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Application of GRACE to the estimation of groundwater storage change in a data-poor region: A case study of Ngadda catchment in the Lake Chad Basin

Alla Skaskevych[1] | Jejung Lee[2] | Hahn Chul Jung[3,4] | John Bolten[4] | John L. David[3,5] | Frederick S. Policelli[4] | Ibrahim B. Goni[6] | Guillaume Favreau[7] | Soma San[2] | Charles M. Ichoku[8]

[1]AECOM Technology Corporation, Kansas City, Missouri, USA
[2]Department of Earth and Environmental Sciences, University of Missouri: Kansas City, Kansas City, Missouri, USA
[3]Science Systems and Applications, Inc., Lanham, Maryland, USA
[4]Hydrological Sciences Laboratory, National Aeronautics and Space Administration Goddard Space and Flight Center, Greenbelt, Maryland, USA
[5]Earth Sciences Division, National Aeronautics and Space Administration Goddard Space and Flight Center, Greenbelt, Maryland, USA
[6]Department of Geology, University of Maiduguri, Borno, Nigeria
[7]HydroSciences, Institute of Research for Development, Grenoble, France
[8]Interdisciplinary Studies, Atmospheric and Environmental Sciences, Howard University, Washington, District of Columbia, USA

Correspondence
Jejung Lee, Department of Earth and Environmental Sciences, University of Missouri: Kansas City, 5110 Rockhill Road, Kansas City, MO 64110.
Email: leej@umkc.edu

Abstract
The present study is to explore the feasibility of GRACE-based estimation of a groundwater storage change in a data-poor region using a case study of the Ngadda catchment in the Lake Chad Basin. Although the Ngadda catchment has only one set of *in situ* time series data of groundwater from 2006 to 2009 and a limited number of groundwater measurements in 2005 and 2009, GRACE-based groundwater storage change can be evaluated against the *in situ* groundwater measurements combined with specific yield data. The cross-correlation analysis in the Ngadda catchment shows that maximum rainfall reached in July and August, whereas both the maximum total water storage anomaly and the maximum groundwater storage anomaly occurred 2months later. Whereas the mean annual amplitude of total water storage anomaly is about 17cm from both the average total water storage anomaly from three mascon products and the one from three spherical harmonic products, the mean annual amplitude of soil moisture storage anomaly is substantially varied from 5.58cm for CLM to about 14cm for NOAH and Mosaic. The goodness-of-fit tests show that CLM soil moisture produces the closest estimation of groundwater storage anomaly to the *in situ* groundwater measurements. The present study shows that GRACE-based estimation for groundwater storage anomaly can be a cost-effective and alternative tool to observe how groundwater changes in a basin scale under the limitation of modelling and *in situ* data availability.

KEYWORDS
GRACE, groundwater, Lake Chad Basin

1 | INTRODUCTION

Groundwater is a vital resource experiencing increasing demands around the globe. Especially in the arid and semiarid regions, groundwater is the primary source of freshwater that is exploited for domestic, agricultural, and industrial uses. More regions around the world are facing water stress and scarcity by population growth, overexploitation, and climate change. A better monitoring system is, therefore, critical to understand the dynamics of groundwater flow and to develop more sustainable water resource management plans. However, in many parts of the world, data collection is challenged by

The present paper explores feasibility of GRACE-based estimation for groundwater storage change in a data-poor region by using a case study of Ngadda catchment of the Lake Chad Basin.

sparsely distributed ground stations, temporal data gaps, and limited data sharing due to political and societal boundaries. The Lake Chad Basin (LCB) in sub-Saharan Africa is one of the examples experiencing such challenges. The lake was one of the largest freshwater lakes in Africa but has been dramatically shrinking to about 1/20 of its original size since the 1960s. Coe and Foley (2001) showed that the shrinkage of Lake Chad had been caused by both climate change and overexploitation of water with population growth. Whereas the lake water has been used mainly for irrigation and fishing, groundwater became the predominant source of potable water supply for domestic livestock consumption. Wells dug in proximity to Lake Chad are mainly hand-dug, unlined, or concrete-lined open wells with a diameter of about 1m.The wells are mostly located in local villages, and there is no monitoring network of groundwater. To overcome such limitations, remotely sensed monitoring by using satellite data would be an alternative. Remote sensing often offers free-access datasets that can help further in monitoring hydrological changes in remote areas. Here, we define "data-poor region" as an area where only few hydrological monitoring stations are available to collect continuous time series data. Whereas many data-poor regions may still have a set of spatially distributed hydrological data collected at different times, continuous time series data are essential to understand temporal patterns of hydrological changes in a given space and time. Remote sensing applications for data-poor regions were adopted more actively for studies of rainfall and surface water. Armanios and Fisher (2014) assessed the feasibility of water budget calculations using the Tropical Rainfall Measuring Mission (TRMM), Moderate Resolution Imaging Spectroradiometer, and the Gravity Recovery and Climate Experiment (GRACE), integrated with geographic information system, for the Rufiji Basin in Tanzania. The study shows the improved accuracy of estimation of precipitation, evapotranspiration, and water storage change by comparing with other past studies in the same basin. Stisen, Jensen, Sandholt, and Grimes (2008) and Stisen and Sandholt (2010) studied water budgets of the Senegal River basin by only using remote sensing data, including METEOSAT-7, the polar orbiting advanced very high resolution radiometer, TRMM, Climate Prediction Center MORPHing technique, and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks for modelling accuracy of rainfall and run-off in the region. Both studies show that the inclusion of *in situ* data in remote sensing–based models enhanced accuracy of the models. Becker et al. (2018) adopted ENVISAT radar altimeter, TRMM, GRACE, and the Global Inundation Extent from Multi-Satellites time series to estimate the surface water extent and storage in the Congo River basin. Their study defined the sum of soil moisture and groundwater as a "subsurface water storage" and showed that some subbasins such as Ubangi, Sangha, and Lualaba basins have significant portion of the subsurface water storage change in the total water storage change.

Whereas many satellite-based remote sensing data were actively adopted for hydrological monitoring and prediction, the emergence of GRACE significantly advanced global and regional water storage monitoring efforts in the recent decades. In the early development of GRACE application, the monthly derived GRACE data were applied globally in defining the dominating seasonal components of the continental water cycle (Rodell et al., 2007; Schmidt et al., 2006; Tapley, Bettadpur, Ries, Thompson, & Watkins, 2004). GRACE studies have been extended to the definition of individual hydrological components from the integral GRACE signals such as the evapotranspiration (Rodell et al., 2004; Swenson & Wahr, 2006), droughts (Houborg et al., 2010; Zhang, Zhang, Werner, & Liu, 2016), ice mass variations (Xiaolei, Yunzhong, & Zizhan, 2014), and the surface run-off with flooding events (Reager, Thomas, & Famiglietti, 2014). Applications to the groundwater storage change have been widely developed for different hydrologic conditions in a different scale (Feng et al., 2013; Rodell, Velicogna, & Famiglietti, 2009; Tang et al., 2017; Voss et al., 2013; Yeh, Swenson, Famiglietti, & Rodell, 2006). One of the early studies was Rodell et al. (2007) to estimate the groundwater storage variations for the Mississippi River basin using GRACE and the National Aeronautics and Space Administration (NASA) Global Land Data Assimilation System (GLDAS). They compared the GRACE estimation with the *in situ* groundwater measurements to discuss the strengths and limitations of the GRACE application to groundwater. Strassberg, Scanlon, and Chambers (2009) compared the GRACE-derived groundwater change with *in situ* groundwater measurements to prove that the GRACE-derived modelling is capable of addressing the observational gap in monitoring groundwater storage changes over a scale of basin. Henry, Allen, and Huang (2011) compared the GRACE-based recharge estimation in 2002–2008 with the annual net recharge rate calculated from the water-table fluctuation method using *in situ* groundwater measurements from 1982 to 2002 in Mali, Africa. They pointed out that GLDAS might poorly predict the soil moisture, especially when the groundwater table is deeper than the model depth of soil layers. Whereas many studies compared GRACE-based groundwater storage with *in situ* groundwater along with specific yield from limited pumping tests or other literatures, Sun, Green, Rodell, and Swenson (2010) attempted to calibrate uncertain aquifer storage parameters using GRACE. Their study addresses the importance of aquifer storage parameters and their uncertainty in the estimation of groundwater storage.

