Science of the Total Environment 1001 (2025) 180421

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

A multi-source approach to groundwater storage and recharge assessment in the Volta Basin

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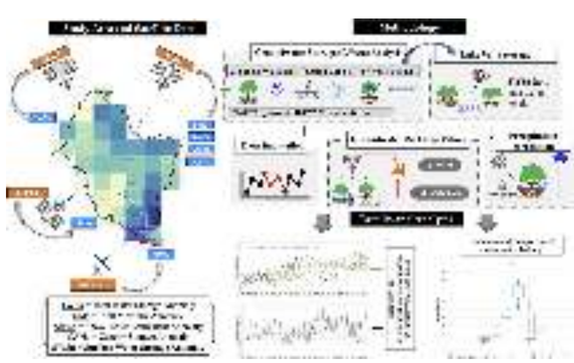
HIGHLIGHTS

- Multi-source satellite data reveal 20-year groundwater trends in the Volta Basin.
- Lake Volta accounts for ~50 % of water storage and must be included in GWS estimates.
- GRACE and GLDAS v2.2 support recharge estimates consistent with field observations.
- Recharge rates of 5–17 cm/year highlight vulnerability and storage sensitivity.
- The method is transferable to data-scarce basins under climate and development stress.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Earth observations
GRACE
Groundwater
Recharge estimation
Surface water–groundwater interaction
Volta Basin

ABSTRACT

Assessing groundwater storage changes is important in semiarid regions such as the Volta Basin in sub-Saharan Africa but can be challenging due to data scarcity. This study presents a multi-source approach combining NASA's Gravity Recovery and Climate Experiment (GRACE) mission data, Climate Hazards group Infrared Precipitation with Stations (CHIRPS) precipitation data, the new Global Land Data Assimilation System (GLDAS) v2.2 CLSM groundwater storage anomaly dataset, traditional non-groundwater terrestrial water storage components from GLDAS v2.1, and Copernicus satellite data for surface water dynamics to analyze groundwater storage changes and recharge rates in the Volta Basin. Our study reveals: (1) A small change in groundwater storage from 2002 to 2012, followed by a significant increase from 2012 to 2022; (2) A total groundwater increase of approximately 30 cubic kilometers or about 10 cm of liquid water equivalent over the entire study period; (3) Water storage in the basin is dominated by fluctuations in Lake Volta, which accounts for ~50 % of terrestrial water storage; (4) Groundwater recharge rates estimated using the Water Table Fluctuation Method on GRACE- and GLDAS-derived data, aligned with values from monitoring wells and previous studies; (5) The

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https://doi.org/10.1016/j.scitotenv.2025.180421
Received 30 June 2025; Received in revised form 20 August 2025; Accepted 2 September 2025
Available online 17 September 2025

GLDAS v2.2 dataset exhibits similar seasonal trends with periodic peaks and troughs, yet the amplitude of anomalies from GLDAS are larger compared to the GRACE dataset; and (6) Groundwater recharge shows a weak correlation with extreme precipitation events, suggesting more water percolates rather than evaporates during such events. However, other factors, including land use changes and agricultural practices, may also impact groundwater storage and recharge.

1. Introduction

Water security is a growing global issue driven by population growth, climate change, and rising demand across sectors (Obuobie et al., 2012; Kirby and Ahmad, 2022; Mensah et al., 2022). In sub-Saharan Africa, the situation is critical—only 31 % had access to safe drinking water in 2022, defined as water from an improved source that is available on premises, reliable, and free from contamination (UN-Water, 2023). Water supply depends on surface sources (rivers, lakes, reservoirs) and groundwater (springs, boreholes), but surface water is often seasonal, prone to contamination, and increasingly unreliable due to climate variability (Coulibaly et al., 2001; Sylla et al., 2016).

The Volta Basin exemplifies these challenges. Spanning multiple West African countries, it experiences highly variable rainfall across its diverse climatic zones (Ferreira et al., 2012). Most rivers are ephemeral, making them unreliable for dry-season water supply, which increases dependence on groundwater—often the only viable source in some areas (Ferreira et al., 2012; Djessou et al., 2022). Lake Volta plays a crucial role as the main surface water reservoir, helping to regulate both surface and groundwater availability (Ndehedehe et al., 2017).

At the same time, the basin faces mounting pressure from rapid urbanization, agricultural expansion, and industrial development (Dzikunoo et al., 2020; Yidana et al., 2020; Mensah et al., 2022). Ensuring the sustainable use of groundwater resources under these conditions requires a detailed understanding of aquifer dynamics, especially the spatial and temporal variations in groundwater storage and recharge. While localized studies have provided insights into aquifer properties and recharge in sub-regions of the basin (Dzikunoo et al., 2020; Aliou et al., 2022), comprehensive, basin-wide assessments remain limited.

Advances in global hydrological modeling have increasingly enabled the integration of reservoir operations and surface–groundwater interactions, enhancing the accuracy of large-basin simulations (Wada et al., 2016; Hanasaki et al., 2018; Sutanudjaja et al., 2018; Müller Schmied et al., 2021; Pokhrel et al., 2021; Dong et al., 2022). In the Volta Basin, some studies have used satellite data to assess terrestrial water storage (TWS). Ndehedehe et al. (2017) combined in-situ data with GRACE and altimetry observations, showing Lake Volta accounted for about 41.6 % of water storage increases from 2002 to 2014. Similarly, Ni et al. (2017) applied principal component analysis to GRACE-derived TWS data from 2002 to 2016, demonstrating that long-term variations in Lake Volta storage largely drive the basin-wide TWS signal. Atayi et al. (2024) used GRACE, CHIRPS, and Independent Component Analysis (ICA) to examine the influence of climate variability—particularly ENSO events—on TWS changes, identifying strong spatial gradients in rainfall and storage patterns across the basin. However, despite these important insights, none of these studies disaggregate TWS into its individual components or provide estimates of groundwater resources, such as storage or recharge. Complementing these findings, another study assessing water budget closure in the Volta Basin reported that Lake Volta alone controlled 48 % of the total accumulated water gain from January 2003 to December 2012, reinforcing its dominant role in modulating TWS dynamics (Ferreira and Asiah, 2016). On the other hand, Mohasseb et al. (2024) analyzed GRACE-based groundwater trends across 11 major Africa basin, including the Volta. Although their water balance included surface water storage (SWS), this component was treated as nearly constant in the Volta Basin, neglecting substantial fluctuations caused by Lake Volta, However, as surface water covers a significant portion of the basin, a small change in water levels translates to a large change in the total water storage anomaly. Finally, Djessou et al. (2022), assessed water storage variability in the Volta River Basin using GRACE and WGHM data from 2002 to 2016, estimating groundwater storage anomalies (GWSa) while accounting for surface water contributions from both the Volta and Bui lakes. However, they attributed approximately 62 % of total terrestrial water storage changes to groundwater, with surface water and soil moisture contributing about 12 % and 26 %, respectively. Notably, their study only covers data up to 2016, and their estimate of surface water contribution (~12 %) was about 37 % lower than previous studies. In contrast, our study extends the analysis through 2023, incorporates the latest GRACE-FO satellite data, applies a method to fill gaps between the GRACE satellites, uses the updated GLDAS 2.2 datasets, and introduces a novel approach for estimating recharge, which was not addressed in Djessou et al. (2022).

Most GRACE groundwater studies neglect the surface water storage component as for most of the earth, gravity anomalies from terrestrial (surface) water storage changes are small and neglected when computing the groundwater anomaly. Previous GRACE-based studies (e.g., Chen et al., 2014; Richey et al., 2015) typically omit surface water, potentially underestimating total water storage in basins with significant reservoirs. By addressing this gap, our approach offers a valuable framework for more precise groundwater assessments in other regions with similar conditions. This is because while reservoir or lake levels might change by several meters, then the volume is averaged over a large areas, such as a GRACE pixel, the water equivalent change is on the order of millimeters, and not significant (Rodell et al., 2004; Syed et al., 2008; McStraw et al., 2021). There are a few regions, such as the Volta Basin, where the gravity anomaly from surface water storage changes are significant because surface water covers a significant part of the basin and a few centimeters change in lake levels contributes significantly to the total storage anomaly. When analyzing groundwater trends over time, recharge estimates are important as recharge and pumping are the main drivers of groundwater change. By estimating recharge, trends in groundwater can be attributed to specific environmental or anthropogenic processes. While there are a number of published studies on groundwater in the Volta Basin, the impacts of surface water storage and recharge have not been explored. These gaps highlight the need for a comprehensive, basin-wide assessment that quantifies both groundwater recharge and storage, while accounting for the major role of surface water—particularly Lake Volta—in the basin's hydrological balance.

To address these gaps, this study introduces a novel satellite-based multi-source approach for assessing groundwater storage and recharge in the Volta Basin. This method does not require in situ groundwater measurements, which are sparse in this region. While most satellite-based studies on groundwater omit surface water contributions, our approach explicitly includes Lake Volta's storage changes, which constitute approximately 50 % of the total terrestrial water storage in the basin. This refined mass balance approach enables a more accurate groundwater storage assessment and highlights the importance of surface water dynamics in large basin contexts. This method can be applied to similar basins globally.

The study utilizes data from NASA's Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE Follow-On (GRACE-FO), which provide monthly gravity field variations indicative of terrestrial water storage anomalies (Tapley et al., 2004b; Landerer et al., 2020). We estimate groundwater storage anomalies by subtracting contributions from soil moisture, canopy storage, surface water, and snow (when applicable), typically obtained from land surface models such as NASA's Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004; Syed et al., 2008; McStraw et al., 2021). In the Volta Basin, where surface water storage changes significantly influences TWSa, the exclusion of Lake Volta in traditional approaches introduces considerable bias.

To overcome this, we use both GLDAS v2.1 and the recently enhanced GLDAS v2.2 Community Land Surface Model (CLSM), which integrates GRACE-based assimilation and provides a higher-resolution (0.25°) groundwater storage anomaly dataset. GLDAS v2.1 is used to estimate non-groundwater components of terrestrial water storage—such as soil moisture, snow water equivalent, and canopy water—while surface water storage changes in Lake Volta are derived independently using satellite altimetry data from the Copernicus program. GLDAS v2.2 is then used to obtain groundwater storage changes directly, incorporating recharge potential and groundwater pumping effects. GLDAS 2.2 has been successfully applied in diverse hydrological settings, including groundwater storage analysis in Ethiopia's Tana subbasis (Berhanu et al., 2024) flood dynamics in the Yangtze River basin (Yan et al., 2022) drought impacts in South Africa's Western Cape (Nenweli et al., 2024), and aquifer validation in Spain (Guardiola-Albert et al., 2024).

Accurately characterizing groundwater recharge is vital for assessing sustainable use, especially under climate change; however, it remains particularly challenging in data-poor regions. The Water Table Fluctuation (WTF) method—based on seasonal groundwater level changes—is widely applied but requires in situ data (Healy and Cook, 2002; Nimmo et al., 2015). Consequently, in regions like sub-Saharan Africa where such data are limited, GRACE satellite observations have been used to estimate recharge (Henry et al., 2011; Obuobie et al., 2012; Gonçalvès et al., 2013; Ahmed and Abdelmohsen, 2018; Barbosa et al., 2022). However, most of these studies rely solely on GRACE and do not incorporate surface water variability or next-generation modeling products like GLDAS v2.2. To date, Guardiola-Albert et al. (2024) is among the very few studies that have combined GLDAS v2.2 with the WTF method for recharge estimation. Their work, however, was limited to a medium-scale aquifer in Spain and did not account for the influence of major surface water bodies—reducing its applicability to more hydrologically complex, large-scale systems.

Accordingly, this study aims to: (1) assess changes in groundwater storage in the Volta Basin over the period between 2002 and 2022, using three different approaches (a) a traditional approach using a GRACE and GLDAS water balance, (b) a modified approach using GRACE and GLDAS where we augment the water balance using storage change estimates from Lake Volta using satellite altimetry to estimate storage change, (c) an approach that uses the new GLDAS 2.2 CLSM data, also adjusted for Lake Volta storage; (2) examine the correlation between rainfall and changes in groundwater storage in the basin to determine patterns or correlations; and (3) estimate annual groundwater recharge values in the Volta Basin using the WTF method based on GRACE and GLDAS 2.2 derived groundwater storage datasets, and compare the results with observed data in the basin.

