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Spatial Analysis of Ecological Impacts of Global Change on Dry Lands and Their Implications for Desertification in Algeria

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Abstract

Desertification is a crucial environmental problem in the Algerian steppe. Land degradation is a reduction and loss of land productivity due to natural processes, climate change and human activities. The sandy lands in the zone of Naâma constitute a region based on important pastures in west of Algeria. It is therefore increasingly necessary to monitor the situation to better understand the desertification processes and to fight against this phenomenon. Climate, soils, vegetation and land use play an important role in desertification. Therefore, the land surface temperature and a monitoring indicator that highlight the hottest areas as well as their delineation are important to characterize the phenomenon of desertification. In this study, we analyzed desertification since 2008 using remote sensing technology. In order to recognize desertification through land-use changes, our research was aimed at extracting classification categories representing the state of the land, which we subdivided into normal classification categories of vegetation groups. To this end, we have classified land use by combining several spectral indices in particular, which can be calculated from satellite data on each Land sat satellite spectral band, to construct multi-band input data for a supervised classification approach based on a support vector (SVM). By applying this method to Land sat archival imagery in 2008, 2011, 2014 and 2017, we produced land use maps for the four periods. Using GIS, we integrated climatic parameters with rainfall and land surface temperature combined with land use land cover and slope, in this step; we adopted proposals from expert judgments to determine weights in order to assign weights to each parameter. This allowed us to clarify the situation with regard to desertification, to classify the study area in areas vulnerable to desertification and to determine the spatiotemporal changes during the 10 years.

Keywords: Desertification, Land Degradation, Remote Sensing, GIS Analysis, Climate Change, Landsat Imagery, Spatial Analysis, Algerian Steppe, Drought Monitoring, Land Surface Temperature (LST), Precipitation Variability, Soil Erosion.

Introduction

Desertification is a critical environmental problem that limits social, economic and political development in arid and semi-arid areas [1, 2]. Desertification is precisely land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activity. In recent years, many environmental and population issues have emerged, such as land scarcity, environmental degradation, and reduced biological and economic productivity. Water scarcity, poverty and migration have increased due to the rapid spread of desertification. These problems have threatened human survival and sustainable economic development [3-5]. It is known that the wilaya of el Naâma is a fragile ecological zone, intended in particular for the breeding.

This work is a contribution to the analysis of steppe degradation followed by a spatiotemporal analysis in area of the Algerian steppe. It is an area where pastoral activity has always been the basis of social organization and the main economic resource. Today, and faced to the social disorganization, the phenomena of desertification and erosion, take an intense degradation compromising the future of the pastoral activity. It is in this way that a methodological approach is developed to characterize the current ecological situation, using powerful tools such as remote sensing and GIS, and the integration of parameters (Vegetation, Climate and topography) for cartography of sensitivity to desertification. Data from LANDSAT imagery are used, combined with neo-channels. The work is based on the method of follow-up and understanding. The objective is to highlight the importance of the phenomenon of desertification and to analyze the main discriminating factors in the evolution of this ecological problem and its socio-economic consequences on the equilibrium of the system of traditional pastoral organization. Finally desertification risk maps will be developed containing a characterization of the different area.

Purpose of this Study

The main objectives of this research are the monitoring and analysis of an ecosystem whose deterioration of ecological systems as a result of progress in desertification. The land degradation process was presented by an analysis of LULC change sub classes, using time series of Land sat data at different scales as spatial and temporal scales over the last 10 years (2008, 2011, 2014 and 2017). This study is based in the steppe region of the wilaya of Naâma in the south-west of Algeria, is known for its vast rangelands. Quantitative variations of the soil surface were calculated to analyze the state of desertification. At the same time, this study examined the links between the driving forces of desertification such as physical factors, land degradation, erosion and climatic variations such as land surface temperature and precipitation.

Presentation of The Study Area

The study area belongs to a region with pastoral vocation covering three municipalities, MECHERIA, NAAMA and AIN SEFRA, with the geographical coordinates (33 ° 13'47.83 "N, 0 ° 08'28.20" E), consisting of golf courses of Alfa, forests and shrub and unproductive land. It is located between the Tellian and Saharan Atlas in its western part. The territory of the wilaya of Naâma is characterized by three large geographical areas namely; Northern Steppe Flat Area with a Mountainous Area and the Chott Area of the Wilaya Consists of the Gharbi Chotts in the West and Chergui in the East.

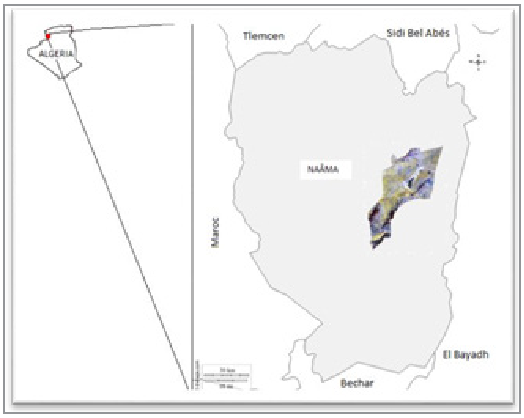

Figure 1: Location Map of the Study Area Displayed the Landsat-8 Data Based False Colour Composite

Datasets

The study was carried out on images Land sat acquired in 2008, 2011, 2014 and 2017 to evaluate vulnerability of desertification. The DEM Aster 2002 was used to elaborate slope map to define the influence of these parameters in desertification. Characteristic of this bands are in table number 1.

