Assessing Spatiotemporal Variations in Terrestrial Water Storage, Groundwater Anomalies, and Drought Severity Across Nigeria (2002–2024) Using GRACE Data

Bawa Swafiyudeen [a] *, Abubakar Adamu Musa [b], Abdulmumin Lukman [b] Moses Mefe [a], Aliyu Bamaiyi Usman[c]

[a]Department of Geomatics, Ahmadu Bello University, Nigeria
[b]Department of Surveying and Geoinformatics, Nuhu Bamalli Polytechnic, Nigeria
[c]Department of Water Resources and Environmental Engineering, Ahmadu Bello University, Nigeria

Abstract: This study leverages GRACE mascon solutions (CSR RL06) satellite data (2002–2024) to analyze spatiotemporal Terrestrial Water Storage (TWS) dynamics across Nigeria, integrating Groundwater Anomalies (GWA) and GRACE Drought Severity Index (GRACE-DSI) to assess hydrological extremes. The modified Mann-Kendall (MMK) and Sen's Slope methods were used to detect trends analysis over two decades (2003–2024). A Seasonal decomposition: DJF (Dec-Jan-Feb), MAM (Mar-Apr-May), JJA (Jun-Jul-Aug) SON (Sep-Oct-Nov) on a major Basin-scale assessment (8 major basins) and Climate zone Tropical Savannah (Aw), Tropical Monsoon (Am) and Arid/Semi-Arid (BSh) stratification was done. Results reveal pronounced seasonal cycles, with wet-season recharge (June–September) offset by dry-season depletion (November–April), superimposed on interannual variability driven by climate oscillations. Northern Nigeria (Sokoto Basin, Lake Chad region) exhibits severe groundwater declines (−15 to −20 cm/yr) linked to prolonged drought and irrigation, while southern basins (Niger Delta) show modest increases (+5 cm/yr) due to elevated rainfall. Critical drought episodes (2012–2016, 2016, 2019) coincide with GWA deficits ($< -2\sigma$), whereas flood-induced surpluses (2012, 2022) underscore hydrological volatility. The Lake Chad Basin demonstrates resilience through seasonal replenishment, contrasting with southern Nigeria's escalating water scarcity from anthropogenic pressures. This study advances GRACE-based hydrological monitoring in Nigeria, providing a framework for adaptive water governance in climate-vulnerable regions.

1. Introduction

Weather and temperature changes over a long period of time as a result of anthropogenic activities and variation in solar cycle is referred to climate change (United Nation, n.d.). Countries whose development depends on rain-fed agriculture are mostly affected by climate change (Ayugi et al., 2022). For example, despite having contributed very low to global warming, Africa is the most vulnerable continent to the impact of climate change, thereby posing systemic risks to its economies, water and food systems, and livelihoods. In fact, climate change is the greatest setback to Africa reaching Sustainable Development Goals (SDGs)(African Development Bank, 2019). As a result of climate change, devastating floods, droughts and water stress have affected about 250 million people and are expected to rise to about 700million by 2030(World meteorological organization). This shows how shortage of water and water stress can affect social development, ecological security and agro-meteorological variables (K. Zhao & Li, 2017) by reducing surface and ground water resources, thereby limiting Africa from achieve SDG.

A very good metric for climate change assessment and which equally plays a significant role in global water cycle is Terrestrial Water Storage (TWS) (which represents the summation of; soil moisture, groundwater, snow water, surface water, and canopy water) (M. Zhang et al., 2022;

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K. Zhao & Li, 2017). TWS changes constitute variation in precipitation, groundwater, runoff, evaporation (Öztürk, 2022). On the other hand, Terrestrial Water Storage changes (TWSCs) is the integrated changes of varying water, storage component, in the vertical, which comprises of snow water equivalent, surface water reservoir, soil moisture and ground water storage(M. Zhang et al., 2022).

About 300 million people livelihood depend on rain-fed agriculture - in-depth understanding of the spatial and temporal characteristics of TWS is important for sustainable decision and effective management of groundwater resources (Ndehedehe et al., 2016). In monitoring and estimating TWSCc, in situ data like meteorological stations and ground based absolute gravimeters are used. One major setback of these data is their poor spatial coverage. With the advancement of modern space geodesy, hybrid satellite data like Gravity Recovery and Climate Experiment (GRACE) launched in 2002 and its follow-on mission (GRACE-FO) launched in 2018 have been used in mapping TWSc and drought monitoring and forecasting (Arungwa et al., 2023; Barbosa et al., 2022; Öztürk, 2022; Syed et al., 2008; J. Zhang et al., 2020; M. Zhang et al., 2022; K. Zhao & Li, 2017). It provides TWS at global and regional scale at an unprecedented accuracy of 400km.

Nigeria, like several locations worldwide, has substantial difficulties in efficiently managing its water supplies (Shiru et al., 2021). Terrestrial Water Storage (TWS) is essential for a range of socio-economic activities, such as agriculture, industry, and human consumption. Nevertheless, the precise determination of TWS continues to be a difficult task, especially in areas such as Nigeria where there is a scarcity of in-situ monitoring systems. Therefore, it is imperative to create reliable techniques for estimating TWS in Nigeria to facilitate sustainable water resource management and reduce the likelihood of water-related hazards.

Current techniques for TWS estimation frequently depend on ground-based measurements, which are limited in number and unevenly spread throughout Nigeria. This constraint impedes thorough and prompt evaluations of water storage fluctuations, obstructing efficient decision-making. Utilizing several satellite data sources presents a hopeful resolution to this obstacle. The integration of data from satellite gravimetry, altimetry, and remote sensing allows for the ongoing monitoring of total water storage (TWS) with high levels of detail in both space and time. This approach overcomes the restrictions of relying solely on ground-based observations.

This study aims to evaluate variations in TWS across Nigeria to provide a thorough assessment of TWS dynamics with a view to properly understand the water cycle dynamics, and support climate research, water resource management, and disaster mitigation initiatives in Nigeria. The objectives are to: a) analyse seasonal and interannual variations in TWS across Nigeria (2002–2024), b) Identify regions with significant trends (increasing/decreasing TWS), c) Determine Ground water anomaly (GWA), d)

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Determine GRACE drought severity index (GRACE -DSI)

2. Materials

2.1. Study area

Nigeria is located on the West-coast Africa. It shares border to the with Niger republic, Benin and Cameroon to the North, West and East respectively (Fig. 1). Its terrain is made up of plains in the North and South which are broken up by hills and plateaus in the centre (*Nigeria | History, Population, Flag, Map, Languages, Capital, & Facts | Britannica*, n.d.). Chappal Waddi, which is about 2,419m above mean sea level is the highest area, which is along the South-eastern border with Cameroon. The Jos Plateau which is about 1,200m above mean sea level rises approximately at the centre of the country. River Niger and river Benue are the major river basins in the country.

