Combining Remote Sensing and Space-Time Analysis for Desertification Monitoring in the Semiarid Dryland of Nigeria

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Abstract

Desertification has been identified as the resultant effect of dryland loss. Desertification is catalysed by anthropogenic modifications and variations in environmental/climatic conditions. The situation in Nigeria is further exacerbated by the growing demand for land by the population. To this effect, this study performed a space-time analysis of vegetative cover between 2001 and 2020 to unravel patterns and trends across the semiarid region of the dryland system in Nigeria. The dynamics during the rainy season (May and September) were examined using the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) dataset subjected to space-time analysis. Generalised Difference Vegetation Index (GDVI) was computed to the power of 2 to quantify vegetative cover across the study area. The results showed that the average of the GDVI ranges between -0.40 and 0.94, with a standard deviation of 0.11. Time series cluster analysis revealed that there are two temporal clusters: (1) no statistically significant trend (Statistics= 1.33, p-value = 0.18) and (2) statistically significant downtrend (Statistics = -2.37, p=0.02), with cluster 1 covering 95% of the areas examined. The most dominant (97% of the area) emerging space-time pattern was cold-spots (persistent, diminishing, sporadic, oscillating, and historical types). In conclusion, most of the areas showed no definite temporal pattern of vegetation pattern during the period, while more than 90% of the areas have witnessed a decline in vegetative cover. There is a need for a more coordinated approach to desertification control, constant monitoring is pertinent while new approaches to restoring degraded land are recommended.

Keywords: Space-time analysis, Generalised Difference Vegetation Index, Desertification, Drylands, Land Degradation

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Introduction

Desertification results from a complex interaction between human and environmental factors spanning several decades. The dryland system covers around 41% of the earth's surface (Reynolds et al., 2007), and land degradation in this region often results in desertification. Due to the high variability of the environmental conditions and the high vulnerability of the ecosystem to change, people over time have developed very resilient land management systems. However, with the continued pressure on the land and the changing climate, the system has been pushed beyond its capacity, and many of the land management systems are no longer able to cope. Increasing pressure to extract living and resources out of marginal lands undermines the resilience built into the already adapted and robust land management hence the increase in desertification. This process is initiated by a gradual within-state change in which there is a spatial decline of grassland and replacement with sparse vegetation – leading to a loss of productivity for land users and managers. This is followed by state conversion whereby the sparse vegetation is soon replaced with the desert as the impact of human and environmental factors combined – further exploitation by humans created an opportunity for further desert encroachment on the degraded land. Due to the dynamics between humans and natural factors, there is a need to monitor the evolution of vegetative cover and, thus, identify emerging patterns across the dryland systems. This will ensure that necessary actions are taken to mitigate impending degradation in the region. It is based on this that this study carried out a space-time analysis of vegetative cover between 2001 and 2020 to identify trends and patterns across the semiarid region of the dryland system in Nigeria.

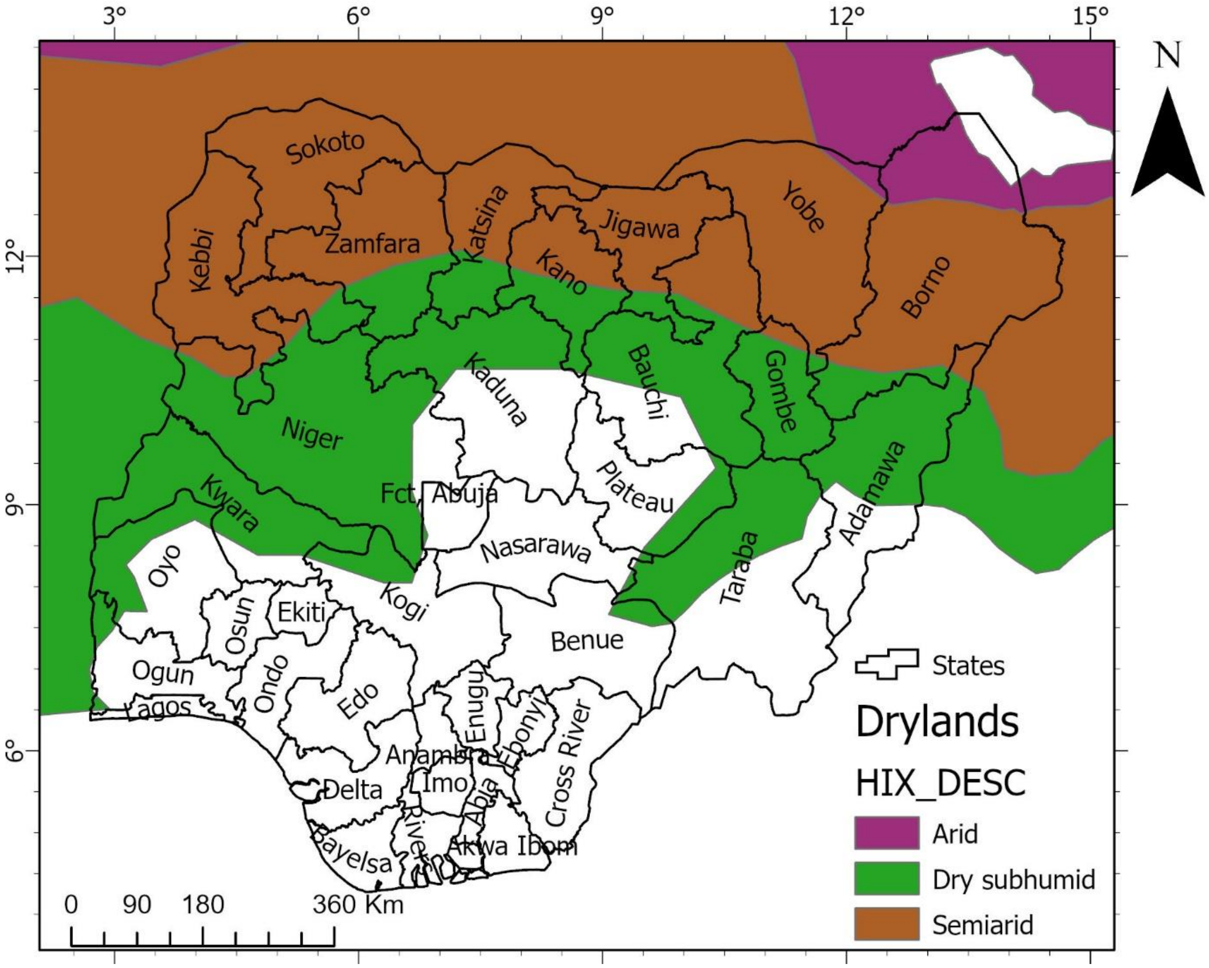

Figure 1: Dryland Systems across the Nigeria States

In Nigeria, the human factors in this dryland degradation complex include the poor management of land, poor irrigation practices, excessive groundwater abstraction, overgrazing, and deforestation. The situation is further aggravated by increasing demand for land in a country with a population of over 200 million, human pressure on marginal lands has been incessant and resulting in the growing extent of desert in the drylands region of the country.

Currently, more than 19 States across the north and the middle belt regions of Nigeria (Figure 1) are within the dryland ecosystem and under the threat of desertification. The challenge created by this loss of ecosystem services and decline in productivity goes beyond food security. It is now impacting human security, leading to various conflicts and clashes across many parts of the country. And this is creating a drag on the overall development efforts of the government and spill over effects across the West African region. Nigeria ratified the UN Convention to Combat Desertification in 1997. It developed a National Action Plan, which has raised the awareness and mainstreaming of the development of mitigation actions against desertification in the country.

Land degradation resulting from the adverse impact of climatic variations and human activities across the arid, semiarid and dry, humid regions of the world could be termed desertification (UNEP, 1992). Recent estimates indicated that about 41% of the earth surface (dryland systems) is currently either deserts or under the threat of desertification (Davies et al., 2015). Estimates by the UN put the annual loss to desertification at around 6 million hectares of productive land, and the loss of arable land per person was projected to drop to around 0.16ha from 0.21ha in 1998 (Saier, 2010).

Controlling desertification is a major global challenge. Because of the enormity of the challenge, various methods and techniques have been developed, which can be broadly grouped into three categories – engineering, chemical, and vegetative methods (Ci & Yang, 2010). From the Millennium Ecosystem Assessment (2006) dryland systems (Figure 1) coverage, we estimated that about 672km^2, 317km^2 and 617km^2 belong to the arid, semiarid, and dry subhumid zones respectively, across Nigeria's dryland ecosystem.

