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Exploring the Dynamics of Terrestrial Water and Groundwater Storage across Nigeria: Insights from GRACE/GRACE-FO

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Received: 30 March 2026; Accepted: 08 June 2026; Published: 29 July 2026

ABSTRACT: This study utilized nearly two decades of temporal gravity field observations from the Gravity Recovery and Climate Experiment (GRACE/GRACE-FO) satellite missions to analyze the spatial and temporal variations of terrestrial water storage (TWS) and groundwater storage (GWS) in Nigeria. Advanced statistical techniques, including Singular Spectrum Analysis (SSA), Principal Component Analysis (PCA), and Empirical Orthogonal Function (EOF), were applied to characterize and quantify these variations at a basin scale. Results show that TWS exhibits biennial, annual seasonal fluctuations (between ± 10 to ± 55 mm), reaching its lowest levels during the dry season (February–June) and peaking in the wet season (August–October). Anomalous high TWS in 2012 coincided with one of Nigeria's worst nationwide flooding events. Trend analysis reveals an overall increase in both TWS and GWS. While GWS oscillates annually and seasonally (± 20 mm), it peaks between September and November and declines around May–June. Temporal decomposition reveals annual, inter-annual (3–4 years), and multi-annual (~ 10 –12 years) cycles, suggesting influences from climate phenomena such as the El Niño–Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD), along with human-induced factors like groundwater abstraction and land-use changes. The increasing trend in TWS and GWS implies enhanced aquifer recharge due to rising precipitation, but it also raises the risk of recurrent flooding. Notably, an out-of-phase pattern in the western littoral region suggests significant anthropogenic influence. This study highlights the value of GRACE-based monitoring for water resource management in Nigeria, particularly in regions where *in-situ* hydrological data are scarce.

KEYWORDS: GRACE/GRACE-FO; Terrestrial Water Storage (TWS); Groundwater Storage (GWS); Empirical Orthogonal Function (EOF); Principal Component Analysis (PCA); Singular Spectrum Analysis (SSA); climate change

1 Introduction

Global warming & climate change are central issues in contemporary scientific and public discourse, manifesting through natural phenomena such as flooding, drought, and rising sea levels [1–5]. Globally, researchers are actively investigating these impacts on natural resources, particularly freshwater availability, which is critical for sustaining Earth's ecosystem [3,6–10].

Water resources are fundamental to Nigeria's economy, agriculture, and public health, particularly as one of the most populous nations in Africa [11]. Unfortunately, the country's water resources and hydrological cycle are under increasing stress from rapid population growth (which drives demand for irrigation and domestic use) and the intensifying effect of climate change, which leads to highly variable rainfall and extreme weather events [12,13].

The terrestrial water storage (TWS), defined as the aggregate of all water stored above and below the earth's surface, including snow/ice, surface water, soil moisture, and groundwater is the most comprehensive indicator of regional water availability [14,15]. It is also a key indicator of the effect of climate change, hydrological extremes, and ecosystem dynamics [15–17]. Similarly, groundwater storage (GWS), defined as the freshwater underground in aquifers, is vital for long-term water management, especially in densely populated regions where it constitutes the largest source of accessible freshwater [18,19]. GWS, together with TWS, is critical for assessing water availability and predicting hydrological extremes like floods, droughts, and informing water resources management policy [20–22].

Accurate spatiotemporal characterization of TWS & GWS requires dense hydro climatic monitoring networks; unfortunately, in many developing regions, including Nigeria, sparse, beleaguered *in-situ* stations limit holistic assessment and characterization of TWS & GWS [23–25]. Due to limitations of traditional ground-based methods, the twin Gravity Recovery and Climate Experiment (GRACE) satellite mission (launched in 2002) and its successor GRACE-FOLLOW-ON (GRACE F O) (launched in 2018) have become indispensable tools for continental and country-scale hydrology [26]. The GRACE/GRACE-FO mission operates by measuring minute changes in the Earth's gravitational field, which is mainly caused by mass redistribution due to water movement [27]. The GRACE/GRACE FO mission provides an unprecedented cost-effective and large-scale observation of TWS anomalies, thus offering important insight into the total water mass change in the data-scare region [15,17,26–28]. The value of this GRACE-based approach is well demonstrated in diverse hydrological contexts. Studies have successfully employed it to assess drought conditions by comparing soil moisture and groundwater indices, project future groundwater storage declines under climate change scenarios, and even monitor the propagation of dry hydrological droughts through reservoir systems [29–33]. In the West, research has utilized GRACE to analyze TWS variations over large river basins, highlighting the influence of climate teleconnections [17]. However, existing studies on Nigeria remain limited. Some have focused only on TWS without isolating groundwater, while others have examined broader regions like the Niger basin or West Africa without a nationwide dedicated analysis that integrates advanced statistical decomposition to untangle the complex signal within Nigeria's distinct hydrological zones or temporal dispensations [34–37].

Indeed, there is a growing body of literature on terrestrial water storage (TWS) and groundwater storage (GWS) using GRACE/GRACE-FO data. In the context of Nigeria, however, several critical gaps remain. While GRACE-based studies have been successfully applied globally to assess drought, groundwater depletion, and the influence of climate teleconnections on water storage [29–33], existing research on Nigeria remains limited. Existing studies have either focused solely on TWS without isolating groundwater storage, or examined broader regions such as the Niger River Basin or West Africa without providing a dedicated nationwide analysis [38–40]. These approaches both limit insights into subsurface hydrological dynamics and obscure country-specific hydrological patterns across Nigeria's diverse climatic and hydrological zones. Furthermore, a combined, national-scale assessment of both TWS and GWS (linking satellite observations with groundwater storage separation and validation) has been lacking, particularly one that applies advanced techniques such as Singular Spectrum Analysis (SSA), Principal Component Analysis (PCA), and Empirical Orthogonal Function (EOF) to identify dominant trends, seasonal cycles, and interannual variability across Nigeria's major hydrological basins [ibid]. Such assessment is quite important considering that Nigeria has different hydrological and geophysical delineations as seen in Fig. 1 [41].

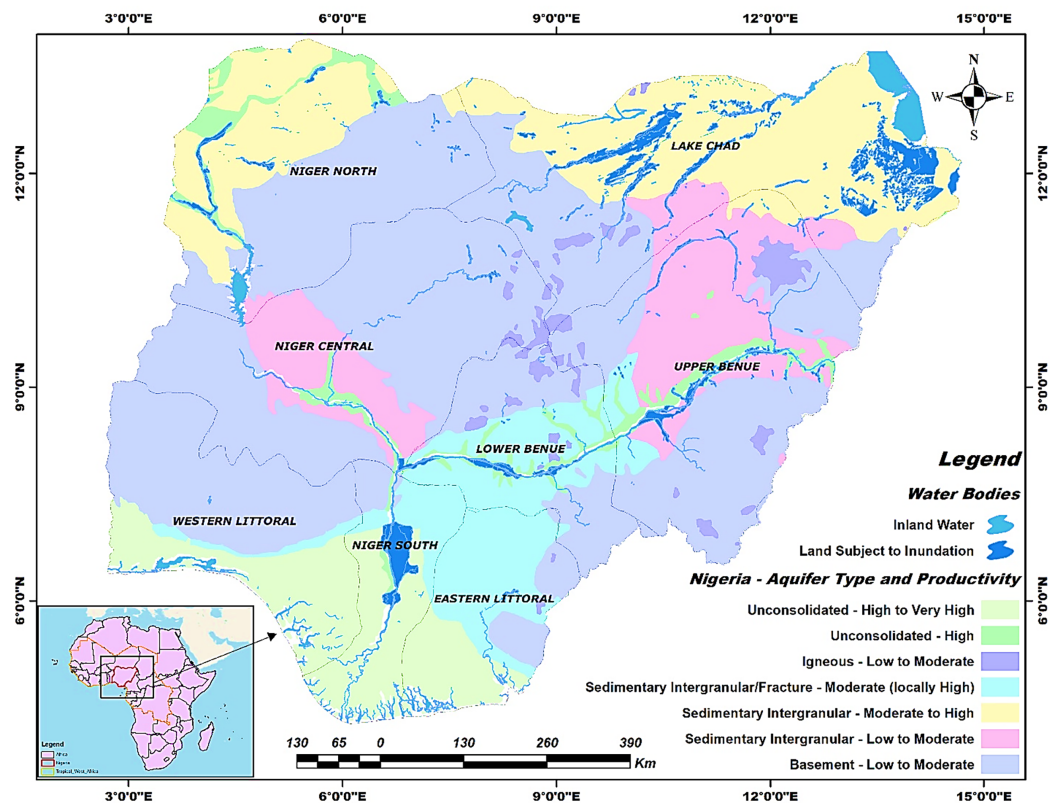


Figure 1: Map showing Nigeria's hydrological areas, aquifer type, and productivity. Modified after British Geological Surveys BGS, [41].

This study addresses these critical gaps by conducting the first comprehensive national-scale analysis of the spatiotemporal dynamics of both terrestrial water storage (TWS) and groundwater storage (GWS) across Nigeria's major hydrological basins, utilizing nearly two decades of GRACE/GRACE FO observations. The main contributions of this research are as follows: First, the study provides the first nationwide assessment of both TWS and GWS dynamics in Nigeria using nearly two decades (2002–2021) of GRACE/GRACE FO mascon solutions. Second, advanced statistical techniques—namely principal component analysis (PCA), empirical orthogonal function (EOF) analysis, and singular spectrum analysis (SSA)—are applied to decompose storage signals, revealing dominant trends, seasonal cycles, and interannual to multiannual variability. Furthermore, the influence of climate teleconnections (e.g., ENSO and IOD) and anthropogenic factors on water storage variations is identified and quantified, with particular attention to regional differences, including out of phase patterns linked to human activities in the western littoral zone.

The remainder of this paper is structured as follows: [Section 2](#) describes the study area, including Nigeria's major hydrological basins, climatic zones, and aquifer characteristics. [Section 3](#) details the materials and methods, covering the GRACE/GRACE-FO mascon datasets, GLDAS auxiliary products, *in-situ* groundwater level data from the Nigerian Hydrological Services Agency (NIHSA), and the statistical techniques employed—namely Principal Component Analysis (PCA), Empirical Orthogonal Function (EOF) analysis, and Singular Spectrum Analysis (SSA). [Section 4](#) presents the results and discussion, first examining terrestrial water storage (TWS) dynamics (trends, seasonal cycles, and spatial patterns), followed by groundwater storage (GWS) dynamics and their validation against *in-situ* measurements. This section also includes a discussion of uncertainties, limitations, and recommendations for future research. [Section 5](#)

concludes the study by summarizing the key findings, their implications for water resource management and flood risk mitigation in Nigeria, and the value of satellite-based monitoring in data-scarce regions.

2 Study Area

Nigeria is located within the West African region and experiences diverse climatic conditions affecting water availability. Shown in Fig. 1 is the country's hydrology, which is characterized by major river basins, including the Niger, Benue, and Chad basins, which influence surface and groundwater resources. Recent studies indicate increasing variability in water storage due to climate change and anthropogenic activities [34,35,40,42].

Nigeria's hydrological landscape is shaped by four distinct regions, each defined by unique rainfall patterns and drainage systems. The Coastal Region in the south, including the Niger Delta, experiences heavy rainfall (over 4000 mm annually) and features mangrove swamps and major rivers like the Niger and Benue [43,44]. The Southern Inland Region, with moderate rainfall (1500–2500 mm), is drained by rivers such as the Cross and Ogun. The Central Region (Middle Belt) sees lower rainfall (1000–1500 mm) and is dominated by the Niger and Benue rivers, which converge at Lokoja [45]. The arid Northern Region (500–1000 mm rainfall) relies on seasonal rivers like the Sokoto and Hadejia-Jama'are, facing challenges like desertification and droughts [45].

Nigeria's major water basins underpin its water resources and economic activities. As seen in Fig. 1, the Niger River Basin, the largest, spans 25% of the country and includes tributaries like the Benue, Kaduna, and Sokoto. The Benue River Basin merges with the Niger and supports agriculture and hydropower. The shrinking Lake Chad Basin in the northeast, fed by the Hadejia-Jama'are system, highlights transboundary water challenges. Other key basins include the Cross River Basin (biodiversity-rich), Sokoto-Rima Basin (critical for northern irrigation), Ogun-Osun Basin (supplying southwest cities), and Imo-Anambra Basin (agricultural hub) (cf. Fig. 1). These basins are vital for irrigation, fisheries, and urban water needs.

3 Materials and Methods

This study employs a satellite-based approach to quantify spacetime variations in terrestrial and groundwater storage in Nigeria. The research design integrates GRACE/GRACE-FO data, ancillary datasets from GLDAS, and available *in-situ* measurements to provide a comprehensive analysis of water storage dynamics.

3.1 Data and Data Sources

To achieve the study's objectives, we utilized the GRACE/GRACE-FO Level 3 mascon datasets provided by the CSR, along with GLDAS products and groundwater level data from the Nigerian Hydrological Service Agency (NIHSA). Sections 3.1.1 and 3.1.2, and Table 1 describe the data used in this research. The entire research workflow is accordingly illustrated in Fig. 2.

Table 1: Dataset.