Nigeria is tropical climate region with two distinct seasons classified as either dry or rainy season. The Southern part of the country has rainy season which starts from March to November while rainy season starts from May to October. It is almost wet and hot all year long in the South-eastern and South-western part of the country. In summary, there is a decrease in rainy season from the North to the Southern part of the country (*Nigeria | History, Population, Flag, Map, Languages, Capital, & Facts | Britannica*, n.d.). A short interruption in rainfall is experienced in August (August break) in the South, while in the North, the month of August is characterized by intense rainfall. By implication, precipitation decreases from the South-east to the Northern part of the country. The Southern region of the country is characterized with relatively constant temperature and humidity across the year. The Eight (8) different River basins are the Niger North, Niger Central, Upper Benue, Lower Benue, Niger South, Western Litoral, Eastern Litoral, and Lake Chad (Arungwa et al., 2023).

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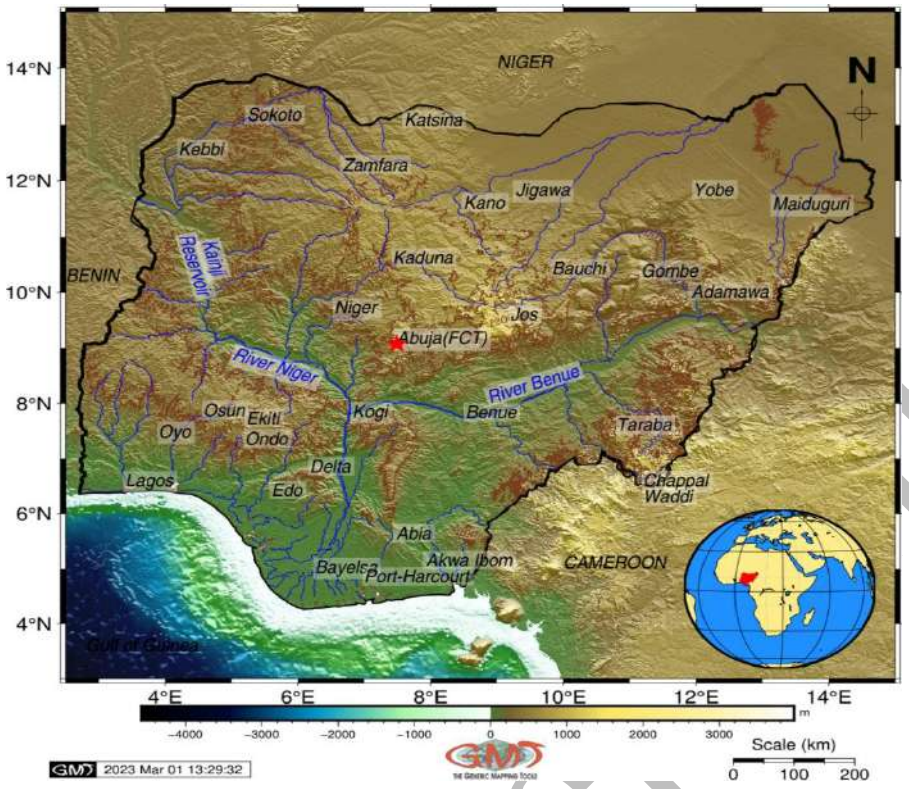

Fig. 1. Study Area

2.2. GRACE Data

The study took the advantage of GRACE Mascon (equivalent water height) level 3 data product from April 2002 to December 2024. The data product is produced by three centres: JPL (Jet Propulsion Laboratory), CSR (Center for Space Research), and GSFC (Goddard Space Flight Center)**.** This study utilizes monthly mass grids from the GRACE RL06 mascon solutions, processed by the CSR (https://www2.csr.utexas.edu/grace/RL06_mascons.html) at a spatial resolution of 0.5° × 0.5°. The dataset provides global monthly water storage. *T*he dataset was pre-processed to remove noise and biases, including the application of a destriping filter, corrections for glacial isostatic adjustment (GIA), and spatial smoothing using a Gaussian filter.

2.3. Trends analysis (increasing/decreasing TWS)

Mann-Kendall (M-K) test (Mann, 1945; Khendall, 1975; Yue *et al*., 2002), a non-parametric statistical test (makes no assumptions about the distribution of a data, and it's rank-based measure, is not influenced by extreme values). It is more suitable for data that are not normally distributed, contain outliers, and have missing data is used to detect the trend in precipitation (Asfaw *et al*., 2018). It is widely used to detect trends in meteorological data (see for example Jensen & Pedersen, 2005; Ahokpossi, 2018; Asfaw *et al*., 2018; Pawar *et al*., 2023). M-K mainly gives three types of information:

a) The Kendall Tau, or Kendall rank correlation coefficient, measures the monotony of the slope. Kendall's

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Tau varies between -1 and 1; it is positive when the trend increases and negative when the trend decreases.

b) The Sen slope, which estimates the overall slope of the time series. This slope corresponds to the median of all the slopes calculated between each pair of points in the series.

c) The significance, which represents the threshold for which the hypothesis that there is no trend is accepted. The trend is statistically significant when the p-value is less than 0.05.

Based on previous studies (see Ahokpossi, 2018; Usman *et al*., 2018; Asfaw *et al*., 2018; Alemu & Bawoke, 2019; Alahacoon & Edirisinghe, 2021; Pawar *et al*., 2023), this study used the MK test to assess the trend in GRACE satellite data over the study area. The mathematical formulations for MK statistics are given as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \tag{1}$$

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1 > (x_j - x_i), \\ 0 = (x_j - x_i), \\ -1 < (x_j - x_i) \end{cases} \tag{2}$$

Where;

n is the number of time-series data/number of observation,

xj and xi are the data sequential annual values.

More often, j is greater than x. The negative and positive values of S respectively represent a "low inclination", and "high tendency". When n is more than 10, the statistic 'S' is approximately normally distributed with the mean and E(S) becomes 0 and the variance statistic is given as Equation (3)

$$\operatorname{var}(S) = \frac{1}{8}\left[n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5) \right] \tag{3}$$

Where;

n has been defined earlier, and t_i is the number of the sample time series in the ith group.

The Z_c statistics is computed using Equation (4), with positive and negative values indicating increasing and decreasing trend for the period of interest respectively.

$$Z_c = \begin{cases} \dfrac{S+1}{\sqrt{Var(S)}} < 0, \\ 0 = \ for \ S = 0 \\ \dfrac{S-1}{\sqrt{Var(S)}} > 0 \end{cases} \tag{4}$$

2.3.1 Sen's slope estimation

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Sen's slope (Sen, 1968) is used to estimate the actual slope and intercept generated by MK test. Compared to linear regression Sen's slope limits the influence of missing values or outliers on the slope (Alemu & Bawoke, 2019).

$$\beta = median\left(\frac{x_j - x_i}{j - i}\right) \quad (5)$$

Where;

β represents the median value of the slope values between data measurements *xi* and *xj* at the time steps *i* and *j (i < j)*.

