Assessing surface-groundwater interactions for sustaining spring wetlands of the Great Artesian Basin, Australia

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\textbf{A B S T R A C T}

The Great Artesian Basin (GAB) is one of the world’s largest actively recharging aquifers. Groundwater discharges from the GAB sustain numerous spring wetlands, which have great ecological, scientific, and socio-economic significance. However, groundwater extraction and variation over time have had an impact on the quantity and area of spring wetlands with a 38% decline in extent since 1900. A major barrier to understanding variability in surface–groundwater interactions in spring wetlands of the GAB is the lack of observational data across critical spatial and temporal scales. Satellite observations have the ability to overcome this barrier and allow the evaluation of spring wetland responses to groundwater storage (GWS) variation. We investigated how GWS, and its associated drivers such as evapotranspiration (ET), soil moisture storage (SMS), and rainfall, in the GAB, influence the extent of surface water at five spring supergroups (Eulo, Barcaldine, Flinders, Springsure, and Springvale). We used satellite observations (2002–2017) to assess ET, SMS, rainfall, the normalized difference vegetation index (NDVI) and the modified normalized difference water index (mNDWI) for observing surface-groundwater interactions. NDVI responded positively to the GWS variation over the GAB and varies from sub-basin to sub-basin, with higher correlations in the Carpentaria sub-basin and some parts of Central and Western Eromanga. GWS variations were correlated with ET, SMS, rainfall, NDVI, mNDWI and surface water level (SWL). After a strong La Niña began in 2010, we uncovered relatively higher linear relationships between different components (ET, SMS, rainfall, NDVI, mNDWI, and SWL) and GWS variation ($R^2 > 0.50$) than before the La Niña ($R^2 < 0.50$), with the Flinders spring supergroup being the exception. NDVI and SMS are found to be the most significant predictor variables among ET, rainfall, SWL, and mNDWI components to influence GWS. This study provides improved understanding of surface-groundwater interaction in spring wetlands and the influence of different hydrological components on variation in spring wetland extent in the GAB region.

\section{1. Introduction}

Wetlands provide multiple ecological, social, and cultural benefits globally, including contributing to important ecological processes and harbouring a rich biodiversity (Seifollahi-Aghmiuni et al., 2019, Thorslund et al., 2017). Based on the dominant source of water, wetlands may be classified into different types, including surface water fed wetlands, rainfall fed wetlands and groundwater fed wetlands (Acreman and Miller, 2006). Of these wetland types, groundwater fed wetlands, or known as spring wetlands (Habermehl, 1982). They can create wetland systems that function as oasis habitats in arid or semi-arid regions (Powell et al., 2015). Individual spring wetlands are often part of larger spring complexes which, if geographically linked, can be part of spring supergroups (Habermehl, 1982). Beside their critical role in supporting ecological communities, spring wetlands can support agricultural production and economic activity as well as the provision of drinking water and recreation, especially for regions away from rivers (Flook et al., 2020). However, the hydrology and ecology of spring wetlands are often tightly linked to fluctuations in surface–groundwater interactions (Schot...
and Winter, 2006). Even relatively minor quantities of groundwater discharge can substantially improve water quality, ecological processes, and wetland communities (Acreman and Miller, 2006). Additionally, the presence of fractures in the aquifer influences the groundwater flow and discharges to the surface. These fractures and discontinuities have an impact on the hydrological characteristics of the surface water, which consequently causes uncertainties in the groundwater and surface water flow (Jahan Mohammadi et al., 2020) thus posing challenges in assessing regional flows. Surface water extent in many spring wetlands has exhibited a decreasing trend over recent times due to rapid groundwater extraction for anthropogenic daily use, agricultural processes, and climate variation (Yu et al., 2018). This has created challenges for human populations and the environment (Mousazadeh et al., 2015).

Direct and precise estimates of variation in spring extent and discharge is difficult (White et al., 2016). Many studies have emphasised the significant potential of data gained from remote sensing technologies for assessing spring wetland extent and discharge as well as the ecological effects of groundwater aquifer decline (Morawitz et al., 2006; Petus et al., 2013; Fu and Burgher, 2015) such as the Normalised Difference Vegetation Index (NDVI) (White and Lewis, 2011) and the Gravity Recovery and Climate Experiment (GRACE) (Kim et al., 2014). Interestingly, relationships have been established between the wetland extent associated with specific springs and their flow, indicating that estimates of vegetated wetland area could be used to evaluate groundwater flow (Petus et al., 2012; Petus et al., 2013; White et al., 2016). Coupling remote sensing data, such as GRACE, NDVI, and modified Normalised Difference Water Index (mNDWI), to monitor hydrological parameters, such as rainfall, spring surface extent, groundwater storage (GWS) variation and surface-groundwater interaction may improve our capability to understand spatial and temporal variation in spring eco-hydrology including how a changing climate may impact them.

Australia’s Great Artesian Basin (GAB) is associated with spring wetlands that perform critical ecological and socio-economic roles in an arid region (Habermehl, 1982; Ponder, 1986). Thirteen spring supergroups exist within the GAB’s boundary spanning multiple management jurisdictions (Habermehl, 2020). One of the major threats to spring wetlands in the GAB is groundwater extraction (Fensham and Fairfax, 2003). Groundwater extraction has significantly decreased the artesian pressure of the reservoir and rendered several of the springs inactive (Fensham and Price, 2004). Furthermore, changes in climate (rainfall variability and aquifer recharge rates) and human activities (e.g., domestic groundwater extraction, agriculture, and mining) over time, have had a detrimental influence on regional aquifer volumes and surface discharge rates, threatening spring sustainability across the entire GAB (Welsh et al., 2012). The sharp decline in the quantity and quality of spring wetlands has caused significant biodiversity losses (Fensham and Fairfax, 2003). However, a complex hydrogeology and uncertainty in the connectivity between the GAB and surface water make it challenging to quantify how springs respond to variation in regional GWS (Flook et al., 2020).