The population of migrating people and livestock from the frontline States of desertification in Nigeria (Kebbi, Sokoto, Zamfara, Kastina, Kano, Jigawa, Bauchi, Yobe, Borno, and Adamawa) is putting enormous pressure on other States such as the Federal Capital Territory (FCT), Plateau, Taraba, Niger, Kwara, Kaduna State. The pressure is gradually extending beyond these States as they are increasingly threatened by desertification due to excessive pressure and the management of marginal lands brought about by increasing demand for land. Recently, the pressure for pasture for livestock has precipitated into violence, and the pressure is not only coming from within the country. Drought across other countries like Chad and Niger is also leading to increasing cross-border migration leading to more security and environmental challenges.

The complexity of the problem of desertification in Nigeria indicates that a multidimensional approach must be implemented to fight it. On the one hand, efforts must be made to stop further desert encroachment – reforestation, stabilisation of dunes, the establishment of shelterbelts, windbreaks, rangeland shelterbelts, etc. there is a need to initiate the reclamation of the degraded land to ease the pressure on marginal lands. As the rate of desertification continues to grow (0.6km/year in Nigeria) and arable land per person continues to decline (Saier, 2010; The World Bank, 2021), there is a need for active and coordinated desertification control. However, before this can be done, there is a need to identify the hotspots of vegetative change that can indicate the emergence of dryland degradation.

There are tremendous opportunities offered by Big Earth Data (BED) to fill the data gap that is often common across many developing countries – lack of monitoring data at appropriate spatial and temporal resolution. This often hampers designs for environmental management and, subsequently, the planning for sustainable development and Disaster Risk Reduction (DRR). Most importantly, to plan and act on environmental management issues and climate change adaptation, countries, and regions need to have access to high-quality data which can guide their actions.

Despite the grave danger posed by environmental degradation (as a result of resource exploitation) and climate change, many countries across the SSA region usually have sparse and non-representative data, which often hampers planning and proper policymaking. As such, it has become pertinent that researchers develop new techniques that can enhance our understanding of earth systems using the latest technologies and developments in earth observation, remote sensing (RS) and geographic information system (GIS). This is crucial as BED is making it possible to cover the entire globe and provide a consistent standard for comparison. However, to be able to use the data, there is a need to transform the data into useful and policy-relevant information for decision-making. It is with this understanding that this study is examining the space-time pattern of vegetative cover across the dryland ecosystem of Nigeria. This is expected to provide insights into patterns and trends of changes across the area. This is vital due to the vastness of this landscape.

The use of RS and GIS in vegetation-related, environmental, and even socio-economic-related studies is a growing trend as it leverages the advantages of RS (coverage of large areas, inaccessible areas, lower cost, and shorter collection and processing time). Many vegetation indices have been developed to study various properties of the environment. They are developed on the basis that various elements of the surface or subsurface react and respond differently to different regions of the electromagnetic spectrum. Thus, a mathematical combination of selected bands can be used to monitor crop health, vegetation canopy water content, vegetation water stress, crop/vegetation chlorophyll content, potential drought condition, etc. This approach is beneficial for monitoring changes in the dryland as there is an increase in temporal and spectral resolution of remotely sensed data which is enhancing the possibilities in several areas of earth observation – providing new opportunities and overcoming previous bottlenecks. There are numerous works on spectral vegetation indices (VI), from the Simple Ratio (SR) (Knipling, 1970), Normalised Difference Vegetation Index (NDVI) (Tucker, 1979) to more recent ones which have corrected the shortcomings or limitations of older indices e.g. Global Environmental Monitoring Index (GEMI), Soil Adjusted Vegetation Index (SAVI), Optimised SAVI (OSAVI), Enhanced Vegetation Index

(EVI), Modified Non-Linear Vegetation Index (MNLI). All these have been very useful in environmental monitoring and ecosystem research globally. However, due to the sparseness of vegetation in the drylands, many of these indices are not adequate for monitoring vegetation across such landscapes. The indices are more sensitive to moderate and densely vegetated lands e.g. forest and cropland. For example, Qi et al. (1994) reported that the dynamic range of SAVI was reduced after the adjustment using the L factor and this is detrimental to the identification of monitoring vegetation in the drylands. Similar observations and uncertainties have also been reported for NDVI and EVI (e.g. Lu et al. (2015)). Wu et al. (2013) in their studies of the desert rangelands in Ordos, China, noted that subtle changes in greenness across the reclaimed or desertification-controlled area are almost impossible to identify because of this insensitivity and low dynamic range of commonly available VIs.

Due to the peculiarity of the dryland ecosystem, new indices are being developed. For example, GDVI was developed by Wu (2014) from NDVI. They also demonstrated that GDVI increases the dynamic range of low and moderately vegetated areas and higher power form ensures saturation of index values in the densely vegetated area. The development of GDVI utilised a heuristic parametric transformation of the NDVI. Camps-Valls et al. (2021) provided a statistical non-linear approach for the monitoring and characterisation of vegetative growth on the planet.

The importance of dryland and wetland vegetation cannot be overemphasised as they play a pertinent role in the ecological functioning of this ecosystem while preventing further encroachment by desert. Therefore, monitoring the vegetation across these ecosystems can indicate their health and status. It is in this light that remote sensing offers an opportunity for the provision of timely information and details for the management of these sensitive environments. It can provide up-to-date and relatively accurate information on the dynamics of this system. The use of vegetation in monitoring dryland ecosystem degradation is commonplace. For example, the works of Lu et al. (2015); Shao et al. (2018); Wu (2014); Wu et al. (2013); Zhu et al. (2019) showcased the relevance of vegetation monitoring in understanding the status and progress of various desertification control projects across different regions.

Recently, Aliero et al. (2021) applied the modified form of Mediterranean Desertification And Land Use (MEDALUS) model (Symeonakis et al., 2016) in identifying desertification-sensitive areas. This approach computed the geometric mean of soil, vegetation, and climate in the identifying sensitive areas. This approach creates an understanding of vulnerable areas, it needs more dynamism that the issue of desertification requires. However, it can support actions to quickly address vulnerable areas and prevent further expansion.

Ibrahim et al. (2022) conducted a 25-year study of north-eastern Nigeria to study desertification in the Sahel region of Yobe State. The study revealed a doubling of areas covered by dunes between 1990 to 2015. Furthermore, they reported that lower temperature and increasing rainfall did not translate into increasing vegetative cover, thus, indicating that other factors are at play. They concluded that desertification in the study area is more of a product of human activities than climate change. The study also highlighted the relevance of monitoring vegetation to identify areas with successful sand dune reclamation. Ekundayo et al. (2021) utilised vegetative cover to assess desertification in the Sudano-Sahelian savanna region of Nigeria. They examined monthly NDVI from MODIS satellite at 1km spatial resolution from 2000-2010. This formed the basis of their classification of different areas into water body, desert and bare-land, semi-desert, steppe, shrub and grassland, dense vegetation and forest. The study revealed the changes in extent of these classes over the period under consideration. These works utilised NDVI in monitoring degradation and changes in vegetation as a proxy of dryland degradation in Northern Nigeria. However, these works were executed based on changes over time and in extent. This approach ignored the importance of spatial and temporal autocorrelation in monitoring desertification or dryland degradation. This current approach addressed this and provided a more holistic monitoring framework. Furthermore, these studies utilised NDVI in an environment where it has been reported to be suboptimal because of its insensitivity and low dynamic range (Lu et al., 2015; Wu, 2014; Wu et al., 2013).

Temporal analysis of land use/land cover and other environmental characteristics is commonplace, which takes into cognisance the relevance of time in allowing the interactions between people and the natural world. Many changes as observed over space often occur in clusters (e.g. deforestation, erosion, pollution episodes, crime activities), the time also plays a role. For example, a perceptively near place may still only be visited if the time to travel to it is allocated, thus spatial proximity does not guarantee a visit to that location. In essence, human activity decision and the way they have modified the planet is not only dependent on space or time, but it is also affected by the combination of spatial and temporal factors – Space-time constraints (Hägerstraand, 1970). The constraints dictated by this understanding may be as a result of laws, rules, norms, ~~etc~~. (authority constraints) or social interaction (coupling constraints) or physical/biological limits (capability constraints). From the perspective of environmental change, space-time pattern analysis examines the distributions and patterns of changes in the context of both space and time, thus, it examines the distribution and pattern of environmental change from three dimensions – space (x,y) and time (z). Application of such approach (space-time analysis) in monitoring drylands could provide a better insight into space-time pattern and trend of vegetation, thereby, creating another approach at understanding progress in desertification control and status of desertification.