As the LCB has been experiencing political and social insecurity and instability by terrorism and civil wars hindering ground data collection, the use of a GRACE-derived model can assist in understanding the dynamics of groundwater change more effectively. Recent applications of GRACE to the LCB were the estimation of total water storage change (Lopez et al., 2016; Ndehedehe, Agutu, Okwuashi, & Ferreira, 2016) and one of groundwater storage change (Boronina & Ramillien, 2008; Buma, Lee, & Seo, 2016). Because *in situ* data are rarely available in the LCB, the groundwater storage changes were estimated by employing other hydrological models such as Simplified Surface Energy Balance Index algorithm (Boronina & Ramillien, 2008) and WaterGAP Global Hydrology Model (Buma et al., 2016). Although an additional numerical model helps fill the gap of subsurface processes in GRACE-based estimation, the model construction is still uncertain due to limited information on basic aquifer properties and simplified assumption.

The present study is to estimate groundwater storage anomalies of the Ngadda catchment, a subbasin of the LCB, using six GRACE products including three mascon products and three spherical harmonic products, and to explore applicability of GRACE data in a data-poor region without numerical models. The conditions of “data poor” in this GRACE model validation are as follows: (1)Only a single set of time series data of groundwater is available from 2006 to 2009, and (2)spatially distributed groundwater measurements are available for November 2005 and July 2009 only. To assess the performance of the present approach, we compared the GRACE outputs with the *in situ* groundwater data and analysed how the combination of GRACE and GLDAS models would affect the estimation of groundwater storage change.

2 | GRACE

GRACE is a twin-satellite mission launched by the NASA and the German Aerospace Center on March 17,2002, to make detailed measurements of Earth's gravity field and investigate Earth's water reservoirs over land, ice, and oceans. The basic concept of GRACE is based on gravity and its proportional relationship with earth density. The Earth's surface is not uniform as it consists of physical bodies with different densities, such as mountains, valleys, oceans, and ice caps; thus, the density varies from place to place on the Earth's surface. Consequently, the variations in density result in moderate variations in the gravitational field, and the unique design of GRACE enables the detection of those changes from space.

With the tandem satellite design of GRACE, two satellites maintain a distance of about 220km and an orbit altitude about 500km. The satellites orbit the Earth 16times a day and produce global coverage every 30days from a single source or position in space. The satellites detect minute spatial variations in the Earth's surface mass below as well as spatial variations in the Earth's gravitational force. When the satellites travel 500km above the earth in space, the front satellite captures the area with higher gravity; it is slightly pulled toward the area with higher density and speeds up.As soon as the front satellite passed over the area of higher gravity, it slows down, but the trailing satellite speeds up.The distance between two satellites changes again. As the trailing satellite passes the region of higher density, it slows down as well, not affecting the front satellite at the same time. These minute expansions and contractions of the distance between satellites are measured using the microwave *K*-band ranging instrument and thus are able to map the gravitational field of the Earth surface. In any one place of the measurement, the data are exactly positioned from Global Positioning System receivers. Consequently, high-resolution maps allow looking at the Earth's gravitational field from the large scale to finer scale over both land and sea. The details of the GRACE instruments are summarized in NASA (2002).

GRACE has three levels of data product: Level-1 (Level-1A), Level-2 (Level-2B), and Level-3. The Level-1 data are the raw data to be calibrated and time-tagged in a nondestructive sense. The Level-1 data are not distributed to public. The Level-2 data are the processed products to generate the monthly gravity field estimates in a form of spherical harmonic coefficients. The Level-2 data are produced from three different centres including Jet Propulsion Laboratory, University of Texas Center for Space Research, and GeoForschungsZentrum Potsdam. The Level-3 data are the processed data for users who are not familiar with the concept of spherical harmonics and prefer to access GRACE data products as mass anomalies in a gridded scale (GRACE Tellus: https://grace.jpl.nasa.gov). Whereas many research about GRACE use Level-2 data (Abiy & Melesse, 2017; Bhanja, Mukherjee, Saha, Velicogna, & Famiglietti, 2016; Feng et al., 2013; Frappart et al., 2011; Strassberg et al., 2009; Sun, 2013; Sun, Green, Swenson, & Rodell, 2012), Level-3 data-based studies are rare due to concerns of accuracy and uncertainty of the data product. In the recent years, though, some studies started to look at the applicability of Level-3 data in a regional-scale model (Becker, Llovel, Cazenave, Guntner, & Cretaux, 2010; Buma et al., 2016; Tang et al., 2017). Becker et al. (2010) applied RL04 Level-3 data to investigate the hydrological behaviour between rainfall and Indian Ocean Dipole in the East African Great Lakes region. Buma et al. (2016) applied the RL05 Level-3 total water storage change into the LCB and revealed the similarities of trends between the lake water volumetric change and the total water storage change of the basin. Tang et al. (2017) also adopted the RL05 Level-3 data to compare the GRACE-derived groundwater storage changes with a parsimonious Budyko model–based storage changes in the Punjab province in Pakistan.

Whereas the spherical harmonic function–based GRACE data had been popularly adopted in many applications, there were efforts to improve data quality such as post processing to remove smoothness using scaling factors and the signal “leakage” and globally covering land and ocean surfaces simultaneously (Landerer & Swenson, 2012; Long, Longuevergne, & Scanlon, 2015; Swenson & Wahr, 2006). The alternative approach was to parameterize the gravity field with regional mass concentration functions (“mascons”), which estimates terrestrial mass changes directly from the intersatellite measurements (Level-1) without post processing (Luthcke et al., 2015; Rowlands et al., 2010; Watkins, Wiese, Yuan, Boening, & Landerer, 2015). The mascon solutions reduce leakage error and, therefore, have potential to lower uncertainties compared with the spherical harmonic solutions (Long et al., 2015; Scanlon et al., 2015). There are three mascon products available: Jet Propulsion Laboratory mascons, Center for Space Research mascons, and Goddard Space Flight Center mascons (M-GSFC). The mascon products are represented on 1° global grids for M-GSFC or 0.5° ones for Jet Propulsion Laboratory mascons and Center for Space Research mascons, but they are highly correlated with its neighbouring elements. Rodell et al. (2019) noted that 3° mascon element corresponds to the “native” resolution of GRACE. In the present study, we used an ensemble average of three spherical harmonic products (S-Ave) and an ensemble average of three mascon products (M-Ave) for the calculation of water storage anomalies.

The hydrologic product from the GRACE is expressed as the total water storage (TWS). TWS measures the distribution of mass above and below the Earth's surface. In other words, TWS represents a vertically integrated water storage system, including groundwater, soil moisture, surface water, and snow. Zaitchik, Rodell, and Reichle (2008) states that monthly water storage changes must be varied horizontally and vertically for a better understanding of the full potential application of GRACE for hydrology. Looking at GRACE TWS and its individual components would greatly improve their scientific value for hydrological research and applications.