Positive value of β indicates an upward trend whereas negative value of β indicates a downward trend. The sign of β reflects data trend direction, whereas its value indicates the steepness of the trend.

2.4 Ground water storage anomaly (GWSA)

The GWSA (Groundwater Storage Anomaly) represents the deviation of groundwater storage (GWS) in each month from its long-term average. It serves as a key metric for assessing changes in groundwater storage over time (Chen et al., 2021; Humphrey et al., 2023).

$$GWSA_{i,j} = GWS_{i,j} - \overline{GWS} \quad (6)$$

Where $GWS_{i,j}$ denotes the Groundwater Storage (GWS) for the j-th month in the i-th year, and $\overline{GWS}$ signifies the long-term average GWS for that same month, calculated from April 2002 to December 2024.

2.5. GRACE drought severity index (GRACE -DSI)

Drought indices are essential instruments for tracking drought conditions. The GRACE-DSI(Equation 7), or Water Storage Deficit Index (Rawat et al., 2022) a dimensionless index that can be used to grade dry and wet conditions, developed by (Zhao et al., 2017) normalizes terrestrial water storage (TWS) data obtained from GRACE inversion, using TWS depletion as an indicator for drought assessment (Rawat et al., 2022; Zhu et al., 2025).

$$GRACE - DSI_{i,j} = \frac{\mathrm{TWSA}_{i,j} - \overline{\mathrm{TWSA}_j}}{\mathrm{TWSA}_{\sigma,j}} \quad (7)$$

where $\mathrm{TWSA}_{i,j}$ represents TWSA of the year i (i = 2002 to 2024) and month j (j = 1 to 12), TWSA_j is monthly mean TWSA and $\mathrm{TWSA}_{\sigma,j}$ is standard deviation of TWSA for month j. Table 3.1 displays a range of values, where negative values indicate dry conditions, and positive values signify wet conditions.

Table 3.1 Range of GRACE-DSI water deficit based on the study of (Rawat et al., 2022; Zhu et al., 2025)

Drought grade	GRACE-DSI
W4: exceptionally wet	> 2

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W3: extremely wet	1.6 – 1.99
W2: severely wet	1.3– 1.59
W1: moderately wet	0.8–1.29
W0: abnormally wet	0.5–0.79
N: near normal	0.49 to − 0.49
D0: abnormally dry	− 0.5 to − 0.79
D1: moderately drought	− 0.8 to − 1.29
D2: severely drought	− 1.3 to − 1.59
D3: extremely drought	− 1.6 to − 1.99
D4: exceptionally dry	< − 2

3. Results and discussion

This section entails the results obtained from the present study and it follows the sequence of the outlined objectives of the research. Since the study used JPL's, CSR RL06 mascon's data, we used Terrestrial Water Storage (TWS) and Land Water Equivalent (LWE) interchangeably

3.1. Seasonal and interannual variations in TWS across Nigeria

Terrestrial Water Storage (TWS) is a vital part of the hydrological cycle, integrating groundwater, soil moisture, and surface water to determine water availability across regions. Fig. 2 illustrates Nigeria's annual Land Water Equivalent (LWE) from 2002 to 2024, showing pronounced upward trend in recent years. A sharp increase in LWE is particularly evident from 2018 onward across major basins, including the Sokoto-Rima River Basin (see Fig. 3), where heightened rainfall and improved groundwater recharge likely contributed to rising water levels. The Upper and Lower Benue River Basin experienced similar gains, potentially due to intensified monsoon patterns or water management interventions. In the Lake Chad Basin, despite historical declines, recent TWS growth suggests possible recovery from improved inflows or reduced extraction. The Upper and Lower Niger River Basin also saw notable increases, possibly linked to greater river discharge or flood events during this period. While this trend enhances water security in drought-prone areas, it also raises flood risks, particularly in basins with high seasonal variability.

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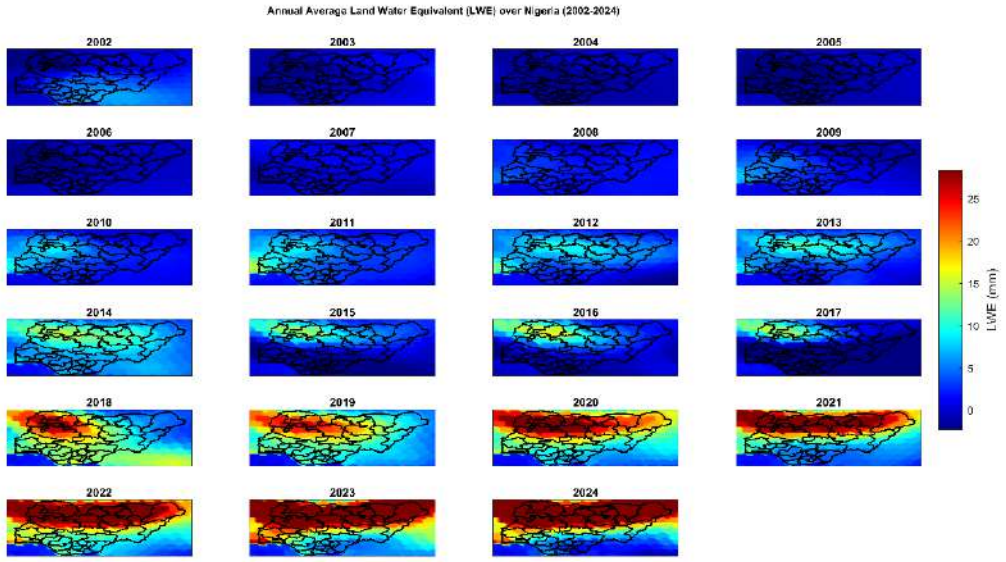

