

Modis Derived Vegetation and Aridity Indices Account for Spatial Variation in Desertification Risk Index in Dry Environment

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ABSTRACT

It was estimated annually that several thousands of hectares (ha) of land has been lost to desertification and the negative impacts are manifested on the environment and general livelihood of people; reduced capacity to provide for the basic needs such as food and water. Although this is true of many countries in Sub Sahara Africa, yet the spatial pattern of the level of desertification and the areas at risk has not been sufficiently quantified and mapped. This study is aimed at determining and mapping the spatial extent of desertification risk index in the 9 frontline states of Northern Nigeria and to identify areas and population that are at risk given the current condition to enhance mitigation and adaptation strategy plan. We used both aridity and vegetation indices in combination with elevation and urban/settlement population data to determine and mapped the risk of desertification in the nine frontline states. To obtain aridity index we used De Martonne aridity index (Iar-DM) equation; this was calculated from the raster layers of mean annual temperature (MAT) and total annual precipitation (TAP) using map algebra. To monitor vegetation conditions we used eMODIS NDVI 10-day maximum-value composite MVC NDVI images at 250m spatial resolution. We created desertification risk index map from spatial overlay of NDVI/ vegetation cover, elevation, population and aridity index. The study shows that aridity in the study area increases northward in curvilinear pattern as 75 % (430,650 km²) of the region falls into three aridity categories: arid, semi-arid and dry sub humid while the remaining 25% (33,000 km²) found in southern Kebbi, Zamfara, Katsina and Bauchi falls under sub humid. Aridity index as proximate of the desertification was however found to be inadequate as the combination of vegetation index produced desertification risk index (DRI) map which has helped to identify "hot spot" these are places where risks to desertification are higher than their surrounding areas. Suggestions such as sound land management, energy substitution strategy are made to combat the menace of desertification with special attention placed on these highly vulnerable "hot spot" areas.

Keywords: Aridity index, vegetation index, desertification, risk, climatic variability

Journal of Economic Literature (JEL) Classification Number: Q 54

1. INTRODUCTION

Since 1994 when United Nation Convention to Combat Desertification (UNCCD) defined desertification as land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including

climatic fluctuations and human activities, several works had been done on its causes, impact, monitoring and mitigation (Giushan, et al 2011, Higginbottom and Symeonakis 2014, Kim J et al., 2018). United Nations Environment Program (UNEP) 1984 in their report identified evaluation of desertification processes to include changes in natural, biological and socio economic parameters, as single parameter may not be adequate to explain the desertification processes (Lambin et al., 2009). In Nigeria, desertification had been identified to have encroached between 35% and 40% of the land mass of the frontline States of Borno, Yobe, Jigawa, Kano, Katsina, Zamfara, Sokoto and Kebbi (Nneji, 2013, Olagunju 2015). Although it was estimated that annually, Nigeria had lost about 350,000 ha of land to desertification and the negative impacts are manifested on the environment and general livelihood of people; reduced capacity to provide for the basic needs such as food and water (Tercula, 2015). Yet the spatial pattern of the level of desertification and the areas at risk has not been sufficiently quantified and drawn (Olagunju 2015) and this has implication on prioritising mitigation and adaptation plan and strategy in view of limited resources. There is an urgent need to identify what proportions of area are under the high risk of desertification and degree of severity.

The Great Green Wall for the Sahara and the Sahel Initiative (GGWSSI) was a regional attempt by the African government through New Partnership for Africa's Development (NEPAD) to combat desertification in Sub Sahara Africa. The project was designed to plant trees and bushes as a protection against sand dune movement and land degradation covering about 7,775 km long from Dakar in Senegal through eleven countries in West Africa, Central Africa to Djibouti in Horn of Africa. Although its focus has been reported to have shifted from planting trees alone but to a more holistic and integrated approach towards sustainable development (FGN 2012) yet its impact on combating the menace of land degradation and control of desertification has been minimal.

Over the years vegetation and plant cover has been used to measure the level of land productivity, loss of vegetation cover has been associated with land degradation through accelerated soil and wind erosion and movement of sand dunes (Li and Zou 2002, Geeson et al., 2002). Climate variability and unsustainable human activities are also identified as the main drivers of desertification and drought not only in Nigeria but across the globe (Le Houerou, 1996; Holtz, 2003 Olagunju, 2015). Unsustainable human activities, such as deforestation for industrial purpose and fuel wood, urbanization, bush burning; agro-activities on marginal lands in the environment have aggravated the role of climate variability in the desertification phenomenon (Olagunju, 2015).