We introduce several advancements over previous GRACE-based groundwater assessments in the Volta Basin. We extend the GRACE time series through 2022 by incorporating GRACE-FO data to capture more recent hydrological variability; we use a method to fill the gap in the GRACE data between the two missions; we use GLDAS v2.2 to independently estimate groundwater storage, providing a novel means of validating GRACE-derived groundwater anomalies in the basin; and we quantify basin-wide groundwater recharge, a component often omitted in earlier studies to have a complete analysis of the groundwater resources. Our framework integrates multiple satellite data sources to improve the robustness of water balance components and explicitly accounts for surface water storage variability in Lake Volta, addressing a key limitation in prior assessments that treated this component as static. By directly comparing groundwater storage anomalies estimated with and without the influence of Lake Volta, we demonstrate the substantial impact that this surface water body has on GRACE-derived groundwater storage estimates.

The unique contributions of this study are threefold. First, it presents the first basin-wide assessment of groundwater storage across the Volta Basin using a multi-source approach that integrates long-term satellite observations and explicitly accounts for Lake Volta—an often-overlooked yet hydrologically dominant surface water body in the region. Second, leveraging this integrated framework, the study conducts a comparative evaluation of traditional and next-generation Earth observation datasets—including the newly released GLDAS v2.2 CLSM product—to assess their performance and limitations in capturing groundwater dynamics. Third, it introduces a transferable method that can be used in other regions that combines satellite-derived groundwater storage anomalies from both GRACE and GLDAS v2.2 with observed groundwater level data to enhance recharge estimation and validation using the Water Table Fluctuation (WTF) method, providing critical insights for managing groundwater resources under increasing climate variability and development pressures.

2. Study area and background

The Volta Basin is a major water basin in sub-Saharan Africa, approximately 400,000 km2 in size, and spans six countries: Ghana, Burkina Faso, Benin, Côte d'Ivoire, Togo, and Mali (Fig. 1). Over 90 % of the basin's population resides in Ghana and Burkina Faso (Martin and van de Giesen, 2009; Djessou et al., 2022). It encompasses at least four different climate types, ranging from lowland rainforest in the south to semi-arid Sahel-Sudan Desert in the north (Rodgers et al., 2007).

The aquifer zones and distribution of groundwater recharge areas are shown in Supplementary Fig. SF1. This information was obtained from the World-wide Hydrogeological Mapping and Assessment Program (BRG and UNESCO, 2023). The Volta Basin is separated into three primary sub-basins: the Nakambe Basin, linked to the White Volta River; the Mouhoun Basin, related to the Black Volta River; and the Oti River basin. Most aquifers in the Volta Basin are shallow, with a major groundwater aquifer located in the upper Volta Basin in the northwestern region (Djessou et al., 2022). The Volta Basin is known for its sedimentary aquifers, which are separated into a fractured zone and a blend of intergranular and fractured regions. The primary fractured area within the southern half of the Volta Basin, referred to as the Volta Fractured Land (outlined by the red line in Supplementary Fig. SF1), provides ideal conditions for groundwater storage during intense wet periods (Bonsor et al., 2018; Carvalho Resende et al., 2019).

A geologic map of the Volta Basin (Supplementary Fig. SF2) shows that the Volta Basin is predominantly underlain by rocks of the Precambrian basement (the Birimian Supergroup) (Hirdes et al., 1996) with its associated granitoids, and the NeoProterozoic Sedimentary rocks constitute the Voltaian Supergroup (Carney et al., 2010). The Birimian Supergroup is associated with rich gold mineralization and has been the focus of multilateral mineral exploration and development. The Birimian and Voltaian Supergroups underlie over 90 % of the total landmass of the Volta Basin. The Birimian Supergroup is characterized by northeast-southwest trending Volcanic belts, separated by sedimentary basins in Ghana. The basins and belts are mineralized and have been the focus of gold mining for centuries. The rest of the terrain comprises unconsolidated and relatively younger sediments.

The Voltaian Supergroup comprises partially metamorphosed sedimentary rocks that unconformably overlay the West African Craton (WAC), specifically, the Man-Leo Shield (Bertrand-Sarfati et al., 1991). The Voltaian rocks form the western border of the Dahomeyide Pan-African belt and extend from parts of Ghana to Togo, Burkina Faso and Niger. They constitute three main groups, differentiated by age and depositional environment. The Bombouaka-Kwahu Group is the oldest and forms the base of the Voltaian. It is overlain, unconformably, by the

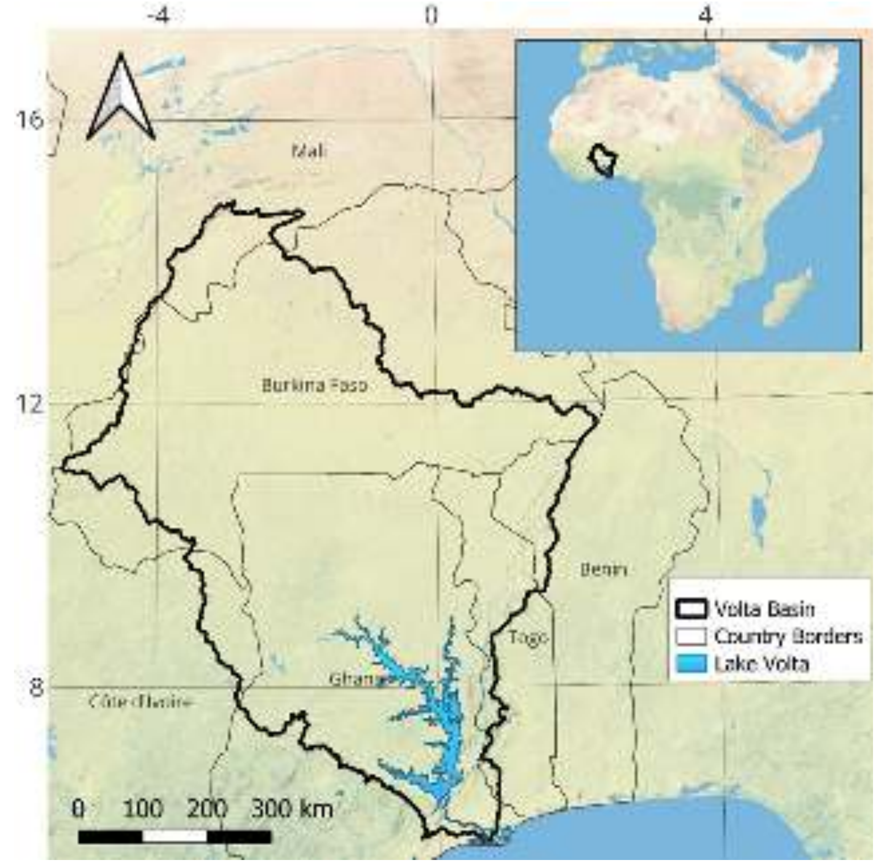


Fig. 1. Volta Basin location.

Oti/Pendjari Group. The youngest and uppermost rock sequence in the Voltaian is the Obosum Group.

The hydrogeology of the basin is based on the presence and degree of interconnection of secondary structures created in the wake of fracturing and/or weathering of the underlying rock. Rocks of the Birimian Supergroup and associated granitoid are more prolific in terms of

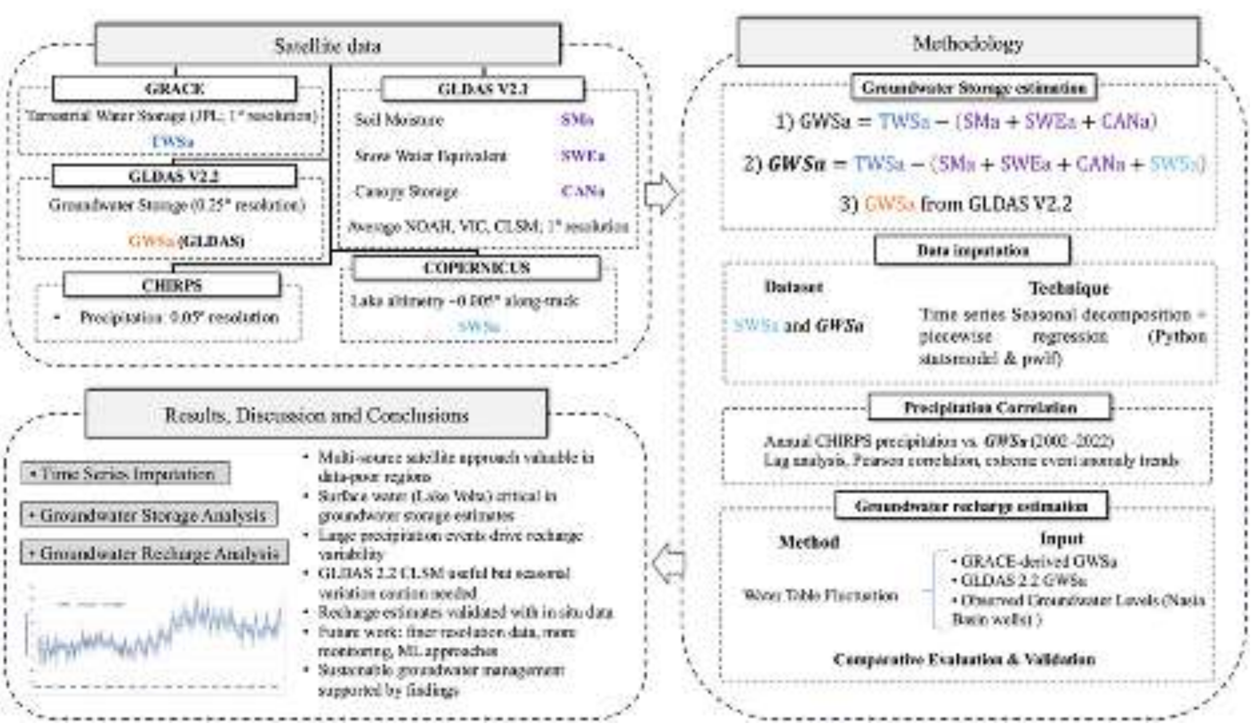


Fig. 2. Overview of the data sources, and analytical steps used to estimate groundwater storage and recharge in the Volta Basin.

groundwater occurrence compared to the highly indurated sedimentary rocks of the Voltaian Supergroup. Borehole drilling success rates in the Birimian generally exceed 80 %, and the rocks are crucial to water economies of particularly rural communities (Yidana et al., 2011). On the other hand, in the Voltaian Supergroup, the historical tectonic events have imposed conditions that render the rocks inherently impervious. Borehole drilling success rates are below 60 % in places (Aliou et al., 2022). In both terrains, the hydrogeological conditions are characterized by three main hydrostratigraphic units: the saprolite, saprock, and fractured bedrock. The regolith, comprising the saprolite and saprock, is a crucial unit in terms of rural water development. Most manually developed wells in rural areas are completed in the regolith. In some communities, especially within the Birimian Supergroup, shallow wells completed within the regolith serve the critical irrigation needs of the smallholder farmers. Due to its high clay content, the saprolite is the least conductive of the three hydrostratigraphic units (Yidana et al., 2011). The saprock is relatively more conductive but generally thinner compared to the saprolite.

3. Data and methods

In Fig. 2, we present a chart outlining the general methodology used in this study, providing a visual summary of the data sources and analytical steps involved. Following this overview, the subsequent sections provide detailed descriptions of the data sets and methods employed in the analysis.

3.1. GRACE and GLDAS data

Raw GRACE data are processed by three institutions using different algorithms, the NASA Jet Propulsion Laboratory (JPL), the University of Texas at the Austin Center for Space Research (CSR), and the German Research Center for Geosciences (GFZ) (Wahr et al., 1998; Tapley et al., 2004a; Dunbar, 2012, 2014; Callery, 2018; Landerer et al., 2020; NASA JPL, 2023). The results from each method are a gridded TWSa dataset distributed by NASA (Swenson, 2012). For our analysis, we used the JPL Global Mascon TWSa dataset, available on a downscaled 0.5-degree grid resolution (Landerer and Swenson, 2012; Landerer, 2021). We selected this product because it provides gridded uncertainty estimates for each cell, enabling rigorous assessment of data processing errors and enhancing confidence in the reliability of the terrestrial water storage anomaly estimates (Scanlon et al., 2012; Khaki et al., 2018; Purdy et al., 2019). While researchers have used several different land surface models to estimate the surface water component, we use GLDAS 2.1 (NASA, 2024b, 2024a) for our comparative analysis due to its proven reliability in providing terrestrial data critical for climatology, hydrological forecasting, and water resources management (Xu and Liu, 2025).