S/No	Variable	Dataset	Source	Period	Spatial Resolution	Temporal Resolution
1	TWS	GRACE CSR Mascon	https://www2.csr.utexas.edu/grace/RL06_mascons.html	2002–2021	$0.25^\circ \times 0.25^\circ$	Monthly
2	Soil moisture and Canopy Water	GLDAS	http://disc.sci.gsfc.nasa.gov/services/grads-gds/gldas	2002–2021	$0.25^\circ \times 0.25^\circ$	Monthly
3	GWS	GWS	Derived	2002–2021	$0.25^\circ \times 0.25^\circ$	Monthly
4	GWL	GWL	Nigeria Hydrological Service Agency	Not uniform	Point scale	Daily

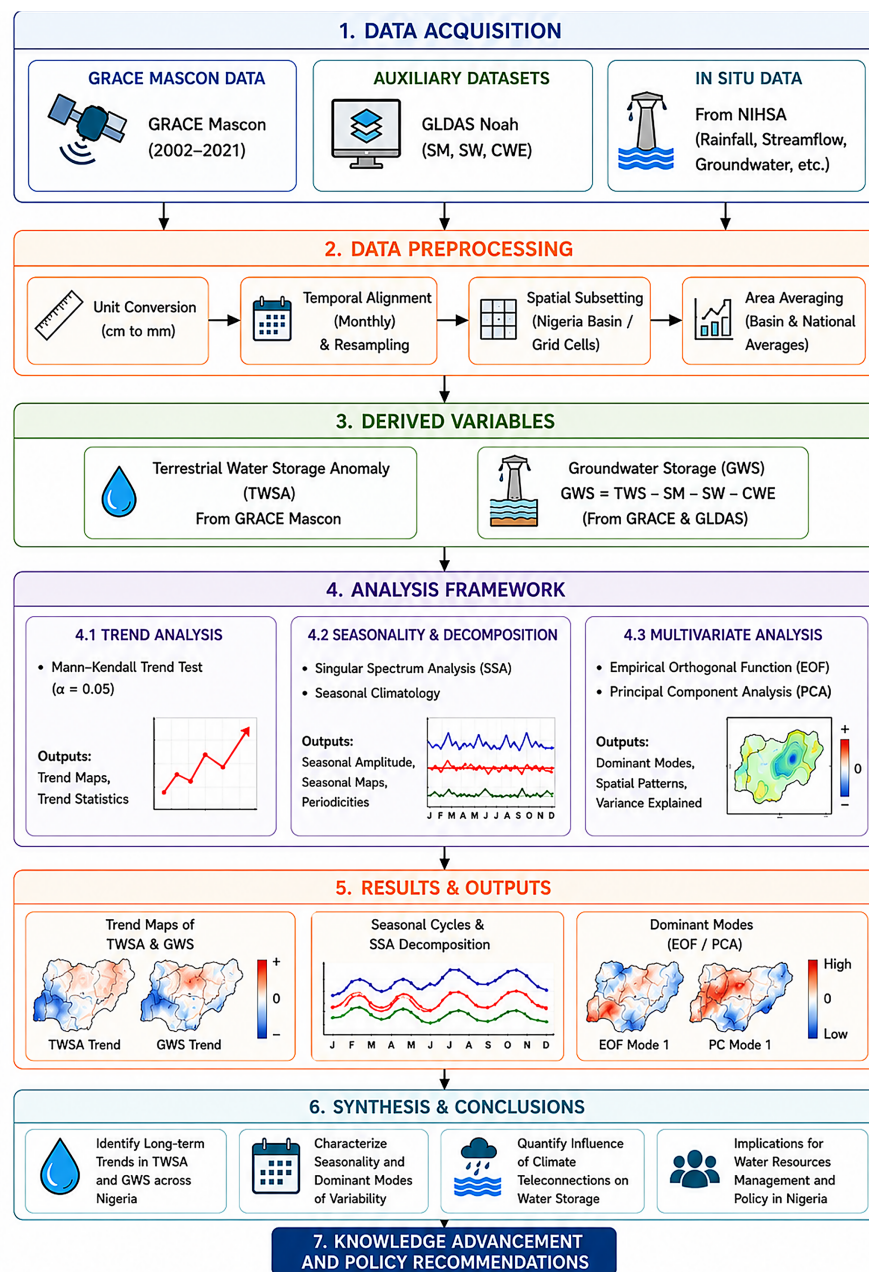


Figure 2: Study flowchart.

3.1.1 Data

The datasets used in this research include soil moisture, terrestrial water storage, canopy water storage, and *in situ* groundwater levels are given below. The source of these datasets will be discussed in this section.

Gravity Recovery and Climate Experiment (GRACE)

The Center for Space Research at the University of Texas at Austin is one of the leading facilities in processing, archiving, and disseminating time-variable gravity field data from the GRACE and GRACE-FO

Missions. This facility processes, archives, and stores all forms of gravitational information. For this research, Level 3 GRACE data in the form of a CSR RL06 mascon product were employed.

This dataset contains some key corrections; the most important being the replacement of C20 coefficients with values obtained using Laser Ranging Techniques as given by Loomis et al. [46]. Likewise, the coefficients C30 have been replaced using the same method. Degree 1 correction, Glacial Isostatic Adjustment-GIA correction, and Gravity Anomaly Detection-GAD correction are some of the adjustments applied to the dataset (ibid).

Regularization constraints based on GRACE and GRACE-FO data were used for dataset computation. The estimation of these parameters is performed by means of the L-ribbon and Tikhonov regularization methods. Based on the methodology presented by Ditmar [47], ellipsoidal corrections were applied separately for land and ocean mass anomalies to reduce leakage issues as much as possible.

The GRACE and GRACE-FO missions represent collaborative efforts by NASA and the German Aerospace Center (DLR). The mission's aim is to measure changes in the Earth's surface mass and water distribution. GRACE's major contribution has been mapping Earth's temporal gravity field with an unprecedented monthly resolution. The first mission commenced on 27 March 2002, and concluded in 2017. Its successor, GRACE-FO, was launched in May 2018.

The GRACE mission consists of a twin-satellite mission orbiting 500 km above Earth, separated from each other by approximately 220 km. The two satellites measure the position of one another as they fly over a region with either a stronger or weaker gravitational pull. The lead satellite would be pulled toward the center of the Earth while approaching regions with stronger gravitational forces, thereby increasing its distance from the trailing satellite. In contrast, it would result in reduction in the distance between the two satellites while passing over an area with weak gravity due to adjusted speeds.

These small changes in separation are measured with very high accuracy by an onboard microwave ranging system that can detect very minute changes indeed [48]. One unique feature of the GRACE mission is that it can observe and study not just one but several interconnected processes that happen on or beneath Earth's surface simultaneously, including those involving the land, ocean, atmosphere, and cryosphere University of Texas Austin Center for Space Research [49].

Notable measurements enabled by the GRACE mission include:

- i. Quantification of land surface mass contribution to sea-level rise.
- ii. Changes in polar ice sheets, continental glaciers, and permafrost should be monitored for mass changes.
- iii. Observing and analyzing regional and global hydrological cycles.

Global Land Data Assimilation System (GLDAS)

The Global Land Data Assimilation System (GLDAS) is the product of a joint effort by scientists at NASA GSFC and NOAA NCEP to utilize the best available ground and satellite-based sensors to produce the forcing data that drives and constrains land surface models [50]. It uses two key methods to constrain land surface models: one, the system uses observed meteorological fields to constrain the biases in atmospheric models. Two, data assimilation methods that input observations of land surface states into the model can, in turn, minimize the most unrealistic model outputs; this process of optimization uses space and ground-based observations and can now enable high-resolution estimates in near real-time of global land surface states and fluxes (ibid).

GLDAS is made up of models such as Mosaic, Noah, and the Community Land Model (CLM), alongside other models like the Variable Infiltration Capacity (VIC) model and the Catchment Land Surface Model. Elaborate descriptions of these models can be found in Rodell et al. [50]. Notably, GLDAS is an evolution

of the North American Land Data Assimilation System (NLDAS), which was initiated in 1998. Key output variables of GLDAS are soil moisture, plant canopy water, snowfall, and rainfall, among others. The outputs are available globally at spatial resolutions between 0.25° to 2.5° and with temporal resolutions ranging from daily to monthly. Further information is available at <http://ldas.gsfc.nasa.gov>. For this study, soil moisture and canopy water storage data were obtained from the GLDAS dataset.

3.1.2 In-Situ Data

To validate groundwater storage (GWS) estimates, *in situ* groundwater level (GWL) measurements are often compared with satellite-derived data from GRACE (Gravity Recovery and Climate Experiment). To achieve this, groundwater level (GWL) changes are converted into groundwater storage by multiplying them by the specific yield (S_y) of the well or aquifer, using the following equation:

$$WS = S_y \times GWL (\Delta h) \quad (1)$$

here, S_y (a dimensionless parameter representing effective porosity) quantifies the volume of water released from storage per unit decline in GWL. While GWL reflects the vertical distance from the land surface to the water table, GWS provides a volumetric measure of aquifer storage.

The use of specific yield (S_y) in conjunction with GRACE satellite observations and groundwater-level data has been widely adopted to assess changes in GWS. In the U.S., for instance, Scanlon et al. [51] measured depletion in key agricultural aquifers, while Faunt [52] applied S_y to model storage reductions in California's Central Valley. In a similar attempt, [53] quantified losses in the Ogallala Aquifer using S_y and well data. Again, Famiglietti et al. [54] and Richey et al. [55] leveraged GRACE to assess groundwater stress in California and other vulnerable regions. In South Asia, Bhanja et al. [56], combined S_y with GRACE and piezometric data to track storage variability in the Ganges-Brahmaputra Basin. Rodell et al. [57] in one of their early studies, established this methodology in India, correlating S_y -adjusted GRACE data with groundwater depletion. Michael and Voss [58] extended these principles to determine sustainable extraction thresholds in the Bengal Aquifer System, while Yeh et al. [59] validated GRACE-derived trends against well data in Illinois using S_y . These efforts highlight Specific Yield's crucial role in transforming hydrological signals from remote sensing and *in-situ* measurements into actionable sustainability strategies.

Table 2 is a summary of estimated specific yield (S_y) values for aquifers, categorized by their geological composition. Empirical S_y values for the studied well locations and adjacent regions are also included, and were sourced from prior studies focused on local or regional hydrogeological contexts. The S_y values (Table 3) applied in this study to derive groundwater storage (GWS) from groundwater level (GWL) measurements align closely with expected ranges (Table 2), ensuring methodological robustness.

Table 2: Summary of predominant aquifer characteristics and Specific Yield (S_y) values for selected locations.

Locations	Predominant Aquifer/Aquifer Characteristic	Representative (Specific Yield S_y) Values/Regional Estimates and Sources
Agbor, Delta State and environs	The Benin Formation is characterized by its predominantly continental sands and gravels, contributing to its high porosity and permeability. It is classified as a moderate to high productivity aquifer zone, with significant groundwater potential due to its unconsolidated sedimentary intergranular structure. The formation is often associated with the Coastal Alluvium Aquifer, which consists of Tertiary sands and gravels, further enhancing its groundwater storage and flow capacity.	19%–22% [60] 21%–33% [61] 19.0%–27.7% [62]* 28.36%–31.96% [63]*

(Continued)

Table 2 (continued)

Locations	Predominant Aquifer/Aquifer Characteristic	Representative (Specific Yield S_y) Values/Regional Estimates and Sources
Sagamu, Ogun State and environs	Sedimentary rock aquifers, particularly those with intergranular porosity, are classified as moderate to high productivity aquifer zones. A notable example is the Coastal Plain Sands Aquifer, which is made up of permeable sands and gravels. These unconsolidated sediments exhibit high porosity and permeability, making them highly effective for groundwater storage and flow.	19%–22% [60] 21%–33% [61] 7%–31% [64]*
FUTO, Owerri, Imo State and environs	Sedimentary rock aquifers, especially those with intergranular porosity, are classified as moderate to high productivity aquifer zones. A notable example is the Ajali Sandstone Aquifer, which features moderate porosity within its sandstone and shale formations. These characteristics enable it to store and transmit groundwater effectively, contributing to its overall productivity.	21%–27% [60] 6% [63] 22.6%–33.2% [65]*

Note: *Estimates of locations and their surroundings from local literatures.

Following methodologies from Bhanja et al. [66] and Seyoum and Milewski [67], GWL data from the Nigeria Hydrological Services Agency (NIHSA) were converted to GWS by scaling observed GWL changes with S_y values.

However, S_y values were sourced indirectly through published literature or neighboring well approximations, as direct acquisition from NIHSA of S_y values was unsuccessful. Moreover, only wells with sufficient data quality and quantity, and with specific yield values determined or approximated—either from neighboring locations or from published literature [63,65,68]—were used for validation. Pearson correlation and RMSE were used to compare GRACE-derived GWS with *in-situ* well data from NIHSA.

Table 3: Correlation and specific yield values for GRACE-derived GWS at selected well locations.

S/No.:	Well Location	Pearson Correlation Coefficient	Specific Yield Value	Sources
1	Agbor (6°15'15.84" N, 6°12'5.04" E)	0.442	30.11%	[63]
2	FUTO (5°24'33.35" N, 6°58'49.45" E)	−0.389	33.3%	[65,68]
3	Sagamu (6°51'17.50" N, 3°38'51.83" E)	−0.559	31%	[64]

3.2 Methods

3.2.1 Separation of GWS from TWS

As mentioned previously, TWS is the sum of all water in different components of the land surface system, ranging from surface water (SW), soil moisture (SM), groundwater (GW), snow water (SnW), and canopy/biomass water (CW). Below is a simple equation that illustrates this concept:

$$TWS = GWS + SMS + SWS + CWS + SnWS \quad (2)$$

Isolating GWS is theoretically achieved by rearranging the equation:

$$GWS = TWS - (SMS + SWS + CWS + SnWS) \quad (3)$$

GRACE data provide TWS estimates, while GLDAS supplies information on SMS, SnWS, and CWS. Contributions of SWS and SnWS are often negligible, depending on the study area. Research shows that SMS and GWS are the primary contributors to TWS in most regions. For example:

- i. Ferreira et al. [69] found that Lake Volta contributed only 8.8% to TWS gains between 2002–2016, with minimal effects on the Niger and Senegal Basins (1.7%).
- ii. Getirana et al. [70] reported that SWS accounts for ~20%–27% of TWS variability in areas like the Amazon and Nile Basins.

In addition to the above studies, runoff in about 168 river basins has been identified to contribute marginally (4.2%) to TWS change [71]. Hence, the contributions of SW may be safely ignored. Moreover, Nigeria is not known to host large lakes, reservoirs, or dams. Existing lakes and dams are small relative to other globally renowned lakes and dams (e.g., the 3 Gorges Dam and Lake Victoria); moreover, the river network is not comparable to that of the Amazon Basin. Finally, groundwater has been estimated (without much attention to Surface water) in regions with similar or even higher precipitation rates, like the Mississippi [59,72–74], the USA [75,76], India [77–80].

In the Niger River Basin, groundwater is the dominant TWS component. GLDAS considers SWS as the intersection of the water table and land surface, often treating SWS as an extension of groundwater. SnWS is negligible in regions without snowfall. Thus, the equation is modified as:

$$GWS = TWS - (SMS + CWS) \quad (4)$$

Monthly TWS anomalies (Mascon) from GRACE and soil moisture and canopy water data from GLDAS were preprocessed for consistency, and areal averages were calculated for Nigeria. Missing GRACE data were interpolated.

For this study, the GLDAS dataset used in conjunction with the GRACE dataset was derived in line with the established practices of previous studies [54,56,81,82]. To create a continuous time series for analysis, the 11-month gap between GRACE and GRACE-FO (July 2017 to May 2018) was filled using linear interpolation. We opted for this transparent, computationally simple method whose assumptions are easily understood, rather than using a technique whose shortcomings, as documented by Gyawali et al. [83], are unknown or cannot be handled by us. Again, this approach also prioritizes the preservation of GRACE's native signal over the introduction of external model data. Furthermore, to ameliorate or bypass the possible impact of the data gap on the time series analysis, sophisticated statistical techniques of Singular Spectrum Analysis were utilized to analyze the time series. It is a nonparametric approach capable of providing insight into the data structure and time series in spite of the incompleteness or noise of data.