The use of Normalized Difference Vegetation Index (NDVI) to assess the level of land degradation and desertification date back to severe droughts witnessed in Sahel region of Sub Sahara Africa in the early 70s and 80s and since then has gained wide application in land cover monitoring and assessment of desertification processes (Higginbottom and Symeonaks 2014). NDVI is the reflectance values in the near infrared and red wave bands and mathematically expressed as $NDVI = (NIR - RED) / (NIR + RED)$ it has been used over the years to measure the biological and physiological characteristics of vegetation using remotely sensed data. NDVI provides the information on the vitality of vegetation that can be measured both at temporal and spatial scale. It has been applied to monitor forest or vegetation

changes and desertification process in different parts of the world (Yao *et al.*, 2008, Guishan, *et al* 2011 Higginbottom and Symeonakis 2014, Kim J *et al.*, 2018)

Many studies on land cover and vegetation mapping especially in large areas have used data from Advanced Very High Resolution Radiometer AVHRR (Defries and Townsend 1994), Multispectral Moderate Resolution Imaging Spectra radiometer-MODIS (Xiao *et al.*, 2003), and Landsat Enhanced Thematic Mapper Plus-ETM+ (Yang and Lo, 2002, Yuan *et al.*, 2005). While, AVHRR was originally designed for meteorological service and has only two spectral bands-red and near infrared which although sufficient for basic vegetation study, MODIS has more spectral bands including short wave infrared (SWIR) which can be used for obtaining greater details and advanced vegetation analysis such as leaf moisture, soil moisture, canopy water contents among others (Cacceto *et al.*,2002 a, b, Boles *et al.*,2004,.). Also NDVI data derived from MODIS sensor has been reported to be more accurate and reliable due to its correction for atmospheric condition (Higginbottom and Symeonakis 2014)

Also If desertification processes is linked to climatic fluctuation, therefore understanding the impact of aridity is an important component of climatic variables that cannot be overemphasized as it describes the dynamics between precipitation and temperature variables (Colantoni *et al.*, 2014).The level of wetness or dryness of a climatic region is dependent upon both the amount of precipitation and evapotranspiration (ET). That is whether or not the precipitation is greater or less than the water needed to offset evaporation and plant transpiration. Aridity is a function of both precipitation and the additional factors affecting aridity is temperature and the annual timing of precipitation [Thorntwaite (1948) as cited in Maliva and Missimer (2012)]. Conceptually, most people picture aridity as dry, desert lands with sparse natural surface-water bodies and rainfall, and commonly only scant vegetation, adapted to an insufficient amount of water (Maliva and Missimer, 2012). The effect of aridity cuts across diverse sectors of economy, environment and society of the affected area (Chen *et al.*,2001; Wang *et al.*,2010). Moisture stress is the major problem in the dry environments, and this represents the most important factor affecting plants (Elrahman and Elrahman, 1973). The stress contributes significantly to the vulnerability of drylands to desertification (Allavipanah *et al.*, 2001). Global increase in water consumption in the dryland rural regions was mainly due to agricultural development (Paparrizos *et al.*, 2016). Colantoni *et al.*, (2015) described aridity an important consequence of climate change.

Aridity indices (AI) are indicators that show the degree of climatic dryness (Gamo *et al.*, 2013). It is expressed as the quantitative indicator of water deficiency or the annual moisture balance at any location, all of which require meteorological data, preferably collected over a number of years so that mean values and trends can be determined. It is a widespread and simple tool that allows the classification and the analysis of the magnitude of aridity and drought phenomena over a reasonable number of years (Colantoni *et al.*, 2015). AI has been used for regional characterization of water scarcity (Bussay *et al.*,2012), and widely used for climate based land classification from the stand point of the dryness (Arora, 2002).

A number of methods exist for measuring AI (Table 1). Data on monthly precipitation (P) and monthly potential evapotranspiration (PET) are required for the moisture balance to be calculated (Maliva and

Missimer, 2012). Direct measurement of PET are not widely available, so that methods for its determination from other climate data have been used, even data from weather stations that collect only rudimentary information such as mean monthly temperature and the number of day light hours. A long time climatic data of annual precipitation and annual mean temperature and other climatic data have been severally used to determine aridity of an area (Table 1). This ranges from simplest aridity index determined solely by precipitation and temperature (De Martone, 1926), to other methods which also combine various climatic parameters e.g. (Emberger, 1932; Thornthwaite, 1948; Bagnouls and Gaussen, 1952; UNEP, 1997).

De Martonne (1926) aridity index (Iar-DM) has gained popularity and has been severally used in most regions to calculate aridity index and moisture stress not only because it is the oldest but found to be simple and more suitable especially in regions where there are insufficient long term climate data on radiation and air humidity (Paltineanu *et al.*, 2007; Hrnjak *et al.*, 2012,). This is particularly true of several locations in developing countries in Africa, Asia and Latin America (Droogers and Allen 2002). (Iar-DM) has also been found to produce similar result when compared to other indices such as UNEP/FAO and Emberger based aridity index (Hrnjak *et al.*, 2012).

