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The Role of Space-Based Observations for Groundwater Resource Monitoring over Africa

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Abstract

Africa is particularly vulnerable to climate change impacts, which threatens food security, ecosystem protection and restoration initiatives, and fresh water resources availability and quality. Groundwater largely contributes to the mitigation of climate change effects by offering short- to long-term transient water storage. However, groundwater storage remains extremely difficult to monitor. In this paper, we review the strengths and weaknesses of satellite remote sensing techniques for addressing groundwater quantity issues with a focus on GRACE space gravimetry, as well as concepts to combine satellite observations with numerical models and ground observations. One particular focus is the quantification of changes in groundwater resources in the different climatic regions of Africa and the discussion of possible climatic and anthropogenic drivers. We include a thorough literature review on studies that use satellite observations for groundwater research in Africa. Finally, we identify gaps in research and possible future directions for employing satellite remote sensing to groundwater monitoring and management on the African continent.

Article Highlights

- Overview on the distribution and characteristics of African groundwater resources including future projections
- Combination of satellite and in situ observations with numerical models allows us to obtain a synoptic view of groundwater-related processes
- Summary of current concepts and achievements of satellite remote sensing-based groundwater monitoring and decision making over Africa

Keywords Satellite remote sensing · Groundwater monitoring · Africa · Climate change · Sustainable development · GRACE

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Abbreviations

AMO	African flood and drought monitor
AMO	Atlantic multidecadal oscillation
ARX	Autoregressive exogenous
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BMA	Bayesian model averaging
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
CI	Continental intercalaire
CT	Complex terminal
CLSM	Catchment land surface model
CMAP	CPC Merged Analysis of Precipitation
CSR	Centre for Space Research
DMDA	Dynamic model data averaging
EADW	East African drought watch
EM	Electromagnetic
EnKF	Ensemble Kalman filter
ENSO	El Ninõ-Southern oscillation
ESA-CCI	ESA climate change initiative
ESM	Earth system model
EWH	Equivalent water height
GDEM	Global digital elevation model
GERD	Grand Ethiopian renaissance dam
GFZ	German research centre for geosciences
GLEAM	Global Land Evaporation Amsterdam Model
GLDAS	Global Land Data Assimilation System
GPS	Global Positioning System
GRACE	Gravity Recovery And Climate Experiment
GRACE-FO	Gravity Recovery And Climate Experiment - Follow On
GW	Groundwater
GWBL	Groundwater base level
ICA	Independent component analysis
ICGEM	International Centre for Global Earth Models
IAS	Iullemeden aquifer system
ICA	Independent component analysis
IOD	Indian ocean dipole
InSAR	Interferometry SAR
JPL	Jet Propulsion Laboratory
KBR	K-band microwave ranging
LU/LC	Land use / land cover
MJO	Madden–Julian oscillation (MJO)
MLR	Multi-linear regression
MODIS	Moderate-Resolution Imaging Spectroradiometer
NDVI	Normalized difference vegetation index
NAO	North Atlantic oscillation
NSAS	Nubian sandstone aquifer system
NWSAS	North-Western Sahara aquifer system
OCOG	Offset center of gravity
PAWS	Potential available water storage
PCA	Principal component analysis

PCI	Princeton Climate Institute
RA	Radar altimetry
SAR	Synthetic aperture radar
SGD	Submarine groundwater discharge
SH	Spherical harmonic
SPI	Standardized precipitation index
SSA	Sub-Saharan Africa
SST	Satellite-to-satellite tracking
TBA	Transboundary aquifer
TEC	Total electron content
TIR	Thermal infrared
TRMM	Tropical Rainfall Measuring Mission
TWS	Terrestrial water storage
TWSA	TWS anomalies
UAV	Unmanned Aerial Vehicle
UBN	Upper blue Nile
VS	Virtual station
WGHM	WaterGap Global Hydrology Model

1 Introduction

Worldwide renewable freshwater resources are estimated to have a magnitude of ~43, 750 km^3 $year^{-1}$ where Africa possesses only 9% of this amount (e.g., FAO 2003; Xu et al. 2019). This percentage hides the fact that, at its continental scale, freshwater supply presents a paradox (Naik 2017). Indeed, even if Africa is considered as one of the driest continents of the world, there are abundant large surface water bodies including (1) rivers, e.g., Congo, Nile, Niger, Zambezi, etc., (2) lakes, such as the second-largest lake in the world, Lake Victoria, and the second-deepest lake in the world, Lake Tanganyika, and (3) wetlands like the Inner Niger Delta, the Cuvette Centrale of Congo, and the Caprivi wetlands in Namibia (Bernacsek et al. 1992). The continent also possesses some of the largest transboundary aquifer (TBA) systems such as the Nubian Sandstone Aquifer System (NSAS) and the North Western Sahara Aquifer System (NWSAS) (Nijsten et al. 2018).

Although groundwater (GW) depletion is small compared to global recharge (Aeschbach-Hertig and Gleeson 2012), regionally GW depletion has severe impacts for society, economy and environment (Famiglietti 2014). Over Africa, Bonsor et al. (2018) identified no significant regional long-term depletion of sedimentary aquifers, but local hot spots exist, such as the Nairobi aquifer system (Oiro et al. 2020). Generally, depletion of GW resources comes along with lowering of water tables, which increases the costs for pumping, leads to drying up of wells (Konikow and Kendy 2005), and might even cause land subsidence accompanied with damaged infrastructure (Chen et al. 2016). Furthermore, lowering of the water table impacts the ecosystems by reduced discharge to rivers, lakes, ponds, and wetlands (Sophocleous 2000). In some basins, excessive human water extraction can lead to aquifer salinization by upwelling of underlying saline water, e.g., in Southern Tunisia (Zammouri et al. 2007), while in coastal regions the danger of salinization by sea saltwater intrusion increases, e.g., in Lybia (Alfarrah and Walraevens 2018). Further water quality issues arise mainly from agricultural areas due to increasing potential of widespread contamination from nutrients and pesticides, and from fecal contaminants due to proximity to sanitation facilities (Upton and Danert 2019).

Characteristics of GW use and GW depletion differ largely over the African continent and mainly depend on climate zones, aquifer types, and urban versus rural areas (Wada 2016). In urban parts of Africa 25% of the population is without access to "safe" drinking water; in rural areas, this is even two thirds of the population (Ahmed and Wiese 2019). For many rural areas, irrigated agriculture makes the largest contribution to GW withdrawal (Johansson et al. 2016). Intensive irrigation (1) leads to changes in surface-energy budgets and can significantly alter regional climate, and (2) redistributes GW as a result of recharge from return flows. A decade ago, only 1% of the agricultural area in Africa was irrigated by GW with 80% of this occurring in North Africa (Siebert et al. 2010). Indeed, in North Africa overexploitation of GW resources is leading to a decrease of pressure in deep wells, a decline in spring discharge, and deterioration of GW quality attributed to interaction between GW and petroleum reservoirs. The increase of water scarcity and pumping costs will come along with conflicts regarding the exploitation of TBAs and socio-economic effects, e.g., farm abandonment and migration (Hamed et al. 2018; Al-Gamal 2021). In the future, the amount of GW used for irrigation is forecasted to increase substantially to guarantee food security for the rapidly growing population (Wada and Heinrich 2013; Gaye and Tindimugaya 2019; United Nations et al. 2019; Cobbing 2020) as anthropogenic pressures will be amplified by climate change (Wada et al. 2016; Serdeczny et al. 2017; Hasan et al. 2019; Schilling et al. 2020).

In view of the strategic significance of GW for water use and management as well as for food security the impact of climate change on GW has moved to the fore of GW research during the last decade. Climate change is expected to further modify the hydrological cycle, temperature balance, rainfall patterns, and to alter basin biodiversity and water productivity across Africa, thus leading to limited access and management of GW (Al-Gamal 2021). Generally, climate related impact through natural and anthropogenic induced processes are distinguished as well as GW related feedbacks on regional and global climatic conditions (Taylor et al. 2013; Serdeczny et al. 2017). Direct effects on GW storage are related to: (1) changes in the infiltration of rainfall water due to changes in precipitation patterns and changes of land use/land cover (LU/LC), (2) interaction with surface water, and (3) GW pumping (Bierkens and Wada 2019). In the future, longer droughts and more intense rainfall events may accelerate changes in recharge (Döll 2009; Taylor et al. 2013) and discharge. Reduction in surface water availability might also further increase the pressure on GW resources.

Comprehensive regional strategies are necessary to adapt GW management to the specific local societal and environmental needs under changing climate conditions in a sustainable way (Aeschbach-Hertig and Gleeson 2012). In this respect, one important challenge is the lack of consistent and reliable observations of GW storage, exchange fluxes with surface waters, and residence time (Wada and Bierkens 2014; Joseph et al. 2020). Due to the limited availability of ground-based GW monitoring, particularly in Africa, remote sensing observations are of tremendous importance. In this article, we review past and future contributions of remote sensing observations to monitor GW resources in Africa. We also summarize findings on the impact of different GW drivers. Furthermore, we provide a comprehensive overview on available data sets and processing strategies to promote the use of remote sensing observations for GW research in Africa.

We will introduce the distribution and hydrogeological properties of African GW resources in Sect. 2. In Sect. 3, relevant remote sensing techniques will be explained including (1) satellite gravimetry, (2) radar altimetry (RA), (3) thermal infrared (TIR) remote sensing, and (4) interferometry synthetic aperture radar (InSAR). Then, in Sect. 4 we will, on the one hand, discuss the link between ground and satellite observations and, on the other hand, provide a systematic summary of analysis techniques for an integrated evaluation of different remote sensing and complementary data sets. In Sect. 5, we will provide an overview on studies that address the status and evolution of African GW resources using remote-sensing observations. In particular, we will emphasis the impact of human influences and climate change on GW resources. We will also highlight examples that show how the combination of different remote-sensing techniques helps to obtain a detailed picture of GW resources and interactions with other water storage compartments and fluxes. Finally, we will conclude on gaps in research and provide recommendations for future directions in Sect. 6.

2 African Aquifers

African GW resources are unevenly distributed and have different characteristics regarding (1) extent and depth/thickness of aquifers, (2) hydrogeological properties, (3) climatic conditions that affect recharge processes, (4) GW use, and (5) management strategies (Fig. 1). In total, MacDonald et al. (2012) estimated the volume of GW in Africa to 0.66 million km^3, which is 20 times the freshwater stored in African lakes and 100 times the amount of annual renewable African freshwater resources. Regarding the geographic distribution, the volume of GW storage in North Africa is one to two magnitudes higher than in Sub-Saharan Africa (SSA) (MacDonald et al. 2012).

In North Africa, large and deep sedimentary aquifers dominate, such as the NWSAS located in the Meso-Cenozoic sedimentary and the NSAS located in the Nubian sandstone (e.g., MacDonald et al. 2012; Margat 2007; Petersen et al. 2018). On the contrary, shallow aquifers are mainly found in alluvial deposits and sand dunes. Besides, dolomitic limestones form important aquifers for local GW resources in the Maghreb region. Harder sandstone, sandy shale, and quartzite aquifers in Central, Eastern, and Western Africa rely on secondary porosity from weathering and fracturing. The humid areas of Eastern Africa are characterized by discrete aquifers of limited extent and low storage potential with weathered or fractured crystalline rocks. Crystalline igneous and metamorphic aquifers dominated by Precambrian rocks occupy about 40% of SSA (MacDonald et al. 2005). These aquifers have substantial permeability within the weathered overburden and fractured bedrock. The weathered zone thickness can exceed 90 m in the humid regions of Africa with porosity generally decreasing with depth, whereas permeability depends on the extent of fracturing and clay content (Chilton and Foster 1995). Volcanic rocks occupy about 6% of SSA, the majority of these are located in Eastern and Southern Africa (MacDonald et al. 2005). Furthermore, in Southern Africa, chalky shales and dolomitic limestones form substantial aquifers, e.g., underlying Zambia and South Africa. A complex sequence of lava flows and sheet basalts are interbedded with pyroclastic rocks that depend mainly on fractures for permeability. Coastal aquifers of SSA consist of sandstone, limestone, and sand and gravel sediments and have low storage potential.

