



# Geospatial analysis of desertification vulnerability using Mediterranean desertification and land use (MEDALUS) model in Kebbi State, Nigeria

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## Abstract

Desertification has been a global concern long ago. However, it has never been as severe as it is in the present day. According to the United Nations Convention to Combat Desertification (UNCCD), almost one-third of the world's agricultural land is facing one form of degradation or another. Assessment of desertification using GIS nowadays presents an efficient means for identifying desertification vulnerable areas. Henceforth, this study aimed to assess desertification vulnerability in Kebbi State, Nigeria, by using Mediterranean desertification and land use-environmental sensitivity area index (MEDALUS-ESAI) approach. The approach is based on biophysical and human indicators. The characteristics and intensity of these indicators contribute to the evolution of different levels of desertification. For the desertification sensitivity index (DSI), quality indexes, and the corresponding individual indicators, a weighted sensitivity score was assigned from 1 to 2. The resultant index layers were merged for generating the DSI theme. The distribution of the DSI indicated that 36% of the area is not affected, and 17% and 30% fall into low and moderately sensitive classes, while 15% and 1% of the area are classified as sensitive and highly sensitive respectively. The result, therefore, indicated that the area is moderately sensitive to desertification. DSI is essentially useful for determining desertification severity. The theme will contribute significantly to the decision-making process most importantly in the selection of priority zones in combating the desertification phenomenon in the area. This study delineates the potential desertification vulnerable areas that need urgent action; the model is thus recommendable for its flexibility and accuracy.

**Keywords** Desertification · Geospatial · Assessment · MEDALUS-ESAI · Kebbi State · Nigeria

## Introduction

Desertification means the decline in the ability of the land to carry out ecosystem main functions and services that maintain the well-being of the society and its development specifically in the drylands (Adeel et al. 2005). Safriel (2009) refers to desertification to mean land degradation (LD) in the drylands (arid, semi-arid, humid, and sub-humid), as manifested by a determined decrease of biological productivity of the land. LD as defined by Raul and Koohafkan (2004) is

the process of gradual or permanent loss of land productivity mainly due to anthropogenic activities, or from the disparity between land quality and the intensity of land use. LD may include such changes in the land as a decline in crop yield or a drastic reduction in the existing vegetative density in a particular area. LD as a prelude to desertification is the term that ascribes the lands affected by the reduction of primary productivity of the earth. About one-third of the world's agricultural land is either highly or moderately degraded (UNCCD 2008); nonetheless, dryland areas are more vulnerable to natural and human destruction due to the limited water content in soil (UNCCD 2007). LD especially when associated with extreme ecological conditions together with particular patterns of drought and human-induced changes (population trends, untenable land use) may transform into an irremediable form of environmental degradation that is desertification.

Desertification is a crucial global phenomenon and, as such, monitoring the desertification process will give

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information necessary to support policies and decisions to conserve, protect, and sustainably manage the land and its resources. Combatting desertification requires enhanced monitoring and understanding its causes, impact, and degree coupled with climate, soil, water, land cover, and socioeconomic factors (Kapalanga 2008).

There are many desertification monitoring systems (Symeonakis et al. 2016; Kapalanga 2008; Alim and Mumuli 2010); however, the Mediterranean desertification and land use-environmental sensitivity area index (MEDALUS-ESAI) framework is presently the most widely used methodology due to its simplicity in model building and its flexibility in the use of available/relevant LD indicators (Basso et al. 2000). Similarly, it allows modification of indicators by the local conditions and the availability of datasets (Contador et al. 2009). MEDALUS-ESAI framework integrates both biophysical factors (climate, soil, and vegetation) and anthropogenic factors and can, therefore, be considered as an established robust system that indicates the area sensitivity to degradation and quantifies the aggregate impact of different factors leading to LD.

Nigeria is faced with a desertification problem accounting for about 68.38% of the country's total land area. However, the extent and severity of desertification in Nigeria have not been fully established, neither is the rate of progression documented (Olagunju 2015; Idris Medugu et al. 2011). The extent to which desertification is encroaching need to be measured and mapped to make proper planning for sustainable management planning. Subsequently, the current study aimed at assessing the sensitivity to desertification in Kebbi State, the extreme Northwest of Nigeria, using the GIS-based MEDALUS-ESAI framework.

## Materials and methods

### The study area

Kebbi State (13 local government areas) is situated between Lat.  $13^{\circ} 54' 58.925''$  N– $11^{\circ} 7' 27.002''$  N and Long.  $3^{\circ} 32' 57.995''$  E– $4^{\circ} 53' 19.708''$  E; it covers around 18,591 km<sup>2</sup>, supporting the population of about 2.758 million people (NBS 2012), in the extreme northwestern part of Nigeria (Fig. 1). The temperature ranges between 35 and 40 °C, with average annual rainfall of about 850 mm, and the relative humidity ranges between 10 and 25% and 51 and 79% during rainy and dry seasons respectively (Ogungbenro and Morakinyo 2014). The vegetation is Sudan savannah in nature and the land is a semi-arid type, characterized by frequent weathering and leaching due to poor soil structure and low organic matter content (Usman et al. 2016). The main economic activity is agriculture with over 70% of the people practising one form of agriculture or the other.