2. MATERIALS AND METHODS

2.1. Study area

The study area comprise 9 frontline states of Borno, Yobe, Bauchi, Jigawa, Kano, Katsina, Zamfara, Sokoto and Kebbi cutting across the North Western and North Eastern geopolitical zones of Nigeria (Fig. 1). It is located on Lat 11.173° – 13.776° N and Lon 3.654° – 14.659° E. It occupies an area of about 426, 909.76 km² and has an estimated population of 45,321,339 according to the 2006 National population census (National Population Commission, 2006). Several of the states bounded Republique du Niger to the North, while Borno bounded Cameroun and Chad to the North East .

In the traditional climatic classification the states fall under Tropical Continental/Savanna climate (Koppen Aw) with distinct long and dry season, short wet season, the average annual temperature is about 26°C and total annual rainfall of 400- 500mm except in southern parts of Bauchi where total annual rainfall can reach 1000 mm Topographically, the study area is mostly a low lying flat surface which forms part of the Great lake Chad Basin and it consists of fertile flood plain of high agricultural values. The average height of the region is about 300m except in the south west of Bauchi and southern Borno around Biu, south east Yobe around Fika which ranges from 500 m to over 800 m and comprises of rugged mountains of old sedimentary rock. The people of the region are mainly agrarian with agriculture (farming and herding) providing employment to about 80% of the populace; a sizeable number of the populace are also engaged in some forms of trading and art and craft for livelihood.

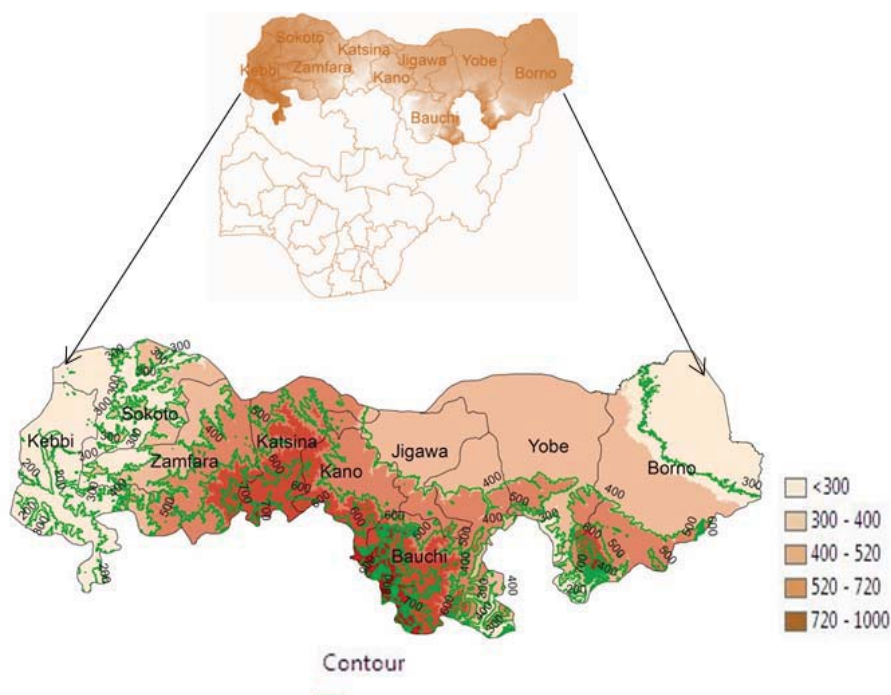


Figure 1. Study area showing altitude and contour

2.2. Data sets

Two climatic variables (total annual precipitation in mm (TAP) and mean annual temperature in °C (MAT) and two non-climatic variables (elevation, land cover/NDVI) data were selected for our computation and analysis of aridity index (fig) not only because of their high correlation with water and energy balance but also because of their impact on plant physiology (Leathwick *et al.*, 2003). De Martonne aridity index was obtained by dividing the Annual precipitation raster by the summation of annual mean temperature with 10

The DIVA GIS software was used to extract the raster layers for the climatic data (TAP, MAT) from the Worldclim database <http://www.worldclim.org/> at 1 km² resolution and was display in R package (Fig 2,3)). Worldclim contains long term (1950- 2000) global climatic database of monthly temperatures and rainfall of over 30,000 stations spread across the globe with spatial resolution of 1 km². WorldClim data base was well documented by Hijmans *et al.*, (2005); to test the validity of Worldclim data, the TAP and MAT obtained from Worldclim were compared with those obtained from three ground meteorological stations at Nguru, Potiskum and Gashua's North east arid zone development programme (NEAZDP) from 2005-2013 and were statistically tested, the results shows that there was no significant difference between the ground data and Worldclim data ($t = 0.4264 < \text{Crit } t = 1.8595$) at $p < 0.05$.