3.2.2 Principal Component Analysis (PCA) & Empirical Orthogonal Function (EOF)

There are a couple of factors that obscure critical information in meteorological data, including noise and the recording of unnecessary dimensions that do not contribute meaningfully to describing the meteorological phenomenon. Consequently, meteorological phenomena are known to have more than one mode of variation, and some of them may represent noise in the observational data. Scientists are often tasked with minimizing such noise and uncovering hidden dynamics within the data. Empirical Orthogonal Function (EOF) and Principal Component Analysis EOF help scientists identify the main modes of variation responsible for most of the variability within the data. EOF and PCA address this challenge by identifying an alternative basis—a linear combination of the original data—those that best re-expresses or describes the data, assuming such a basis exists.

Empirical Orthogonal Function (EOF) and Principal Component Analysis (PCA) can be considered as two sides of the same coin since both methods use the same principles and algorithms to statistically analyse climate data variations in space and time. Both apply a linear transformation that projects the raw data onto a lower-dimensional space in such a way that among the original variables, no correlation is retained, while most of the information (variances) from the data is kept. These result in transformed time series, known as Principal Components (PCs), which are uncorrelated and ordered in descending order of the variance captured. According to Wu et al. [84] and Mishra et al. [85], the first few PCs retain much of the variation in the original dataset, hence making the finding and representation of patterns easier. The main output of this analysis is the explained variance, or the proportion of total variation explained by each of the PCs.

Various authors, like Shang [86] and Ramsay & Silverman [87], note that PCA and EOF belong to the class of methods named functional data analysis. Functional data analysis aims to represent data in a way that facilitates further investigation, highlights critical features, and identifies the primary sources of patterns and variations. Since the development of PCA by Karl Pearson in 1901, it has become one of the most used methods for multivariate data analysis and unsupervised dimensionality reduction [86]. Its main aim is to simplify data representation by retaining just enough information that describes most of the observed variations. Other than its application in climate sciences, PCA can be used in signal de-noising, blind source separation, and image compression [85,88]. The PCA/EOF and its variants have been used by several researchers to solve certain problems encountered in climate and hydrological studies [35,89–92].

By applying mathematical projections, PCA transforms large datasets with many potentially correlated variables into a smaller set of uncorrelated variables (PCs). These PCs retain the most critical features of the data, facilitating the identification of patterns, trends, and outliers. PCA seeks an answer to the question: “Can we find a new linear basis that re-expresses the data optimally?”. In other words, PCA seeks to find a new linear basis in which we can re-express the data optimally [85,93].

The term *Empirical Orthogonal Function* originates from its operational methodology. Namely, a basis function is determined from empirical data, meaning prior knowledge of the system is not required to empirically determine an EOF. The functions must also be orthogonal or orthonormal. This point represents a contrast to model-fitting techniques, in which prior knowledge is necessary to formulate a model or parameters. PCA will work correctly only under the assumption of orthogonality; otherwise, the system or data cannot be represented reliably if the condition is not satisfied. By not requiring prior knowledge, PCA avoids the drawbacks intrinsic in the use of parametric methods, making it a robust tool for analyzing complex systems.

3.2.3 Singular Spectrum Analysis (SSA)

Most climate and meteorological time series can be decomposed into components such as trends, cyclical variations, and random noise. SSA is a robust algorithm designed to decompose time series data into these components: trend, seasonal or cyclical, and noise. The main objective of SSA is to decompose a real-valued sequence into a representative sum of a small number of independent and interpretable components, such as harmonic oscillatory parts, trend variability, and sections of completely random structure. Mathematical implementation is achieved using Singular Value Decomposition (SVD).

The simplicity and versatility of SSA make it a standard analytical tool for climatic, meteorological, and geophysical time series. The primary advantage of SSA is its nonparametric approach, which does not require prior models or assumptions about trends or periodic components. It performs effectively under various statistical conditions, such as linear and nonlinear, stationary and nonstationary, Gaussian and non-Gaussian series. SSA works well even for relatively small sample sizes and can be used for: trend extraction at

different resolutions; data smoothing; seasonal component extraction; simultaneous identification of cycles with short and long periods; detecting periodicities with time-varying amplitudes; separating complex trends and periodicities; identifying structures in short time series, and change point detection.

The mathematical implementation of the SSA consists of two complementary stages (of different steps), namely:

1. First stage: Decomposition
2. Second stage: Reconstruction

In the first stage, the first step (often referred to as embedding) aims to mathematically map a one-dimensional time series $Y_N = (y_1, y_2 \dots y_n)$, into a multidimensional matrix made up of a sequence of lagged vectors [94]. Where N ($N > 2$) is the length of the time series. Y_N is normally composed of some unknown but identifiable and separable components, such as trend, harmonic oscillation, etc., which generally characterize the behavior of the time series [95].

The decomposition of TWS and GWS time series was conducted using the Singular Spectrum Analysis (SSA) framework via the MATLAB *trenddecomp* function. This approach utilizes an automated embedding window (lag) selection and grouping strategy to isolate the long-term trend (*LT*), seasonal components (*ST*), and residual noise (*R*). The algorithm optimizes the window length (L) within the statistically robust range of $N/3 \leq L \leq N/2$ where N represents the total number of monthly observations [93,94]. This automated selection ensures the successful separation of the dominant annual signals and lower-frequency climate-driven cycles (e.g., ENSO/IOD) from the underlying long-term trajectory, ensuring that the decomposition is data-driven and avoids the biases associated with arbitrary window selection.

4 Results and Discussion

4.1 Terrestrial Water Storage (TWS)

Fig. 3a shows the spatially averaged TWS time series of Nigeria for the period 2002–2021. In general, the data show that TWS oscillates between -50 and 10 mm. However, after 2019, there is an upward trend. A significant anomaly occurred in 2012, with TWS reaching a peak of 140 mm, much above the usual amplitude of 100 mm. This peak coincides with one of the major flooding events that took place in Nigeria, in which 32 out of the 36 states were affected. The time series also depicts a mix of seasonal, annual, inter-annual, and multi-annual variations. Peak values generally occur between September and October; this agrees with the seasonal cycle in Nigeria, as depicted in Fig. 3b. It highlights a distinct single-peak seasonal pattern in Terrestrial Water Storage (TWS) across Nigeria. Between January and March, TWS anomalies are predominantly negative, reflecting reduced rainfall and low soil moisture during the late dry season. A sharp increase in TWS begins in May, coinciding with the arrival of the rainy season, and peaks in August. Subsequently, TWS declines gradually from September to December as rainfall diminishes and evapotranspiration remains elevated. The linear trend fitted to the data suggests a net upward trajectory in TWS over the study period, indicating an overall increase in water storage.

There is no doubt that the cause of the TWS anomaly in 2012 was associated with extreme hydrological conditions, given the data available about runoff and floods in the Niger-Benue river basin. First of all, hydrometric measurements indicated that peak discharges for 2012 were significantly above their respective long term means at several gauging stations. Namely, the peak discharge on the Niger River at Jebba amounted to $1567 \text{ m}^3 \text{ s}^{-1}$ against $1159 \text{ m}^3 \text{ s}^{-1}$ long term mean (approximately 35% increase). In Lokoja confluence, on the other hand, the discharge of 29 September 2012 equaled $31,692 \text{ m}^3 \text{ s}^{-1}$ —92% above the peak flow's long term mean of $16,500 \text{ m}^3 \text{ s}^{-1}$. However, the largest deviation was observed on the Benue River, which was supplied with excess water from Lagdo Dam in Cameroon. So, at Worobokri station, peak

discharge in 2012 exceeded long term mean by 384%, coming to $3362 \text{ m}^3 \text{ s}^{-1}$ against $694 \text{ m}^3 \text{ s}^{-1}$, while at Makurdi peak discharge rose to $16,387 \text{ m}^3 \text{ s}^{-1}$, which was 439% above long term mean of $3042 \text{ m}^3 \text{ s}^{-1}$. Thus, the 2012 anomaly is concurrent with one of the most serious flood disasters ever experienced by Nigeria [96].

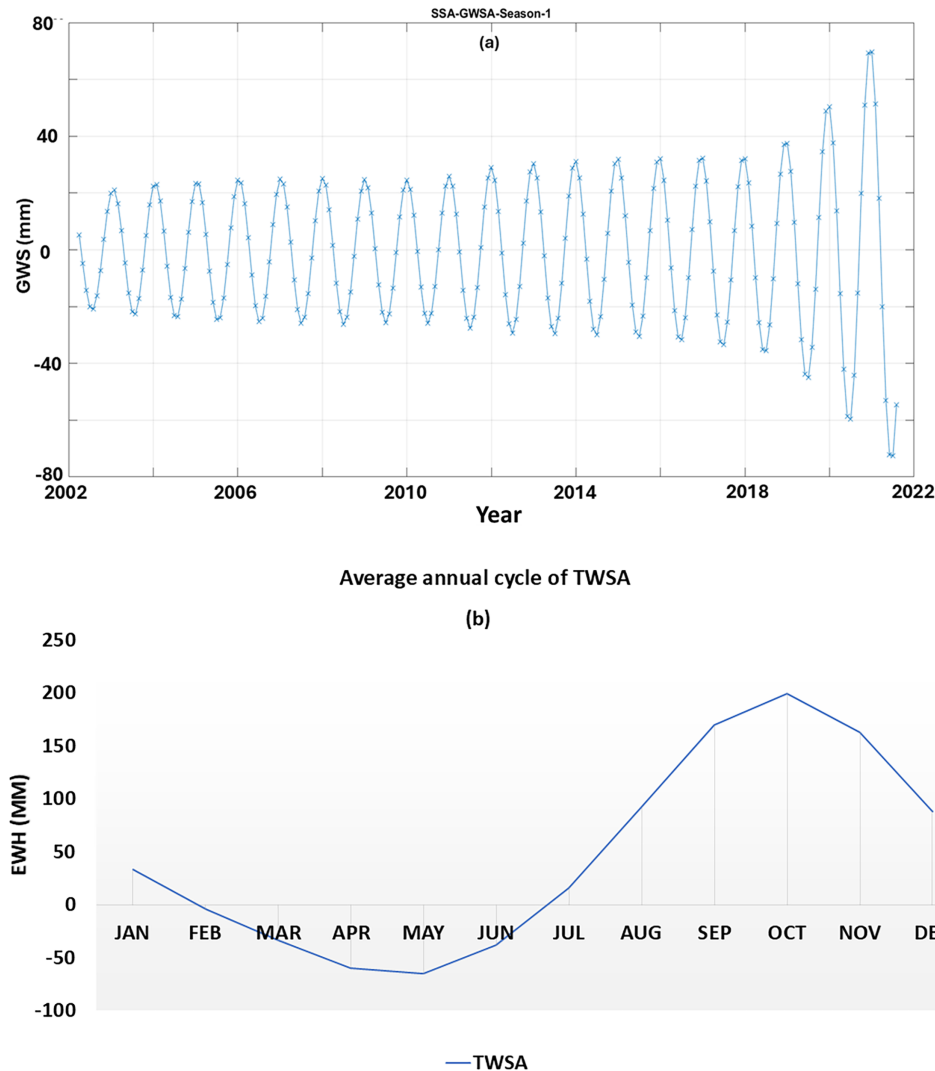


Figure 3: (a) Time series of TWS of Nigeria from 2002 to 2021 (b) average annual cycle of TWS of Nigeria.

The pronounced upward trend in TWS, equally noticed beyond 2019 (Fig. 3a) coincides with one of the strongest positive records of IOD [97,98]. Although the influence of IODs on the West African region is generally weak and indirect, during extreme IOD events like that of 2019 [99], spillover effects (like increased moisture flux from the Indian Ocean that enhances late-season rainfall) cannot be ruled out. Such an effect either amplifies or cancels concurrent events/factors like ENSO and other primary drivers of rainfall within the region. Moreover, there are studies that point to the close connection between IOD & ENSO, which is the major influence within West Africa [98,100–103]. It is, therefore, not out of place to say that the unprecedented positive phase of IOD may have contributed to the unprecedented rise in TWS, after 2019. Again, the unprecedented post 2019 upward trend in TWS may also be likely driven by increased precipitation [103–106], and an increase in groundwater/aquifer recharge [102,107], which ultimately led to net storage gains, without presenting/manifesting as floods, unlike the case of 2012. Another important factor

that possibly induced the 2012 flood (which, of course, did not occur again after 2012) was the opening of the major dams (Lagdo dam in the Cameroon) around the study area [108–112].

The SSA decomposition provides further insights into how different temporal scales contribute to TWS variability. The decomposed timeseries of TWS is shown in Fig. 4. SSA is renowned for its ability to decompose timeseries components into the trend, seasonal (harmonic) patterns, and residual noise. The SSA decomposition of the TWS time series (Fig. 4) reveals a nonlinear trend and six seasonal patterns (Figs. 5–7).

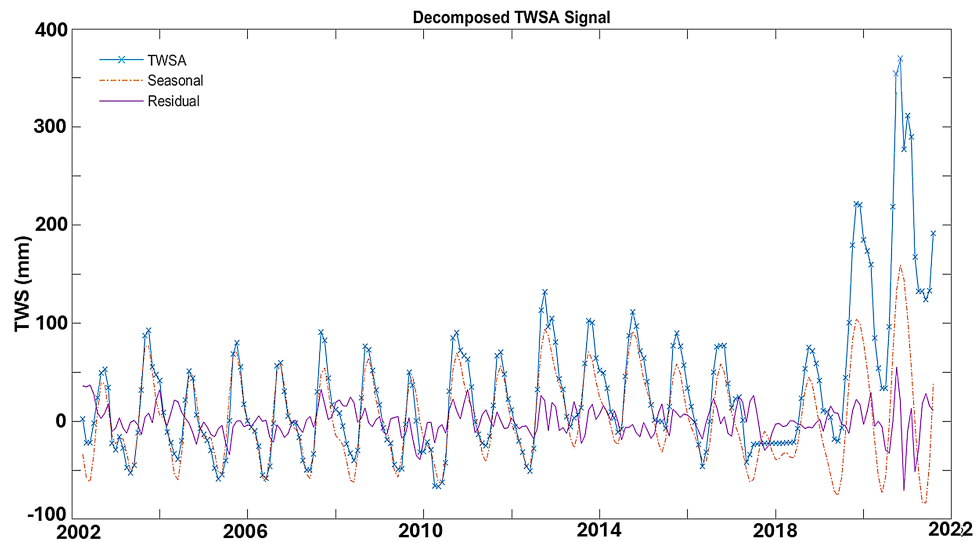


Figure 4: SSA Decomposed time series of TWS over Nigeria.

