World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

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Monitoring rainfall and drought trends using remote sensing-derived climate and vegetation indices in semi-arid eco-zone, Nigeria

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World Journal of Advanced Research and Reviews, 2025, 28(01), 660-674

Publication history: Received on 19 August 2025; revised on 06 October 2025; accepted on 08 October 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.28.1.3340

Abstract

Along with flooding and wildfire, Drought is a major natural hazard that continues to ravage the environment in many parts of the world, causing widespread social and economic devastation as evidence of climate change. This study aimed to assess the spatiotemporal pattern of drought events across Sudano-Sahelian Ecological Zone of Nigeria. This analyzed the daily accumulated precipitation and temperature from seven (7) weather stations in the study. Although scientists have relied on data obtained from meteorological stations. However, meteorological data are mostly scarce, expensive and sparsely distributed, especially in developing countries. This research was conducted using (CHIRPS) datasets from 1987-2022 to calculate SPEI and the SVI derived from MODIS using the Google Earth Engine cloud platform. The spatial and temporal variation of vegetation conditions in the Sudano-Sahelian region of Nigeria were examined using SVI. The results showed mild drought events at some parts of the study area, but there were severe to extreme drought events at Maiduguri station experiencing extreme drought in 2012, severe drought in 2004, 2005 and 1990, and moderately dry conditions in most years. Extremely wet conditions in 2012 and very wet conditions in 1994, 1996, and 1989. Katsina station experienced drought extremes in 2022, 2010, and 2005 while in Kano station, extreme drought was notably recorded in 2004 and 2006 (SPEI > -2). The findings show that drought affects the vegetation health and agricultural activities in the study area (SVI -3.7). The result of the study is important for policy decisions, water resources management in the face of increasing drought risks in the semi-arid region of Nigeria providing evidence-based insights for the development of early warning systems and strategic communication frameworks to mitigate the socio-economic impacts of droughts in vulnerable communities.

Keywords: Drought; Climate change; Rainfall; Temperature; Vegetation; Remote Sensing

1. Introduction

Drought is one of the costliest and the most widespread natural disasters. It is however less understood because of its large spatial extent and the difficulty in determining its onset and cessation compared to flood. (1); (2). Previous studies have reported that there is an increase in the frequency and intensity of extreme weather events such as drought and flood due to the impact of climate change (3). (4) asserted that more than one billion people around the world have been affected by one form of drought or another in the last two decades with a devastating economic loss, especially the droughts of the 1970s and 1980s that ravaged the Sahelian region of West Africa. Drought emerges as compelling

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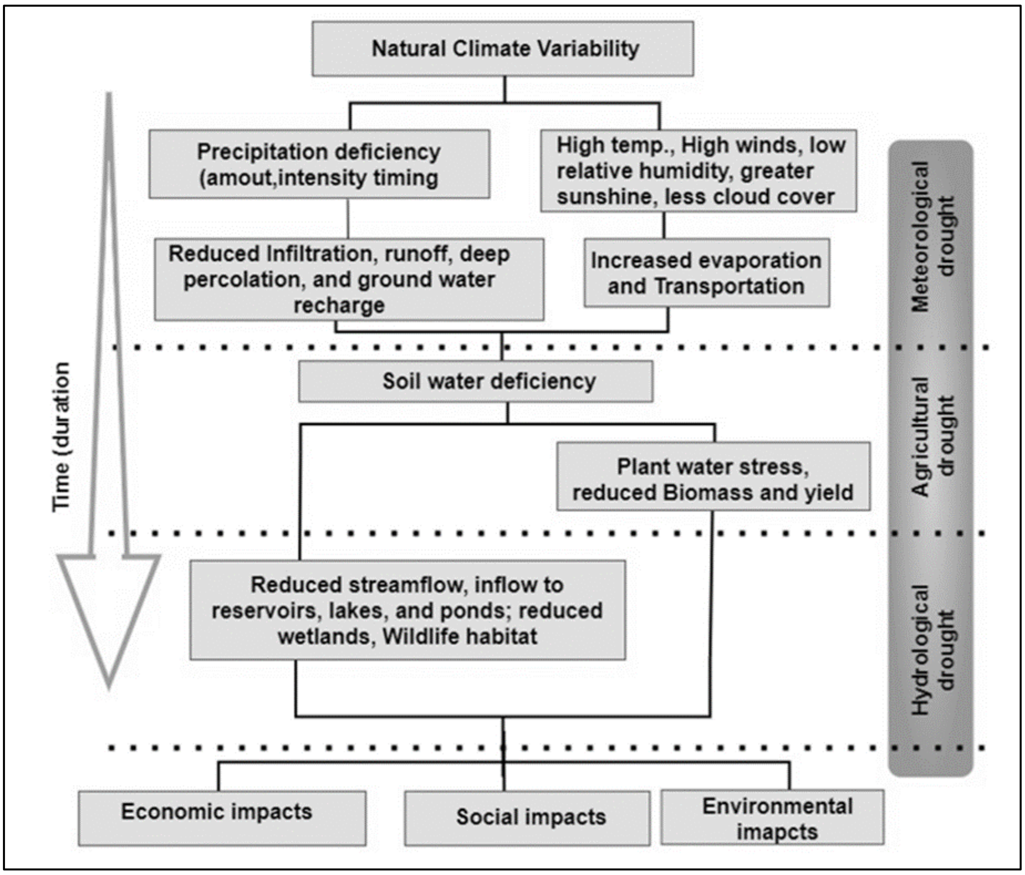
evidence of climate change and a global challenge anticipated to escalate in frequency, duration, and intensity, as projected by Huang (5); (6). This encompasses various dimensions of drought events, including their frequency, severity, duration, and spatial coverage, as outlined by (7).

