Mapping potential desertification-prone areas in North-Eastern Algeria using logistic regression model, GIS, and remote sensing techniques

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Abstract
Desertification is an environmental threat that affects many countries in the world, and it poses specially an ecological issue to Algeria. This study aimed to assess areas sensitive to desertification in North-Eastern Algeria (Tebessa province) using a logistic regression model (LRM), and geomatics-based approaches. Topsoil Grain Size Index (TGSI), Normalized Difference Vegetation Index (NDVI), Aridity index (AI), and Anthropic pressure on the steppe environment (APSE) were selected as desertification indicators for representing land surface conditions from soil, vegetation, climate, and anthropic disruptors. Results indicate that both AI and TGSI are the most crucial indices conditioning desertification risk. Other indices; NDVI and ASPE were appeared as secondary important indices. Herein, although vegetation generally is a key factor for reading desertification, this result shows that vegetation changes in this study are less important than other desertification conditioning parameters. Area under curve value equal 0.94 indicates a satisfactory accuracy for the proposed model. In total, desertification risk changes increasingly along a North-to-South gradient of the whole research area. Besides, slight, moderate, high, and very high classes occupied 0.87%, 21.08%, 19.33% and 58.72% of the total land area, respectively. LRM is recommended as an accurate and easily applied tool to monitor desertification, especially in scarce data environment in developing countries. Additionally, the results obtained in this paper represent a basic scientific tool for implementing current and future policies to control desertification at areas with high risk.

Keywords Desertification · Geomatics · LRM · Land degradation

Introduction
Land degradation is one of the greatest environmental problems caused by unsuitable anthropogenic activities and climate change (Mihi 2021; Mihi et al. 2022). Desertification is defined as the process of land degradation in arid, semi-arid and dry sub-humid regions resulting from various factors, being human activities and climatic variations probably the most important drivers for it to occur (UNEP 1994). Many factors can accelerate or decelerate the rates of desertification processes including climate change, soil pollution, deforestation, drought, overgrazing, unplanned agricultural activities, urbanization, etc. (Becerril-Pina et al. 2015). Desertification brings many problems: a scarcity of land resources, poverty, food supply decline, and a decline in global agricultural production and economic development (Bedoui 2020). Nowadays, the assessment and monitoring of desertification is very important to preserve environmental balance in the global ecological system (Mihi 2018).

Since the 1970s, the phenomenon of desertification has been a persistent problem at local, regional and global scales. Over 900 million people in 100 countries are directly affected by desertification (~4 billion ha of the earth’s land surface) (Panagos and Katsoyiannis 2019). In Africa, the desertification phenomenon affects to near 46% of the total land surface. Moreover, the Mediterranean region...
of Northern Africa is one of the most affected areas by desertification and land degradation in the world (Reich et al. 2019). Within northern Africa, in Algeria, the largest African country, desert dominates ~80% of the land area. Nearly 20 Mha are threatened by the desertification process nowadays, and steppe region remains the most vulnerable with ~600,000 ha (Ali 2009). Typical steppes have a herbaceous vegetation cover of 25–100% (including chamaephytes), but essentially no shrubs or trees except in special edaphic conditions (e.g. riverbeds, disturbed sites). However, desert steppes have a more open vegetation cover of only 10–25%, often with a larger proportion of dwarf and low-growing shrubs (Wesche et al. 2016). Four main steppe vegetation formations are dominates Algeria; Alfa (Stipa tenacissima), Artemisia (Artemisia herba-alba) and esparto (Lygeum spartum) steppes; remt (Arthrophytum scoparium) steppes; halophyte steppes (Atriplex halimus, Atriplex glauca, Suaeda fruticosa, Frankenia thymifolia, Salsola sieberi and Salsola vermiculata); and psammophytic steppes (Aristida pungens, Thymelaeua microphylla, and Retama raetam) (Nedjraoui 2001). In the early 1970s, Algeria launched the green barrier project to control desertification phenomenon in the arid and semi-arid region. The green barrier is located in the pre-Saharan area in Algeria, it stretches between the Moroccan border in the West to the Tunisian border in the East (~1000 km in long), and between isohyets 300 mm in the North and 200 mm to the South of Algeria (~20 km in wide), covering a total area of ~3 Mha. The objective of this project is to recover the extent of the already existing forest to stop the sand expansion. Two types of vegetation were planted; Aleppo pine (Pinus halepensis), which grows easily in this region, and Alfa (Stipa tenacissima) (Benhizia et al. 2021).

