Estimation and Validation of Groundwater Storage Anomalies in the Kwale Aquifer, Kenya

A Case Study on the Applicability of GRACE and GLDAS for Monitoring Groundwater Temporal Variability in Small Coastal Aquifers of Data-Scarce Regions

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ABSTRACT

Monitoring groundwater variability is essential for sustainable water resource management, particularly in regions with limited in-situ observations. This study evaluated the temporal consistency between Gravity Recovery and Climate Experiment (GRACE) derived Groundwater Storage Anomalies (GWSA) and in-situ measured borehole water levels in Kwale County, Kenya. Monthly GRACE Mascon data (CSR RL06.03) and borehole records (January 2007–December 2023) were standardized to z-scores to remove unit and baseline differences, enabling direct pattern-based comparisons. Pattern agreement was quantified using Pearson's correlation, Spearman's rank correlation, Nash–Sutcliffe Efficiency (NSE), and cross-correlation analysis. The results indicate a statistically significant and moderately strong linear relationship between GRACE and borehole anomalies (r = 0.578, p < 0.001), and a weak but significant monotonic association (ρ = 0.327, p = 0.0033). The positive NSE (0.156) demonstrates that GRACE is capable of capturing month-to-month variability in borehole water levels. Cross-correlation analysis identified the highest correlation at lag 0 months, showing that GRACE and borehole water level records respond concurrently to hydrological changes. The findings confirm that GRACE is capable of reproducing local groundwater variability patterns in Kwale County despite differences in the measurement scale and potential noise in borehole data. The demonstrated agreement supports the application of GRACE as a complementary groundwater monitoring tool in data-scarce regions, thus contributing to improved groundwater resource assessment, management, and protection.

Keywords-borehole; GRACE; groundwater; GLDAS; satellite

I. INTRODUCTION

Groundwater is one of the most important freshwater resources in the world, as it supports the needs of industries, agriculture, and residential areas. It provides over 40% of the world's irrigation water and almost 50% of its drinking water [1]. However, climate change, poor management, and increasing demand have caused widespread groundwater depletion, particularly in arid and semi-arid regions [2]. In sub-Saharan Africa, including Kenya, groundwater is the primary water source, especially during prolonged dry seasons [3].

The sustainable management of water resources depends on tracking the changes in groundwater storage. However, limited long-term records, inadequate infrastructure, and low spatial coverage are common drawbacks of conventional approaches that rely on in situ observations [4]. Nonetheless, large-scale water monitoring has been transformed by satellite-based technology, such as the GRACE and GRACE follow-on (GRACE-FO). When paired with Land Surface Models (LSMs), such as the Global Land Data Assimilation System (GLDAS), GRACE's monthly estimates of Total Water Storage Anomalies (TWSA) enable the estimation of GWSA in an area [5].

The usefulness of satellite-derived water data in data-poor areas has been highlighted. Authors in [6] demonstrated the potential of predictive groundwater modeling under climate change scenarios using remote sensing and climatic inputs. Their method emphasizes how crucial it is to incorporate contemporary instruments into groundwater assessments, particularly in light of the pressure from extreme climate.

Drought has become frequent and severe in Kenya, especially in coastal regions that rely primarily on shallow groundwater aquifers, such as Kwale County. The region's water security is at risk due to these droughts, which have been made worse by climate change and unsustainable groundwater removal [7]. There is also an increasing demand for groundwater from industrial activities, notably large-scale mining and irrigation, especially from the sugarcane cultivation sector recently introduced in the area, putting more pressure on local aquifers [8]. Yet, despite their strategic importance, small coastal aquifers remain under-monitored. Effective groundwater management in the region is hampered by a lack of long-term data monitoring. Hence, there is a need to assess the feasibility of using GRACE-GLDAS-based groundwater estimation in such localized data-scarce settings. It has been indicated that, although GRACE's coarse spatial resolution is optimized for large basins, meaningful insights can still be extracted for smaller regions through statistical analysis and validations [4, 9].

The estimation of GWSA in Kwale County, Kenya, is presented in this study through the integration of GRACE Mascon data with GLDAS LSM outputs. Measured groundwater level data from local boreholes were used to validate the satellite-derived GWSA. To assess the degree of agreement between in-situ data and satellite-based observations, statistical techniques, including Pearson's correlation, Spearman's rank correlation, NSE, and cross-correlation analysis, were applied to z-score standardized monthly datasets. The findings provide insights into the suitability and reliability of GRACE-derived data for groundwater monitoring in small coastal aquifers, thereby supporting improved water resource planning and implementation of drought resilience strategies.

II. RESEARCH GAPS

There are still a number of unanswered questions about satellite-based hydrological monitoring, especially in terms of the effectiveness of GRACE-derived groundwater estimations in small-scale aquifer systems. Due to the sensor's coarse spatial resolution (300 km), the majority of GRACE-based studies have concentrated on large river basins or continental-scale groundwater trends, raising questions about its suitability for smaller hydrological units, such as Kenya's coastal aquifers [10, 11]. Furthermore, in East Africa, particularly in data-poor areas, such as Kwale County, very few studies have systematically confirmed GRACE-GLDAS-derived GWSA with in situ borehole data at the local scale. Additionally, limited research has been done on evaluating the statistical robustness (Pearson's correlation, Spearman's rank correlation, NSE, and cross-correlation analysis) of GRACE-based estimates in coastal environments that are vulnerable to saltwater intrusion and seasonal recharge. Therefore, more research is required to fully understand the accuracy and reliability of the groundwater signals derived from satellites in small coastal aquifers.

III. DATA AND METHODS

A. Study Area

Kwale County occupies an area of roughly 8,270 km^2 and is located along Kenya's southeast coast, between latitudes 4°10'S and 4°30'S and longitudes 39°10'E and 30°35'E. It comprises diverse geological strata, such as Quaternary sands, coralline limestones, Magarini sands, and Mazeras sandstones, which underlie the area. The latter has an eastern boundary with the Indian Ocean and is located within the Kenyan coastal sedimentary basin [12, 13]. The terrain varies from sea level flat coastal plains to the higher Shimba Hills in the west, which reach an elevation of about 420 m. The county has a tropical climate, with an average rainfall of 800 to 1,200 mm per year. It has a bimodal rainfall pattern with "long rains," occurring from March to May, and "short rains," occurring from October to December. Its closeness to the Indian Ocean affects its climate, which causes regional variations in Evapotranspiration (ET) and precipitation [13, 14].