This encompasses various dimensions of drought events, including their frequency, severity, duration, and spatial coverage, as outlined by (7). Drought is a recurring natural disaster (9); (10), caused by low rainfall over a prolonged period (8); (9). It is widely regarded as a creeping phenomenon because it accumulates slowly over a long period (11); (13). Rainfall is known as a major contributing factor to drought events, and the aftermath is manifested in the reduction of reservoir water level, decrease of soil moisture, declining river flow and groundwater levels leading to a substantial effect on agricultural production (14), water resources (15), ecosystem function (16) both local and global environment. Virtually all climatic zones experience drought regardless of the region (17), (47). However, the arid and semi-arid areas are prone to drought due to low rainfall and a high rate of evapotranspiration, and the impact varies from one region to another (18). This makes the prediction of the onset and cessation of drought challenging (19); (20). This is common around the Sahelian regions that practice rain-fed agriculture (21).



Source: (Author's work)

Figure 1 Relationship between Meteorological, Agricultural, and Hydrological Drought

The drought events that occur in the Sahel-Sudano region of northern Nigeria are known to be as a result of late onset of the rainy season and early cessation of rainfall whereby causing a reduction in the length of rainy season (22). The Sudano-Sahelian region is known for its source of cereals and animal protein and the region is characterized by low rainfall and severe drought conditions due to climate change (23). The usage of vegetation cover is an important drought indicator since vegetation cannot survive without water. The use of remotely sensed data and GIS applications has proved effective in detecting, mapping, assessing, monitoring, and giving timely information regarding drought event features such as onset, intensity, duration, and spatial extent (24), (48). The sociological impact of drought is often heightened by a gap between scientific data and actionable public knowledge.

Satellite-based indices used to monitor the health of vegetation cover include the Standard Vegetation Index (SVI) (25), the Normalized Difference Vegetation Index (NDVI) (26), the Precipitation Condition Index (PCI), the Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI). The variability of climate in Nigeria, particularly the

Sahel region are experiencing frequent drought events due to frequent evaporative demand (27). Additionally, drought in the region has caused forest mortality that affects Carbon dioxide ($CO2$) sequestration, impacts soil compaction, hinders agriculture, and degrades the aesthetics of the surrounding area. This research will explore the geographical and temporal effects of drought on vegetation health in Nigeria's Sudano-Sahelian ecological zone. Drought can be classified as agricultural, meteorological, hydrological, or socio-economic (28); (29).

2. Material and method

2.1. Study Area

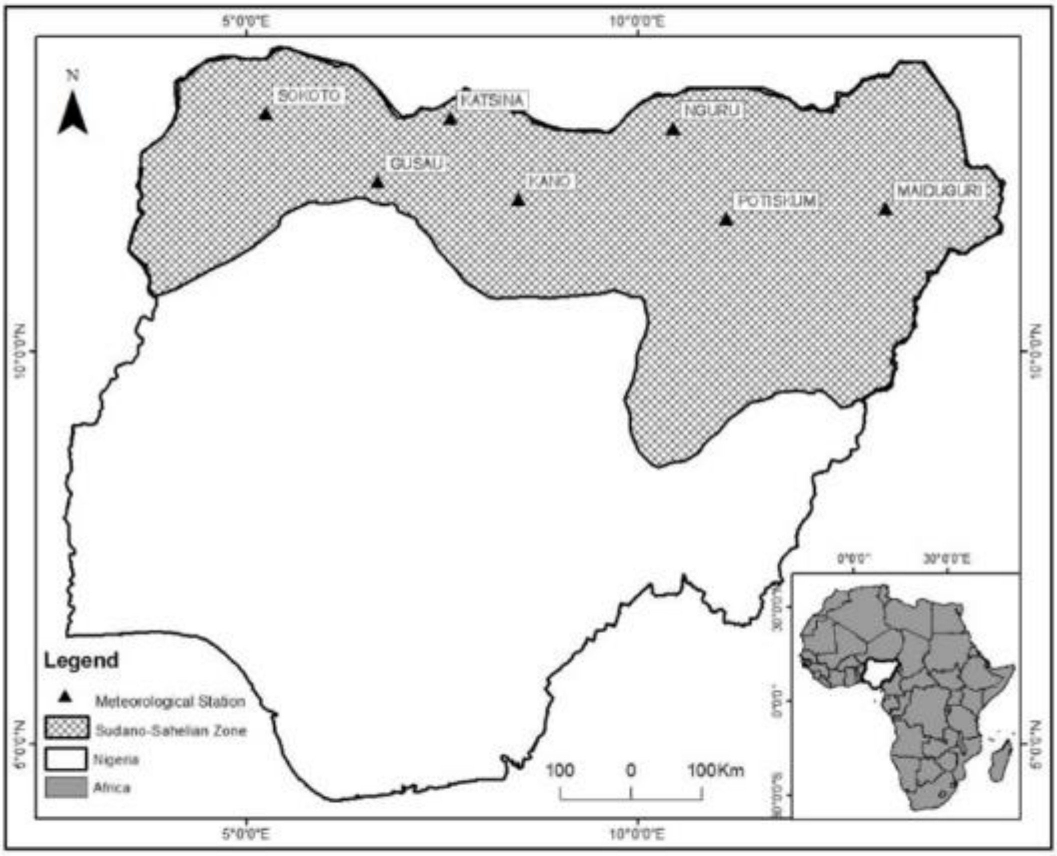


Figure 2 Sudano-Sahelian Ecological Zone (SSEZ) of Nigeria. *Source:* (Author's work)

2.1.1. Location, size and extent

Figure 1.1 depicts the Sudano-Sahelian Ecological Zone (SSEZ), which covers roughly one-third of Nigeria's land area. This region extends longitudinally from 4° E to 14° E and latitudinally from 10° N to 14° N, from the Sokoto lowlands to the northern half of the Hausa high plains and the Chad basin.