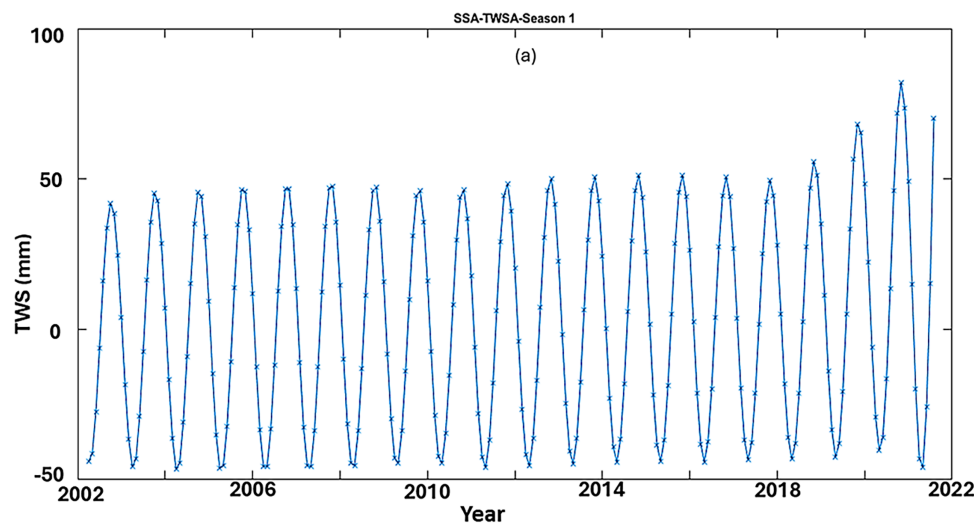


Figure 5: (Continued)

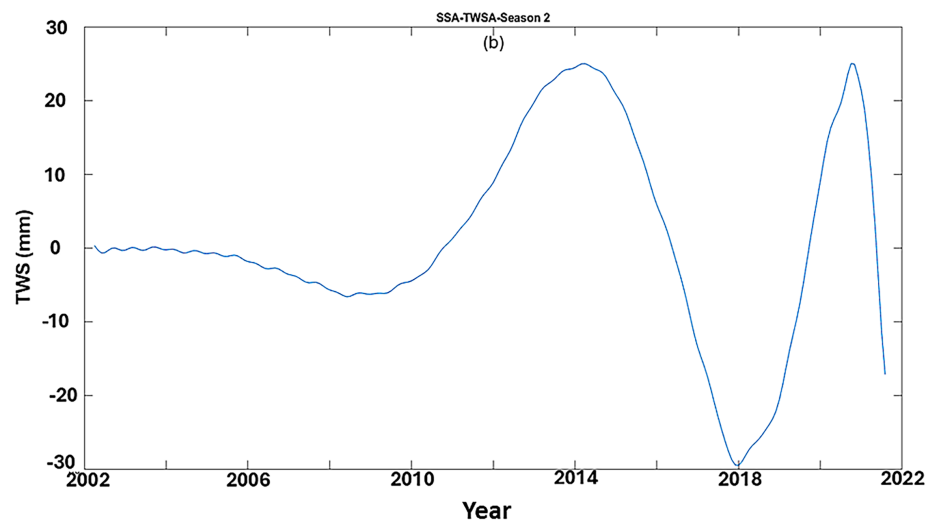


Figure 5: SSA decomposed seasonal cycles for TWS over Nigeria (a) seasonal cycle 1 (b) seasonal cycle 2.

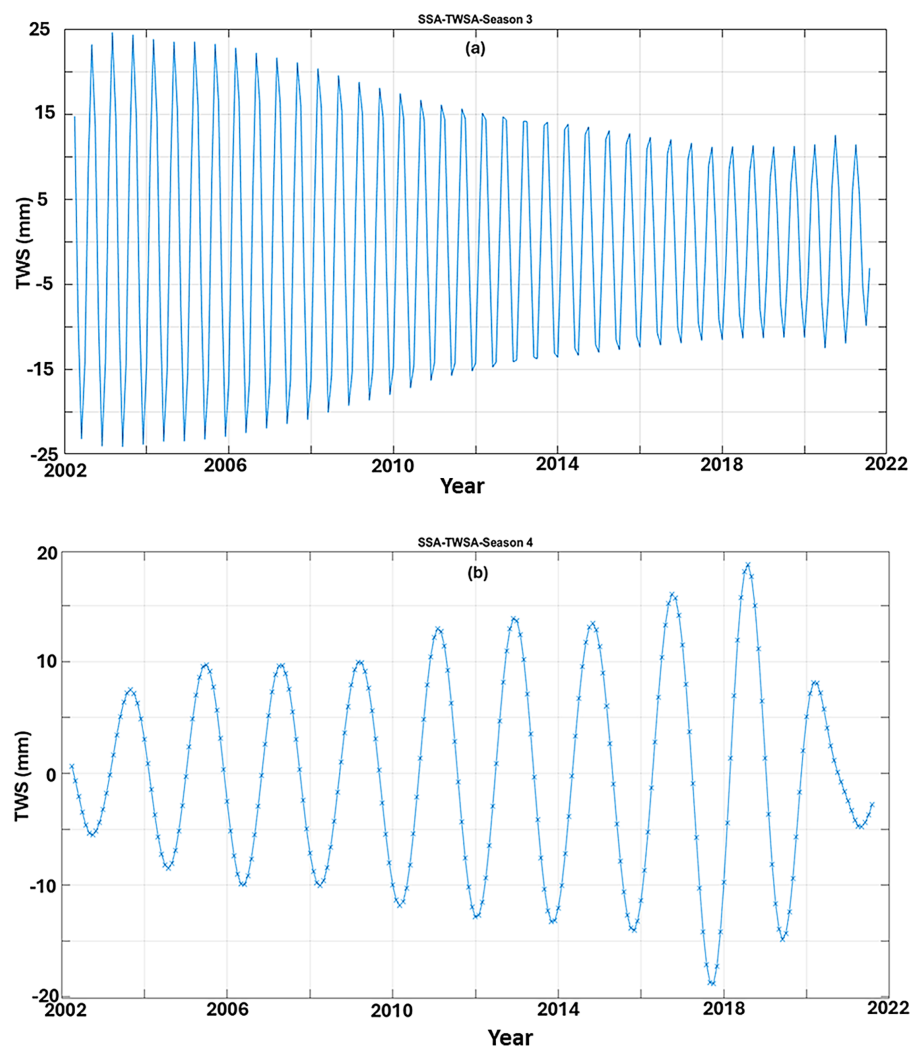


Figure 6: SSA decomposed seasonal cycles for TWS over Nigeria (a) seasonal cycle 3 (b) seasonal cycle 4.

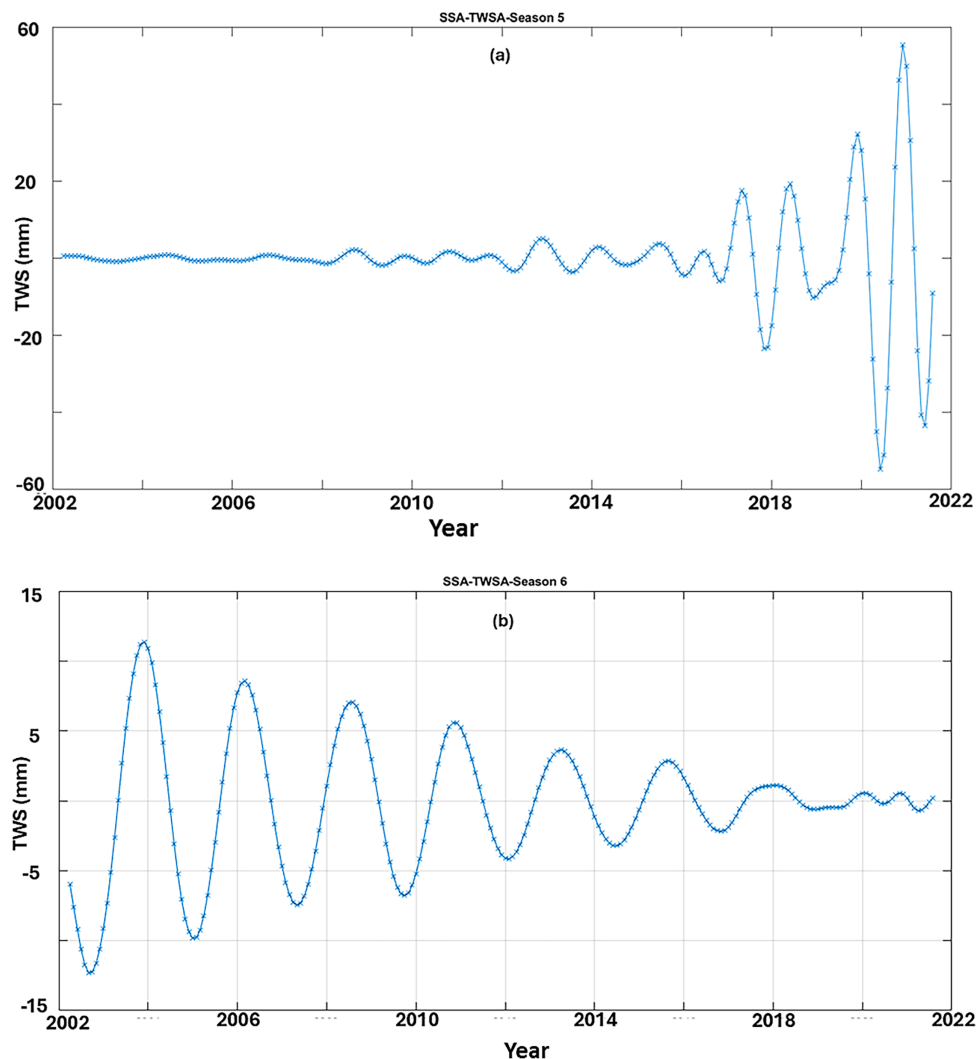


Figure 7: SSA decomposed seasonal cycles for TWS over Nigeria (a) seasonal cycle 5 (b) seasonal cycle 6.

The SSA components reveal the impact and influence of these climate teleconnections: the strong annual cycle (Season 1, Fig. 5a) is likely tied to monsoon rainfall; the 2–4-year oscillations (Figs. 6b and 7b) seem to correlate with ENSO's influence on West Africa rainfall; and the weaker multi-annual signal (10–12 year) is likely a reflection of lower frequency variability such as AMO and PDO (Fig. 5b). These findings align with similar studies by [35,39,113,114] in West Africa that observed an upward trend in TWS.

It is observed that the annual component (Fig. 5a) depicts the largely annual signal, while the biennial and interannual components of the SSA (Figs. 6b and 7b) seem to be in tandem with known climatic modes of ENSO with a periodicity of 2–7 years [102,115,116]. The decadal (and interdecadal) components (Fig. 5b) may be cautiously interpreted to coincide with the Interdecadal Pacific Oscillation (IPO), with a striking low frequency and long-term effects within West Africa. This inference is supported by Mohino et al. [117], who confirmed that PDO/IPO, especially when in phase with ENSO, tend to have a compound effect in West Africa. Again, Lüdecke et al. [118] confirm that IPO contributes to climatic effects within West Africa, while Hassan and Jin [119] suggest the effect of PDO is moderate on rainfall, which, incidentally, is a major contributor to TWS in Nigeria and most parts of West Africa.

Fig. 6b depicts a biennial cycle with amplitude variations of about 10 mm (pre-2010), 13 mm (2010–2016), and 19 mm (2017–2019). In Fig. 7a, no seasonal pattern is evident until after 2012, while an annual cycle emerges after 2017, its amplitude growing to about 55 mm by 2021. Until 2018, the dominant patterns were biennial, with amplitudes decreasing from 1 mm to less than 5 mm after 2018.

Fig. 8a–c displays the temporal characteristics of the data set, which are obtained by applying the PCA, while the EOFs in the same figures depict the spatial characteristics of the respective PCs. As depicted in Fig. 8a–c, PC-1 exhibits a strong, increasing trend over the study period. From a quantitative viewpoint, this mode explains about 85% of the total variability in TWS, with notable increases observed in the Niger Central (Kaduna River Basin), Lower Benue (Benue River Basin), Niger South (Imo and Anambra River Basins), and Eastern Littoral (Cross River Basin) regions. Interestingly, the abrupt rise in amplitude in 2012—coinciding with a major flood event—highlights the sensitivity of this mode to extreme hydrological events. The EOF-1 is a spatial equivalent of the temporal pattern described by the PC-1 timeseries, which is dominated/characterized by an annual seasonal cycle. It explains 85% of the TWS variance, which depicts a heavily homogenous spatial pattern and strong positive loadings and pc trend. These positive loadings appear to be concentrated around the central and southern parts of Nigeria, corresponding with the hydrological regions with the highest annual rainfall. EOF-1 represents a broad-scale signal driven by regional climatic factors that may be attributed to increased precipitation, changes in evaporation, or land-use modifications (e.g., reforestation, dam construction, or agricultural expansion). These patterns in the EOF and PC may be interpreted as the dominant signature of a large-scale climate-driven water accumulation with a near-uniform effect in all hydrological zones. It indicates that most of the country responds synchronously to the seasonal monsoonal cycle. This could also mean that this mode captures the synchronous seasonal water recharge and depletion driven by the West African Monsoon. From a hydrological viewpoint, the result of this dominant mode suggests that large areas of Nigeria are experiencing significant changes in water storage. Monitoring this mode is therefore important for forecasting floods and assessing long-term shifts in regional water availability.