Fig. 2. Annual LWE average of LWE over Nigeria from 2002-2024

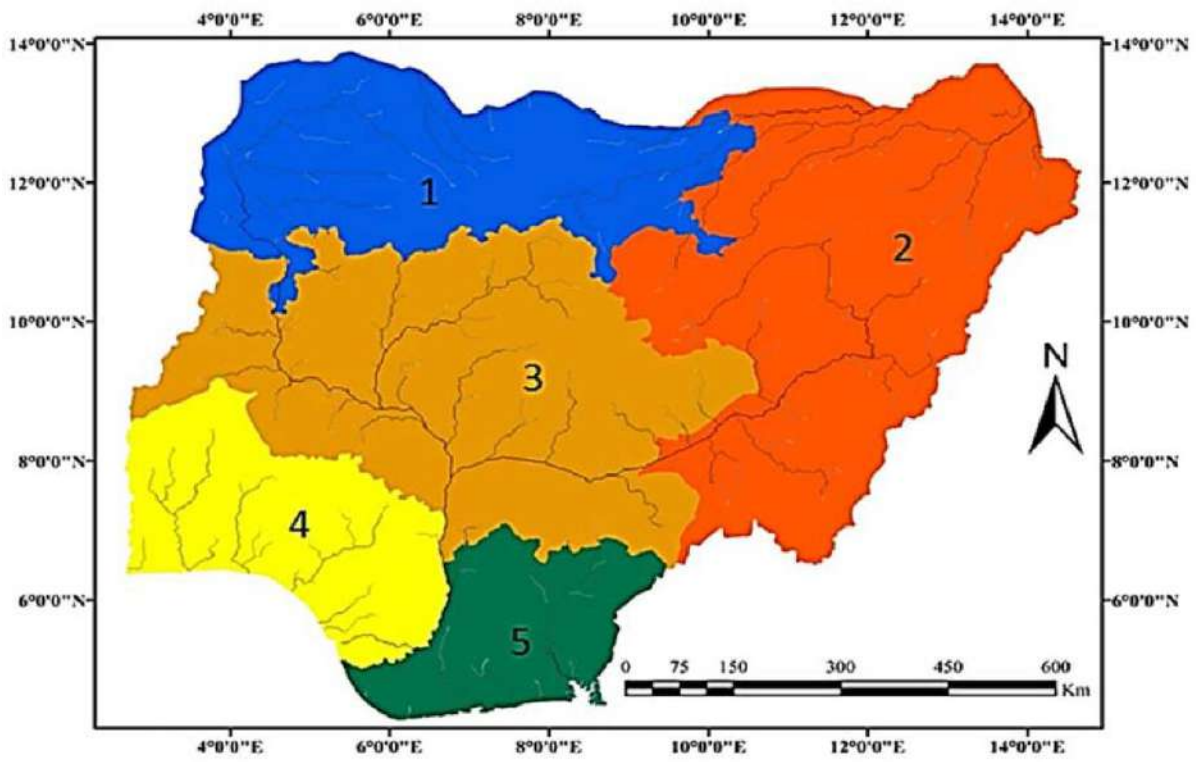

Fig. 3. River basins of Nigeria, namely, the Hadejia-Jama'are, Sokoto-Rima River Basin (Area 1), the Upper/Lower Benue River and Lake Chad Basin (Area 2), the Upper and Lower Niger River Basin (Area 3), the Osun-Ogun, Owena River Basin (Area 4), and the Anambra-Imo, Niger Delta and Cross River Basin (Area 5) (Dasho *et al.* 2020)

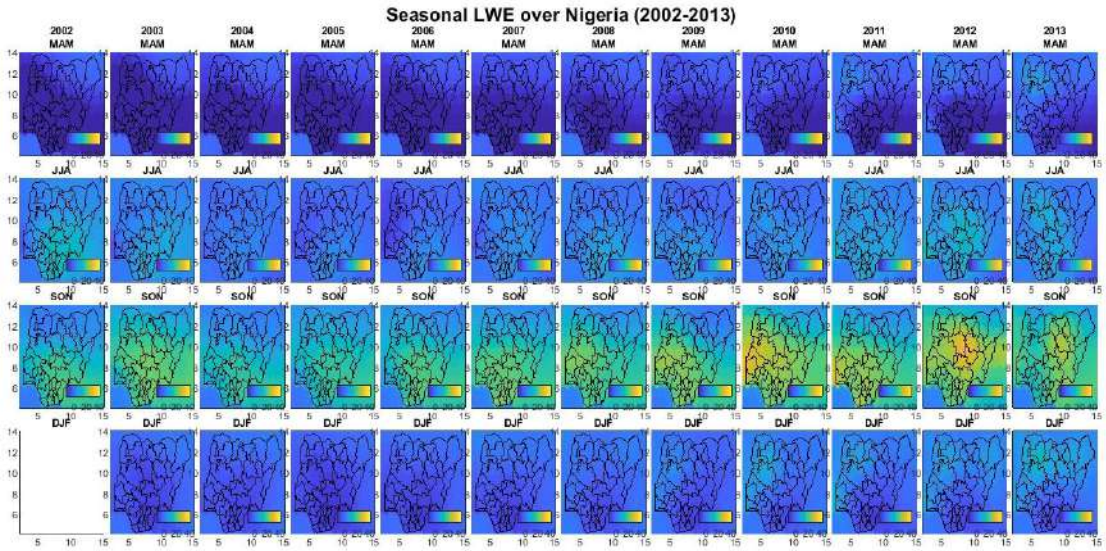

Fig. 4. Yearly Spatial Seasonal Patterns of TWS over Nigeria (2002-2013)

Nigeria's hydroclimatic regime follows a well-defined seasonal cycle, divided into four distinct periods: December–January–February (DJF), March–April–May (MAM), June–July–August (JJA), and September–October–November (SON)(Bawa et al., 2022). As illustrated in Fig. 4 and 5, Land Water Equivalent (LWE) exhibits strong seasonal contrasts, with DJF and MAM characterized by dry conditions, marked by low LWE anomalies due to reduced precipitation and moisture deficits—particularly pronounced in the Sahelian and Sudan savanna regions all around the northern regions of the country.

Conversely, JJA and SON represent the primary wet seasons, with a progressive increase in Terrestrial Water Storage (TWS). Notably, SON displays the most significant LWE anomalies, aligning with peak rainfall in southern Nigeria and delayed soil moisture recharge in the north. This seasonal peak underscore SON's critical role in Nigeria's hydrological dynamics.

Over the study period (2002–2024), a substantial increase in TWS is observed across all seasons, likely driven by climatic variability, including shifting precipitation patterns and potential land-use changes. The pronounced fluctuations during SON highlight its sensitivity to hydrological extremes, emphasizing the need for adaptive water resource management in a changing climate.