Decadal aquifer recharge, which is approximately 2% of the estimated GW storage for the whole continent, has high spatial variability with low recharge rates (< 50 mm per decade) for the deep aquifers in North Africa and high recharge rates (> 1000 mm per decade) for aquifers in the humid climate zones of equatorial Africa (MacDonald et al. 2021). High storage and low recharge rates imply resilience of aquifers to short-term climate changes, but the danger of irreversible long-term depletion. In contrast, aquifers with low storage and high recharge rates are more vulnerable to droughts, but less sensitive to long-term

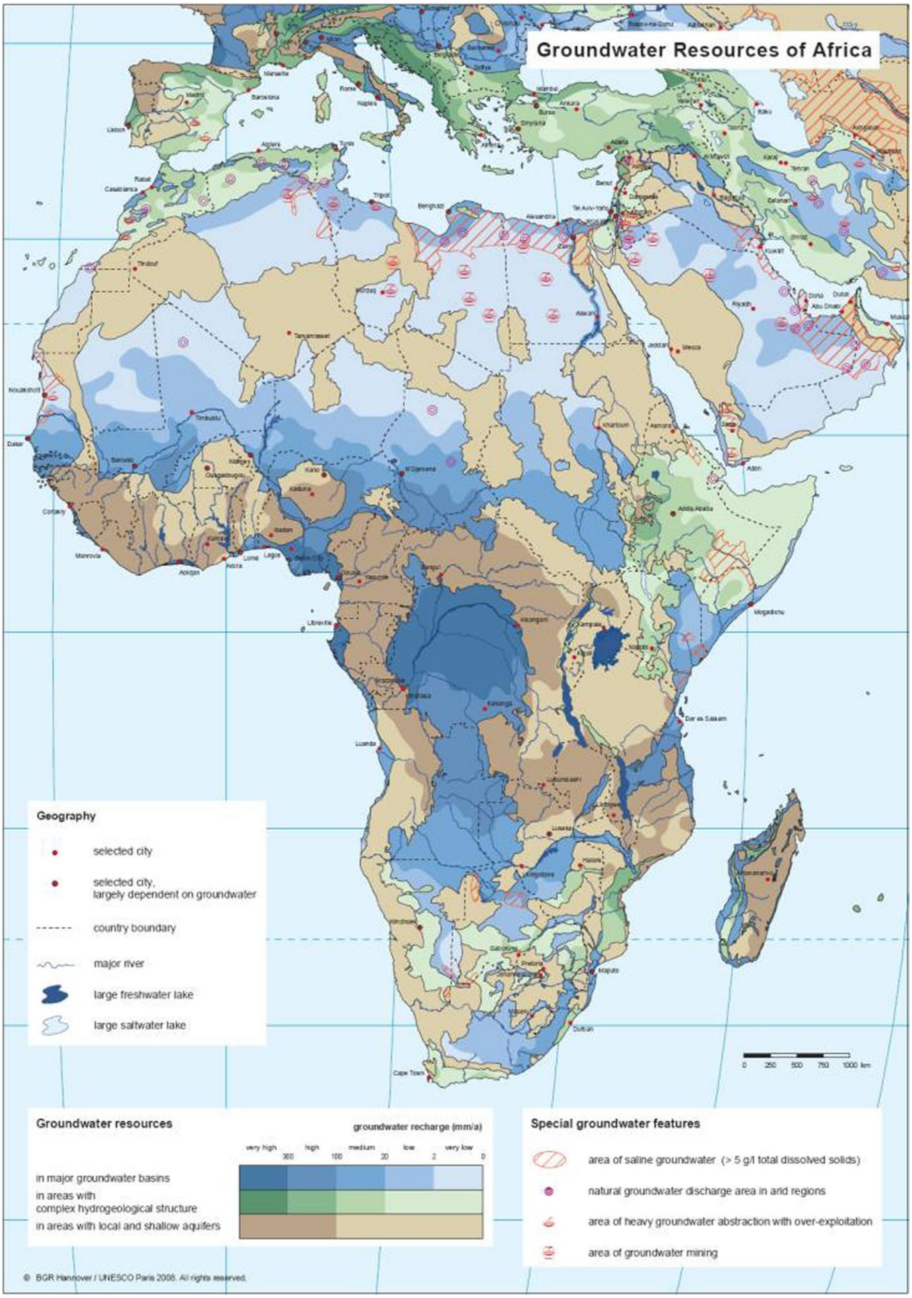

Fig. 1 Groundwater resources and recharge properties of Africa (*source*: BGR & UNESCO, https://www.bgr.bund.de/whymap/EN/Maps_Data/Additional_maps/gwrm_africa_g.html)

depletion. In both cases, careful and sustainable GW management based on continuous aquifer monitoring is necessary to improve current water security taking into account also the needs of future generations.

3 Space-Based Observation Techniques for Groundwater Research

We first introduce four remote-sensing techniques that provide particularly valuable information for GW research with special emphasis on the individual strengths and weaknesses of each technique. Then, we briefly address further complementary remote-sensing observations that help to constrain or understand GW dynamics. Finally, we introduce hydrological models and their deficiencies with respect to the modeling of GW evolution.

3.1 GRACE

The Gravity Recovery and Climate Experiment (GRACE, 2002 - 2017) and GRACE Follow-On (GRACE-FO, 2018 onwards) are the first satellite missions to provide unique information about temporal variations in Terrestrial Water Storage (TWS) (Tapley et al. 2019). TWS includes all water components on and underneath the Earth's surface, i.e., GW, soil moisture, surface waters (wetlands, rivers, lakes), snow water, and canopy water. The GRACE satellites measure tiny changes in the Earth's gravity field, which are due to mass changes in hydrosphere, atmosphere, biosphere, oceans, and to mass variations inside the solid Earth. As contributions of atmosphere and ocean are removed during GRACE data processing, GRACE gravity solutions mainly reflect TWS anomalies (TWSA) (Tapley 2004). Details on the measurement principle and available gravity field solutions are described in Appendix 1.

GRACE-derived TWS anomalies (TWSA) describe the total sum of water mass changes within a vertical column including changes in GW (ΔGW), surface water bodies ($\Delta W_{\mathrm{surface}}$), soil water ($\Delta W_{\mathrm{soil}}$), snow water equivalent (ΔW_{snow}), and canopy water ($\Delta W_{\mathrm{canopy}}$):

$$TWSA = \Delta \mathrm{GW} + \Delta W_{\mathrm{soil}} + \Delta W_{\mathrm{surface}} + \Delta W_{\mathrm{snow}} + \Delta W_{\mathrm{canopy}}. \quad (1)$$

Changes in GW can be derived from GRACE by using external data sources for the other storage compartments based on hydrological model output, remotely sensed observations, or in situ data (e.g., Frappart and Ramillien 2018, for a review):

$$\Delta \mathrm{GW} = \mathrm{TWSA} - (\Delta W_{\mathrm{soil}} + \Delta W_{\mathrm{surface}} + \Delta W_{\mathrm{snow}}) \quad (2)$$

Contributions from canopy storage can be neglected over Africa as they are not significant (e.g., Syed et al. 2008). Snowfall is limited over Africa to some mountainous areas and parts of Southern Africa, which results into small regional contributions of ΔW_{snow} to TWSA. Regarding the contribution of surface water variability $\Delta W_{\mathrm{surface}}$, over Africa a number of large lakes and highly-managed reservoirs dominate regional TWSA, e.g., Lake Victoria, Lake Volta, and Lake Nasser. The total contribution to TWSA can be computed by combining satellite imaging techniques for deriving the extent of the lake with in situ gauging station observations or satellite altimetry (see Sect. 3.2). Most studies evaluate soil moisture variability ΔW_{soil} based on land surface models as remotely sensed soil moisture is sensitive only to the first few centimeters of the soil. However, long-term trends are largely underestimated by hydrological models, which also limits the accuracy of GW trends derived from eq. (2) (Scanlon et al. 2018). Frappart and Ramillien (2018) review in detail the current status, challenges, and limitations of GRACE-based GW monitoring. In particular, they provide a detailed overview on GRACE TWS processing and errors. Indeed, correlated noise contained in monthly GRACE solutions still represents a challenging issue and is addressed by sophisticated filters and/or spatial averaging (Longuevergne et al. 2010, 2013; Ramillien et al. 2014; Chen et al. 2016, see Appendix 1 for further details). For local applications regional GRACE solutions, like, e.g., computed by Ramillien et al. (2014) for the African continent, provide better geographical localization of hydrological signals and are also available at higher temporal resolution.

Few studies performed global analyses of GW variability and trends using different GRACE solutions and auxiliary data from hydrological models. Jin and Feng (2013) showed large scale GW variations globally from 10 years of GRACE data and highlighted discrepancies between modeled and remotely sensed GW variability with respect to external observation-based data sets. These results were confirmed by Chen et al. (2016) and for Africa by Bonsor et al. (2018). Rodell et al. (2018) give an overview about changes in total global freshwater availability based on 14 years of GRACE data and related them to natural and human-induced drivers. They related TWS trends to changing precipitation patterns in Western Africa, the Okavango and Zambezi river basins, and along the South-East African coast. Furthermore, the impact of increasing lake levels and GW changes were identified in the region of the African Great Lakes, as well as GW pumping in North Africa. Scanlon et al. (2022) analyzed TWS trends in 13 major African river basins with the scope to separate persistent long-term trends and natural climate variability. Apparent positive trends were identified in some western African aquifers. In most catchments of eastern and southern Africa, TWS was found to be dominated by interannual climate variability. Bonsor et al. (2018) showed that analyzing TWS responses to precipitation provides useful information about the infiltration process in different African catchments.

Abd-Elmotaal et al. (2018) derived GRACE-based interannual variability of GW by removing all other storage compartments based on outputs of the Global Land Data Assimilation System (GLDAS) model (Rodell et al. 2004). They found similar spatial patterns when comparing to GW modeled by the WaterGAP Global Hydrology Model (WGHM; Döll et al. 2003, 2014). However, the results have limited spatial resolution as spherical harmonic (SH) coefficients are truncated to degree and order 60 and 500 km Gaussian smoothing is applied to GRACE data in order to remove correlated errors. For consistency, spatial filtering was also applied to the output of the hydrological models. Frappart (2020) applied the same approach to the three major North African TBA systems and evaluated GRACE Mascon solutions from CSR (Center for Space Research; Save et al. 2016) and JPL (Jet Propulsion Laboratory; Wiese et al. 2016). The author subtracted soil moisture from the Global Land Evaporation Amsterdam Model (GLEAM; Miralles et al. 2011; Martens et al. 2017) and surface water changes from satellite altimetry and multispectral images made available by Hydroweb (https://hydroweb.theia-land.fr/). Temporal variations in GW storage were compared to patterns in precipitation minus evapotranspiration ($P - \mathrm{ET}$), which provides insights into the nature of the aquifers (fossil or not fossil) and into anthropogenic contributions through local GW pumping. The same approach was also used over Lake Chad showing that 70% of the variations in the water volume originated from the subsurface (Pham-Duc et al. 2020). The importance of altimetry for removing surface water effects from GRACE observations was emphasized by Moore and Williams (2014). They showed that major African lakes (e.g., Lake Volta, Lake Victoria) contribute significantly to trends and seasonal TWS variations perceived by GRACE, and that the magnitude of the effect is rather related to large variability in water level than to the area of the lake.

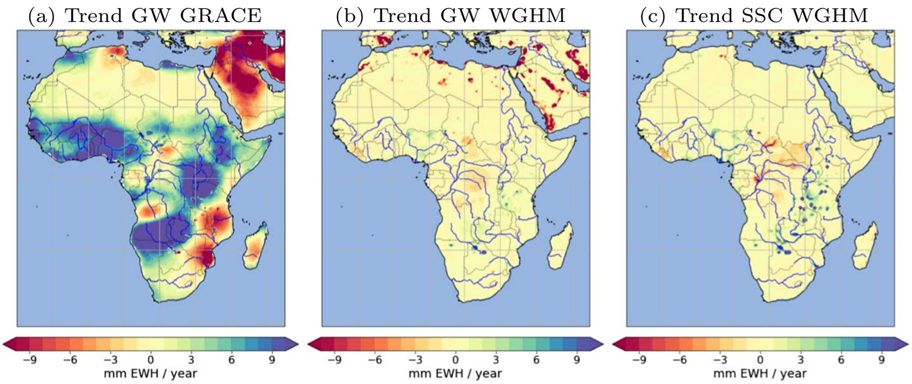

Fig. 2 **a** GW trends based on GRACE TWSA and WGHM storages (soil moisture and surface waters). **b** GW trends modeled by WGHM. **c** Trends of the sum of surface waters, soil moisture, wetland and canopy water (SSC) from WGHM. All values are computed for the time period 2003 to 2016 co-estimating annual and semi-annual frequencies. GRACE data were filtered and rescaled according to Springer (2019)

As stated by Scanlon et al. (2022), time series of TWS and GW are highly correlated for most aquifers over Africa and large differences in the variability of both variables may result from uncertainties in simulated soil and surface water storages. In Africa, modeled GW trends from WGHM are largely underestimated compared to GW trends based on GRACE and modeled soil moisture and surface waters from WGHM (Fig. 2). Yet, spatial GW trend patterns from GRACE and WGHM are similar with positive trends in most parts of West Africa except for Liberia and in the Zambezi basin, and negative trends in Central Africa along the Congo river and at the South-Eastern coast.

In summary, GRACE provides central remotely sensed information about GW storage changes. However, TWSA trends change over time and can even be reversed like it is the case for Angola (northern Kalahari catchment) when we compare trends between 2003 to 2016 and 2003 to 2020 (Fig. 3). Bonsor et al. (2018) related this behavior to the general rainfall patterns in this region and Scanlon et al. (2022) identified large interannual variance in the Northern Kalahari catchment. More reliable GW changes at higher spatial and temporal resolution are obtained by combining GRACE observations and hydrological

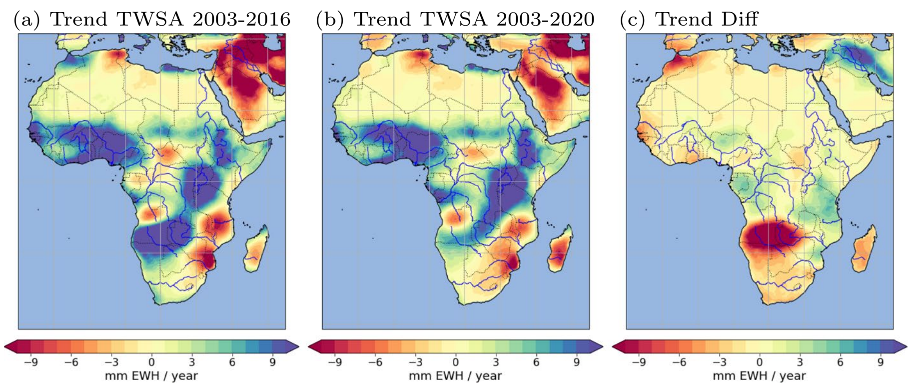

Fig. 3 Trends in TWSA derived from GRACE for the time period **a** 2003 to 2016 and **b** 2003 to 2020 and **c** differences of the trends between the two time periods

model output applying sophisticated statistical tools and by including other independent remote-sensing observations as described in Sect. 4.2.