It is recognized that mapping and monitoring of desertification phenomenon is a challenging task since it is affected by several driving forces and cannot be directly measured at a field scale. For assessing desertification, there are many different models, such as Food and Agriculture Organization/United Nations Environment Programme (FAO/UNEP 1984, 1997), Mediterranean Desertification and Land Use Sensibility (MEDALUS) (Kosmas et al. 1999), Drivers-Pressures-State-Impact-Responses framework (DSPIR) (GIWA 2001), Soil Erosion Risk Assessment Model (PESERA) (Irvine and Cosmas 2003), World Overview for Conservation Approaches and technologies (WOCAT/LADA) (Liniger et al. 2008), Desertification Risk Assessment Support Tool (DRAST) (Karvitis et al. 2020). Nowadays, many multiple mathematical models were developed to evaluate desertification vulnerability like Decision Tree classifier (DT) (Lamchin et al. 2016), spectral mixture analysis (SMA) (Pan and Li 2013), Analytic Hierarchy Process (AHP) (Sandeep et al. 2021), Logistic Regression Model (LRM) (Djeddaoui et al. 2017), Fuzzy Analytic Hierarchy Process (AHP) (Kacem et al. 2021) or machine learning methods (Meng et al. 2021). In this connection, LRM is a type of multivariate analysis, which have been commonly used in various domains like a diagnosis of COVID-19 infection (Mohammadi et al. 2021), landslide susceptibility mapping (Sun et al. 2021), prediction on the fluoride contamination in groundwater (Nafouanti et al. 2021), predicting the deforestation probability (Saha et al. 2020), urban expansion (Sarkar and Chouhan 2020), flood susceptibility mapping (Ali et al. 2020), among others.

In spite of the importance of the desertification phenomenon, only a few researches have tried to quantify this phenomenon in Algeria country. MEDALUS model appeared in most previous literature (Benabderrahmane and Chenchouni 2010; Benmessaud et al. 2010; Boudjemline and Semar 2018; Rabah and Aida 2019; Bouhata and Bensekhria 2021). Overall, MEDALUS is an interdisciplinary program developed by the European Community (1991–1999) to understand and assess desertification in Mediterranean regions. Since 1991, MEDALUS program has included three stages; (1) MEDALUS Phase I, dealt especially with the physical processes at the local scale, (2) MEDALUS Phase II, dealt with both physical and socio-economic processes at the regional scale, (3) MEDALUS Phase III, increasing its relevance to the larger scales. In the the last stage (MEDALUS Phase III), ended in June 1999, four quality factors (climate, soil, plant cover and management) were adopted as indicators to assess and map the sensitivity of the areas to desertification risk (Kosmas et al. 1999). Besides, MEDALUS approach requires precise data with a complex structure, which make it hard to map desertification sensitivity from local to regional or national scale, especially in developing countries where input data is limited due to lack of resources, poor infrastructure, and difficulty of obtaining data in inaccessible areas (rugged topographies).

This work focuses on the North East of Algeria (Tebessa province) as a typical study region to evaluate the sensitivity to desertification. Desertification in this region is extremely severe because of its geographical location, climatic conditions, and long-term unsustainable land use (e.g. extension of agriculture, overgrazing, woodcutting, and misuse of water resources). Knowing the severity of the desertification phenomenon is a crucial factor to control desertification processes. This current method involves analysing deserted areas using field surveys, measurements, investigation, visual observations, and the processing of main desertification indicators by the application of the mathematical and statistical model. The basic aims of this study were: (1) to prepare a regional-scale desertification potential map by using LRM to identify critical areas and levels of desertification in
the Tebessa province (North-Eastern Algeria), and (2) to develop a methodology do not require a determined number of factors and provide more flexibility to introduce other responsible factors in assessing desertification phenomenon through the integration of vegetation, soil, climate, and socio-economic variables.

**Materials and methods**

**Study area**

Tebessa province is located in Northeaster Algeria and includes 28 municipalities (~ 13,261 km²). Belonging to the Eastern end of the Saharan Atlas Mountain, it stretches within Northern latitudes of 35°10′ to 35°22′ and Eastern longitudes of 7°13′ to 7°55′ (Fig. 1b). The elevation of the area ranges from – 1 to + 1713 m (Fig. 1a). Based on long-term meteorological data spanning over 43 years (1972–2015), obtained by the meteorological station of Tebessa province located within the study area (NOM, 2015), the study area has an arid/semiarid Mediterranean climate; the average annual temperatures is 15.8 °C. The mean annual rainfall is 380 mm. The wettest month is September (43 mm), while the driest month is July (14 mm). The hottest month is July (27.3 °C), while the coldest month is January (6.5 °C). Annual wind speeds are weak to moderate (from 0.34 to 10.57 m/s). Six main soil types are distinguished in the study area: saline soil, calcic, calcareous, aeolian soil of ablation, and basic alluvial (Durand and Barbut 1938). Bedrocks are classified into three main classes: (1) alluvium, alluvium sand, and limestone crust, (2) limestone and dolomite, (3) marls (GPRG 2013). Agriculture is the main human activity with ~ 27.7% of the total area, in addition to livestock farming. The vegetation is steppe type including Alfa grass (*Stipa tenacissima*), and many steppe rangeland vegetation types: halophytic (represented by *Atriplex halimus*, and *Salsola vermiculata*),

![Fig. 1](image_url)  
**Fig. 1** Location of Tebessa province in Northern Africa  
(a) Terrain elevation in the study area,  
(b) OLI Landsat image of Tebessa province for the year 2014 (RGB composite, Bands 7–5–2),  
(c–f) Photos showing different forms of desertification training over the study area
chamaephytic (dominated by *Artemisia herba-alba*, *Artemisia campestris*), and psammophytic (*Ligum spartum*).