Table 1: Description of Satellite Data Used in the Study

Datasets	Year	Path/Row	Date acquired	Spatial resolution
Land sat 5 TM	2008	197/37	25-09-2008	30m
Land sat 5 TM	2011	197/37	01-08-2011	30m
Land sat 8	2014	197/37	13-09-2014	30m
Land sat 8	2017	197/37	18- 09-2017	30m
SRTM	-	-	-	30m

Method

In order to recognize desertification through land-use changes, and to evaluate risk of desertification by combination of different parameters , our research was aimed at extracting classification categories representing the state of the land, subdivided into normal classification categories of vegetation groups. After that we have classified land use by combining several spectral indices to construct multiband input data for a supervised classification approach based on a support vector (SVM). We used four dates of LANDSAT archival imagery in 2008, 2011, 2014 and 2017. Vegetation is the most dynamic element of the landscape from a remote sensing perspective. To avoid confusion of seasonal changes in vegetation cover with long term decreases or increases in cover, it is preferable to use images that are recorded at times when development of different vegetation is identical or at a very similar stage. To calculate the risk of desertification it is necessary to model each element of risk, in our case it is necessary to determine the factors which will be considered in risk of desertification, in this research we choose the most important factors, land use land cover, rainfall, land surface temperature and slope. After we produced land use maps for the four periods, in the same way we evaluate land surface temperature from canal 10 of LANDSAT 8 and canal 6 from LANDSAT 5. SRTM 30 m, allowed us to calculate the slopes at all points of the study area, the slope is derived and four classes of slope were retained. To realize the precipitation map rainfall, data of several meteorological stations covering the study area were taken.

Using GIS, we integrated climatic parameters with rainfall and land surface temperature combined with land use land cover and slope, in this step; we adopted proposals from expert judgments to determine weights in order to assign weights to each parameter (table2). According to the methodology of we compared the relative importance of all the elements belonging to the same level of the hierarchy taken in pairs according to the pair's comparison scale [6]. The desertification index was calculated according to the formula (equation 1). This allowed us to clarify the situation with regard to desertification, to classify the study area in areas vulnerable to desertification and to determine the spatiotemporal changes during the 10 years.

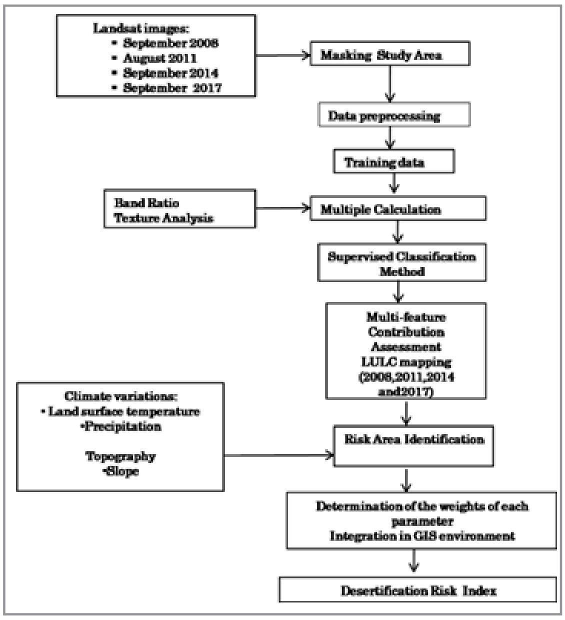

Figure 2: Methodology

Table 2: Index Factor

Parameters	Index value	Index factor
LULC Class	1	0,593
Precipitation	4	0,124
Land Surface Temperature	5	0,218
Slope	7	0,063

ID = [LULC*0.59+PP*0.12+LST*0.21+Sp*0.06] / 0.98 (1)

- **ID:** index of desertification
- **LULC:** land use land cover
- **PP:** precipitation
- **LST:** land surface temperature
- **Sp:** slope

Analysis of Desertification Based on LULC Change

Land Use/Cover Classification

A wide range of methods for classification of remote sensing image continuously proposed, and SVM are particularly popular in the remote sensing field compare to the other classification methods such as maximum likelihood method, decision tree method, and neural network method. The principle of the SVM was originally introduced and improved by Vapnik and Chervonenkis. SVM is a non-parametric classification method which can also work with the small amount of training data and produce higher classification accuracy [7] In this study, desertification is natural vegetation coverage degradation between 10 categories of general land use land cover in semi-arid desertification area primarily destroyed by unsustainable, climate, human such as irreversible land resource exploitation for variety of utility combined with the effect of significant inter annual change of climate variations including temperature and precipitation. We show in table number 3 descriptions of different classes in this study.

Table 3: Land Use Lands Cover Classification System and Description

Level classes	Descriptions
Shrub	Lands covered by trees less than 2 m high.
Forest	Natural or planted forests.
Land of Psammophytes	Plants on sand and gravels.
Land of Alfa	Land with Stipa tenacissema.
Sandy land	Sandy land covered with less than 5% vegetation cover.
Dense Sand	Dense Sand
Cultivated lands	Cultivated lands for crops. Including mature cultivated land and newly cultivated land
Bare land	Bare exposed soil with less than 5% vegetation cover.
Salina land	Lands with Salina accumulation.
Urban built-up	Lands used for urban.

Feature Calculation and Combination

The study area is mixed of the diverse types of LULC, Considering the spectral complexity such as same object with different spectral, different objects with same spectrum of ground object, we calculated multi-feature such as NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built-Up Index), NDSI (Normalized Difference Salinity Index), to validate LULC classification in this research.