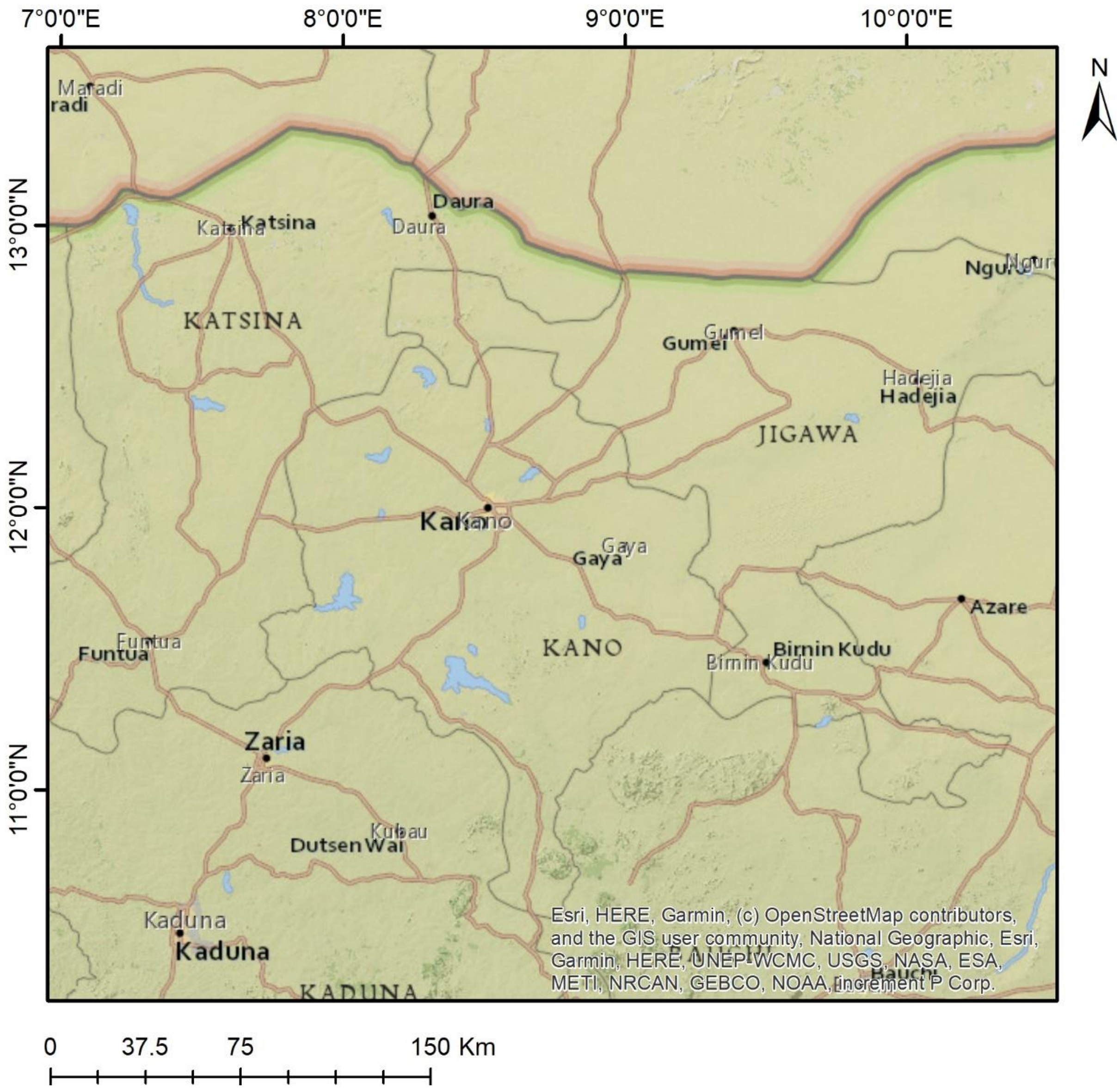

Figure 2: Kastina, Kano and Jigawa States and environs

Data and Methods

Study Area

The study focussed on Kastina, Kano, and Jigawa States (Figure 2). The area is dissected by several rivers, major ones include Karaduwa, Bunsuru, Turami, Watari, Chalawa, Kano, Jakara, Gari, Hadejia, Dudurun Gaya, Dudurun Warwade, Iggi, Dogwala, Garanga, etc. Some of these formed large water accumulations that could be found around places like Djibia, Kadaji, Garfi, Dustin Wai in Katsina. In Kano, such could be found near places such as Bawai, Unguwar Fari, Ungwuwa Kwari, Kongo Kura, Dan Amale, Fegi, Bagwai, Baita, Sakkwatawa, Kofar Chiri and around places like Warwade, Limawa in Jigawa State.

With every part of the globe impacted by human activities, identifying biomes across any part of the world should indicate anthropogenic biomes. According to Ellis and Ramankutty (2008), the common biomes across these States includes Cropped and pastoral villages, rainfed villages and dense settlements (Figure 3). Residential irrigated cropland and residential rangeland could also be found scattered across the landscape. While some pastoral villages are found across Katsina, none of such can be found across Kano and Jigawa States. The mapping showed that every aspect of the landscape had been impacted by human activities in one form or the other.

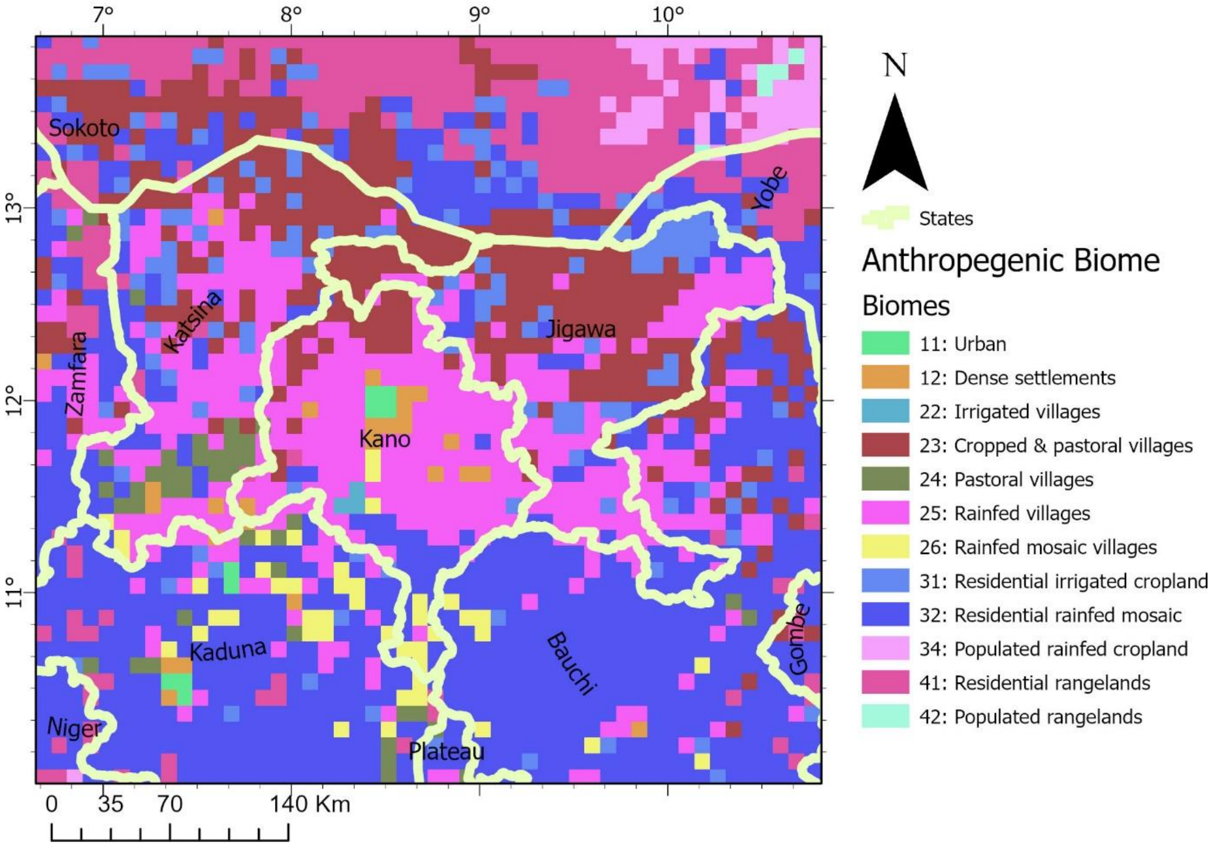

Figure 3: Spatial distribution of anthropogenic biomes across Katsina, Kano, Jigawa and neighbouring States

