strategies in fragile dryland ecosystems.

Author Contributions

A.M. conceived the main idea of the study, conducted the GIS and fuzzy analysis, and wrote the first draft of the manuscript. S.T. revised the manuscript, corrected the errors, and selected the target journal. All authors reviewed and approved the final version of the manuscript.

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Data Availability

All data generated or analyzed during this study are included within the manuscript.

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