Understanding the dynamics and potential drivers of surface–groundwater interactions in spring wetlands is essential given the important ecosystem services, including water supply and societal needs, provided by spring wetlands, in the GAB (Habermehl 1982; Habermehl 2020). This is because, among other things, surface–groundwater interactions may have a big impact on the managing strategies of the aquifer storage and spring discharge (Fensham and Fairfax, 2003). The potential to evaluate the impact of GWS variation on spring wetlands is still lacking even though the spring wetlands across the GAB’s Surat sub-basin have been examined in terms of identifying effects of their source aquifers and groundwater extraction (Flook et al., 2020; Powell et al., 2015). Thus, an assessment of the hydrological properties and vegetation of spring wetlands that can result from surface water and groundwater interactions is crucial and can improve knowledge of surface–groundwater interactions in the GAB.

The main objective of this study is to assess surface–groundwater interaction to improve understanding of the variability of springs extent in the geologically complex GAB. The ability to accurately quantify surface–groundwater linkages is critical for effectively managing groundwater-dependent ecosystems and the unique biodiversity they sustain (Fensham and Fairfax, 2003). Our approach explores multivariate methods to assess GRACE-derived GWS variation in relation to other hydrological stores (e.g., soil moisture) and direct measures of surface water discharge and surface water extent. The specific objectives of this study are to (a) investigate the potential of GRACE to assess GWS anomalies by evaluating groundwater level monitoring data on different scales (monthly, seasonally), (b) quantify changes in surface water extent and vegetation greenness using mNDWI and NDVI, respectively over the spring supergroups using MODIS and Landsat, and (c) assess the surface–groundwater interactions with data from objectives 1 and 2 using partial least squares regression (PLSR). This study is vitally important for the GAB region for (a) conservation and maintenance of the springs, (b) understanding the GWS variation impacts on surface water through surface–groundwater interaction, and (c) land use management processes and policies.

2. Study area

The GAB is a multilayered, semi-confined to the confined aquifer that underlies over 1.7 million km² or nearly one-fifth of Australia (Fig. 1). The northern part of the GAB receives substantial amounts of rainfall seasonally while the majority of the basin is beneath arid and semi-arid regions with lesser amounts of rainfall (Habermehl, 2006). Since European colonization, human communities have relied heavily on the GAB’s groundwater resource for different purposes, such as pastoral activity, cattle farming, domestic water supplies, petroleum exploration, and mining activities (Habermehl, 1998). Four sub-basins, namely, Surat, Carpentaria, Western Eromanga, and Central Eromanga, with individual depocenters, are included in the GAB. Major aquifers and other geological units in the GAB all traverse the sub-basins and are interconnected through ridges or local basement highs between the geological units (Habermehl, 2009). More information on geology and hydrogeology of the GAB basin can be found in Habermehl (1998), and Habermehl (2009).

While climatic conditions vary throughout the GAB, most of the regions are either hot desert (i.e., max temp over 40 °C) or hot semi-arid regions (i.e., coldest month average temp above 0 °C (Fu et al., 2020). However, the eastern and southern regions have the hottest climate conditions (Peel et al., 2007). High rainfall occurs in the northern region of the GAB in summer (December to February) with less in winter (June to August) (Yan et al., 2017). The GAB’s eastern region, borders the Great Dividing Range, receives the highest rainfall, whereas the western region receives the least rainfall (Fu et al., 2020). Major recharge across the GAB occurs through the areas where aquifers exist in eastern peripheral zones. These zones are primarily on the western sides of the Great Dividing Range, and experience relatively significant rainfall with an average of 400–500 mm annually, in contrast to the low levels of rainfall (100–200 mm) received in the arid western boundary areas of the GAB (Fu et al., 2020). Groundwater flows towards the GAB’s southern, western, southwestern, and northern borders, where discharges occur in the form of springs (Habermehl, 1982). Many springs have unique flora and fauna and were recognised by Aboriginal people as reliable water supplies in arid regions (Ponder, 1986; Fensham and Fairfax, 2003; Habermehl, 2020). This study area comprises five regions of the GAB, including Springvale, Flinders, Eulo, Barcaldine, and Springsure spring supergroups (Fig. 1A; green clustered dots). The GAB region’s aquifers, partial aquifers, and leaky aquitards are depicted in Fig. 1B.
3. Data collection and processing

GRACE-derived GWS, soil moisture storage (SMS), and evapotranspiration (ET) from Global Land Data Assimilation System (GLDAS), in-situ GWS and surface water level from the Bureau of Meteorology (BoM), silo rainfall, NDVI, and surface water extent from MODIS are used in this study. The details of these datasets are given in the Table 1.

3.1. Groundwater storage variation

Changes in groundwater were computed using GRACE mascon products (RL06). These products were retrieved from the Center for Space Research data portal and cover the period between April 2002 and June 2017 (183 monthly intervals). The mascon method uses a time variable regularisation approach to limit the space-based range rates to gravity fields, avoiding the requirement for postprocessing. The mascon products compare well with other GRACE products, capturing the temporal and spatial characteristics of terrestrial water storage (TWS) across the globe (Scanlon et al., 2016; Save et al., 2016). The monthly GRACE observations used in this study are available on a global 0.5-degree grid. GRACE-derived TWS is the sum of changes in groundwater, surface water (e.g., lakes and reservoir storage), soil moisture, and canopy water storage. Groundwater can be quantified by subtracting relevant water storage components (e.g., soil moisture, surface water, etc.) from TWS (e.g., Agutu et al., 2019). To this end, the water budget approach (e.g., Chen et al., 2016; Ferreira et al., 2020; Ndehedehe et al., 2021) was used to compute changes in GWS by subtracting changes in model-derived soil moisture (Table 1) from TWS. Given that the GAB region is typically dry or semi-arid and has no sufficient canopy and significant changes in water bodies, GWS variation estimation from GRACE in this study was assumed to be the difference between TWS variation and changes in soil moisture. On the basis of this assumption, it is acknowledged that changes in inland surface water within the GAB

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Table 1
List of various datasets used in this study.