From the Koppen-Gieger Classification (Kottek et al., 2006), the three States fall within the Equatorial savanna with dry winter (Aw) and Steppe Climate (BSh) – Figure 4. The Steppe climate zone is typical of the arid region – hot and arid conditions. The equatorial savannah or tropical savanna found in this region has a longer dry season with rainfall amount decreasing with distance from the equator. The hot desert climate (BWh) is found in Yobe and beyond in the Northeast of Nigeria

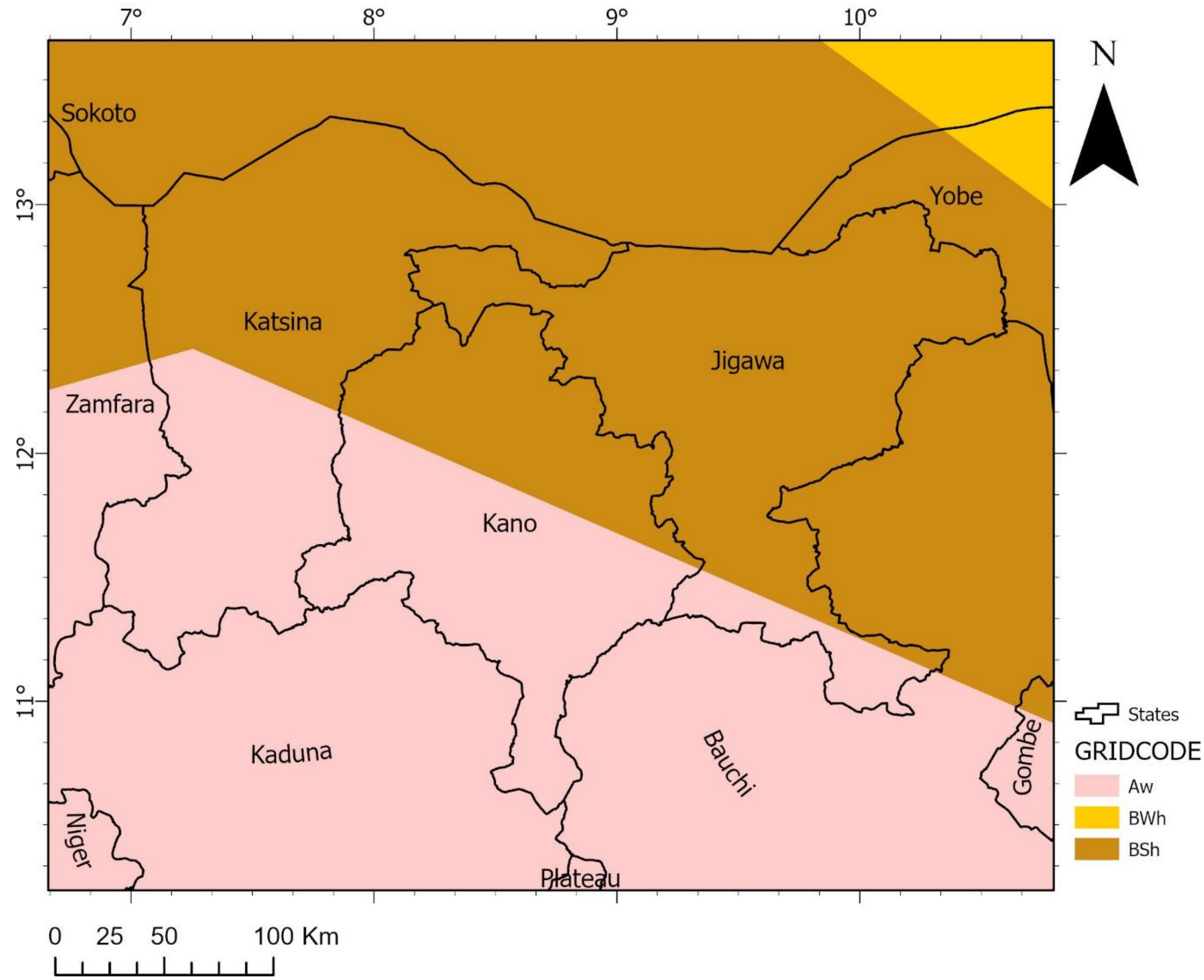

Figure 4: General climate classification according to Koppen-Gieger

The States has a mixture of high, low activity and sandy soils (Figure 5), these include Leptosols, Chernozems, Podzols, Podzoluvisols and Gleysols. These soils vary in their distribution across each State. However, across the northern part of these States, sandy soils are dominant. while the podzols and the podzoluvisols constitute a segment of the high activity soils. The gleysols and some of the podzols constitute the low activity soils along the southern edges of the States.

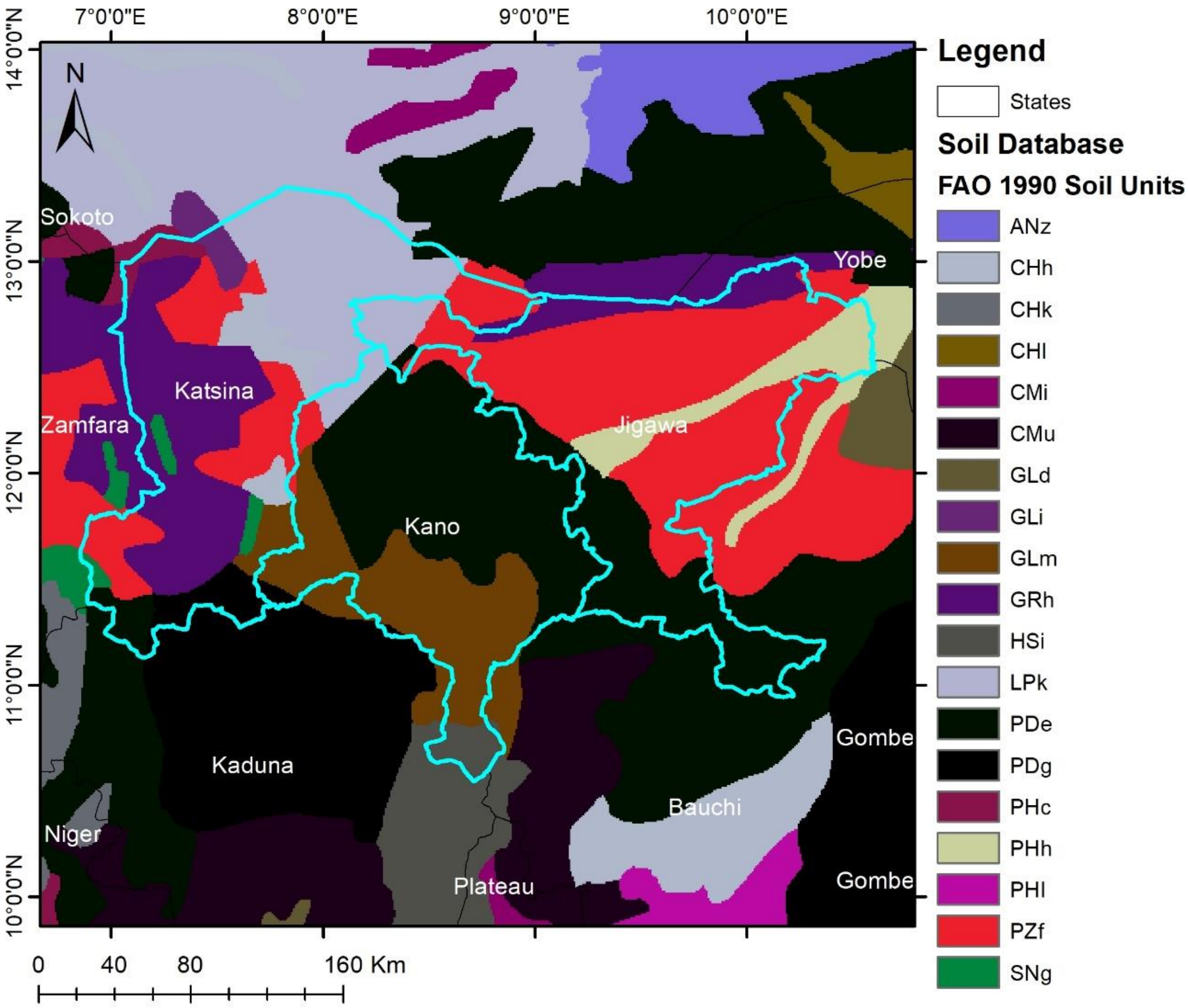

Figure 5: Soil distribution across the three States and their neighbours

Combining the socio-economic and demographic characteristics of the populaces, Lawal and Adesope (2019) showed that adaptive capacity varies across the States (Figure 6). The capacity to adapt declines as the distance from the major urban centre increases. The situation is worse across many parts of Jigawa, northern and western parts of Katsina State (Figure 6).