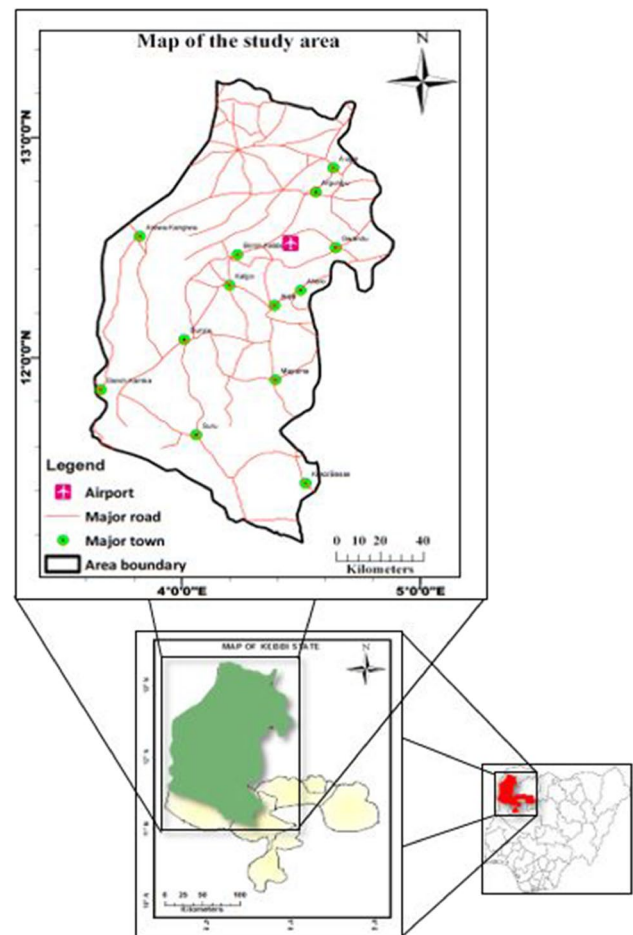


Fig. 1 Map of the study area from a Nigerian map

### Referenced methodology: the MEDALUS framework

The MEDALUS stands for Mediterranean desertification and land use. It is a GIS-based environmental modelling approach that allows for cross-analysis and elaborations of the variable targeting particular aspects of desertification and their assessment with respect to their spatial distribution. It was developed by Kosmas et al. (1999) based on four groups of several biophysical and human-induced variables, designated as soil (soil texture, soil drainage, soil parent material, rock fragments, and soil depth), climate (aspects, aridity, and rainfall), vegetation (fire risk, vegetation cover, resistance to aridity, and erosion protection), and management practices or human factors (pastures and forest areas, the intensity of land use, and managerial policies).

The basic premise here is that each triggering variable of desertification will be allotted a threshold value based on the relevant starring role played in the LD process in a given land. One of the outstanding features of MEDALUS is its flexibility and allows modification of indicators in accordance with the local circumstances and obtainability of the dataset (Contador

et al. 2009). In general, the MEDALUS approach is centered towards recognizing environmental sensitive areas (ESAs) through multi-factor approaches. The characteristics and intensity of these factors contribute to the evolution of different levels of environmental conditions in an area.

**The environmental sensitivity area index**

Drylands are generally characterized by limited water content, which is regarded as a restraint factor for its ecosystem potentials. In such areas, LD is a serious challenge, as the manifestation of vulnerability to desertification processes; therefore, its evaluation presents an essential step for realizing the sustainability of land use. To describe the environmental sensitivity area index (ESAI) in drylands, soil, climate, vegetation, and management/human qualities are commonly considered (Kosmas et al. 1999).

Figure 2 shows the procedure for the MEDALUS-ESAI approach. The weighted scores are assigned to each contributing indicator based on the ability of the soil to retain moisture and favorable condition for plant growth (Kosmas et al. 1999). The scores vary from “1 = good” (lower sensitivity) to “2 = poor” (higher sensitivity). Table 2 summarizes the data source, weighted score, and sensitivity class for each of the selected indicators.

The soil, climate, and vegetation quality indicators are generally related to the biophysical environment such as water availability, water retention capacity, and plant cover, while human quality indicator relates to human-induced pressure on the environment such as population density, farming intensity, and grazing pressure (Kosmas et al. 1999). In the MEDALUS-ESAI framework, computing the final environmental sensitivity requires each quality index to be assigned an equal-weighted score and likewise to each principal indicator (Symeonakis et al. 2016). The general formula for the abovementioned indicators in accordance with the standard MEDALUS-ESAI approach is given as:

$$\text{Index}(i) = (\text{indicator}1 * \text{indicator}2 * \text{indicator}3 * \dots * \text{indicator}(n))^{1/n} \tag{1}$$

where *i* = quality indices and *n* = number of indicators.