GRACE has no vertical resolution. In cases where it is necessary to determine one individual component of water storage changes, TWS must be disaggregated horizontally, vertically, and temporally. Zaitchik et al. (2008) disaggregated GRACE data vertically and assimilated TWS into the NASA catchment land surface model (CLSM). Originally, the CLSM model was developed for global-scale coupled land and atmosphere modelling. There have been several improvements in stream flow estimates in the model, but CLSM-estimated groundwater has not been validated extensively due to the lack of *in situ* measurements. By employing ensemble Kalman filtering within CLSM, GRACE data assimilation can constrain TWS anomalies and improve the detection of groundwater change and its seasonality in several basins (Zaitchik et al., 2008). Rodell et al. (2007) computed the groundwater storage variations over the Mississippi River basin and its four major subbasins by using soil moisture and snow water equivalent components from the GLDAS. Assuming vegetation and surface water contributions to be negligible, GLDAS was used to estimate the groundwater storage variations from GRACE TWS. This is a simple approach for estimating regional groundwater storage change including large aquifer systems. Rodell et al. (2007) also suggested that estimation of groundwater anomalies for smaller subbasins has larger seasonal amplitudes that makes results poorer in comparison with larger subbasins. Early studies indicated that the minimum area in which GRACE could resolve water mass changes should be no less than 500,000 km^2 (Rodell & Famiglietti, 1999) or 150,000 km^2 (Swenson, Yeh, Wahr, & Famiglietti, 2006). The continuous improvement of GRACE preprocessing and postprocessing techniques enhanced the accuracy of modelling in a scale of 10^5 km^2 (Famiglietti et al., 2011; Tang et al., 2017). The GRACE modelling, therefore, can be a feasible alternative to fill the data gap and analyse groundwater changes in a data-poor region such as the LCB, of which surface area is 2.5 million km^2.

3 | STUDY AREA

In the last century, many closed lakes and seas all over the world have declined in size or completely dried out due to anthropogenic or natural causes (Thomas, Meybeck, & Beim, 1992). Lake Chad is one of them; it used to be one of the largest endorheic lakes in the world with a lake area of 25,000km^2 in 1963. It has been known that the lake area has declined to less than 2,000km^2 in the 1990s (Grove, 1996). Recent studies by Leblanc, Lemoalle, Bader, Tweed, and Mofor (2011) and Policelli, Hubbard, Jung, Zaitchik, and Ichoku (2018) though found that the measurement of lake water including open water and flooded vegetation would lead to significantly greater total water area of the lake in the late 1980s through 2016 than had been suggested before. Many studies explain human and natural impacts on the water resources of Lake Chad as well, such as two severe droughts that occurred in the periods 1972–1974 and 1983–1987 (Kimmage & Adams, 1992), desertification (IPCC, 2001), overgrazing (FAO, 2009), irrigation activities (Isiorho & Njock-Libii, 1996), vegetation removal and modification (Keith & Plowers, 1997), and deforestation (Neiland & Verinumbe, 1990), along with population increase (UN Population Division, 2002). Whereas the lake shrinkage has been studied broadly using remote sensing data, understanding of groundwater variations remains poor in the region due to the lack of data and limited accessibility from insecurity by decades of violence, such as civil wars in Chad from 2005 to 2010 and insurgence of militants like Boko Haram from 2009 to present. Occasional efforts for groundwater data collection were made by various scientific studies or by government, but data distribution is scarce, and continuous time series data are rarely available. Because Lake Chad is a closed lake, its surface water completely depends on its inflow (Figure 1). The largest subsystem feeding the lake is the Chari/Logone River system (650,000-km^2 basin area), which supplies over 90% of the total inflow to the lake (FAO, 2009). The Chari River flows from the Central African Republic and reaches the southern pool of the lake. The second important subsystem is

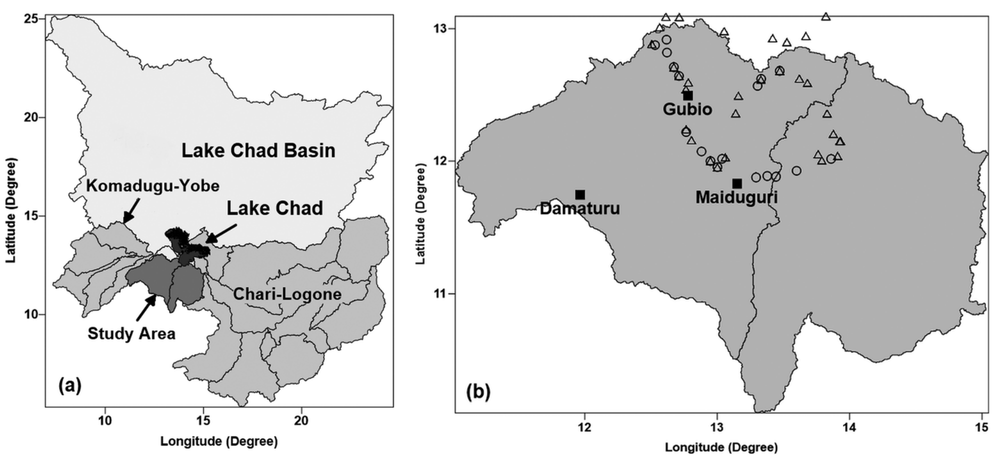

FIGURE 1 The study area of Ngadda catchment in the Lake Chad Basin. Triangles indicate the locations of *in situ* groundwater depth data in November 2005, and circles indicate the ones in July 2009

Komadugu Yobe River (148,000-km^2 basin area), which flows in from the northern Nigeria and Niger. Although the Komadugu Yobe River contributes only about 2–5% of the total inflow to the lake, it is the only persistent river flowing into the northern pool of the lake. The LCB is a sedimentary basin formed during the Cretaceous Period (Gumnior & Thiemeyer, 2003). The major aquifer system lies under the Chad Formation consisting of three major aquifers: the upper, middle, and lower aquifers. The Chad Formation mostly consists of sand and clay. The upper aquifer is located at depths approximately 30m deep and contained within the Quaternary fine-grained sediments (Edmunds, Fellman, & Goni, 2002). This aquifer is hydrologically connected to Lake Chad. Groundwater in the upper aquifer is suitable mainly for domestic use through open wells and boreholes (Odada, Oyebande, & Oguntola, 2006). Whereas the upper aquifer is unconfined, the middle aquifer is a confined aquifer consisting of fine sands and clays between 450- and 620-m depths from the surface (Kindler, Warshall, Arnould, Hutchinson, & Varady, 1990). The water from the middle aquifer is mainly used for domestic and livestock use. Finally, the lower aquifer is also a confined aquifer consisting mostly of sand and clay deposited in the Cretaceous Period. The lower aquifer is hardly explored, as the approximate depth to the aquifer is more than 700m from the ground surface. The city of Maiduguri, a major city in the study area, heavily drilled boreholes in and around the city for gas exploration, which provides most of the information about the lithology, geometry, and hydrogeology of the aquifers (Bumba, Kida, & Bunu, 1985).

The present study focuses on the Ngadda River system, of which area includes Ngadda basin (42,535km^2) and Magay basin (36,893km^2) in the southwest region of Lake Chad as shown in Figure 1. The climate is semiarid with a long dry season and a short rainy season lasting generally between May and September. The main city in the area is Maiduguri with a population of about 1.2 million by 2009. The Ngadda River system originates from the Mandara Hills in Northern Cameroon and passes through the city of Maiduguri before entering the lake. The Ngadda River makes a very negligible contribution to the lake's inflow during the wet season because it loses most of its water in a 7-km-wide flood plain and swamps in its northwestern flow. The contribution of surface water storage change has been known to be less than at least an order of magnitude compared with groundwater and soil moisture storage changes in GRACE modelling unless an area experiences extreme flooding or is located in rainforests (Henry et al., 2011; Rodell & Famiglietti, 2001). Also, because the surface water loses to subsurface, it is expected that the lost water would be reflected in the soil moisture estimation. The assumption of no surface water change, therefore, would be a valid assumption in the present study. The area of study includes one of the largest natural piezometric depressions of the Quaternary aquifer named as the Borno piezometric depression. Zaira (2008) collected groundwater data in November 2005 during dry season, and we did it in July 2009 during wet season in the same area. We adopted both groundwater datasets to explore a potential use of scarce *in situ* groundwater data in the GRACE application.