We downloaded Normalized Difference Vegetation Index (NDVI) data from Moderate Resolution Imaging Spectroradiometer eMODIS NDVI 6 <https://earthexplorer.usgs.gov/> we used eMODIS NDVI 10-day maximum-value composite NDVI images at 250m spatial, the data cover between 26 October and 5 November 2019 This period coincides with the peak of vegetation growth in the study area, the NDVI of the study area was georeferenced and subset from the Africa data as shown in (Fig.). Given that eMODIS values are stretched linearly to bytes values, we used the equation $NDVI = (value - 100) / 100$; example: $[(150 - 100) / 100 = 0.5$ NDVI V to rescale to standardized NDVI values of -1 to +1 (Swets *et al.*, 1999)

Land cover data of Nigeria, 2017 update at 1 km² resolution was downloaded from Global Land Cover Facility dataset <http://glcf.umiaccs.umd.edu/index.shtml> and was subset to the study area boundary, the details of its processing was explained in Lotanna and Salako *et al.*, 2019). A 90 m Digital Elevation Model (DEM) from NASA/Shuttle Radar Topographic Mission- SRTM at 90 m was down loaded from Diva GIS country level data at <http://www.diva-gis.org/data>. All the layers were resampled to 1km for spatial uniformity. Administrative boundary and population data shapefile of the study were obtained from DIVA GIS country specific data base.

Table 1. Table of aridity indices

Aridity index equation	Climate classification	Reference
$\frac{P}{t + 10}$ P = Annual rainfall (mm) t = Annual average temperature (°C)	< 7.5 = Hyper arid 7.5 – 14.5 = Arid 14.5 – 20.5 = Semi-arid 20.5 – 30.5 = Dry sub humid > 31= Humid	De Martonne (1926)
$\frac{100 * P}{M^2 - m^2}$ P = Annual average rainfall (mm) M = Average temperature of the hottest month (°C) m = Average temperature of the coldest month (°C)	< 30 = Arid 30 – 50 = Semiarid 50 – 90 = Subhumid > 90 = Humid	Emberger (1932)
$\sum_{n=1}^{n=12} 115 * \left(\frac{p}{T - 10}\right)^{10/9}$ P = Monthly precipitation (inches) T = Temperature (°F) n = months = 12	< 16 = Arid 16 – 31 = Semiarid 32 – 63 = Subhumid 64 – 127 = Humid > 127 = Wet	Thornthwaite (1948)

$\sum_{i=1}^{n=12} (2t_i - P_i) * K_i$ t = Average monthly air temperature k = Coefficient indicating the number of months in which 2t > p pi = Average rainfall of the month i (i = 1 to 12)	> 130 = Very Dry 50 – 130 = Dry 0 – 50 = Moist 0 = Humid	Bagnouls and Gaussien (1952)
$\left(\frac{P}{ET_o}\right)$ P = Precipitation ET_o = Potential evapotranspiration	< 0.05 = Hyper-arid zone 0.05 – 0.2 = Arid 0.2 – 0.5 = Semiarid 0.5-0.65 = Dry sub humid 0.65 - 1 = Subhumid > 1 = Humid	UNEP (1997)

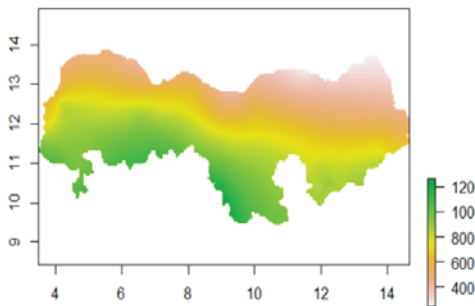


Figure 2. Total Annual Precipitation

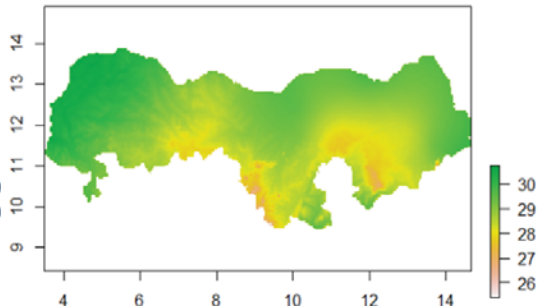


Figure 3. Mean Annual Temperature

2.3. Determination of Aridity and Desertification risk index

We selected De Martonne aridity index (lar-DM) to overcome data challenges that would have been associated with other indices especially the UNEP based index. The downloaded climatic data in grid raster layers was converted to tiff in ArcMap. Map algebra using lar-DM equation $\frac{P}{t+10}$ was performed in ArcMap 10.2 on these raster data across the states to generate aridity index.