Unlike its predecessors, GLDAS 2.2 integrates data assimilation from GRACE and other ground-based observational data, enhancing the accuracy of the hydrological simulations. It also includes a new groundwater storage anomaly (GWSa) variable, which is of particular interest in this study. The GWSa is found using a classic water balance approach where groundwater infiltration minus evapotranspiration (i.e., recharge potential) over a selected time period is used to estimate groundwater storage change. Since this estimate does not include the effect of pumping or groundwater discharge to streams, it is adjusted during an assimilation step using GRACE-derived storage anomalies and output as a liquid water equivalent, similar to the GRACE variables. Currently, its temporal coverage spans two decades of daily continuous data, from February 2003 to January 2025. Global data are available at a spatial resolution of 0.25 degrees. A total of 24 output variables are included in the dataset, including soil moisture, terrestrial water storage, and groundwater storage. GLDAS2.2 uses European Center for Medium-range Weather Forecasting (ECMWF) metrological forcings for model simulations.

3.2. Lake Volta altimetry data

To compute storage data for Lake Volta, we downloaded lake water levels from the Copernicus online data repository of lake water levels (Copernicus Climate Change Service, 2020). This site provides water levels derived from satellite observations for 229 lakes across 4 continents, including Lake Volta. Water levels are reported in meters above mean sea level from 1992 through the end of 2022. The frequency varies – there is at least one observation for most months, but some months early in our study period did not have water levels. We averaged the values in each month to estimate a monthly value and imputed data for months with missing data as described below.

3.3. Precipitation data

We used daily and monthly precipitation data in millimeters (mm) from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015). These data are available on a 0.05 $\times$ 0.05-degree spatial resolution grid in hourly, pentadal (five-day), and monthly periods from 1985 until the present. CHIRPS data represent the total precipitation over the hour, five-day period, or month.

3.4. In situ well data

We used data collected from 10 wells in the Nasia Basin (Fig. 3) over a period of four years, from 2017 to 2020 for comparison and validation. These wells were drilled as part of a project funded by the Danish International Development Agency (DANIDA, 2024) and are monitored by the Department of Earth Science, University of Ghana. Not all wells contained data for every year; some wells had data for only one or two years. This is because the monitoring did not start simultaneously for all the wells. However, for most wells, monitoring began in March 2017. Each of them was equipped with a sensor which computes groundwater level by measuring pressure variations. The data are retrieved quarterly and processed into groundwater-level data by discounting the barometric effect. All the wells are open and have not been screened. The depths are summarized in Supplementary Table ST1.

3.5. Regional groundwater storage analysis with GRACE data

To compute groundwater storage anomaly (GWSa) data, we used a mass balance approach validated by numerous researchers (Rodell et al., 2004, 2007, 2009; Syed et al., 2008; Nanteza et al., 2012; Joodaki et al., 2014; Richey et al., 2015; Xiao et al., 2015; Khaki et al., 2018; Barbosa et al., 2022). This method subtracts surface water storage changes, estimated using GLDAS 2.1 data (Rodell et al., 2004; NASA, 2024a, 2024b), from TWSa changes computed using GRACE data. GLDAS includes three models (Noah, VIC, and CLSM), each of which estimates surface water volume in three components: canopy storage (CAN), snow-water equivalent (SWE), and soil moisture (SM). We converted GLDAS data to an anomaly format (CANa, SWEa, and SMa) based on the deviation from the 2004–2009 mean for each GLDAS model. The VIC and CLSM datasets have a grid resolution of 1.0 degrees, while the NOAH datasets have a resolution of 0.25 degrees. The TWSa data from the NASA JPL model has a 0.5-degree resolution. We upscaled the GLDAS Noah model components and the TWSa to a 1-degree resolution to match the resolution of all the data sets.

With the data sets at the same resolution, we averaged the data from the Noah, VIC, and CLSM land surface models to generate average values for CANa, SWEa, and SMa. We calculated the groundwater storage anomaly (GWSa) by subtracting the average GLDAS surface water anomaly components data from the GRACE TWSa data at a 1-degree resolution using the following formula:

$$\mathrm{GWSa} = \mathrm{TWSa} - (\mathrm{SMa} + \mathrm{SWEa} + \mathrm{CANa}) \tag{1}$$

We used the GRACE Groundwater Subsetting Tool (GGST)

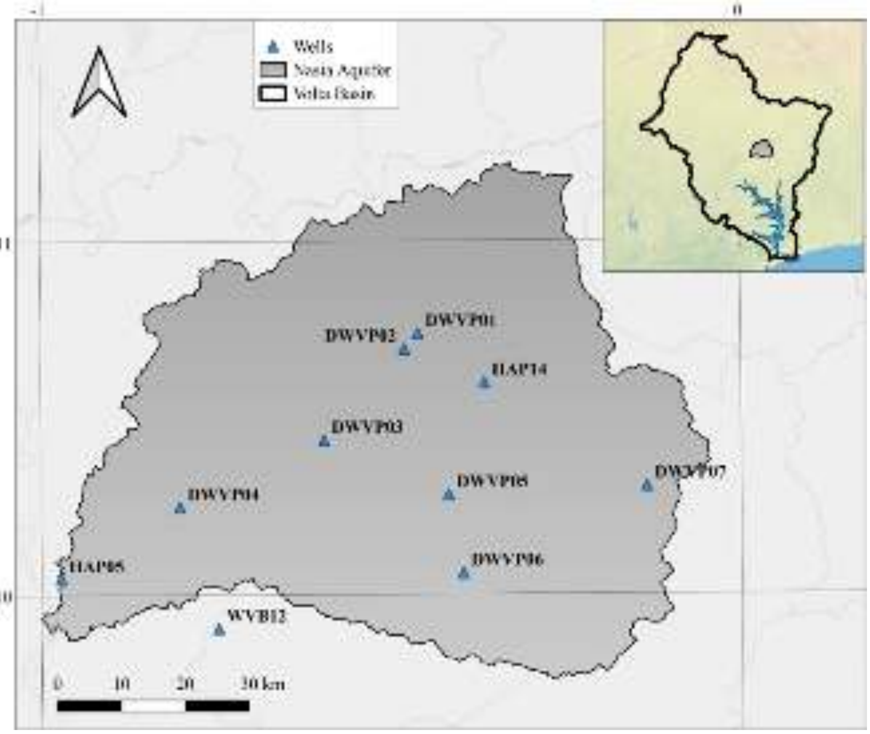


Fig. 3. Nasia aquifer and well locations.

application to perform this processing (McStraw et al., 2021). The GGST clips each dataset to a selected region, producing a set of clipped raster data for each dataset, and then applies Eq. (1) to generate a raster of GWSa. It averages the monthly GWSa data to generate a time series of the temporal variations of each dataset since 2002. The GGST calculates the cumulative water storage change for the region in units of millions of cubic meters or cubic kilometers by multiplying the time-varying GWSa rasters by the region area to estimate a change in water volume for the aquifer (McStraw et al., 2021). It generates a total uncertainty estimate for the water storage anomaly by combining the GRACE TWSa uncertainty values provided by NASA with GLDAS uncertainty estimates using the methodology described in Purdy et al. (2019).

While Eq. (1) is the method most commonly used to derive groundwater storage, it ignores the surface water storage anomaly (SWSa), which represents water stored in lakes and streams. For most basins in the world, this is a reasonable assumption. However, Lake Volta, at the southern end of the Volta Basin, is the largest reservoir in the world by area and represents approximately 2 % of the total basin area. Several researchers have found that Lake Volta water storage is a significant part of the total water storage for the basin, and neglecting it can lead to substantial errors in the basin's water budget (Ferreira et al., 2012; Ahmed et al., 2014; Moore and Williams, 2014; Ferreira and Asiah, 2016; Ni et al., 2017). Therefore, we calculated the SWSa for the basin and subtracted it from the GWSa obtained by the GGST tool, using the following equation:

$$\mathrm{GWSa} = \mathrm{TWSa} - (\mathrm{SMa} + \mathrm{SWEa} + \mathrm{CANa} + \mathbf{SWSa}) \tag{2}$$

We computed the SWSa using Lake Volta altimetry data from the Copernicus website. We generated a lake elevation anomaly time history over the study period by calculating the average lake elevation from 2004 to 2009 and subtracting this average from the lake elevations to obtain a lake elevation anomaly in meters. To find the change in storage, we multiplied this anomaly by the lake area. Since the lake area varies with elevation, we computed the area at a given lake elevation using the equation provided by Ni et al. (2017):

$$\mathrm{A} = 6.25 \times 10^4\mathrm{h} + 3875 \tag{3}$$

where A = area in meters and h = lake elevation in meters. We then computed the lake storage anomaly in cubic meters divided by the area of the Volta Basin multiplied by 100 to obtain the SWSa for the basin in centimeters of liquid water equivalent (LWE) to be consistent with the other terms in Eq. (2).

3.6. *Groundwater and surface water storage anomaly data imputation*

The first GRACE mission provided nearly complete data up to 2010, with periodic data gaps in the following seven years from 2011 to 2017, including an 11-month gap between the original and GRACE-FO missions (Flechtner et al., 2014; Yi and Sneeuw, 2021). There are no gaps in the GRACE-FO data. The lake altimetry data used to compute the SWSa included periodic monthly gaps during the first few years of the study period. We imputed the gaps in both time series to obtain a complete monthly record over the study period to compute GWSa (Eq. (2)).

To impute missing values in both the GWSa and SWSa datasets, we used a modified version of the seasonal decomposition method described by Barbosa et al. (2022) and Jones (2024). This method uses the *statsmodel* Python library (Perktold et al., 2023) to decompose the time series data into trend, seasonal, and random components (Cleveland et al., 1990). In the mentioned study, the time series showed a consistent increasing trend, allowing for a single linear fit. In contrast, the current analysis reveals both increasing and decreasing segments, for which a single linear trend is not appropriate. To better capture this variability, we improved this method by dividing the trends into multiple sections using the *piecewise-regression* Python library (Pilgrim, 2021). We implemented this data imputation method in a Google Colab notebook, which can be publicly accessed (BYU Hydroinformatics Laboratory, 2023).

3.7. *Regional groundwater storage analysis with GLDAS 2.2 GWSa data*

For the analysis using the GLDAS 2.2-derived GWSa, we used the

GLDAS 2.2 CLSM collection from Google Earth Engine (GEE) and used GEE to load, clip and process the data. The data came with 24 different bands of different daily average data. We selected the groundwater storage band and used a date range from February 2003 to December 2022. We clipped the gridded data to our study area. We computed the mean groundwater storage for each month by aggregating daily groundwater storage and dividing it by the number of days. To compute the groundwater anomaly, we normalized the data by subtracting an average of the reference period from 2004 to 2009. The GLDAS 2.2 groundwater storage simulation does not consider surface water storage. Therefore, as was the case with GRACE data, we then adjusted the GWSa estimate by subtracting the SWSa corresponding to storage changes in Lake Volta.

3.8. The Mann-Kendall test

We used the non-parametric Mann-Kendall (M-K) test (Mann, 1945) to quantify trends. The M-K test uses an exhaustive pair-wise computation on the data to determine if a trend exists and if it is statistically significant. The US EPA recommends the M-K test to identify data trends (Meals et al., 2011). The M-K test is a non-parametric statistical test, which means that data do not need to follow any specific statistical distribution. In addition to testing for a trend, we computed the slope of the trend (i.e., rate of change) using both a linear least squares fit and the Sen slope estimator, which is integral to the M-K test. We computed the Sen's slope estimate as (Helsel et al., 1992):

$$\beta_1 = median\left(\frac{y_j - y_i}{x_j - x_i}\right) \tag{4}$$

for all $i < j$ and $i = 1, 2, \ldots$, n-1 and $j = 2, 3\ldots$, n. The Sen slope is the median slope value of each data pair that was used in the M-K analysis.