4 | METHODOLOGY

The present study adopted six GRACE products including three spherical harmonic products from JPL, CSR, and GFZ and three mascon products from JPL, CSR, and GSFC for monthly changes in TWS. To estimate the monthly groundwater storage variations using GRACE, we adopted a water storage equation (Scanlon, Lonquevergne, & Long, 2012):

$$\Delta TWS = \Delta GW + \Delta SM + \Delta SW + \Delta SWE, \tag{1}$$

where ΔTWS is the total water storage anomaly, ΔGW is the groundwater (GW)storage anomaly, ΔSM is the soil moisture (SM)anomaly, ΔSW is the surface water (SW)anomaly, and ΔSWE is the snow water equivalent (SWE) anomaly. If we assume ΔSW and ΔSWE are negligible for the study area, the ΔGW is defined as

$$\Delta GW = \Delta TWS - \Delta SM, \tag{2}$$

ΔTWS calculates the difference between the TWS and its mean:

$$\Delta TWS_{i,j,k} = TWS_{i,j,k} - \sum^{n} TWS_{i,j,k}/n, \tag{3}$$

where $n$is the total number of months, $i$is the longitude cell number, $j$is the latitude cell number, and $k$is the number of month. Similarly, ΔSM calculates the difference between the SM and its mean:

$$\Delta SM_{i,j,k} = SM_{i,j,k} - \sum^{n} SM_{i,j,k}/n, \tag{4}$$

We adopted GLDAS for the estimation of ΔSM. GLDAS provides optimal estimates of land surface fluxes and storages of water and energy using satellite- and ground-based data. GLDAS derives land surface parameters such as soil moisture and surface temperature and flux parameters such as evaporation and sensible heat flux. As a land surface component of the hydrological cycle, soil moisture is the most critical parameter to link the atmospheric processes to the terrestrial water processes. GLDAS consists of two versions, GLDAS version 1(GLDAS-1) and GLDAS version 2(GLDAS-2). GLDAS-1 includes high-quality observational precipitation and solar radiation input datasets for the period 1979 to present. GLDAS-1 is a combination of National Oceanic and Atmospheric Administration/Global Data Assimilation System fields, National Oceanic and Atmospheric Administration Climate Prediction Center Merged Analysis of Precipitation fields (Xie & Arkin, 1997), and the Air Force Weather Agency radiation fields. In comparison, GLDAS-2 uses reanalysed meteorological input datasets that have been corrected using ground-based products for the period 1948–2010. Consequently, GLDAS-2 is more applicable for a long-term analysis that requires consistency over a long period of time. In the present study, we used GLDAS-1 because we were interested in the period from 2005 to 2009, when the *in situ* groundwater data were collected. The GLDAS-1 data are updated within 1–2 months of realtime.

GLDAS runs four land surface models including the common land model (CLM) (Dai et al., 2003), the National Centers for Environmental Prediction (NCEP)/Oregon State University/Air Force/Hydrologic Research Lab Model (NOAH) (Chen et al., 1996; Ek et al., 2003; Koren et al., 1999), Mosaic (Koster & Suarez, 1996; Koster, Suarez, Ducharne, Stieglitz, & Kumar, 2000), and variable infiltration capacity (VIC) (Liang, Lettenmaier, Wood, & Burges, 1994; Liang, Xie, & Huang, 2003). The CLM is the land model for the Community Earth System Model and Community Atmosphere Model. CLM can be run as a stand-alone one-dimensional model coupled and uncoupled to the atmosphere model. The soil model is divided into 10horizontal layers up to 3.433 m deep. Thus, CLM model has more dynamic soil moisture with a smaller depth range, which tends to produce higher run-off and lower evapotranspiration under wet conditions (Zaitchik, Rodell, & Olivera, 2010). Noah was developed by a collaboration of public and private institutions with the leadership of the National Centers for Environmental Prediction. NOAh simulates soil temperature and moisture (both liquid and frozen) for four soil layers up to 2m deep, snowpack depth, snowpack water equivalent (one-layer model), canopy water content, and the energy flux and water flux of the surface energy and water balance. The Mosaic model was originally developed for the NASA global climate change research. The model is based on one of the simple biosphere models with surface flux calculations. It consists of three soil layers up to 3.5 m deep and a simple one-layer snow model. VIC was developed by a collaboration of the University of Washington and the Princeton University (Liang et al., 1994, 2003; Nijssen, Lettenmaier, Liang, Wetzel, & Wood, 1997) with emphasis on vegetation heterogeneity with variable infiltration and nonlinear base flow. The model consists of three soil layers up to 1.9 m deep. The VIC has two modes—water balance mode having water balance calculations only and water-and-energy mode having energy fluxes. The present study used GLDAS-1 version and averaged three soil moisture models from CLM, NOAH, and Mosaic. The average soil moisture is the depth-averaged amount of water in a specific soil layer beneath the surface.

TWS and SM have different spatial resolution and data format. TWS is available only as a 1° monthly data, but SM has 1° and 0.25° monthly data. The units of the original files for TWS and SM are different as well. TWS are in centimetre, whereas SM is measured in millimetre, which should be converted to centimetre to make it consistent with the TWS unit. The GRACE modelling outputs are, therefore, presented in centimetre in the present study. All six GRACE products in the present study are downloadable from the GRACE Tellus website (http://grace.jpl.nasa.gov). The spherical harmonic products are spatially smoothed during the data processing. The sampling of all cells is 1° in both latitude and longitude, which is approximately 111km near the equator. In applying spherical harmonic GRACE data to the GW estimation, spatial-scale discrepancy tends to be attenuated due to the postprocessing of GRACE observations (Landerer & Swenson, 2012). To overcome the attenuation problem, a user needs to multiply the spherical harmonic GRACE data by a set of scaling coefficients from the GRACE Tellus website. The time series at one grid (1° bin) location must be multiplied by the scaling factor at the same 1° bin position. Because the GRACE data are the change of TWS from the average TWS from 2004 to 2009 (Landerer & Swenson, 2012), the TWS for the given time period of interest must be reaveraged using Equation (3). The same averaging procedure for the same time period should be implemented for ΔSM using Equation (4).

5 | RESULTS

Figure 2 shows the total water storage anomalies from the ensemble average of M-Ave and one of S-Ave in (a), and the soil moisture storage anomalies from CLM, NOAH, Mosaic, and their average in (b). The precipitation is collected from TRMM 3B43monthly data with 0.25° resolution from January 2005 to December 2009 in the Ngadda catchment. According to the cross-correlation analysis, whereas the maximum rainfall mostly occurred in July (in2007) or August (inall other years), the maximum total water storage anomalies for both M-Ave and S-Ave occur 2months later in October (in2005–2007) or November (in2008). These results are consistent with the results of Buma et al. (2016) showing the lagged response of maximum total