To understand which variable has high correlation with De Martonne aridity index, we sampled 40 points by subdividing the study area into grid of 100 km x 100 km with an average of 4 sample points per states, we extracted MAT and TAP data in Worldclim database using climate point tool in Diva GIS. We then performed Pearson's correlation coefficient test between MAT, TAP and AI

Table 2. Classification of Indicators and DR Index score

S/No	Indicators	Values	Description	Index values	Index description
1	NDVI/land cover	0.1	Water/Barren land	1	Very High
		0.2	Settlements	2	High
		0.3	Shrubs land	3	Moderate
		0.4	Grassland	4	Low
		0.5	Forest	5	Very low (Marginal)
2	Aridity	< 7	Hyper arid	1	Very High
		14	Arid	2	High
		20	Semi-arid	3	Moderate
		30	Dry sub humid	4	Low
		> 31	Humid	5	Very low (Marginal)
3	Elevation (slope)	10%	Flat	1	Very High
		20%	Very gentle	2	High
		30%	Gentle	3	Moderate
		40%	Steep	4	Low
		50%	Very steep	5	Very low (Marginal)
4	Population	10Km Buffer		1	Very High
		20 '		2	High
		50 '		3	Moderate
		80 '		4	Low
		100 '		5	Very low (Marginal)

To create desertification risk index map, NDVI, land cover, elevation, population data and aridity index were used (this data encompass climatic, biological and human indicators) to delineate the region into desertification risk index map. NDVI and land cover data were used to classify the study area according to Global land cover classification (GLCC 2000) into different vegetation classes: barren land/water body, grassland, shrub land, forest and settlements. We used slope data calculated in % (derived from elevation) to assess exposure of land to wind erosion and we adopted the classification of Boudjemline and Semar (2018) into flat, very gentle, gentle, steep and very steep. Aridity index (prepared from total annual rainfall and mean annual temperature) was used to measure water stress and classified into 5 categories according to De Martonne. Each indicator was assigned an index score in relation to the potential risk posed. For NDVI/land cover indicator, forest cover was assigned 5 which means marginal

risk, while barren land was assigned 1 or very high risk. Flat and gentle slope is highly prone to wind erosion and was assigned 1 compared with rugged steep slope assigned 5. (Table 2) present details of the classification and risk index scores To identify population at risk, we performed a multiple ring proximity analysis (buffering) at 10km, 20km, 50km 80km and 100km around urban and large settlements. The features were converted into raster layer and overlay on desertification risk index layer

3. RESULTS

3.1. NDVI/Land cover and Elevation

Spatial analysis of vegetation cover in the study shows the NDVI values ranges from 0.0 (water body/ barren land) to 0.5-0.6 (shrub land/forest). Over 60% of land in Sokoto, Zamfara, Katsina, Kano and Jigawa had low NDVI values between 0.0 and 0.2 which denote sparse vegetation or denuded grassland, while about 15% of land mostly in southern parts of Bauchi, Yobe and Borno had cluster of forest (Fig. 4)

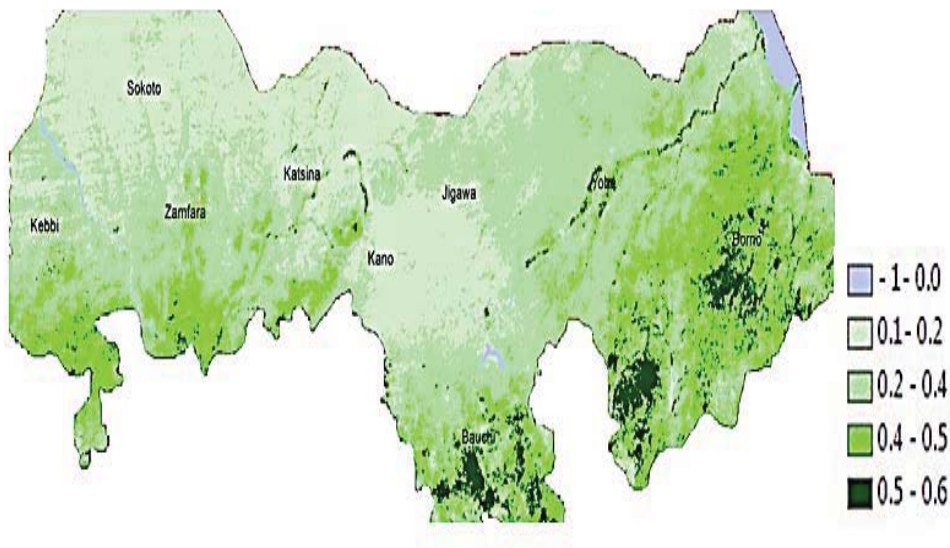
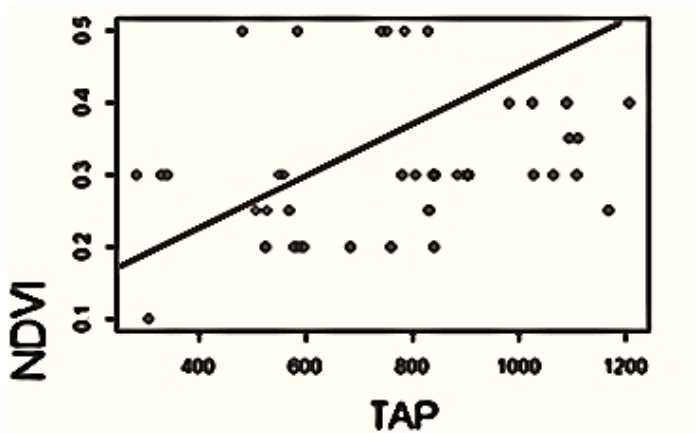