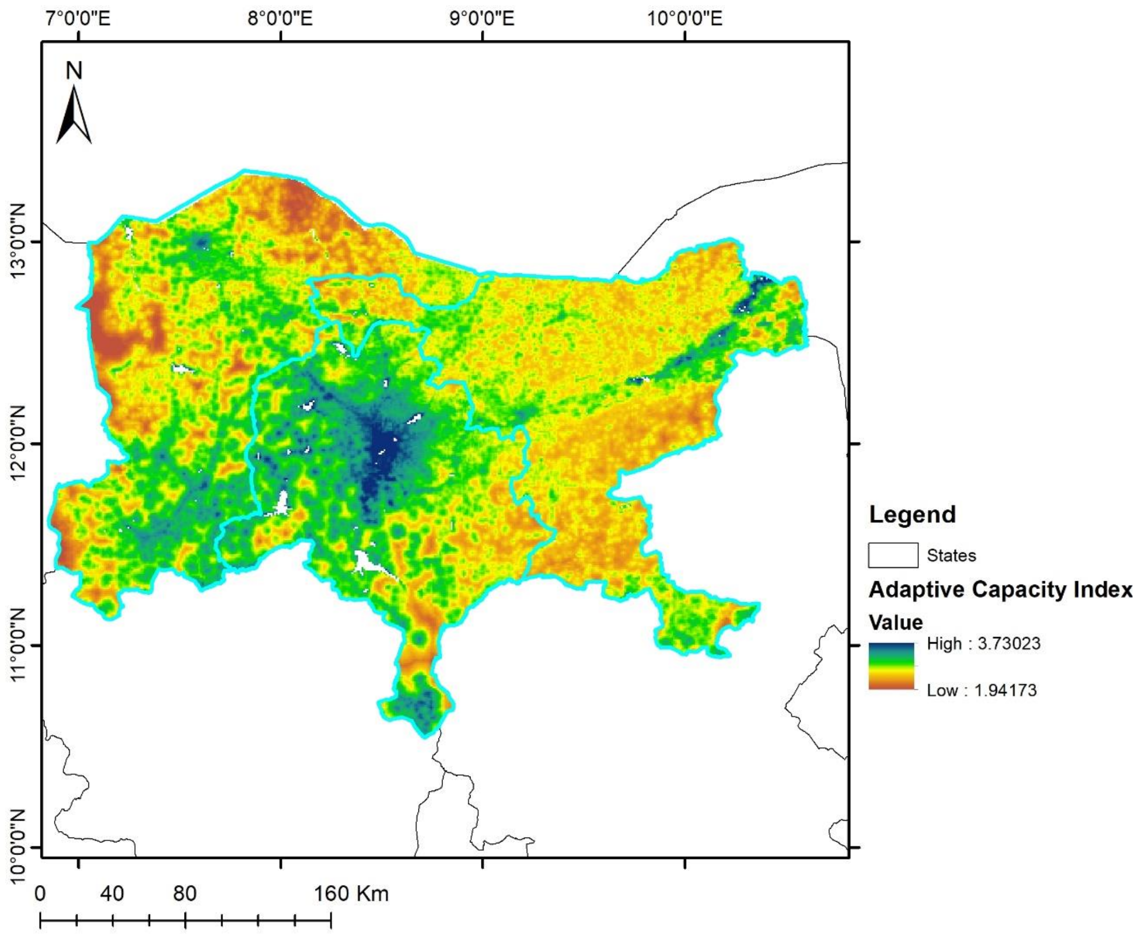

Figure 6: Combination of socio-economic and demographic characteristics- adaptive index for the three States

Data and Methods

Data

The study utilised the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) dataset. The data was extracted from the vegetation indices (MOD13Q1) Version 6 data (Didan, 2015) and this version is made up of 16 days average of the NDVI and the other bands at 250m resolution. However, we collated only the Near Infrared (NIR) and the Red bands for this study. The study focussed on the dynamics during the rainy season; therefore, data were collated for periods between May and September from 2001 to 2020.

Method of Analysis

The study utilised GDVI based ability to augment the dynamic range of the typical NDVI values. This approach addresses the poor sensitivity of NDVI. The GDVI was calculated as follows:

$$GDVI^n = \frac{\rho_{NIR}^n - \rho_R^n}{\rho_{NIR}^n + \rho_R^n} \qquad \text{Equation 1}$$

Where n is power, an integer greater than 1, ρNIR and ρR are reflectance values from the NIR and Red bands, respectively.

The dynamic range for the GDVI is equal to that of NDVI if n=1, and the values range between -1 and 1. This study computed GDVI for n = 2. This allows for the amplification of the dynamic range for the low and moderately vegetated areas as found in the drylands.

Space-time analysis can shed more light on the relationship between space and time regarding the occurrence of certain events. Many of the techniques for this analysis were developed in the field of epidemiology (e.g., Besag and Newell (1991); Knox and Bartlett (1964); Kulldorff and Nagarwalla (1995); Mantel and Bailar (1970)). These techniques are also useful in the analysis of crime, conflicts, and other events with spatial and temporal dimensions (Lawal, 2018). The work of Lawal and Chimenwo (2019) provides details of the procedure utilised in the implementation of the Space-time analysis within ArcGIS. For this analysis, the GDVI across each year's rainy season was averaged to create a single raster for each year. This averaging resulted in 20 raster files covering the study area. The trend was examined at yearly intervals.

Result and Discussion

GDVI Distribution

Over the 20 years of the rainy season data, the GDVI average ranges between -0.40 and 0.94 (Figure 7) with a standard deviation of 0.11. The distribution of the average values reflects the season with most of the area showing an indication of some vegetative cover (GDVI > 0.45). More so, the standard deviation shows that the variability of GDVI values is moderate across the areas. Areas with high GDVI values (>0.6) occurred in a linear pattern which indicates vegetation growth around floodplains (croplands). The reservoirs around the study area were easily identified with most of them having GDVI values less than 0.19. There are lots of sparse vegetation patches around the northern and the western part of the study area. Moderately (0.56 – 0.66) vegetated areas are most the predominant based on the average of the 20 years rainy season data.