Coastal sands and coral limestones make up the shallow unconfined aquifer of Kwale, whereas the Magarini and Mazeras formations include deeper confined aquifers. The main supply of water for households, agriculture, and tourism comes from these aquifers. However, population expansion, climate change, industrialization, and seawater intrusion are putting strain on both groundwater quantity and quality [15].

Seawater intrusion has been documented in areas as far as 6.5 km inland, particularly in the coralline limestone aquifers of coastal areas, such as Msambweni and Ukunda [13]. Public health issues have also been raised by reports of microbial contamination and salinity in the shallow wells and community boreholes [16, 17]. Studies using satellite remote sensing and hydrogeological modeling have brought to attention the region's temporal unpredictability, especially during extreme climate events like the La Niña drought of 2016-17 [18]. More than 80% of the wells under observation showed a decrease in Groundwater Storage (GWS) during this period, but recovery usually took 2-3 years [15]. These dynamics make Kwale County a suitable site for integrated satellite-based groundwater monitoring using GRACE, GLDAS, and in situ observation data. Figure 1 shows the study area and monitored borehole locations.

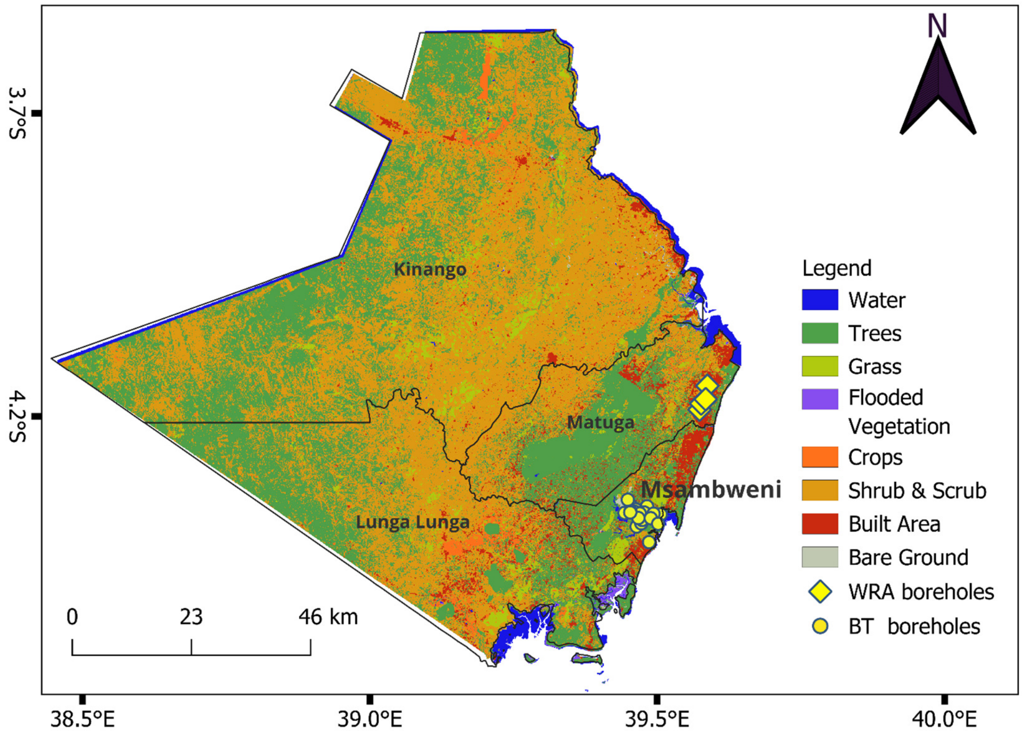

Fig. 1. Monitored borehole locations in the study area overlaid on the 2024 Dynamic World land cover map (processed in QGIS).

B. Data Sources

1) GRACE

The GRACE satellite project, collaboratively constructed by NASA and the German Aerospace Center (DLR), has significantly enhanced the global surveillance of Terrestrial Water Storage (TWS) fluctuations since its inception in 2002. GRACE operated until 2017 and was then subsequently succeeded by the GRACE-Follow-on (GRACE-FO) mission, which was launched in May 2018, perpetuating the tradition of monthly mass change observations on a near-global scale [19, 20].

The GRACE and GRACE-FO satellites quantify temporal fluctuations in the Earth's gravitational field using twin satellites in a polar orbit, roughly 220 m apart. Variations in inter-satellite distance, predominantly due to mass redistribution on the Earth's surface (such as alterations in water storage), are transformed into spherical harmonic solutions or gridded mass concentration, Mascon products that depict anomalies in Liquid Water Equivalent (LWE) thickness [21, 22].

This study employed the GRACE/GRACE-FO RL06.03 Mascon "All Corrections" monthly product created by the Center for Space Research (CSR) at the University of Texas at Austin. This dataset includes all proposed geophysical and geodesic corrections, such as Glacial Isostatic Adjustment (GIA), atmospheric and ocean dealiasing, and geocenter motion corrections, and is referenced to a mean baseline over the period 2004-2009 [21, 23]. The RL06.03 version features refined destriping and scaling methodologies, enhanced instrument calibration, and revised background models [19, 24].

The benefit of using mascon solutions is their enhanced signal-to-noise ratio and minimal post-processing smoothing requirement compared to conventional spherical harmonic solutions [25]. This product is already scaled and adjusted for signal leakage, making it appropriate for regional-scale hydrological applications without the need for further gain factor modifications [22]. Several investigations have confirmed the efficacy of CSR Mascon data in relation to solutions from NASA Jet Propulsion Laboratory (JPL) and German Research Center for Geosciences (GFZ), determining that CSR solutions exhibit strong consistency for regional hydrological applications, particularly in Africa [26, 27].