The sub-index(es) for the MEDALUS-ESAI framework stands as soil (SQI), climate (CQI), vegetation (VQI), and human (HQI) quality index. The desertification sensitivity index (DSI) was formulated by slightly modifying the standard MEDALUS-ESAI based on the data available in the study area. Therefore, each quality index and the DSI were calculated as the geometric average of each of the corresponding indicators in the index as:

$$\text{SQI} = (\text{soil texture} * \text{organicmatter} * \text{bulk density} * \text{slope} * \text{porosity} * \text{pH})^{1/6} \tag{2}$$

$$\text{CQI} = (\text{Temperature} * \text{aridity} * \text{aspect} * \text{PET})^{1/4} \tag{3}$$

$$\text{VQI} = (\text{Vegetation cover} * \text{Stand density})^{1/2} \tag{4}$$

$$\text{HQI} = (\text{Pop.density} * \text{farmingint.} * \text{gazing int} * \text{fuelwood usage})^{1/4} \tag{5}$$

The DSI was derived by merging the resultant index (SQI, CQI, VQI, and HQI) as in the equation:

$$\text{DSI} = (\text{SQI} * \text{CQI} * \text{VQI} * \text{HQI})^{1/4} \tag{6}$$

The index results were categorized into five based on the MEDALUS approach as (1) not affected, (2) low sensitivity, (3) moderate sensitivity, (4) sensitive, and (5) high sensitivity areas to desertification as in Table 1.

**Index data source**

For this study, the MEDALUS-ESA Index is composed of 16 different indicators (desertification indicators) as in Table 2, which were grouped into the soil, vegetation, climate, and human quality indices. The data were obtained from various sources via field sampling, field survey, website domain, and government agencies.

**Soil dataset**

For this research, soil samples were collected randomly from different locations in the study site. Multistage sampling technique was used to collect 12 soil samples from each of the 13 local governments in the study area. This gives us a total of 156 samples. The basic premise of applying multistage sampling for the study is that it allows us to collect samples randomly after determining the cluster samples in the study area. The soil physical properties were considered to avoid biases that are not due to soil itself but due to other properties, i.e., chemical properties. However, while trying to reduce spatial redundancy, caution was taken to maintain an average of 10–15 km distance in between sampling points except for a situation beyond control such as lack of access road network. The samples were taken to the soil laboratory of Kebbi State University of Science and Technology, Aliero, for testing and analysis. Table 2 shows the methods used for testing each of the selected indicators.

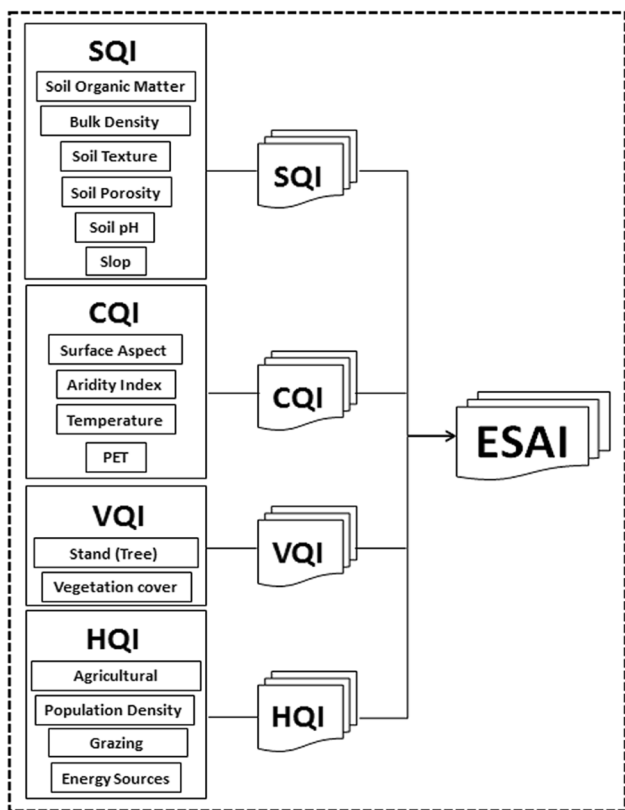


Fig. 2 Methodology flowchart for the DSI

**Climatic dataset**

For this research, the climatic variables used include temperature, aspect, aridity index, and potential evapotranspiration (PET); however, in the study area, there is a limited number of the meteorological station as only 2 stations were available with inadequate data coverage and obsolete equipment. Subsequently, climatic datasets from online domains were used. For the aspect, the elevation data were collected from the USGS website domain as well. The temperature data were obtained from the analysis of land surface temperature (LST), a remote sensing-based technique using Landsat OLI thermal bands (Avdan and Jovanovska 2016; Sameen et al. 2014). The aridity index and PET data were obtained from *CGIAR-CSIGeoPortal*; however, they use the

**Table 1** The DSI classes

Designation	Not affected	Low sensitivity	Moderate sensitivity	Sensitive	High sensitivity
	1.0–1.17	1.18–1.22	1.22–1.40	1.41–1.53	1.54–2.0

Adopted from Kosmas et al. (1999)

Penman–Monteith method for the derivations (Allen et al. 1998). Table 2 illustrates the indicators selected and the data source.

**Vegetation dataset**

Vegetation analysis is an important indicator because it is highly correlated to the net primary productivity (NPP). Vegetation cover and standing tree density are used. Vegetation cover is determined from the analysis of the normalized difference vegetation index (NDVI) while stand (Tree) density of the area was obtained from the primary field survey using the Quadrat method. The GPS receiver is first used to determine the location (x, y) of the sampling point of 150 × 150 m (2.25 ha) “quadrat.” The tree counting was conducted manually to ascertain the number of standing trees in the quadrat. The inclusion criterion for selecting an individual tree is any living tree with a DBH ≥ 10 cm diameter and an observable canopy cover. A total of 156 quadrats were sampled randomly in the study area using a multistage sampling technique with 12 quadrats from each of the 13 local government councils in the study area. Table 2 shows the indicators selected and the data source.