<table>
<thead>
<tr>
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<td><a href="https://www2.cs.r.utexas.edu/grace/RL06_mascons.html">https://www2.cs.r.utexas.edu/grace/RL06_mascons.html</a></td>
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1 https://www2.csr.utexas.edu/grace/RL06_mascons.html.
and much of Australia is negligible, and that utilising these components to distinguish changes in GWS from TWS variation may result in increased uncertainty when calculating GWS variation (Chen et al., 2016; Ndehedehe et al., 2021). GWS variation over the GAB from TWS (neglecting surface and canopy water storage components) are calculated by using Eqs. (1) and (2), respectively.

GWS variation = TWS variation - Surface water storage variation - Soil moisture storage variation

GWS variation (GAB region) = TWS variation – Soil moisture storage variation

3.2. Groundwater aquifers in the Great Artesian Basin

Monitoring bores used for validation of GRACE-derived GWS are screened in the Condamine Alluvial aquifer (CA). The CA ranges in thickness from less than 10 m to approximately 130 m in the central part of the region. The CA sediments were deposited beginning in the Tertiary in lacustrine environments, evolving into fluvial meandering stream deposits during the Quaternary (Kelly et al., 2006; Dafny and Silburn, 2014). The structure of the resulting formation is a laterally and vertically heterogeneous mix of fine, mixed, and coarse granular materials. The CA is underlain by a confining unit, separating it from the Jurassic bedrock aquifers below it.

Cenozoic cover of the bedrock aquifers throughout the GAB is not isolated within the Surat basin, but is common, in varying degrees, across the entire GAB (Radke and Ramley, 2020). Furthermore, these surficial, semi-confined, unconsolidated units show varying degrees of hydrologic connectivity between the underlying confined aquifer and surface water bodies. This may create a complex system of inputs and outputs from a given hydrogeologic unit depending on conditions in bounding units (e.g., Dafny and Silburn, 2014, Pandey et al., 2020).

Within the CA, Dafny and Silburn (2014) described the potential inputs and outputs. Direct input from the underlying bedrock aquifers is limited due to the transitional confining unit. This, however, may vary locally depending on the thickness or lack of the underlying transitional confining unit. Streambed recharge is another source of recharge to the CA, but this source would vary considerably seasonally and from year to year. Finally, diffuse recharge to percolation through the vadose zone is an input flux. Historically, this was considered to be negligible or absent, but it is possible that this source has increased over time with increasing furrow irrigation within the region. Overall, the lack of monitoring bores, especially within the bedrock aquifers across the GAB, variability in trans-basin through-flow, and vertical interconnectivity between aquifers create a complex system of water fluxes.

In this study, in-situ borewell data from 30 borewells was accessed from BoM using the Groundwater Explorer tool (https://www.bom.gov.au/water/groundwater/explorer/map.shtml) to extract data between 2002 and 2017. The depth of the groundwater borewells is between 13 m and 120 m, with the 30 borewells studied considered to be shallow unconfined aquifers. Groundwater anomalies were evaluated individually by removing mean values of water levels from the existing values at all borewell locations, followed by a depth conversion by reversing the sign. This data was used to validate the GRACE-derived GWS variation.

3.3. Groundwater level monitoring

The accessed groundwater level monitoring data from BoM are multiplied by the specific yield to convert it into GWS variation for unconfined aquifers. Specific yield (Sy) is a dimensionless value and can be defined as the water quantity that can be drained from an unconfined aquifer under gravity. Groundwater level monitoring data can be converted into GWS variation using equation (3) as

\[
\Delta \text{GWS} = S_y \cdot \Delta \text{GWL},
\]

where \( \Delta \text{GWS} \) represents GWS variation, \( S_y \) represents specific yield for the unconfined aquifer, and \( \Delta \text{GWL} \) represents changes in groundwater levels (Gehman et al., 2009; Rateb et al., 2020). For the GAB region, the specific yield value used is 0.01 (OGIA, 2019). This way, the groundwater level was converted to groundwater anomalies by multiplying groundwater level values by the specific yields for all the borewells.

3.4. Soil moisture and evapotranspiration

In this study, GLDAS Noah data was used for accessing soil moisture data at monthly intervals. The mean values from April 2002 to June 2017 (183 monthly intervals) were removed from all the data to provide the anomalies that could be compared to GRACE data. The GLDAS Noah data used in this study has a spatial resolution of 0.25° * 0.25°. We upscaled the soil moisture data to 0.5° * 0.5° resolution to make it consistent with the GRACE terrestrial water storage data. Soil moisture storage data was removed from GRACE terrestrial water storage data to obtain the GWS variation over the GAB. Furthermore, GLDAS Noah data was also used for retrieving evapotranspiration data for the selected sites from 2002 to 2017.

3.5. Rainfall and surface water level

Queensland’s monthly gridded rainfall data was provided by BoM on 0.05° * 0.05° spatial resolution from April 2002 to June 2017 (183 monthly intervals consistent with other data). The surface water levels for the same time frame as rainfall data were obtained from BoM. The rainfall and surface water level data in this study were used for the purpose of assessing impacts on spring surface water extent within five spring superfroups.

3.6. Normalized Difference Vegetation Index

The NDVI, defined as a ratio of reflectance of the ground surface in the red (Rred) and near-infrared (Rnir) wavelength channels describes changes in the greenness of vegetation cover globally (Bhanja et al., 2019). High NDVI values indicate increasing healthy vegetative cover and a low NDVI values indicate the possibility of decreasing vegetation cover due to water stress.

Monthly MODIS and Landsat 7 satellite data were used in this study to determine the GAB region’s NDVI variability between 2002 and 2017. MODIS satellite observations were used for the spring superfroup regions (Springvale, Eulo, Flinders, Barcaldine, Springvale), whereas Landsat data was used for regions that lie in spring superfroups. Spring superfroups are the ones which are in close proximity spatially, aquifer sources are same and have quite same water chemistry. The spatial resolution of MODIS (500 m) was a limitation in the small regions, while data gaps caused by the impacts of clouds restricted the availability of continuous Landsat data for the superfroups. To make NDVI data consistent with the GRACE GWS, NDVI from MODIS satellite data were reprojected and quantified to 0.5° * 0.5° grid. Here, we investigated the possibility of using NDVI as a GWS indicator.