Strengths and weaknesses The core advantage of remote-sensing observations from the GRACE satellites is a unique and complete picture of the whole sum of water storage changes on the continents. This, however, is at the same time a caveat of GRACE observations in the context of GW monitoring as individual water storage compartments cannot be distinguished without additional information from external data sets. Depending on the data source, the required auxiliary data sets for soil moisture and surface waters can have substantial uncertainties (Chen et al. 2016). Other limitations arise from the limited spatial and temporal resolution of GRACE observations and uncertainties due to spatial filtering/leakage errors and rescaling procedures. However, with longer data records, uncertainties of GRACE-based trends become less of a concern for deriving GW trends. In summary, GRACE remote-sensing observations are the only kind of observations that are sensitive to large scale GW changes.

3.2 Radar Altimetry

Radar altimetry (RA), initially developed to determine ocean topography through a continuous measurement of the distance between the Earth's surface and the sensor on-board the satellite (Stammer and Cazenave 2019), is now commonly used for monitoring inland water bodies (Cretaux et al. 2017). Time series of water levels are constructed at the cross-sections between an inland water body and a RA ground-track to form a so-called Virtual Station (VS). RA valid data are identified and averaged to generate the time series of water levels at a temporal sampling corresponding to the repeat period of the altimeter (e.g., 10, 27, or 35-days). Networks of VS are defined at regional or basin scales as the gathering of all VS defined over the study area, e.g., over lakes, reservoirs, rivers, and even wetlands and floodplains (Cretaux et al. 2017). These dense mono- or multi-mission networks can be used to provide new information on the GW table depth of alluvial aquifers in flat areas. In these areas, the minimum surface water stage and the GW level coincides (Lesack 1993, 1995; Lesack and Melack 1995; Hodnett et al. 1997a, b; Cullmann et al. 2006). The minimum in water level recorded by a VS at a cross-section with a river, a lake, or a floodplain connected to the alluvial aquifer is used to define the GW Base Level (GWBL). Annual maps of GWBL can be generated interpolating the yearly minimum of water stage from the different VS. Using a dense network of ~500 VS, annual maps of GWBL were obtained in the Central Amazon (70° W < longitude < 54° W and 5° S < latitude < 0°) over 2003 - 2009 (Pfeffer et al. 2014). A similar work, achieved by the authors in the Inner Niger Delta is presented in Sect. 5.1.

Strengths and weaknesses The major strength of RA is its global availability over a long time period starting in 1991 with the launch of ERS-1. The quite coarse temporal resolution of RA missions (between 10 and 35 days) is not an important drawback for GWBL monitoring as low water periods generally last longer than high water ones. Nevertheless, VS networks are mostly available over permanent waterbodies as the definition of VS is more complex over floodplains and wetlands. Only one study demonstrated yet the potential of RA for GW monitoring in the floodplains of the central Amazon area (Pfeffer et al. 2014).

3.3 Thermal Infrared Remote Sensing

Thermal Infrared (TIR) images provide indirect information on GW movements via measured surface temperature (e.g., Lopez et al. 2016). These movements can be detected by the emergence of thermal anomalies where the surface temperature exceeds (warm anomalies) or is lower (cold anomalies) than the surrounding temperature. Interpretation of the anomalies origin is not straightforward especially if the anomaly temperature difference ranges between 5 and 10 °C. Indeed, in that range, many factors influence the signal such as solar radiation, local topography, physico-chemical properties of the surface, geothermal heat flow, the presence of vegetation, and local atmospheric conditions. However, in certain climatic zones (mostly in (semi-)arid regions), when considering only night time images (in order to reduce the topography and solar radiation effect) and/or focusing on water bodies, most of these factors can be neglected.

Water surface temperature of rivers and lakes as the Dead Sea has mainly been studied with airborne and Unmanned Aerial Vehicle (UAV)-based TIR sensors (e.g., Liu et al. 2016; Dole-Olivier 2019) but also by satellites (e.g., Lalot et al. 2015; Mallast

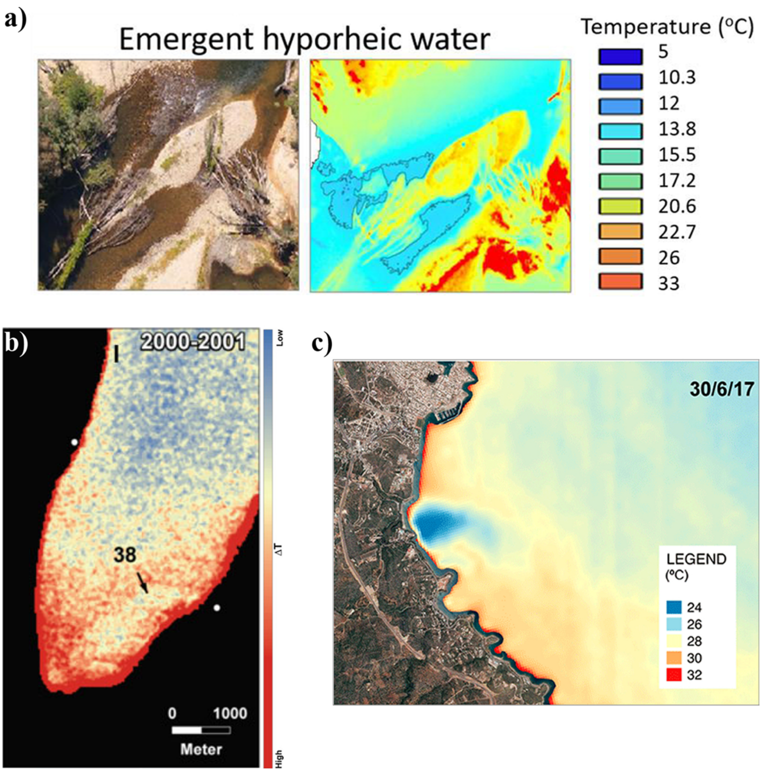

Fig. 4 Some GW discharge examples of observations in TIR images, within different contexts and obtained from different vectors : **a** in a river (Australia) with an UAV where the GW discharge is associated with a ΔT of ~-2.5 K (blue polygons) (modified from Casas-Mulet et al. 2020), **b** in the Dead Sea with Landsat ETM+ where here also the GW discharge is associated with low-temperature water (modified from Mallast et al. 2013) and **c** along the Mediterranean Sea coast (Crete, Greece) where the GW discharge is ~6 K lower than the surroundings (obtained from Landsat 8 (modified from Jou-Claus et al. 2021))

et al. 2013, 2014; Siebert et al. 2014) in order to detect lateral variations of surface temperature to precisely locate GW discharge (Fig.4 a-b). Identification of aquatic GW discharge relies on the presence of a thermal contrast between the discharging GW and the water body (Fig. 4 c). The objectives of these studies were (1) to estimate the recharge of the aquifer through these connected water bodies and (2) to map and evaluate GW discharge into rivers/lakes. Indeed, as GW discharge estimation is one main component for sustainable management, for coastal aquifers without hydrogeological information, detection of submarine groundwater discharge (SGD) springs using TIR data can be used as a first approach to localize them. Accordingly, the detection of SGD will narrow the sampling surveys and allows discharge estimation with direct measurements. These studies were performed using different vectors for TIR sensors, such as UAVs (Young and Pradhanang 2021), planes, and satellites (Landsat) along the Mediterranean Sea coasts (Jou-Claus et al. 2021; Mejías et al. 2012; Shaban et al. 2005).

Space-based TIR data obtained from different sensors such as METEOSAT, MODIS (Moderate-Resolution Imaging Spectroradiometer), Landsat, and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) have been used in the (semi-) arid region of the Lake Chad basin (Leblanc et al. 2003; Lopez et al. 2016) in order to study regional GW evolution. These authors (1) demonstrated that over the Lake Chad basin land surface temperature highlights the relationship between the evapotranspiration/condensation cycle at the surface and the localization of GW close to the surface, (2) suggest a new understanding of the GW cycle via the modeling of a basin-wide convective circulation taking into account the geological/geophysical characteristics of the basin, and (3) show that the combination of warm regions with highly permeable formations at the surface in (semi-) arid regions may indicate areas where GW is close to the surface and, thus, possible zones of water extractions.

Besides surface temperature information, TIR data can be used to determine the surface lithology with the specific TIR spectral properties of some minerals. This lead to the creation of specific indices known as ASTER indices such as the Carbonate Index, Quartz Index, and Mafic Index that have been used in Egypt to identify new areas of GW potentiality (Aboelkhair et al. 2020).

Strengths and weaknesses TIR space-based images can be a useful tool to understand the functioning of GW reservoirs and their relationship with surface conditions, e.g., the surface lithology, and local atmospheric conditions. Surface temperature provides complementary information and is a real asset when combined with in situ data sets and/or associated with other types of space-based sensors. Nevertheless, one major drawback for the systematic use of space-based surface temperature images is their actual spatial resolution (from ~100 m to 5 km) that limits studies to wide regions and rather large water bodies. This drawback might be alleviated by the next generation of TIR missions at higher spatial resolution as TRISHNA (Lagouarde et al. 2018) and the Copernicus' Land Surface Temperature Monitoring (LSTM) mission (Koetz et al. 2018).

3.4 InSAR Observations

First applications of InSAR data in hydrology demonstrated the ability of this technology to retrieve information on GW storage variation indirectly from ground deformation (e.g., Galloway and Hoffmann 2007; Bell et al. 2008; Chaussard et al. 2014). This ground deformation mapping via space-based radar sensors, such as ERS, RADARSAT, ENVISAT, ALOS, and/or Sentinel-1 relies on different techniques, namely the conventional InSAR (e.g., Motagh et al. 2017; Wonnacott et al. 2015; Neely et al. 2021; Castellazzi et al. 2016b; Castellazzi and Schmid 2021), the persistent scatterer interferometry (PSI) (e.g., Béjar-Pizarro et al. 2017; Agarwal et al. 2020; Bell et al. 2008), and the coherence change detection (CCD) (e.g., Gaber et al. 2018). InSAR studies highlighted that observed subsidence is caused by GW extraction (Castellazzi et al. 2016a; Castellazzi and Schmid 2021; Motagh et al. 2017; Agarwal et al. 2020) while ground uplift is associated with recharge of the aquifer (Neely et al. 2021; Agarwal et al. 2020), i.e., when the compaction of unconsolidated sediments have not caused irreversible and inelastic deformation of the aquifer (Motagh et al. 2017, and references therein). The combination with GRACE data is a current matter of research due to the resolution mismatch but has high potential for investigating GW flow dynamics and aquifer confinement (Castellazzi et al. 2016a). At this time, very few studies have been conducted over Africa to retrieve information on GW changes with InSAR data. Wonnacott et al. (2015) compared deformation data provided by Global Navigation Satellite Systems (GNSS), InSAR, and in situ micro-gravity measurements on an artesian aquifer in South Africa. Their study showed that GNSS monitoring recorded a subsidence of ~15–20 mm while InSAR and micro-gravity measurements data were inconclusive, suggesting the need of further experimentation with both techniques. The technique based on CCD was applied in Egypt in order to detect alternation of fluvial and aeolian deposits that could have permitted the existence of lakes, thus, being a preferential entry point for aquifer recharge (Gaber et al. 2018). Localization of these ancient ephemeral lakes enables to suggest more targeted areas for in situ GW exploitation.

Strengths and Weaknesses Castellazzi and Schmid (2021) observed that ground deformation may be interrelated to other displacement sources before detecting the GW storage variation, such as the clay content at the surface, land use, and climate. Nevertheless, compaction measurements and land subsidence detection from InSAR techniques have the potential to provide high-resolution information on aquifer dynamics. Moreover, combination of GRACE and InSAR data demonstrates that both methods complement each other as InSAR retrieve GW information of small aquifers at a more local scale while GRACE estimation of GW changes can only be used for very large aquifers and with strong GW anomalies (Agarwal et al. 2020; Castellazzi et al. 2016a, b).

3.5 Complementary Remote-Sensing Observations

The above introduced remote-sensing techniques for GW research are often used along with other remote-sensing observations that provide additional information for validation or signal separation.

3.5.1 Microwave Remote Sensing

Common long-term products of near-surface soil moisture (SM) are based on passive and active microwave sensor data starting in 1978 (Mohanty et al. 2017). Passive sensors such as the Advanced Microwave Scanning Radiometer for EOS (AMSR-E/AMSR-2; Jackson et al. 2010) and the Soil Moisture and Ocean Salinity (SMOS; Kerr et al. 2001) mission operated by the European Space Agency (ESA) measure the intensity of emitted microwaves from the soil, which change due to the different dielectric constants of dry soil and water. Active microwave sensors such as the Advanced SCATterometer (ASCAT; Wagner et al. 2013) send a microwave pulse and receive a signal of different power. From both signals a backscattering coefficient is computed that is sensitive to soil moisture. A combined active/passive approach is realized, e.g., by the Soil Moisture Active Passive (SMAP) mission, which leads to products of higher spatial and temporal resolution with better accuracy (Entekhabi et al. 2010). Blended long-term products from various passive and active microwave sensors are available, e.g., by the ESA Climate Change Initiative (CCI) (Liu et al. 2012). Reviews of SM remote-sensing techniques including also thermal and optical approaches are provided, e.g., by Mohanty et al. (2017) and Babaeian et al. (2019). Over Africa, Mousa and Shu (2020) investigated the performance of different microwave soil moisture products.