Figure 4. NDVI of the study area



$$R = 2.768$$

Figure 5. Correlation plot between NDVI and TAP

Elevation in the area is generally low ranges between 20- 450 m especially in Borno, Yobe Jigawa, Sokoto and Kebbi, however, central Katsina, southern Kano, Bauchi and Borno are

relatively higher reaching over 800 m in Biu plateau (Fig. 6). There is a strong relationship between the elevation and slope as areas of higher elevation are equally areas of steep slopes and vice versa. The low lying gentle slope in Jigawa, Yobe, and Borno are highly prone to wind erosion and frequent sand storms (Fig. 7)

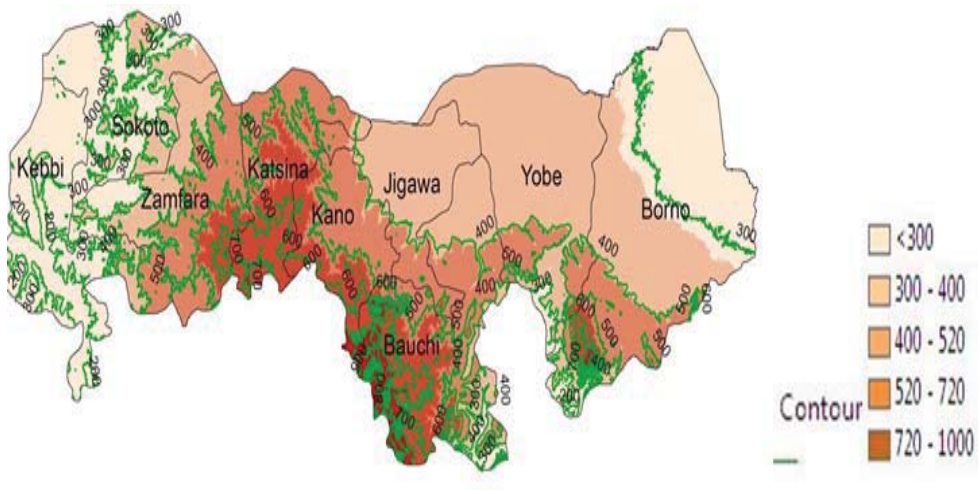


Figure 6. Elevation in metres

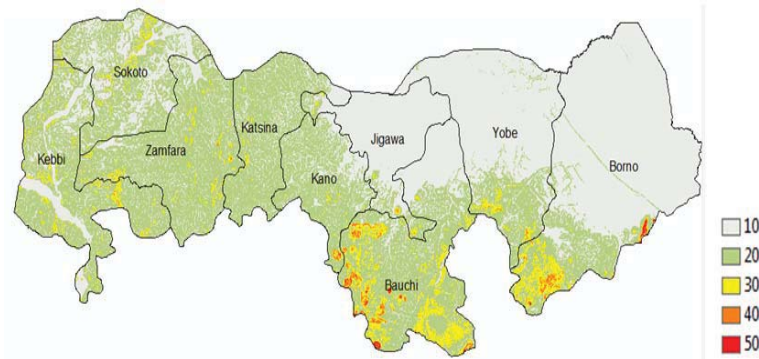


Figure 7. Slope in % derived from elevation

3.2. Aridity index

The aridity index ranges between 7.5 - >30 and falls within the De Martonne's arid, semi arid, dry sub humid and humid zone, the lower index values denote higher aridity. The aridity nature of the study area increases northwards (Fig. 8). While 10-35%, northern fringes of all the frontlines states falls under arid zone, about 35% (50,945 km²) of land in Yobe and Borno fall into arid zone