NDBI (Normalized Difference Built-Up Index)

NDBI, Zha et al. (2003) calculated with following equation:

$$NDBI = \frac{MIR-NIR}{MIR+NIR}$$

NDBI derived image show that build-up areas have the higher reflectance in MIR wavelength range than in NIR wavelength range.

NDSI (Normalized Difference Salinity Index)

The concept of Normalized difference soil salinity index (NDSI) is designed to suppressing the vegetation and highlights the saline zones.

$$NDSI = \frac{Red-NIR}{Red+NIR} \times 100$$

NDVI (Normalized Difference Vegetation Index)

The NDVI is one of the first successful vegetation indices based on band ratio.

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

Top Soil Grain Size Index

The combination of the multiple features (spectral indices) calculated from the satellite data were used to improve the accuracy of the LULC classification.

The increase in the spectral reflectance of soil at the soil surface involves soil degradation or desertification. In arid and semi-arid areas, wind erosion strongly affects the physical properties of the soil surface. Xiao et al. (2006) presented very well the soil grain size index, which shows the physical properties (grain size composition) of the GSI soil [8].

In principle, in the GSI formula, the difference value between the red band and the blue band is designed to distinguish the area covered with vegetation or water and the bare ground. The difference value between the red band and the blue band will be close to 0 in the vegetation zone, and the difference value will be negative for the body of water; while the difference value is great for bare soil.

$$GSI = \frac{P\ red - P\ blue}{P\ red + P\ blue + P\ green}$$

Climate Variations

To characterize desertification we used remote sensing techniques for detecting changes in land use and land cover category, and also identify the physical properties changes of the land surface by utilizing associated indices.

In the arid and semi-arid regions, temperature and precipitation are important climatic factors of the land degradation and desertification, in this research therefore land surface temperature and mean of annual precipitation was used.

Land Surface Temperature

Temperature is one of the fundamental factors to realize bio-physicochemical phenomena in the environment. Surface temperature is a basic criterion for the studying of thermal behaviour of features in the environment. Hence, thermal infrared remote sensing, in having utilities such as the estimation of land surface temperature (LST), will provide more information about the thermal properties of nature. Two approaches have been developed to recover LST from multispectral TIR imagery [9]. The first approach utilizes a radiative transfer equation to correct the at-sensor radiance to surface radiance, followed by an emissivity model to separate the surface radiance into temperature and emissivity. The second approach applies the split-window technique for sea surfaces to land surfaces, assuming that the emissivity in the channels used for the split window is similar [10]. We calculate land surface Temperature by:

First : Convert digital number (DN) to spectral radiance

$L\lambda\ (\mathrm{TOA}) = ML * Qcal + AL$ (2)

$L\lambda$ is indicate TOA spectral radiance (Watts/(m2* srad * μm))

ML is band-specific multiplicative rescaling factor from the metadata (radiance_mult_band_10/11)

AL is band-specific additive rescaling factor from the metadata (radiance_add_band_10/11)
Qcal is quantized and calibrated standard product pixel values (DN).

Second: Conversion to at-satellite Brightness temperature
BT = (K2 / (ln (K1 / L) + 1)) − 273.15 (3)
T is at-satellite brightness temperature (K)
$L\lambda$ is the TOA spectral radiance (Watts/ (m2* srad * µm))
*K*1 is Band-specific thermal conversion constant from the metadata
*K*2 is Band-specific thermal conversion constant from the metadata

Third: Conversion from at-satellite Temperature to Land Surface Temperature

$LST = TB/ 1+(\lambda+TB)/\rho)\ln\varepsilon$ (4)
LST = (TB / (1 + (0.00115 * TB /1.4388) *Ln (ε)))
λ is wavelength of emitted radiance (for which the peak response and the average of the limiting wavelengths (11.5)

Precipitation
Naâma has a warm Mediterranean climate with dry summer according to the Köppen-Geiger classification. The average annual temperature in Naama is 18 ° C, and the precipitation averages 214 mm. The least amount of rainfall occurs in July. The average in this month is 6.3 mm. In October, the precipitation reaches its peak, with an average of 40.6 mm. In July, the average temperature is 30.6 ° C. July is therefore the hottest month of the year. December is the coldest month of the year the average temperature is 7.8 ° C . 09 meteorologic station was chosen to cover all the study area , description is in table 4.

Table 4: Annual Precipitation Value

City	Naâma	Mecheria	Ain Sefra	El Bayadh	Sidi bel Abbés	Bechar	Saida	Mascara	Tiaret
Years	Rainfall : mm								
2008	384	499	436	410	405	135	451	403	369
2011	309	243	230	493	399	141	405	412	347
2014	215	198	231	302	415	246	356	422	542
2017	143	72	87	150	243	37	327	311	295

Influence of Topographic Parameters (Slope)
To analyse the influence of topographic parameters in desertification, we used the Aster SRTM (30 m) to generate slope, this map was reclassified and affected risk index (see table 5). This information was combined with bands ration results to evaluate the risk of desertification.

Table 5: Slope Risk Index

Risk index	Slope value
4	3 - 6 %
3	6- 12 %
2	12-25 %
1	> 25%

Influence of Topographic Parameters (Slope)
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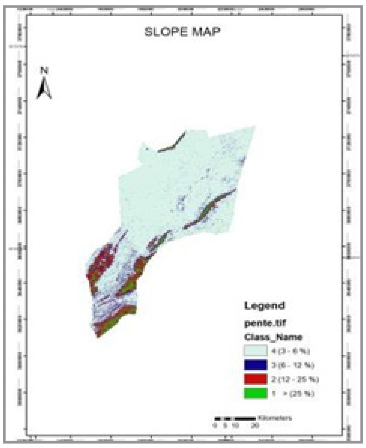

Figure 3: Map of Slope

Results and Discussions

LULC Classification Results

The LULC classification maps of year 2008, 2011, 2014 and 2017 produced in the research are displayed in figures 4, 5, 6 and 7 respectively. Each of these maps includes 10 secondary classes in the study area.