**Input data**

The most important step for modelling data is to choose the factors that could be used in LRM.

Desertification processes depend on a multiplicity of interacting variables. Main characteristics of desertification are vegetation decline, soil degradation, climate alteration, and human activities. However, it is difficult to consider the entire variables for mapping desertification risk, as well as, data availability represents a limiting factor in the modelling process (the selection of these depends on the availability of data). Based on the previous literature (e.g. Becerril-Pina et al. 2015; Lamchin et al. 2016; Prăvălie et al. 2020; Ozgul and Dindaroglu 2021; Hereher and El-Kenawy 2021; Kalyan et al. 2021; Salih, et al. 2021; Parmar et al. 2021; Wijitkosum 2021), four thematic layers were used (NDVI, Albedo, AI, and APSE) for mapping the desertification potential. The data required in this study were collected from different cartographic material, statistical data, and previous studies: (1) mean annual reference evapotranspiration (mm) and total annual precipitation (mm) at ~5-km-pixel resolution for 10 years (2009–2018) extracted from the Food and Agriculture Organization (FAO) Water Productivity Open-access portal (WaPOR) < database available at https://wapor.apps.fao.org>; (2) four Landsat 8 OLI images (path/row 192/35, 192/36, 193/35 and 193/36) were used to build mosaic image for the year 2014. All images were recorded in August because there is less cloud cover during the summer period (cloud cover < 2%). These images, provided by the US Geological Survey Landsat archive (http://landsat.usgs.gov) and have a 1 T level of correction; (3) digital elevation model (DEM) with a 30-m-pixel resolution was used to extract the slope from the website http://gdem.ersdac.jspacesystems.or.jp; (4) statistical data on agriculture, grazing, and population during the year 2015 were sourced from the spatial planning department and directorate general for agriculture. All layers were georeferenced at Universal Transverse Mercator (UTM), datum World Geodetic System 1984 (WGS84), zone 32 Nord. The spatial resolution of all raster parameters cited above was resampled to the 30×30 m pixel resolution, and vector parameters were prepared at a nominal scale of 1:60,000 to ensure a cartographic tolerance compatible with raster data at 30×30 m resolution.

**Image processing**

ENVI 4.5 was used for radiometric calibration and correction to compute image indices. Complex radiometric corrections were not necessary for such a study. Here, Top-Of-Atmosphere (TOA) planetary reflectance provides good results. Moreover, TOA reflectance was widely adopted for analysing LU/LC changes in different regions (Vicente-Serrano et al. 2008). Hence, TOA planetary reflectance was used to convert digital number (DN) values to TOA reflectance for OLI bands using reflectance rescaling coefficients provided in the product metadata file (MTL file). Firstly, the following equation (Eq. 1) was used to compute TOA reflectance without sun angle correction (Zanter 2016):

\[ p\lambda' = M_p \times Q_{cal} + A_p, \]

where \( p\lambda' \) = Top-Of-Atmosphere planetary reflectance, without correction for solar angle. Note that \( p\lambda' \) does not contain a correction for the sun angle, \( M_p \)= band-specific multiplicative rescaling factor from the metadata, \( A_p \)= band-specific additive rescaling factor from the metadata, \( Q_{cal} \) = quantized and calibrated standard product pixel values [digital numbers values]. Secondly, the TOA reflectance corrected for the sun angle is thus computed using the given equation (Eq. 2):

\[ p\lambda = p\lambda' / \cos(\theta_{SZ}). \]

where: \( p\lambda \) = Top-Of-Atmosphere planetary reflectance, \( \theta_{SZ} \) = local sun elevation angle. The scene centre sun elevation angle in degrees is provided in the metadata, \( \theta_{SZ} \) = local solar zenith angle where: \( \theta_{SZ} = 90^\circ - \theta_{SE}. \)

**Preparation of data layers**

**Soil** Soil characteristics are a critical factor for soil desertification assessment, the latter increases in fragile soils (Wijitkosum 2021). TGSI is widely applied in several studies on the desertification phenomenon (Becerril-Pina et al. 2015; Lamchin et al. 2016). TGSI was adopted to detect surface soil texture or grain size composition of the topsoil layer. The following equation was used to compute the TGSI index (Eq. 3) (Xiao et al. 2006).