However, this northward pattern is rather curvilinear as there are few southerly located areas in the eastern section that had similar or more arid condition than the northerly located areas in the western part. Potiskum in Yobe on latitude 11.7139°N has aridity index of 14.5 - 20.5 (semi arid) as compared to northerly located places such as Birnin Kebbi (Kebbi) and Kaura Namoda (Zamfara) which are dry sub humid with aridity index of 20-30. The case of Azare (Lat 11.7039°N) and Potiskum (lat 11.7139°N) is a typical example of settlements of almost the same latitudinal position but different aridity index. Figure 8 shows Azare with aridity index of 20.5-30.5, dry sub humid while Potiskum is on the boundary of semi arid region (14.4-20.5).



Figure 8. Aridity index

To understand the relationship between De Martonne aridity index and the two climate variables used, the Pearson's correlation coefficient test between MAT, TAP and AI reveals the pattern of correlation. The total annual precipitation shows a positive high and linear correlation with AI as shown with correlation coefficient of 0.99464 at $p < 0.05$ (Fig. 9 left). as compared to the relatively low but negative correlation of -0.6392 at $p < 0.05$ between MAT and AI (Fig. 9 right) This suggests that rainfall rather than temperature greatly influence the level of aridity as rainfall increase; it becomes more humid that is the aridity index reduce (Gamo *et al.*, 2013). However it should be noted that De Martonne numeric values increase with lower aridity

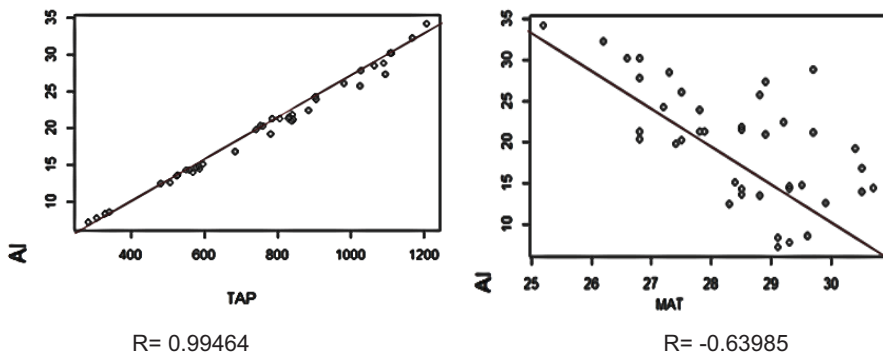


Figure 9. Correlation plot between AI and TAP (left) and between AI and MAT (right)

3.3 Desertification risk index (DRI)

The spatial overlay of aridity and vegetation indices produces Desertification Risk Index (DRI) map (Fig.10). using the Global desertification vulnerability class we classified the DRI in the area into very high, high, moderate, low and very low or marginal (USDA-NRCS 2003). Although there is a similar pattern between aridity index and DRI in the study area, the DRI equally increases northward with northern Borno and Yobe accounting for over 30% (50,945 km²) of their land under very high risk.

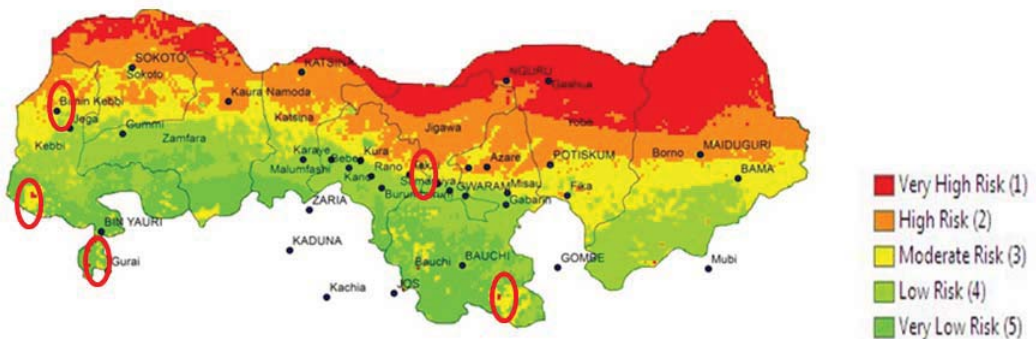


Figure 10. Desertification Risk Index with hotspots in red rings



Plate 1. Satellite image showing Gurai a “hotspot” area



Figure 11. Population at Desertification risk

4. DISCUSSION AND CONCLUSION

Many studies have reported a positive and sometimes strong correlation between NDVI and rainfall both in dry and humid region (Maselli *et al.*, 1992, Higginbottom and Symeonakis 2014). However, situation in dry environment do present certain level of variation (Gamo *et al.*, 2013). The correlation between NDVI and rainfall in this study although was positive but with low coefficient of 2.768 at $p < 0.05$ (Fig.5). It shows that rainfall alone may not be responsible for vegetation cover in the area, this confirms the possible role and influence of human activities on the landscape such as irrigation along river estuary and tributaries, plantation and reservation zones (Gamo *et al.*, 2013) This is specifically true of high vegetation in an otherwise arid lands along river komadugu Yobe, and the Sambisa forest in south west Lake Chad with total annual rainfall of less than 700mm. Gamo *et al.*, 20013 in his classification of arid lands categorize this landscape into I and describe them as areas with plenty vegetation despite low rainfall