2) GLDAS Land Surface Data Model

GLDAS is an LSM framework created by NASA's Goddard Space Flight centre in partnership with NOAA. It integrates satellite data, terrestrial observations, and atmospheric model outputs using sophisticated LSMs to worldwide reframe terrestrial hydrological and energy cycles at elevated spatial and temporal resolutions [28].

GLDAS operates multiple LSMs, notably Noah, CLM, VIC, and MOSAIC, to quantify essential surface and subsurface variables, including Soil Moisture (SM), Canopy Water Storage (CWS), Snow Water Equivalent (SWE), ET, and surface runoff [28]. This study employed the Noah LSM version 2.1 for its established stability, global applicability, and reliable efficacy in modeling water balance components in data-scarce areas, such as Eastern Africa [29].

3) Measured Borehole Groundwater Level Data

This study employed in-situ groundwater level data from the Water Resources Authority (WRA) of Kenya, covering a network of thirty-nine boreholes throughout Kwale County. The spatial distribution of the monitoring network is markedly unequal, with the bulk (35 boreholes) positioned in Msambweni sub-county from the base titanium water resource monitoring network, while the remaining 4 boreholes are located in Matuga sub-county. These borehole water level observations are indicated in m above mean sea level, documenting site-specific observations of aquifer conditions across several hydrogeological zones of the county [14]. The dataset covers the period from 2007 to 2023. Nevertheless, the measurement records are in some cases irregular and sparse. Figure 1 illustrates the study area location and provides a spatial representation of the borehole locations.

C. Methods

1) TWSA from GRACE

The RL06.03 Mascon product used in this study presents LWE anomalies at a spatial resolution of 0.5° × 0.5°, based on a climatological baseline from 2004 to 2009, and includes all proposed geophysical corrections [21]. Monthly GRACE LWE anomalies were extracted for the period 2002-2025 and restricted to the geographic limits of Kwale County using a bounding box delineated by its administrative boundaries. Ocean grid cells and regions with missing values were excluded to isolate terrestrial signals, while the remaining data were spatially averaged to generate a representative monthly times series of TWS anomalies for the county. The CRS RL06.03 Mascon product is pre-scaled to minimize signal leakage and does not necessitate additional gain factor modifications, making it appropriate for regional hydrological research [19, 25]

The TWSA series reflects monthly variations in terrestrial water content relative to the long-term average, including GWS, SM, surface water, and Biomass Water Storage (BM), which can also be expressed as CWS and SWE [30]. This is expressed by:

$$\mathrm{TWS_{GRCAE}} = \mathrm{GWS + SM + SWE + CWS} \quad (1)$$

where $\mathrm{TWS_{GRCAE}}$ is GRACE-derived Total Water Storage (TWS) (cm/month), and GWS, SM, SWE, and CWS are also in cm/month.

The processed GRACE TWS anomalies were used in conjunction with GLDAS LSM outputs to estimate GWSA in the study area [21, 31].

2) TWSA from GLDAS and Estimation of GRACE-Derived GWSA

The Noah LSM version 2.1 used in this study offers monthly worldwide estimates on land surface states and fluxes with a spatial resolution of 0.25° × 0.25°. The GLDAS-derived TWSA over Kwale County was extracted from 2002 to 2025. The dataset was then clipped to match the spatial coverage of GRACE data using the same bounding box over the county. The TWS is determined by aggregating the water retained in diverse land surface components:

$$\mathrm{TWS_{GLDAS}} = \mathrm{SM + SWE + CWS} \quad (2)$$

CWS is often omitted unless the study area involves dense forests, which is not characteristic of Kwale County, which is a semi-arid and coastal ecosystem. Due to the equatorial environment of Kwale County, SWE was deemed insignificant but kept in the storage budget [30]. In this study, the GLDAS TWS was calculated as the aggregate of SM and SWE:

$$\mathrm{TWS_{GLDAS}} = \mathrm{SM + SWE} \quad (3)$$

where *SM* and *SWE* are in cm/month.

The GWSA was estimated by deducting GLDAS-modeled TWS from GRACE TWS:

$$\mathrm{GWS} = \mathrm{TWS_{GRACE}} - (\mathrm{SM + SWE})_{\mathrm{GLDAS}} \quad (4)$$

3) Validation of GRACE-Derived GWSA Using the Measured Borehole Water Levels

The borehole water level records from WRA for Kwale County were utilized as ground-based reference data to validate the GRACE-derived GWSA. The borehole time series, initially sampled at various times for each borehole, were combined to one dataset and then aggregated into monthly averages to align with the temporal resolution of GRACE data. Temporal alignment was accomplished by deriving monthly averages through the start-of-month resampling (MS) method [32]. The GRACE-derived GWSA measurements and borehole water levels were subsequently synchronized by month over their shared timeframe in the period 2002 to 2025. Since GRACE measurements indicate spatially averaged TWSA in cm of LWE, and borehole records point-based water levels in m above sea level, both time series were standardized through z-score normalization to facilitate a direct trend comparison. The z-score was calculated as:

$$z = \frac{X - \mu}{\sigma} \quad (5)$$

where X is the observed value, μ is the mean of the time series, and σ is the standard deviation. This treatment removes scale and unit discrepancies while maintaining relative variability [33].

The agreement between GRACE-derived GWSA and borehole water level time series was assessed following the statistical evaluation framework proposed in [34], for monthly datasets with low serial dependence. Three complementary statistical measures were also employed to evaluate the similarity between the normalized GRACE and borehole series:

- Pearson's correlation coefficient (r) assessed linear association:

$$r = \frac{\sum_{i=1}^{n}(Gi - \bar{G})(yi - \bar{y})}{\sqrt{\sum_{i=1}^{n}(Gi - \bar{G})^2} \cdot \sqrt{\sum_{i=1}^{n}(yi - \bar{y})^2}} \quad (6)$$

where Gi and yi are the paired observations from GRACE and borehole series, and $\bar{G}$ and $\bar{y}$ are their respective means.

- Spearman's rank correlation coefficient (ρ) measures monotonic relationships and is less sensitive to outliers and non-linear patterns:

$$\rho = \frac{6\sum_{i=1}^{n} di^2}{n(n^2-1)} \quad (7)$$

where di is the difference between the ranks of paired values, and n is the number of observations.