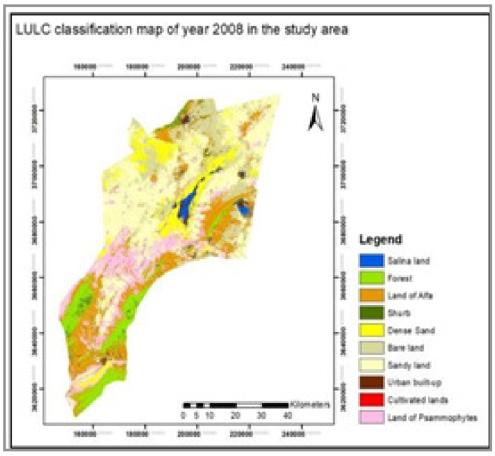

Figure 4: LULC Classification Map of Year 2008

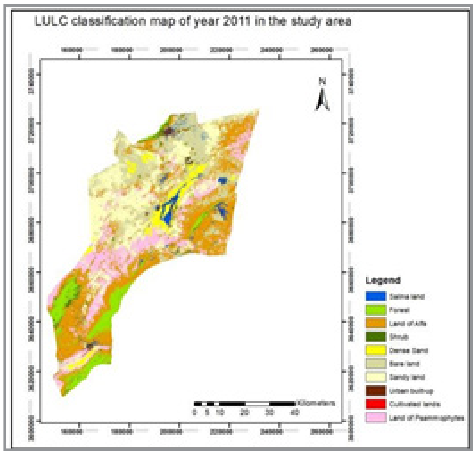

Figure 5: LULC Classification Map of Year 2011

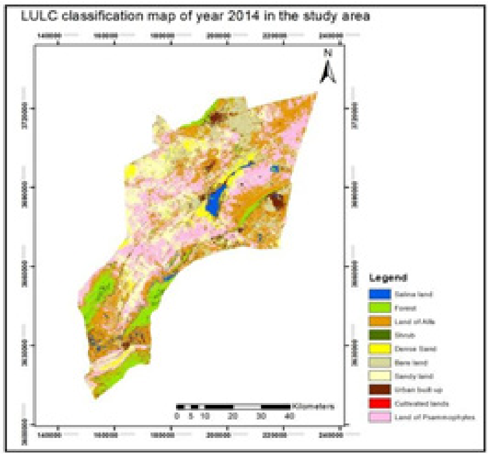

Figure 6: LULC Classification Map of Year 2014

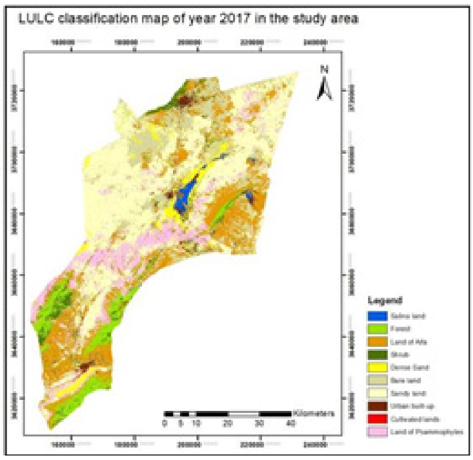

Figure 7: LULC Classification Map of Year 2017

According to the LULC classification maps of each year (2000, 2009, 2014 and 2017) and statistical figure present clearly Shrub, Alfa land, Psammophytes, Salina land, Sandy land, Bare land and urban built-up. This study area is characterized by a typical steppe environment.

In this zone of study we find a weak forest formation which is generally found in the high plains and the mountains, wherever other vast pastureland based of Alfa and low-recovery of Psammophytes. In the medium of the study area there are the saline zones surrounding by halophyte vegetations. In the south near the municipality of Ain Sefra located sand dunes and some cultivated area. Description of LULC classes in table 6.

Table 6: The Areal Coverage of 10 LULC Classes of Years 2014 and 2017 in the Study Area

LULC types	Area (Square kilometers)			
	2008	2011	2014	2017
Shrub	36,03	50,54	48,97	22,53
Forest	261,61	444,69	279,25	233,96
Land of Psammophytes	59,55	798,62	1263,78	1082,9

Land of Alfa	1549,37	1483,47	1371,42	1245,98
Sandy land	1660,92	856,2	705,03	1142,37
Dense Sand	94,9	111,69	126,61	126,4
Cultivated lands	1,26	6,84	0,975	1,87
Bare land	383,63	302,86	192,77	151,51
Salina land	28,13	19,395	83,57	63,68
Urban built-up	67,67	68,77	70,7	71,87