**Human (socio-demographic) data**

This data is particularly important in the determination of human influence on desertification (Table 2). For this research, the survey was conducted using a structured questionnaire using a multistage sampling technique with 6 respondents from each of the 5 selected villages of the 13 local government areas of the study site. A total of 390 respondents/data were collected from the study area. The data collected include agricultural intensity, farming intensity (Kosmas et al. 1999), and the percent of people using other alternative energy sources (non-fuelwood). The population density data were obtained from the National Population Commission of Nigeria. Data were statistically analyzed using Excel via the descriptive method.

**Data conversion to GIS environment**

For this study, multi-source datasets are involved. While some (dataset) are already in raster format and automatically possess spatial reference, i.e., satellite data; however, for certain type datasets (i.e., Soil), the spatial reference has to be transferred manually and then converted into raster format within ArcMap 10.3 environment. These data without automatic spatial references are converted into decimal degrees and transferred to ArcMap 10.3 Environment for further processing. Subsequently, the data spatial reference (coordinates) was transformed into Universal Transverse

**Table 2** Description of indicators, class range, and weighted score for SQI, CQI, VQI, and HQI

Index	Indicator	Data sources	Class range	Sensitivity score	Weighted score
Soil quality index (SQI)	Soil texture	Field/lab analysis	L, SCL, SL, LS, and CL	Low	1.0
			SC, SiL, and SiCL	Moderate	1.5
			Si, C, SiC, and S	High	2.0
	Soil organic matter (%)	Field/lab analysis	> 3	Low	1.0
			2.3–3	Moderate	1.5
			< 2.3	High	2.0
	Soil porosity (%)	Field/lab analysis	< 35	Low	1.0
			35–40	Moderate	1.5
			> 45	High	2.0
	Bulk density (g/cm <sup>3</sup> )	Field/lab analysis	< 1.55	Low	1.0
1.5–1.6			Moderate	1.5	
> 1.6			High	2.0	
Soil pH	Field/lab analysis	< 6.5	Low	1.0	
		6.5–7	Moderate	1.5	
		> 7	High	2.0	
Slope (°)	SRTM data/spatial analyst tool	< 6	Very Gentle	1.0	
		6–35	Gentle	1.5	
		> 35	Steep	2.0	
Climate quality index (CQI)	Temperature (°C)	Landsat (OLI)/LST	< 25	Low	1.0
			25–35	Moderate	1.5
			> 35	High	2.0
	Potential evapotranspiration (PET)	CGIAR-CSIGeoPortal	< 1985	Low	1.0
			1985–2025	Moderate	1.5
			> 2025	High	2.0
Aridity index	CGIAR-CSIGeoPortal	> 0.4	Low	1.0	
		0.3–0.4	Moderate	1.5	
		< 0.3	High	2.0	
Aspect	SRTM data/spatial analyst tool	NE, NW	Good	1.0	
		SE, SW	Poor	2.0	
Vegetation quality index (VQI)	Vegetation cover (%)	Sentinel II/NDVI	> 25	Low	1.0
			10–25	Moderate	1.5
			< 10	High	2.0
	Standing tree density (tree/ha)	Field survey	> 7	Low	1.0
5–7			Moderate	1.5	
< 5			High	2.0	
Human quality index (HQI)	Population density (people per km <sup>2</sup> )	National Population Commission, Nigeria	< 100	Low	1.0
			100–200	Moderate	1.5
			> 200	High	2.0
	Farming intensity	Field survey	< 6	Low	1.0
			6–8	Moderate	1.5
			> 8	High	2.0
	Energy source	Field survey	> 20%	Low	1.0
			15–20%	Moderate	1.5
< 15%			High	2.0	
Grazing intensity	Field survey	> 2.8	Low	1.0	
		2.3–2.8	Moderate	1.5	
		< 2.3	High	2.0	

Mercator (UTM) zone 31, World Geodetic System 1984 (WGS84). An inverse distance-weighted (IDW) spatial interpolation method was executed (Li and Heap 2011). IDW was used to interpolate the datasets across the study area because it is the best interpolation method and most importantly on continuous surfaces (Yao et al. 2013). The data quality was also assessed using the split-sample technique.

## Result and discussion

### Soil quality index

Soil quality index (SQI) was assessed using indicators (texture, organic matter, bulk density, porosity, pH, and slope). The general indication according to the analysis of the



indicators that made up the SQI is that, in terms of soil texture, most of the soil in the area is textually loamy and clay soil type, while the larger portion of it also has a percentage of pore spaces of less than 40%. The majority of the soil in the study area has more than 2.5% organic matter content, as well as more than 70% of the soil has a grain size between 1.35 and 1.6 g/cm<sup>3</sup>.

According to the result of the slope analysis, more than 97% of the area is located on a 0–35° slope. Table 3 shows the spatial distribution of the SQI of the area, which shows that about 16% of the area is not affected, about 17% falls within a low sensitive class, and about 25% falls in the moderately sensitive class. However, 29% and 12% of the area fall within sensitive and highly sensitive classes respectively. Figure 3a illustrates clearly the thematic map of the sensitivity classes of the final SQI of the study area described herein; the overall analysis shows that the area soil coverage is dominantly a medium-quality soil. This is an indication that the soil is generally moderately sensitive to desertification. The theme, however, shows remarkably the highly sensitive areas are more concentrated in the upper central part of the area.