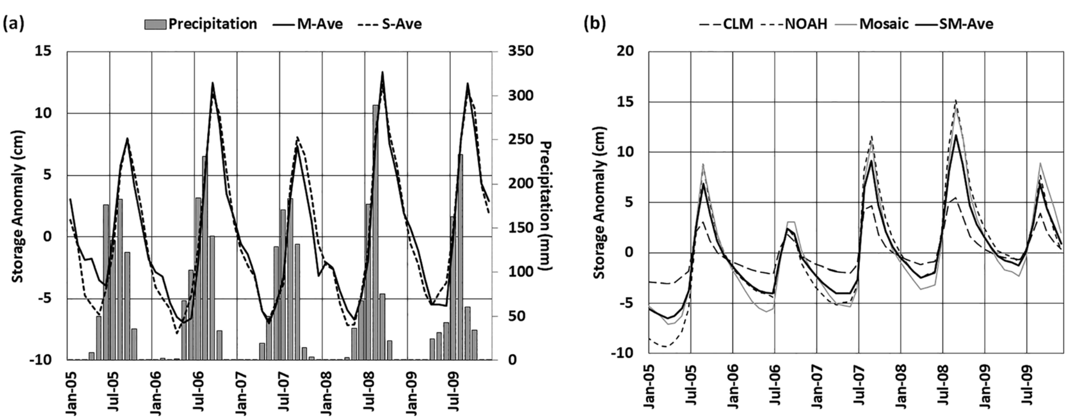

FIGURE 2 Monthly time series of storage anomaly for the period of January 2005 to December 2009. (a) Averaged ΔTWS from three mascon products (M-Ave) and three spherical harmonic products (S-Ave). The precipitation is the monthly mean of TRMM data in the study area. (b) ΔSM from CLM, NOAH, and Mosaic and the average of three soil moisture models (SM-Ave)

water storage about 1.5months after rainfall from the GRACE modelling for the entire LCB. The mean annual amplitude in ΔTWS between 2005 and 2009 is 17.09 ± 2.98cm for M-Ave and 17.25 ± 2.28cm for S-Ave, which are very close to each other. The mean annual amplitude of ΔSM, however, varies significantly depending on the model. The mean amplitude is 5.58 ± 1.26cm for CLM, 13.62 ± 5.44cm for NOAH, 14.08 ± 3.85cm for Mosaic, and 11.05 ± 3.51cm for SM-Ave. The mean amplitude of NOAH and Mosaic is more than twice the one of CLM, which would substantially change the estimation of groundwater storage anomaly. In addition, whereas ΔTWS does not show any significant increase or decrease in its trend during the study period (only smaller maximum peaks in 2005 and 2007), ΔSM shows an increasing trend from all three models. The maximum ΔSM occurs 2months after the rainfall peak, which is similar to the occurrence of maximum ΔTWS.

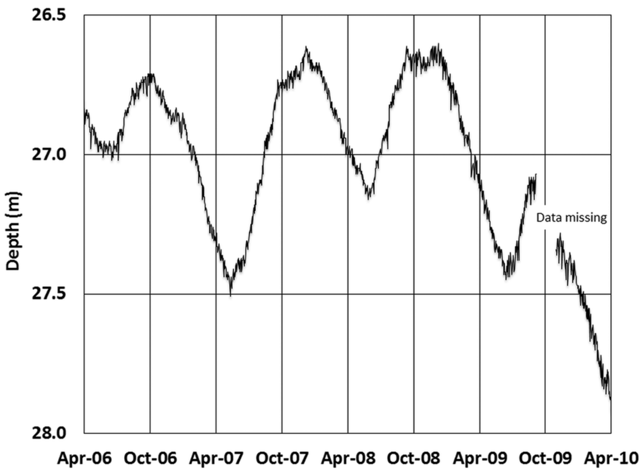

FIGURE 3 *In situ* groundwater depth from April 2006 to June 2010 collected in the city of Maiduguri, Nigeria

To validate ΔGW from the GRACE under limited availability of in situ data in the region, we performed two different approaches of water storage comparison. The first approach was to compare ΔGW from different combinations of M-Ave and S-Ave for ΔTWS, and CLM, Noah, Mosaic, and SM-Ave for ΔSM. Eight combinations of ΔGW are compared with ΔGW of *in situ* groundwater data collected at a groundwater monitoring station in Maiduguri. For the given time period, only one time series dataset from June 2006 to December 2009 is available in the study area. Figure 3 shows *in situ* groundwater level (depth) with seasonality except 2009 when the data from September 24to November 16are missing. The groundwater level reached maximum peaks between September and December and minimum peaks in May or June. Comparing to the TRMM precipitation using the cross-correlation, the lagged time interval for the peak groundwater level from the *in situ* data is 2or 3months, which is consistent with the comparison with ΔTWS and ΔSM in Figure 2. For the groundwater storage calculation (ΔGW) from the average groundwater depth, we used a conversion equation, $\Delta S = S_y * \Delta h$ where ΔS is the *in situ* groundwater storage anomaly, S_y is the specific yield, and Δh is the groundwater depth anomaly out of the average of groundwater depths from April 2006 to April 2010. Guideal, Bala, and Ikpokonte (2011) collected 26specific yield measurements around N'djamena, Chad, of which the upper aquifer is the same Quaternary aquifer as that of Ngadda catchment. The range of specific yield is from 0.010 to 0.052 with the mean of 0.028, the median of 0.018, and the skewness of 1.208. Specific yield value can significantly change the estimation of ΔGW(*in situ*). Figure 4 shows ΔGW(*in situ*) for the range of S_y from 0.01 to 0.03. The mean annual amplitude of ΔGW(*in situ*) is 6.15cm for S_y = 0.01 and 18.44cm for S_y = 0.03, which shows threefold difference. Finding more accurate specific yield is utmost critical for the estimation of ΔGW. In our calculation, we adopted the specific yield of 0.02 for the *in situ* ΔGW calculation.

Figure 5 shows ΔGW from eight combinations of GRACE and soil moisture models with ΔGW from *in situ* data. Due to the substantial

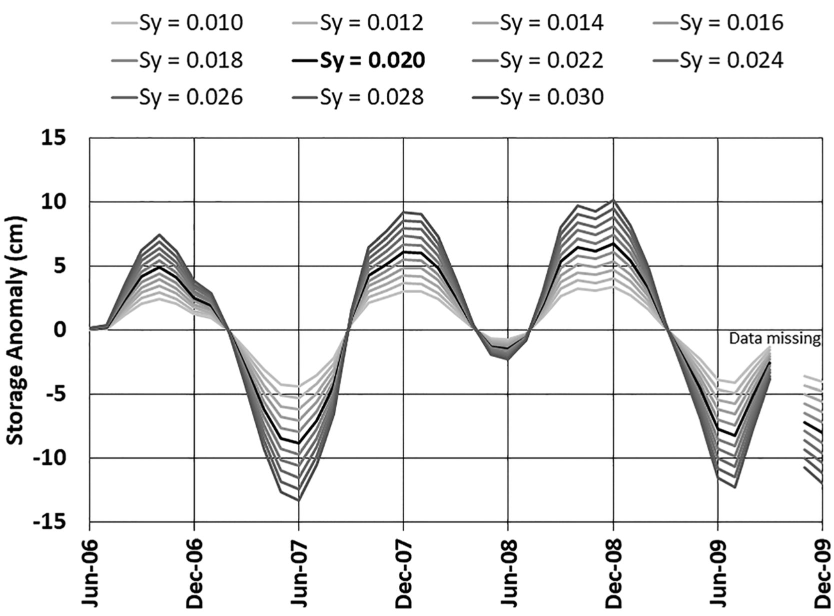

FIGURE 4 ΔGW from the *in situ* groundwater data from the Maiduguri station when its specific yield ranges from 0.01 to 0.03 with 0.002 interval. For the comparison with GRACE-derived ΔGW, S_y = 0.02 (bold line) is used