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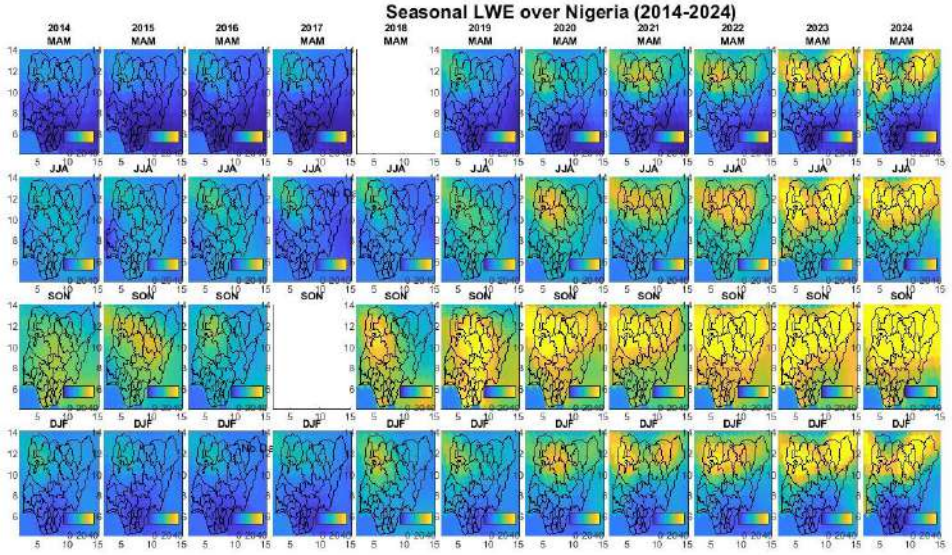

Fig. 5. Yearly Spatial Seasonal Patterns of LWE over Nigeria (2014-2024)

3.2. Seasonal means and LWE Significance

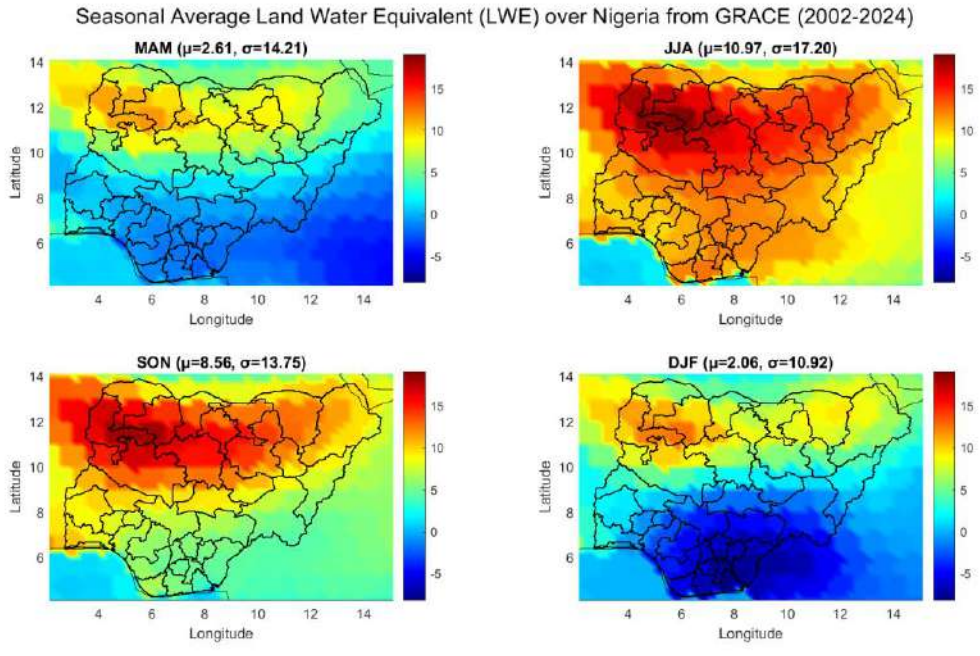

Fig. 6. Seasonal Average of LWE over Nigeria from 2002-2024

The seasonal TWS anomalies reveal distinct hydrological patterns across Nigeria, characterized by significant differences in mean water storage and variability (see Fig. 6). JJA exhibits the highest mean TWS (10.97 cm), consistent with the peak of the West African monsoon, which drives intense rainfall and river discharge, particularly in southern and central Nigeria. SON follows closely (mean = 8.56 cm), reflecting prolonged soil moisture retention and delayed

groundwater recharge, especially in the northern Sahelian regions where rainfall persists into early autumn. MAM and DJF show significantly lower means (2.61 cm and 2.06 cm, respectively), aligning with the dry Harmattan season and minimal precipitation outside the monsoon phase.

For the Interannual Variability (Standard Deviations), JJA displays the highest variability (σ = 17.20 mm), suggesting strong year-to-year fluctuations in monsoon intensity, possibly linked to Atlantic Ocean Sea surface Temperature anomalies. SON (= 13.75 mm) also shows notable variability, likely due to erratic rainfall cessation and land-atmosphere feedback in the transition to the dry season. MAM (σ = 14.21 mm) has unexpected variability for a dry season, possibly due to early pre-monsoon showers or irrigation effects in agricultural zones. DJF (σ = 10.92 mm) is the most stable season, as cold, dry Harmattan winds dominate with minimal hydrological activity.

3.3. Regions with significant trends (increasing/decreasing TWS) using Mann-Kendall test

A two-tailed Mann–Kendall trend test was first employed to identify seasonality of LWE trends at 95% confidence levels at location specific permanent GNSS stations called NIGNET over Nigeria strategically tied to the Nigeria regional climate classifications based on Köppen-Geiger (Beck et al., 2018) (see Fig. 7). A spatial variability of the Mann–Kendall trend and Sen's slope are also presented in Fig. 8 and 9 respectively. In Fig. 8 the MAM season is predominantly associated with a decreasing trend. While as expected JJA and SON are associate with an increasing trend. Kendall's Tau falls between -1 and 1, where a positive value signifies an increasing trend, while a negative value denotes a decreasing trend.

To estimate the magnitude and direction of trends identified by the Mann-Kendall (MK) test, we applied Sen's slope estimator. Fig. 9 illustrates the spatial distribution of Sen's slope across Nigeria, with values ranging from -2.0 to 2.0 cm/yr. For further analysis, we computed Sen's slope at permanent GNSS stations within the Nigerian GNSS Network (NIGNET), which are strategically aligned with Nigeria's regional climate classifications based on the Köppen-Geiger system. The analysis of GRACE-derived liquid water equivalent (LWE) trends across Nigeria reveals significant spatial and seasonal variations in hydrological storage, closely tied to regional climate classifications. Stations in Tropical Savannah (Aw) zones, such as ABUZ, BKFP, and OSGF, exhibit strong increasing trends during the December–February (DJF), March–May (MAM), and June–August (JJA) seasons, with the most pronounced trends occurring in MAM (3.58–4.29 cm/yr). These findings suggest an intensification of pre-monsoon and early monsoon rainfall, possibly linked to enhanced convective activity or shifts in the West African Monsoon (WAM) system. However, the September–November (SON) season shows weaker or even declining trends in some stations (e.g., CGGT, OSGF), indicating potential changes in the timing of monsoon withdrawal or increasing dry spells.