### Climate quality index

The climate quality index (CQI) was evaluated with its constituent indicators (temperature, aridity, aspect, and potential evapotranspiration). The general indication according to the result of the indicators that made up the CQI is that the area is found to be less sensitive to desertification in terms of temperature with more than 96% of the area falling within the suitable range (i.e., 19–35 °C). The aridity index shows that the study area is averagely sensitive to desertification since more than 76% of the area has in-between 0.3 and 0.49 aridity index, while less than 24% has an aridity index less than 0.3. Concerning this aspect, it is clear that about 62% of the area lies within a highly sensitive class and 38% falls within a low sensitivity class. However, the PET result shows that a greater portion (74%) of the study area lies within a suitable range of PET. Table 4 shows the distribution of the CQI of the study area with about 13% of the area not affected, about 19% fall within a low sensitive class, and about 22% fall into the moderately sensitive class.

**Table 3** The sensitivity classes and area coverage for SQI map

Sensitivity class	Land area (ha)	Land area (%)
Not affected	3,030,430.8	16.3
Low sensitivity	3,253,530	17.5
Moderately sensitive	4,592,125.2	24.7
Sensitive	5,428,747.2	29.2
Highly sensitive	2,286,766.8	12.3
Total	18,591,600	100

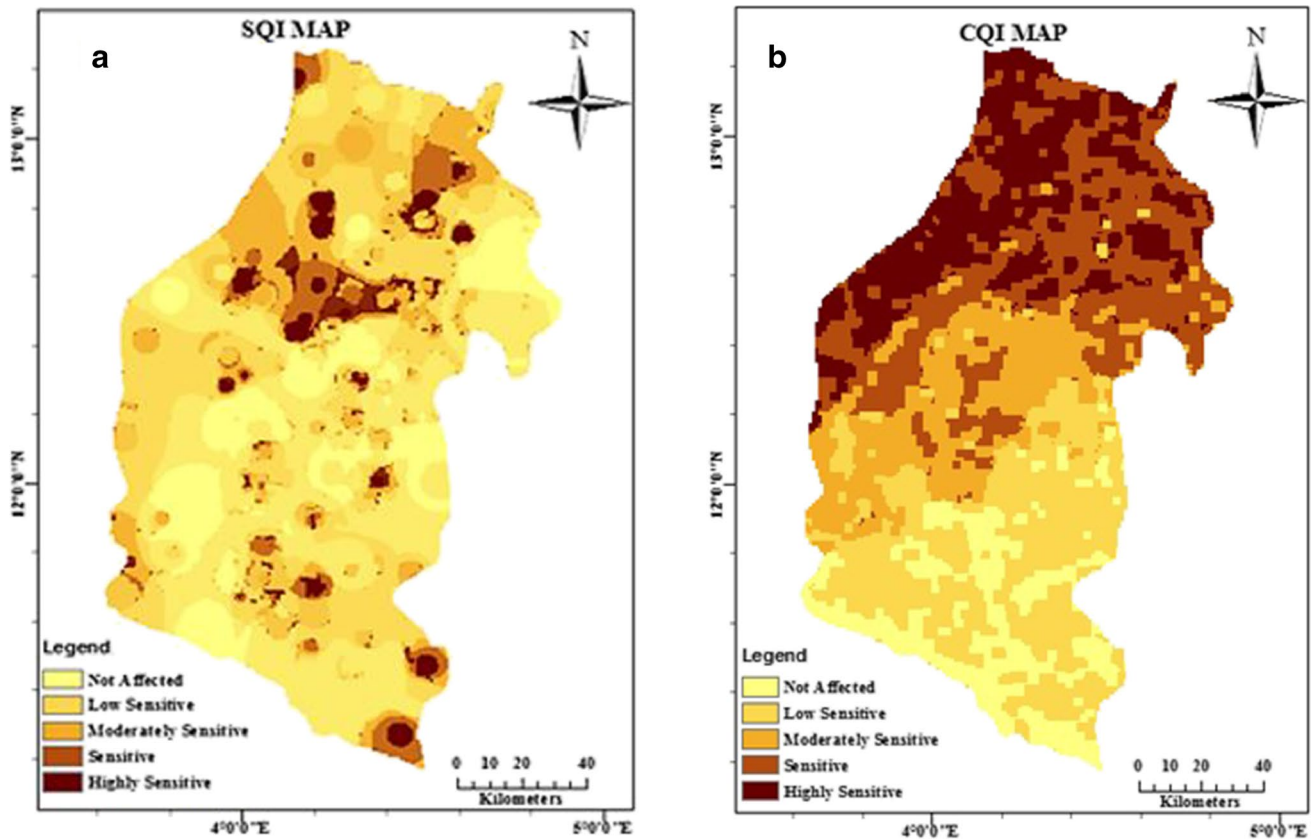
However, 21% and 25% of the area fall within sensitive and highly sensitive classes respectively. Figure 3b displays the thematic map of the sensitivity classes of the final CQI of the study area. The overall analysis shows that the climate of the area under study is mainly of a medium-quality type; this, however, indicates that it is moderately sensitive to desertification. The thematic layer, nevertheless, shows that the climatic quality of the area increases as one moves north-southward.