3.7. Total surface water extent

MODIS Landsat-7 satellite observations were used to obtain the spring superfroups surface water extent. Specifically, MODIS/061/MOD09GA1 terra surface reflectance 8-day global 500 m MODIS product was used to generate surface water extent based on the modified Normalised Difference Water Index (mNDWI; e.g., Xu, 2006). The Google Earth Engine (https://code.earthengine.google.com/) tool was used to obtain and process the Landsat 7 data record (e.g., Yan et al., 2020) from 2002 to 2017. Here, the mNDWI data over the GAB were extracted from
the Landsat satellite observations. Landsat 7 data was used according to data availability for each spring supergroup site represented in Fig. 1A. The surface water extent rasters were based on the median values of overlapping cells in all images for a specific period (monthly). These rasters were calculated on a monthly basis and compared with GRACE-derived GWS variation and other parameters, such as surface water level, surface water extent, evapotranspiration, soil moisture storage, rainfall, and mNDWI.

4. Methodology

The details of the method used in this study are provided in this section. The flowchart of the methodology used here is shown in the Fig. 2.

4.1. Validation of the GRACE-derived groundwater storage variation

GRACE-derived GWS variation was compared and validated with in-situ GWS variation data. A linear regression method was used to evaluate this relationship. Even though many borewells exist across the GAB, most are used for water production and not for monitoring groundwater levels. For that reason, in this study the validation exercise of GRACE-derived groundwater focused on the Surat sub-basin of the GAB region, which exhibits the highest GWS variation. In-situ borewell data was retrieved from 30 borewells with depths ranging from 13 to 120 m. Due to temporal discontinuities, missing information, and changes in the number of time series data observations for the borewell depth from borewell to borewell, identifying a relevant well group for pre-processing is required to produce reliable observations (Bhanja et al., 2019). Therefore, we validated the in-situ high-quality observations with the GRACE-derived GWS variation over the GAB (Bhanja et al., 2016).

4.2. Correlation Analyses for GWS-vegetation cover and GWS-Surface water extent

Various methods such as correlation analysis, cross-spectral analysis, coefficient of determination and autoregression, among others have been used to assess the relationships or measure the similarity between two multivariate datasets (e.g., GRACE TWS and rainfall) recorded at different periods (e.g., Ndehedehe, 2022b). Here, the degree of agreement was assessed for GWS variation with NDVI and surface water extent in spring supergroups of the GAB region using the Pearson correlation coefficient ($r$). The time lag between GWS variation and NDVI is assessed using cross-correlation (e.g., Ndehedehe et al., 2016). The cross-correlation approach helps to understand the similarity in both data and how one responds to the other in time and space through the displacement of one variable (e.g., NDVI) relative to the other one, e.g., GWS (e.g., Boker et al., 2002; Ndehedehe, 2022b). Spatial correlation between NDVI and GWS variation monthly grids were undertaken. The time lag when the maximum correlation occurred between the two hydrological signals (i.e., GWS variation signal and NDVI signal) is reflected by the maximum correlation point in the cross-correlation method. Using the cross-correlation method, the regions with the maximum correlation between NDVI and GWS variation was observed. Furthermore, the temporal relationships of GWS-NDVI and GWS-Surface water extent were explored in the spring supergroup sites. This helped to identify locations in the GAB with the potentially stronger relationship between vegetation cover and surface water extent with GWS.

4.3. Identifying the response of different hydrological components to GWS variation

Partial Least Square Regression (PLSR) was used to identify the response of different hydrological components to GWS variation. PLSR involves regressing dependent variables on predictor scores that are a linear combination of actual predictors (e.g., Chen et al., 2018; Ndehedehe et al., 2021). The PLSR model was used in this study to assess the relationship between predictors or hydrological units (e.g., Rainfall, ET) and GWS variation within the supergroups. Modelling the response of GWS variation to these variables is critical to help improve groundwater forecasts in a potentially non-linear groundwater system, such as the GAB, and to diagnose important drivers of changes in GWS or its role in supporting springs and forest ecosystems. Unlike other parameter
estimation methods (e.g., linear regression), the PLSR helps to mitigate the effects of multi collinearity, and, more importantly, is a robust double-barrel (i.e., performs statistical decomposition on predictors prior to regression) multivariate tool that maximises the covariance between two hydrological quantities (e.g., Ndehedehe et al., 2020). Comprehensive overviews, explanations, and implementations of this approach are provided in past studies (e.g., Agutu et al., 2017; Okwuashi et al., 2020; Ndehedehe et al., 2021). In this study, the dependent variable is GWS variation, and the predictor variables are surface water level (SWL), NDVI, ET, SMS, rainfall, and mNDWI. Thus, the dependence of GWS variation in spring supergroups (Eulo, Barcaldine, Flinders, Springvale, and Springsure) on the predictor variables was measured using the PLSR (e.g., Okwuashi et al., 2020; Ndehedehe et al., 2020). To evaluate the response variable GWS variation, the predictor data matrices are statistically rotated such that only relevant PLSR components are used in predicting GWS variation (Eq. (4)). The PLSR coefficients (β in Eq. (4)) inform which members of the predictor data matrix are significant to the response variable (GWS variation).

\[ Y = X\beta + F \]

Here, β represents the PSRL coefficients, \( X_{SWL}, NDVI, ET, SMS, Rainfall/mNDWI \) represents the predictor variables, \( Y_{GWS}\) in spring supergroups represents the response variable, and F represents residuals.

5. Results

5.1. Validation of GRACE and in-situ groundwater storage variation

The average annual time series of GWS from GRACE and borewell monitoring GWS variation are similar throughout the period except for 2012, which shows a pronounced peak of almost 150 mm (Fig. 3a). GRACE GWS variation and in-situ time series are almost similar, and strong climatic influences like those of La Niña, caused by an unusually high amount of rainfall, are captured in the temporal variation of both observations.