- NSE evaluates how well the temporal variation in the borehole series is produced by GRACE anomalies:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(yi - Gi)^2}{\sum_{i=1}^{n}(yi - \bar{y})^2} \quad (8)$$

with values > 0 indicating better than mean performance [35, 36]. Finally, lagged relationships were assessed by computing the cross-correlation function between the z-score series for lags from -12 to +12 months. This identifies whether one dataset systematically leads or lags the other [34].

IV. RESULTS

A. Comparison of TWSA from GRACE and GLDAS

A comparative analysis of TWSA obtained from the GRACE/GRACE-FO satellite Mascon product and GLDAS LSM was performed to assess consistency and discern the structural differences between remotely sensed and model-based hydrological estimates in Kwale County for the period 2002-2025. Figure 2 illustrates the temporal progression of GRACE TWSA and GLDAS TWSA, averaged across the study region and adjusted for baseline to the common reference period 2004-2009. The monthly trends from both datasets demonstrate comparable timing of peaks and troughs, reflecting consistency in seasonal water storage dynamics at the regional level. Nonetheless, GRACE TWSA consistently exhibits greater amplitudes than those from GLDAS estimations. This disparity is anticipated, as GLDAS models water retained in surface SM, snow, and CWS, while excluding the groundwater component that GRACE explicitly measures through its sensitivity to total mass change [37, 38].

A regression analysis of the two datasets, as shown in Figure 3, yields a coefficient of determination (R^2 = 0.23), which falls within the acceptable range of 0.2-0.5, as reported in [30, 39] for comparisons involving GRACE-based data. This level of agreement supports the utility of GRACE in reflecting regional hydrological variability, even in a small area like Kwale County.

The overall consensus in monthly fluctuations corroborates the reliability of GRACE-derived TWSA in the study area, consistent with prior regional evaluations that illustrated GRACE's effectiveness in comparatively small watersheds [30, 40].

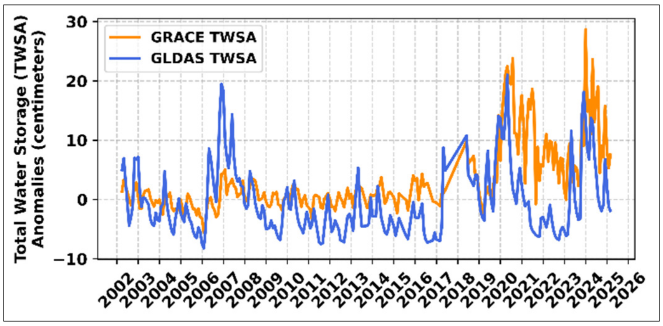

Fig. 2. Comparison of monthly GRACE and GLDAS TWSA over Kwale County, spatially averaged, baseline: 2004-2009, CSR Mascon RL06.03 and GLDAS Noah V2.1.

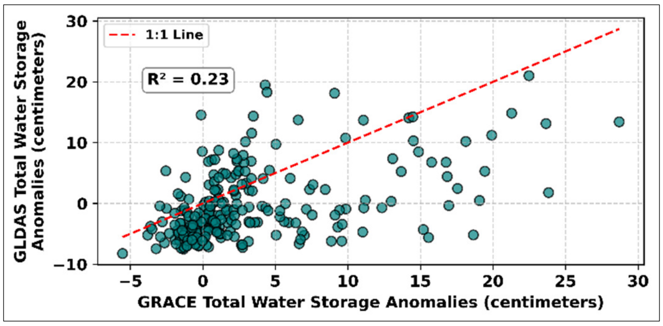

Fig. 3. Scatter plot of monthly GLDAS TWSA versus monthly GRACE TWSA.

1) Validation of GWSA with Borehole Data

The statistical agreement between GRACE-derived GWSA and borehole water level series is summarized in Table I.

TABLE I. STATISTICAL COMPARISON BETWEEN MONTHLY GRACE-DERIVED GWSA AND BOREHOLE WATER LEVEL SERIES (2007–2023)

Metric	Value	*p*-value
Pearson correlation (r)	0.578	< 0.001
Spearman correlation (ρ)	0.327	0.0033
NSE	0.156	–
Cross-correlation (max) at lag 0 months	0.578	< 0.001

The z-score standardized GRACE-derived GWSA and borehole water level time series showed a moderate to strong positive association over the 79 months of overlapping data. The Pearson correlation coefficient was r = 0.578 (ρ < 0.001), indicating that months with above-average GRACE anomalies generally coincided with above-average borehole water levels, and months with below-average GRACE anomalies coincided with below-average borehole water levels. This confirms that the two datasets track the same general pattern of groundwater variation [41]. Figure 6 displays the scatter plot of the two datasets.

The Spearman's rank correlation coefficient was $\rho = 0.327$ ($p = 0.0033$), suggesting that the association between the two series is preserved even when considering only the rank order of anomalies, though the relationship is weaker than the linear correlation. This implies that while the datasets agree on the direction of change most of the time, differences in the magnitude of those changes reduce the strength of the rank correlation [42].

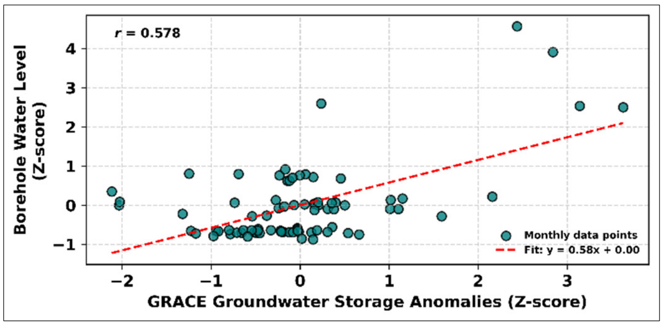

Fig. 4. Scatter plot of standardized monthly GRACE-GWSA and monthly borehole water level time series.

The NSE was 0.156, which, although low, is positive, meaning that GRACE anomalies provide a better fit to the borehole time series than simply using the borehole mean as a predictor. Given that the two datasets measure different hydrological signals (satellite-integrated storage against point-scale water level) and cover a relatively short and discontinuous overlap, this NSE still supports the utility of GRACE for capturing local groundwater variability in Kwale County [35].