3.9. Estimating groundwater recharge

We employed the WTF method (Henry et al., 2011) to estimate groundwater recharge in the Volta Basin using these GWSa data. The WTF method estimates recharge by analyzing seasonal variations in measured groundwater levels. It assumed that declining groundwater levels during the dry season primarily stem from pumping and groundwater discharge, while the rise during the wet season is predominantly attributed to recharge. Using water levels, we can, therefore, estimate the recharge as follows:

$$R = S_y\frac{\Delta h}{\Delta t} \tag{5}$$

where R represents the groundwater recharge in centimeters per year, Δh is the change in height of the water table in centimeters, t is the time interval (one year), and Sy is the specific yield (Nimmo et al., 2015).

There are two approaches to estimating the recharge rate using the WTF method. The first (shown in blue in Supplementary Fig. SF3) is based on the distance between the decline trough and the rise peak, and the second, shown in red in Supplementary Fig. SF3, by projecting the previous year's peak to the trough. Method 1 provides a more conservative estimate than method 2.

Usually, the recharge calculation requires an estimate of the aquifer storage coefficient to convert water level rise to water volume, as groundwater only occurs in the soil voids. However, if we apply the WTF method to GWSa data from GRACE as proposed by Wu et al. (2019), we do not need to estimate the storage coefficient because the anomaly is expressed in liquid water equivalent. Thus, using the GWSa data from GRACE, we estimate the recharge as follows:

$$R = \frac{\Delta GWSa}{\Delta t} \tag{6}$$

For this study, we use Eq. (6) to find the average recharge for the basin for each year using the imputed GRACE GWSa, and then we apply Eq. (5) to water level data from monitoring wells in the Volta Basin as a comparison.

4. Results and analysis

4.1. Time series imputation

We imputed gaps in the SWSa and the GWSa time series data. Fig. 4 displays the original and imputed data for both the SWSa and GWSa datasets. Visually, the imputed data maintains the seasonality and trend observed in the original data and appears to be a reasonable approximation over the gaps.

4.2. Groundwater storage analysis with GRACE

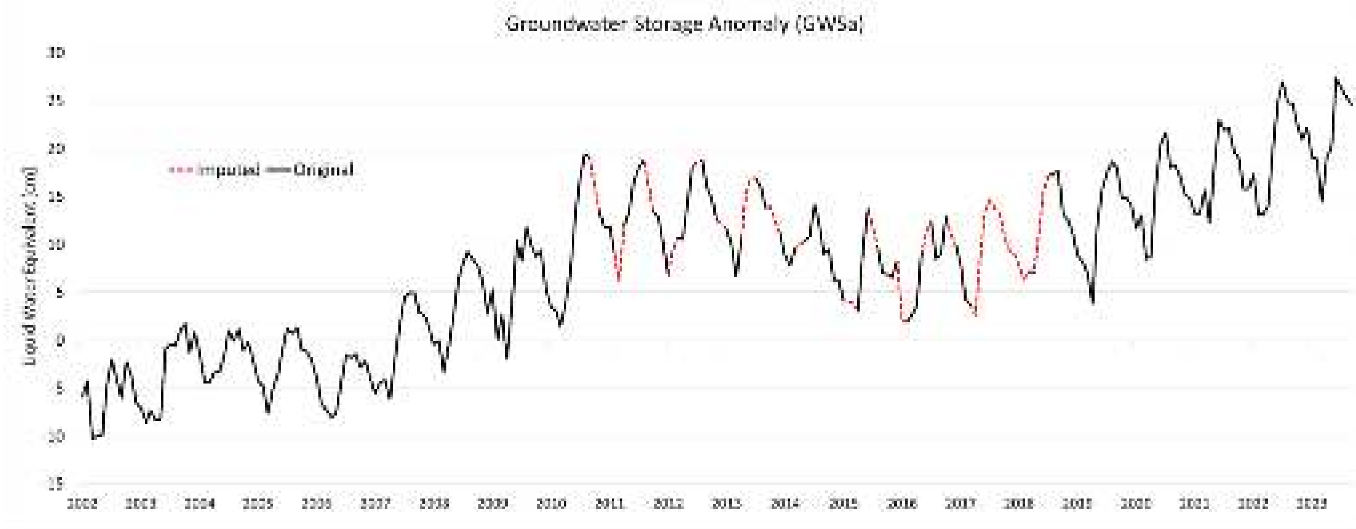
To examine the changes in groundwater storage in the Volta Basin, we used the GGST tools to compute time series with uncertainty estimates for each water storage component, including TWSa, SWEa, CANa, SMa, and GWSa. We computed SWSa from water level changes in Lake Volta and subtracted it from the GWSa estimate provided by the GGST tools to obtain the corrected GWSa estimate using Eq. (2). Fig. 5 depicts the resulting GWSa as liquid water equivalent (LWE) in the Volta Basin between April 2002 and December 2022. The gray band is the uncertainty associated with these data. These data exhibit four main trends. Between 2002 and 2012, the trend is relatively flat, from 2012 to 2016 there is a steep upward trend, followed by a mild downward trend from 2016 to 2020, and finally a slight increase from 2020 to 2022. The anomaly from 2014 to 2019 averages approximately +12 cm.

The trend and magnitude of changes in groundwater storage we computed in the Volta Basins are consistent with a recent study performed by Barbosa et al. (2022) for the Iullemeden aquifer in southern Niger. The overall trend of increasing groundwater storage change is consistent with results found by other researchers who also used GRACE and GRACE-FO to analyze groundwater storage change in the Volta Basin over a similar time frame (Djessou et al., 2022; Scanlon et al., 2022; Mohasseb et al., 2024; Yidana et al., 2024). However, the shape and magnitude of the storage change time series differ among the various studies. This could be due to the methodology used by the different studies to derive GWSa. Both Scanlon et al. (2022) and Mohasseb et al. (2024) computed GWSa by subtracting the GLDAS soil moisture anomaly (SMa) from the GRACE TWSa, neglecting canopy storage (CANa) and surface water storage (SWSa). Djessou et al. (2022) included soil moisture (SMa) and surface water storage (SWSa) found by lake altimetry, but neglected canopy storage (CANa). In contrast, we used a more complete water balance approach, subtracting GLDAS-derived SMa, SWEa, and CANa, and further adjusting for Lake Volta's SWSa using altimetry data—capturing both vegetation and surface water contributions to improve GWSa accuracy.

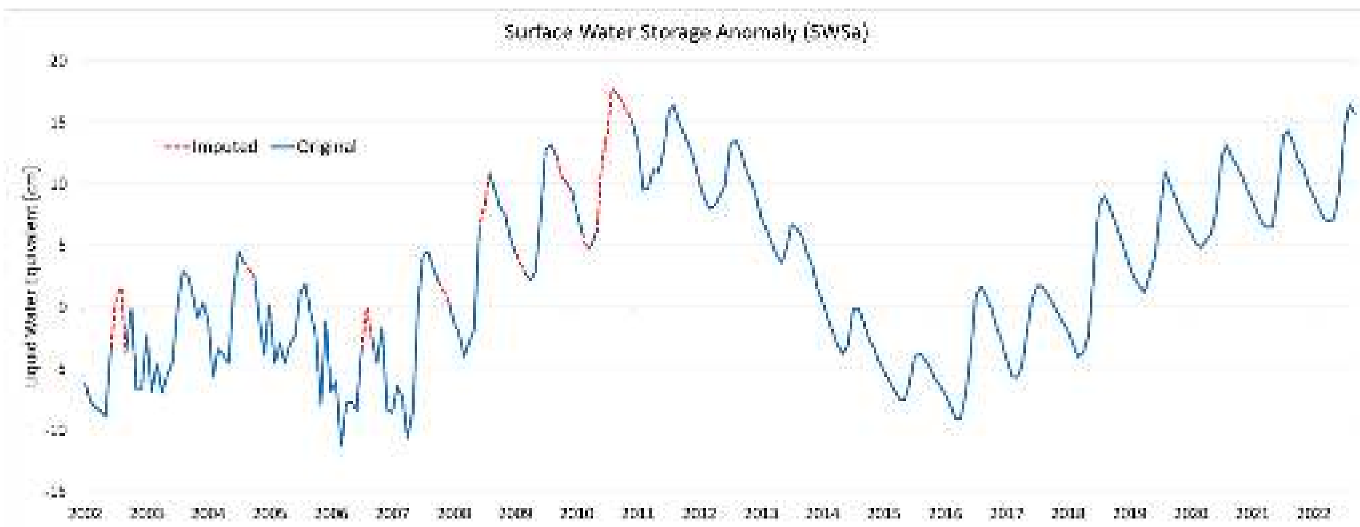
Our results highlight the importance of including storage changes from Lake Volta when computing groundwater storage change in the Volta Basin. The SWSa time series we derived using altimetry data from Lake Volta is shown by the dashed line in Fig. 6. The GWSa found using Eq. (1), which does not include SWSa, and Eq. (2), which does include SWSa, are also shown. From 2002 to 2012, the SWSa is approximately equal to the entire GWSa found by Eq. (1). By magnitude, we found that SWSa represents an average of 49 % of the terrestrial water storage changes on the right-hand side of Eq. (2). This is consistent with the results of Ferreira et al. (2012), who found that Lake Volta storage accounts for 48 % of the gain in TWSa for the basin from 2003 to 2012. Ni et al. found similar results (Ni et al., 2017).

4.3. Groundwater storage analysis with GLDAS v2.2

We derived the GWSa over the same time range using groundwater storage from GLDAS2.2 CLSM and surface water storage from Volta



(a)



(b)

Fig. 4. Original and imputed (a) groundwater storage anomaly and (b) surface water storage anomaly data for the Volta Basin.

Lake, (Fig. 7). The anomalies exhibit a strong seasonal cycle with peaks and troughs, reflecting the influence of periodic recharge and discharge events. The results show a flat trend from 2003 to 2010 and a steep increase between 2010 and 2016, with a total anomaly increase of 25.2 cm; the years between 2016 and 2021 shows a mild decreasing trend with a total of 11.5 cm. The anomaly trend is similar to what is observed with the GRACE data. However, the amplitude of anomalies from GLDAS 2.2 CLSM is larger, showing more pronounced seasonal variability.

4.4. Correlation with regional precipitation

We compared cumulative monthly rainfall and monthly GWSa in the Volta Basin from 2002 to 2022 and found a weak correlation ($r(12) = -0.11$) between precipitation and GWSa. A monthly time step was chosen to align with the GRACE revisit interval and to capture seasonal cycles. Interestingly, if we applied a two-year lag to the precipitation data, the correlation improves to a moderate level ($r(10) = 0.3, p = 0.2$), similar to findings in Niger (Barbosa et al., 2022). This suggests that while precipitation significantly impacts groundwater storage, other factors, such as evapotranspiration and the complex vadose zone, also influence groundwater levels. More detailed analysis is provided in the supplementary information (Text S1, S2 and S3).

4.5. Groundwater recharge analysis

4.5.1. Groundwater recharge estimation using GRACE and CLSM data

We estimated the annual recharge for the Volta Basin using both WTF methods applied to the GWSa data. We used a moving 3-month average of the data to smooth the noise in the time series curve to better highlight the seasonal highs and lows. We could only derive recharge estimates for 2010 to 2020 as the years from 2002 to 2009 did not exhibit a clear seasonal signal. The results for WTF Method 1 and Method 2 are shown in Table 1. The results show higher recharge values from 2010 to 2014, corresponding to increased groundwater storage during the same period and lower values for the remaining years. These trends are generally consistent with the changes in groundwater storage.