GRACE-GWS variation and borewell-monitored GWS variation were significantly related (\( R^2 = 0.60, p < 0.01 \); Fig. 3b). Variation in GRACE GWS was positively and significantly related to variation in monitoring borewell GWS in both dry (\( R^2 = 0.54, p < 0.01 \)) and wet seasons (\( R^2 = 0.75, p < 0.01 \)) (Fig. 4).

5.2. Groundwater storage variation-land surface interaction.

5.2.1. Groundwater storage variation and vegetation

To understand the response of vegetation to GWS variation, the cross-correlation between GWS and NDVI was assessed. Fig. 5a and b represent the value of the correlation coefficient between NDVI and GWS variation spatially and the corresponding lags in months, respectively, at which GWS variation and NDVI depicts maximum correlation. Cross-correlation analysis between NDVI and GWS variation showed that NDVI responds to GWS variation for the Carpentaria (north) sub-basin and some parts of Western Eromanga (south-west) and Central Eromanga (central) sub-basins and shows that GWS variation precedes vegetation (lags range from 2 to 12 months; Fig. 5a and b). For some locations in the Surat sub-basin (south-east) and Central Eromanga (central region), it is observed that GWS variation lags vegetation. The cross-correlation between GWS and NDVI in the Surat sub-basin is considerably low (\( r \sim 0.1 \)). This could imply the complexity of the Surat sub-basin (where higher GWS variation occurs but no response to vegetation) and presence of leaky aquitard in the south-east region of the GAB shown in the Fig. 1B.

5.2.2. Groundwater storage variation and interactions with vegetation cover and surface water extent in spring supergroups

GWS variation and NDVI show a strong relationship (\( r = 0.7 \) to 0.9) in the northern region and around the central regions (Fig. 5). We further investigated the relationship between GWS variation and NDVI in five selected spring supergroups (Springvale, Eulo, Barcaldine, and Springsure; Fig. 1a). These selected spring supergroups consisted of small springs, and the clustering of small springs that made spring supergroups. The Flinders spring supergroups lie in the northern region of the GAB (Fig. 1a) and show a significantly strong relationship (\( r \sim 1 \)) between GWS variation and vegetation (Fig. 5a). Fig. 6b also confirms that the Flinders’ springs have the highest ratio coefficient value between GWS variation and NDVI (r = 0.60). The higher relationship between GWS variation and NDVI for the small sites within the Flinders spring supergroup is summarized in a supporting document (Fig. S2). The Barcaldine spring supergroup is located in the central GAB region, which also indicates a moderately higher (\( r > 0.5 \)) relationship between GWS variation and NDVI (Fig. 5a). Fig. 5d also shows a relatively higher correlation coefficient between GWS variation and NDVI (r = 0.58). For small sites within the Barcaldine spring supergroup, the relationship between GWS variation and NDVI is summarised in supporting Fig. S3. The Eulo spring supergroup that exists in the southern GAB region also represents a relatively higher correlation coefficient between GWS and NDVI (r = 0.52), which is also shown in Fig. 5a. Further information about the GWS-NDVI relationship in the Eulo spring supergroup can be seen in supporting Fig. S4. The GWS-NDVI relationship is lower in the Springvale (in the western GAB region) and Springsure (eastern GAB region) spring supergroups with r = 0.23 and 0.39, respectively (Fig. 6a, c) and for small sites, which are given in supporting Fig. S1 and S5. Even though the GWS-NDVI relationship appears to be moderately weak in two supergroups (Springvale and Springsure), the temporal evolutions of GWS variation and NDVI during the period seems fairly consistent (Fig. 6a and b).

To further investigate the spring supergroups response to GWS variation, the GWS-spring surface water extent relationship is explored. The surface water extent for spring supergroups from MODIS satellite was correlated with GWS variation. No significant relationship exists between GWS-surface water extent in the selected spring supergroups.

![Fig. 3.](image-url) (a) Time series of annual GWS variation derived from GRACE (blue) and borewell monitoring data (orange) over a 15-year time window from 2002 to 2017. Borewell monitoring data was determined from unconfined aquifers. Y-axis show GWS variation in mm. (b) Regression results using GRACE-GWS variation and borewell groundwater monitoring data between 2002 and 2017 for the Surat sub-basin of the GAB region. R² represents the coefficient of determination that exists between two GWS variation datasets. The regression line (orange) provides the relationship between GRACE-GWS and GWS changes obtained from borewell monitoring data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
However, GWS variation indicates a moderately weak association (correlation coefficient of 0.21) with spring surface water extent in Eulo (Fig. 6h). The GWS-spring surface water extent relationship for small four sites in each of the spring supergroups is provided in supporting Fig. S1, S2, S3, S4, and S5. Overall, Eulo shows a significantly higher relationship of GWS variation with vegetation cover and surface water extent compared to other spring supergroups (Fig. 6h). Furthermore, vegetation and GWS variation show a good relationship in the GAB spring supergroups. The areas of the four selected small sites within each spring supergroup are summarised in supporting Table S1. Additionally, the correlation coefficient for each small, selected site within the spring supergroup is provided in the supporting Table 2. The selected small sites in Flinders and Barcaldine spring supergroups have shown a significant GWS-NDVI relationship (Table 2). Exceptionally, site 4 in the Springsure supergroup shows a good GWS-surface water extent relationship (Table 2) and Springsure exists along the eastern border (GDR) of the GAB (Fig. 1a). The small sites within the Eulo spring supergroup depict poor or no correlation for the GWS-NDVI and GWS-surface water extent relationships (Table 2).

5.3. Surface-groundwater interaction in spring supergroups

Rainfall variability over the GAB influenced changes in GWS and surface water extent in the spring supergroups. Consequently, variation in GW resulted in difference in Land use land cover (in sq. km.) for different categories in the GAB region is provided in supporting Table S2.