The northward increase in aridity in the study corroborates with the findings of Doerr (1962) in aridity index studies of Oklahoma in United States, Central Anatolia and Akgündüz, Turkey, Türkeş (2011)

Hodna basin in Algeria (Boudjemline and Semar 2018) and world atlas map (WAD 2019). While northern fringes of all the frontline states falls under arid zone, the pattern was curvilinear in shape. The possible explanation for the curvilinear pattern in aridity movement was the East - West disparity in rainfall distribution due to westerly movement of rain bearing southwest wind which tends to drop more rain on western side of the continents than the eastern side, as it moves upward from the coast to the interior continent (Kowal and Kwabe 1972; Kowal and Kassam 1978; Maryah 1997, Gamo *et al.*, 2013).

The inclusion of vegetation index and slope data presents a much details and better insight into the spatial distribution pattern of DRI. Clusters of high risk were found within the moderate and even low risk regions as found in Birnin Kebbi, Gurai, in Kebbi state in western part and along Gombe Bauchi axis in an otherwise low risk region, the high resolution satellite image viewable in Google Earth around Gurai confirmed this (Plate 1). This is probably due to loss of vegetation cover as a result of pressure on land resources occasioned by overgrazing and land cultivation thus reflect high correlation between aridity, desertification on one hand and vegetation and land use on the other hand (Trabucco and Zomer, 2014). The case of Nguru and Gashua in Yobe state is another example of where vegetation cover could make a difference. These two settlements of about 56 km apart and almost similar latitudinal location fall differently into high and very high risk zone respectively. The cluster of vegetation cover in Nguru could be the result of trees conservation within few kilometers to the centre of the town and the presence of aquatic vegetation around the wetlands (Salako *et al.*, 2016).

Buffering at 10, 20, 50, 80 and 100kms in the selected urban centers and large settlements and overlay on DRI reveals that the risk increase as one moves closer to large settlements and urban centers (Fig.11). The high risk is noted along Kano urban center field, spanning from Kano through Azare to Potiskum (Fig. 11) this supported earlier observation of rapid urbanization within the Kano axis as a strong indicator for desertification processes (Nneji 2013). The more the population grows the more foods needed to be grown and invariably exerting more pressure on the land to sustain the growing population. This is much more devastating in arid and semi-arid land with limited capacity for biological productivity (WAD 2019).

This study presents the role of vegetation and aridity indices in determining spatial distributional pattern of desertification risk of nine desertification prone frontline states and use population data to highlight settlements and people at risk of desertification. 75 % (403,650 km²) of the region falls into three aridity categories: arid, semi-arid and dry sub humid while the remaining 25% (33,000 km²) found in southern Kebbi, Zamfara, Katsina and Bauchi falls under sub humid. By and large, aridity in the study area increases as we move northward, however, the study findings also show that a numbers of south west located areas are more arid than the northerly located area in the eastern side possibly due to westerly movement of rain bearing southwest wind which tends to drop more rain on western side of the continents. Similarly, some areas with similar latitudinal locations show variation in aridity index. Aridity index as proximate of the desertification was however found to be inadequate thus informed the inclusion of vegetation index, this has helped to identify the vegetation status of the area which is vital in assessing land degradation and desertification and its combination with aridity index produce

desertification risk map. This map has helped us to identify places which risks to desertification are higher than their surrounding areas. These are actually the hotspots which require urgent attention as found in Birnin Kebbi, and Gurai in Kebbi state, Kano axis comprises Azare and Potiskum especially when it is interpreted in the light of urbanization and population data.

In as much as over 75% of the frontline states fall into very high and high desertification risk zones, efforts should be made to combat the menace of desertification with special attention placed on these highly vulnerable areas as earlier highlighted in the work. Sound land management, aggressive drought resistant tree plantings and stock density control should be incorporated as measures of desertification control especially in the identified hot spots. Also there is a serious need for the substitution of both domestic and light industries sources of fuel, from over 95% reliance on fuelwood to at least 50% or below. Introduction of charcoal generated from waste through pyrolysis should be vigorously pursued..

5. REFERENCE

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