The average recharge rates using GRACE with WTF Method 1 for the 2010–2014 and 2015–2020 periods are 7.1 cm/yr and 4.8 cm/yr, respectively. Using GRACE data with WTF Method 2 estimated higher average recharge rates of 14.1 cm/yr and 7.9 cm/yr for the same periods, respectively. The averages for the entire period were 5.8 cm/yr

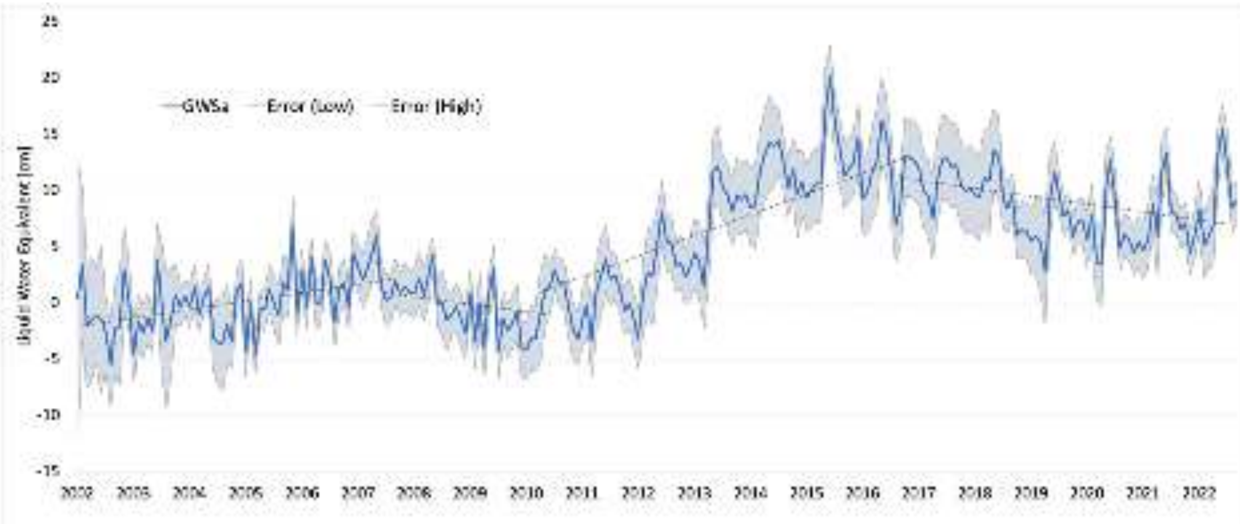


Fig. 5. Groundwater storage anomalies changes in liquid water equivalent (cm) in the Volta Basin.

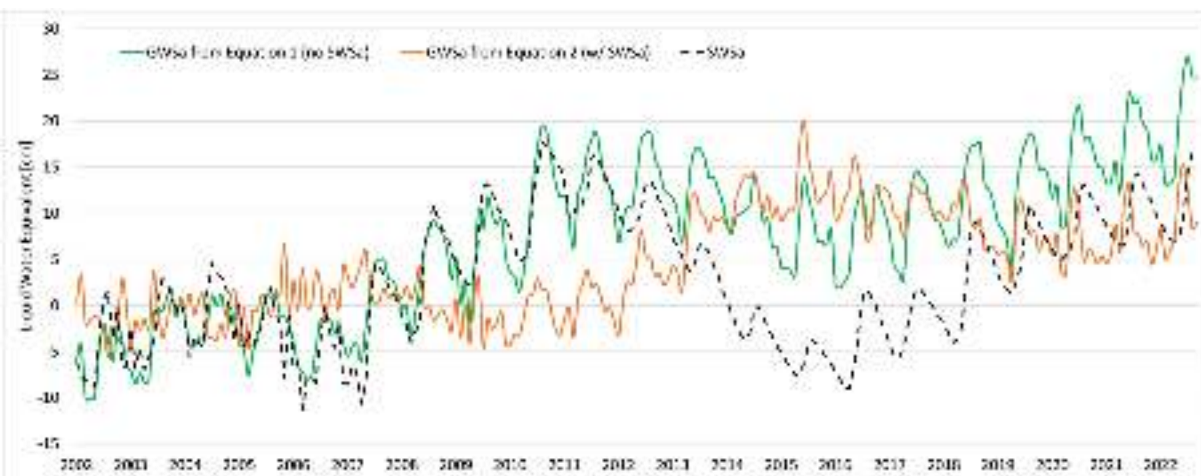


Fig. 6. Surface water storage anomaly (SWSa) computed from Lake Volta altimetry data and groundwater storage anomaly (GWSa) found with and without considering SWSa.

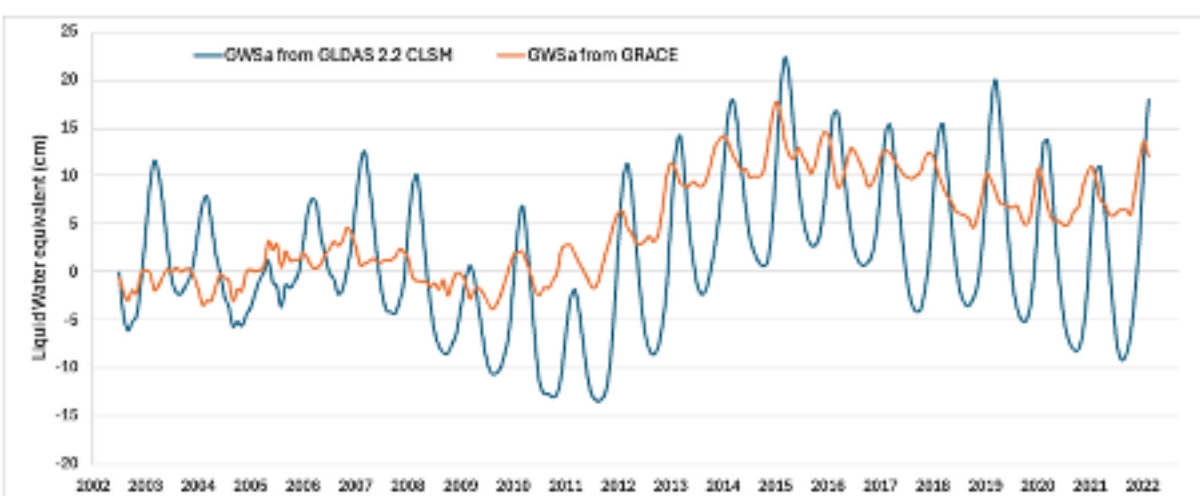


Fig. 7. Groundwater storage anomaly (GWSa) for Volta Basin derived from the GLDAS 2.2 CLSM model.

Table 1
Recharge estimates in the Volta Basin from GRACE and GSLDAS 2.2 CLSM.

Year	Recharge (cm/year)			
	GRACE		GLDAS 2.2 CLSM	
	Method 1	Method 2	Method 1	Method 2
2010	5.1	12.7	12	24
2011	7.96	15.26	20	37
2012	8.5	15.4	11	27
2013	6.1	12.1	19	43
2014	8	15	16	37
2015	4.3	7.5	17	35
2016	4	7.8	18	37
2017	2.63	5.13	16	32
2018	5.61	7.91	20	38
2019	5.9	7.1	17	42
2020	6.2	12	25	45

and 10.7 cm/yr for using GRACE data with WTF Method 1 and WTF Method 2, respectively.

We developed groundwater recharge estimates using GLDAS 2.2 CLSM data and WTF Methods 1 and 2. The recharge estimates for both WTF Method 1 and Method 2 using GLDAS 2.2 data are substantially larger than the estimates from the GRACE data, owing to the extreme seasonal fluctuations illustrated in Fig. 7. The averages using GLDAS 2.2 data are 17.4 cm/yr for WTF Method 1 and 36.1 cm/yr for WTF Method 2.

4.5.2. Groundwater recharge estimates using observed data

To validate our GRACE and GLSDAS 2.2 recharge estimates, we used water level data from the ten wells in the Nasia Basin to estimate recharge using both WTF methods (Table 2). As spatially varying storage values are unavailable over the entire basin, we assumed a specific yield of 0.05, consistent with field estimates in the area, to convert elevation change to LWE (Addai Obeng et al., 2023). The average values computed using WTF Method 1 and WTF Method 2 are 10.7 and 19.2 cm, respectively. Wells HAP014 and DWVP06 show significantly lower recharge values, ranging between 2 and 6 cm lower than the averages. Some wells, DWP02, DWP05, and HAP05, exhibit high recharge values, with rates above 30 cm. This variation reflects the spatial variability in hydraulic properties and the effect of such variations on groundwater recharge. These variations were also found in previous studies in the area (Water Resources Commission, 2011; Fynn et al., 2023).

4.5.3. Estimated groundwater recharge values comparison

We compared our WTF estimated recharge values using GRACE and GLDAS 2.2 data with the recharge values from the monitoring wells. We also compared a set of recharge values estimated in the Volta basin published by Obuobie et al. (2012) which were derived from groundwater level measurements in monitoring wells. Box plots of the recharge estimates from each source are shown in Fig. 8.

Fig. 8 shows that the median recharge values computed using GRACE data with the two WTF methods are 5.9 and 12.0 cm/yr. Recharge estimates using in situ *data* have a median value of 10.4 cm/yr, and those using GLDAS2.2 CLSM data with the WTF Method 1 and Methods 2 have a median value of 17 cm/year and 37 cm/year, respectively. Estimates from the published recharge rate have a median value of 8.6 cm/yr. The recharge rates computed from observations well data have the largest variability, and those computed using GRACE data and WTF Method 1 have the least variability. Most of the computed recharge rates are relatively consistent. The rates computes using WTF Method 1 are most conservative, and we have found they generally compare more favorably with other methods (Barbosa et al., 2022). The rates computed using GLDAS 2.2 data with the WTF Method 2 generate the most extreme estimates and do not correlate with recharge rates estimated using in situ data.

Groundwater recharge estimates we computed using GRACE data with WTF Methods 1 and 2, and GLDS2.2 CLSM data using WTF Method 1 are statistically similar to estimates made using methods other than WTF. The Water Resources Commission (2011) used the soil moisture balance method to estimate groundwater recharge for parts of the Volta Basin and obtained values in the range of 0.5–38.9 cm/yr; Addai et al. (2016) used the chloride mass balance technique for the Nasia Basin (in the Volta Basin) and obtained estimates of 7.3–11.0 cm/yr; and in the Nabogo sub-basin, Yidana et al. (2016) used stable isotope data of porewater in the vadose zone and estimated groundwater recharge rates in the range of 1.1–18.5 cm/yr. Yidana et al. (2016) used the WTF method with limited data and estimated groundwater recharge in the range of 6.5–15.2 cm/yr.

5. Discussion

Our groundwater storage estimates in the Volta Basin highlight the importance of multi-source satellite-based approach, particularly in regions with limited in situ data. However, while our analysis offers valuable insights into groundwater dynamics, it is crucial to contextualize our results within the broader landscape of existing research.

5.1. Groundwater storage dynamics and the role of surface water

A limited comparative analysis of results from other semi-arid and tropical basins globally underscores the uniqueness and similarities of the Volta Basin's groundwater dynamics. For instance, studies using GRACE data in the Indus Basin (Pakistan and India) and the Nile Basin have similarly reported significant shifts in groundwater storage correlated with monsoon patterns and agricultural extraction (Ahmed et al., 2014; Asoka et al., 2017). These findings emphasize the vulnerability of groundwater systems in areas with high extraction pressure and irregular climatic inputs.

In contrast, unlike these basins, where groundwater depletion is often driven by agricultural demand, the Volta Basin demonstrates a net increase in storage—primarily due to intense seasonal precipitation and its interaction with surface water bodies like Lake Volta, highlighting a

Table 2
Estimated recharge values in liquid water equivalent (cm) from monitoring wells located in the Nasia aquifer using method 1 (M1) and method 2 (M2).