The cross-correlation analysis showed that the highest correlation occurred at lag 0 months ($r = 0.578$), indicating that changes in GRACE-derived storage occur in the same month as changes in borehole water levels. Figure 7 depicts the correlation between GWSA and the borehole water level.

Figure 6 illustrates the monthly GWSA derived from GRACE. Figure 7 shows the monthly mean of the borehole water level timeseries and the GRACE-derived GWSA. Figure 8 presents the GWSA and borehole monthly mean aligned common period direction of change, while Figure 9 exhibits the comparison between normalized GRACE-derived GWSA and monthly mean borehole water level time series.

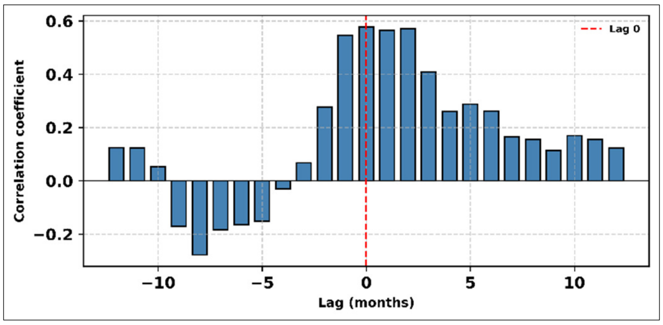

Fig. 5. Cross-correlation between monthly GRACE-GWSA and monthly borehole water level time series.

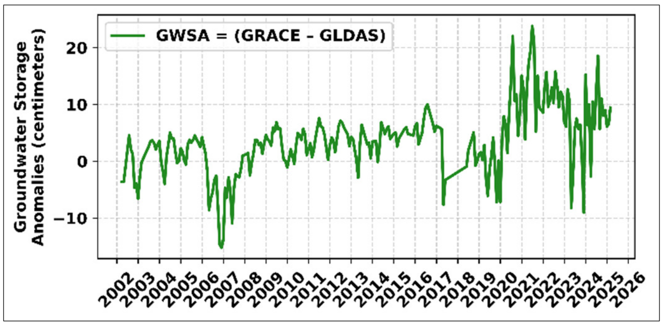

Fig. 6. Monthly GWSA over Kwale county, difference between GRACE CSR RL06.03 and GLDAS Noah V2.1, baseline 2004-2006.

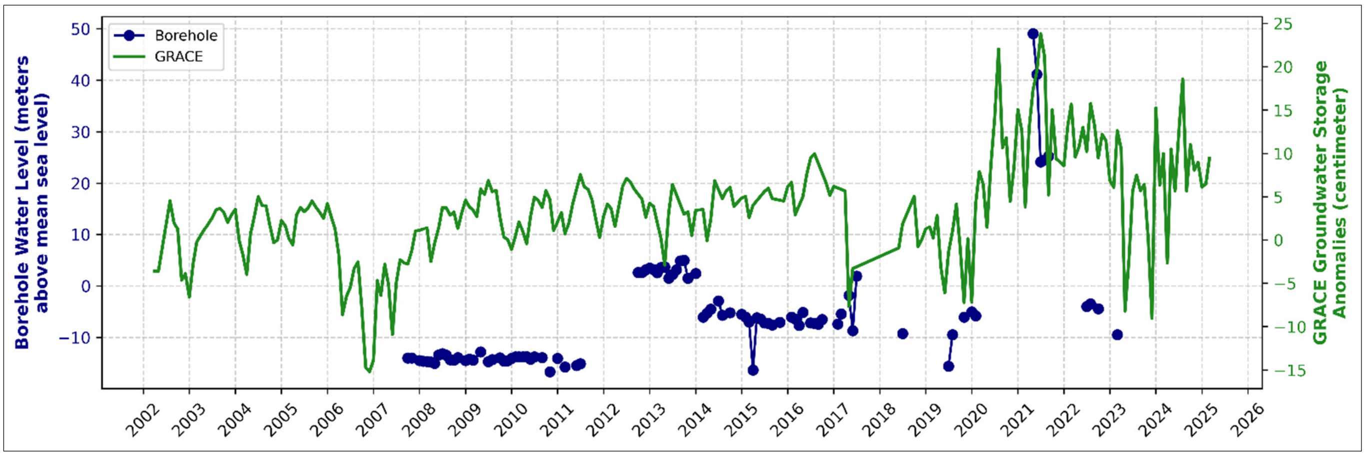

Fig. 7. Visual comparison of unaligned monthly mean borehole water level timeseries and GRACE-derived GWSA.

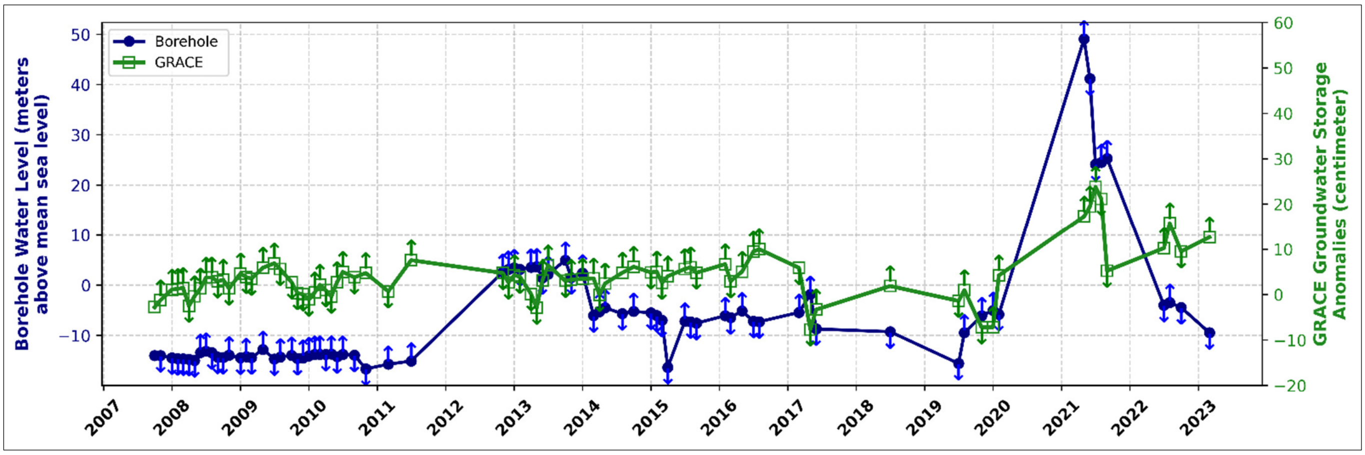

Fig. 8. Direction of change in borehole water level and GRACE-derived GWSA, monthly aligned time series over Kwale County.