The coarse resolution of microwave soil moisture products can be improved for regional applications by various downscaling methods (Peng et al. 2017, 2021). Because of the limited measurement depth of microwaves, remotely sensed SM is representative only for the first few centimeters of the soil. Root-zone SM can be derived by combining microwave SM products with hydrological models via data assimilation approaches (Mohanty et al. 2017). Furthermore, joint assimilation of remotely sensed SM and GRACE data has the potential to improve modeled soil moisture and GW simultaneously (Tangdamrongsub et al. 2020; Girotto et al. 2019). Few seminal studies also show the potential of microwave remote sensing for detecting shallow GW (Soylu and Bras 2021, 2022).

3.5.2 Other Related Climate Variables

Remotely sensed precipitation (P) and evapotranspiration (*ET*) and their difference are further variables that are often involved in GW related studies to investigate the origin of water storage variations, e.g., via time series analysis (Khaki et al. 2018; Mohamed and Gonçalvès 2021; Frappart 2020). Furthermore, ET can serve for calibration purposes in hydrological models (Poméon et al. 2018; Cheema et al. 2014) with the aim of improving modeled GW storage evolution. Satellite-based rainfall measurements can be obtained from the Tropical Rainfall Measuring Mission (TRMM) operated from 1997 to 2015. Remotely sensed ET can be computed from data of the MODerate-resolution Imaging Spectroradiometer (MODIS) mission based on the Penman-Monteith equation (Mu et al. 2007).

3.5.3 The WATer EXploration (WATEX) Approach

The WATer EXploration technique was developed to identify GW resources using a wide range of information including geological data, climate indicators such as rainfall estimates, hydrology-related information such as well locations, and various remote-sensing data, such as high-resolution multi-spectral and SAR images and DEM from SRTM (Verjee and Gachet 2006). The approach is based on proprietary algorithms that combine the various inputs. WATEX was applied in several semi-arid regions of Africa such as Chad (Verjee and Gachet 2006), Kenya (International 2013) and Ethiopia (Godfrey and Hailemichael 2016). WATEX evaluation over Ethiopia by the International Groundwater Resources Assessment Centre (IGRAC) reported a lack of information about the approach that was a limiting factor for supporting the results obtained earlier by Verjee and Gachet (2006).

3.6 Issues of Hydrological Models

Estimates of GW evolution can also be obtained from hydrological models. Numerical hydrological models aim at representing water, energy, and biogeochemical fluxes at different spatial and temporal scales, and thereby contribute to a better understanding of the individual components of the terrestrial water cycle. Hydrological models can be classified into two categories: (1) land surface models (LSMs) that aim at mapping physical processes of the real world through mathematical equations as realistically as possible (e.g., the GLDAS models; Rodell et al. 2004), and (2) hydrological and water resource models (HMs) that describe different components of the water cycle through empirical equations with model parameters that need to be calibrated (e.g., the WaterGap Hydrological Model, WGHM; Döll et al. 2003). While HMs model also GW and human abstraction, LSMs usually do not incorporate GW and have large temporally and spatially varying uncertainties (Schewe et al. 2014; Scanlon et al. 2018; Vishwakarma et al. 2021a), which limit their use for GW research. Uncertainties arise from insufficient realism of model equations and structure, imperfect model parameters, and imperfect forcing and surface data sets.

Scanlon et al. (2018) showed that both kind of hydrological models underestimate trends in TWS, and, thus also GW trends derived from these models have large uncertainties. Furthermore, in tropical and semi-arid catchments, most models underestimate seasonal TWS amplitudes (Scanlon et al. 2019). Swenson and Lawrence (2015) showed that deficits of LSMs in represented GW dynamics can be related to inappropriate storage capacity. Yet, globally, spatial patterns of GW depletion modeled by WGHM were found to be captured adequately (Döll et al. 2014). However, reliability of GW variability modeled by WGHM depends strongly on optimal irrigation estimates and the corresponding GW abstraction rates. Improved GW variability and trends are obtained when assimilating GRACE-based TWSA into the models (Schumacher et al. 2018; Li et al. 2019; see Sect. 4.2.2).

4 Analysis and Validation Concepts for Groundwater Monitoring

Comparing and merging observations from different remote-sensing techniques and additionally taking into account in situ data and numerical models allows for (1) obtaining a more realistic picture of GW storage changes and their natural and anthropogenic drivers, (2) assessing interactions between different components of the water, energy, and carbon cycles, and (3) providing predictions and recommendations for GW management actions. Insights from joint evaluation of in situ measurements and remote-sensing data over Africa are discussed in Sect. 4.1. Concepts for jointly evaluating different observation types and models range from simple time series and correlation analysis to data assimilation and deep learning methods. In Sect. 4.2, we provide an overview on common concepts for combining remote-sensing observations with auxiliary information for quantifying GW resources with particular focus on studies addressing the African continent. Major conclusions for African GW resources are then reported in Sect. 5.

4.1 Link Between Ground and Satellite Observations

Of all shallow GW records of the world, Africa provides less than 0.001% of GW data (Khadim et al. 2020). However, in situ data, even if available only for a short period of time, can still be used for comparisons with GRACE-based GW variations (Skaskevych et al. 2020) in order to better understand and monitor TWS fluctuations and also to provide information where the spatial resolution of GRACE/GRACE-FO missions is too large. Indeed, as an example, in the Nairobi volcano-sedimentary regional aquifer in Kenya, Oiro et al. (2020) demonstrated that analyses of multi-decadal in situ piezometry data together with LU/LC changes observed by Landsat allows to map and quantify local to regional scale GW depletion. These authors demonstrated that agricultural surface reduction may (1) modify the hydroclimatic influence of GW recharge and (2) increase the number of extraction boreholes thus increasing GW abstraction locally.

Besides, GW piezometry changes have been used to study a possible relationship between climate indices (the El Niño-Southern Oscillation, ENSO; and the Atlantic Multi-decadal Oscillation, AMO) and temporal variations in TWS and GW reservoirs in nine large African aquifers basins, i.e, NWSAS, NSAS, Lake Chad, Irhazer-Iullemeden basin, Senegalo-Mauritanian Basin, Volta Basin, Karoo Carbonate, Stampriet TBA System, and Karoo Sedimentary (Carvalho Resende et al. 2019). These authors demonstrated that (1) in situ shallow GW fluctuations are correlated with TWS changes estimated by GRACE and (2) shallow aquifers are highly responsive to temporal rainfall patterns.

In order to improve drought resilience by better water forecasting and reliable GW distribution systems, Thomas et al. (2019) combined three remote-sensing data sets (rainfall from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS), Landsat-8 Normalized Difference Vegetation Index (NDVI), and GRACE-based TWS) with 221 in situ GW extraction observations across Northern Kenya and Afar (Ethiopia). Relying on this combination, the authors highlighted the fact that increased use of GW occurs only during the dry season when rainfall is low as population has a preference for surface water sources. Their results demonstrate the significance of GW access during dry seasons and the importance of monitoring GW extraction.

These studies demonstrate the ability of even sparse GW in situ data to address the lack of spatial resolution of GRACE/GRACE-FO TWS estimation.

4.2 Statistical Analysis Techniques

4.2.1 Signal Separation

Investigating correlations between GW storage changes and other water cycle related variables and geophysical data sets enhances the understanding of complex relationships and GW-related processes. In this direction, Abdelmohsen et al. (2020) investigated interactions between lake Nasser and the NSAS. They correlated GRACE TWSA spatially and temporally with precipitation, lake levels, lake area, and surface water storage, and showed that GRACE can be used for estimating aquifer recharge. Finally, this study led to a revised GW flow model. In order to detect significant short-term changes in African water resources, Ahmed and Wiese (2019) applied break point detection algorithms to GRACE-derived TWSA and interpreted the results based on many different remotely sensed water cycle variables, such as precipitation, evapotranspiration, temperature, and lake levels from altimetry. In this way, they were able to relate TWS changes over North Africa to excessive GW extraction from fossil aquifers and to some extent to changes in atmospheric fluxes.

Multi-Linear Regression (MLR) is a common tool to derive spatial and temporal patterns of trends, seasonal cycles, and climate modes in geophysical data sets. Other statistical techniques like Principal Component Analysis (PCA) and inversion methods allow for (1) investigating dominant modes of GW variability and (2) adjusting data from different sources toward each other in order to represent different water storage compartments consistently. As PCA or Independent Component Analysis (ICA) are available in libraries and toolboxes, these techniques are commonly used for a number of different observation types and model outputs. Ndehedehe et al. (2016) applied PCA and MLR to GRACE data, GLDAS model outputs, and precipitation from TRMM and compared dominant spatio-temporal patterns also to satellite altimetry data in order to understand TWS variability over West Africa. They identified the contribution of strong rainfalls to interannual variability of TWSA, but also revealed inconsistencies between the individual data sets in specific parts of the study area. Using PCA, Awange (2022a) extracted simultaneous temporal patterns of TWSA, rainfall, and soil moisture over Ethiopia and corresponding dominant regions. Figure 5 shows exemplary spatial and temporal patterns of GRACE TWSA and precipitation from the Global Precipitation Measurement (GPM, https://gpm.nasa.gov/data/imerg) in the Nile basin (Khaki and Awange 2021). Major trends of both TWSA and precipitation are visible in the first PCs with a strong positive anomaly in Aril 2019. The first EOFs show that these anomalies affect mainly the southern parts of the Nile catchment, the region of Lake Victoria.

A more complex analysis by Anyah et al. (2018) with focus on climate teleconnections was based on ICA and correlation analysis of GRACE TWSA and five global climate indices. The authors of the study characterized the impact of individual climate modes on terrestrial water storage in different parts of the African continent. The ICA approach was also used by Forootan et al. (2014a) to identify teleconnections between GRACE TWSA and remote-sensing-based precipitation and sea surface temperature (SST) over West Africa. Similarly, Awange (2021a) used ICA to relate the climate modes ENSO and IOD to TWSA over the Greater Horn of Africa.

Forootan et al. (2014b) applied ICA to TWS from a land-surface model and to surface water from satellite altimetry to obtain statistically independent spatial patterns for the individual water storage compartments over Iran. Then, they adjusted the temporal components to GRACE TWS observations and finally reconstructed TWS changes and surface water changes. Validation with in situ GW well data showed that GW trends were well captured by the adjusted data set. Later on, Forootan et al. (2017) applied the ICA approach to GLDAS-based time series of soil moisture, canopy, snow, and surface

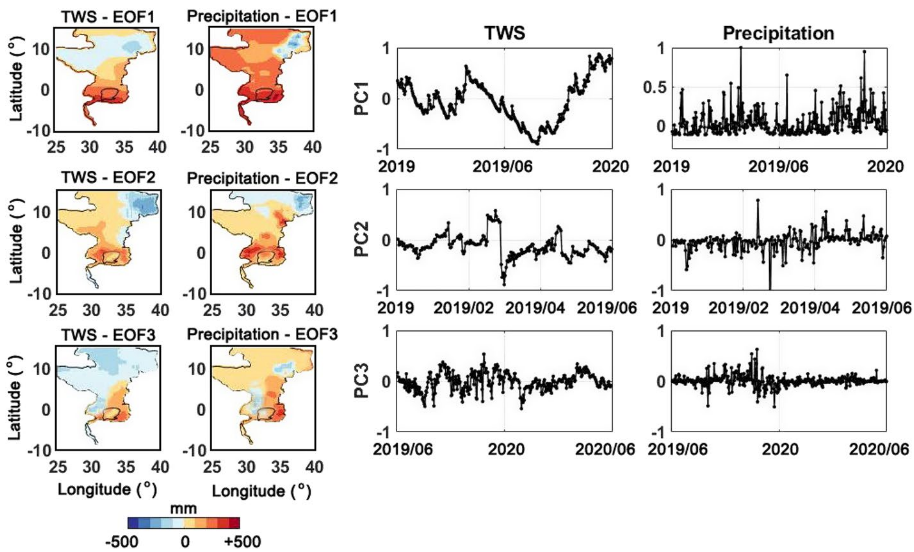

Fig. 5 PCA decomposition of GRACE-based TWSA and precipitation time series in the Nile catchment: first three spatial and temporal components (*source*: Khaki and Awange 2021)

water and fitted the temporal patterns to GRACE TWSA. Then, GW changes and trends were computed from GRACE TWSA and from the reconstructed storage compartments.

4.2.2 Merging Data Sets

A major drawback of the above described approaches is the limited spatial and temporal resolution of GRACE-based GW changes. This drawback can be overcome by combining GRACE and other remote-sensing observations with land-surface or hydrological models using simple correction algorithms like the one suggested by Ahmed et al. (2016), or by applying Bayesian approaches such as data assimilation (Li et al. 2019) with twofold benefits: (1) the GRACE observations are downscaled horizontally, vertically, and temporally, and (2) modeled TWS is pulled toward the observations, which potentially leads to more realistically simulated water storages and fluxes. Ahmed et al. (2016) improved outputs of CLM4.5 over the European continent by applying a first-order correction to simulated ET (based on remotely sensed ET) and redistributing the excess water to surface and GW compartments on a monthly basis. Observations and numerical models can also be combined using data assimilation concepts, e.g., based on Ensemble Kalman Filter (EnKF) algorithms. Girotto et al. (2017) showed that the assimilation of GRACE TWSA into a hydrological model can induce missing long-term trends to GW storage and improve interannual variability. Joint assimilation of GRACE TWSA and surface soil moisture has the potential to simultaneously improve GW and soil moisture estimates (Tangdamrongsub et al. 2020). Khaki and Awange (2021) jointly assimilated GRACE TWSA and lake levels of Lake Victoria derived from satellite altimetry into the World-Wide Water Resources Assessment Model (W3RA) and show detailed patterns of water storage evolution in different compartments with focus on an extreme water storage increase during the period 2019-2020. Li et al. (2019) provided a detailed study on the benefits and challenges of GRACE data assimilation for GW and drought monitoring on a global scale and identified major problems in regions with intensive GW abstraction.