Sokoto, Kano, Katsina, Maiduguri, Nguru, Potiskum, and Gusau are the seven meteorological stations selected for this area. This ecological zone is home to more than a quarter of Nigeria's population and sustains three-quarters of the country's cattle population, over 75% of its goats and sheep, and virtually all its donkeys, camels, and horses. The predominant crops cultivated in this region include cereals, cowpeas, groundnuts, and cotton, as highlighted by (30).

2.2. Data Description and Sources

This study calculated the daily accumulated precipitation and temperature from daily data of 1987–2022 for seven (7) weather stations from Sudano-Sahelian ecological zone of Nigeria. The weather stations include Sokoto, Katsina, Gusau, Kano, Nguru, Potiskum and Maiduguri. The satellite-based precipitation product was obtained from CHIRPS product obtained from www.climateserv.servirglobal.net covering 1987 to 2022 while the temperature data were defined from the website of Power.larc.nasa.gov.

Table 1 Data and their sources

S/N	Data type	resolution	Source	Date
1.	MOD13Q1.006	250-1000m	https://glovis.usgs.gov./app.	2000-2022
2.	CHIRPS Precipitation Dataset	0.05° × 0.05°	https//climateserv.servirglobal.net	1987-2022
3.	Temperature data	1° × 1°	https//Power.larc.nasa.gov.	1987-2022

Table 2 List of the meteorological stations in the study area

S/N	Name of Station	Latitude (^{0}N)	Longitude (^{0}E)
1	Nguru	12.87	10.45
2	Kano	11.96	8.47
3	Maiduguri	11.84	13.17
4	Gusau	12.19	6.68
5	Katsina	12.99	7.61
6	Sokoto	13.05	5.26
7	Potiskum	11.71	11.12

Source: (Adegun and Odunuga, 2022)

2.3. Variability of Meteorological Drought

2.3.1. The Standardized Precipitation Evapotranspiration Index (SPEI)

This study used the Standardized Precipitation Evapotranspiration Index (SPEI) to determine the duration and severity of drought occurrences in the study area. SPEI uses both precipitation and potential evapotranspiration (PET) data, accounting for the influence of air temperature, as opposed to the Standardized Precipitation Index (SPI), which only uses monthly precipitation data (35). SPEI can be calculated at any timescale, such as 1-, 3-, 6-, 12- and 24- months respectively (36). But in this study, six months' timescale was used to calculate the SPEI. The SPEI values above zero signify moisture conditions that are higher than average, whereas values below zero indicate drier conditions. SPEI was calculated using the SPEI calculator application. This software was run from the Windows prompt, with input from a data file including a monthly time series of precipitation (mm), mean temperature (°C), and geographic coordinates of meteorological stations in the research area. The application calculates the SPEI accumulation using the 6-month timeframes and generates a new data file with the SPEI time series. SPEI data was analyzed to determine the intensity, duration, and severity of drought (37).

Table 3 Classification of SPI and SPEI Values (Fung *et al.,* 2020)**.**

Classification	SPI (McKee et al., 1993)	SPEI (Vicente-Serrano et al., 2010)
Extremely wet dry	≥ 2.00	≥ 2.00
Very wet	1.50 to 1.99	99 1.50 to 1.99
Moderately wet	1.00 to 1.49	1.00 to 1.49
Normal	-0.99 to 0.99	−0.99 to 0.99
Moderately dry	−1.49 to −1.00	−1.49 to −1.00
Extremely dry	≤ −2.00	≤ −2.00

2.4. Standardized Vegetation Index (SVI) Calculation

The Standardized Vegetation Index (SVI) was developed by (25) and describes the probability of variation from the normal Enhanced Vegetation Index (EVI) over several years of data, on a weekly (or 16 days). The SVI can either be calculated through Enhanced Vegetation Index (EVI) or based on the Normalized Difference Vegetation Index (NDVI). Several studies have used the NDVI as an indicator for vegetation's growth status and level of greenness; however, numerous studies have demonstrated that EVI outperforms NDVI in terms of vegetation coverage (38). More so, the EVI tends to boast the vegetation signals and enhance the monitoring of vegetation (39).

This study used monthly EVI data from MOD13Q1 with a spatial resolution of 250m and a temporal resolution of 16 days. SVI was used to visualize vegetation changes for drought monitoring in the study area. This was calculated with the Google Earth Engine (GEE) code editor. EVI can separate soil and atmospheric influences from the plant signal by introducing a feedback term for simultaneous correction, and it has higher sensitivity under thick vegetation conditions and less influence from aerosols. The SVI is a z-score deviation from the mean in units of the standard deviation. When a Z-score is less than zero (0), it denotes an element less than the mean, when it is equal to zero (0), it is an element equal to the mean but when it is greater than zero (0), it means the element is greater than the mean. The Z-score shows how many standard deviations an item is from the mean; generally, the standard deviation indicates how dispersed the data set is (25).