The findings suggest that there exists a linear relationship between the predictor variables and response variables (Tables 3 and 4, Fig. 7). The predicted and observed GWS variation in spring supergroups was moderate for Flinders and Springsure supergroups, with moderate correlations of 0.51 and 0.48, respectively (Table 3; Fig. 7c and i) for the 2002–2009 period, and lower correlations for Eulo and Barcaldine, with $R^2$ values of 0.16 and 0.24, respectively (Table 3, Fig. 7e and 7g). On the other hand, for the 2010–2017 period, the relationship between the predicted and observed GWS variation in spring supergroups was relatively stronger for each spring supergroups, with $R^2$ values of 0.51, 0.62, 0.51, and 0.54 for the Eulo, Barcaldine, Flinders, Springsure, and Springvale supergroups, respectively (Table 4; Fig. 7b, d, f, h, j). The results suggest that the most contributing predictor variable in GWS variability in the Eulo, Barcaldine, Flinders, Springsure, and Springvale spring supergroups during the 2002–2009 period (Table 4) was NDVI (i.e., in terms of their PLSR coefficients 0.41, 0.8, 0.47, 0.97 and 0.37). However, the impact of the predictor variables on GWS variation was different during the 2010–2017 period for different spring supergroups. For example, NDVI was the best predictor variable for Eulo and Barcaldine, with relatively higher PLSR coefficient values (Table 4). But in the Flinders, Springsure, and Springvale spring supergroups, SWL and SMS had higher PLSR coefficients, suggesting they are more important predictors of GWS variation. (Table 4). Ultimately, the PSLR model results suggest NDVI, SMS, and SWL to be better predictor variables for GWS variability in spring supergroups.
The low to moderate strength of relationships between GWS variation and predictor variables ($R^2 = 0.16–0.62$; Table 3, 4) indicates the proportion of variability in GWS driven by different components in some supergroups like the Flinders (2002–2009 period), Springsure (2010–2017 period), and Springvale (2010–2017 period). These values suggest that GWS variation was fairly reasonably well predicted in those locations, especially during the 2010–2017 periods. However, it is noticeable that the temporal variation of the predicted and observed GWS variation across all supergroups between 2002 and 2008, a period that coincided with the Millennium drought, have large residuals or uncertainties (Fig. 7a, c, e, g, i).

There are also relatively large residuals during the ‘big wet period’ (2009–2012) in the Barcaldine and Springsure supergroups (Fig. 7h and j). But overall, the temporal variation of GWS in these supergroups are somewhat better predicted during the 2010–2017 period, as opposed to the Millennium drought period. The large uncertainties associated with GWS during the Millennium drought arguably may be linked to human water extraction during the period and not the suitability of the PLSR model.

6. Discussion

6.1. GRACE groundwater storage variation validation

In this study, we demonstrated that satellite-derived information on GWS variation during a 15-year period was significantly related to borewell GWS variation, indicating that GRACE can potentially be (a) used to remotely monitor porewater GWS and (b) provide important information on the hydrological characteristics of linked spring wetlands. GRACE-derived GWS variation has been used in numerous previous studies and identified as a method to quantify GWS variation (Kaushik et al., 2021). The quantification of GWS variation using GRACE suggests it is a reliable data source to support the assessment of GWS variation in a region (Shamsudduha et al., 2012; Watkins et al., 2015). Our study further provides insights into stronger correlations between borewell GWS and GRACE-derived GWS during the wet (December to February) than dry (May to August) season. Generally, the strength of the relationship between GRACE-derived groundwater and data from monitoring bores may have been affected by the impact of the Millennium Drought period due to antecedent conditions and response time. Groundwater fluxes in typically dry regions like the GAB are likely to be less responsive due to the impacts of climate variability, and when human water extraction is intensified under such conditions as was seen during the period, this relationship may be compromised (e.g., Ndehe-dehe et al., 2021), and not be as high as what we observed during the big wet period. Accounting for hydraulic memory of complex groundwater 

![Fig. 6. Plots showing comparisons between monthly variation in groundwater storage (GWS) and vegetation greenness (NDVI) for each spring supergroup (a, b, c, d, e) from 2002 to 2017. Also shown is monthly variation in groundwater storage (GWS) and surface water extent for each spring supergroup (f, g, h, i, j). The correlation coefficient ($r$) represents the relationship between each time series.](image-url)

<table>
<thead>
<tr>
<th>Table 2</th>
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<tbody>
<tr>
<td>Comparison of GWS with NDVI and surface water extent for four small sites (site 1, site 2, site 3, site 4) selected in the spring supergroup areas.</td>
</tr>
<tr>
<td>Group Name</td>
</tr>
<tr>
<td>Springvale Supergroup</td>
</tr>
<tr>
<td>Flinders Supergroup</td>
</tr>
<tr>
<td>Eulo Supergroup</td>
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<tr>
<td>Barcaldine Supergroup</td>
</tr>
<tr>
<td>Springsure Supergroup</td>
</tr>
</tbody>
</table>

![Table 2](image-url)
systems like the GAB is thus crucial in adaptation strategies because of the possibility of such systems diminishing the impacts of climate change on available water resources (e.g., Ferreira et al., 2020; Agutu et al., 2019; Cuthbert et al., 2019). Hydraulic memory can also coalesce with infiltration capacity, soil conductivity, and land use change to further impact on the response of groundwater systems and its consistency with what GRACE observes at different time scales (e.g., wet vs dry periods as in our case). The West African Sahel exemplified this when, despite a prolonged extreme drought, groundwater from extensive monitoring bores showed considerable rise during the period, a phenomenon now known as the Sahelian Paradox (e.g., Ndehedehe, 2022a, b).

Moreover, we also demonstrated that borewell-monitored GWS and GRACE derived GWS in the GAB region are similar for a year following La Niña conditions. The higher temporal similarity in monitored GWS and GRACE-derived GWS post La Niña is probably due to unusually high amount of rainfall. The validation of GRACE-derived GWS with borewell-monitored GWS data calculated for the GAB region was proved in previous studies (Yan et al., 2017). Our findings also highlight that GWS variation can change substantially during high or low rainfall periods. For example, during the Millennium drought period (i.e., from 2002 to 2009), the annual peak amplitudes of GWS variation decreased after a certain time while after a La Niña period (i.e., 2010), the annual peak amplitudes GWS variation increased.