Another possibility to merge information from different data sources (e.g., output from different hydrological models or GRACE solutions based on different algorithms) is Bayesian Model Averaging (BMA). The posterior distribution of a variable of interest (e.g., TWSA or GW) is constructed by averaging the posterior distribution of each model weighted by the corresponding posterior model probabilities. The posterior distribution of each individual model with respect to a set of observations of the variable of interest is obtained from the Bayes' theorem. Long et al. (2017) applied BMA to derive uncertainties for different GRACE TWSA products in the major river basins of the world. Mehrnegar et al. (2020) went further and developed a novel approach of Dynamic Model Data Averaging (DMDA), which combines the benefits of BMA and Kalman Filter techniques. Applying DMDA, they computed time-variable weights for six different hydrological and land-surface models to derive averaged outputs that best fit to GRACE TWS observations for the 33 major river basins of the world. Indeed, DMDA was found to introduce the impact from anthropogenic influences (e.g., GW pumping) into the models. GW trends significantly changed due to DMDA compared to the original models for most of the considered basin. Furthermore, a synthetic example for the Niger basin showed significantly improved representation of derived GW storage change when applying DMDA instead of BMA. Over the United States, Mehrnegar et al. (2021) applied a Bayesian Markov Chain Monte Carlo-based data assimilation approach to integrate GRACE TWS into a hydrological model and showed successful downscaling with improved GW storage simulations compared to in situ GW data. Moreover, the representation of ENSO-related variability of GW and soil moisture was significantly improved.

4.2.3 Long and Continuous Groundwater Time Series

Recently, the appropriateness of tools like multivariate regression, artificial neural networks, and extreme gradient boosting techniques for downscaling satellite observations, filling temporal gaps, and extending time series have moved to the forefront of research. All these approaches aim at generating long and continuous data records. The multivariate regression approach estimates regression coefficients assuming a linear relationship between the variable of interest (e.g., GW or TWSA) and a set of explanatory independent variables (Sahour et al. 2020). Artificial neural networks mimic the computations done by a brain – a highly interconnected network of neurons – to learn solutions for many different type of problems, i.e., to establish empirical non-linear relationships between a target variable and a set of input variables (Govindaraju et al. 2000). Extreme gradient boosting applies gradient boosting with decision trees (Zounemat-Kermani et al. 2021). A tree-like model is learned to go from a set of input variables (branches of the tree) to a prediction of the variable of interest (leaves of the tree). The model is fit by minimizing a loss function using a gradient descent optimization algorithm.

So far, in the context of water storage prediction most of these approaches were applied to generate TWS time series, but the results could also be transferred to individual storage compartments (see, e.g., Sahoo et al. 2017). Humphrey and Gudmundsson (2019) provided a global reconstruction of climate-driven TWS changes, based on GRACE observations, precipitation and temperature by calibrating a simple statistical model. For West Africa, Forootan et al. (2014a) applied a combination of ICA and Autoregressive Exogenous (ARX) approach for learning TWS from rainfall and sea surface temperature, which led to better TWS estimates than provided by global hydrological models. Further on, Li et al. (2020) compared MLR, an artificial neural network, and ARX approaches to reconstruct long-term TWS changes globally based on climate input data. They found MLR in combination with PCA being the most robust choice for predicting TWS. Contrary to Li et al. (2020), Sun et al. (2020) found that deep neural networks outperform ARX and MLR approaches in reconstructing TWS from GRACE in most of 60 studied basins. Similarly, Sahour et al. (2020) compared three statistical techniques for deriving relationships between monthly GRACE TWS and hydrological variables from remote sensing, in situ data, and from a land-surface model for downscaling GRACE data spatially. They found that extreme gradient boosting outperforms MLR and ANN for local applications. Finally, GW variations at increased spatial resolution were extracted from downscaled GRACE data and the land-surface model using eq. (2). Downscaled GW changes showed higher correspondence to well measurements compared to original GW changes. However, the best method for reconstructing TWS and GW storages might depend on the respective setup, the input data sets, and the study region. Ahmed et al. (2019) used an ARX model to forecast GRACE like TWS in 10 major catchments over central Africa based on climate input data and to predict drought events with very good performance for a majority of the catchments. In order to predict GW abstraction rates, Gemitzi and Lakshmi (2018) trained an artificial neural network against GW abstraction estimates for farms using GRACE TWS and climate data as input data. With this approach GRACE TWS was downscaled to estimate water abstraction from a small aquifer body.

5 Status and Evolution of African Groundwater Resources

In this section, we review the current knowledge on the evolution of GW storage and related processes in Africa based on remote-sensing data. An overview of relevant studies is provided in Table 1. We discuss the current status of African GW storage, the individual drivers of detected GW trends, and we provide an overview on how the findings from satellite observations can be used for decision making.

5.1 Examples of Groundwater Storage Evolution over the African Continent

While global studies of GW trends usually focus on broader spatial patterns (e.g., Richey et al. 2015a, b; Mehrnegar et al. 2020), regional studies often provide also detailed insights into GW related processes for selected aquifers. Most studies that treat the African continent focus on the deep aquifers of Northern Africa, but there are also a few studies considering individual aquifer systems in SSA.

North Africa For North Africa, an overview on GW storage and its changes as well as GW capacity based on GRACE TWS and GLDAS model outputs is provided by Lezzaik and Milewski (2018) for the 2003 to 2014 period. High GW depletion rates are concentrated along the coastal areas from Algeria to Egypt and along the Nile River. The authors associated these regions with areas of high population density, but also considered the influence of climate driven droughts.

Frappart (2020) derived GW storage anomalies for three North African aquifers (the Tindouf Aquifer System (TAS), the NWSAS and the NSAS) from GRACE TWS observations by correcting for soil moisture, and in the case of the NSAS also for surface water (Lake Nasser) for the time period 2003 to 2016 (Fig. 6a-c). Subsequently, the author correlated GW estimates with atmospheric flux $P - E$. Small GW changes mainly arising from changing regimes in atmospheric fluxes were obtained for the TAS. In contrast, large water losses of about 30–50 km^3 during the 13 years study period were found for the NWSAS and the NSAS (Fig. 6a-c). For the NWSAS, mixed contributions from GW pumping and changes in atmospheric fluxes confirm that this aquifer is not a fossil system (Frappart 2020). External data sets about annual GW abstraction and population growth as well as satellite observations of urbanization processes lead to the conclusion that the NSAS GW depletion is mainly related to anthropogenic impact. This conclusion confirms the one made by Sultan et al. (2014) at a more local scale in the Dakhla aquifer in Egypt (North-Eastern part of the NSAS). Sultan et al. (2014) suggested that the large observed depletion rate is due to the increasing exploitation of GW for irrigation in the Western Desert of Egypt that led to a ~60 m water table drop since the 1960's (Fig. 6d). Indeed, Ahmed (2020) concluded that sustainable GW use in the Dakhla sub-basin requires a reduction of annual GW withdrawals by 2.27 km^3. Also a recent study by Rateb et al. (2022) investigated sustainability of GW use in North Africa with positive results for the coastal countries and countries which have either high GW reserves or apply desalination. Abdelmohsen et al. (2020) revisited the NSAS and focused on the interaction between surface water and GW by spatially and temporally correlating GRACE TWS, precipitation, lake levels of Lake Nasser, lake area, and water volume. In this study, the authors derived a new recharge model for the NSAS consisting of a slow GW flow through porous medium and a fast flow through a network of faults and fractures. Lake Nasser was identified as the main source of recharge for NSAS, which accounts for some of the GW loss identified by Sultan

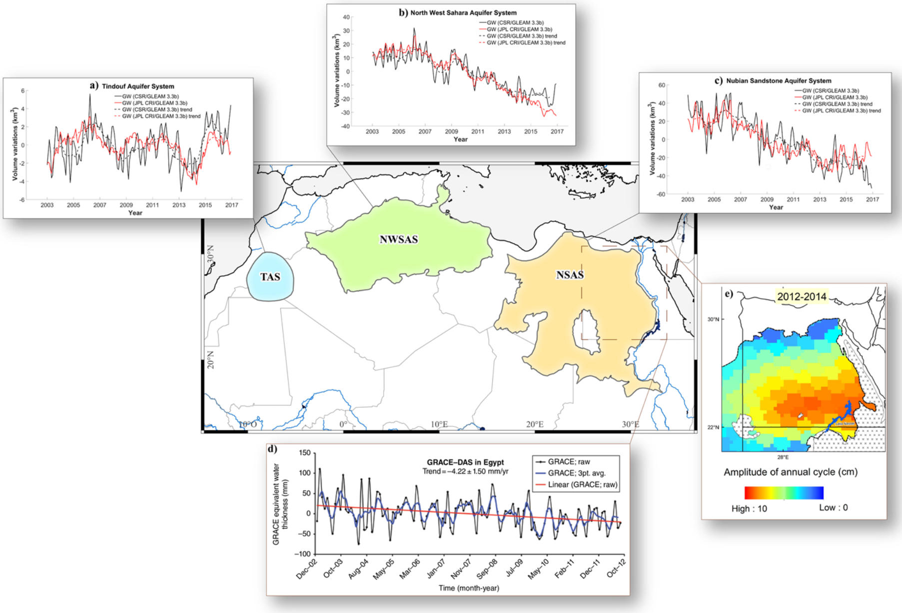

Fig. 6 Localization map of the largest North Africa TBAs : TAS, NWSAS and NSAS in blue, the main rivers and lakes. Plots **a**, **b** and **c** are time series of monthly anomalies of GWS derived from GRACE-based TWS from mascon CSR RL06, SM from GLEAM 3.3b (black), from mascon JPL CRI RL06, SM from GLEAM 3.3b (red) and associated trends (dotted lines of the same color) between 2003 and 2016 for TAS, NWSAS and NSAS, respectively (modified from Frappart 2020). The burgundy insert delimits approximately the sub-basin DAS where **d**) the time series of monthly anomalies of GRACE solutions were estimated (modified from Sultan et al. 2014), and **e**) the amplitude of annual cycle were derived from monthly GRACE solutions during 2012-2014 period marked by an increase of the Lake Nasser volume (modified from Abdelmohsen et al. 2020)

et al. (2014) (Fig. 6e). Later on, Mohamed et al. (2017) studied in more detail recharge and depletion rates as well as pathways of GW flow for the subbasins of NSAS within an integrated framework of remote-sensing data, land surface models, and geochemical and geophysical data. In a first step, they developed a conceptual hydrogeological model based on insights from GRACE observations and LSMs, which was, in a second step, tested against geophysical observations, field, isotopic, and chronological data. Their results indicate natural GW flow from precipitation-based recharge zones in the South to Northern parts of the NSAS, which experience heavy extraction and no recharge. Abotalib et al. (2016) considered the implication of GW processes within the NSAS on long-term landscape evolution by evaluating a number of mainly image-based remote-sensing data sets together with GW well data. Their findings suggested intensive GW discharge and denudation activities in the NSAS during previous wet climatic conditions. At a more local scale, Ouatiki et al. (2022) compared GW evolution based on GRACE and auxiliary data to GW well observations in Morocco and conclude on a depletion of water resources during the study period 2002 to 2017 over Marocco with a major recharge event in 2008/2009.

Sahel Region The Sahel region is a particularly interesting region as GW stocks and surface runoff increase even in dryer years, the so-called Sahelian Paradox (Favreau et al. 2009; Descroix et al. 2013). Key mechanism is an increased focused recharge through expanding gully networks and an increasing number of ponds (Mamadou et al. 2015). For the whole Niger, Werth et al. (2017) estimated the increase in GW storage to 93 km^3 between 2003 and 2013 based on GRACE observations and output from a land surface model and, thus, confirmed previous studies indicating a water table rise. Dasho et al. (2017) provided details on aquifer depth, aquifer thickness, and GW potential for a small sub-basin of the Niger catchment based on Landsat multispectral images. In the study area, aquifer depth varies between 1 m to 46 m and GW potential is poor to moderate in most parts of the region. Over Lake Chad, GW, which exerts a strong control on the lake water cycle, was found to slightly increase (Pham-Duc et al. 2020). Recently, Barbosa et al. (2022) evaluated aquifer sustainability of several large aquifers in Niger based on GRACE-derived GW storage and recharge estimates. They found GW storage increasing over the past 10 years indicating possible long-term use.