Table 4 The classification of SVI and drought levels (Juntakut *et al.,* 2021)

Level	SVI Value	SVI category Drought	Drought category
1	1 1.50 to 2.50	Very high vegetation	Very low drought
2	0.50 to 1.50	High vegetation	Low drought
3	-0.50 to 0.50	Moderate vegetation	Moderate drought
4	-1.50 to -0.50	Low vegetation	High drought
5	-2.50 to -1.50	Very low vegetation	Very high drought

Source (Author)

3. Results and discussion

3.1. Meteorological Drought: Severity, Intensity, and Frequency

Understanding drought characteristics is critical for developing adaptive solutions to alleviate drought-related harms. Drought severity is determined by the cumulative values of SPI or SPEI within a drought episode (Mckee et al., 1993), whereas drought frequency is determined by the total number of years of drought based on annual or seasonal indices (40). Figure 3(a-g) depicts meteorological drought patterns that provide a thorough understanding of the vulnerability of various meteorological stations to drought events in the study area. The results from the Gusau station (Figure 3a) show drought severity in 2004, 2022, and 1990, with significantly higher drought frequencies. Notable is the transition from mild drought in earlier years to more severe drought in later periods, with a sudden shift to an exceptionally wet period in 1991. This dynamic pattern agrees with findings from previous studies by (41) and (42), who similarly highlighted the variability in drought occurrences and the abrupt nature of climate shifts in the region. The rapid shift from extreme drought in 1990 to exceptionally wet conditions in 1991 in Gusau suggests a result of peculiarities of regional climatic changes and human activities such as deforestation (43).

Kano's experience of extreme drought in 2004 and 2006, followed by a period of moderate drought between 2012 and 2022, agrees with the fluctuating nature of drought cycles. Nguru's extreme drought peaks in 1987 and 2004, along with an abrupt change of more frequent wet years in 2013, 1988, 1994, 1998, and 2020 because of climate change. Examining the meteorological conditions in Potiskum (Figure 3d) demonstrates a tendency towards moderately dry conditions with the highest drought recorded in 2022 (SPEI = -2). Conversely, 2020 marked the wettest year, exceeding SPEI 2.5. Most years displayed near-normal conditions, except for 1994, 2004, and 2013, exhibiting very wet indicators (SPEI > 1.5). This understanding aligns with assessments of Potiskum's climatic tendencies, emphasizing the importance of long-term drought risk assessments (28).Katsina (Figure 3e) faced drought extremes with a higher frequency in 2022, 2010, and 2005, to periodic severe drought events. Sokoto (Figure 3f) exhibited extreme and severe drought interspersed with moderately dry conditions which coincided with (44) recognition to recurrent drought with intermittent wet periods. In Figure 4.2g, Maiduguri experienced an extreme drought in 2012 and severe drought in

2004, 2005, and 1990, along with predominantly moderately dry conditions in most years. Extreme wetness in 1989 decreased to very wet conditions in 2012, followed by moderately wet conditions.

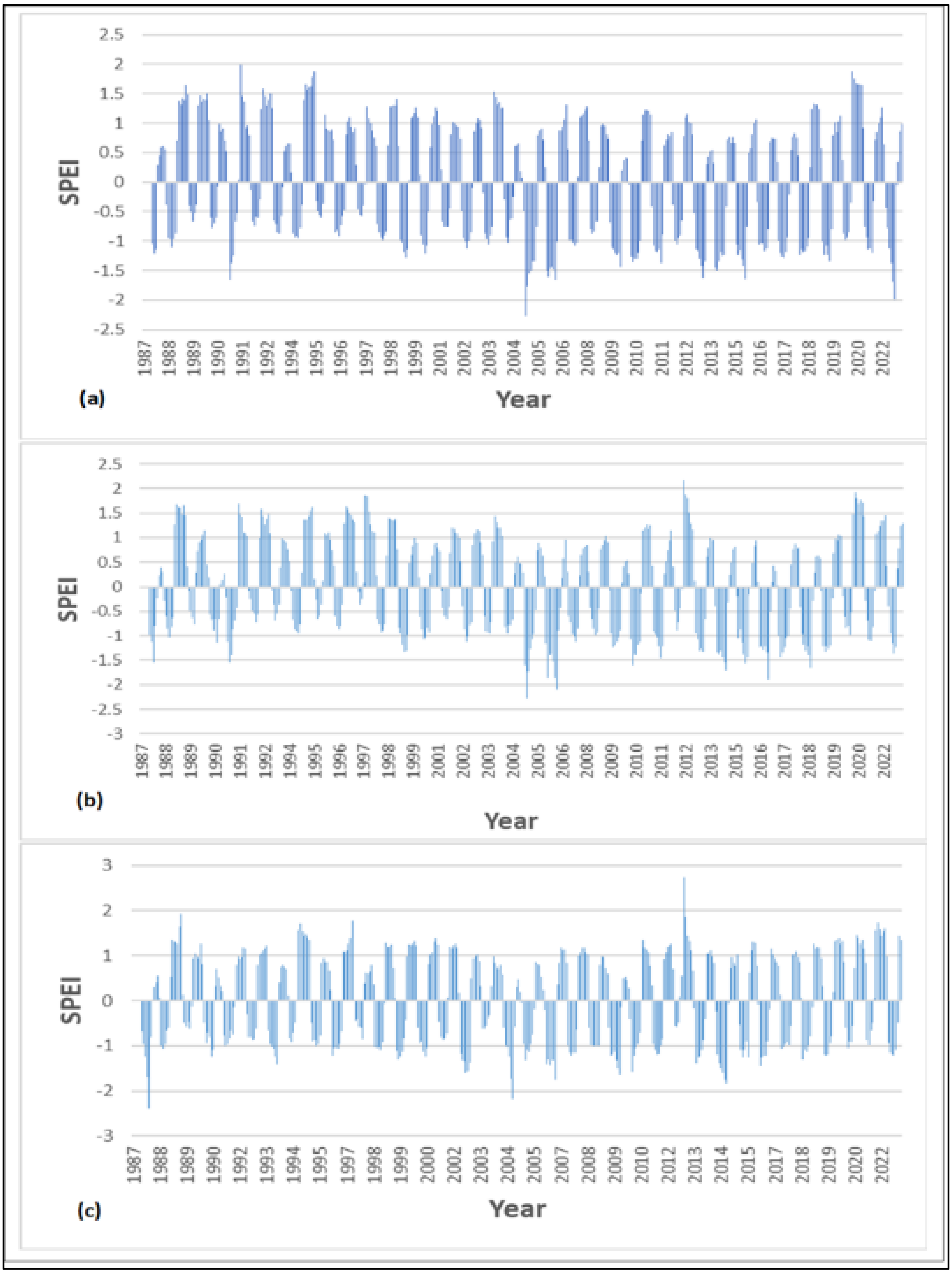


Figure 3a-c Drought characteristics in (a) Gusau; (b) Kano; (c) Nguru (1987-2021)