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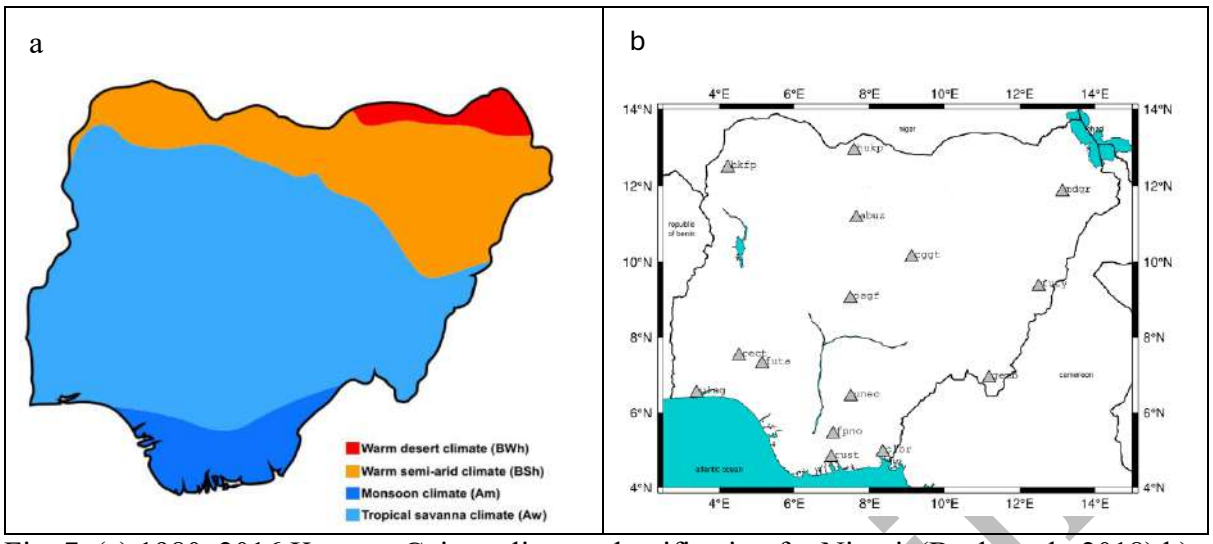

Fig. 7. (a) 1980–2016 Köppen-Geiger climate classification for Nigeria(Beck et al., 2018) b) NIGNET GNSS stations(Bawa et al., 2022)

In contrast, stations under the Tropical Monsoon (Am) classification, including CLBR, FPNO, and RUST, display a distinct seasonal pattern. While MAM trends remain strongly positive (2.89–3.37 cm/yr), SON trends are significantly negative (-1.95 to -3.15 cm/yr), suggesting a reduction in late-season water storage. This could reflect an early cessation of monsoon rains or increased evaporative losses as temperatures rise. Notably, JJA trends in these regions are mostly non-significant or slightly negative, deviating from the expected peak monsoon rainfall period. This anomaly may be attributed to monsoon weakening, land-use changes, or large-scale climate oscillations such as the El Niño–Southern Oscillation (ENSO)(Emmanuel, 2022).

Arid and semi-arid regions (BSh), represented by stations like FUTY and HUKP, show more complex trends. While FUTY experiences significant increases in MAM (3.33 cm/yr) and DJF (1.43 cm/yr), it records a decline in SON (-0.69 cm/yr), highlighting growing seasonal variability. HUKP, which lies in a transitional zone between Aw and BSh, demonstrates consistent increases across all seasons (1.33–3.56 cm/yr), possibly due to localized factors such as irrigation or groundwater extraction. These trends underscore the vulnerability of arid regions to hydrological extremes, where even modest increases in seasonal water storage may be offset by high evaporation rates and growing water demand.

The spatial heterogeneity in LWE trends suggests that Nigeria's hydrological systems are responding differently to climatic and anthropogenic pressures. The strong MAM increases in savannah and monsoon regions could enhance agricultural productivity but also raise flood risks, particularly in urban areas with poor drainage infrastructure. Conversely, the declining SON trends in monsoon zones may strain water resources during the dry season, affecting irrigation and domestic supply. In arid regions, the observed variability underscores the need for adaptive water management strategies to mitigate droughts and ensure sustainable use of limited resources.

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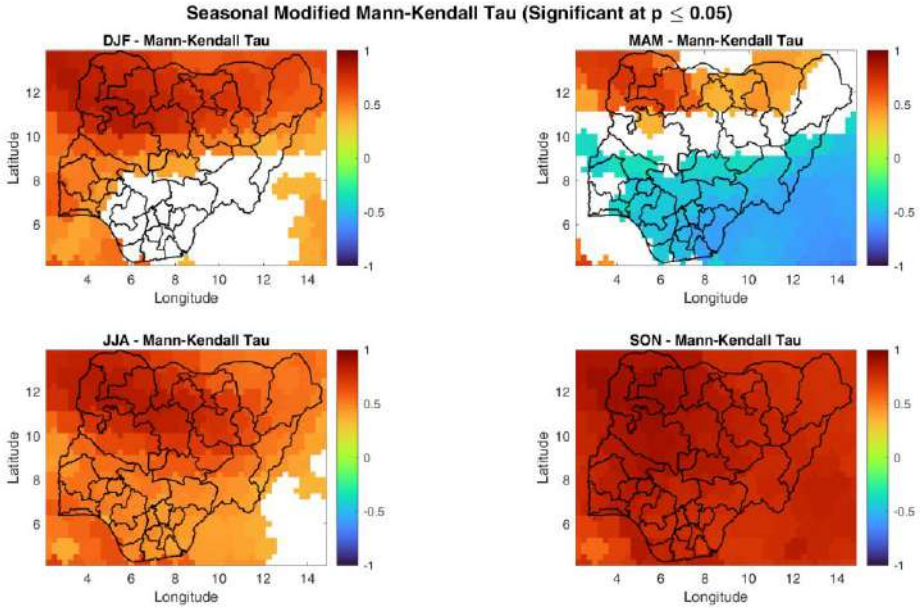

Fig. 8.: Seasonal Mann–Kendall's trend test TWS variations estimated by GRACE for the period of 2002–2024. and Sen's slope estimator "S"