Well	2017		2018		2019		2020		2021	
	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
DWVP01	14.9	17.4	9.6	16.3	15	17.8				
DWVP02	23.1	30.6	24.8	31.2						
DWVP03			5.9	14.5						
DWVP04	7	12.2	22.3	28.6	5.9	23	11.3	20.8		
DWVP05							11.8	18.4	14.7	31.1
DWVP06			11.7	29.2	10.6	27.9	11.8	17.4		
DWVP07			1.2	3.4	2	6.7	3.1	5.8	2.4	5
HAP05			5.5	11.4	27.6	45.6	17.1	28.9	17.3	31.7
HAP014			2.9	4.8	4.2	8.4	3.1	5.6	3.3	6.6
WVB12			8.5	24.9	10.2	22.1	12.5	27		

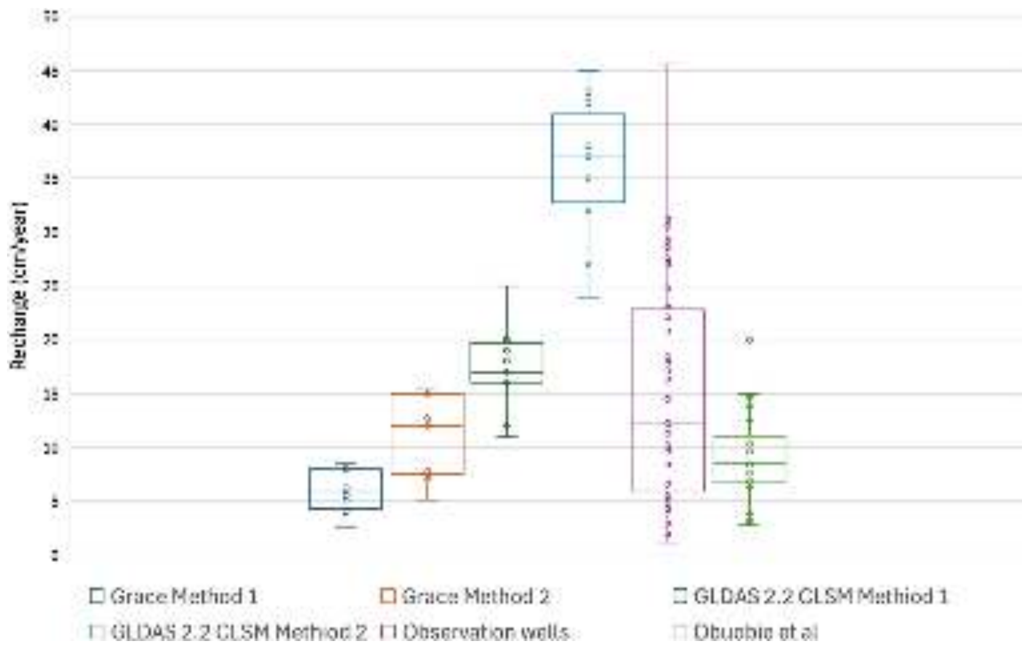


Fig. 8. Boxplot of recharge in the Volta Basin estimated with the WTF Methods 1 and 2 using GRACE data, using the new dataset from GLDAS V2.2, WTF using observation well data, and from a prior study by Obuobie et al. (2012).

different groundwater dynamic. This interaction between surface and groundwater systems plays a crucial role in sustaining aquifer levels, especially during the wet season when excess surface runoff contributes to groundwater recharge.

This comparison highlights the importance of localized hydrology features-especially large reservoirs-in shaping groundwater variability. It also reinforces the need to account for surface water interactions when interpreting satellite-based groundwater storage estimates, particularly in similar basins worldwide where surface water–groundwater interactions are pronounced.

5.2. Implications of large precipitation events on groundwater recharge

We found that large or extreme precipitation events impact groundwater recharge, potentially buffering these resources against seasonal droughts as these large precipitation events appear to significantly contribute to groundwater recharge (see Supplementary Materials for details). Such patterns are observed in comparable regions, including parts of the Sahel, where episodic recharge from intense rainfall offsets otherwise arid conditions (Taylor et al., 2013). In the Volta Basin, extreme precipitation likely contributes to the observed increase in groundwater storage since 2012. This suggests that, under climate change scenarios—where such events are expected to intensify—these recharge events could help sustain groundwater levels.

This insight is particularly relevant for water resource managers in regions with similar hydroclimatic patterns, emphasizing the potential of high-rainfall events to support sustainable groundwater supplies. Djessou et al. (2022) analysis further supports this perspective, demonstrating a correlation between heightened extreme precipitation and increased groundwater recharge. This reinforces the necessity for adaptive management strategies, underscoring the significance of high-rainfall events in maintaining sustainable groundwater resources.

5.3. Methodological contributions and literature context

This study makes a significant methodological contribution by introducing a multi-source satellite-based approach to groundwater assessment, integrating GRACE terrestrial water storage anomalies, GLDAS v2.1 and v2.2 model outputs, CHIRPS precipitation data, and Copernicus Lake altimetry. A particularly novel aspect is the explicit incorporation of Lake Volta's surface water storage using altimetry-derived estimates. Previous GRACE-based studies (e.g., Chen et al., 2014; Richey et al., 2015) typically omit surface water, potentially underestimating total water storage in basins with significant reservoirs. By addressing this gap, our approach offers a valuable framework for more precise groundwater assessments in other regions with similar conditions. Furthermore, the use of the Water Table Fluctuation (WTF) method on both GRACE- and GLDAS-derived GWSa provides a robust means of estimating groundwater recharge. The strong agreement between satellite-based recharge estimates and in situ well data in the Nasia Basin validates this approach and supports its applicability in other data-poor.

5.4. Pathways for sustainable groundwater management

The outcomes of this study underscore the utility of using Earth observation data to generate information that can be used to promote groundwater sustainability, especially in regions where comprehensive, in situ monitoring networks are absent. We demonstrate that integrating GRACE data with other complementary datasets provides actionable insights into groundwater dynamics, offering a feasible solution for resource management. For the Volta Basin, and similar basins globally, these methods can inform sustainable groundwater use strategies, supporting decision-makers in identifying periods of surplus and deficit more accurately. In particular, understanding recharge patterns following extreme precipitation can guide water management policies, such as establishing groundwater recharge zones or optimizing surface water storage in alignment with seasonal patterns.

5.5. Potential of GLDAS2.2 CLSM

The new GLDAS 2.2 CLMS dataset includes a value for GWSa, seemingly eliminated the requirement to estimate GWSa using other methods. GLDAS 2.2 has a spatial resolution of ¼ degree, allowing it to be applied to small aquifers. The data are gap-free, which eliminates the issue with GRACE-based groundwater storage data if a complete record is required. We observed similar trends with both GLDAS 2.2 and GRACE-based groundwater anomaly results. However, seasonal variations in the GLDAS 2.2 GWSa exhibited a much higher amplitude, thereby impacting the recharge estimates based on the WTF method.

This discrepancy arises from various limitations inherent in GLDAS-2.2. As discussed by Guardiola-Albert et al. (2024), the precision of GLDAS-2.2 estimates is affected by several factors including spatial variability and uncertainty in input climate data, oversimplified representations of subsurface hydrologic processes, and inaccuracies in surface and subsurface parameterizations such as vegetation, soil texture, and elevation. These issues may result in exaggerated responses in modeled groundwater storage and, consequently, overestimation of recharge. As a result, recharge estimates derived using the WTF method with GLDAS 2.2 GWSa are likely to be significantly overestimated and should be interpreted with caution.

As an example, Guardiola-Albert et al. (2024) report that in the Almonte-Marismas aquifer system, recharge estimates derived from GLDAS-2.2 using the WTF method average around 120 mm/year, representing approximately 22 % of the annual precipitation. This value is notably higher than the 70 mm/year estimated by the soil-water mass balance method, especially outside of wet years. These differences likely reflect additional contributions beyond precipitation, such as lateral groundwater inflows and subsurface hydraulic connectivity. This example highlights the need to recognize the limitations of GLDAS-2.2 data and to apply caution when using it for precise recharge quantification.

Despite these limitations for accurately estimating volumetric recharge, GLDAS-2.2-derived GWSa remains a valuable resource for monitoring regional groundwater trends, supporting seasonal water cycle assessments, calibrating numerical groundwater models, and filling data gaps in regions lacking dense in situ monitoring networks.

Based on our results and other findings, we do not recommend using GLDAS 2.2 GWSa to estimate recharge using the WTF methods. However, its readily available GWS anomaly products are well suited for broader-scale groundwater assessments and can inform regional water management efforts, especially when combined with complementary datasets and modeling tools.

5.6. Limitations and future work

Despite the strengths of our approach, several limitations remain. First, the reliance on global satellite datasets introduces spatial resolution constraints. Second, although Lake Volta—one of the largest man-made lakes in the world, formed by the Akosombo Dam in 1964 (Ferreira et al., 2018) —is explicitly included in the analysis, other smaller reservoirs and ephemeral streams across the Volta Basin were not considered. This omission may lead to underrepresentation of surface water dynamics in the basin. However, as the total surface area of these water bodies are small, even changes of several meters, if averaged over the basin, only result in water equivalent changes on the order of millimeters, well within our uncertainty range.

Third, although in situ well data were used for validation, they were limited to the Nasia Basin, leaving much of the Volta Basin—an area with diverse hydrogeological settings—without direct observational support. Consequently, caution is necessary when extrapolating recharge estimates basin-wide, as variations in geology, climate, and land use can substantially influence groundwater recharge processes. Fourth, estimating recharge from well data required assuming a uniform specific yield (Sy = 0.05) due to the lack of spatially distributed values. While based on local field estimates, this assumption introduces uncertainty, especially in areas with heterogeneous aquifer properties. Fifth, we imputed missing GRACE and altimetry data, while we hold that this approach is accurate, this does result in uncertainty that can propagate through the calculations on recharge. Additional work should be done to more fully characterize the impacts of this approach.

Future work should focus on several fronts. Improved integration of finer-resolution satellite imagery and local hydrogeological data could enhance spatial resolution and recharge accuracy. Expansion of in situ monitoring across additional sub-basins would allow for better calibration of GLDAS v2.2 data and refinement of storage coefficient estimates. Additionally, future studies could explore machine learning approaches to correlate recharge with land use, soil type, and hydro-climatic factors. Finally, incorporating socio-economic data could support scenario-based water resource planning under projected land-use and climate change conditions.

6. Conclusions

We developed and applied a novel, transferable methodology for assessing and analyzing groundwater storage and recharge in data-sparse regions, integrating GRACE satellite data, traditional GLDAS v2.1 outputs, the newly released GLDAS v2.2 CLSM product, and surface water estimates from satellite altimetry. Applied over a 20-year period in the Volta Basin (2002 to 2022), the following key conclusions were drawn:

1) Three distinct groundwater storage trends were identified: (i) a stable period from 2002 to 2008, (ii) a marked increase between from 2008 to 2015, and (iii) increased variability with a continued upward trend from 2015 to 2022. Overall, the basin experienced a net gain of approximately 30 km^3 in groundwater storage, equivalent to about 10 cm in liquid water equivalent.
2) We showed that it is critical to include storage changes in Lake Volta when studying the Volta Basin, as the lake storage represents approximately 50 % of the overall terrestrial water storage even though surface water storage is neglected in the water balance used to derive groundwater storage estimates from GRACE data for most studies.
3) Groundwater recharge estimates derived using the Water Table Fluctuation (WTF) method—applied to both GRACE and in situ groundwater level data—show strong agreement with one another and with values reported in previous studies. This confirms the value of satellite-based data for characterizing recharge in regions with limited monitoring infrastructure.
4) We analyzed the new GLDAS2.2 CLSM data for GWSa; we found a similar trend to the conventional method, but seasonal fluctuations were large and seemingly unrealistic, resulting in extreme recharge estimates. Nevertheless, the ease of access to this dataset, the lack of gaps, and the higher resolution make it a promising tool for regional groundwater analysis.

Overall, this study demonstrates the robust potential of integrating multi-source satellite-based Earth observation data with conventional hydrological methods to improve groundwater storage and recharge assessments. Such approaches can significantly advance groundwater monitoring and management in regions where traditional data are scarce, supporting more informed decision-making for sustainable water resource use.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.180421.

CRediT authorship contribution statement

Sergio A. Barbosa: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Norman L. Jones:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Gustavious P. Williams:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Henok Teklu:** Writing – original draft, Software, Methodology. **Sandow M. Yidana:** Writing – review & editing, Validation, Methodology, Data curation. **Sarva T. Pulla:** Writing – review & editing, Software. **Jorge Luis Sanchez:** Writing – review & editing, Software. **E. James Nelson:** Writing – review & editing. **Daniel P. Ames:** Writing –

review & editing. **A. Woodruff Miller:** Writing – review & editing, Methodology.

Software availability

Name of software: GRACE Groundwater Subsetting Tool (GGST)
Developer: BYU Hydroinformatics Laboratory
Program language: Python, JavaScript
Availability: https://github.com/BYU-Hydroinformatics/ggst, https://ggst.readthedocs.io/en/latest/index.html
Documentation: https://ggst.readthedocs.io/.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the NASA ROSES SERVIR Applied Research Grant 80NSSC20K0155 and from USAID under the SERVIR-WA hub.

Data availability

Data will be made available on request.