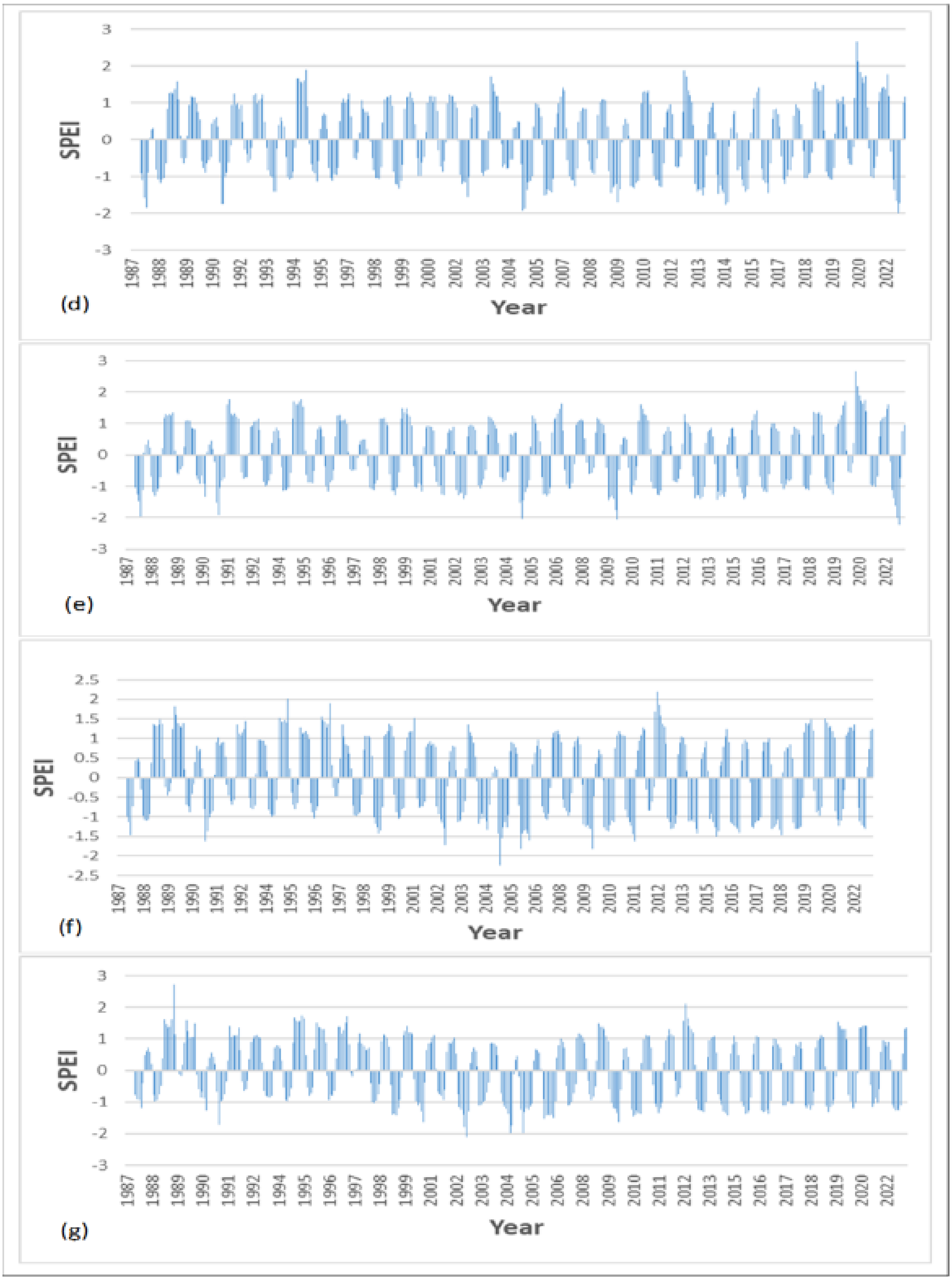


Figure 3d-g Drought characteristics in (d) Potiskum; (e) Katsina; (f) Sokoto, and (g) Maiduguri (1987-2021)

3.2. The spatial distribution of vegetation conditions in the study area

The application of the Standardized Vegetation Index (SVI) emerged as a pivotal tool in assessing and monitoring vegetation conditions in the Sudano-Sahelian zone of Nigeria during the years 2001, 2010, and 2020. The impact of drought on vegetation varies significantly across seasons and differs among regions as a result of precipitation stress. Figures 4-6 present a comprehensive spatio-temporal comparison of the vegetation conditions in the study area.