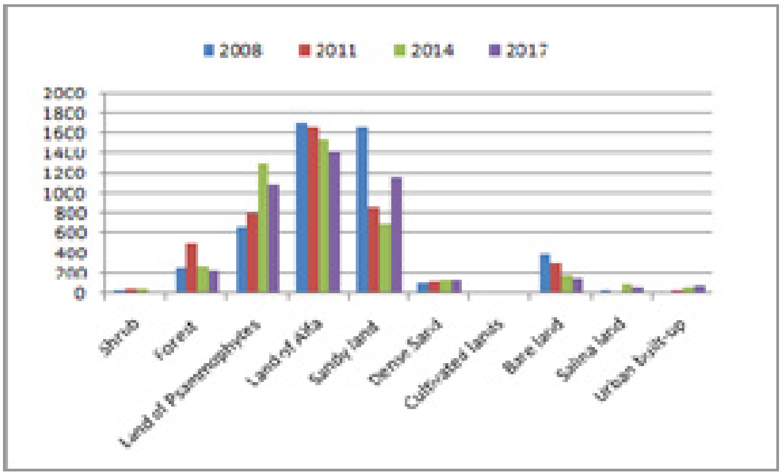

Figure 8: Histogram of Areal Coverage 2008, 2011, 2008, 2011, 2014 and 2017 in the Study Area

Validation of LULC Map

The LULC classification was carried out for each year (2008, 2011, 2014 and 2017), And to validate the classification we used and analyzed ratio bands (NDBI, NDSI, GSI and NDVI), respectvely in figure (,9,10, 11,and 12) for 2008. notably for vegetation with chlorophyll such as forests, Shrub and cultivated areas, at this moment in of the year grassland are in low activity, other distinguished between agglomeration and salty soils. However the experimental result of GSI showed that index is negatively related to vegetation coverage (figure11), is designed to distinguish the area covered with vegetation or water and bare soil. With this result GSI is possible to monitor land desertification in arid and semi-arid area using remote sensing technique.

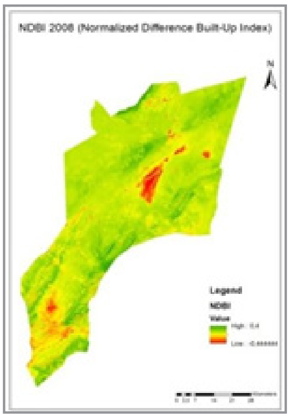

Figure 9: NDBI

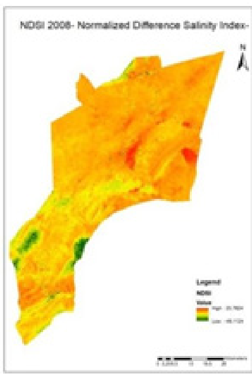

Figure 10: NDSI

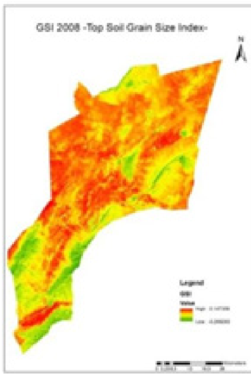

Figure 11: GSI

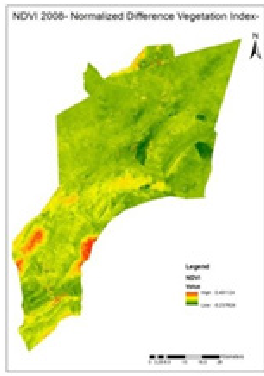

Figure 12: NDVI

Land Surface Temperature

In this study we calculate the land surface temperature of study area using the Landsat image for each year 2008, 2011, 2014 and 2017. The different parameter used form metadata of Landsat 5 and Landsat 8. The land surface temperature images shown in from figure 13 to figure 16. After we reclassified the land surface temperature map in four classes

- Low class risk
- Moderate class risk
- Hight class risk
- Very hight class risk