References

Addai Obeng, M., Fynn, O.F., Loh, Y.S.A., Chegbeleh, L.-P., Alo, C., Yidana, S.M., 2023. Climate and irrigation scenario analyses using three-dimensional numerical modelling: a case study of the Nasia sub-Basin in the White Volta Basin, Ghana. Hydrogeol. J. https://doi.org/10.1007/s10040-023-02632-7.

Addai, M.O., Yidana, S.M., Chegbeleh, L.-P., Adomako, D., Banoeng-Yakubo, B., 2016. Groundwater recharge processes in the Nasia sub-catchment of the White Volta Basin: analysis of porewater characteristics in the unsaturated zone. J. Afr. Earth Sci. 122, 4–14. https://doi.org/10.1016/j.jafrearsci.2015.04.006.

Ahmed, M., Abdelmohsen, K., 2018. Quantifying modern recharge and depletion rates of the Nubian aquifer in Egypt. Surv. Geophys. 39, 729–751. https://doi.org/10.1007/s10712-018-9465-3.

Ahmed, M., Sultan, M., Wahr, J., Yan, E., 2014. The use of GRACE data to monitor natural and anthropogenic induced variations in water availability across Africa. Earth Sci. Rev. 136, 289–300. https://doi.org/10.1016/j.earscirev.2014.05.009.

Aliou, A.-S., Dzikunoo, E.A., Yidana, S.M., Loh, Y., Chegbeleh, L.P., 2022. Investigation of geophysical signatures for successful exploration of groundwater in highly indurated sedimentary basins: a look at the Nasia Basin, NE Ghana. Nat. Resour. Res. 31, 3223–3251. https://doi.org/10.1007/s11053-022-10125-9.

Asoka, A., Gleeson, T., Wada, Y., Mishra, V., 2017. Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India. Nat. Geosci. 10, 109–117. https://doi.org/10.1038/ngeo2869.

Atayi, J., Anornu, G.K., Awotwi, A., Andam-Akorful, S.A., Kabo-bah, A.T., Twumasi, Y. A., et al., 2024. Terrestrial water storage and climate variability study of the Volta River Basin, West Africa. Theor. Appl. Climatol. 155, 309–325. https://doi.org/10.1007/s00704-023-04636-5.

Barbosa, S.A., Pulla, S.T., Williams, G.P., Jones, N.L., Mamane, B., Sanchez, J.L., 2022. Evaluating groundwater storage change and recharge using GRACE data: a case study of aquifers in Niger, West Africa. Remote Sens. 14, 1532. https://doi.org/10.3390/rs14071532.

Berhanu, K.G., Lohani, T.K., Hatiye, S.D., 2024. Long-term spatiotemporal dynamics of groundwater storage in the data-scarce region: Tana sub-basin, Ethiopia. Heliyon 10, e24474. https://doi.org/10.1016/j.heliyon.2024.e24474.

Bertrand-Sarfati, J., Moussine-Pouchkine, A., Affaton, P., Trompette, R., Bellion, Y., 1991. Cover sequences of the West African Craton. In: Dallmeyer, R.D., Lécorché, J. P. (Eds.), The West African Orogens and Circum-Atlantic Correlatives. Springer, Berlin, Heidelberg, pp. 65–82. https://doi.org/10.1007/978-3-642-84153-8_4.

Bonsor, H.C., Shamsudduha, M., Marchant, B.P., MacDonald, A.M., Taylor, R.G., 2018. Seasonal and decadal groundwater changes in African sedimentary aquifers estimated using GRACE products and LSMs. Remote Sens. 10 (904). https://doi.org/10.3390/rs10060904.

BRG, UNESCO, 2023. World-wide Hydrogeological Mapping and Assessment Programme. Available at: https://www.whymap.org/whymap/EN/Home/whymap_node.html. (Accessed 14 May 2023).

BYU Hydroinformatics Laboratory, 2023. GRACE groundwater subsetting tool documentation. Available at: https://ggst.readthedocs.io/en/latest/index.html. (Accessed 26 June 2023).

Callery, S., 2018. GRACE-FO launches aboard a SpaceX Falcon 9. Available at:, GRACE-FO. https://gracefo.jpl.nasa.gov/resources/77/grace-fo-launches-aboard-a-spacex-falcon-9. (Accessed 4 March 2020).

Carney, J.N., Jordan, C.J., Thomas, C.W., Condon, D.J., Kemp, S.J., Duodo, J.A., 2010. Lithostratigraphy, sedimentation and evolution of the Volta Basin in Ghana. Precambrian Res. 183, 701–724. https://doi.org/10.1016/j.precamres.2010.08.012.

Carvalho Resende, T., Longuevergne, L., Gurdak, J.J., Leblanc, M., Favreau, G., Ansems, N., et al., 2019. Assessment of the impacts of climate variability on total water storage across Africa: implications for groundwater resources management. Hydrogeol. J. 27, 493–512. https://doi.org/10.1007/s10040-018-1864-5.

Chen, J., Li, J., Zhang, Z., Ni, S., 2014. Long-term groundwater variations in Northwest India from satellite gravity measurements. Glob. Planet. Chang. 116, 130–138. https://doi.org/10.1016/j.gloplacha.2014.02.007.

Cleveland, Robert, Cleveland, William, McRae, J., Terpenning, I., 1990. STL: a seasonal-trend decomposition procedure based on loess. J. Off. Stat. 6, 3–73.

Copernicus Climate Change Service, 2020. Lake Water Levels From 1992 to Present Derived From Satellite Observations. https://doi.org/10.24381/CDS.5714C668.

Coulibaly, P., Anctil, F., Aravena, R., Bobée, B., 2001. Artificial neural network modeling of water table depth fluctuations. Water Resour. Res. 37, 885–896. https://doi.org/10.1029/2000WR900368.

DANIDA, 2024. The Danish International Development Agency. UM-ENEN. Available at: https://um.dk/en/danida. (Accessed 13 August 2024).

Djessou, R.D., Wan, X., Yi, S., Annan, R.F., Su, X., Wang, S., 2022. Water storage variation and its possible causes detected by GRACE in the Volta River Basin. Remote Sens. 14, 5319. https://doi.org/10.3390/rs14215319.

Dong, N., Wei, J., Yang, M., Yan, D., Yang, C., Gao, H., et al., 2022. Model estimates of China's terrestrial water storage variation due to reservoir operation. Water Resour. Res. 58, e2021WR031787. https://doi.org/10.1029/2021WR031787.

Dunbar, B., 2012. "GRACE Mission". Spacecraft. Available at:, NASA. http://www.nasa.gov/mission_pages/Grace/spacecraft/index.html. (Accessed 1 May 2023).

Dunbar, B., 2014. "GRACE Mission" Mission overview. Available at:, NASA. http://www.nasa.gov/mission_pages/Grace/overview/index.html. (Accessed 29 January 2022).

Dzikunoo, E.A., Vignoli, G., Jørgensen, F., Yidana, S.M., Banoeng-Yakubo, B., 2020. New regional stratigraphic insights from a 3D geological model of the Nasia sub-basin, Ghana, developed for hydrogeological purposes and based on reprocessed B-field data originally collected for mineral exploration. Solid Earth 11, 349–361. https://doi.org/10.5194/se-11-349-2020.

Ferreira, V.G., Asiah, Z., 2016. An investigation on the closure of the water budget methods over Volta Basin using multi-satellite data. In: Jin, S., Barzaghi, R. (Eds.), IGFS 2014. Springer International Publishing, Cham, pp. 171–178. https://doi.org/10.1007/1345_2015_137.

Ferreira, V.G., Gong, Z., Andam-Akorful, S.A., 2012. Monitoring mass changes in the Volta River basin using GRACE satellite gravity and TRMM precipitation. Bol. Ciênc. Geod. 18, 549–563. https://doi.org/10.1590/S1982-21702012000400003.

Ferreira, V.G., Asiah, Z., Xu, J., Gong, Z., Andam-Akorful, S.A., 2018. Land water-storage variability over West Africa: inferences from space-borne sensors. Water 10, 380. https://doi.org/10.3390/w10040380.

Flechtner, F., Morton, P., Watkins, M., Webb, F., 2014. Status of the GRACE Follow-On Mission. In: Marti, U. (Ed.), Gravity, Geoid and Height Systems. Springer International Publishing, Cham, pp. 117–121. https://doi.org/10.1007/978-3-319-10837-7_15.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2, 150066. https://doi.org/10.1038/sdata.2015.66.

Fynn, O.F., Dzikunoo, E.A., Chegbeleh, L.P., Yidana, S.M., 2023. Enhancing adaptation to climate change through groundwater-based irrigation. Sustain. Water Resour. Manag. 9, 36. https://doi.org/10.1007/s40899-023-00814-5.

Gonçalvès, J., Petersen, J., Deschamps, P., Hamelin, B., Baba-Sy, O., 2013. Quantifying the modern recharge of the "fossil" Sahara aquifers. Geophys. Res. Lett. 40, 2673–2678. https://doi.org/10.1002/grl.50478.

Guardiola-Albert, C., Naranjo-Fernández, N., Rivera-Rivera, J.S., Gómez Fontalva, J.M., Aguilera, H., Ruiz-Bermudo, F., et al., 2024. Enhancing groundwater management with GRACE-based groundwater estimates from GLDAS-2.2: a case study of the Almonte-Marismas aquifer, Spain. Hydrogeol. J. https://doi.org/10.1007/s10040-024-02838-3.

Hanasaki, N., Yoshikawa, S., Pokhrel, Y., Kanae, S., 2018. A global hydrological simulation to specify the sources of water used by humans. Hydrol. Earth Syst. Sci. 22, 789–817. https://doi.org/10.5194/hess-22-789-2018.

Healy, R.W., Cook, P.G., 2002. Using groundwater levels to estimate recharge. Hydrogeol. J. 10, 91–109. https://doi.org/10.1007/s10040-001-0178-0.

Helsel, D.R., Hirsch, R.M., Ryberg, K.R., Archfield, S.A., Gilroy, E.J., 1992. Statistical Methods in Water Resources. U.S. Geological Survey, Reston, VA. https://doi.org/10.3133/tm4A3.

Henry, C.M., Allen, D.M., Huang, J., 2011. Groundwater storage variability and annual recharge using well-hydrograph and GRACE satellite data. Hydrogeol. J. 19, 741–755. https://doi.org/10.1007/s10040-011-0724-3.

Hirdes, W., Davis, D.W., Lüdtke, G., Konan, G., 1996. Two generations of Birimian (Paleoproterozoic) volcanic belts in northeastern Côte d'Ivoire (West Africa): consequences for the 'Birimian controversy.'. Precambrian Res. 80, 173–191. https://doi.org/10.1016/S0301-9268(96)00011-3.

Jones, N.L., 2024. GGST — GRACE Groundwater Subsetting Tool 2.0 documentation. Available at: https://ggst.readthedocs.io/en/latest/. (Accessed 22 March 2024).

Joodaki, G., Wahr, J., Swenson, S., 2014. Estimating the human contribution to groundwater depletion in the Middle East, from GRACE data, land surface models, and well observations. Water Resour. Res. 50, 2679–2692.