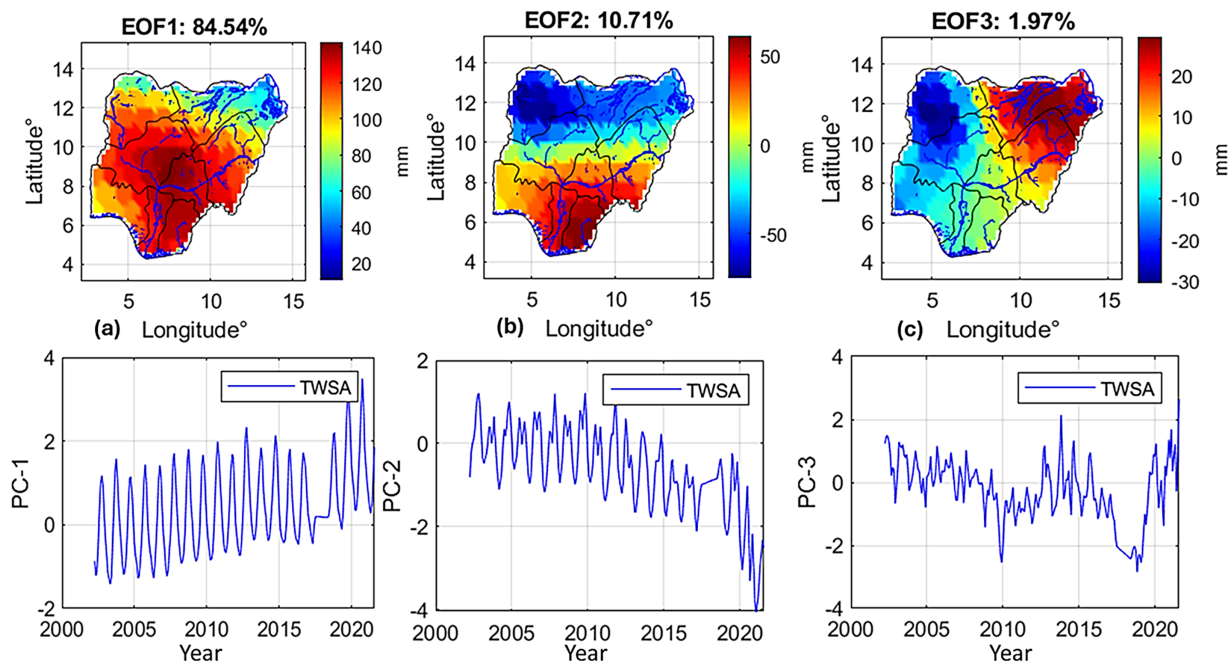


Figure 8: PC ((a–c): lower frame) and EOF ((a–c): upper frame) of TWS.

While PC-1 & EOF-1 capture the broad/regional and long-term variations of TWS within Nigeria, PC-2 explains about 11% of the variance and reveals both annual and multi-annual oscillations. Its temporal behavior, characterized by pronounced seasonal fluctuations, suggests that periodic climate phenomena—such as ENSO or PDO—play a significant role. It shows a striking latitudinal dipole pattern of positive loadings in the humid south and negative loadings in the relatively arid north. It reflects the contrasting hydrological response between the humid southern basins and the relatively arid northern basin. This pattern is analogous to the country's hydrological regimes across climatic zones and highlights the influence of interannual monsoon penetration. This is similar to findings in [42].

PC-2 also reveals periods that may be interpreted as wet periods. These periods are characterized by relatively consistent high values or peaks in PC values (~2002–2003; ~2007–2008; ~2010–2012). The oscillations are roughly 1–3 years and consistent with ENSO-related teleconnections that often affect rainfall, soil moisture, and groundwater recharge. It exhibits interannual variability superimposed on a persistent declining trend, particularly after 2010. This is suggestive of a climate-driven modulation of TWS, likely associated with large-scale climate oscillation.

Collectively, the modes (EOF-1 & 2, and PC-1 & 2) reveal that TWS variations in Nigeria arise from both coherent, countrywide climate forcing & region-specific responses associated with rainfall gradients and climatic teleconnections.

Fig. 9 presents the spatial distribution and temporal evolution of terrestrial water storage (TWS) trends across Nigeria from 2002 to 2021, an overall statistically significant ($p < 0.05$) upward trend in water storage, which is primarily driven by increased precipitation and enhanced aquifer recharge. The spatial pattern is consistent with the overall upward trajectory shown in the TWS time series (Fig. 3a) and aligns with the dominant mode (EOF 1/PC-1, which explains a dominant 85% of the total variability in water storage and exhibits a strong increasing trajectory) in Fig. 8a, which captures a broad, climate driven increase across most of the country. The map reveals a predominantly positive trend, with the strongest increases (exceeding +20 mm/yr) concentrated in the Niger North (Sokoto Rima) and Niger Central (Kaduna) basins. Furthermore, the positive TWS trends in the northern basins corroborate the increasing groundwater storage (GWS) trends shown in the spatial trend map of GWS over Nigeria, suggesting enhanced aquifer recharge, likely driven by rising precipitation as noted in other West African studies [35,39].

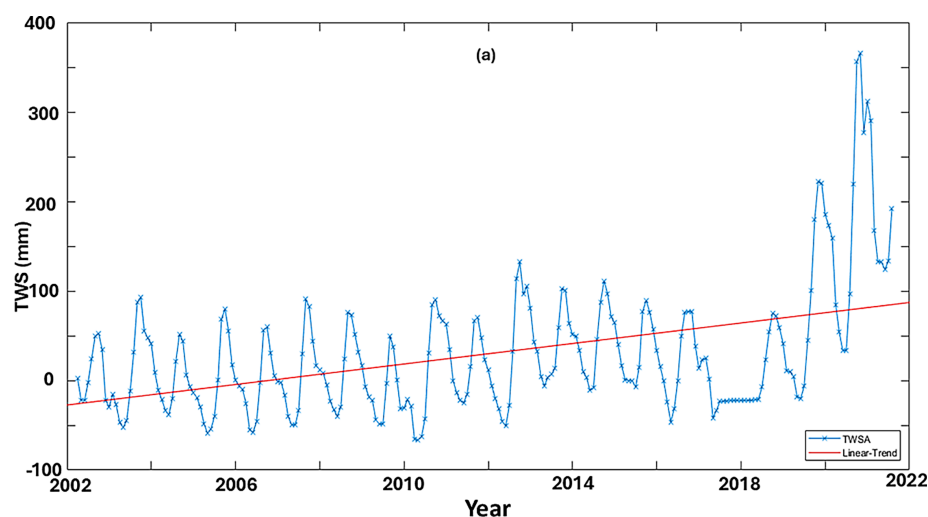


Figure 9: (Continued)

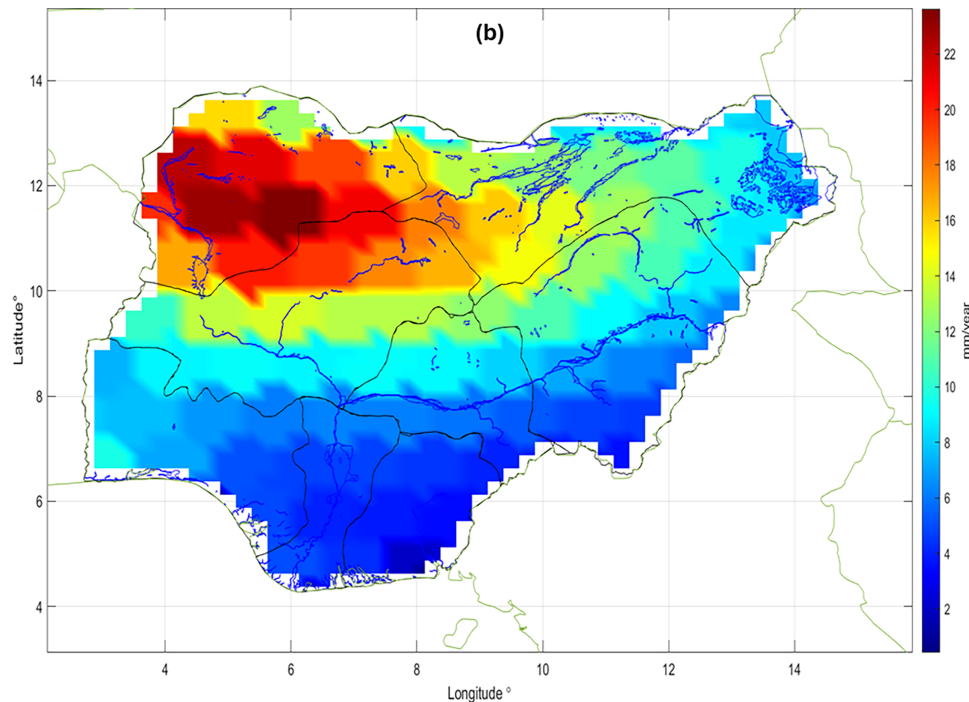


Figure 9: (a) Linear trend of TWS; (b) spatial distribution of the TWS trend over Nigeria.

Our findings are broadly consistent with the global scale analysis of Shi et al. [120]. They reported an increasing TWS trend (0–10 mm/year) across most biomes and climate zones during 1948–2012 (with climate change explaining >80% of the observed trends). In Nigeria, we similarly observed overall increasing TWS and GWS trends. These trends are mostly attributed to enhanced precipitation and climate variability, particularly the influence of teleconnections such as ENSO and IOD. Both studies converge on the conclusion that while climate-induced precipitation patterns dominate storage trends, anthropogenic factors and LULCC serve as vital secondary drivers that can induce localized nonlinearities in water storage behaviour. This underscores the importance of regional-scale analyses in complementing global assessments, particularly in data-scarce regions where localized human impacts may be underrepresented.

In contrast to the global increasing trend, a recent study over the Middle East by Youssefi et al. [121] documented a severe, statistically significant decline in TWS from 2002 to 2024, with an average depletion of $-45 \text{ km}^3/\text{year}$, driven primarily by groundwater extraction under hyper-arid conditions. This opposing trajectory highlights the divergent hydroclimatic contexts: the Middle East's chronic aridity, intense anthropogenic extraction, and limited recharge contrast sharply with Nigeria's monsoon-driven system, where increasing precipitation appears to enhance aquifer recharge.

Both studies confirm the dominant role of GWS in TWS dynamics within their respective regions and the utility of advanced decomposition techniques (e.g., SSA/EOF in Nigeria vs. Component Contribution Ratio and Least-Squares Cross Wavelet Analysis in the Middle East).

Quarterly analysis (Fig. 10a–d) shows high TWS from July to December and lower values from January to June. A north-south dipole reflective of Nigeria's climatic zone is observed for Fig. 10a,b. The spatial distribution of TWS in Fig. 10d resembles that of Fig. 8a, suggesting that the dominant mode of TWS spatial variation is most pronounced from October to December.

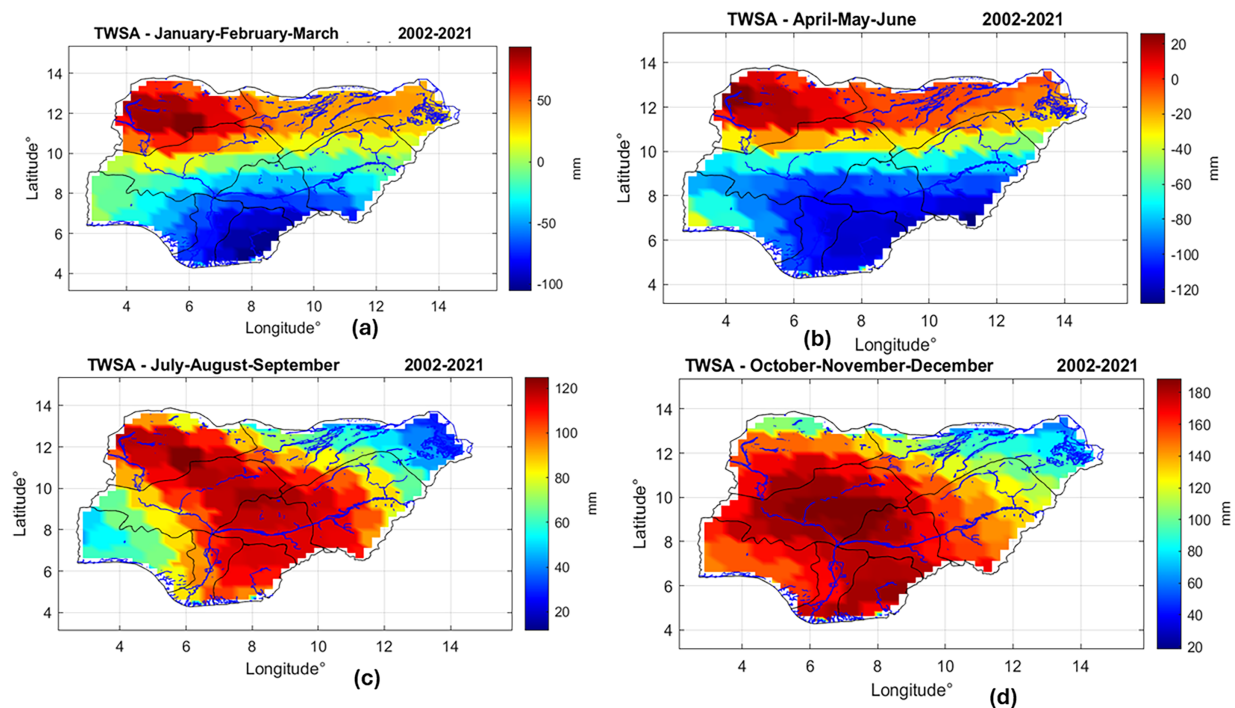


Figure 10: Quarterly spatial distribution of TWS: (a) January–March; (b) April–June; (c) July–September; (d) October–December.

From the quarterly analysis as shown in Fig. 10a–d, it indicates that TWS values for the year are higher during the periods of July, August, September, October, and November & December, while the minimum periods are during January, February, March, April, May, and June. A North-south dipole, typical of Nigeria's climate regions, is depicted in Fig. 10a,b.

4.2 Groundwater Storage (GWS)

In Fig. 11a, GWS is observed to oscillate between ± 50 mm from 2002 to 2010 with no significant trend. It should be noted, however, that an upward trend appears after 2010. Seasonal patterns shown in Fig. 11b identify GWS highs from September to November and lows from May to June. This rising trend in GWS is in tandem with other researchers' results, such as [36,39,114], who ascribed it to enhanced precipitation. Unlike Terrestrial Water Storage (TWS), Groundwater Storage (GWS) begins the year at elevated levels, likely sustained by residual recharge from the previous wet season. During the dry season (February to early May), groundwater anomalies progressively decline, driven by minimal rainfall replenishment. Recovery initiates in late July as the wet season resumes, with GWS steadily increasing through December, reflecting renewed recharge from rainfall. This pattern underscores groundwater's delayed response to seasonal climate shifts compared to TWS.

While both Terrestrial Water Storage (TWS) and Groundwater Storage (GWS) are strongly influenced by Nigeria's monsoon-driven climate, their seasonal highs and lows occur at staggered intervals, highlighting differences in their hydrological dynamics. TWS reacts swiftly to rainfall, peaking in August when surface water and soil moisture levels are highest. Conversely, GWS exhibits delayed behavior, dipping to its lowest levels mid-year and rebounding later as gradual infiltration replenishes underground reserves. In essence, TWS reflects rapid, surface-level changes driven by immediate rainfall, while GWS tracks slower subsurface

processes tied to aquifer recharge. This results in distinct yet complementary temporal patterns: TWS captures short-term variability, and GWS embodies longer-term groundwater shifts.