Concepts from GW - surface water interactions allow for deriving information about the GW table from altimetry data (Pfeffer et al. 2014). One of the largest wetlands of the Sahel region is the Inner Niger Delta (IND) (Mahé et al. 2009). The extent of the flooded area varies with the intensity of the West African Monsoon. During the wettest rainy seasons, which occur between August and December, the flooded extent can reach 35,000 km^2 (Zwarts et al. 2005; Jones et al. 2009; Bergé-Nguyen and Crétaux 2015; Ogilvie et al. 2015). A long-term network of altimetry VS was created to monitor the time variations of water levels over the rivers and the wetlands of the IND (Normandin et al. 2018). It is composed of 52 VS from ERS-2 (1995-2003), 63 from ENVISAT (2002-2010), 62 from SARAL (2013-2016), and 32 from SENTINEL-3A (2016-ongoing) and manually generated using the Multi-mission Altimetry Processing Software (MAPS) (Frappart et al. 2015). We used this data to generate GWBL maps in the IND following the approach proposed by Pfeffer et al. (2014). Annual minima of water levels were first identified. Then, GWBL were computed interpolating annual minima of water levels over the IND. Only water levels from ERS-2 and ENVISAT were considered to avoid introducing artifacts due to biases between the different RA missions which have no overlapping period. The 1995-2010 average GWBL map over the IND is presented in Fig. 7a. It shows a slope of ~0.09 m/km in the flow direction. Standard deviations (stds) of GWBL derived from ERS-2 and ENVISAT data over 1995–2010 were smaller than 0.5 m over most of the IND, except in the upstream part, downstream Douna (−5.9°W, 13.22 °N), on the Bani River, and also in the downstream part of the IND in a region

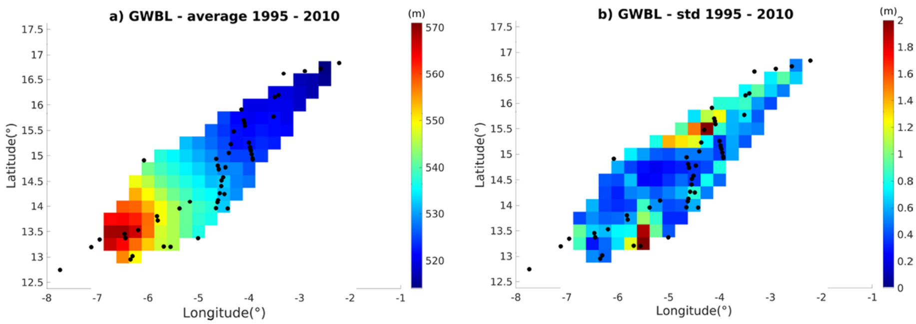

Fig. 7 Map of groundwater base level (GWBL) from ERS-2 and ENVISAT radar altimetry data (1995-2010) in the Inner Niger Delta: **a** average, **b** standard deviation (std) over the whole period. Black dots represent the locations of the radar altimetry virtual stations used to built the GWBL maps

Table 1 Studies using remote-sensing observations to quantify GW resources over Africa. *Acronyms: thermal infrared (TIR), radar altimetry (RA), InSAR (Interferometric synthetic-aperture radar), precipitation (P), evapotranspiration (ET), temperature (T), hydrological model (HM), land-surface model (LSM), soil moisture (SM), surface water (SW)*, digital elevation model (DEM)

Author	Study Area	GRACE	TIR	RA	InSAR	Other Data	Analysis Tool	Research Questions
Awange (2022a)	Ethiopia	x	–	–	–	LSM (GLDAS), P	Time series analysis, PCA	Understand linking between GW variability rainfall
Barbosa et al. (2022)	Niger	x	–	–	–	LSMs (GLDAS)	Time series analysis	Evaluate aquifer sustainability
Ouatiki et al. (2022)	Morocco	x	–	–	–	LSMs (GLDAS), P, SM, SW storage, snow cover, GW wells	Time series analysis	Evolution of GW level
Scanlon et al. (2022)	Africa	x	–	–	–	LSMs (GLDAS), P (IMERG), NDVI	Time series analysis	GW variability in major African aquifers, climate teleconnections
Ramjeawon et al. (2022)	Usutu-Mhlatuze	x	–	–	–	LSM (GLDAS), SW level, GW boreholes	Time series analysis	Drivers of GW storage change
Khaki and Awange (2021)	Lake Victoria	x	–	x	–	LSM (CSIRO)	Data assimilation	Imact of lake level rise on water storage compartments
Mohamed and Gonçalvès (2021)	NWSAS	x	–	–	–	LSMs (GLDAS), P (TRMM/CRU)	Time series analysis, data assimilation	Reconstruct GW storage variation, quantify anthropogenic effect
Aboelkhair et al. (2020)	Egypt	–	x	–	–	geophysical data, P, GW wells	Data assimilation	Assess GW potential
Ahmed (2020)	North Africa	x	–	x	–	LSMs (GLDAS), SW storage, P	Time series analysis	Practices for sustainable fossil GW use
Frappart (2020)	North Africa	x	–	–	–	ET (GLEAM), P (TRMM), lake water volume	Time series analysis	GW trends
Khaki and Awange (2020)	Nile	x	–	x	–	HM (W3RA), SM, river discharge	Data assimilation	Performance of assimilating satellite altimetry data
Mehrnegar et al. (2020)	global	x	–	x	–	HMs, LSMs	Dynamic model averaging	Disaggregation of GRACE data into different storage compartments, improved characterization of water storage

Table 1 (continued)

Author	Study Area	GRACE	TIR	RA	InSAR	Other Data	Analysis Tool	Research Questions
Pham-Duc et al. (2020)	Lake Chad basin	x	–	x	–	lake extent, P (in situ), SM (GLEAM)	Time series analysis	Surface-aquifer exchanges
Agutu et al. (2019)	Greater Horn of A.	x	–	x	–	HM (WGHM), LSM (GLDAS), P (TRMM)	Time series analysis, ICA	Potential of GW for irrigated agriculture
Ahmed et al. (2019)	Africa	x	–	–	–	P, ET, T	Artificial neural networks	Drought monitoring
Ahmed and Wiese (2019)	Africa	x	–	x	–	P, ET, T	Time series analysis, breakpoint detection	Drivers of TWS changes
Hasan et al. (2019)	Africa	x	–	x	–	LSM, P (TRMM), SM, ET, GW wells	Index computation	Potential available water storage indicator
Li et al. (2019)	global	x	-	–	–	LSM (CLSM), GW wells	Data assimilation	GW and drought monitoring
Abd-Elmotaal et al. (2018)	Africa	x	–	–	–	LSMs (GLDAS), HM (WGHM)	Time series analysis	GW variability
Bonsor et al. (2018)	Africa	x	–	–	–	LSMs, P	Time series analysis	Long-term and seasonal GW trends
Gaber et al. (2018)	Egypt	–	–	–	x	visible images	Time series analysis	Detection of morphodynamics changes
Khaki et al. (2018)	Nile	x	–	x	–	LSMs, HM (WGHM) P (TRMM), SM	Time series analysis	Association between climate variability and water storage changes
Lezzaik and Milewski (2018)	North Africa	x	–	–	–	LSM (GLDAS), GW wells	Time series analysis	GW trends
Abiy and Melesse (2017)	Lake Tana basin	x	–	–	–	DEM, P	Time series analysis	Aquifers potential evaluation
Dasho et al. (2017)	Nigeria	–	x	–	–	Landsat-7, DEM, vertical electrical sounding	Lineament maps	Deriving GW potential
Felfelani et al. (2017)	Global	x	–	–	–	LSMs, HMs	Time series analysis	Human induced changes in TWS
Mohamed et al. (2017)	NSAS	x	–	–	–	P (TRMM/CMAP), Bouguer gravity map, GW wells	Time series analysis	Understanding hydrogeological conditions
Werth et al. (2017)	Niger catchment	x	–	x	–	LSM, HM, P	Time series analysis	Significance of GW rise

Table 1 (continued)

Author	Study Area	GRACE	TIR	RA	InSAR	Other Data	Analysis Tool	Research Questions
Ahmed et al. (2016)	Africa	x	–	–	–	LSMs, ET	A first order correction technique	Correcting LSM output toward remote sensing
Lopez et al. (2016)	Lake Chad basin	x	x	–	–	geophysics, geochemistry	Time series analysis, data assimilation	Basin-wide GW circulation characterization
Nanteza et al. (2016)	East Africa	x	–	x	–	well data, LSM	Time series analysis	GW storage changes in complex basement aquifers
Ouma et al. (2015)	Nzoia River basin	x	–	x	–	LSM, R, P	Time series analysis	Understanding GW storage variability at small basin scale
Wonnacott et al. (2015)	South Africa	–	–	–	x	GNSS, in situ micro-gravity	Time series analysis	Aquifer changes, surface subsidence
Moore and Williams (2014)	Africa	x	–	x	–	LSM (GLDAS)	Time series analysis	TWS / GW Changes and contributions of SW
Sultan et al. (2014)	Sahara	x	–	–	–	P, SM	Time series analysis	Aquifer depletion
Gonçalvès et al. (2013)	NWSAS	x	–	–	–	LSMs (GLDAS)	Time series analysis	Estimating recharge
Leblanc et al. (2003)	Lake Chad basin	–	x	–	–	–	Time series analysis	Aquifer recharge processes

centered on 4.5°W, 15.5°N. In these two regions, standard deviations can reach 1.5–2 m (Fig. 7b).

Sub-Saharan Africa Further south, SSA is a challenging study region for GW research by remote sensing due to the presence of large surface water bodies. Nanteza et al. (2016) confirmed shallow and/or permeable aquifer systems with rapid recharge from precipitation in Southern East Africa, based on GRACE-derived GW storage changes, lake altimetry, remote-sensing-based precipitation data, soil moisture models and in situ data. In contrast, aquifer systems in the North-Western part of the study area (upper Nile) were classified as deep and less permeable and therefore sensitive to GW extraction. In Northern Kenya, the study indicated hydraulic connections to recharge zones outside the basin boundary. GW development in the area of the Greater Horn of Africa was also investigated by Agutu et al. (2019) in an integrated framework including GRACE data, altimetry, numerical modeling, climate indices, well data and secondary information on soil types and water quality. GW variations in nine major aquifer systems were derived and analyzed with respect to recharge and correlation with rainfall and climate indices. The authors derived the potential for irrigated agriculture, which is particularly high in the Upper Nile, the Karoo Sandstone, and the Ethiopian highland.

At a more local scale, Awange (2022a) sub-divided Ethiopia into 10 regions and extracted year to year changes and intra-annual changes of GW from GRACE and GLDAS model output. They found significant variability of GW in all regions for almost all months of the year – and particular strong variability during rainy seasons. Abiy and Melesse (2017) analyzed GRACE data together with aquifer potential zones over the Tana basin (Ethiopia) to derive aquifer characteristics. Ouma et al. (2015) investigated interannual GW variability in the Nzoia River Basin in Kenya and found strong correlation with drought periods and ENSO years. In the very south of Africa, Ramjeawon et al. (2022) derived GW storage anomalies from GRACE and the GLDAS land surface model and validated them with in situ GW observations. They found similar trends and significant correlations with uncertainties arising from the resolution mismatch and limited number of boreholes.

5.2 Separating Drivers of Groundwater Trends

Freshwater resources in Africa are sensitive to (1) natural variability, i.e., cycles in precipitation and temperature due to climate modes like ENSO (e.g., Ni et al. 2018), (2) direct anthropogenic interventions, e.g., population growth, deforestation, GW extraction, and (3) an increasing number of extreme events that are related to climate change (Fasullo et al. 2016; Taylor et al. 2013). It is essential to understand the impact of climate modes on GW storages in order to separate them from human contributions to GW trends and from impacts through an intensification of the water cycle.

Ahmed et al. (2014) and Ahmed and Wiese (2019) provide a detailed overview on natural and anthropogenic causes for mass variations observed by GRACE by analyzing several remote sensing, geological, and hydrological data sets. In particular, they found ocean warming leading to increased precipitation over Western and Central Africa, and causing droughts visible in TWS observations over Eastern Africa. Direct anthropogenic influences were identified in the Congo river catchment due to deforestation, in the Nile catchment due to dam construction, and in the Sahara due to GW pumping.

Anyah et al. (2018) analyzed the link between different climate modes and TWS variability over Africa by applying ICA and correlation analysis with the following results: the North Atlantic Oscillation (NAO) leads to declining TWS over Southern Africa, the

Indian Ocean Dipol (IOD) increases TWS over equatorial and Eastern Africa, and ENSO and Madden–Julian Oscillation (MJO) lead to increased TWS over Southern and equatorial Eastern Africa. Ndehedehe et al. (2017) focused on the impact of climate modes in West Africa and found that here TWS is primarily impacted by ENSO and AMO, while IOD was found to have only minor impact on TWS in West Africa. These studies assessed TWS variability and not directly GW variability, however, including hydrological models can in future provide insights into the compartment where these major changes take place.

In this regard, Felfelani et al. (2017) showed that for the Congo and Niger basins major trends are predominantly related to variations in subsurface (and not surface) storage. Carvalho Resende et al. (2019) showed the impact of ENSO and AMO for GW recharge in nine aquifers distributed over the African continent, applying wavelet transform analysis on GW level, GRACE-based estimates, climate-driven models, and climate indices time series. They assumed that TWS derived from climate models via the water budget equation $\Delta\mathrm{TWS} = P - E - R$ represents GW dynamics. In Northern Africa, they found strong correlations between GW variability and NAO and a minor influence from AMO. In the Sahel region the multidecadal impact from AMO and El Nino on GW was evident, which agrees with the results of Ndehedehe et al. (2017). Furthermore, Carvalho Resende et al. (2019) confirmed the impact of ENSO in Southern Africa and the impact of IOD in Eastern Africa. The IOD can also be related to an exceptional increase of water in various storage compartments, including GW storage, in the region of Lake Victoria during the years 2019 and 2020 (Khaki and Awange 2021). In fact, the response of aquifer systems to climate modes depends primarily on the hydraulic memory, i.e., the hydraulic response time to anomalous precipitation (Opie et al. 2020). Li and Rodell (2021) focused particularly on natural controls of GW variability and GW drought monitoring. They assessed the lagged impact (from months to years) of precipitation events, hydrogeological conditions, and climate modes on GW variability. For Central Africa, they concluded that short-term precipitation deficits lead to GW droughts due to shallow water tables, which however, also leads to quick recovery during intense precipitation periods.