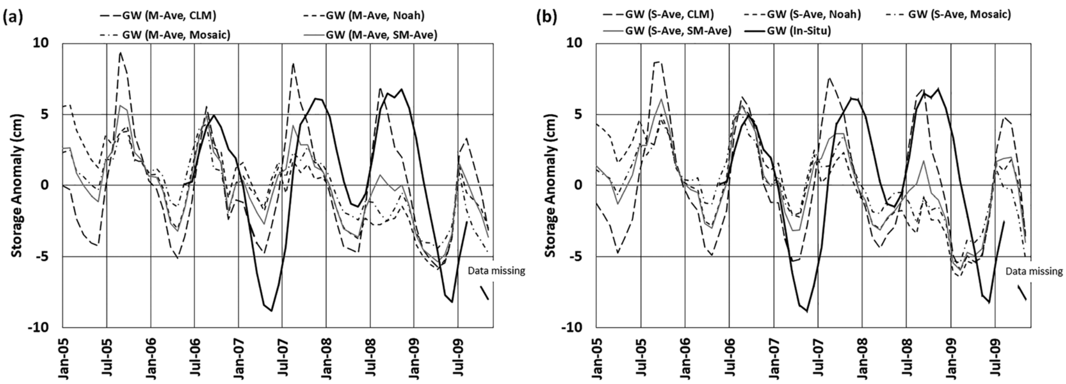

FIGURE 5 Monthly groundwater water storage anomalies estimated from eight combinations of GRACE and GLDAS for the Ngadda catchment from January 2005 to December 2009. (a) ΔGW from the combinations of M-Ave for ΔTWS and four soil moisture estimation. (b) ΔGW from the combinations of S-Ave for ΔTWS and four soil moisture estimation

amplitude variations of soil moisture models, ΔGW also shows significant variation of its mean annual amplitude, which ranges from 4.86 ± 1.01cm for (M-Ave, Mosaic) and 5.34 ± 1.01cm for (S-Ave, Mosaic) to 11.72 ± 1.96cm for (M-Ave, CLM) and 11.94 ± 1.21cm for (S-Ave, CLM). ΔGW from *in situ* data has its mean annual amplitude of 12.29 ± 3.56cm, which is closest to the amplitudes from both (M-Ave, CLM) and (S-Ave, CLM).

To verify how each combination of ΔGW fits to the ΔGW from the *in situ* data, we employed four goodness-of-fit methods including the root-mean-square error (RMSE), the relative Nash–Sutcliffe efficiency (rNSE), the index of agreement (I_d), and the Pearson's correlation coefficient (ρ) (Table 1). RMSE is one of the most common methods to evaluate the errors between modelled values and observed values (Legates & McCabe, 1999; Moriasi et al., 2007). Smaller RMSE means better fit, and 0indicates perfect fit. The NSE (Nash & Sutcliffe, 1970) indicates how well the observed values and modelled values fits the 1:1 line. rNSE is a modified version when some part of data is missing. rNSE, just like NSE, ranges from $-\infty$ to 1(perfect match), and the values between 0and 1are generally considered as acceptable (Moriasi et al., 2007; Sun et al., 2012). I_d was introduced by Willmott (1981) as a standardized measure of the degree of model prediction error. I_d ranges from 0(noagreement) to 1(perfect agreement). As seen in Table 1, (M-Ave, CLM) and (S-Ave, CLM) combinations show the best fit to the ΔGW of *in situ* data from all four goodness-of-fit tests.

TABLE 1 The goodness-of-fit tests between ΔGW from the *in situ* groundwater data and ΔGW from eight combinations of ΔTWS from M-Ave and S-Ave and ΔSM from CLM, Noah, Mosaic, and SM-Ave

	RMSE	rNSE	I_a	ρ
GW (M-Ave, SM-Ave)	4.31	-36.94	0.56	0.47
GW (S-Ave, SM-Ave)	4.60	-3.94	0.54	0.35
GW (M-Ave, CLM)	4.18	0.89	0.72	0.55
GW (S-Ave, CLM)	4.59	0.96	0.69	0.48
GW (M-Ave, Noah)	4.87	-45.55	0.50	0.27
GW (S-Ave, Noah)	5.16	-18.67	0.48	0.20
GW (M-Ave, Mosaic)	4.56	-2.20	0.54	0.36
GW (S-Ave, Mosaic)	4.78	-8.71	0.52	0.28

We also conducted cross-correlation analysis between precipitation and ΔGW from four combinations having SM-Ave and CLM only as they are most comparable combinations from the goodness-of-fit analysis. As seen in Figure 6, all four ΔGW show 2-month lag for the precipitation. Their correlation coefficients are acceptably high between 0.6 and 0.9at 2-month lag. Figure 7 shows mean monthly storage anomalies of ΔTWS, ΔSM, and ΔGW and precipitation from TRMM. All water components show strong seasonality to follow the seasonal rainfall with time lag of 1month (peak in September) or 2months (peak in October). Most of the lowest are observed in May (and April for TWS [S-Ave]). Note that the unusually high storage change of ΔGW (*in situ*) from January to May during dry season is due to the small number of data (only 3from 2007 to 2009).

The second approach of validation was to compare the difference of average groundwater depth measured in November 2005 and July 2009, respectively, to the difference from the GRACE ΔGW for the same time periods of 2005 and 2009. Figure 8 shows the groundwater depth distribution in 2005 and 2009. The average groundwater depth in November 2005 is 38.88 m with the standard deviation of 21.48 m from 31wells, and the average groundwater depth in July 2009 is 40.95 m with the standard deviation of 14.90 m from 18wells. The wells were open wells in local villages, and they were assumed to be dug into the Quaternary upper aquifer. Assuming the groundwater level reaches maximum around October and November after the rainy season (Goes, 1999; Offodile, 2002), the higher groundwater level in November 2005 compared with July 2009 is expected unless there is a significant change of recharge or pumping between those years. The city of Gubio is located where Bornu piezometric depression has been observed since the 1960s when it was first mapped in Lake Chad Basin Commission (1969) and Schneider (1966). It is still reportedly observed in Lopez et al. (2016). Although Figure 8 shows groundwater depths rather than groundwater levels, the southwestern flow through discharge from the lake is observed in both years. Figure 9 shows the comparison of groundwater storage anomalies using

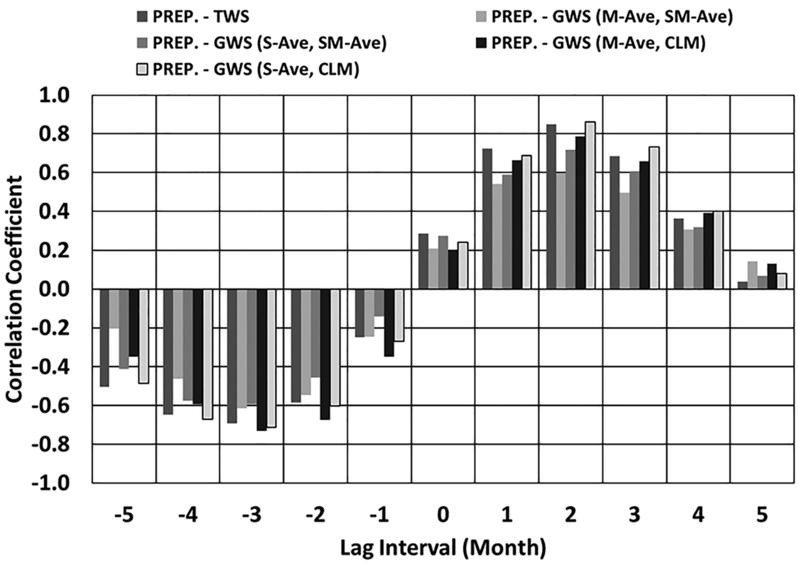

FIGURE 6 Cross-correlation between TRMM precipitation (PREP.) and TWS change and the ones between PREP. and GW storage changes (GWS)