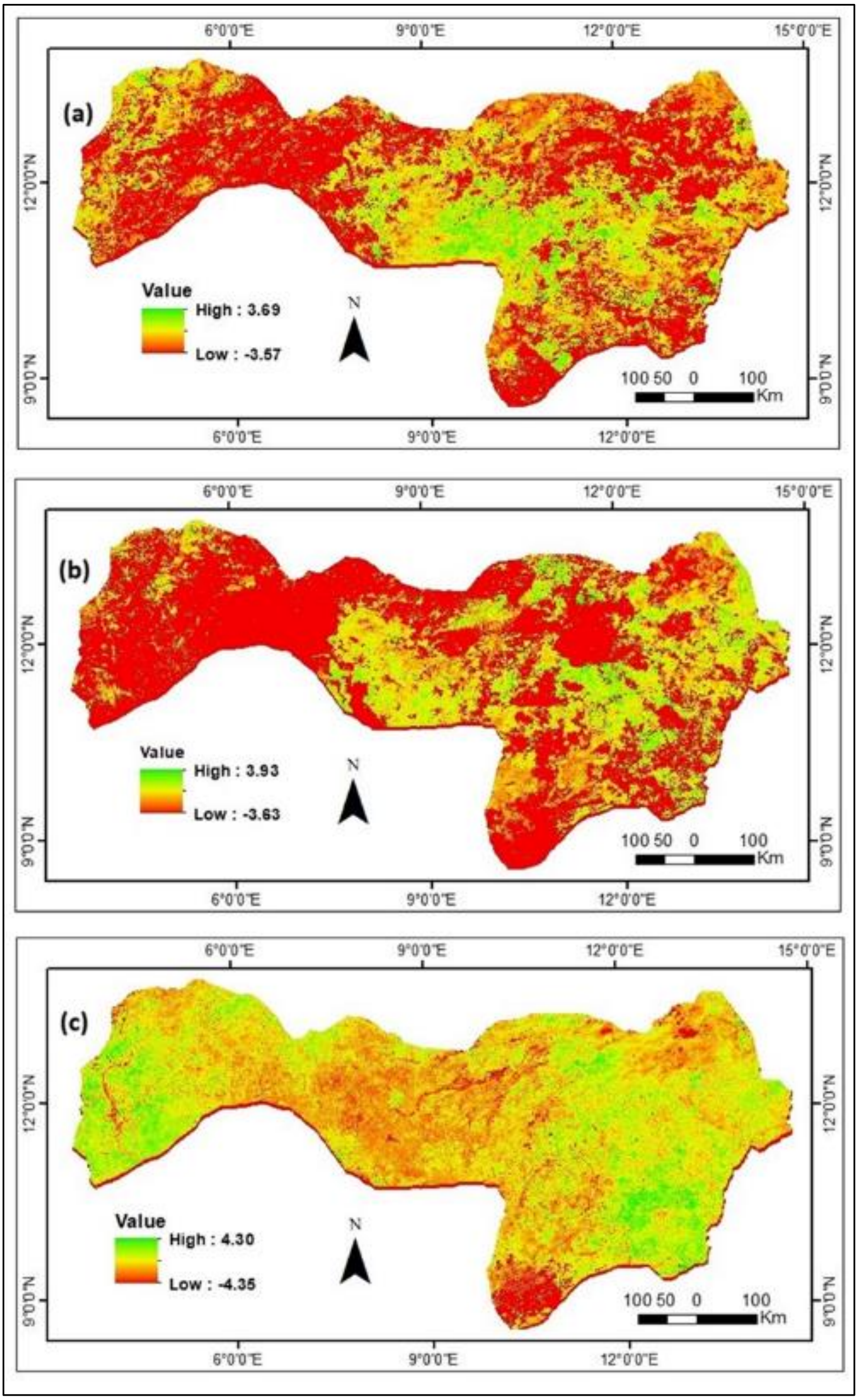


Figure 4 Standardized Vegetation Index at the Sudano-Sahelian Zone for (a) July, (b) August and (c) September, 2001. *Source:* (Author's analysis)