### Vegetation quality index

The vegetation quality index (VQI) was evaluated with its constituent indicators (vegetation cover and stand (tree) density). The index was derivative of the cumulative effect of these indicators (Eq. 4), which accorded with the standard DSI methodology. The general indication according to the analysis of the indicators that made up the VQI is that the area is found to be unsuitable (low quality) in terms of vegetation cover with more than 50% of the area falling within the sensitive area range (i.e., less than 10% vegetation cover). The result of tree density is another indication that the study area is very sensitive (low quality) since more than 50% of the area has in-between less than 5 trees/ha. The cumulative result of vegetation cover and standing tree density was tabulated in Table 5. The tabular distribution of VQI of the study area shows only 3% of the area is not affected, about 13% falls within a low sensitive class, and about 19% falls into the moderately sensitive class. However, 37% and 26% of the area fall within sensitive and highly sensitive classes respectively. Figure 4a shows the thematic map of the sensitivity classes of the final VQI of the area. The overall result shows that the vegetation of the area is a low-quality type characterized by scattered trees and very scanty shrubs which is an indication of highly desertification sensitive areas. The theme, however, shows noticeably the high desertification sensitivity of the area decreases south-westward.

### Human quality index

Human quality index (HQI) was measured by indicators such as population density, grazing density, farming intensity, and alternative energy source. The result of human quality indicators that made up the HQI is that the area is believed to be moderately suitable in terms of farming intensity because a larger portion (about 78%) of the area is considered to be of medium farming intensity. The common farming practices are those allowing low-mechanized farming, with an average use of agrochemicals, as well as a majority of the farming systems are rain-fed with a local variety of crops (Kosmas et al. 1999). Likewise, the rate of grazing in the area makes it less sensitive to desertification



**Fig. 3** The quality index maps for **a** soil and **b** climate

since the population of grazing animals is less in the area. The same is true also with the population density of the area; about 83% of the study area has a population density of fewer than 200 people/km<sup>2</sup>.

However, the result of the alternative energy source (other than fuelwood) manifests a contrary pattern; about 81% of the inhabitants in the study area use fuelwood as means of domestic energy supply, while less than 19% of the study area use alternative means of domestic energy. This is mainly since larger percentages of the population in the rural areas live under endemic poverty (FGN 2015), with not much access to the infrastructure.

Table 6 shows the distribution of HQI, 22% of the area is considered not affected, and about 16% falls within a low sensitivity class with only 10% falling in the moderately

sensitive class. However, 31% and 19% of the area fall within sensitive and highly sensitive categories respectively. Figure 4b shows the spatial distribution of the sensitivity classes of the final HQI of the study area. The result illustrates that the area may be considered averagely sensitive in terms of human indices which generally is an indication of low quality (sensitivity to) desertification. The theme, however, shows clearly the sensitive areas are mostly in the southwestern areas.

**Desertification sensitivity index**

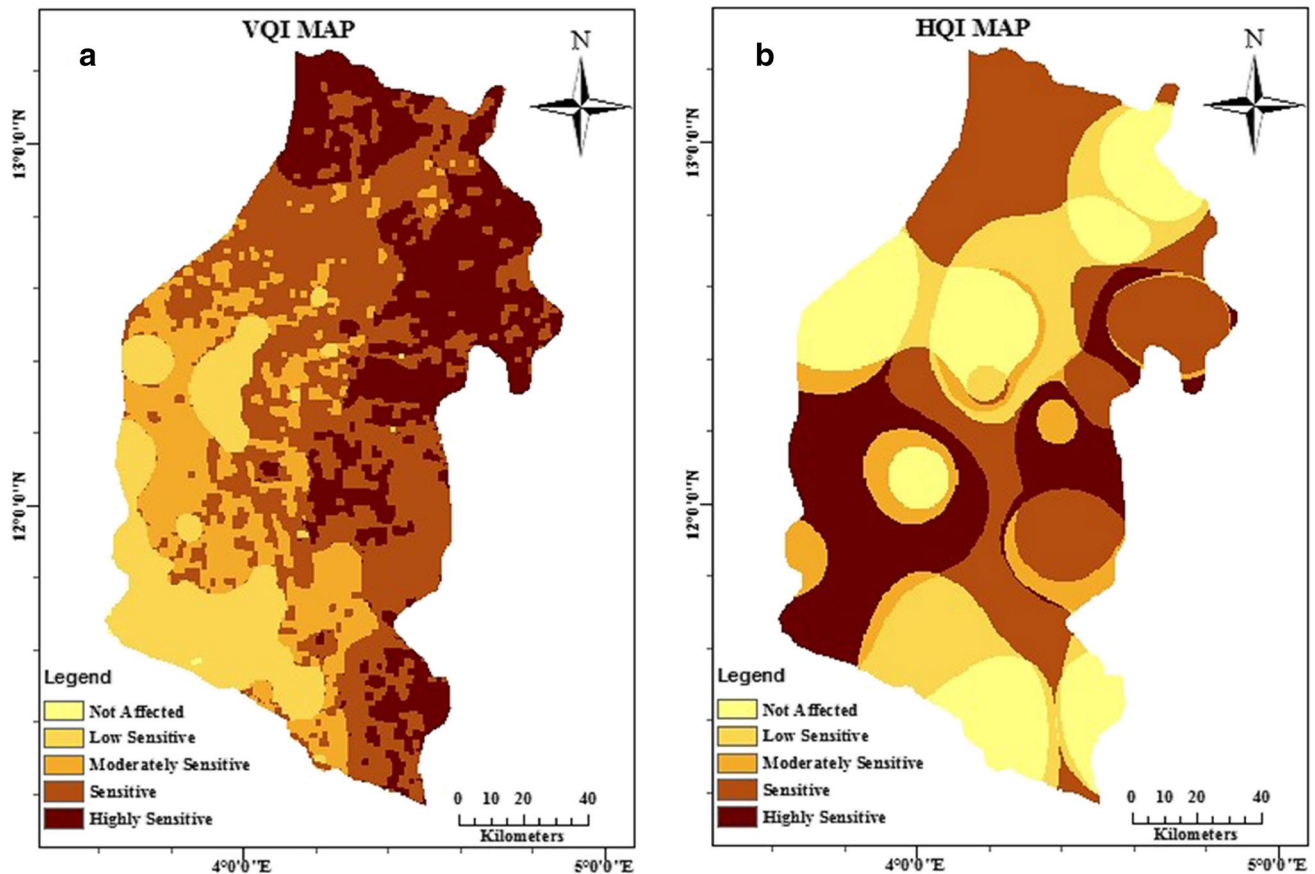
Desertification sensitivity in the area was evaluated based on the MEDALUS-ESAI framework with 16 indicators as described before in the different sections of quality indices (SQI, CQI,