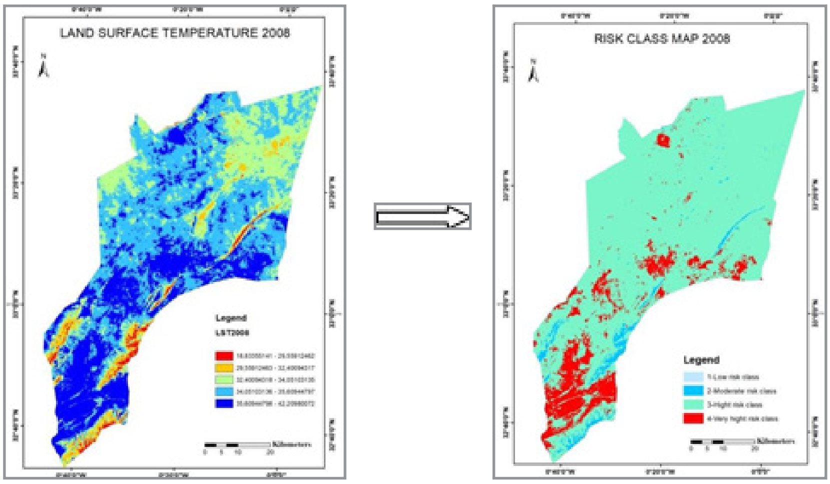

Figure 13: Land Surface Temperature of the Year 2008 Reclassified in Index

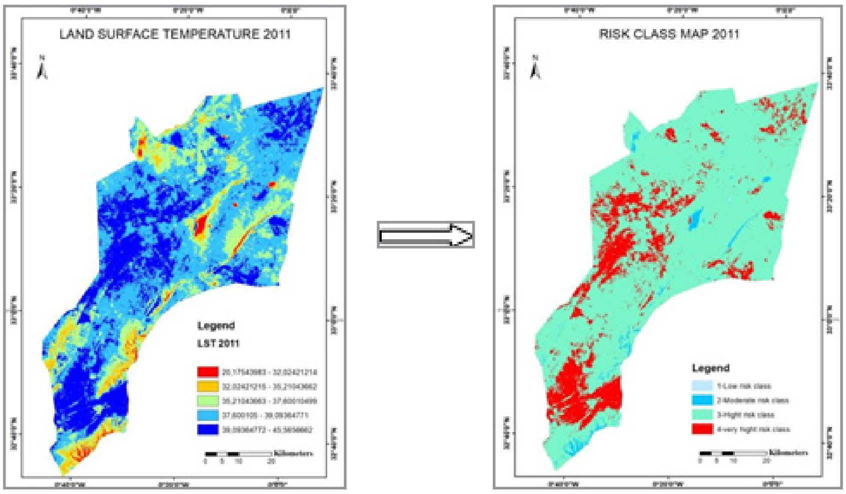

Figure 14: Land Surface Temperature of the Year 2011 Reclassified in Index

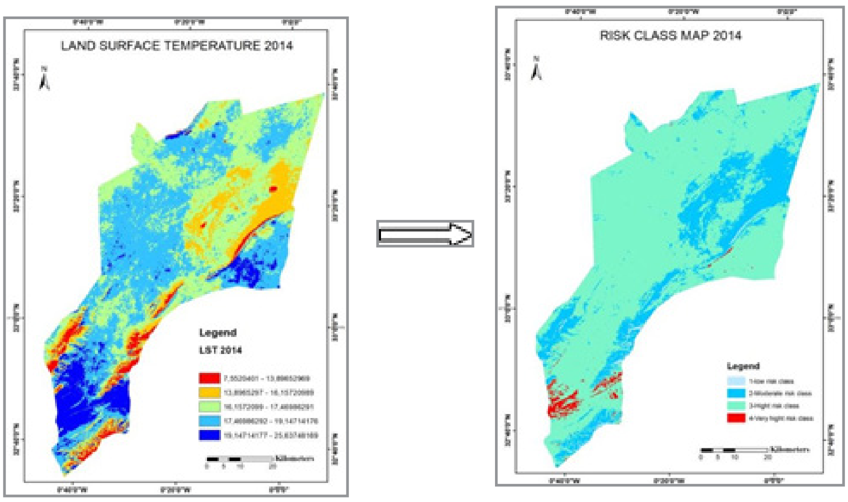

Figure 15: Land Surface Temperature of the Year 2014 Reclassified in Index

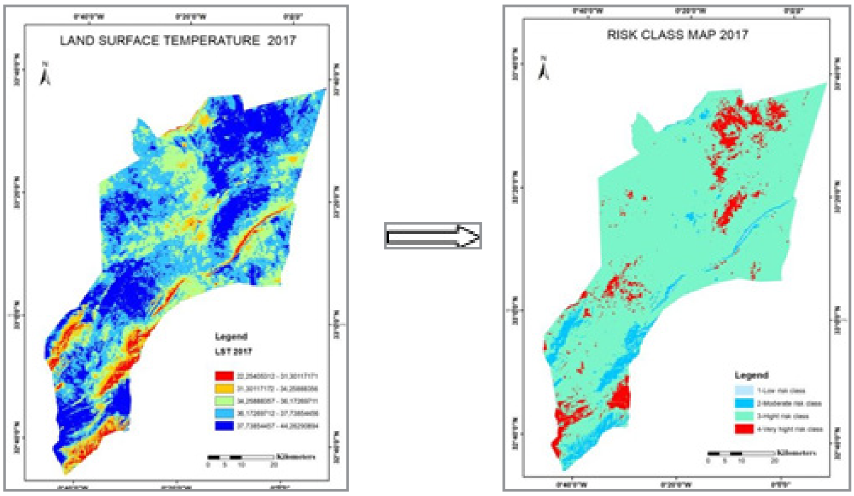

Figure 16: Land Surface Temperature of the Year 2017 Reclassified in Index

The images of the land surface temperature of the years 2008, 2011,2014 and 2017 show that ground temperature in exposed sandy soils, dry farmland and in areas with plant cover is generaly high. In addition, the linear soil surface temperature is positively correlated with the vegetal cover. The land surface temperature is high generaly at the surface soil whene becomes dry. All these factors cause the size of the soil grains and consequently a drying up of the steppic vegetation which causes the degradation of the grounds.

Climate Index

To realize map of precipitation in the study area we have proceded to generate all the meteorologic station covering the region with annual precipitation for the periode of 2008, 2011, 2014 and 2017. We dsitingue four slice and each slice was reclassifed in in index, to generate and to share the study area in rainfall zone from weak to strong, we distingue:

1. From 0 to 150 mm (very hight risk)
2. From 150 to 300 mm (hight risk)
3. From 300 to 400 mm (moderate risk)
4. From 400 mm and more (low risk)