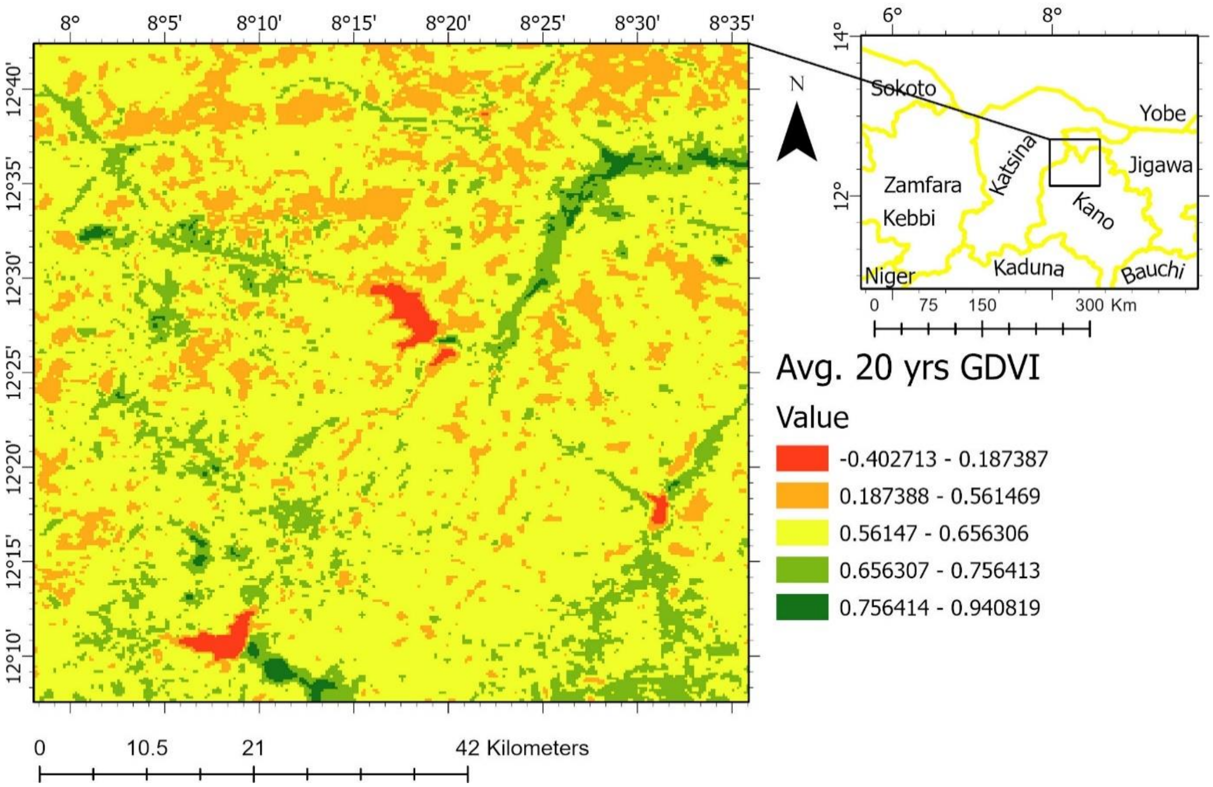

Figure 7: The 20 years rainy season GDVI average

Space-Time Trend

From the computation, the space-time cube (x,y,z) of the GDVI results (Figure 8) showed that during the rainy season when vegetative cover emerges, about 43% of the area examined showed an upward trend in GDVI values over the 20 years examined. Within this area (those with an upward trend in GDVI values), 15%, 17.5% and 10.5% displayed an upward trend with 99%, 95% and 90% confidence. These levels of confidence are statistically robust to still consider such areas as locations with improvements in vegetative cover.

About 2% of the area (Figure 8) displayed a downward trend over the same period. This computation indicated that over the 20 years across the selected area, about 86.54km^2 displayed a decreasing value of GDVI in the study region. This indicated that during the rainy season over the 20years, just about 2% of the area examined showed a decline in vegetative cover.

More than half (55%) of the area showed no statistically significant temporal trend in GDVI values. This result indicated that while there are changes, the trends observed are not statistically distinct to be classified as uptrend or downtrend. However, it should be noted that there are changes across the period.

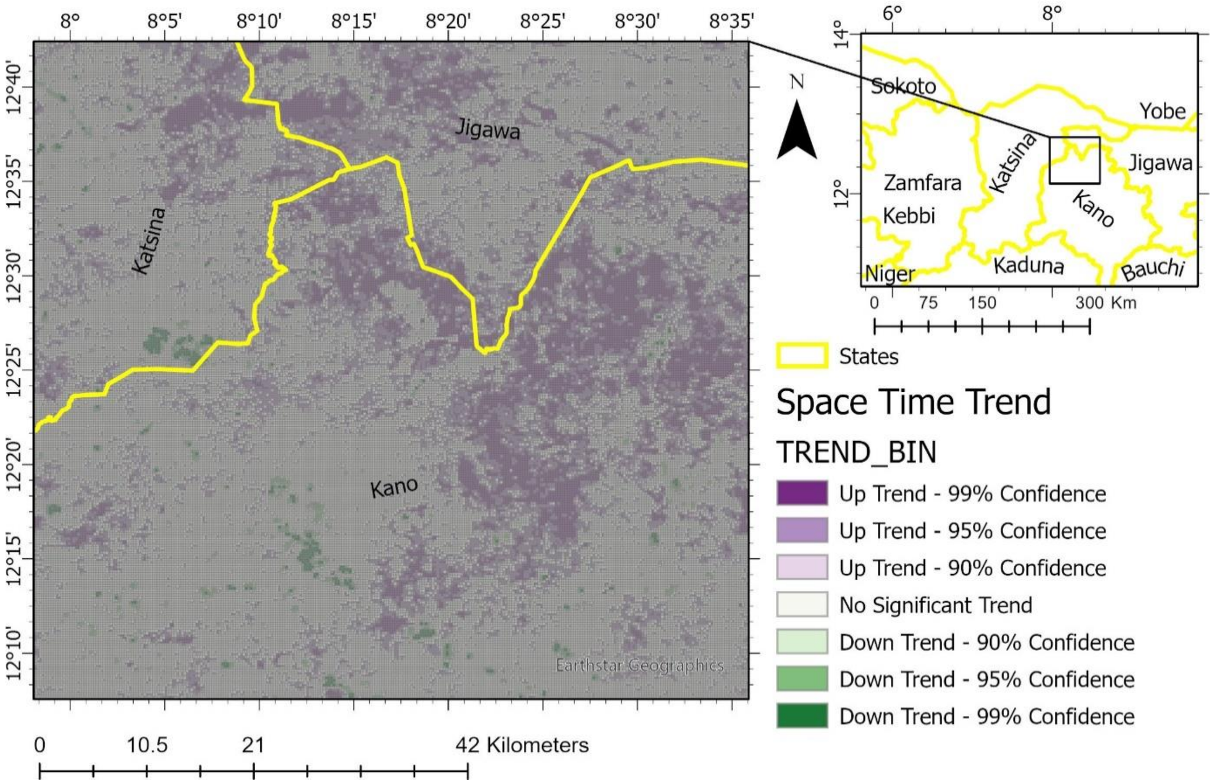

Figure 8: Space-time trend of GDVI values 2001 -2020

The analysis of the time series showed, based on the values, that there are two clusters of time series discernible from the dataset (Figure 9) – using the Mann-Kendal trend statistics (MKTS). Cluster 1 (Figure 9a) showed an average ranging between 0.54 and 0.62 over the 20 years. Therefore, these areas maintain a moderately vegetated cover through the period under consideration. It should be noted there were some sharp declines – notably 2006 – 2008, 2012 – 2016 and 2019 -2020 for this cluster. The trend statistics showed that for these areas, there is no statistically significant trend (MKTS = 1.33, p-value = 0.18). In the case of Cluster 2 (Figure 9b), the average GDVI across the 20 years is higher (0.74 -0.80) than that of Cluster 1. However, this time series cluster experienced more fluctuation across the years. A decline started in 2004 and ended in 2010; this was followed by a sharp increase till 2012 after which another decline started and continued until 2016. This cluster has witnessed on average an increase and stabilisation of GDVI since then. From the trends statistics, the cluster displayed a statistically significant decreasing trend of GDVI (MKTS = -2.37, p=0.02).

Examination of the distribution of these clusters (Figure 10) showed that about 95% of the area belongs to Cluster 1 with the remaining belonging to Cluster 2. The second time series clusters appear most often around floodplains indicating that they are croplands (so also due to their relatively high GDVI).