\[ \text{TGSI} = \frac{(R - B)}{(R + B + G)}. \]

where \( R \), \( B \), and \( G \) are the red, blue, and green reflectance bands, respectively. TGSI values varied between \(-1 \) to \(+1\), which positively correlated with fine sand content. Negative values or those near 0 indicate areas with vegetation or water bodies, and values superior to 0.20 represent areas fully covered by fine sand, i.e. desert (Xiao et al. 2006). Four classes of soil components were distinguished according to their contribution degrees to desertification processes (Table 1): (1) soil covered by vegetation or water bodies (~0.27 to 0), medium contents of fine sand (0.0-0.10), high contents of fine sand (0.10-0.20), and soil is fully covered by fine sand.
Generally, desertification risk increases with increasing fine sand content.

**Vegetation** Vegetative cover (density) is one of the main driving forces of desertification occurs in arid and semi-arid regions (Martínez-Valderrama et al. 2018). Overall, more than 20 vegetation indices have been reported in previous literature. Nevertheless, many authors (Mihi et al. 2019; Hereher and El-Kenawy 2021; Shao et al. 2022) recommended to use NDVI as a good indicator for vegetation analyses in arid and semi-arid environments. NDVI index was calculated based on the following equation (Eq. 4) (Rouse et al. 1974):

\[
\text{NDVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})},
\]

where: NIR and R are the near infrared and visible red. NDVI values ranged between – 1 to + 1, in areas of water bodies, NDVI have negative values, barren soil characterized by zero values, whereas areas with high vegetation density are represented by values of + 0.6 to + 1 (Rouse et al. 1974). Four vegetation types can be defined in the research land area (Table 1): water bodies (− 0.71 to 0), desert steppe (0–0.15), steppe (0.15–0.30), and forest steppe (0.30–0.88). Here, desert steppe is deemed as the worst type of vegetation cover regarding desertification risk, followed by steppe, and forest steppe.

**Climate** Climate is found to be an important factor that should be considered in the assessment of desertification risk (Xu et al. 2011). Here, aridity factor is deemed one of the most important factors among all climatic parameters (Karavitis et al. 2020). Various aridity indices have been proposed and used since the beginning of the twentieth century (Becerril-Pina et al. 2015). Zarei et al. (2019) choose the United Nations Environment Program-Aridity index (UNEP-AI) as a good index to evaluate drought conditions in different regions. AI can be computed as shown in the following equation (Eq. 5):

\[
\text{AI} = \frac{P}{\text{ETP}},
\]

where \( P \) is total annual precipitation (mm) and \( \text{ETP} \) is reference evapotranspiration (mm). AI values varied between 0 to 1 (Zarei et al. 2019). Areas with an AI values less than 0.05 is considered hyper-arid land, whereas humid areas characterised by values superior to 0.65 (Zarei et al. 2019). The AI of the study area was divided into two classes (Table 1): arid (0.06–0.2), semi-arid (0.2–0.35). Clearly, areas with high aridity are more sensible to desertification risk.

**Human impact** Korpinen et al. (2012) defined anthropogenic pressure as a human-derived stress factor causing either temporary or permanent disturbance or damage or lossing of one or several components of an ecosystem. Thus, pressure may cause immediate impacts or it may also be low enough not to cause immediate adverse impacts on biota. Anthropic pressure on the steppe environment (APSE) map was prepared during the year 2015 based on the methodology developed by Mihi and Benaradj (2022). Overall, the human factors can be grouped into three major classes namely; urbanization, population, economic growth and consumption/use of resources. Based on existing data in the present time, and after consulting experts, specialist, planners, and decision makers from universities, research insti-

| Factors | Classes | Description | Area |
|---------|---------|-------------|------|
| Topsoil grain size index | [-0.27–0] | Soil covered by vegetation or water bodies | 162.66 | 1.23 |
| | [0–0.10] | Medium contents of fine sand | 1151.15 | 8.68 |
| | [0.10–0.20] | High contents of fine sand | 11,413.87 | 86.07 |
| | [0.20–0.26] | Soil is fully covered by fine sand (desert) | 533.31 | 4.02 |
| NDVI | [0–0.15] | Desert steppe | 7716.07 | 58.19 |
| | [0.15–0.30] | Steppe | 5186.32 | 39.11 |
| | [0.30–0.88] | Forest steppe | 357.41 | 2.70 |
| Aridity index | [0.06–0.20] | Arid | 8365.15 | 63.08 |
| | [0.20–0.35] | Semi–arid | 4895.85 | 36.92 |
| Anthropic pressure on the steppe environment | [0–63] | Distant | 730.67 | 5.51 |
| | [63–127] | Nearby | 1436.85 | 10.84 |
| | [127–190] | Close | 4347.20 | 32.78 |
| | [190–255] | Very close | 6746.28 | 50.87 |
tutions, and government agencies about anthropic factors that generate change in the steppe environment and which, need to be taken into account. Six thematic data maps were used, namely; distance to an urban area, distance to roads, slope gradient, livestock density, population density, and farmland presence. The AHP approach was developed by Thomas L. Saaty in the early 1970s. It’s a kind of Multi-Criteria Decision-Making (MCDM), which allows users to organise and analyse complex decisions, using math and psychology (Saaty 1977). APSE was generated according to the principle of AHP and with a weighted linear combination (WLC) based on pairwise comparison judgments (human judgment). The latter is done based on a numerical scale of nine levels; 1 (equal importance) to 9 (extremely more important). Reciprocals values are used for the inverse relationship. The consistency of judgements is strongly dependent on the consistency between expert opinions. Therefore, the consistency index (CI) and consistency ratio (CR) were adopted to assess the consistency of judgments as shown in the following equations (Eqs. 6 and 7):