**Table 4** The sensitivity classes and area coverage for CQI map

Sensitivity class	Land area (ha)	Land area (%)
Not affected	2,416,908	13.0
Low sensitivity	3,513,812.4	18.9
Moderately sensitive	4,108,743.6	22.1
Sensitive	3,829,869.6	20.6
Highly sensitive	4,722,266.4	25.4
Total	18,591,600	100

**Table 5** The sensitivity classes and area coverage for VQI map

Sensitivity class	Land area (ha)	Land area (%)
Not affected	576,339.6	3.1
Low sensitivity	2,379,724.8	12.8
Moderately sensitive	3,495,220.8	18.8
Sensitive	7,362,273.6	39.6
Highly sensitive	4,778,041.2	25.7
Total	18,591,600	100



**Fig. 4** The quality index maps for **a** vegetation and **b** human

VQI, and HQI) (Eq. 6). The result of the desertification sensitivity index (ESAI) in the study area was tabulated in Table 7. The spatial distribution illustrates that 36% of the area is considered not affected, and about 17% falls within a low sensitive class with only 30% falling in the moderately sensitive class. About 15% of the area falls into the sensitive category, while only less than 1% falls in the highly sensitive categories. The general indication according to results obtained from the analysis of different quality index that made up the DSI is that the area is understood to be moderately suitable and sensitive desertification.

Based on SQI, the result shows that the soil of the area is dominantly a medium-quality type, characterized by good

drainage (slope gradient) and moderate texture, organic matter content, and porosity, as well as bulk density. These indicators are put together to render the soil of the study area average quality for water holding capacity and less water erosion as well as an ameliorable environment for plant growth. Therefore, the soil is considered averagely sensitive to desertification. The climate of the area is considered to be low quality (sensitive) in the sense that the land surface temperature was found to be moderately sensitive, so are the aridity and potential evapotranspiration. However, in terms of aspect, the area is highly sensitive (low quality). The indicators of vegetation quality of the study area prove it to be of the low-quality type

**Table 6** The sensitivity classes and area coverage for HQI map

Sensitivity class	Land area (ha)	Land area (%)
Not affected	4,536,350.4	24.4
Low sensitivity	2,956,064.4	15.9
Moderately sensitive	1,821,976.8	9.8
Sensitive	5,800,579.2	31.2
Highly sensitive	3,476,629.2	18.7
Total	18,591,600	100

**Table 7** The classes and area coverage for DSI map

Sensitivity classes	Land area (ha)	Land area (%)
Not affected	6,750,069.4	36.3
Low sensitivity	3,191,224.3	17.2
Moderately sensitive	5,635,988.7	30.3
Sensitive	2,865,025.6	15.4
Highly sensitive	149,292.0	0.8
Total	18,591,600.0	100.0



with all its constituents via vegetation cover and standing tree density categorized as highly sensitive (low quality).

The HQI demonstrates that the area is rendered as average quality when considering its constituents. In its part, the farming activities in the area is the moderate quality type since the farming practices in the area are performed with low-mechanized systems, with average use of agrochemicals as well as most of the farming systems are rain-fed with a local variety of crops (Kosmas et al. 1999). The grazing density pattern of the area also makes the area less sensitive to desertification since the number of grazing animals is less when compared with the land mass of the area. Similarly, the population density of the area indicates that the area is less sensitive. However, the result of the analysis of other alternative energy sources (other than fuelwood) indicates a contrary pattern; about 86% of the inhabitants in the study area are using fuelwood as a means of energy; this is mainly because larger percentages of the population in the rural areas are living under endemic poverty (FGN 2015), with less access to infrastructure. Figure 5 shows the thematic map of the sensitivity classes of the DSI of the study area.

The general analysis shows that the study area can be considered averagely sensitive under the cumulative effect of the different quality indices (SQI, CQI, VQI, and HQI) which generally indicate an average quality to desertification. The

theme, however, shows that the sensitivity towards desertification decreases from north to south.