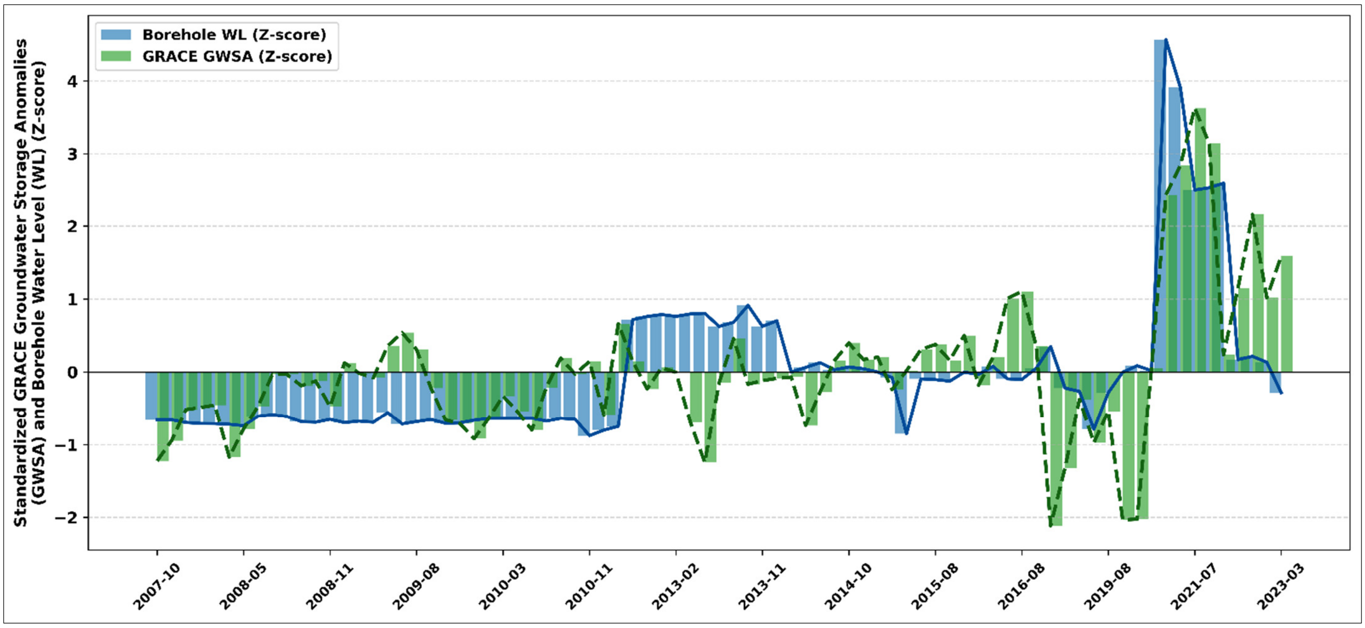

Fig. 9. z-score normalized aligned monthly GWSA and monthly mean borehole water level.

V. CONCLUSION

This study evaluated the consistency between Gravity Recovery and Climate Experiment (GRACE) derived Groundwater Storage Anomalies (GWSA) and in-situ borehole water level anomalies in Kwale County, Kenya, using monthly data aggregated and standardized to z-scores. Applying the pattern agreement framework used in [34], the results showed a statistically significant and moderately strong linear correlation (r = 0.578, p < 0.001) and a weaker but still significant monotonic association (ρ = 0.327, p = 0.0033). The positive Nash–Sutcliffe Efficiency (NSE) (0.156) further indicated that GRACE captured a meaningful portion of the observed temporal variability. The cross-correlation analysis revealed the highest correlation at lag 0 months, confirming that GRACE and borehole records respond concurrently to hydrological changes.

These findings demonstrate that GRACE is capable of reproducing the month-to-month variability observed in local borehole water levels despite the differences in measurement scale and potential sources of noise. While the correlation strengths indicate that GRACE does not fully capture all site-specific dynamics, the concurrent patterns support its use as a complementary tool for groundwater monitoring in data-scarce regions. In settings, such as Kwale County, where long-term and continuous borehole records are limited, GRACE offers a valuable resource for assessing regional groundwater variability and supporting water resource management decisions.

DATA AVAILABILITY

The dataset utilized in this study, CSR GRACE/GRACE-FO RL06.3 Mascon Solutions (RL0603), is publicly accessible and can be downloaded from the Center for Space Research (CSR) at the University of Texas at Austin: http://www2.csr.utexas.edu/grace.

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REFERENCES

[1] L. Wang, C. Chen, X. Ma, Z. Fu, Y. Zheng, and Z. Peng, "Evaluation of GRACE Mascon Solutions Using in-situ Geodetic Data: The Case of Hydrologic-induced Crust Displacement in the Yangtze River Basin," *Science of The Total Environment*, vol. 707, Mar. 2020, Art. no. 135606, https://doi.org/10.1016/j.scitotenv.2019.135606.

[2] F. Alshehri and A. Mohamed, "Analysis of Groundwater Storage Fluctuations Using GRACE and Remote Sensing Data in Wadi As-Sirhan, Northern Saudi Arabia," *Water*, vol. 15, no. 2, Jan. 2023, Art. no. 282, https://doi.org/10.3390/w15020282.