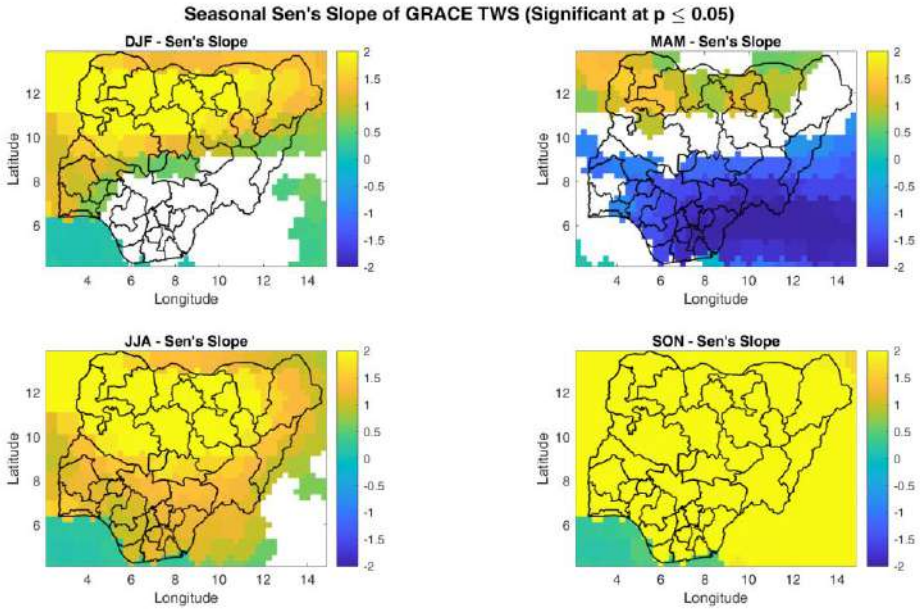

Fig. 9. Seasonal Sen's slope estimate of TWS variations estimated by GRACE for the period of 2002–2024

3.4. Groundwater anomalies (GWA)

GRACE-derived groundwater anomalies (GWA) measure how much groundwater storage deviates from its typical seasonal average. For Nigeria, negative GWA values signal lower-than-normal groundwater

levels, often due to drought or excessive extraction, whereas positive values indicate higher-than-normal storage, typically resulting from recharge or unusually wet conditions.

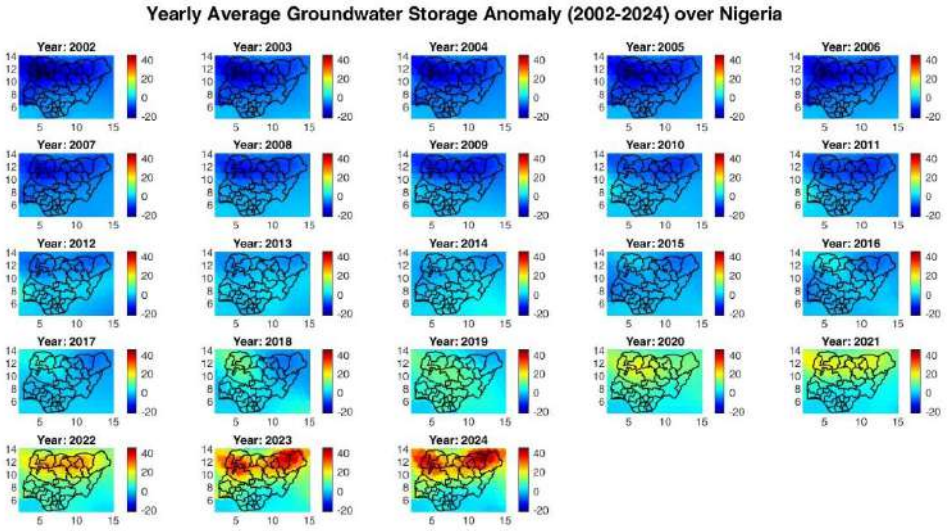

Fig. 10: Yearly average GWA over Nigeria

Fig. 10 shows that years 2002 to 2015 recorded the highest level of ground water depletion recorded by grace in Nigeria. This timeframe represents a phase of significant hydrological stress, where groundwater extraction and climatic conditions combined to produce the most severe depletion levels in the dataset. The observation suggests that these years were marked by either prolonged drought conditions, increased agricultural or urban water demand, or a combination of both, leading to unsustainable groundwater withdrawal. The severity of depletion during this period implies a disruption in the natural recharge cycle, were water removal consistently outpaced replenishment. This trend is particularly concerning given Nigeria's reliance on groundwater for irrigation, drinking water, and industrial use, especially in the Sahel regions with limited surface water availability. The GRACE data's ability to capture this depletion underscores the satellite's utility in monitoring large-scale hydrological changes, providing empirical evidence of water resource vulnerability during this 13-year span. The identification of this period as having the highest depletion levels serves as a crucial reference point for understanding long-term groundwater sustainability challenges in Nigeria, emphasizing the need for integrated water management strategies to mitigate future risks.

3.5. GRACE drought severity index (GRACE -DSI)

GRACE data serves as a groundbreaking resource for continental-scale drought assessment, offering unique capabilities for evaluating groundwater and hydrological drought conditions that remain challenging to quantify using traditional measurement

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approaches. Fig. 11 and 12 shows GRACE -DSI over Nigeria for years 2002 to 2012 and 2013 to 2024 respectively. The plots were segregated for visualization purposes. Drought is basically a long stretch of unusually low precipitation, causing a water deficit. Since rainfall periods is Nigeria starts in June and ends in October, we computed the DSI for the five months. A meteorological drought is recognized when two conditions are simultaneously satisfied: first, the drought index must register values below -0.5, and second, these sub-threshold values must persist continuously for a minimum period of three months (Rawat et al., 2022). We therefore used the suggestion by Rawat et al., (2022).

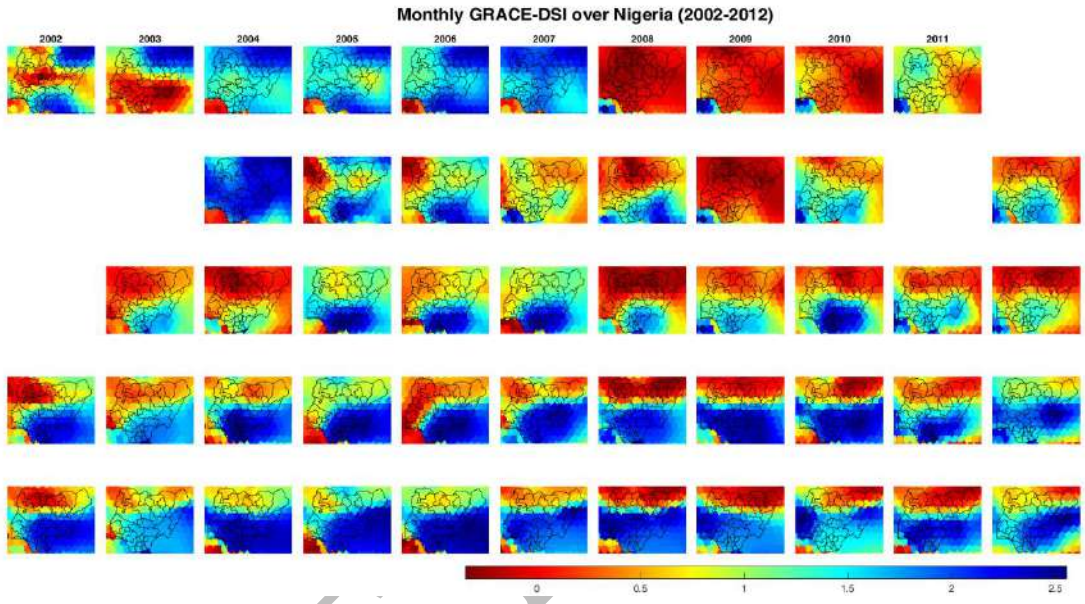

Fig. 11. GRACE drought severity index (GRACE -DSI) from 2002 to 2012 for months June, July, August, September to October (top to button for the respective years plotted)