\[ CI = \frac{\lambda_{\text{max}} - n}{n - 1}, \quad (6) \]

\[ CR = \frac{CI}{RI}, \quad (7) \]

where \( \lambda_{\text{max}} \) and \( n \) are the largest eigenvalue and order of a matrix, respectively. Random Index depending on the order of the matrix given by Saaty (1977). Consistency ratio changes from 0 to 1; if the consistency ratio index is greater than 0.10, the preference matrix should be revised. In this current study, CR equal to 0.02, which indicated a sufficient consistent in the pairwise comparison matrix of judgments. ASPE can be calculated based on the following equation (Eq. 8):

\[ \text{APSE} = \sum_{i=1}^{n} W_i \times X_i; \quad \text{with} \sum W_i = 1, \quad (8) \]

where, \( W_i \) is the weight values of the criteria \( i \), and \( X_i \) is the potential rating of the criteria \( i \). The weight of each criterion cited above is given according to its importance to anthropic pressure factor based on the expert judgement. This judgement (pairwise comparison) used in AHP approach refers to the relative importance of each factor with respect to another to determine its weight to reflect its importance to human impact (Mihi et al. 2020). Saaty’s AHP multicriteria method (1980) is integrated into the IDRISI Kilimanjaro GIS software. APSE was formulated mathematically as defined by the equation below (Eq. 9).

\[ \text{APSE}_{\text{AHP}} = 0.4225 \times \text{Distance to urban area} + 0.1742 \times \text{Distance to roads} + 0.1812 \times \text{Slope gradient} + 0.0740 \times \text{Livestock density} + 0.0740 \times \text{Population density} + 0.0740 \times \text{Farmland presence}, \quad (9) \]

where the distance module in IDRISI Kilimanjaro GIS software was used (Euclidean distance method) to compute distance to an urban area and to roads in the study area. Slope degree map was derived from the digital elevation model (DEM) using the slope method IDRISI. Farmland presence, population, and livestock density areas were computed by dividing farmlands surface, population, and number of livestock (sheep, cattle, dromedaries, and goats) per unit area (overall study area). APSE map is classified into four classes from weak values (low human impact) to strongest values (high human impact) as shown in Table 1. Areas with high anthropic pressure are more vulnerable to desertification risk and vice versa.

Methodology

Application of logistic regression model (LRM) The overall methodology applied in this paper is illustrated as a flowchart in Fig. 2. McFadden introduced the LRM method in the 1970s (McFadden 1973), to explain the probability that a spatial phenomenon will occur on any given parcel of land. Logistic regression models are defined as statistical models, which describe the relationship between a dependent variable and several independent variables (Nick and Campbell 2007). The key to LRM is that the dependent or response variable is dichotomous (or binary), such as success/failure or presence/absence. The independent or explanatory variables may be either continuous, discrete, dichotomous, or a mix of these qualities like nominal, ordinal, interval, or ratio scale data (McFadden 1973). In the case of desertification risk mapping, the objective of LRM would be to find the best fitting model to describe the relationship between the presence (1) or absence (0) desertification (dependent variable) and a set of independent indices namely TGS, NDVI, AI, and APSE. In logistic regression modelling, the maximizing likelihood function is used to obtain the coefficients of independent variables (Shahabi et al. 2014). LRM is explained as a linear equation (Eq. 10 and 11):

\[ Y = \text{Logit}(P) = \ln \left( \frac{P}{1 - P} \right) \quad (10) \]

\[ Y = C_0 + C_1 \times X_1 + C_2 \times X_2 \ldots C_n \times X_n, \quad (11) \]
where $P$ is the probability of desertification incidence ($Y$), $P/(1 - p)$ are the probability of presence divided by the probability of absence (the odds of desertification incidence), $C_0$ is the model intercept, and $(C_1, \ldots, C_n)$ are the partial regression coefficients for each desertification determining independents indices ($X_1, \ldots, X_n$). For the functionality of this model, it is necessary to standardize all the indices adopted to a common scale of measurement to a byte-level range of 0–255 (Eq. 12), with 0 and 255 represent the best and worst vulnerability areas to desertification for each criterion, respectively. Sigmoidal (s-shaped) fuzzy membership functions integrated into the IDRISI Kilimanjaro GIS software were applied to rescale all values for each index used, i.e., monotonically increasing for TGSI, AI, and APSE indices, and monotonically decreasing for NDVI index.