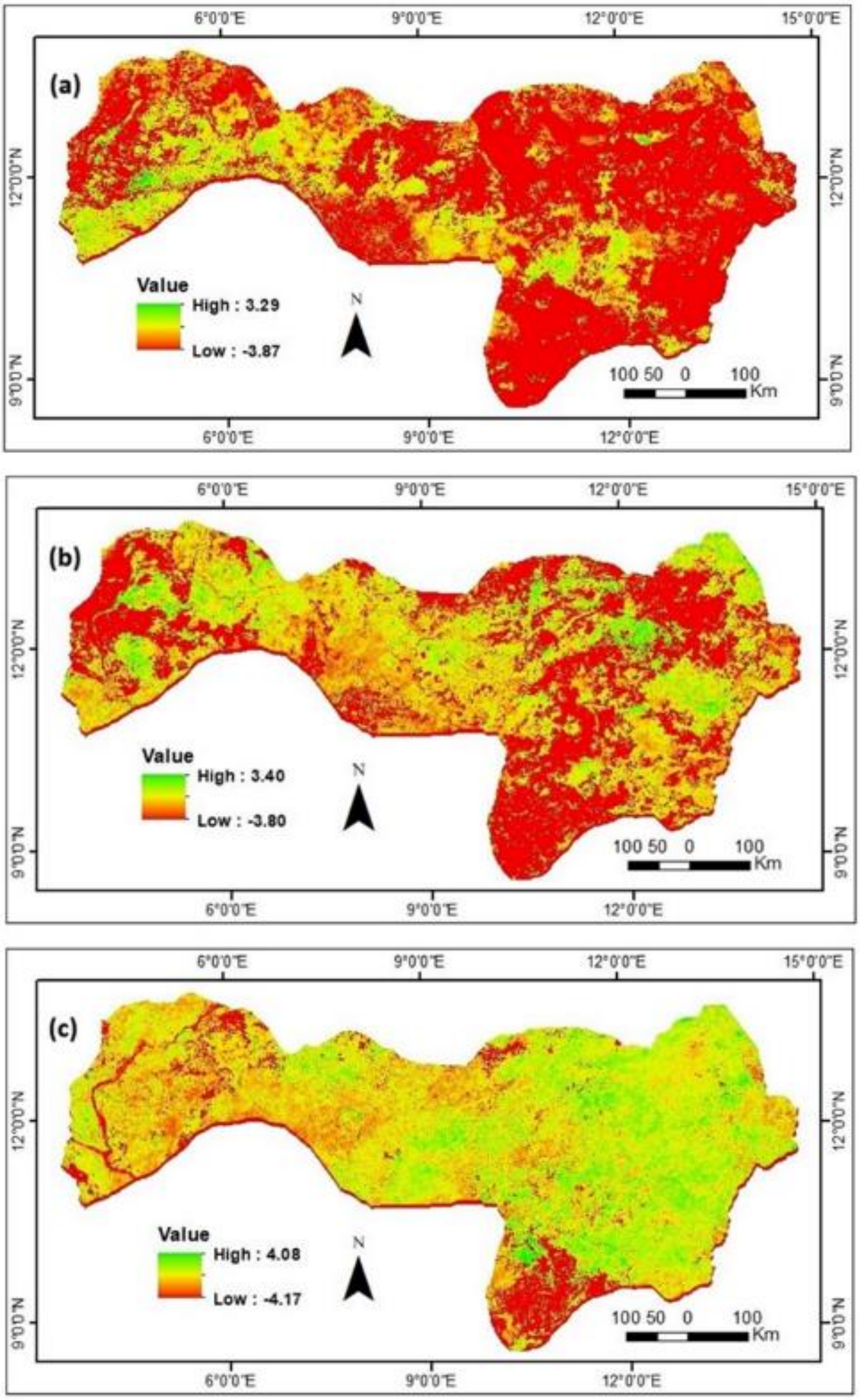


Figure 5 Standardized Vegetation Index at the Sudano-Sahelian Zone for (a) July, (b) August and (c) September, 2010.
Source: (Author's analysis)

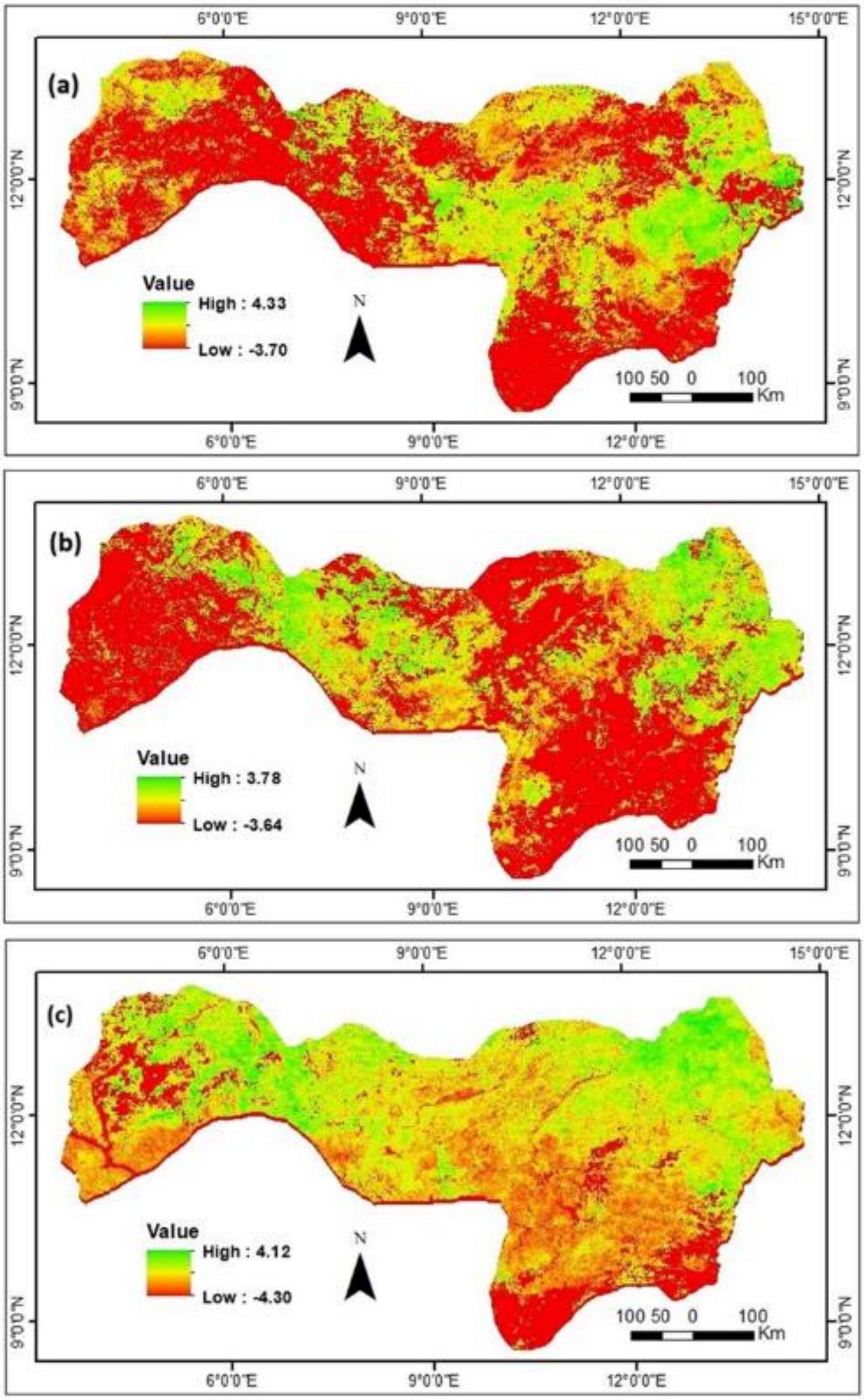


Figure 6 Standardized Vegetation Index at the Sudano-Sahelian Zone for (a) July, (b) August, and (c) September 2020. *Source:* (Author's analysis*)*