[3] E. Nkiaka, R. G. Bryant, M. Okumah, and F. F. Gomo, "Water Security in Sub-saharan Africa: Understanding the Status of Sustainable Development Goal 6," *WIREs Water*, vol. 8, no. 6, Nov. 2021, Art. no. e1552, https://doi.org/10.1002/wat2.1552.

[4] J. Nanteza, C. R. De Linage, B. F. Thomas, and J. S. Famiglietti, "Monitoring Groundwater Storage Changes in Complex Basement Aquifers: An Evaluation of the Grace Satellites Over East Africa," *Water Resources Research*, vol. 52, no. 12, pp. 9542–9564, Dec. 2016, https://doi.org/10.1002/2016WR018846.

[5] M. Rodell, J. Chen, H. Kato, J. S. Famiglietti, J. Nigro, and C. R. Wilson, "Estimating Groundwater Storage Changes in the Mississippi River Basin (USA) using GRACE," *Hydrogeology Journal*, vol. 15, no. 1, pp. 159–166, Jan. 2007, https://doi.org/10.1007/s10040-006-0103-7.

[6] R. A. Ramadan and S. Boubaker, "Predictive Modeling of Groundwater Recharge under Climate Change Scenarios in the Northern Area of Saudi Arabia," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13578–13583, Apr. 2024, https://doi.org/10.48084/etasr.7020.

[7] T. D. Bhaga, T. Dube, M. D. Shekede, and C. Shoko, "Impacts of Climate Variability and Drought on Surface Water Resources in Sub-Saharan Africa Using Remote Sensing: A Review," *Remote Sensing*, vol. 12, no. 24, Dec. 2020, Art. no. 4184, https://doi.org/10.3390/rs12244184.

[8] N. Ferrer *et al.*, "How Does Water-reliant Industry Affect Groundwater Systems in Coastal Kenya?," *Science of The Total Environment*, vol. 694, Dec. 2019, Art. no. 133634, https://doi.org/10.1016/j.scitotenv.2019.133634.

[9] B. D. Vishwakarma, "Monitoring Droughts from GRACE," *Frontiers in Environmental Science*, vol. 8, Dec. 2020, Art. no. 584690, https://doi.org/10.3389/fenvs.2020.584690.

[10] J. K. Dharpure, I. M. Howat, and S. Kaushik, "Declining Groundwater Storage in the Indus Basin Revealed Using GRACE and GRACE-FO Data," *Water Resources Research*, vol. 61, no. 2, Feb. 2025, Art. no. e2024WR038279, https://doi.org/10.1029/2024WR038279.

[11] Y. Zhong *et al.*, "Reinterpreting Global GRACE Trends Based on Century-Long GRACE-REC Data," *Water Resources Research*, vol. 59, no. 12, Dec. 2023, Art. no. e2023WR035817, https://doi.org/10.1029/2023WR035817.

[12] M. Groen, H. Rolf, C. Rutto, and M. Lane, "Geophysics Kwale," Technical Report II, SamsWater, Phoenix, AZ, USA, Mar. 2019.

[13] C. Beatrice, "Assessment of the Potential for Managed Groundwater Recharge as a Mitigation to Saline Water Intrusion - Case Study of Coastal Aquifers, Kwale County, Kenya," Master of Science Thesis, University of Nairobi, Nairobi, Kenya, 2024.

[14] N. F. Ramos *et al.*, "Evidence of groundwater vulnerability to climate variability and economic growth in coastal Kenya," *Journal of Hydrology*, vol. 586, July 2020, Art. no. 124920, https://doi.org/10.1016/j.jhydrol.2020.124920.

[15] N. Ferrer Ramos and A. Folch Sancho, "Assessment of a Groundwater System Under Global Change Scenarios: The Case of Kwale (Kenya)," Ph.D thesis, Universitat Politècnica de Catalunya, 2019.

[16] J. W. Kilwake, "Assessment of Water Quality in Boreholes and Wells in Waa Location, Kwale County- Kenya," Master of Science Thesis, Pwani University, Kilifi, Kenya, 2016.

[17] M. P. Schlegelmilch, A. Lakhani, L. D. Saunders, and G. S. Jhangri, "Evaluation of Water, Sanitation and Hygiene Program Outcomes Shows Knowledge-behavior Gaps in Coast Province, Kenya," *Pan African Medical Journal*, vol. 23, 2016, https://doi.org/10.11604/pamj.2016.23.145.7546.

[18] N. Ferrer, A. Folch, M. Lane, D. Olago, J. Odida, and E. Custodio, "Groundwater Hydrodynamics of an Eastern Africa Coastal Aquifer, Including La Niña 2016–17 Drought," *Science of The Total Environment*, vol. 661, pp. 575–597, Apr. 2019, https://doi.org/10.1016/j.scitotenv.2019.01.198.

[19] B. D. Loomis, S. B. Luthcke, and T. J. Sabaka, "Regularization and Error Characterization of GRACE Mascons," *Journal of Geodesy*, vol. 93, no. 9, pp. 1381–1398, Sept. 2019, https://doi.org/10.1007/s00190-019-01252-y.

[20] B. D. Tapley *et al.*, "Contributions of GRACE to Understanding Climate Change," *Nature Climate Change*, vol. 9, no. 5, pp. 358–369, May 2019, https://doi.org/10.1038/s41558-019-0456-2.

[21] H. Save, S. Bettadpur, and B. D. Tapley, "High-resolution CSR GRACE RL05 Mascons," *Journal of Geophysical Research: Solid Earth*, vol. 121, no. 10, pp. 7547–7569, Oct. 2016, https://doi.org/10.1002/2016JB013007.

[22] F. W. Landerer *et al.*, "Extending the Global Mass Change Data Record: GRACE Follow-On Instrument and Science Data Performance," *Geophysical Research Letters*, vol. 47, no. 12, June 2020, Art. no. e2020GL088306, https://doi.org/10.1029/2020GL088306.

[23] V. G. Ferreira *et al.*, "Estimating Groundwater Recharge Across Africa During 2003–2023 Using GRACE-derived Groundwater Storage Changes," *Journal of Hydrology: Regional Studies*, vol. 56, Dec. 2024, Art. no. 102046, https://doi.org/10.1016/j.ejrh.2024.102046.