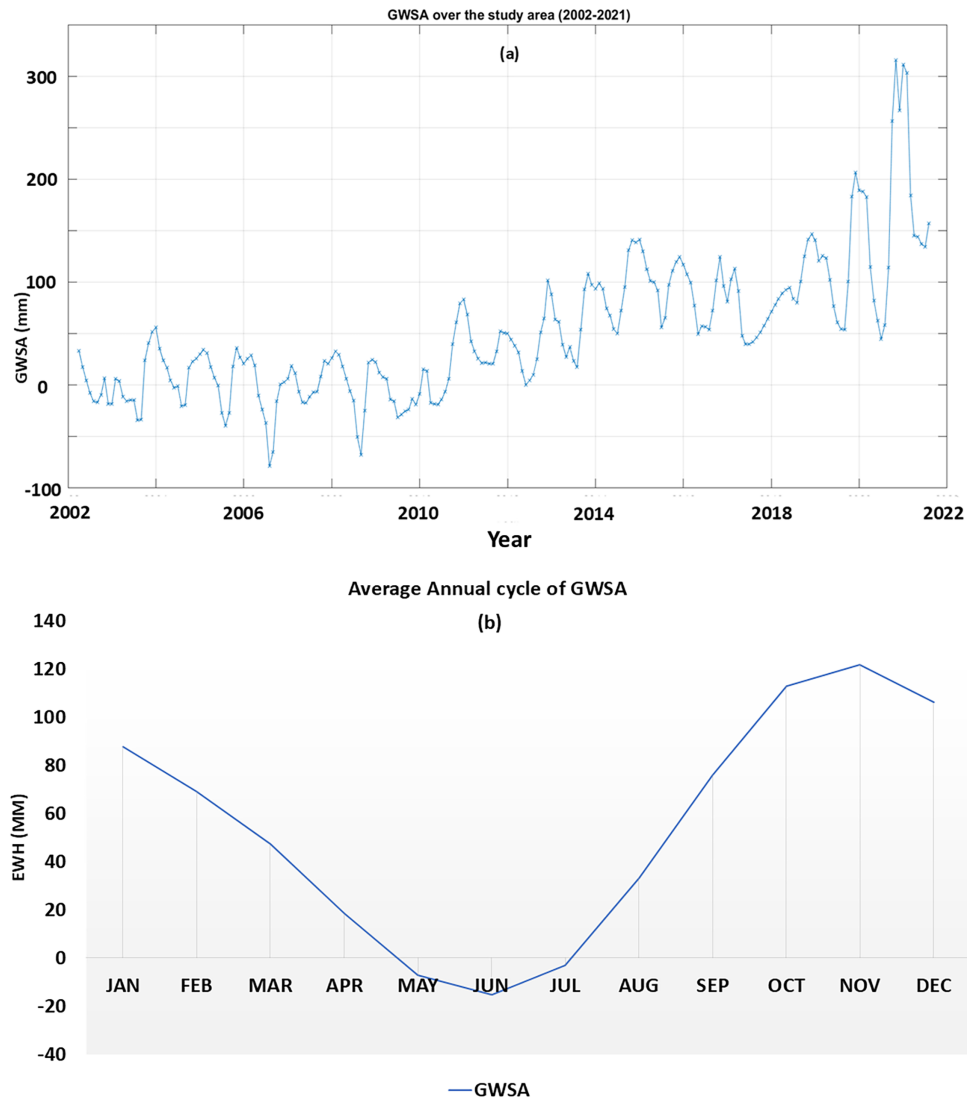


Figure 11: (a) Time series of GWSA (b) Average annual cycle of GWSA.

Results of GWS decomposition using SSA are presented in Fig. 12. The deseasoned time series (Fig. 12b) retains cyclical variability, suggesting additional influences such as climate variability or human activities. The annual cycles combined with the amplitude modulation after 2018 are also evident in the detrended time series (Fig. 12c), implying inter-annual and multi-annual characteristics not linked to annual climate alone. The seasonal cyclical patterns are shown in Fig. 13a–c: the amplitude of the annual cycle increases, and the range of variation is ± 20 mm (Fig. 13a), suggesting that non-annual forcing exists. It also indicates the presence of a multi-annual cycle with an approximate period of ~ 10 – 12 years, which might be connected to climate modes, such as ENSO and IOD (Fig. 13b). Furthermore, the inter-annual cycle occurs every 3–4 years and shows a remarkable correlation with the inter-annual climatic variability (Fig. 13c).

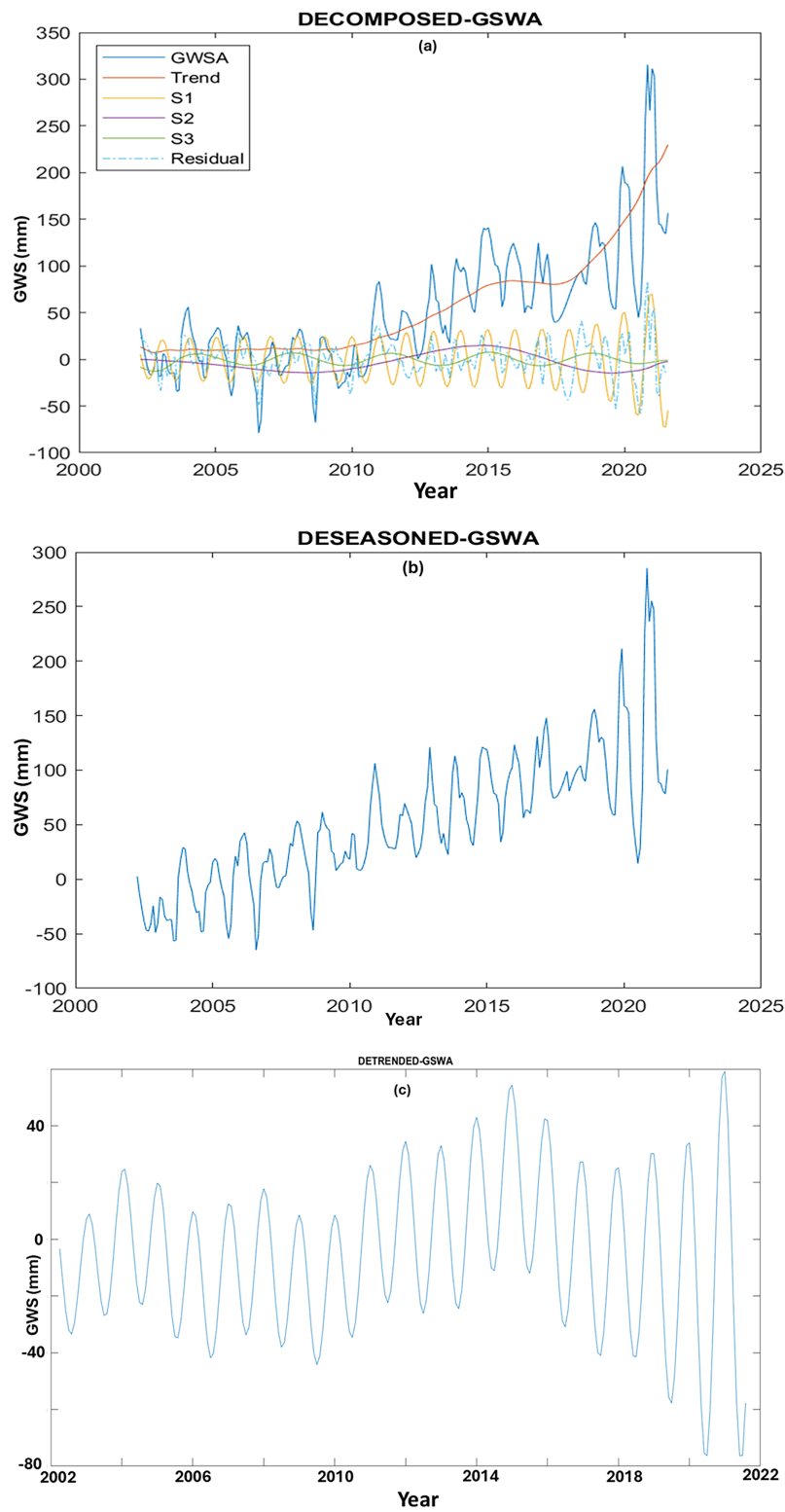


Figure 12: Time series of GWS ((a): decomposed, (b): de-seasoned, and (c): detrended).

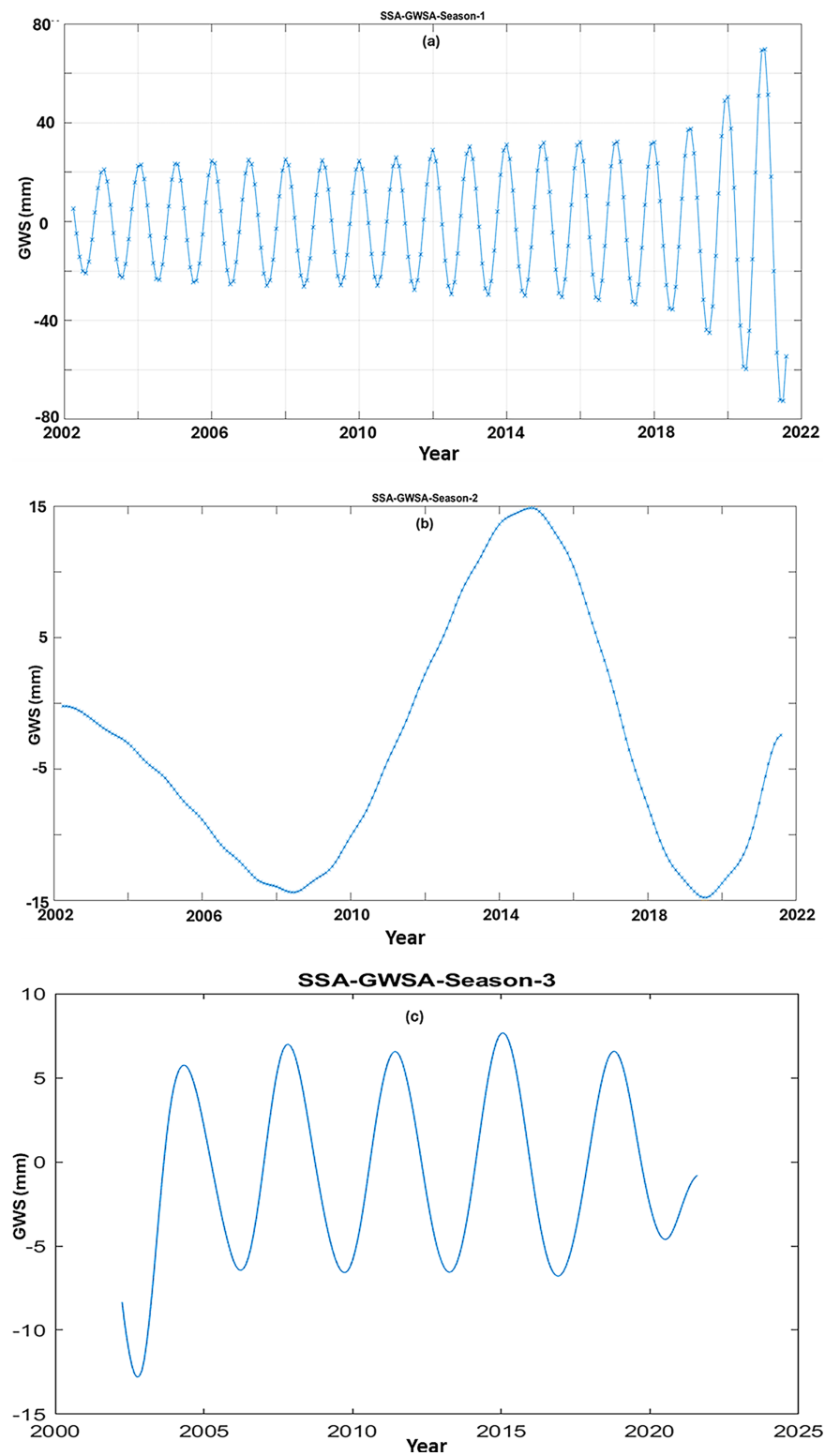


Figure 13: SSA decomposed seasonal cycles for GWS over Nigeria (a) seasonal cycle 1; (b) seasonal cycle 2; (c) seasonal cycle 3.

The SSA decomposition of GWS reveals a more subdued but physically meaningful set of temporal modes. The inter-annual (3–4 years) and decadal (≈ 10 –12 years) oscillations identified by SSA (Fig. 13b and c) are indicative of the influence of climate teleconnections (such as ENSO, PDO) [35,122]. Thus, it reinforces the vital role played by climate variability. The 3–4-year cycle in GWS has revealed that groundwater levels are not just recovering seasonally, but are being repeatedly modulated by low-frequency climate variability. Hence, consecutive years linked with negative ENSO phases may suppress recharge for multiple seasons, compounding depletion from ongoing abstraction.

The divergence between TWS and GWS trends in certain regions also suggests that a portion of rainfall-induced TWS variability may be confined to the soil moisture layer rather than contributing to deeper groundwater recharge.