In 2001 (Figure 4), the SVI values in July ranged from 3.69 to -3.57, indicating severe drought affecting most of the study area as it is evident in the vegetation condition. Notably, the central and eastern regions around Potiskum exhibited milder drought conditions, showing some vegetation resilience with the highest SVI value of 3.69. August continued to witness widespread drought (SVI -3.63), but scattered vegetation pockets emerged in the central and northwestern areas. By September, the central region displayed moderate drought conditions as result of the presence of vegetation, while the southern part experienced severe drought, demonstrating a dynamic spatial-temporal evolution and scarcely vegetation in the region. This demonstrates that SVI is a useful metric for determining the length, intensity, and spatial distribution of drought. That is, the drought conditions is associated with plant failure and productivity (45).

This suggests that the classes of drought severity (from mild to extreme) that were identified have to do with the production and general health of Sudano-Sahelian plants and crops (46). Moving to July 2010, drought (SVI -3.87) covered the entire study area, with the southwestern region witnessing moderate drought and sporadic vegetation patches in places like Gusau, Kano, and Potiskum (SVI 3.29). August saw a shift with a decrease in extreme drought (SVI -3.80), transforming several areas into moderate drought. The western and northeastern extremities exhibited improved vegetation conditions (SVI 3.80). Like 2001, September revealed a mixture of strong vegetation in the north and east (SVI 4.30) and moderate drought in the central and northeastern axes (SVI -4.35).

In July 2020 (Figure 6a), extreme drought (SVI -3.7) traversed from the west to the east, interspersed with vegetation conditions (SVI 4.33) around Maiduguri, Potiskum, and Nguru. Slight vegetation was observed in Katsina and Sokoto in the extreme north. August 2020 (Figure 6b) witnessed intensified extreme drought in the southwest and east-central parts (SVI -3.64), while the northeast and north-central regions displayed improved vegetation (SVI 3.78) amid moderate drought. September 2020 (Figure 6c) portrayed a resilient northern part with strong vegetation, while the south saw an escalation to extreme drought and moderate drought persisted around the northwest.

3.3. Implication for Strategic Disaster Communication and Policy

The spatiotemporal analysis of drought severity and its impact on vegetation health provides more than just climatological insights but invaluable evidence for interventions from agencies like the National Emergency Management (NEMA) and the Ministry of Agriculture. The results show that drought conditions in Gusau, Kano, Nguru, Potiskum, Katsina, Sokoto and Maiduguri vary widely, largely shifting from severe dryness and sudden wet spells. This variableness, as noted by (49) and (50) makes it impossible to rely on a unified response prompting the need for location-specific, anticipatory and flexible disaster communication and policy strategies. (51) add that rural communities respond more effectively to drought warnings when information is framed around their livelihoods like when to plant, irrigate or harvest rather than abstract meteorological data. The import of this is that drought forecasts presented through indices such as SPI or SVI will be more useful to Northern Nigerian farmers in Gusau, Kano, Katsina, Potiskum, Nguru, Maiduguri and Sokoto when translated to practical advice on agriculture, water use and conservation and health. (52)

The vegetation stress analysis in this study highlights hotspots that overlap with major food production areas. Several scholars such as (51), Ebi and (53) have highlighted radio and agricultural extension workers as the most trusted messengers of drought and disaster alerts in Africa. NEMA could strengthen its response by embedding advisories into community radio broadcasts in local languages, adopting in addition to SMS alerts and extension agents ensuring that monitoring results influence farmers' household decisions.

The sharp transition from extreme drought in 1990 to excessive rainfall in 1991 observed in some stations like Gusau suggest that communities face multiple environmental hazards in quick succession. As in (52) study, Malawi experience shows that alerts and messages from disaster management agencies like NEMA should integrate messages covering environmental issues like flood, drought, pests, diseases etc sent through community and traditional leaders as this would not only be effective but engender trust and preparedness instead of treating drought in isolation. This underscores the need for participatory and people-centered communication in Nigeria, incorporating indigenous knowledge, involving community authorities, and using familiar languages and channels (52).

4. Conclusion

The research shows that drought occurrences in the Sudano-Sahelian ecological region of Nigeria are increasing in frequency and intensity, adversely affecting vegetation health and agricultural output. This research establishes a dependable framework for monitoring drought patterns in areas with scarce meteorological data by merging satellite-based climate datasets (CHIRPS) and vegetation indices (SVI) using Google Earth Engine. This research establishes a dependable framework for monitoring drought patterns in areas with scarce meteorological data by merging satellite-based climate datasets (CHIRPS) and vegetation indices (SVI) using Google Earth Engine. The SPEI identified the characteristics and spatial extent of meteorological dryness in the research area, whereas the SVI demonstrates the impact of drought on vegetation. Spatio-temporal mapping of SVI reveals how vegetation responds to meteorological dry occurrences in the study area, where most stations are bare ground. The observed patterns show that the Sudano

Sahelian region is vulnerable to drought, with notable variations between years. The central and northeastern axes of the study area often experience more severe drought, while the northwest tends to exhibit better vegetation resilience. The study also shows that SVI is a reliable tool for analyzing drought impacts on vegetation and essential for policy decisions, water resources management and resilience-building efforts in the face of increasing drought risks in the semi-arid region of Nigeria associated with climate change. This can be achieved through the integration of drought monitoring and intelligence with strategic communication frameworks translating technical insights to clear actionable decisions for at-risk communities, policy makers and disaster managers. This can be achieved through the integration of drought monitoring and intelligence with strategic communication frameworks translating technical insights to clear actionable decisions for at-risk communities, policy makers and disaster managers.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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