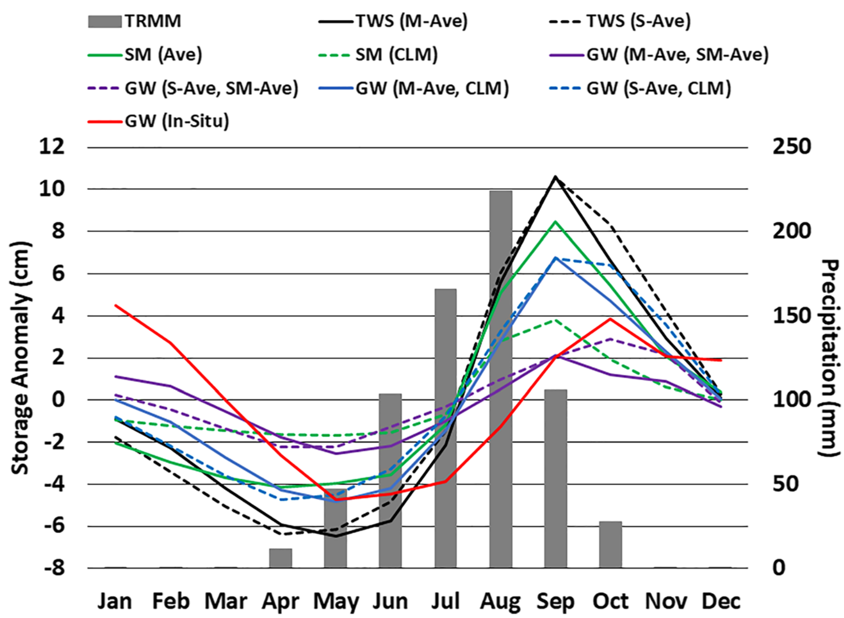

FIGURE 7 Monthly mean from 2005 to 2009 of TRMM monthly rainfall, ΔTWS from M-Ave and S-Ave, ΔSM from SM-Ave and CLM, ΔGW from combinations of M-Ave, S-Ave, SM-Ave, and CLM, and ΔGW from *in situ* groundwater data

26specific yield measurements on the difference of the average groundwater depth in November 2005 and the one in July 2009 from Figure 8. The GW storage anomaly from GRACE (2.98cm) for the same time period is reasonably located within a quartile from the median of *in situ* based GW storage anomalies distributed by 26specific yield measurements. This approach shows that even the scattered collection of groundwater measurements at different times can be used for the validation of GRACE modelling when specific yield data are available.

6 | DISCUSSION

We applied six different gridded GRACE products including three mascons from JPL, CSR, and GSFC and three spherical harmonic products from JPL, CSR, and GFZ. All six products for the study area show minimal variations of ΔTWS with distinctive seasonality. If you compare the annual amplitude of ΔTWS and the annual total precipitation (Figure 10) to see how ΔTWS responds to the total amount of rainfall each year, they show clear positive correlation except 2006, which means the increase of total rainfall would lead to the increase of total water storage. The soil moisture, however, responds differently to the annual total precipitation. All soil moisture models show positive correlation with the annual total precipitation except 2006, but due to the substantial variation of amplitudes, the rate of change is very different especially between CLM and NOAH/Mosaic. If we take the amplitude as an amount of increase in the water storage anomaly, ΔSM from CLM explains 33% of ΔTWS, whereas ΔSM from NOAH and Mosaic does 80% and 83%, respectively. Such differences of seasonal variability of ΔSM, especially with the one from CLM, is

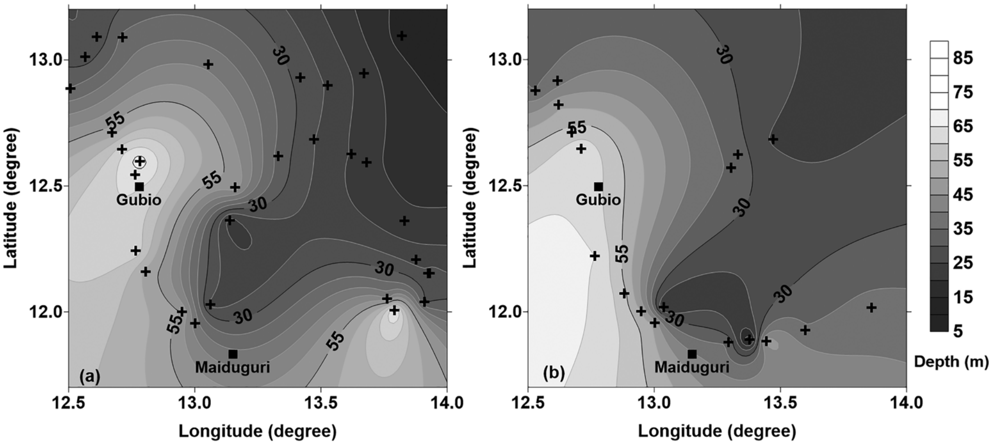

FIGURE 8 Groundwater depth distribution maps. (a) November 2005, (b) July 2009. Crosses indicate the data locations

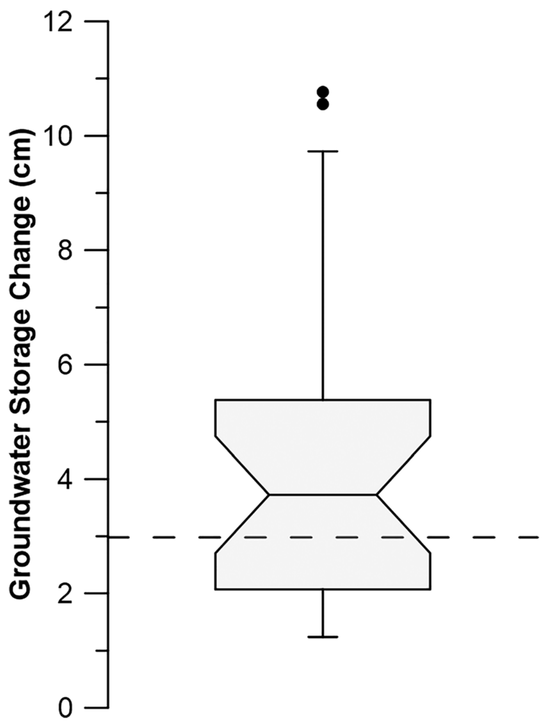

FIGURE 9 A box whisker plot of *in situ* groundwater storage changes estimated by using 26 measurements of S_y from Guideal et al. (2011). The dashed line shows the estimated groundwater storage change from GRACE (2.98 cm)

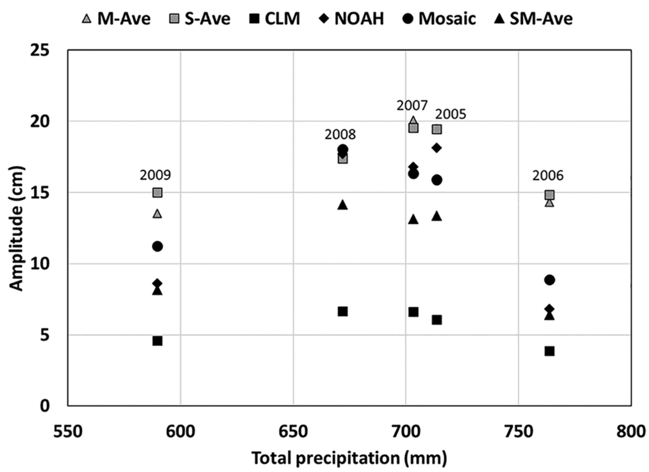

FIGURE 10 A scatter plot between annual total precipitation from TRMM and the mean annual amplitudes of ΔTWS from M-Ave and S-Ave and ΔSM from CLM, NOAH, Mosaic, and SM-Ave

also observed in Shamsudduha, Taylor, and Longuevergne (2012) for the Bengal Basin and Shamsudduha et al. (2017) for the Upper Nile Basin. As Henry et al. (2011) discussed, potential inaccuracy of soil moisture estimation results from various factors such as an assumption that the soil below the depth of the soil moisture column is saturated while groundwater level is much deeper. The complexity of vegetation classification and soil types in land surface models is also a factor when their regional data are lacking. The recent update of CLM version 4.5 (Swenson & Lawrence, 2015) attempted to enhance the model accuracy with the addition of the soil evaporative resistance parameterization and additional aquifer layer representing the time-varying volume of soil between the deepest layer of the static soil column and the water table. It is expected that more additional studies with enhanced land surface models for GRACE would emerge soon, especially for data-poor regions.