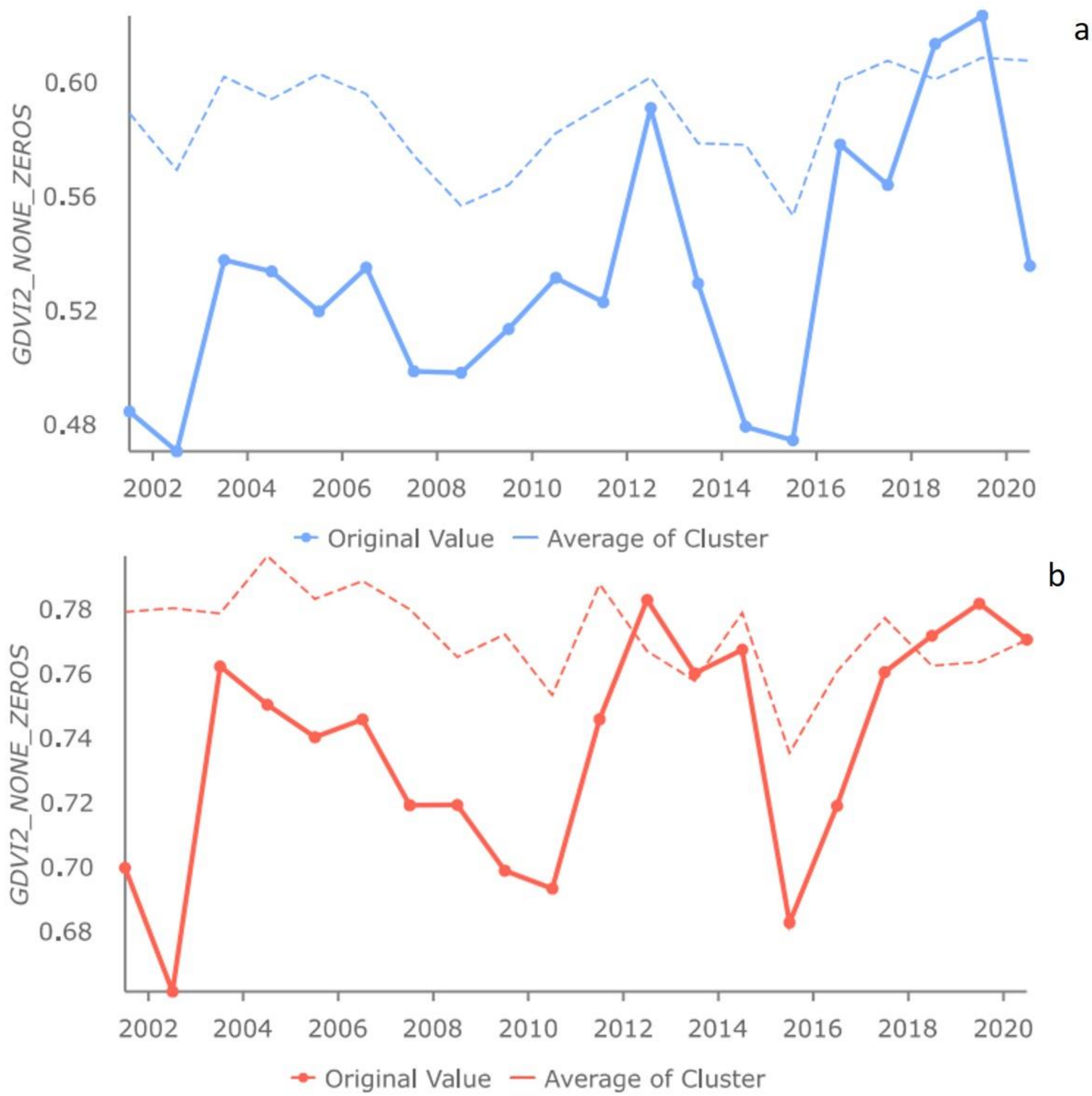

Figure 9: Typical time-series clusters identified from GDVI values across the rainy season in the study area (a) Cluster 1 and (b) Cluster 2.

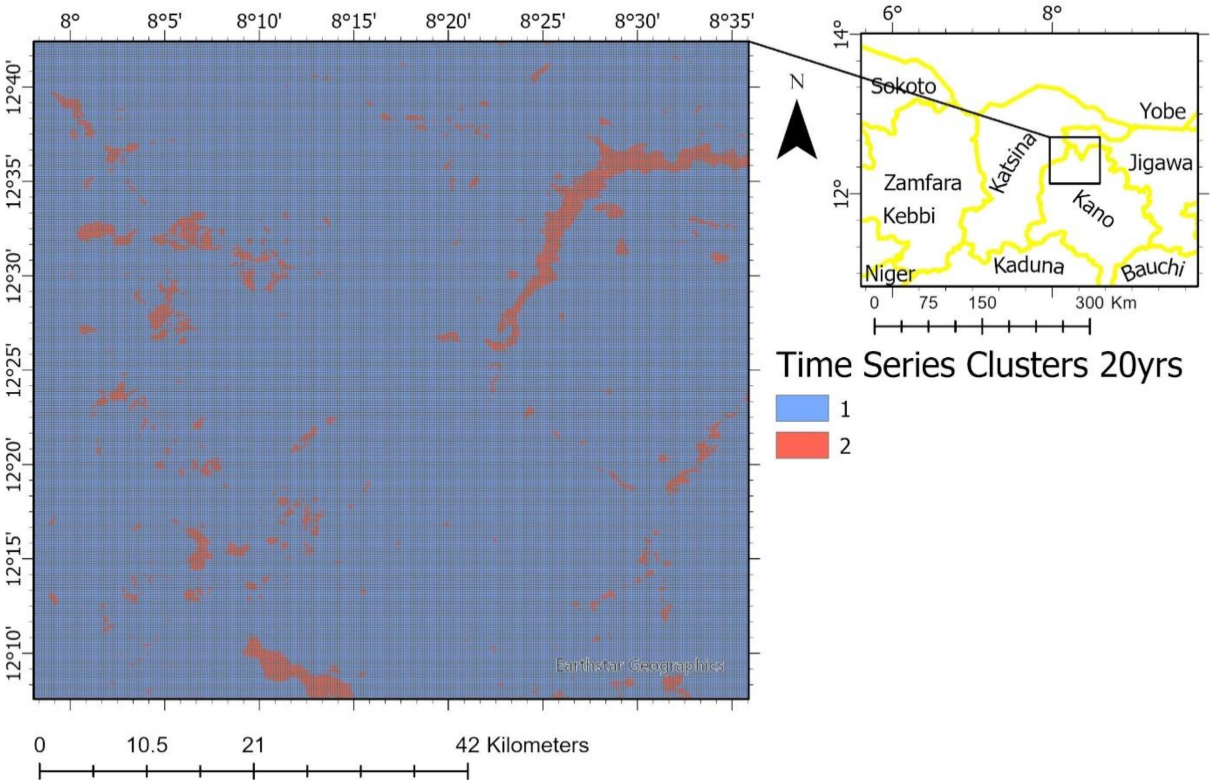

Figure 10: Time series cluster distribution across the study area

Emerging Space-Time Pattern

The space-time pattern combines the neighbourhood effect for time and space to identify the emerging pattern of the GDVI values over the 20 years considered for the study area during the rainy season. The result (Figure 11) showed that there are 7 different emergent space-time patterns. About 2% of the patterns were found to be statistically significant hot spots for the GDVI. New hot spots are areas that became hot spots (in time and space) just in the last time step and were never hot spots in previous years i.e., these are areas where GDVI values increased across neighbours both in time and space just in the year 2020. Another type of hot spot identified is the oscillating hot spot. These areas were found to be hot spots in 2020 but had cold spots sometimes in the past while being hot spots for less than 90% of the time steps. These areas have witnessed changes from a cold spot to a hot spot and vice versa in the past; however, they are hot spots in the final time step. This oscillation captures the trend of the GDVI values both in time and space. About 1% of the area showed no discernable space-time pattern, thus, even though there are noticeable changes in space and time, the patterns are not statistically significant to be classified. This result indicated that a very small proportion of the area considered could not be spatiotemporally distinguished in terms of their GDVI values during the rainy season between 2001 and 2020.