$$y = \frac{(x_i - x_{\min})}{(x_{\max} - x_{\min})} \times \text{standardized range,}$$

where $y$ is the normalized value of each index, and $x_i, x_{\max}, x_{\min}$ are actual value, maximum and minimum values observed in all actual measurement, respectively. IDRISI Kilimanjaro GIS software was used for all statistical assessment. The desertification training areas (Fig. 1c–f) was input as dependent variable (Boolean map), while the desertification conditioning indices maps (Fig. 3a–d) were input as independent indices. To check the goodness of fit of LRM, Relative Operating Characteristic (ROC) and Pseudo $R^2$ values were computed. The ROC values change between 0.5 to 1; if the ROC value is close to 1, it indicates a perfect fit (good correlation between the dependent and the independent variables), whereas ROC value equal 0.50 represents a random fit (Ayalew et al. 2004). Pseudo $R^2$ value can be calculated from $1 - (Ln(Likelihood)/Ln(LO))$; $Ln(Likelihood)$ is the best-fitting model, and $Ln(LO)$ is the null hypothesis in, which all the coefficients are set to zero. Therefore, $R^2$ equal 1 shows an excellent result, whereas 0 indicates no relationship. When $R^2$ is superior than 0.20, this is evidence of a relatively goodness of fit (Clark and Hosking 1986). In this current study, ROC and $R^2$ values equal 96.92%, and 0.3893%, respectively, as summarized in Table 2. These values indicate that the logistic regression method yields acceptable results. Finally, the logistic regression equation can be formulated mathematically as given in Eq. 13. Equal interval method was applied to classify

Fig. 2 Flow chart of a general method used for mapping desertification risk
Fig. 3 Parameter maps standardized using the fuzzy membership functions (0–255). a Topsoil Grain Size Index, b Normalized Difference Vegetation Index, c Aridity index, and d Anthropic pressure on the steppe environment.
the synthetically final map of desertification risk into four categories as “slight”, “moderate”, “high” and “very high”.

Logit (Desertification) = −237.7689 + 0.355944 × TopsoilFrainSizeIndex + 0.014675 × NormalizedDifferenceVegetationIndex + 0.570812 × Aridityindex − 0.003177 × Anthropicpressureonthesteppeenvironment, (13)

Validation of the desertification risk map

Prediction without testing data accuracy is not recommended in science. Therefore, it is mandatory to evaluate a model’s prediction accuracy. Actually, accuracy assessment of the constructed model in its natural context is extremely difficult at this scale (technically and economically is not easy feasible). Therefore, desert areas were mapped and checked starting from high-resolution image (google earth) and field survey. Here, the choice of stations greatly depends on different parameters including proximity to roads, homogeneity, security, accessibility, aspect, and altitude. In this current research, the validation of spatial prediction models for desertification risk mapping was achieved by comparing the known desert location data with the desertification risk map using Area Under Curve (AUC) method. The AUC method is widely used to estimate the accuracy of predictive models (Mihi and Benaradj 2022). The ROC curve graphs are plotted with respect to the false positive rate values (X-axis) and the true positive rate (Y-axis). In the AUC method, AUC values fall between 0.5 and 1 noting the rate of goodness. It can be classified into five levels to represent different levels of accuracy: 0.90–1.00 (excellent), 0.80–0.90 (good), 0.70–0.80 (satisfactory), and 0.60–0.70 (poor), and 0.50–0.60 (failing). ROC module in IDRISI Kilimanjaro GIS software was used to compute the AUC value.

Results and discussion

Outs of TGSI (Fig. 3a; Table 1), show that almost the total region is occupied by the class of high contents of fine sand with approximately 86%. Medium contents of fine sand, and soil covered by vegetation or water bodies’ classes, representing 8.68%, and 1.23%, respectively, of the whole land area, and diffused in the North. The class of very high contents of fine sand (desert) is poorly represented and spread exclusively in the far South of Tassous province (depression, and sebkha) with not more than 5% (4%). Two lithologic/morphologic units can be defined over the study area; (1) Sedimentary rock/consolidated bedrock (marls, conglomerates, sandstone, dolomite, limestone, and friable limestone), which represent ~63%, and (2) unconsolidated parent materials (alluvium, alluvium sand) with only 37% of the whole study area.