Kusche et al. (2016) detected regions with frequent extreme events by analyzing TWS from GRACE and hydrological fluxes from atmospheric reanalyses. They showed that climate modes influence rather the occurrence of extreme wet events than the occurrence of droughts. Hot spot regions for both dry and wet extremes, were located along the equator and in the Zambezi river basin (see also Humphrey et al. 2016, for dry extremes). Cammalleri et al. (2019) compared GRACE TWSA estimates corrected for climatology to Standardized Precipitation Index (SPI) for different accumulation periods (1 month to 48 months) and showed high correlation between GRACE and SPI for accumulation periods longer than 12 months and dependence of correlation on regional hydrogeological properties. Further assessment of GRACE-based drought indices and the SPI was performed by Hosseini-Moghari et al. (2020) for two catchments outside Africa. They also estimated the recovery time from the drought and the impact of unsustainable GW pumping on accelerated drought conditions. Awange (2022b) computed a total storage deficit (TSD) index over the Greater Horn of Africa based on GRACE and compared to SPI. They show inconsistencies between model-based and observation-based drought classification. Based on GRACE TWSA, several instances of hydrological droughts were classified (see also Awange 2021b). Likewise, Awange (2022a) computed TSD indices for ten regions over Ethiopia and related water loss to possible human exploitation for irritation, but also to lagged impact of rainfall variability. Hasan et al. (2019) developed a physical water scarcity index for the African continent by combining GRACE data and remotely sensed precipitation and dividing by population density, called the Potential Available Water Storage

(PAWS) indicator. The PAWS shows water stress affecting the African population. High water stress was found for Northern Africa, for most parts of the Greater Horn of Africa, and for South Africa. Future projections indicate increase of water scarcity along the Niger river and for countries located along the Indian ocean.

One region where several drivers of GW trends interact is the Nile river basin. GW availability and management in the Nile River basin is particularly complex due to a combination of (1) natural variability such as the aquifers characteristics and their hydrogeological properties, the multiplicity among climatic zones, and climatic-driven rainfall variations, and (2) human-induced changes such as water abstraction for irrigation (Johnston 2012; MacAlister et al. 2012; Pavelic et al. 2012). Generally, Khaki and Awange (2020) found GW variability derived from a altimetry-assimilating hydrological model being rather small in the majority of the Nile basin. Khaki et al. (2018) performed a comprehensive study of GW variability, surface water and soil moisture in the three regions of the Nile catchment, i.e., Upper, Central, and Lower Nile. They evaluated multi-mission satellites and land-surface model output for the time period 2002 to 2016. In their study, the authors identified large rainfall events in the Upper Nile during the 2002–2016 period related to ENSO events. As a consequence, in the Upper Nile changes in surface water came along with an increase in TWS and GW. In contrast, in the Lower Nile human-induced impact on TWS changes were found to dominate climate regulation. Furthermore, the relation between climatic influences and GW changes have been studied in the Upper Blue Nile (UBN) river basin (Seyoum 2018). Two drought events (2002–2004 and 2009–2010) were clearly observed in GW decrease and were related to the ENSO climate index. Further on, Awange (2021a) provided a detailed ICA-based analysis of influences of climate modes on the hydro-meteorological conditions in the individual subbasins of the Nile based on GRACE TWSA. However, Shamsudduha et al. (2017) highlighted the lack of correlation between GRACE-derived GW variations and in situ data in the Upper Nile basin. Indeed, GRACE-derived GW variations are greatly constrained by uncertainties in both soil moisture and low long-term amplitude of GW changes as the Upper Nile basin aquifers are in deeply weathered crystalline rocks. Consequently, as 40 % of SSA aquifers are located in that environment (e.g., MacDonald et al. 2012; Shamsudduha et al. 2017), GRACE-derived GW variation must be used with caution in these specific areas.

5.3 Satellite Observations for Decision Making

GW management strategies that aim at effective mitigation of climate change and changes in anthropogenic water use have to be applied at regional to local scale, which often implies a transboundary level in Africa. Indeed, 72 TBAs underlie 40% of the continent (IGRAC 2015). Only seven TBAs are subject to specific agreements on joint research, monitoring, or governance. Thus, different managing strategies of sharing countries make TBAs particularly prone to conflicts of interests (Nijsten et al. 2018). Moreover, as several drivers (Section 5.2) act on GW resources, the development of GW management strategies is a complex issue (Cuthbert et al. 2019). Satellite observations can make an important contribution to the understanding of regional drivers of GW variability that are essential for decision makers, for example:

– future projections of aquifer depletion rates can be made depending on different user scenarios (e.g., Sultan et al. 2014; Oiro et al. 2020),

- identification of hydro-climatological patterns that need to be considered for decision making (e.g., Carvalho Resende et al. 2019),
- regional GW resources monitoring for deriving local-scale GW availability (e.g., Nanteza et al. 2016).

Over the course of the past decade, the contribution of satellite observations to GW management concepts has become increasingly important. Indeed, Ahmed (2020) suggested management scenarios for North African aquifers based on GW sustainable withdrawal rates derived from GRACE. Agutu et al. (2019) used GRACE-based TWSA and hydrological models to assess the sensitivity of GW variability over the Greater Horn of Africa to climate modes, and subsequently, explored the potential of irrigated agriculture based on auxiliary data sets. The results showed where the extension of irrigated areas can be reconciled with sustainable GW management. Ameur et al. (2017) suggested a user-oriented perspective to identify the individual contributors to GW use and an enhancement of cooperative management strategies.

Long and continuous time series of hydrological storages and fluxes are a major asset to improve GW management, but rare due to limited life time of satellite missions and missing in situ measurements over the continent. One approach to close gaps and to extend time series are statistical tools and deep learning methods (Ahmed et al. 2019; Humphrey and Gudmundsson 2019, see Sect. 4.2.3 for details). The resulting data sets represent a useful basis for assessing changes in the frequency and intensity of droughts and for preparing for them.

Several studies compared GRACE observations with traditional drought indices, like the SPI (McKee 1993), and applied GRACE TWSA for computing alternative drought indices. Drought indices are particularly suited to get a general overview on current drought conditions with the particular advantage that they are easily understood by the general public. Thus, they contribute to raise awareness of water scarcity issues and related measures. Recent studies demonstrated that drought indicators based on GRACE-assimilating LSMs overcome constraints due to the limited spatial resolution of GRACE observations and thus better support local decision making (e.g., Li et al. 2019).

6 Gaps in Research and Future Directions

In 2004, the "African Water Vision for 2025" was published by the African Development Bank, the Economic Commission for Africa, the African Union, and the United Nations. The publication provides an overview on key water resources issues and challenges with a vision to achieve equitable and sustainable use of water by 2025. Yet, still today 40% of the African population has no access to clean water, which is however mainly related to a lack in infrastructure and to inappropriate water management rather than to a lack of resources (Naik 2017; Gaye and Tindimugaya 2019; Cobbing 2020). Today, GW management strategies can rely on a growing number of satellite remote-sensing missions that provide (1) observations of GW storage related variables with (2) ever improving spatial and temporal resolution (3) consistent for increasingly longer time spans. In this paper we reviewed different remote-sensing techniques and methodologies for GW research. We showed the complementarity of individual remote-sensing techniques and numerical models for obtaining a diverse picture of GW-related processes, like the impact of climate modes, anthropogenic influences, but also surface water – GW interactions. Furthermore, we summarized insights from using remote-sensing data sets for GW monitoring and decision making in Africa. Indeed, the potential of remote sensing for understanding and dealing with GW issues on the African continent is far from being fully exploited.

Observations of the GRACE and GRACE-FO missions provide an unique almost 20-year record of large-scale GW evolution. However, auxiliary data (i.e., variations in soil moisture, surface waters,...) are needed for deriving GW estimates from TWSA observations. As a consequence the derived GW changes can have substantial uncertainties. In future, downscaling methods have to be developed further for breaking down large-scale GRACE observations for regional and local applications. The contribution of RA to GW research is manifold: (1) the 30-year time series (Abdalla et al. 2021) allows for investigating GW – surface water interactions and is extremely valuable seen the declining number of gauging stations, (2) based on water levels from RA surface water contributions can be removed from GRACE TWSA (for lakes see Crétaux et al. (2016) and Birkett et al. (2021), for wetlands see Papa and Frappart (2021)) and (3) GWBL can be computed from networks of VS, which however is challenging for non-permanent water bodies (Pfeffer et al. 2014). As stated before, TIR studies for GW resources are mainly made via the surface temperature evolution of small water bodies to localize GW inputs, excluding the use of space-based TIR sensors as their spatial resolution is too low (Lopez et al. 2016). Moreover, airborne campaigns are expensive to implement. However, with the dissemination of UAV observations, one can hope that also TIR-based studies will further increase our knowledge about GW resources in Africa. Ground deformations obtained by InSAR have the potential to detect GW extraction areas and to provide information on aquifer dynamics. However, only few studies exist for the African continent. In particular the combination of InSAR measurements with GRACE has a high potential for investigating GW flow dynamics and is a current matter of research with particular challenges arising from the resolution mismatch. In future, GW potential mapping that uses RS observations and machine learning approaches to identify optimal zones for GW development could be of increasing importance for the African continent (Díaz-Alcaide and Martínez-Santos 2019; Al-Djazouli et al. 2021).

In general, the great chance of Africa is its vast amount of GW resources, which, however, have to be used in a sustainable way and have to be distributed efficiently, where they are needed. Remote sensing can help by quantifying the potential of individual regions, e.g., for increasing irrigated agriculture and by contributing to early warning systems for droughts and floods (e.g., Lopez et al. 2020, and references therein). Remote sensing also enables to quantify unsustainable abstraction of aquifer resources. From a scientific point of view, the North African region is very well covered by GW-related studies, whereas only few studies analyze the evolution of GW resources in SSA. One challenge for systematic GW monitoring and sustainable management over the African continent are the strongly varying regional hydro-geological properties, climate regimes, and climate change impacts. Integrated studies such as performed by Khaki et al. (2018) for the Nile catchment or by Abdelmohsen et al. (2020) for the NSAS are needed for the individual regions to obtain a more complete picture of complex GW processes and issues, with the final scope to use these insights for deriving regional water management strategies. In this regard, the joint evaluation of remote-sensing observations, in situ data, and appropriate models is essential to derive future projections of GW evolution.

From a water management perspective, also the connection of regional aquifers with surface water bodies (either direction) is of interest in terms of regional availability of water resources. GW – surface water interaction includes a variety of processes and flow directions (e.g., Cook 2015): (1) GW discharge to surface water bodies (river, lakes, coast), (2) GW recharge from surface water bodies, and (3) hyporheic exchange, which often operates in both directions on comparatively short spatial and temporal scales.

However, although it is well known that GW and surface water resources are interconnected, in many countries they are treated as more or less separate entities, in terms of research effort as well as decision making. This can lead to overallocation of water resources with sometimes significant consequences in (semi-)arid zones, e.g., in the Australian Murray Darling basin (Young and McColl 2009; Cook 2015), or in South Africa (Levy and Xu 2012). There are wide-ranging examples (mostly from outside of Africa) of rivers, wetlands, or lakes where flow or storage volume substantially decreased due to GW pumping, which lead to a reduction of GW flows to surface water bodies (e.g., Postel 2000; Sophocleous et al. 1995). Conversely, diversion or extraction of river or lake water has the potential to reduce GW recharge, thus affecting GW levels and GW availability.

An improved understanding of the connection between GW and surface water is also fundamental for addressing water quality issues of both surface and GW resources, in particular with respect to nutrient and contaminant enrichment and transport in GW or the protection of riparian and GW-dependent ecosystems. Indeed, some of the largest inland deltas are located on the African continent (Niger, Kavango), and they arguably must be considered some of the largest GW-dependent ecosystems.

Whilst aquifer recharge by streamflow is more or less well understood on a large scale, e.g., from the Chari-Logone and Niger Rivers (e.g., Gonçalvès et al. 2021; Andersson et al. 2017), little research has been carried out on discharge to surface water bodies, with exception of the large inland deltas of the Niger and Okavango Rivers (e.g., Nganje et al. 2017; Milzow et al. 2009).

Submarine Groundwater Discharge (SGD) to the coast is a special case of GW – surface water interaction, because it represents a ‘loss’ of continental freshwater resource (unlike GW – river interaction). Whilst SGD fluxes can be locally important, global estimates derived from hypsometric modeling suggest little freshwater ‘loss’ to the ocean from African shorelines except on the coastlines of Guinea, Nigeria, Cameroon, Gabon and Madagascar (e.g., Zhou et al. 2019). Local quantitative estimates of GW – ocean flow remain rare on the continent, some exceptions being SGD rates derived from the Tunisian Djeffara aquifer applying a GRACE water balance (Gonçalvès et al. 2021) and GW inflow into the Knysna estuary in South Africa (Petermann et al. 2018). In addition to being a well-recognized process delivering dissolved elements from land to sea (e.g., Taniguchi et al. 2019), freshwater SGD forms a natural barrier against salinization of coastal aquifers. Where coastal aquifers are pumped, the reduction in water level can lead to infiltration of seawater, often rendering coastal GW resources unusable. This is increasingly observed on the African continent, mainly due to large coastal population density and uncontrolled shallow GW extraction (e.g., Agoubi 2021). Due to substantial urbanization and concentration of mega cities in Africa’s coastal zone, this is a particular problem in urban hydrology on the continent, as documented e.g., in Port Harcourt, Nigeria (Ofoma et al. 2008).