While rainfall has been widely considered an essential factor in driving GWS changes and availability, GWS variation can vary seasonally between dry seasons and wet seasons due to human water use (e.g., Ndehedehe et al., 2021; Fu et al., 2020). We found that this seasonality impacts the strength of the observed relationship between GRACE-derived GWS and borewell-monitored GWS. For dry seasons with a low amount of rainfall, the correlation between GRACE-derived GWS and borewell-monitored GWS was relatively low. This correlation was

<table>
<thead>
<tr>
<th>Spring supergroup</th>
<th>R²</th>
<th>Predictor variables and parameter estimates</th>
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</thead>
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<tr>
<td></td>
<td></td>
<td>mNDWI</td>
</tr>
<tr>
<td>Eulo</td>
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</tr>
<tr>
<td>Barcaldine</td>
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</tr>
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<td>Flinders</td>
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<tr>
<td>Springsure</td>
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<td>-0.11</td>
</tr>
<tr>
<td>Springvale</td>
<td>0.35</td>
<td>-0.09</td>
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</tbody>
</table>

Table 3: R² values and parameter estimates from PLSR models relating GWS variation to environmental predictor variables (mNDWI, SWI, NDVI, ET, SMS, Rainfall) for each spring supergroup from 2002 to 2009.

<table>
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<tr>
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</tr>
<tr>
<td>Eulo</td>
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<td>0.24</td>
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<td>Barcaldine</td>
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<td>Flinders</td>
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<tr>
<td>Springsure</td>
<td>0.51</td>
<td>-0.04</td>
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<tr>
<td>Springvale</td>
<td>0.54</td>
<td>-0.16</td>
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</tbody>
</table>

Table 4: R² values and parameter estimates from PLSR models relating GWS variation to environmental predictor variables (mNDWI, SWI, NDVI, ET, SMS, Rainfall) for each spring supergroup from 2010 to 2017.

Fig. 7. PLSR results for GWS variation for different spring supergroups with NDVI, mNDWI, SWL, rainfall, ET, and SMS as predictor variables between 2002 and 2009 (7a, c, e, g, i) and between 2010 and 2017 (7b, d, f, h, j).
evaluated for the Surat sub-basin of the GAB region, lying in the south-east and well suited for this evaluation due to occurrence of the highest GWS variation and human intervention (Kaushik et al., 2021). In other areas affected by the wet season, we found that the correlation between GRACE GWS and borewell-monitored GWS was higher. Rainfall (or climate signal) alone is not responsible for the correlation observed in the studied sub-basin seasonally. In other words, both groundwater monitoring bores and GRACE-based GWS have inherent climate-induced signals. Arguably, the studied area extent, uncertainty in GRACE signals and GWS processing (e.g., uncertainties from soil moisture depths), and the number of borewells undertaken for GWS data extraction in the study region might be driving the GRACE GWS and borewell-monitored GWS relationship.

Although it was not possible to evaluate GWS variation in the whole GAB region, we focused our evaluation on the Surat sub-basin with maximum observed borewell GWS data. Our hypothesis would be more robustly validated by more investigations of spatiotemporal GWS variation using data from additional monitoring borewells. With the GRACE-GWS validation information, we can establish seasonal GWS variation and its validation in the study region.

6.2. Role of surface–groundwater interaction in spring supergroups

Variation in the linkages between groundwater, climate, vegetation, and surface water are responsible for the spatio-temporal variation of wetland ecosystems in the GAB (White and Lewis, 2011). Additionally, GWS varies in response to groundwater extraction, NDVI changes, variation in climatic conditions, and changes in surface water flow (Foster et al., 2000). Climatic conditions (i.e., rainfall) recharge the groundwater aquifer, whereas surface discharge and groundwater extraction lead to lower the levels of GWS in the aquifer (Bhanja et al., 2018). Kaushik et al. (2021) also showed rainfall and groundwater extraction as the likely key drivers of GWS variation in the GAB region. In this study, we demonstrated how GWS variation responses in the five key spring supergroups of the GAB are related to rainfall, NDVI, mNDWI, SWL, ET, and SMS (Fig. 7). In particular, we found that GWS variation was positively related with vegetation after a La Niña (i.e., high rainfall) climatic period in the Eulo and Barcaldine spring supergroups and that GWS variation was positively related with SMS in the Flinders, Spring- sure, and Springvale spring supergroups (Fig. 6). While the impacts of surface–groundwater interaction on vegetation, wetlands, groundwater resources, and surface water ecosystems variation (e.g., Wu et al., 2020; Van der Kamp and Hayashi, 2009; Sophocleous, 2002) may change in some areas due to climate changes and human intervention, the GWS variation response to rainfall, NDVI, mNDWI, SMS, ET, and SWL during and after flood event correlates well in all spring supergroups. To corroborate this argument, we used multivariate analyses to identify the predictors for GWS variation over the spring supergroups. We found that climate variation affects the influence of different hydrological variables on GWS variation in different spring supergroups. For instance, mNDWI in the Eulo, SWL in the Flinders, vegetation in the Eulo and Barcaldine, ET in the Eulo, and SMS in the Flinders, Springsure and Springvale. Variation in spring surface water extent, for instance, were similar with periods dominated by positive extreme rainfall and surface discharges.