The results of NDVI (Fig. 3b; Table 1), show that the majority of the vegetation type in the study region was highly sensible to desertification (represented by desert steppe) and occupies more than half of the whole area (58.19%). It is followed by steppe type with 39.11%, and then dense vegetation represented by forest steppe (2.70%), which is located in the Northern part of the study area, and finally water bodies (Safsaf El-Oussera water dam), which almost does not exist and poorly represented with only 0.01 of the land area. Here, NDVI is related to the photosynthetic activity of green vegetation, in this case, forest steppe is characterised by a high level of photosynthetic activity (high NDVI values), compared to the scattered desert steppe (annual species) characterized by low NDVI values (low level of photosynthetic activity).

The data of AI parameter is displayed in Fig. 3c and Table 1. In short, aridity increases from the North to the South of the total of Tassous province. It shows two climatic zone, arid zone which dominate the Southern part and covered ~63% of the study area, and semi-arid zone occupy the rest of the study area with 36.92% of the whole area.

APSE is classified into four classes (Fig. 3d; Table 1), ranging increasingly from the areas distant to human activities, which is covered only 5.51% of the total study area, to the areas nearby to human activities, with approximately 10.84%, while areas close to human activities is diffused over 32.78% of the total area. Very close areas to human activities occupy approximately one-half (50.87%) of the research area.

According to Eq. 10 above, TGSI, NDVI, and AI positively affect the occurrence of desertification, whereas APSE indicates a negative impact on desertification occurrence. Here, both TGSI and AI factors have a higher impact on
the occurrence of the desertification phenomenon compared to other governing factors of desertification. Desertification risk map of Tebessa province was obtained by geospatial integration of soil, vegetation, climate, and human impact maps (Fig. 3a–d), the outcome is as given in Fig. 4, and the statistics are as shown in Table 3. Besides, AUC value equal 0.96 (Fig. 5) indicates an excellent accuracy for the proposed model. It is clear that the risk of desertification changes from one zone to another throughout the study area, depending on the impact of each four driving forces, which controls the desertification phenomenon. Clearly, desertification risk increases gradually from North to South of the total of Tebessa province. According to the results, those areas falling into the class of very high-risk area distributed in the low-lying Southern part of the whole total land area. These areas dominate almost the research area with 58.72%. Areas of high risk cover 19.33% of the whole land area, mainly in the central part of Tebessa province on plains morphologies. Areas at moderate risk are found in the Northern part, representing 21.08% of the total area, and are located in the hilly and slightly mountainous morphologies. Elsewhere, areas at low risk are also found mainly in the northern part of Tebessa province, covering only 0.87%, and are distributed in zones where there are large expanses of natural forest (good vegetation density).

Results of the desertification risk map are similar to the findings of many studies in the Algeria Saharan atlas region (Benabderrahmane and Chenchouni 2010; Benmessaud et al. 2010; Ahmed 2015; Boudjemline and Semar 2018; Rabah and Aida 2019; Bouhata and Bensekhria 2021), which confirmed the high severity of desertification risk in these regions, depending of the interactive effects of responsible factors which encourage desertification processes such as harsh climatic conditions, degraded soil structure, human activities and degradation of natural vegetation.

Desertification risk is clearly low in the far North of the research area. This is because of the good quality of vegetation dominated by forests with thick undergrowth (*Pinus halepensis* Mill. and *Juniperus phoenicea* L.), as well as dense canopy structure, and plant roots increase the structural stability of the soil, allowing the accumulation of organic matter, and hence increases its resistance against soil degradation (Zamani and Mahmoodabadi 2013). Besides, the highest precipitation quantity (> 479–604 mm/year) coincides with good vegetation density and play a key role in mitigating soil degradation (Mihi et al. 2020). Moreover, the steeply topographic of those areas (16–35°) makes them

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**Table 3** Classes of desertification risk within Tebessa province

| Desertification risk classes | Surface area | % |
|-----------------------------|--------------|---|
| Slight                      | 114.73       | 0.87 |
| Moderate                    | 2795.68      | 21.08 |
| High                        | 2563.69      | 19.33 |
| Very high                   | 7786.91      | 58.72 |

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![Fig. 4 Final map of desertification risk of the study area (Tebessa province, Northeast Algeria)](image)

![Fig. 5 AUC assessment of the logistic regression-based model](image)
less suitable for human activities (human preferred to settle close to roads networks and urban areas).

Desertification risk remains moderate in the North of the study area. The vegetation in those areas is characterised by flora with Alfa grass (*Stipa tenacissima* L.). In addition, to the energy content of this species for pastoral livestock, Alfa grass persists during extreme droughts conditions by maintaining its physiological activity (Aidoud 2002). Here, vegetation progression causes positive changes in the chemical and physical proprieties of soil, as well as the micrometeorological parameters of land surface such as evapotranspiration, temperature, albedo, and radiation (Xu et al. 2009). The relatively good vegetation cover (open forest) together with high precipitation amount (355–478 mm/year) decreases the soil vulnerability of the area toward land degradation (Mihi et al. 2020).