PCA results of Fig. 14 reveal that EOF-1 accounts for nearly 70% of the total variation and is predominant in the Niger North and Central hydrological areas, with a negative trend despite the overall rising trend in Figs. 11 and 12a. EOF-2, which accounts for $\sim 20\%$ of the variance, is characterized by a north-south dipole mode consistent with Nigeria's climatic zones. EOF-3 ($\sim 3\%$ variability) suggests localized influences, with no clear periodicity. EOF-1 and PC-1 reveal a negative trend, majorly localized in the Niger-North (Sokoto-Rima) and Niger Central (Kaduna) basins

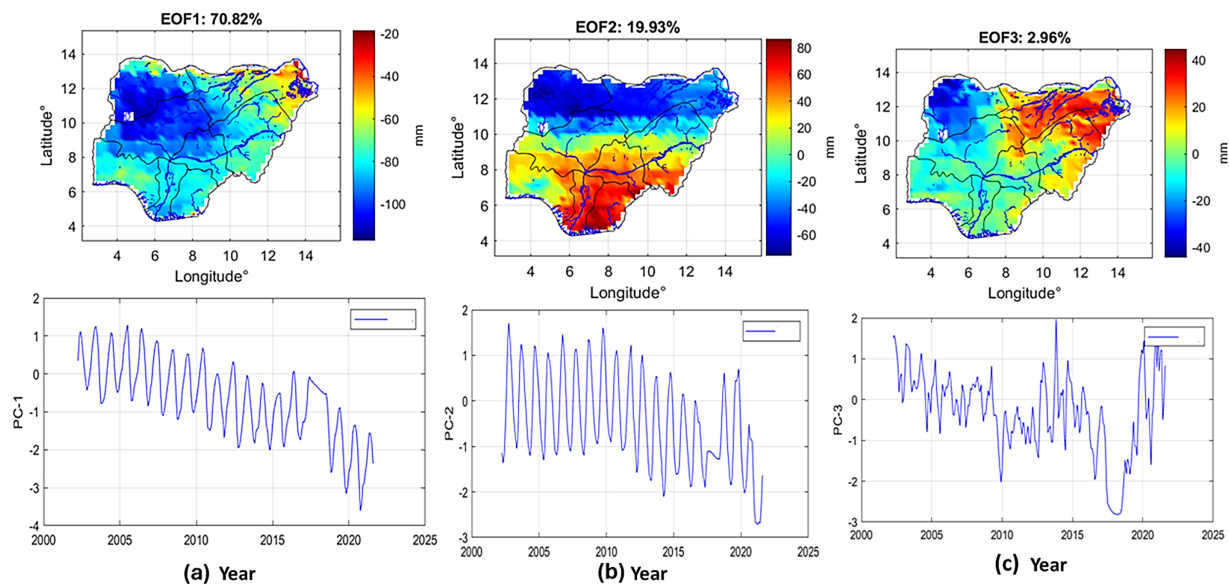


Figure 14: PC ((a–c): lower frame) and EOF ((a–c): upper frame) of GWS.

The primary spatial pattern identified by EOF-1 (Fig. 14a) is centered on the Niger North (Sokoto-Rima River Basin) and Niger Central (Kaduna River Basin) hydrological zones. This leading mode accounts for approximately 70% of groundwater storage (GWS) variability in Nigeria, reflecting large-scale trends such as depletion in over-extracted urban centers (e.g., Lagos, Kano) and recharge in sedimentary basins like the Sokoto Basin. Notably, the associated principal component (PC) reveals a downward trend, contrasting with the upward trajectory observed in Fig. 12a. This inconsistency might arise from localized recharge processes, such as urban runoff infiltration or shifts in land-use practices. Further research is needed to clarify the drivers of these anomalous patterns.

The secondary dominant mode (EOF-2), accounting for roughly 20% of Nigeria's groundwater storage (GWS) variability, exhibits a pronounced latitudinal or regional divergence (Fig. 14b). The dipole pattern

observed in EOF-2, showing positive loadings in the southern region and negative loadings in the northern sedimentary basins, is interpreted as differential stress levels on the aquifers in these regions, and a hydrological regime that is consistent with the climatic settings of the country (humid south and arid north). This pattern likely stems from contrasts in hydrogeological conditions, climatic zones (arid northern vs. humid southern regions), groundwater extraction rates, and recharge processes. Such spatial differences align with Nigeria's climatic and environmental gradients, where factors like reduced recharge in the arid north and higher pumping demands in populated areas may drive regional disparities. This mode underscores the interplay of natural and anthropogenic influences shaping groundwater dynamics across the country.

PC-3 (Fig. 14c) exhibits high variability without clear periodic patterns, accounting for only 2.96% of the total groundwater storage (GWS) variability. These fluctuations are likely tied to short-term, localized influences such as regional climate conditions or irregular rainfall. The pattern may also signal localized depletion zones, driven by irrigation, industrial extraction, or limited recharge capacity in areas like the Hadejia-Nguru wetlands and urban centers with intensive groundwater use.

The out-of-phase patterns that are evident in the quarterly analysis of GWS, shown in Fig. 15 of the Western Littoral hydrological area, could be attributed to anthropogenic impacts. The attribution of the out-of-phase groundwater storage (GWS) pattern in the western coastal zone to anthropogenic influences is supported by independent evidence on rapid urbanization, population growth, and associated water demand pressures, particularly in Lagos and its surrounding regions. The region has experienced explosive population growth, with the urban extent expanding from approximately 66 km² in 1962 to over 1200 km² by 2015 [123]. Lagos State, the primary economic hub in this region, has experienced an extraordinary population surge of approximately 754% between 1963 and 2015, maintaining an annual growth rate that consistently ranks among the highest globally [124,125]. This demographic explosion has catalyzed a profound land-use transformation, with urban built-up areas expanding from 230.8 km² in 1976 to 805.4 km² by 2015 [125]. Such extensive urbanization increases surface impermeability, which limits natural aquifer recharge. This reduction in natural replenishment coincides with a massive surge in groundwater demand, driven by a population that has increased by over 754% since 1963. In Lagos, water demand skyrocketed from approximately 172,000 m³/day in 1963 to over 2.39 million m³/day in 2015, while the public water supply has consistently failed to meet this need, fulfilling only about one-third of the daily requirement of an estimated 650 million gallons [125]. Consequently, an estimated 90%–95% of the population has turned to private boreholes, leading to rampant, unregulated groundwater abstraction [126].

The patterns for the first and second quarters are identical to Nigeria's climatic zones and TWS distribution (Fig. 15a,b). Peak values for GWS are observed around October to December, while lower values are observed around April to June. Analysis of spatial trends presented in Fig. 16 shows that Niger North has the highest values (~25 mm/year); local trends observed in the Western Littoral area are most likely due to non-natural influences. By analyzing the two reference timeseries separately in Fig. 17, TWS was found to be slightly ahead of GWS, about a month.

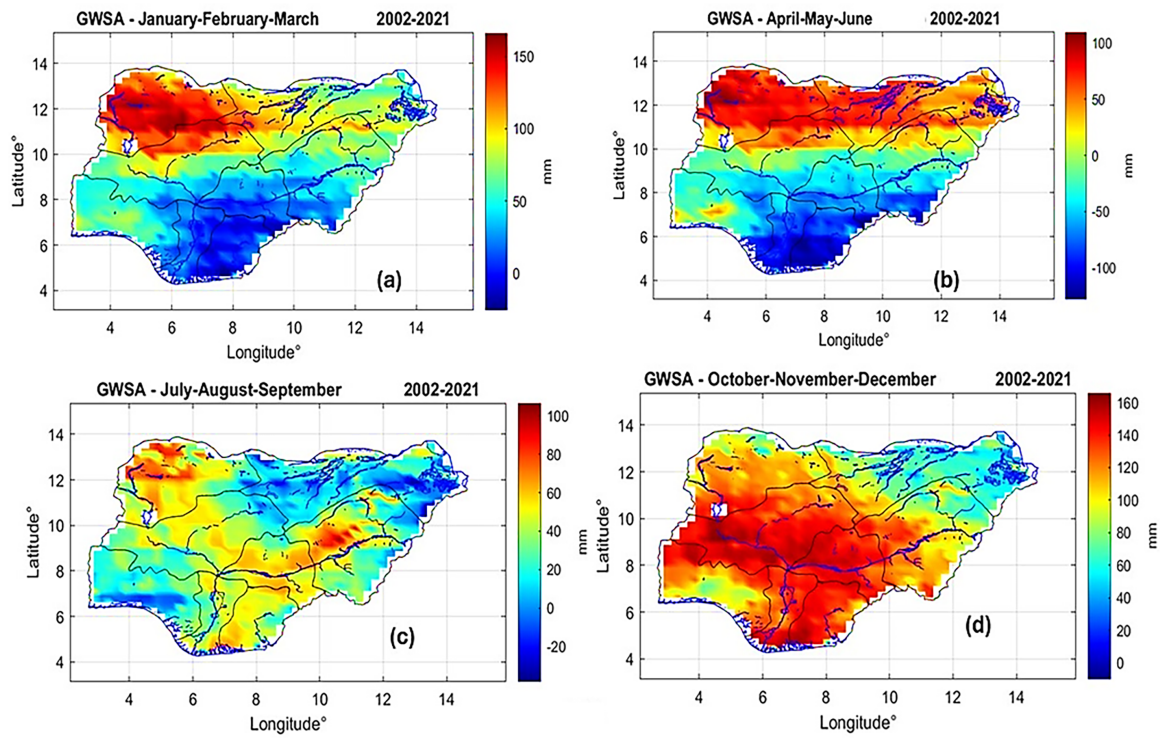


Figure 15: Quarterly spatial distribution of GWS: (a) January–March; (b) April–June; (c) July–September; (d) October–December.

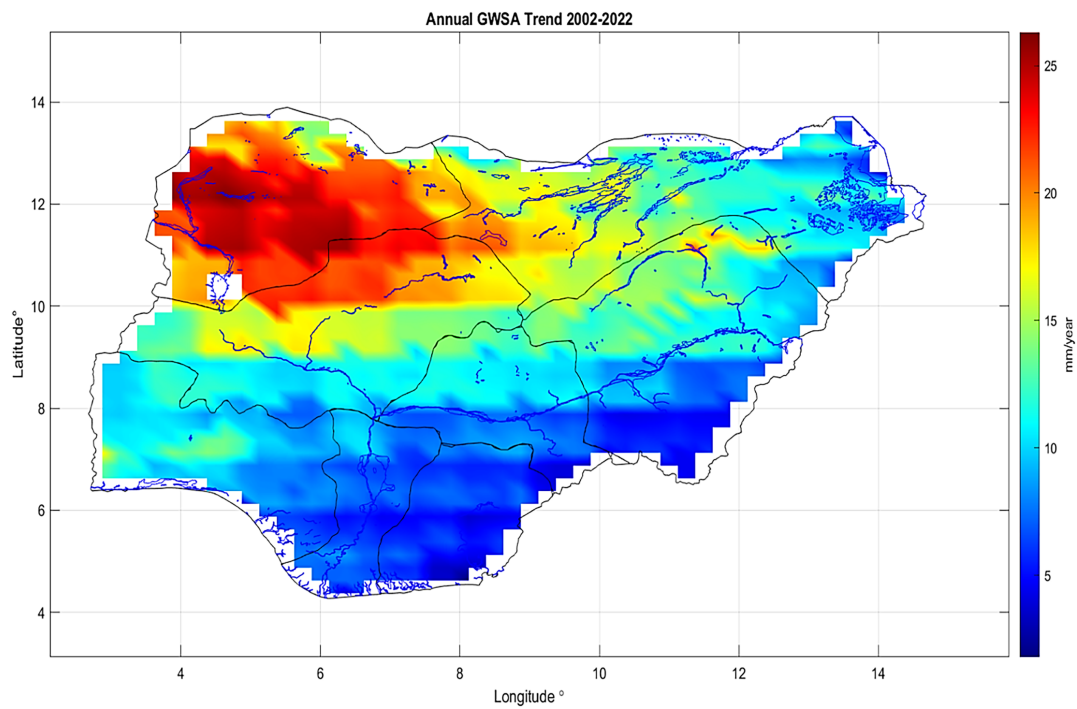


Figure 16: Spatial trends of GWS.

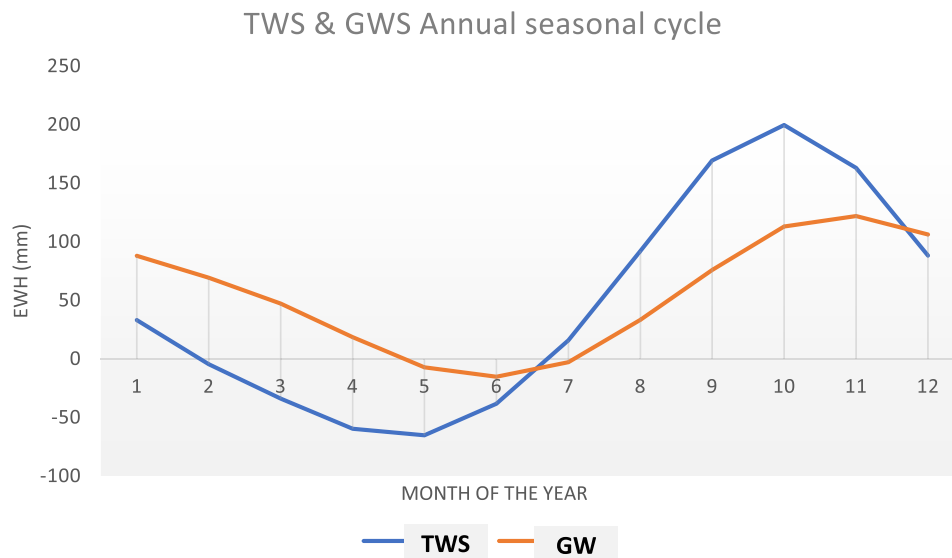


Figure 17: Annual cycle of TWS and GWS.

4.3 Assessment of GRACE-Derived GWS over Nigeria

To validate the GRACE-Derived GWS estimates, *in situ* GWS estimates from 3 groundwater monitoring stations (see section) were compared with corresponding GRACE-Derived GWS estimates. The results are presented in Table 3 and Figs. 18–20.

The overall correspondence between the two datasets, the comparisons made in Table 3, and shown in Figs. 18–20, is comparatively moderate. This implies that the estimate of GWS using the data derived from GRACE moderately captures groundwater storage variations estimation within Nigeria. The negative correlation observed at two well locations is the result of a phase shift, which manifests as one dataset leading or lagging behind the other. This phase lag of the GRACE-derived GWS estimates is clearly shown in Fig. 19b,c, using data from the Sagamu and Agbor monitoring stations. This difference is expected because the *in-situ* measurements made at rates of two times a day are more sensitive to local groundwater fluctuations in space and time. In comparing the two, the GRACE data is obtained after monthly measurements, so it tends to collect much data from bigger areas, which evens out local fluctuations, and is relatively slow to respond to changes in such conditions.

It must be mentioned that the Specific Yields values used were sourced from secondary sources, and in some cases (FUTO and Sagamu), Specific Yields of neighboring/adjacent regions were adopted. This was done since NIHSA could not provide the Specific Yields values of the wells, therefore the use of secondary or Specific Yields of the adjoining areas may be responsible for the moderate correlation obtained, as opposed to the regular high correlation obtained in other studies [127–129]. As it has been well documented, specific yield plays a role in GWS estimates [60,130,131].

Although the period under consideration is over 200 months, validation was performed using data from a relatively few months only. This decision was made because the majority of monitoring well data began in 2015, and in some months GRACE data were unavailable. Consequently, only corresponding months after 2015 were used for validation.