As seen in Figure 5 and the goodness-of-fit tests in Table 1, ΔSM(CLM) combined with both ΔTWS (M-Ave) and ΔTWS (S-Ave) produces ΔGW closest to ΔGW(*in situ*); however, it does not mean CLM is superior to NOAH and Mosaic. Firstly, ΔGW(*in situ*) was estimated from one single time series data to present the entire catchment, whereas other GRACE-based groundwater studies (Bhanja et al., 2016; Feng et al., 2013; Rodell et al., 2007, Scanlon et al., 2012; Shamsudduha et al., 2012) used a network of time-series data with more uniform coverage of study area for validation. If more *in situ* time-series data are available, other soil moisture models or their average would provide better ΔGW estimation.

A number of applications of GRACE on monitoring groundwater in data-poor regions have been made in the past decade. Table 2 compares the use of *in situ* groundwater data in GRACE studies for data-poor regions such as Mali of Africa (Henry et al., 2011), Negro River Basin of Brazil (Frappart et al., 2011), and Upper Nile Basin (Shamsudduha et al., 2017). Although their *in situ* groundwater data

TABLE 2 Comparison of remote sensing groundwater studies in data-poor regions

Study area	RS/models	GW in situ data (# of stations/source)		Reference
		Continuous in time	Distributed in space	
Lake Chad Basin, Africa	GRACE, GLDAS	2006–2009 data (1/by authors)	2005 survey (30/Zaira, 2008), 2009 survey (17/by authors)	Present study
	GRACE/2-D convective model	None	1960s survey (NA/Schneider, 1966), 2005 survey (NA/Zaira, 2008)	Lopez et al. (2016)
	GRACE, GLDAS, ENVISAT/WGHM	None	None	Buma et al. (2016)
	GRACE, SRTM/S-SEBI	None	1960s survey (NA/Schneider, 1966)	Boronina and Ramillien (2008)
Punjab, Pakistan	GRACE, GLDAS/Budyko	Reconstructed from the distributed data from 1980–2012	1980–2012 tube well data (2377, Water and Power Development Authority, Pakistan)	Tang et al. (2017)
Upper Nile Basin, Africa	GRACE, GLDAS, TRMM	2003–2012 daily data (6/Ugandan Ministry of Water and Environment)	2003–2012 daily data (6/Ugandan Ministry of Water and Environment)	Shamsudduha et al. (2017)
North China	GRACE, GLDAS	2003–2010 daily data (40/National Earthquake Precursory Network, China)	2003–2010 daily data (40/National Earthquake Precursory Network, China)	Feng et al. (2013)
Southern Mali, Africa	GRACE, GLDAS	1982–2002 data (15/Malian government)	1982–2002 data (15/Malian government)	Henry et al. (2011)
Negro River Basin, Brazil	GRACE, AVHRR, ENVISAT/WGHM, LaD	2003–2005 dipwell data (3/Tomasella et al., 2008)	1982–2002 data (15/Malian government)	Frappart et al. (2011)

Abbreviation: AVHRR, Advanced Very-High-Resolution Radiometer; ENVISAT, Environmental Satellite; GLDAS, Global Land Data Assimilation System; GRACE, Gravity Recovery and Climate Experiment; Lad, Land Dynamics; SRTM, Shuttle Radar Topography Mission; S-SEBI, Simplified Surface Energy Balance Index; TRMM; Tropical Rainfall Measuring Mission; WGHM, WaterGAP Global Hydrology Model were limited, still, they were able to employ a network of groundwater monitoring stations with time-series data for validation of GRACE models. The studies for groundwater in LCB, however, were not able to use any time-series data; instead, they used other numerical models such as Simplified Surface Energy Balance Index (Boronina & Ramillien, 2008) and WaterGAP Global Hydrology Model (Buma et al., 2016) to fill a temporal gap of groundwater change. The present study shows that even with a single set of time-series data, it is still possible to monitor the variation of groundwater storage change by combinatorial use of GRACE and land surface models. It is in line with Becker (2006) stating that the remote sensing data are most useful when they are combined with numerical modelling, GIS, and *in situ* grounddata.

7 | CONCLUSIONS

The present study explored the feasibility of GRACE-based estimation of a groundwater storage change in the Ngadda catchment of the LCB as a case of data-poor region using three mascon products from JPL, CSR, and GSFC and three spherical harmonic products from JPL, CSR, and GFZ. Although only a single set of *in situ* time-series data of groundwater is available in the region, still, it is possible to compare the GRACE-based groundwater storage change to the *in situ* groundwater measurements for validation to specific yield data. After the maximum rainfall reached in July or August during the study period, the maximum total water storage anomaly and the maximum groundwater storage anomaly both occurred 2months later. The mean annual amplitude of ΔTWS is about 17cm from both M-Ave and S-Ave. The mean annual amplitude of ΔSM is, however, substantially varied from 5.58cm for CLM to about 14cm for NOAH and Mosaic; therefore, the choice of soil moisture model affects the estimation of ΔGW significantly. The goodness-of-fit tests show that CLM soil moisture produces the closest estimation of ΔGW to the *in situ* ΔGW as its RMSE is 4.18 with 55% correlation, whereas other combinations of soil moisture and GRACE show RMSE in the range of 4.31–5.16 with 20–48% correlation. The mean monthly ΔTWS, ΔSM, and ΔGW show strong seasonality to follow the seasonal rainfall with a time lag of 1month or 2months. Understanding the time lag of groundwater peak after the rainy season is very important for local stakeholders and farmers. As Lakshmi (2016) suggested, GRACE-based modelling is still limited to make specific decisions on groundwater management and pumping schedules due to its coarse resolution and uncertainty during predata processing and post data processing. When *in situ* data are limited and its collection schedule is sparse, however, GRACE-based modelling can be a cost-effective and alternative tool to observe a general trend of groundwater change and develop a plan for water use ahead of time in a basin-scale domain. In the case of Ngadda catchment, 6months would be an appropriate timescale to make a feasible plan of groundwater use for the given amount of rainfall with seasonality.

Whereas the present study aims at a better understanding of groundwater dynamics using remote sensing data in a data-poor region, more international collaborative efforts of *in situ* data collection must continue. After the GRACE-based groundwater study of Skaskevych (2014), authors realized the importance of *in situ* data, especially distributed time-series data in the LCB. In 2015–2016, authors set up over five real-time monitoring stations for groundwater, soil moisture, and meteorological data along the Chari and Logone rivers in the LCB. Its first set of groundwater data was employed by Li et al. (2019) for global groundwater and drought monitoring. Currently, the Lake Chad Basin Commission is building the LCB observatory network by installing over 30real-time monitoring sensors for groundwater through the international collaboration with the Federal Institute for Geosciences and Natural Resources and the German Corporation for International Corporation in Germany. Such international collaborative efforts of ground data collection will benefit not only scientific communities but also local government and water resource managers for a better water management by recognizing the importance of both ground and remote sensingdata.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ORCID

Jejung Lee https://orcid.org/0000-0002-8253-3710

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