In 2002, the lack of data for July (second subplot from the top) and August (third subplot from the top) precludes definitive conclusions regarding drought conditions. In 2003, anomalously wet conditions (0.5 to 0.79) were observed during August, September, and October, particularly in the northern Sahel region of the country. From 2004 to 2007, no clear spatial or temporal pattern is evident. However, a distinct consecutive pattern (persisting for more than three months) emerges between 2008 and 2011 in the Upper/Lower Benue River Basin and the Lake Chad Basin (located within Nigeria's Sahel region). Although the threshold defined in Table 1 is not met across Nigeria, the persistence of this multi-month pattern suggests a potential association with drought conditions. This is particularly evident during August, September, and October, when precipitation levels are typically high.

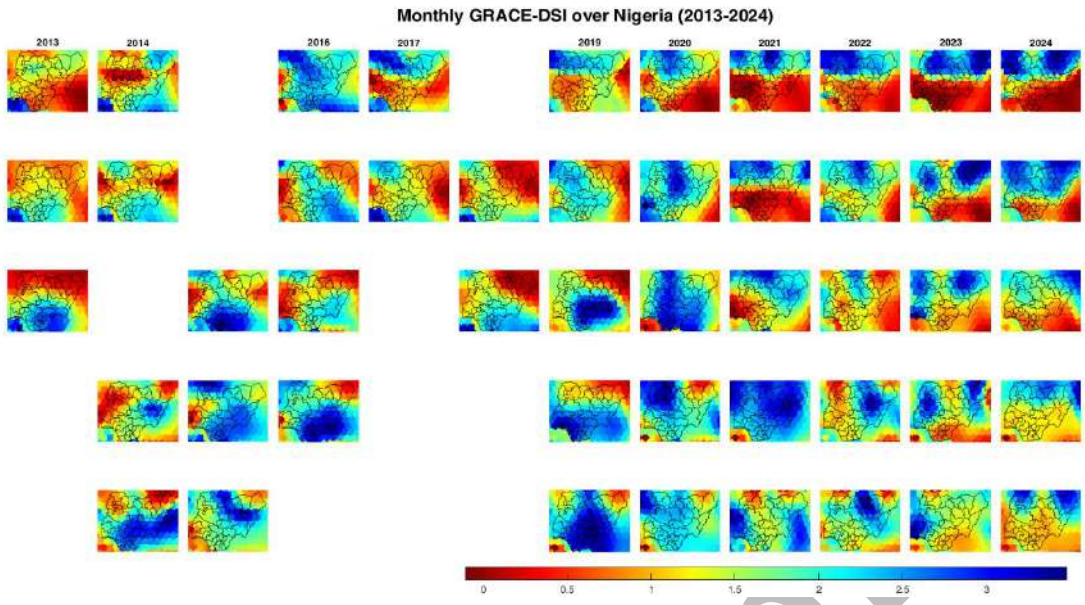

Fig. 12 GRACE drought severity index (GRACE -DSI) from 2013 to 2024 for months June, July, August, September to October (top to button for the respective years plotted)

Analysis of Fig. 12 reveals minimal drought likelihood across the Lake Chad Basin from 2013 to 2015. However, a pronounced drought signal emerges in 2016, particularly during July–September, with a similar pattern recurring in 2019. Notably, the period 2020–2024 exhibits a marked hydrological recovery, characterized by a shift from negative to positive GRACE-DSI values in the Sahelian regions and Lake Chad Basin. This aligns with recent studies (Pham-Duc et al., 2020; Sylvestre et al., 2024); demonstrating the basin's resilience, where seasonal replenishment mitigates long-term declines in surface water extent and volume. The observed variability underscores the interplay between episodic drought events and the basin's inherent capacity for seasonal recovery-a critical feature of Sahelian hydrology.

Southern Nigeria, including the Osun-Ogun, Owena, Anambra-Imo, Niger Delta, and Cross River Basins, shows a marked decline in GRACE-DSI values, signaling a substantial reduction in terrestrial water storage. This pattern points to escalating water scarcity in the region, resulting from the combined influence of climatic shifts (such as erratic rainfall and heightened evaporation) and human activities like excessive groundwater pumping and deforestation. The most severe water losses occur in the southeast, consistent with documented cases of aquifer depletion and diminished seasonal river flows(Nasara et al., 2025). These results highlight the susceptibility of Southern Nigeria's water-rich ecosystems to drying trends, contradicting the long-held belief that tropical regions are immune to water shortages.

4. Conclusion

The GRACE-based analysis of TWS variations in Nigeria (2002–2024)

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demonstrates critical spatial and temporal patterns in water availability. Importantly, due to its relatively coarse spatial resolution (~300km) and broad basin-scale delineations, GRACE may struggle to capture fine-scale hydrological variations. The absence of direct ground-based validation as well measurements also introduce uncertainty in trend estimate, especially in arrears with intricate groundwater systems or heavy human water use. These constrains may reduce the precision of water storage assessments, highlighting the importance of integrating field data for more robust analysis. However, the GRACE-derived assessment of Nigeria's TWS variability highlights some valuable insights:

Seasonal TWS fluctuations dominate, with JJA/SON peaks (10.97 cm/8.56 cm) and DJF/MAM troughs (2.06 cm/2.61 cm), modulated by West African Monsoon dynamics. Northern arid zones (Sen's slope: −1.5 cm/yr) face compounding stress from irrigation and drought, while southern humid regions grapple with unsustainable extraction (−0.8 cm/yr).

GRACE-DSI identifies episodic droughts (2016, DSI < −1.3) and post-2020 recovery (DSI > 0.5) in the Lake Chad Basin, aligning with Pham-Duc et al. (2020) on seasonal resilience. Conversely, southern basins (e.g., Anambra-Imo) exhibit progressive drying (DSI −0.8 to −1.29), contradicting tropical water abundance assumptions. GWA trends reveal groundwater depletion (2002–2016) in agricultural hotspots (e.g., Upper Benue), emphasizing the urgency of policy interventions.

These findings validate GRACE as a transformative tool for hydrological monitoring and underscore Nigeria's bifurcated water challenges—aridification in the north and demand-driven scarcity in the south

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Declaration of Competing Interest

The authors declare no Competing Interest

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