Khaki, M., Forootan, E., Kuhn, M., Awange, J., Papa, F., Shum, C.K., 2018. A study of Bangladesh's sub-surface water storages using satellite products and data assimilation scheme. Sci. Total Environ. 625, 963–977.
Kirby, M., Ahmad, M.-D., 2022. Can Pakistan achieve sustainable water security? Climate change, population growth and development impacts to 2100. Sustain. Sci. 17, 2049–2062. https://doi.org/10.1007/s11625-022-01115-0.
Landerer, F., 2021. TELLUS_GRAC_L3_CSR_RL06_LND_v04. Ver. RL06 v04. PO.DAAC. GRACE Tellus. https://doi.org/10.5067/TELND-3AC64 (Accessed July 26, 2024).
Landerer, F.W., Swenson, S.C., 2012. Accuracy of scaled GRACE terrestrial water storage estimates. Water Resour. Res. 48. https://doi.org/10.1029/2011WR011453.
Landerer, F.W., Flechtner, F.M., Save, H., Webb, F.H., Bandikova, T., Bertiger, W.I., et al., 2020. Extending the global mass change data record: GRACE Follow-On instrument and science data performance. Geophys. Res. Lett. 47, e2020GL088306.
Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259. https://doi.org/10.2307/1907187.
Martin, N., van de Giesen, N., 2009. Spatial Distribution of Groundwater Production and Development Potential in the Volta River Basin of Ghana and Burkina Faso. https://doi.org/10.1080/02508060508691852.
McStraw, T.C., Pulla, S.T., Jones, N.L., Williams, G.P., David, C.H., Nelson, J.E., et al., 2021. An open-source web application for regional analysis of GRACE groundwater data and engaging stakeholders in groundwater management. JAWRA J. Am. Water Resour. Assoc. https://doi.org/10.1111/1752-1688.12968 (n/a).
Meals, D.W., Spooner, J., Dressing, S.A., Harcum, J.B., 2011. Statistical Analysis for Monotonic Trends.
Mensah, J.K., Ofosu, E.A., Akpoti, K., Kabo-Bah, A.T., Okyereh, S.A., Yidana, S.M., 2022. Modeling current and future groundwater demands in the White Volta River Basin of Ghana under climate change and socio-economic scenarios. J. Hydrol. Reg. Stud. 41, 101117. https://doi.org/10.1016/j.ejrh.2022.101117.
Mohasseb, H.A., Shen, W., Jiao, J., Hassan, A.A., 2024. Estimation of groundwater storage variations in African river basins: response to global climate change using GRACE and GRACE-FO among past two decades. Adv. Space Res. 74, 1164–1182. https://doi.org/10.1016/j.asr.2024.05.003.
Moore, P., Williams, S.D.P., 2014. Integration of altimetric lake levels and GRACE gravimetry over Africa: inferences for terrestrial water storage change 2003–2011. Water Resour. Res. 50, 9696–9720. https://doi.org/10.1002/2014WR015506.
Müller Schmied, H., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., et al., 2021. The global water resources and use model WaterGAP v2.2d: model description and evaluation. Geosci. Model Dev. 14, 1037–1079. https://doi.org/10.5194/gmd-14-1037-2021.
Nanteza, J., Reager, J.T., Richey, A.S., Liu, H., Famiglietti, J.S., Rodell, M., 2012. The link between surface and groundwater variations over East Africa using GRACE and Altimetry data. In: AGU Fall Meeting Abstracts, H31F-1185.
NASA, 2024a. NASA earth data - GES DISC. Available at: https://disc.gsfc.nasa.gov/datasets. (Accessed 31 July 2024).
NASA, 2024b. NASA LDAS - Land Data Assimilation System. Available at: https://ldas.gsfc.nasa.gov/gldas. (Accessed 31 July 2024).
NASA JPL, 2023. Prolific earth gravity satellites end science mission. Available at:, NASA Jet Propulsion Laboratory (JPL). https://www.jpl.nasa.gov/news/prolific-earth-gravity-satellites-end-science-mission. (Accessed 12 May 2023).
Ndehedehe, C.E., Awange, J.L., Kuhn, M., Agutu, N.O., Fukuda, Y., 2017. Analysis of hydrological variability over the Volta river basin using in-situ data and satellite observations. J. Hydrol. Reg. Stud. 12, 88–110. https://doi.org/10.1016/j.ejrh.2017.04.005.
Nenweli, R., Watson, A., Brookfield, A., Münch, Z., Chow, R., 2024. Is groundwater running out in the Western Cape, South Africa? Evaluating GRACE data to assess groundwater storage during droughts. J. Hydrol. Reg. Stud. 52, 101699. https://doi.org/10.1016/j.ejrh.2024.101699.
Ni, S., Chen, J., Wilson, C.R., Hu, X., 2017. Long-term water storage changes of Lake Volta from GRACE and satellite altimetry and connections with regional climate. Remote Sens. 9, 842. https://doi.org/10.3390/rs9080842.
Nimmo, J.R., Horowitz, C., Mitchell, L., 2015. Discrete-storm water-table fluctuation method to estimate episodic recharge. Groundwater 53, 282–292. https://doi.org/10.1111/gwat.12177.
Obuobie, E., Diekkrueger, B., Agyekum, W., Agodzo, S., 2012. Groundwater level monitoring and recharge estimation in the White Volta River basin of Ghana. J. Afr. Earth Sci. 71–72, 80–86. https://doi.org/10.1016/j.jafrearsci.2012.06.005.
Perktold, J., Seabold, Skipper, Sheppard, K., Fulton, Chad, Shedden, Kerby, Jbrockmendel, et al., 2023. statsmodels/statsmodels: Release 0.14.0. https://doi.org/10.5281/ZENODO.593847.
Pilgrim, C., 2021. piecewise-regression (aka segmented regression) in Python. JOSS 6, 3859. https://doi.org/10.21105/joss.03859.
Pokhrel, Y., Felfelani, F., Satoh, Y., Boulange, J., Burek, P., Gädeke, A., et al., 2021. Global terrestrial water storage and drought severity under climate change. Nat. Clim. Chang. 11, 226–233. https://doi.org/10.1038/s41558-020-00972-w.
Purdy, A.J., David, C.H., Sikder, M., Reager, J.T., Chandanpurkar, H.A., Jones, N.L., et al., 2019. An open-source tool to facilitate the processing of GRACE Observations and GLDAS outputs: an evaluation in Bangladesh. Front. Environ. Sci. 7, 155.
Richey, A.S., Thomas, B.F., Lo, M.-H., Reager, J.T., Famiglietti, J.S., Voss, K., et al., 2015. Quantifying renewable groundwater stress with GRACE. Water Resour. Res. 51, 5217–5238.
Rodell, M., Houser, P.R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., et al., 2004. The Global Land Data Assimilation System. Bull. Am. Meteorol. Soc. 85, 381–394. https://doi.org/10.1175/BAMS-85-3-381.
Rodell, M., Chen, J., Kato, H., Famiglietti, J.S., Nigro, J., Wilson, C.R., 2007. Estimating groundwater storage changes in the Mississippi River basin (USA) using GRACE. Hydrogeol. J. 15, 159–166. https://doi.org/10.1007/s10040-006-0103-7.
Rodell, M., Velicogna, I., Famiglietti, J.S., 2009. Satellite-based estimates of groundwater depletion in India. Nature 460, 999–1002. https://doi.org/10.1038/nature08238.
Rodgers, C., van de Giesen, N., Laube, W., Vlek, P.L.G., Youkhana, E., 2007. The GLOWA Volta Project: a framework for water resources decision-making and scientific capacity building in a transnational West African Basin. Water Resour. Manag. 21, 295–313. https://doi.org/10.1007/s11269-006-9054-y.
Scanlon, B.R., Faunt, C.C., Longuevergne, L., Reedy, R.C., Alley, W.M., McGuire, V.L., et al., 2012. Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. Proc. Natl. Acad. Sci. 109, 9320–9325.
Scanlon, B.R., Rateb, A., Anyamba, A., Kebede, S., MacDonald, A.M., Shamsudduha, M., et al., 2022. Linkages between GRACE water storage, hydrologic extremes, and climate teleconnections in major African aquifers. Environ. Res. Lett. 17, 014046. https://doi.org/10.1088/1748-9326/ac3bfc.
Sutanudjaja, E.H., van Beek, R., Wanders, N., Wada, Y., Bosmans, J.H.C., Drost, N., et al., 2018. PCR-GLOBWB 2: a 5 arcmin global hydrological and water resources model. Geosci. Model Dev. 11, 2429–2453. https://doi.org/10.5194/gmd-11-2429-2018.
Swenson, S., 2012. GRACE Monthly Land Water Mass Grids NETCDF release 5.0. Available at:, Physical Oceanography Distributed Active Archive Center (PO.DAAC). https://podaac.jpl.nasa.gov/dataset/TELLUS_LAND_NC_RL05. (Accessed 2 February 2022).
Syed, T.H., Famiglietti, J.S., Rodell, M., Chen, J., Wilson, C.R., 2008. Analysis of terrestrial water storage changes from GRACE and GLDAS. Water Resour. Res. 44. https://doi.org/10.1029/2006WR005779.
Sylla, M.B., Elguindi, N., Giorgi, F., Wisser, D., 2016. Projected robust shift of climate zones over West Africa in response to anthropogenic climate change for the late 21st century. Clim. Chang. 134, 241–253. https://doi.org/10.1007/s10584-015-1522-z.
Tapley, B.D., Bettadpur, S., Ries, J.C., Thompson, P.F., Watkins, M.M., 2004a. GRACE measurements of mass variability in the Earth system. Science 305, 503–505.
Tapley, B.D., Bettadpur, S., Watkins, M., Reigber, C., 2004b. The gravity recovery and climate experiment: mission overview and early results. Geophys. Res. Lett. 31.
Taylor, R.G., Todd, M.C., Kongola, L., Maurice, L., Nahozya, E., Sanga, H., et al., 2013. Evidence of the dependence of groundwater resources on extreme rainfall in East Africa. Nat. Clim. Chang. 3, 374–378. https://doi.org/10.1038/nclimate1731.
UN-Water, 2023. Sub-Saharan Africa – safely managed drinking water services (SDG indicator 6.1.1). Available at:, SDG 6 Data Portal. https://sdg6data.org/en/region/Sub-Saharan%20Africa. (Accessed 31 July 2025).
Wada, Y., de Graaf, I.E.M., van Beek, L.P.H., 2016. High-resolution modeling of human and climate impacts on global water resources. J. Adv. Model. Earth Syst. 8, 735–763. https://doi.org/10.1002/2015MS000618.
Wahr, J., Molenaar, M., Bryan, F., 1998. Time variability of the Earth's gravity field: hydrological and oceanic effects and their possible detection using GRACE. J. Geophys. Res. Solid Earth 103, 30205–30229.
Water Resources Commission, 2011. Final Technical Report Hydrogeological Assessment of the Northern Regions of Ghana.
Wu, Q., Si, B., He, H., Wu, P., 2019. Determining regional-scale groundwater recharge with GRACE and GLDAS. Remote Sens. 11 (154). https://doi.org/10.3390/rs11020154.
Xiao, R., He, X., Zhang, Y., Ferreira, V.G., Chang, L., 2015. Monitoring groundwater variations from satellite gravimetry and hydrological models: a comparison with in-situ measurements in the mid-Atlantic region of the United States. Remote Sens. 7, 686–703.
Xu, H., Liu, D., 2025. Study on groundwater storage changes in Henan Province based on GRACE and GLDAS. Sustainability 17, 6316. https://doi.org/10.3390/su17146316.
Yan, X., Zhang, B., Yao, Y., Yin, J., Wang, H., Ran, Q., 2022. Jointly using the GLDAS 2.2 model and GRACE to study the severe Yangtze flooding of 2020. J. Hydrol. 610, 127927. https://doi.org/10.1016/j.jhydrol.2022.127927.
Yi, S., Sneeuw, N., 2021. Filling the data gaps within GRACE missions using singular spectrum analysis. J. Geophys. Res. Solid Earth 126, e2020JB021227. https://doi.org/10.1029/2020JB021227.
Yidana, S.M., Banoeng-Yakubo, B., Akabzaa, T., Asiedu, D., 2011. Characterization of the groundwater flow regime and hydrochemistry of groundwater from the Buem formation, Eastern Ghana. Hydrol. Process. 25, 2288–2301. https://doi.org/10.1002/hyp.7992.
Yidana, S.M., Fynn, O.F., Adomako, D., Chegbeleh, L.P., Nude, P.M., 2016. Estimation of evapotranspiration losses in the vadose zone using stable isotopes and chloride mass balance method. Environ. Earth Sci. 75, 208. https://doi.org/10.1007/s12665-015-4982-6.
Yidana, S.M., Dzikunoo, E.A., Aliou, A.-S., Adams, R.M., Chagbeleh, L.P., Anani, C., 2020. The geological and hydrogeological framework of the Panabako, Kodjari, and Bimbilla formations of the Voltaian supergroup – revelations from groundwater hydrochemical data. Appl. Geochem. 115, 104533. https://doi.org/10.1016/j.apgeochem.2020.104533.
Yidana, S.M., Dzikunoo, E.A., Mejida, R.A., Ackom, E.K., Chegbeleh, L.P., Loh, Y.S.A., et al., 2024. Evaluating groundwater resources trends through multiple conceptual models and GRACE satellite data. Environ. Monit. Assess. 196, 290. https://doi.org/10.1007/s10661-024-12457-w.