The Results of this Reclassification is Schowed in Figure

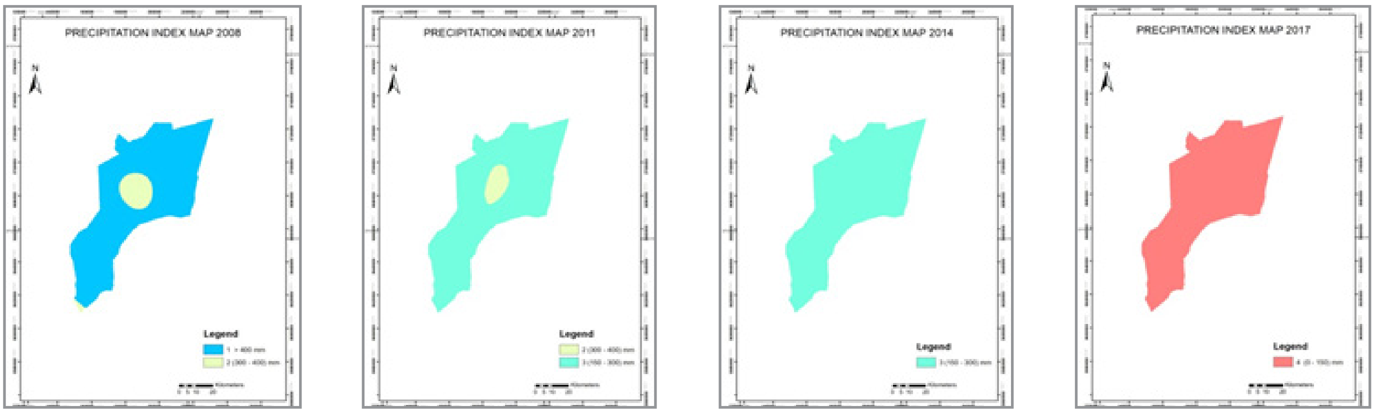

Figure 17: Climate Index Reclassified for The Year 2008, 2011, 2014 and 2017

Desertification Vulnerability Index

Indicators are useful to simplify and determine the status and tendency (prediction) of complex processes such as desertification. Moreover, they are applied as synthetic information layer in GIS to determine the spatial distribution of the affected lands, which are impacted by human activity (causes) or environmental conditions (effects). Indicators for desertification are the various causal factor involved in soil and land degradation including erosion, sedimentation, land use changes, the abuse of pastureland, the destruction of renewable resources, and exploitation lands [11].

There are a many approch in remote sensing to explore and to identify the land degradation and desertification . Therefore, it will be helpful to define and clarify the meaning and property of the indices. In this research we introduce and define indexes of desertification related to remote sensing data and ancillary data. Regarding the objective of research, LULC Vegetation Index, Land Surface Temperature (LST), rainfall, and slope wa used to define the desertification vulnerabily index.

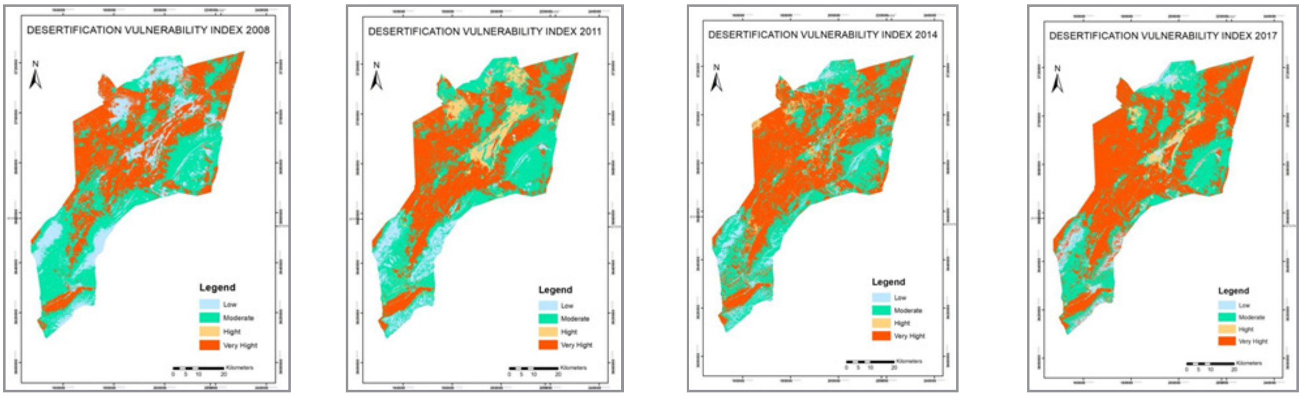

Figure18: (a,b,c and d) Desertification Vulnerability Index for the Year 2008, 2011, 2014 and 2017

After determining the four desertification factors that are land use, which is a very important factor in land degradation, the land surface temperature also plays an important role in determining the areas most exposed to ground temperature, rainfall because this climatic factors determines, according to the annual rainfall in each region, the regeneration of the steppe species and the density of the vegetation cover, in addition to this, slope which is a non-negligible factor in the determination of desertification in the steppic environment. These factors are studied each according to their influence and ranked in degree of risk according to a well-defined matrix.

The land use that is the most important factor in this study, 10 classes were identified and reclassified according to their resistance to the phenomenon of desertification and the density on the ground. After calculating the land surface temperature using the LANDSAT8 channel10 and the LANDSAT5 channel6, the land surface temperature maps indicating year-variant values are shown in figure 13, 14, 15 and 16 after there are reclassified in degree of risk.

Rainfall maps indicate the areas with the highest rainfall and least rainfall in this semi-arid climate of the study area. This map are reclassified them according to the amount of annual rainfall for each year ranging from 0 mm to over 400 mm per year, four climatic zones have been identified (0- 150 mm, 150-300mm, 300-400mm and more than 400mm) which are classified respectively (very high risk, high risk, medium risk and low risk).

The slope also influences desertification because low slope areas are more exposed to the phenomenon. And according to the (Saaty 1980) approach, we have identified weights for each parameter taking into account the importance of each factor as well (0.59 for land cover, 0.21 for surface temperature, 0.12 for rainfall, and 0.06 for the slope.

And in a GIS environment we have established the Desertification Risk Maps for the years 2008, 2011, 2014 and 2017, the result is in Figure 18.