Between 2010 and 2017 surface water was found to play a critical role in the groundwater recharge process in most supergroups within GAB. The impacts of the La Niña are particularly underpinned by soil moisture and is evident in the latter’s PLSR coefficients for supergroups (e.g., Springsure and Springvale) indicating moderately strong relationships. Extreme wetness conditions caused by high rainfall contribute to high rates of groundwater recharge (e.g., Nebehede, 2022b). We found that the total surface water extent was an important predictor of GWS variation and for semi-arid regions, the conversion of rainfall to groundwater recharge could be slower compared to wetter recharge landscapes (e.g., Nebehede et al., 2021; West et al. 2022). Arguably, this may be the case for complex aquifer systems like the GAB and could be the reason for the low and negative PLSR coefficients of surface water extent during the 2010–2017 period (Table 2). We highlight that the spring supergroups within the GAB, such as Flinders, experienced extensive flooding during 2009 and 2010 due to higher amount of rainfall. These rainfall events helped in the recharge of the groundwater aquifers. Understanding the relationship between rainfall and groundwater recharge is crucial as it pertains to the importance of spring wetlands and how GWS variation responds to rainfall, vegetation, and other factors.

In this study, GWS variations were likely to be highly associated with vegetation greenness in the Flinders, Eulo, and Barcaldine spring supergroups (moderate rainfall regions). Springvale, lying in a drier region, did not show a strong correlation between vegetation greenness and GWS variation, indicating climate conditions are driving the relationship between vegetation and GWS variation. Consequently, vegetation greenness is another important indicator identified in the GWS recharge process, given its PLSR coefficient in supergroups (e.g., Flinders, Springsure, etc.) where the predicted and observed GWS variation were relatively stronger during the Millennium Drought period. This suggests vegetation plays an important role on the groundwater recharge process, especially during extreme drought periods, as confirmed by previous research (Kim and Jackson, 2012). This leads to the view that vegetation could be seen as an indicator of GWS variation within the spring supergroups depending upon the climate conditions.

Interaction between surface water and groundwater in wetlands is necessary to maintain biodiversity, surface water flows, ecosystem services, surface water levels, soil moisture, and vegetation which all indicate of GWS variation responses during and after maximum surface water extents. These surface–groundwater interactions are anticipated to be the key markers of GWS variation responses in the Eulo, Flinders, Barcaldine, Springvale, and Springsure spring supergroups if vegetation, surface water levels, mNDWI, SMS, and ET are predictors during heavy surface water extent periods. For the heavy rainfall in 2009, 2010 and post heavy rainfall periods, GWS variation responded well in relation to the predictor variables over all spring supergroups. In contrast to heavy rainfall periods (i.e., 2002–2009), GWS variation responded well but only within the Flinders and Springsure spring supergroups. This highlights the potential role of climate variation as a crucial factor for understanding the GWS variation response to the predictors within the spring supergroups. In general, we discovered that the Flinders spring supergroup shows the most significant spring supergroup to identify how well GWS variation responds to different predictors (NDVI, mNDWI, rainfall, SWL, ET, and SMS) even before the heavy rainfall period. The findings obtained from this study focus predictor variables, such as NDVI, mNDWI, rainfall, SWL, ET, and SMS, as critical drivers in identifying GWS variation response within the spring supergroups. The hydrology of the Flinders and Springsure wetlands existing in the GAB has historically been correlated with groundwater resources, climate variation, biodiversity, and vegetation. The response of GWS variation to climatic variations, spring surface water extent, and vegetation greenness is a critical finding that offers scientific understanding of the effects of different hydrological components on GAB’s aquifer. In addition to this, a multivariate model to enhance the identification of different hydrological components that escalates the variation in GWS in the spring supergroups of the GAB region is also an important outcome.

Field investigations for all locations may not be permitted, and the associated cost with those investigations would be high; therefore, it may not be possible to assess interaction–groundwater interaction at all locations. Our newly acquired in-depth information, which is based on publicly accessible satellite observation data, offers an opportunity to evaluate land use and rainfall effects, which is essential for developing better water resource management. Using this PLSR and correlation approaches, it is possible, for instance, to assess spring supergroup dynamics and use the resulting information to understand better how ground surface water interaction affects spring supergroup extent. Data on surface-groundwater interaction for the selected spring supergroup...
sites would be valuable for spring conservation monitoring, especially for springs under the Environment Protection and Biodiversity Conservation Act (EPBC).

We suggest implementing a similar approach for other poorly known EPBC-listed spring superfrozen groups in the GAB. This will make it possible to monitor land use, assess surface-groundwater interaction, and provide the supporting information needed for effective water resource management to sustain biodiversity. Springs are unique, providing high biological diversity and serving as an important source of several surface-water systems, and managing them to improve aquifer-surface water stewardship has been advocated (Cantonati et al., 2021). Moreover, in the spring superfrozen groups where groundwater was associated with vegetation, the representation of vegetation structure in hydrological models can significantly reduce uncertainties in the simulation of groundwater in such regions, thus improving the accuracy of outputs from models and reanalysis data.

7. Conclusion

This study validates the GRACE GWS using borewell-monitored GWS data in the GAB’s Surat sub-basin and confirms that GRACE-derived GWS can be used to monitor GWS variation in the local regions. The study also tested the implementation ability of a new indicator that can be used to identify GWS variation response in spring superfrozen groups to understand surface-groundwater interaction in the complex region. Through the estimation of some hydrological factors (NDVI, mNDWI, SWL, ET, SMS, rainfall) to predict the response of GWS variation, our study directs further research towards investigating more spring superfrozen and hydrological parameters for a better understanding of surface-groundwater interaction. This study has shown that climatic variation influences the hydrological characteristics of spring wetlands and also improves the understanding of interactions between groundwater and surface water in spring wetlands in the GAB.

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CRediT authorship contribution statement

Pankaj R. Kaushik: Conceptualization, Methodology, Visualization, Data curation, Investigation, Writing - original draft. Christopher E. Ndehedehe: Conceptualization, Data curation, Methodology, Writing - review & editing. Ryan M. Burrows: Conceptualization, Writing - review & editing. Mark R. Noll: Conceptualization, Writing - review & editing. Matthew J. Kennard: Conceptualization, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pankaj R. Kaushik reports financial support was provided by the Griffith University. Pankaj R. Kaushik reports a relationship with Griffith University that includes: funding grants. There are no patents to disclose. There are no additional activities to disclose.

Data availability

I have used publicly available datasets.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110310.

References