In summary, in comparison to other continents, GW – surface water interactions are not well understood, and present a significant opportunity for water resource research on the African continent with important contributions from RS.

Generally, remote-sensing-based GW observations have a high potential for the following applications over Africa:

- Fresh water security: Continuous monitoring of GW evolution is the basis for developing water management strategies that guarantee fresh water availability for population, agriculture, and industry. Furthermore, GW and SW should be used conjunctively to make it easier to react on short-term water shortage.

- Early warning systems: Existing drought and flood monitors for the African continent like the African Flood and Drought Monitor (AFDM Sheffield et al. 2014) developed by the Princeton Climate Institute (PCI, https://www.princetonclimateinstitute.org) or the East African Drought Watch (EADW, https://droughtwatch.icpac.net/) do not include GW or TWSA observations, which however could add valuable information.
- Climate change resilience: Deriving water management strategies that adapt to changing climate conditions requires reliable predictions of GW evolution and drivers. Understanding the impact of climate modes can help to develop management strategies, where e.g., water is stored from wet to dry climate cycles.

The above applications require long and continuous time series with near real-time availability. From a methods point of view, most GW-related studies over Africa are based on simple time series analysis (e.g., multi-linear regression) of different climate variables. Yet, in particular for future projections and for increasing the spatial and/or temporal resolutions more sophisticated evaluation concepts are needed. In this regard, we introduced advanced statistical tools in Sect. 4.2. PCA and ICA can be used to extract dominating modes from data sets and also to adjust data originating from different sources toward each other. Via data assimilation observations and numerical models can be combined. On the one hand, the model is pulled models toward the observations, and, on the other hand, observations are downscaled horizontally, vertically, and temporally. Alternatively, other Bayesian approaches like BMA or DMDA can be used to merge information from different data sources and have great potential for future applications. Furthermore, different approaches based on artificial intelligence can be applied to downscale remote-sensing observations and are particularly suited to generate long and continuous data records and projections into the future.

Obviously, future satellite missions will even further increase the role of remote sensing for GW research. Relevant missions are in particular future gravity missions (to continue the GRACE/GRACE-FO) time series, but also new sensors like the Surface Water and Ocean Topography (SWOT, Altenau et al. 2021; Wang et al. 2022) mission, which aims at measuring terrestrial surface waters with unprecedented accuracy. Furthermore, during the next few years several Sentinel satellites will be launched (https://sentinels.copernicus.eu/web/sentinel/missions/copernicus-expansion-missions) and provide additional observations of e.g., soil properties, soil moisture, and land cover. Another great opportunity for GW monitoring are regional Earth Systems Models (ESMs) that run at high spatial resolution and integrate a number of remote sensing and in situ observations. ESMs are particular interesting to study the interactions between the different components of the water cycle, e.g., the impact of GW changes on atmospheric circulation. They can also be used to study possible impacts of climate change scenarios and anthropogenic drivers.

However, there remains a gap between scientific insights regarding GW management strategies based on remote sensing (or model / in situ approaches) and their actual application on the African continent. In order to make better use of remote-sensing-based information of GW changes at the local scale, better accessibility of the data sets for the responsible authorities is required. Scientific achievements need to be broken down to central insights that are understandable by local authorities. Workshops and manuals explaining the application of individual remote-sensing techniques for GW monitoring may help to increase their use. Furthermore, cloud computing tools like Google Earth Engine can contribute to a broader use of remote-sensing-based information.

All in all, we conclude that remote-sensing-based GW observations together with numerical models and improved communication with local research institutions, government agencies, local stakeholders including the private sector are essential for designing appropriate management strategies to meet the UN sustainable development goals for the African continent.

Appendix 1 GRACE: Measurement Principle, Gravity Field Solutions, and Postprocessing

The GRACE and GRACE-FO missions consist of two identical satellites, chasing each other at a distance of about 220 km, and at an initial height of 500 km, which decreased with duration of the GRACE mission down to 330 km. The near circular orbit at 89° inclination ensures near global coverage. The orbital period of 94 minutes leads to a dense spatial coverage after 30 days of continuous observations. The low–low Satellite-to-Satellite Tracking (SST) concept realized by the GRACE mission assumes that the change in distance between the two co-orbiting satellites is related to the difference in the Earth's gravitational potential at the respective locations. When the first satellite approaches a gravity anomaly, it is attracted toward this anomaly and the distance to the trailing satellite increases. When the trailing satellite is also attracted toward the gravity anomaly, the distance decreases again. The inter-satellite range is measured with an accuracy of 1 μm using a dual one-way K-Band Microwave Ranging (KBR) system. The Earth's gravity field is computed from measured ranges, positions from Global Positioning System (GPS) measurements, the satellites' orientation from star cameras, and non-gravitational forces measured by accelerometers.

Three official processing centers, the Centre for Space Research (CSR) in Texas, the German Research Centre for Geosciences (GFZ) in Potsdam, and the NASA Jet Propulsion Laboratory (JPL), provide monthly solutions of GRACE gravity fields in three different formats: (1) as Spherical Harmonic (SH) or Stokes coefficients, (2) as gridded time series of TWSA where post processing is already applied, and (3) as regularized solutions based on so-called mass concentration blocks (mascons, only provided by CSR and JPL). For a given application the user can chose the appropriate type of solution and download it from the websites of the processing centers.

(i) Stokes coefficients represent the global structure of the gravity field in spectral domain. Due to the measurement configuration of the GRACE mission SH coefficients of degree 1 and 2 need to be replaced by external data sets during post processing (Chen et al. 2005). Furthermore, correlated noise leads to North-South striping patterns and has to be removed by spatial filtering. Since the start of the GRACE mission large improvements have been made regarding the development of tailored filtering approaches (Werth et al. 2009). The optimal filter depends on the geographical location, shape and signal characteristics. Signal loss induced by filtering can be restored by rescaling the filtered data (Long et al. 2015). Rescaling factors on a global grid including uncertainty estimates are provided by e.g., Landerer and Swenson (2012). In his seminal paper, Wahr et al. (1998) derives the computation of TWSA in terms of Equivalent Water Height (EWH) from the (filtered) Stokes coefficients. c_{nm} and s_{nm} as following:

$$\mathrm{TWSA}(\theta,\lambda)=\frac{M}{4\pi R^2\rho_w}\sum_{n=0}^{n_{\max}}\sum_{m=0}^{n}\frac{2n+1}{1+k'_n}\left(c_{\mathrm{nm}}\cos(m\lambda)+s_{\mathrm{nm}}\sin(m\lambda)\right)P_{\mathrm{nm}}(\cos\theta), \quad (3)$$

where θ and λ are geocentric colatitude and longitude, respectively, R is the Earth's mean radius, M is the mass of the Earth, P_{nm} are the fully normalized associated Legendre functions of degree n and order m, $n_{\max}$ is the maximum degree of the SH coefficients, and k'_n are the dimensionless degree-dependent gravitational load Love numbers, which represent the average Earth properties (Farrell 1972). In many applications, GRACE data are evaluated for river basins described by a given polygon or basin function. Expressing the basin function in terms of SH coefficients ζ^c_{nm} and ζ^s_{nm} spatially averaged TWSA can be directly computed from the Stokes coefficients according to Swenson and Wahr (2002):

$$\mathrm{TWSA}_{region}=\frac{M}{4\pi R^2\rho_w}\sum_{n=0}^{n_{max}}\sum_{m=0}^{n}\frac{2n+1}{1+k'_n}\left(\zeta^c_{nm}c_{nm}cos(m\lambda)+\zeta^s_{nm}s_{nm}sin(m\lambda)\right)P_{nm}(cos\theta). \quad (4)$$

The accuracy of catchment averaged TWSA depends on regional mass distribution, which governs signal leaking inside or out of the basin, and the catchment size (Longuevergne et al. 2010). Again signal attenuation can be taken into account by rescaling, e.g., according to Long et al. (2015).

(ii) All processing centers also provide gridded time series of monthly TWS anomalies (TWSA) where post processing is already applied. The user can chose the filter that should be applied. If rescaling is necessary for the application, rescaling factors must either be computed or downloaded from data provided by previous studies, e.g., Landerer and Swenson (2012).

(iii) Regularized solutions based on so-called mass concentration blocks (mascons) are constrained with information from geophysical models and are originally estimated on 1° or 3° grids and then resampled to a 0.5° grid (Watkins et al. 2015; Save et al. 2016). In contrast to the SH approach, noise reduction and signal restoration are implemented within the processing framework of mascon solutions by applying constraints. In comparison to SH solutions, leakage of land signal into the ocean is reduced by explicitly defining the mascons over the continents. Further postprocessing is not required. Still, even if mascon solutions are provided on a 0.5° grid the native resolution of GRACE data of about 300 km cannot be increased.

Scanlon et al. (2016) compared SH and mascon solutions for hydrological applications and provides recommendation regarding the choice of the solution for a given application. During the last few years, the number of hydrological studies using GRACE mascon solutions exclusively or in comparison to SH solutions increased (e.g., Shamsudduha et al. 2017; Vishwakarma et al. 2021b; Sun et al. 2020). Differences between the individual solutions are shown for Africa by e.g., Grippa et al. (2011); Rateb et al. (2017); Ahmed and Wiese (2019); Ramillien et al. (2014).

The actual spatial resolution of GRACE data is difficult to quantify due to the spatial correlation structure and varies depending on latitude and signal strength (Longuevergne et al. 2010). Usually, at the equator a spatial resolution of about 300 km is assumed at an accuracy of few cm in terms of EWH (Landerer and Swenson 2012). The accuracy of GRACE-based TWSA increases toward the poles due to higher spatial coverage. A higher accuracy is also achieved by averaging over larger catchments and reaches from 0.7 cm EWH for catchments of 400,000 km^2 area to 0.3 cm EWH for catchments of 400,000,000 km^2 (Swenson et al. 2003). Recent GRACE solutions even enable the evaluation of TWSA in catchments with moderate hydrological signals that are smaller than 100 000 km^2 (e.g., Biancamaria et al. 2019). Some groups also provide solutions (SH coefficients or mascons) at increased temporal resolution down to weekly or daily gravity fields (Kurtenbach et al. 2012; Ramillien et al. 2015, 2020; Croteau et al. 2020), which goes at the expense of the spatial resolution (less than 1000 km for daily gravity fields), except for the regional solutions (i.e., similar to mascons) from Ramillien et al. (2015, 2021) which updates the grids of GRACE-based TWS using an approach based on the Kalman filter. Another option are regional GRACE solutions using e.g., optimized radial base functions, which might increase the spatial resolution of the data in the focus region (Eicker 2008). The user needs to chose the solution appropriate for a given application (Scanlon et al. 2016).

The International Centre for Global Earth Models (ICGEM, http://icgem.gfz-potsdam.de) provides a number of different solution in SH format (filtered or unfiltered), allows for online evaluation and download on user-defined grids, and also provides visualization tools for gridded data and catchment averaged time series. Mascons can also be downloaded from the GRACE Tellus website https://grace.jpl.nasa.gov/data/get-data/.

Radar Altimetry and its Specificities over Inland Waterbodies

The principle of radar altimetry is the following. The orthometric height h observed by the altimeter is obtained as the difference between the altitude of the satellite platform on its orbit H, the measured range R taking into account several propagation $\Delta R_{propagation}$ and geophysical $\Delta R_{geophysical}$ corrections, and the geoid height N (Chelton et al. 2001; Frappart et al. 2017):

$$h = H - (R + \sum \Delta R_{propagation} + \sum \Delta R_{geophysical} - N) \quad (5)$$

with:

$$R = \frac{c\Delta t}{2}, \quad (6)$$

where c is the velocity of the light in the vacuum and Δt is the two-way round-trip of the electromagnetic wave emitted by the sensor.

The propagation corrections for path delays due to the ionosphere (ΔR_{ion}) and the dry and wet troposphere components (ΔR_{dry}, and ΔR_{wet}), respectively, are computed according to

$$\sum \Delta R_{propagation} = \Delta R_{ion} + \Delta R_{dry} + \Delta R_{wet}. \quad (7)$$

Over land surfaces, these corrections are derived from Total Electron Content (TEC, for the ionosphere) and meteorological models (for the troposphere) (Cretaux et al. 2017).

Geophysical range corrections are computed from

$$\sum \Delta R_{geophysical} = \Delta R_{solidEarth} + \Delta R_{pole}, \quad (8)$$

where $\Delta R_{solidEarth}$ and ΔR_{pole} are the corrections to account for the crustal vertical motions due to the solid Earth and pole tides, respectively.

Over inland water bodies, RA echoes or waveforms (i.e., the histogram of the energy received by the sensor as a function of time) generally exhibit a peaky shape, except over large lakes where the waveform is similar to the ocean case, or over complex water bodies (e.g., braided rivers) where several peaks can be observed (Cretaux et al. 2017). The tracking point, where the range is accurately determined, cannot be obtained applying a retracking algorithm based on the Brown model devoted to ocean-like radar echoes (Brown 1977). The purpose of retracking is to reprocess the collected waveforms with a particularly suited algorithm to provide a reliable estimate of the range. Several studies showed that the altimeter ranges derived from the Offset Center Of Gravity (OCOG) retracking algorithm, empirically representing the waveform as a rectangle (Wingham et al. 1986), provide the more suitable results for estimating water levels over inland water bodies (e.g., Frappart et al. 2006; Santos da Silva et al. 2010; Shu et al. 2021).

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Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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