Despite the high amount of precipitation (355–478 mm/year) in these areas, the desertification risk was high. Those areas show a predominance of open rangelands. Here, phe-nological cycles of vegetation change over the course of a year (intra-annual variability) and from year-to-year (inter-nological cycles of vegetation change over the course of a year) in these areas, the desertification risk was high. Those areas show a predominance of open rangelands. Here, phe-nological cycles of vegetation change over the course of a year (intra-annual variability) and from year-to-year (inter-nological cycles of vegetation change over the course of a year) in these areas, the desertification risk was high. Those areas show a predominance of open rangelands. Here, phe-nological cycles of vegetation change over the course of a year (intra-annual variability) and from year-to-year (inter-nological cycles of vegetation change over the course of a year) in these areas, the desertification risk was high. Those areas show a predominance of open rangelands. Here, phe-nological cycles of vegetation change over the course of a year (intra-annual variability) and from year-to-year (inter-nological cycles of vegetation change over the course of a year) in these areas, the desertification risk was high. Those areas show a predominance of open rangelands. Here, phe

The areas which record very high desertification risk are characterized by an arid climate where precipitation amount does not exceed usually 355 mm yearly, and the vegetation quality is very poor; high evapotranspiration rate and low rainfall amount, triggering affect plant growth (low production of biomass) (Mihi et al. 2020). In reality, the regression in vegetation quality alone does mainly indicates desertification (Becerril-Pina et al. 2015). Here, United Nations (UNEP 1994) stated that climate variations and inadequate human activities are the two main factors driving forces in the desertification process. For centuries, nomads were the original inhabitants at Tebessa province, where livestock grazing (sheep, goats, and dromedaries…) and cultivation of cereals were the main human activities in the province (Martínez-Valderrama et al. 2018). Nowadays, sheep farming is the main economic activity in Tebessa province, with 933,000 heads of sheep according to the Ministry of Agriculture and Rural Development (Benlakehal et al. 2019). Here, rotational grazing in arid and semi-arid steppe rangelands can significantly increases plant diversity and vegetation homogeneity (Merdas et al. 2021; Koubâ et al. 2021; Macheroum et al. 2021). Still, overexploited by grazing and harvesting under harsh climatic conditions (droughts, and irregular rainfall events) accelerates the desertification process (Martínez-Valderrama et al. 2018), where Alfa grass steppes (hemicyrptophyte type) were gradually replaced by other vegetation taxa, depending on soil type like halophytic (represented by *Atriplex halimus* L., and *Salsola vermiculata* L.), chamaephytic (dominated by *Artemisia herba–alba* Asso, *Artemisia campestris* L.), and psammophytic (*Ligeum spartum* L.).

Generally, each method/model has limitations, which cause a level of uncertainty in the accuracy assessment of the model. Two crucial steps should be considered to produce a reliable desertification risk map. The first is the selection of a relevant assessment approach, and the second is to identify the appropriate parameters that affect the desertification phenomenon (Akgun and Türk 2010). In this way, The LRM method needs data conversion for access by statistical software and is of limited value when the dataset is large, as well as if there is a limited data set like desertification training or inventory for a large region, in this case the application of LRM is not recommended for the assessment (Akgun and Türk 2010; Park et al. 2013). Besides, the calculation weights via LRM were done via statistical software program without any questionnaire survey, as well as the LRM accepts all kinds of data set and does not require any precise data (Park et al. 2013; Djeddouank et al. 2017). Consequently, the model developed in this paper can be applied in data-poor areas (developing countries) with similar conditions. However, this proposed model should be examined under different conditions (climate, geographical environment, and different temporal and spatial scales).

**Conclusion**

The results, based on all four sensitivity indicators (biophysical and anthropogenic), showed that Tebessa province is highly exposed to desertification. LRM reached 94% of overall accuracy (AUC method). TGSI and AI indices play a key role in the assessment of desertification risk. Globally, desertification risk increases gradually from the North to the South of the total research area. Slight, moderate, high, and very high vulnerable zones constitute 0.87%, 21.08%, 19.33% and 58.72% of the whole area, respectively. Desertification risk increased with the decrease of soil quality, vegetation density, and climate conditions, and decreased whenever the human impact decreased. The obtained thematic map of desertification level represents a useful tool for engineers, planners, and authorities to control desertification more effectively. Based on the results, the methodology adopted in the framework of this paper seems robust enough to extend desertification risk mapping for other parts of Algeria country. Furthermore, the
model is very adaptable, practical, and its can be easily adjusted to the locally existing data in developing countries. Although the approach applied in this study, showed an excellent performance accuracy, further studies should be conducted with further field measurements at small-scale level and by incorporating additional data such as soil wetness, soil erosion, and landforms.

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