Table 7: Result area of Desertification Risk Index

	Area of Desertification Risk (ha)				Proportion (%)			
RISK INDEX	**2008**	**2011**	**2014**	**2017**	**2008**	**2011**	**2014**	**2017**
Low Risk	72761,4	32426,82	29328,08	72761,4	17,5	7,8	7	17,5
Moderate Risk	166201	178168,5	153654,2	166201	40	43	37	40,11
Hight Risk	472,68	33174,18	18913,5	472,59	0,2	8	4,5	0,11
Very Hight Risk	174872,7	170538,28	212412	174872,79	42,3	41,2	51,5	42,28
Total	414307,78	414307,78	414307,78	414307,78	100	100	100	100

The monitoring of the desertification dynamics and its modeling, based on remote sensing data, make it possible to propose significant indicators of the risks of desertification, such as land-use change, for the purpose of identifying desertified areas. To be interpreted, the evolution, obtained on desertified surfaces by remote sensing, the results show that at present, 40% of the territory of Naâma has lost all of its vegetation. 3.4% of the continuous territory to become desertified. In total, two-thirds of the communes (Naama, Mecheria and Ain safra) are in risk of desertification. In this research the risk of desertification in the study area, between 2008 and 2017, classified the severity of the risk of desertification into four levels: low, moderate, high and very high. The study also assessed the evolution of the risk of desertification during the period, as shown in figure19.

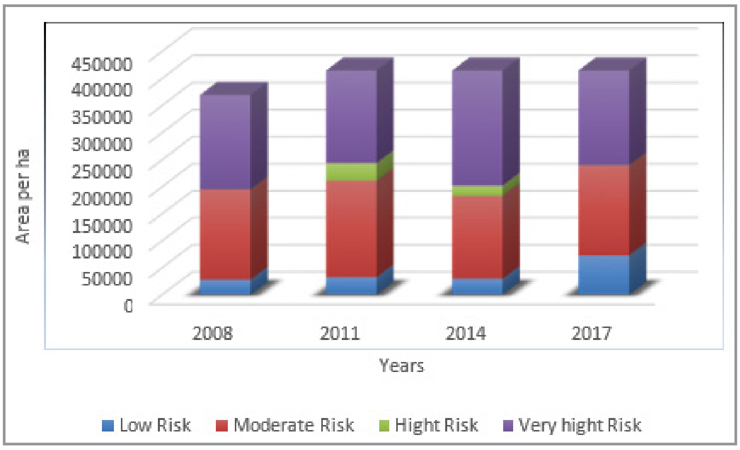

Figure 19: The Change of Zones at Risk of Desertification in the Study Area Between 2008 and 2017.

The combination of LULC index, land surface temperature index, the precipitation index and slope index derived from satellite image indicates that land degradation in the study area are different from year to year. Figure 17 define the results of the combination of those indices for each year. The proportion of low risk class in year 2008 is 17,5 % decrease in 2011 and 2014 and increase 2017, that mean in this year was an important period of rainfall and a dense vegeation cover. The moderate risk class is in proportion in the four years and show non-degraded areas is between (37- 40 %) and we note a, this class in generaly pastureland of Alfa and dense vegetation. The degraded area, hight risk class and verry hight risk class is a sand- covered area and salina land and area of overpasture, that increase from year to year and represente more than 40 % of the global of the sudy area. We notice that degradation intensified in 2014, with almost the entire area showing very hight risk class.

The 2014 year showed that most areas (51.5%) of naama were at high risk of desertification and that most areas (42%) remained at the same high risk level in 2014. The results of the analysis Spatial risk of desertification showed that high-risk areas increased by 1.3% per year. High risk areas decreased at a rate of 0.88% per year.

Steppe rangelands are the most affected by desertification, particularly because of excessive grazing and poor farming practices. On the other hand, the region of Naama, given the practice of pastoralism, also dedicates large areas of its territory to alfa. Many of these spaces are not adequately managed, which facilitates soil erosion, especially in sandstorms. The results of the spatial analysis indicate that changes in land use have influenced the risks of desertification; Figure 1 summarizes changes in the risks of desertification. The change in land use to reforestation areas and agricultural areas also reduced the high level of risk. Conversely, the risk of desertification has risen from a high level of risk to a very high level when rangelands have been converted to bare lands and the onset of the wind erosion effect.

Conclusion

In this study, we attempted to understand desertification by analyzing different factors such as LULC, land surface temperature, rainfall and slope, between 2008, 2011, 2014 and 2017 in Naama area.

The study and the identification of the desertification are is possible by this method, because it integrates the main factors of the desertification, vegetation, climate and relief, the results obtained show that more than 40% of the studied surface is classified during the four years 2008, 2011, and 2017 in the high risk zone to desertification, and in 2004 year showed that most areas (51.5%) of naama were at high risk of desertification. This class is represented by sandy sails, sand and Psammophytes groups.

The moderate risk class also has a high percentage is 40% in 2008, 43% in 2011, 37% in 2014 and 40.11% in 2017, a slight decrease in 2014 is probably due to heavy precipitation.

By analyzing the results of the desertification risk index, it is found that more than half of the studied area is threatened by desertification, which is consistent with the land use maps showing that the area represented in general by the sandy sails the dunes and the pastureland of Alfa.

Thus the methodology identifies the risk areas with their severity and facilitates appropriate decision making for combating desertification and preventive methods. The future scope of the study is to predict the risk severity in future and to validate this approach efficiency with future status.

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