[24] S. Deng, Y. Liu, and W. Zhang, "A Comprehensive Evaluation of GRACE-Like Terrestrial Water Storage (TWS) Reconstruction Products at an Interannual Scale During 1981–2019," *Water Resources Research*, vol. 59, no. 3, Mar. 2023, Art. no. e2022WR034381, https://doi.org/10.1029/2022WR034381.

[25] D. N. Wiese, F. W. Landerer, and M. M. Watkins, "Quantifying and Reducing Leakage Errors in the JPL RL05M GRACE Mascon Solution," *Water Resources Research*, vol. 52, no. 9, pp. 7490–7502, Sept. 2016, https://doi.org/10.1002/2016WR019344.

[26] P. Wang, S.-Y. Wang, J. Li, J. Chen, and Z. Qi, "Comparison of GRACE/GRACE-FO Spherical Harmonic and Mascon Products in Interpreting GNSS Vertical Loading Deformations over the Amazon Basin," *Remote Sensing*, vol. 15, no. 1, Jan. 2023, Art. no. 252, https://doi.org/10.3390/rs15010252.

[27] M. Zhang *et al.*, "Evaluation of Terrestrial Water Storage Changes over China Based on GRACE Solutions and Water Balance Method," *Sustainability*, vol. 14, no. 18, Sept. 2022, Art. no. 11658, https://doi.org/10.3390/su141811658.

[28] M. Rodell *et al.*, "The Global Land Data Assimilation System," *Bulletin of the American Meteorological Society*, vol. 85, no. 3, pp. 381–394, Mar. 2004, https://doi.org/10.1175/BAMS-85-3-381.

[29] L. V. Santarosa, G. V. F. Pinto, J. S. Blandón Luengas, and D. Gastmans, "Remote Sensing to Quantify Potential Aquifer Recharge as a Complementary Tool for Groundwater Monitoring," *Hydrological Sciences Journal*, vol. 69, no. 16, pp. 2455–2465, Dec. 2024, https://doi.org/10.1080/02626667.2024.2412741.

[30] Y. O. Ouma, D. O. Aballa, D. O. Marinda, R. Tateishi, and M. Hahn, "Use of GRACE Time-variable Data and GLDAS-LSM for Estimating Groundwater Storage Variability at Small Basin Scales: A Case Study of the Nzoia River Basin," *International Journal of Remote Sensing*, vol. 36, no. 22, pp. 5707–5736, Nov. 2015, https://doi.org/10.1080/01431161.2015.1104743.

[31] M. Rodell *et al.*, "Emerging Trends in Global Freshwater Availability," *Nature*, vol. 557, no. 7707, pp. 651–659, May 2018, https://doi.org/10.1038/s41586-018-0123-1.

[32] B. R. Scanlon, L. Longuevergne, and D. Long, "Ground Referencing GRACE Satellite Estimates of Groundwater Storage Changes in the California Central Valley, USA," *Water Resources Research*, vol. 48, no. 4, Apr. 2012, Art. no. 2011WR011312, https://doi.org/10.1029/2011WR011312.

[33] N. Fei, Y. Gao, Z. Lu, and T. Xiang, "Z-Score Normalization, Hubness, and Few-Shot Learning," in *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, Montreal, QC, Canada, Oct. 2021, pp. 142–151, https://doi.org/10.1109/ICCV48922.2021.00021.

[34] M. E. Coffey, S. R. Workman, J. L. Taraba, and A. W. Fogle, "Statistical Procedures for Evaluating Daily and Monthly Hydrologic Model Predictions," *Transactions of the ASAE*, vol. 47, no. 1, pp. 59–68, 2004, https://doi.org/10.13031/2013.15870.

[35] F. Lin, X. Chen, and H. Yao, "Evaluating the Use of Nash-Sutcliffe Efficiency Coefficient in Goodness-of-Fit Measures for Daily Runoff Simulation with SWAT," *Journal of Hydrologic Engineering*, vol. 22, no. 11, Nov. 2017, Art. no. 05017023, https://doi.org/10.1061/(ASCE)HE.1943-5584.0001580.

[36] P. Sedgwick, "Pearson's Correlation Coefficient," *BMJ*, vol. 345, no. jul04 1, pp. e4483–e4483, July 2012, https://doi.org/10.1136/bmj.e4483.

[37] M. Rodell, I. Velicogna, and J. S. Famiglietti, "Satellite-based Estimates of Groundwater Depletion in India," *Nature*, vol. 460, no. 7258, pp. 999–1002, Aug. 2009, https://doi.org/10.1038/nature08238.

[38] D. Long, B. R. Scanlon, L. Longuevergne, A. Y. Sun, D. N. Fernando, and H. Save, "GRACE Satellite Monitoring of Large Depletion in Water Storage in Response to the 2011 Drought in Texas," *Geophysical Research Letters*, vol. 40, no. 13, pp. 3395–3401, July 2013, https://doi.org/10.1002/grl.50655.

[39] D. D. Rowlands *et al.*, "Global Mass Flux Solutions from GRACE: A Comparison of Parameter Estimation Strategies — Mass Concentrations Versus Stokes Coefficients," *Journal of Geophysical Research: Solid Earth*, vol. 115, no. B1, Jan. 2010, Art. no. 2009JB006546, https://doi.org/10.1029/2009JB006546.

[40] M. Ahmed, M. Sultan, J. Wahr, and E. Yan, "The Use of GRACE Data to Monitor Natural and Anthropogenic Induced Variations in Water Availability Across Africa," *Earth-Science Reviews*, vol. 136, pp. 289–300, Sept. 2014, https://doi.org/10.1016/j.earscirev.2014.05.009.

[41] P. Schober, C. Boer, and L. A. Schwarte, "Correlation Coefficients: Appropriate Use and Interpretation," *Anesthesia & Analgesia*, vol. 126, no. 5, pp. 1763–1768, May 2018, https://doi.org/10.1213/ANE.0000000000002864.

[42] P. Sedgwick, "Spearman's Rank Correlation Coefficient," *BMJ*, Nov. 2014, Art. no. g7327, https://doi.org/10.1136/bmj.g7327.