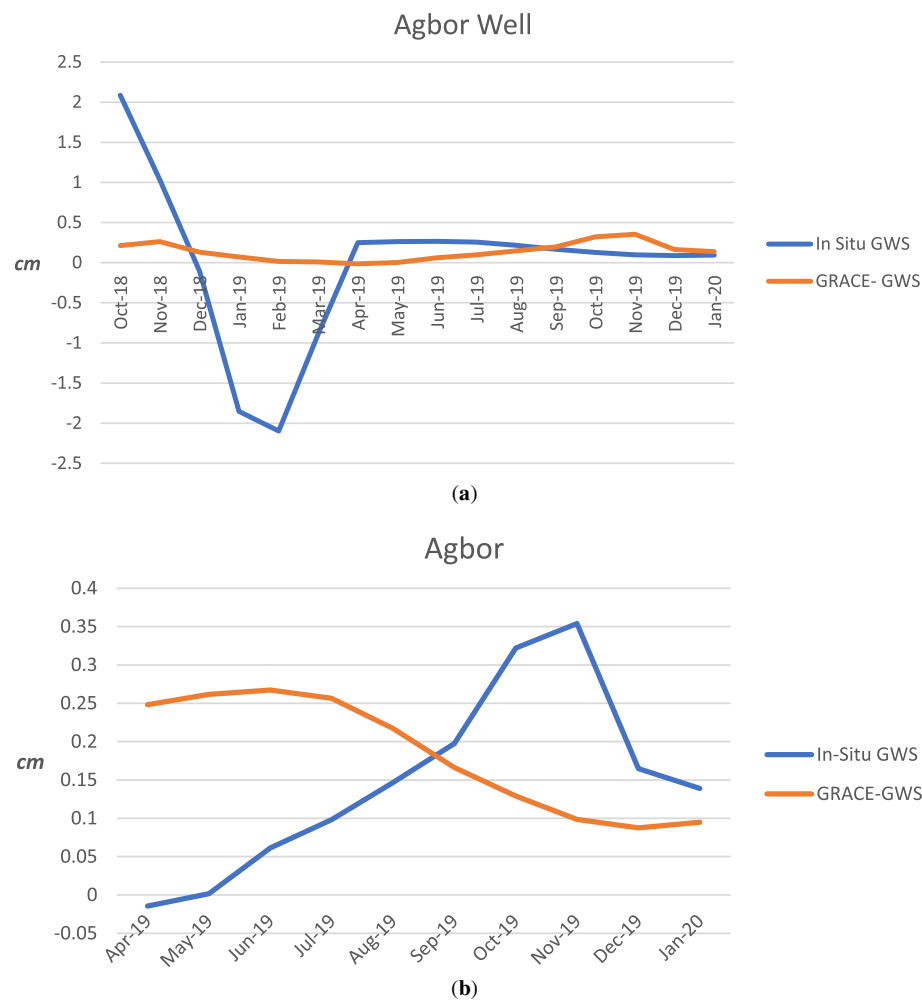


Figure 18: (a): Plot of GRACE-Derived GWS and *In Situ* GWS. (b): plot of GRACE-derived GWS and *In Situ* GWS.

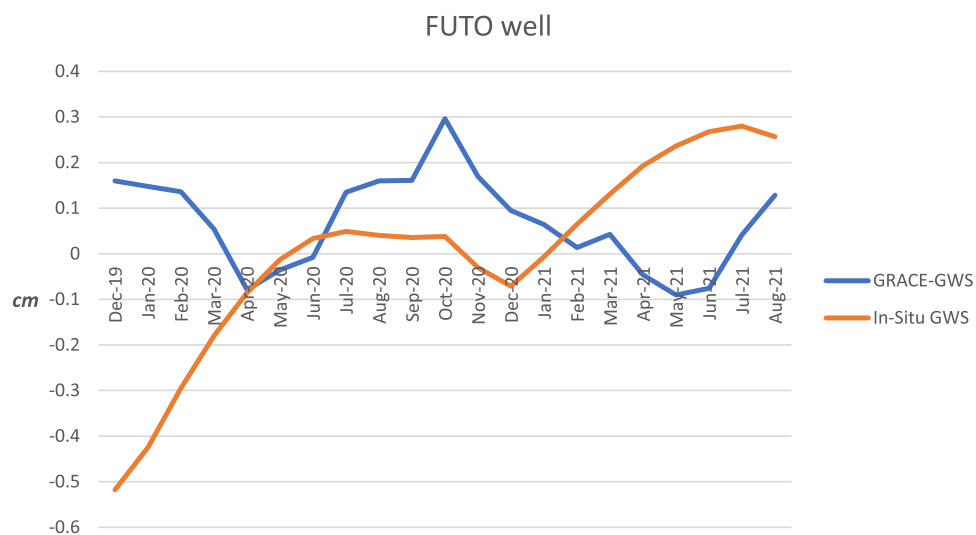


Figure 19: Plot of GRACE-derived GWS and *In Situ* GWS.

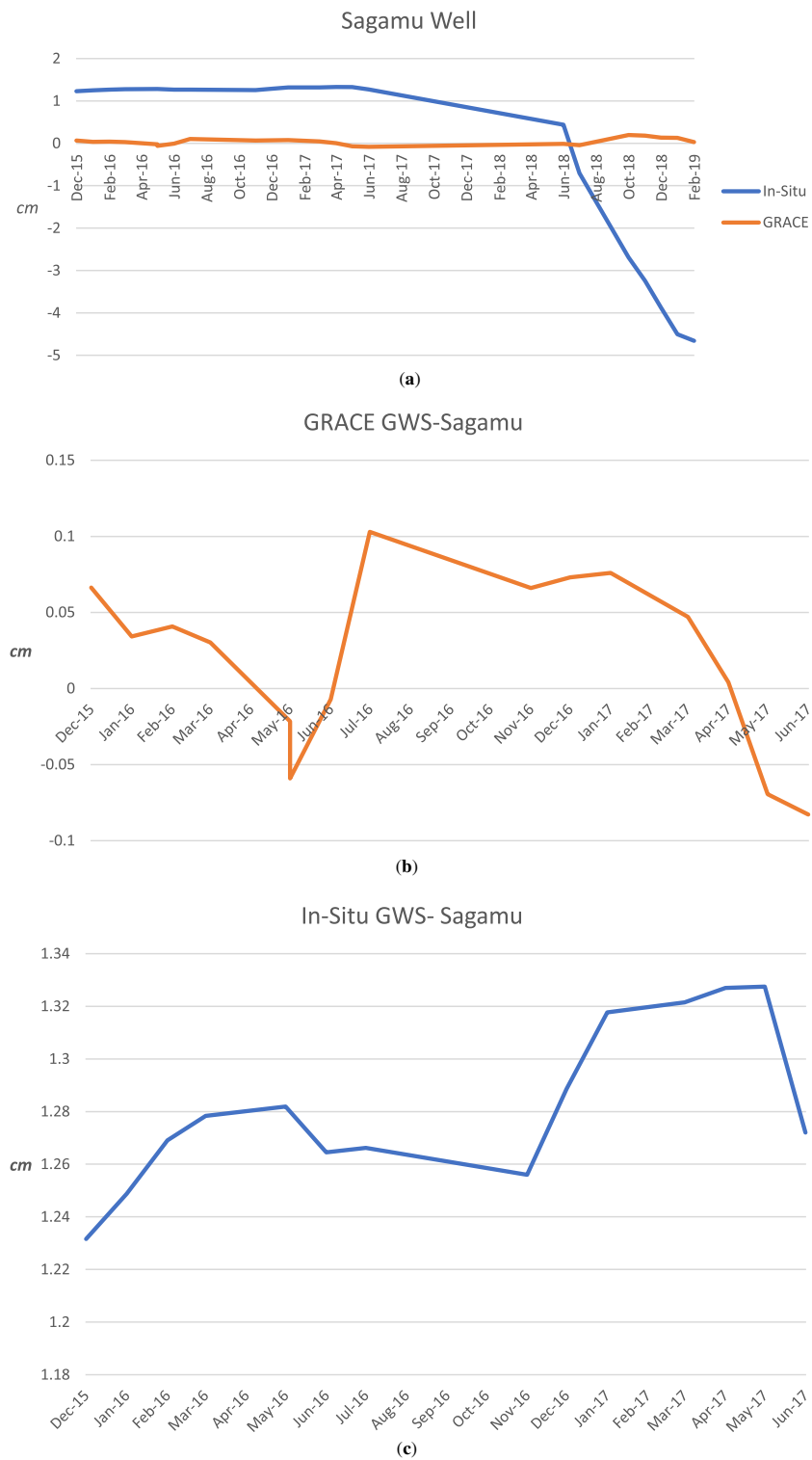


Figure 20: (a): Plot of GRACE-derived GWS and *In Situ* GWS. (b): Plot of GRACE-derived GWS and *In Situ* GWS. (c): Plot of GRACE-derived GWS and *In Situ* GWS.

4.4 Limitations and Future Directions

The findings of this research should be considered in light of several key limitations. Despite the use of CSR RL06 GRACE/GRACE-FO mascon that has already incorporated leakage corrections and destriping, however, the relatively coarse resolutions of the dataset will still inevitably smooth local variabilities, possibly resulting in the underestimation of extremely high frequency storage variations in local basins. Besides that, measurement noise and errors in GRACE data (due to atmospheric and oceanic mass variations, and incomplete corrections: GIA, degree-1, and replacement C20/C30 coefficients) will also be transferred into the estimation of terrestrial water storage. Similarly, temporal gaps, specifically the gap of 11 months between GRACE and GRACE-FO (from July 2017 to May 2018), were treated by using linear interpolation, an unrefined yet transparent method that might have been masking actual hydrological behaviors during the gap period (interannual climate variability).

GLDAS soil moisture and canopy water storage products are also model-dependent, carrying their own uncertainties due to the disparities in model parameters and forcing variables used to generate them. The study was also constrained by a paucity of primary *in situ* data, necessitating the use of secondarily sourced Specific Yield (Sy) values. This reliance on proxy and very limited (*in-situ*) data hindered a robust comparison between GRACE-derived Groundwater Storage (GWS) and *in situ* GWS measurements. The limited number of validation wells reflects the broader scarcity of reliable groundwater monitoring infrastructure in Nigeria, which motivated the adoption of satellite-based approaches in this study. These constraints contributed to the suboptimal agreement between GRACE-derived groundwater storage (GWS) and *in situ* measurements, resulting in only moderate correlation and notable amplitude (and in some cases phase) discrepancies between the two datasets.

Alternative gap-filling techniques to account for the missing 11-month transition period (such as sophisticated interpolation methods or diverse reconstruction products like the Multi-Channel Singular Spectrum Analysis—MSSA) were not explored. These alternative approaches might have offered deeper insights into the spatiotemporal variations of TWS and GWS across the Nigerian landscape.

All of these uncertainties (in addition to the sparsity and relatively brief record length of the groundwater measurements) limit the accuracy of interpretation at the local scale and partly account for the moderate correlation values observed in the validation process ([Section 4.3](#)).

In light of these limitations, future research should prioritize the following improvements: (i) the incorporation of more comprehensive *in situ* monitoring datasets; (ii) the acquisition and application of primary, regionally representative specific yield values; and (iii) the evaluation of alternative GRACE data reconstruction products and advanced interpolation methodologies. These steps would likely enhance the agreement between GRACE-derived and *in situ* GWS estimates, thereby enabling a more robust validation of satellite-based groundwater assessments in the region.

5 Conclusions

This study aimed to identify the temporal and spatial patterns and changes in TWS and GWS across Nigeria through analysis of the GRACE-derived data. In achieving this aim, it was also necessary to assess TWS and GWS variations across different regions, understand the relationships between these variations and hydrological fluxes, and identify potential drivers of these changes. These objectives were attained by incorporating satellite data with other hydrological data that enabled the provision of extended information on the TWS and GWS trends in various hydrological zones and river basins in Nigeria.

The main conclusions of the study are outlined below:

- i. It was observed from the result that the annual variability of GWS and TWS was the most predominant pattern in all the basins, accounting for more than 70% of the temporal and spatial variation in Nigeria.
- ii. The increasing trend in both GWS and TWS suggests that Nigeria's aquifers are gradually storing more water, likely due to increased precipitation from climate change. However, this also raises concerns about continued flooding, as seen in the persistent flood events following the 2012 disaster. The rapid GWS and TWS increase in the Sokoto-Rima River Basin aligns with findings from other West African studies.
- iii. The presence of an out-of-phase signal around the western littoral, which does not coincide with other basins, is sufficient evidence that the fluctuations in GWS in this zone cannot be attributed to climate variation only, and therefore is induced by human activities. This could well be the case if one considers the fact that the zone plays host to one of the largest and most populous cities in Africa. The abstraction pattern and changing landscape may likely be responsible for this effect.
- iv. Variations in TWS and GWS are strongly influenced by climate variability, including ENSO and PDO. As climate change alters precipitation and temperature patterns, its impact on Nigeria's water storage will persist.

These main conclusions and other results within the body of the work highlights the key spatial and temporal patterns of TWS and GWS, which provide valuable information to the policymakers/scientists of Nigeria regarding the spacetime aspects of freshwater in the country.

The result of this study helps fill the existing literature gap on terrestrial water storage and the dynamics of the groundwater system in Nigeria as influenced by climate change and human activities. Consequently, this research has brought to light a valuable tool using GRACE satellite data for large-scale and sustained monitoring that can inform the policy process and resource deployment on the stewardship of sustainable water futures in Nigeria.

The assessment revealed how useful GRACE data can be, especially when there are few data points on the ground in Nigeria. As a result, it appears to be a reliable method for the country to monitor water resources on a national level.

Despite the results obtained so far, the study faced certain limitations, such as the spatial resolution of GRACE, which most likely affected the analysis and interpretation of localized signals; the quality, quantity, and distribution of *in-situ* well data, which also affected the validation process.

Acknowledgement: The authors gratefully acknowledge the Nigeria Hydrological Services Agency (NIHSA) for kindly providing the groundwater data used in this study. We are also grateful to mentors, senior colleagues, and colleagues (Late Prof. F. I. Okeke, and Drs V. G. Ferreira, C. E. Ndehedehe, I. Kalu) who helped out in many ways in the course of the study. Finally, we extend our gratitude to the various open data platforms and organizations whose freely available datasets contributed significantly to this research.

Funding Statement: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions: Ikenna D. Arungwa: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing—original draft. Elochukwu C. Moka: conceptualization, supervision, validation, writing—review & editing. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The groundwater data used in this study were obtained from the Nigeria Hydrological Services Agency (NIHSA), and authors are not permitted to redistribute the data. The remaining datasets analyzed during the current study are freely available online from public/open-access repositories (specific sources and links are provided in the Data Sources section or relevant references).

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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