The identification of the relationship between desertification and effective predictive factors can help in quantifying the desertification process. The northern part of the study area is identified as more sensitive to desertification; this agreed with the finding of Ayuba (2016) and Idris Medugu et al. (2011); however, the southern part appears to be less sensitive. This study identifies that the north part of the study area is more vulnerable to desertification and therefore deserves special attention. The DSI provides a satisfactory methodology for identifying desertification-prone areas in Kebbi State, Nigeria, that needs to be given special consideration by the relevant organization.

### Conclusion

The assessment of desertification sensitivity in Kebbi State, Nigeria, was accomplished by the use of the MEDALUS-ESAI framework with 16 indicators grouped as soil, climate, vegetation and anthropogenic, or human quality indicators. The general indication according to sensitivity results obtained from the analysis of different quality index that made up the DSI is that the area is understood as moderately

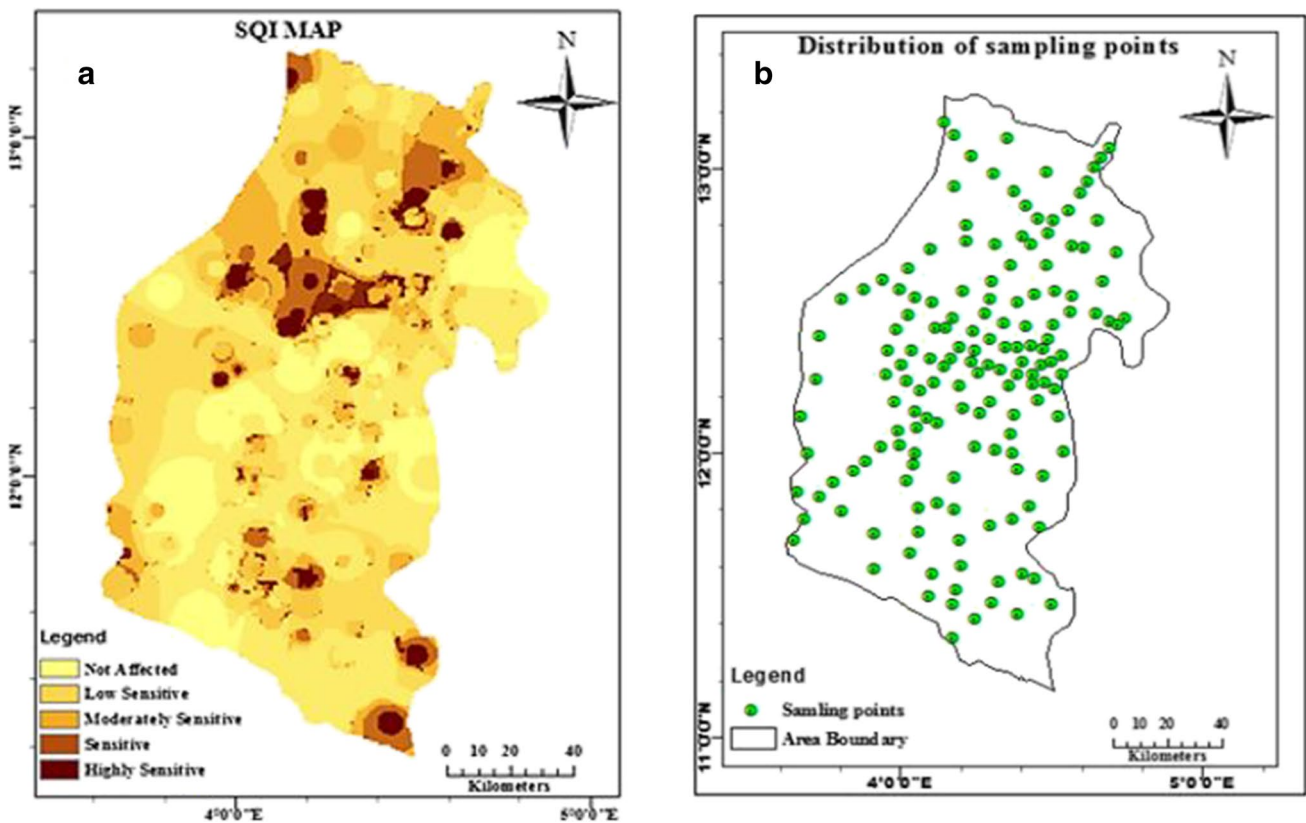


Fig. 5 a Desertification sensitivity index map. b Distribution of soil sample points

sensitive to desertification. DSI is essentially useful for determining different classes of sensitive areas to desertification. The resultant DSI map of the area will be beneficial as a decision-making tool especially in the assortment of vulnerable areas for combatting desertification phenomenon in the study area. The model provides spatially explicit results and it is, therefore, recommendable for its accuracy and flexibility in computing constituent indices and the desertification map of an area. There is little or no doubt that the existing threats of the land degradation process will continue in the area as population increases. Therefore, the drivers, as well as the underpinning pressure (especially fuelwood usage), of these threats have to be identified and essentially addressed holistically in order to sustainably manage the environment. This research is unique in the study area since it attempts to integrate multi-source data for a better understanding of phenomena under investigation.

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## Declarations

**Conflict of interest** The authors declare no competing interests.

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