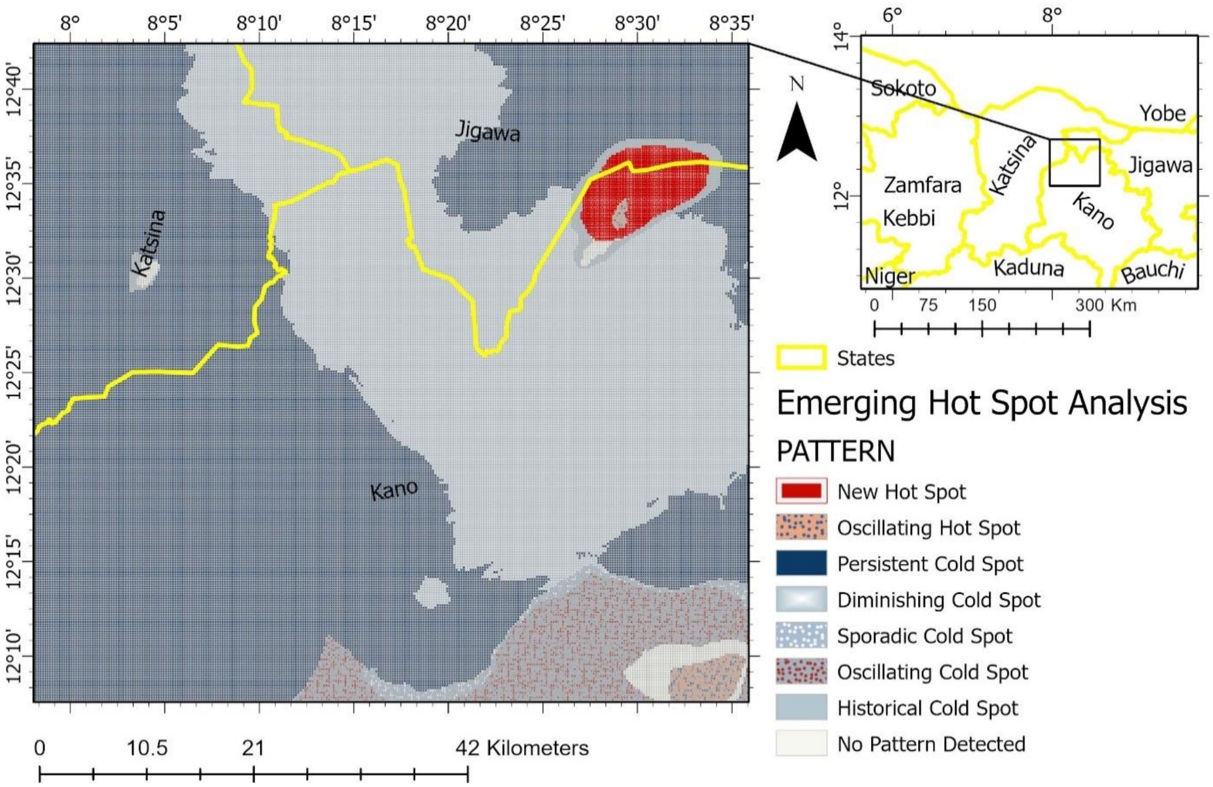

Figure 11: Space-time emerging pattern of GDVI (2001-2020)

About 97% of the total area examined belongs to the space-time cold spot. These areas have low GDVI value neighbours in time as well as in space. Five statistically significant classes of cold spots were identified. The majority belongs to the Persistent cold spot, these areas have been cold spots for 90% of the time with no clear trend of increase or decrease in the values of GDVI over time. These areas have neighbours with low GDVI values surrounded by neighbours with low GDVI values while over time shows no clear trend of increase or decrease in GDVI values. The indication is that these areas are slightly stable with low vegetative cover. The diminishing cold spot is the second dominant type of cold spot. This cold spot type covered about 36% of the area considered in this analysis. They represent areas where for 90% of the time, they were cold spots (including the last time step - 2020), moreover the clustering of low GDVI values was decreasing across each time step. This indicated that these areas are cold spots over time however, the intensity of the clustering of the cold spot is decreasing over space. Oscillating cold spot covers around 5% of the area, these areas are cold spots in the final time step but in the 20-year history have been hot spots at some time and less than 90% of the time step have been cold spots. These areas changed from cold to hot spots at some time during the 20 years, however, they are cold spots in the most recent time. Sporadic and Historical cold spots were also found with each covering about 1% of the study area. Historical cold spots have the most recent time not as cold spots but at least 90% of the time they were cold spots. Thus, for at least 18years these areas were cold spots for GDVI during the rainy season, but they were hot spots in 2020. In the case of sporadic hot spots, they were never hot spots during any period, but have been cold spots for less than 90% of the time while sometimes changing between cold spots and no pattern areas.

Discussion

The result of the temporal analysis (Figure 7) showed that across the 20 years examined, most areas displayed no clear trend in vegetative cover, while many other places showed a temporal increase (over the 20 years) in GDVI values. This finding indicated that vegetative cover, as indicated by GDVI witnessed no distinct trend over this period. Furthermore, another 43% of the areas showed an uptrend in their GDVI values. It should be noted that an increase in GDVI value does not necessarily mean we have luxuriant vegetation - an increase is just an increase in GDVI. However, clustering the time series data (20 years average) showed two clusters. The clusters thus point to the cropped areas around floodplains and other vegetated areas, which combine cropped woodland and rangeland. The first time-series cluster identified could be seen as a mixed vegetative surface that could survive with the available rainfall (most notably sparse vegetation of shrubs, woody perennials, and some grasses). Due to the spatial resolution of the dataset, it is not possible to clearly distinguish between these different classes of vegetative covers. These findings revealed the importance of considering the temporal dimension in spatial analysis.

From the spatial distribution of the 20 years average of the GDVI, it is evident that relatively high GDVI values are compact - occurring around floodplains. This observation is understandable since the terrain, or the characteristics of the place influence the occurrence of more luxuriant vegetation around such areas. This phenomenon captures the first-order effect whereby the conduciveness of a place for specific events to occur drives the non-randomness in the distribution of the GDVI. Therefore, the abundance of water in and around the floodplains drives the clustering of high GDVI values around these places.

The space-time analysis created an understanding of how vegetative covers are clustered over space and in time. Thus, revealing where the changes in time and space create new conditions for vegetative cover. Over the 20 years across the rainy season, there is an indication of more cold spots than hot spots. This result showed that there are more areas where vegetative cover remained low over time and space. More so, emerging patterns like diminishing cold spots represent areas that require attention, as the results suggest that such areas are witnessing declining GDVI. This observation could help identify where dryland degradation may be emerging.

The locations with decreasing GDVI values represent areas that require further examination because the declining GDVI values could:

1. signify an initial phase of degradation;
2. highlight areas with opportunities to intervene before the situation worsens;
3. represent areas with high human pressure resulting in negative impacts; and
4. reveal areas with a need for more monitoring to prevent further degradation.

The hot spots identified are also worth monitoring due to the delicate nature of the dryland ecosystem. If the pressure becomes excessive and land management is not carefully executed, these highly productive areas could quickly become badlands. As pressure on high-quality lands and water mounts due to increasing population, the need for closer monitoring of the drylands becomes pertinent in ensuring that desertification does not set in. Sporadic and historical cold spots are likely to be areas where production is currently low due to the interaction between human activities and the climate. While they may be less productive now, there is an opportunity that since there is less pressure on such places, it is plausible that soil restoration across these areas could enhance ecosystem services in the region.

The resilience of the dryland ecosystem is well known; however, the pressure from human activities is one of the leading causes of its degradation. This resilience has often given land managers the confidence to continue to manage the land as they deem fit without paying attention to sustainability. The results have shown that there is a decline across the period examined, and the lack of attention toward building the resilience of the system will have dire consequences if appropriate actions are not taken at all levels. This challenge has implications for food security, human security, and the economic sustainability of the entire country.

Conclusion and Recommendations

From the temporal analysis, we conclude that there seems to be no temporal pattern for most places across the 20 years of rainy season data of vegetative cover. However, other places within the area have indications of an uptrend in vegetative cover. Thus, a mix of both increase and no pattern.

Time-series clustering examined the GDVI values across time to find statistically significant trend clusters. From the findings, we conclude that most of the areas showed no particular temporal trend, while a small proportion (5%) showed decreasing trend. These areas are found around the floodplains and represent areas where there is a need for attention to mitigate continued ecosystem service degradation.

The space-time analysis revealed the pattern formed over time and in space; thus, we can conclude that 97% of the area has witnessed a decline in GDVI, and there is a need to pay close attention to controlling dryland degradation. If the delicate balance continues to be tipped in the direction of unsustainable utilisation of resources (bush burning, deforestation, firewood collection, overgrazing, etc.), restoration of the dryland and negative impacts of degradation might continue in this region. The impacts are likely to remain in the northern region of the country. Therefore, addressing dryland degradation is not just a northern issue; it is a national issue.

It is recommended that further studies should explore higher power GDVI in studying dryland degradation in the region. Furthermore, higher resolution remotely sensed data and the computing facilities to handle such Big Earth Data should be deployed to facilitate monitoring and prompt delivery of solutions.

Deployment of desertification control measures and programmes is laudable, however, without active monitoring and coordinated actions, the impact of such projects and programmes will remain minimal owing to the enormity of the task. There is a need for a new dimension in the effort to reverse desertification and dryland degradation in Nigeria, such a new dimension should include the restoration of degraded soil, bringing such lands back to a state where they can be utilised sustainably.

Data Availability

Data used for this study is openly available from USGS MODIS Data Archive.

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