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Groundwater Risk Assessment in the Arabian Basin of Saudi Arabia Through Multiple Dataset

Arya Pradipta[1] · Mohammad Makkawi[1] · Ghozian Karami[1] · Mohamed Yassin[2] · Mohammed Benaafi[2] · S. I. Abba[2] · Sinatrya Prayudi[1] · Pantelis Soupios[1]

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Abstract

Global groundwater resources have been threatened by both climate change and anthropogenic activities. Both factors could lead to groundwater depletion that might seriously threaten the living environment and food security. As one of the world's most water-stressed countries, Saudi Arabia has experienced long-term groundwater depletion due to excessive groundwater abstraction to meet the irrigation water demand. Moreover, rainfall and groundwater recharge are considered extremely low in most places in the Kingdom. Hence, a comprehensive assessment of groundwater risk in Saudi Arabia is necessary to avoid a worse scenario. The main objective of this study is to use the composite index to evaluate the groundwater risk in the Arabian Basin in Saudi Arabia. To achieve the objective, multiple variables, such as groundwater storage variations, groundwater reserves, total cropland area, and cropland expansion were integrated. The integration between physical hydrogeological assessment and anthropogenic factors is assumed to be a comprehensive risk measurement. Based on the final score, results demonstrated that Jouf and Najran could be classified as high-risk (17/100) and low-risk areas (71/100), respectively. The groundwater risk status was affected mainly by anthropogenic factors. Results of this study could serve as a diagnostic tool for decision-makers to prioritize and develop sustainable schemes, especially in high-risk areas.

Keywords Groundwater · Multicriteria decision-making · Composite index

1 Background

Groundwater is a fundamental resource that contributes to maintaining ecosystem function, achieving food security, and supporting economic growth. Since it represents approximately more than 90% of the world's available freshwater resources, groundwater can be regarded as a key element in achieving sustainable development goal 6 (SDG-6) which has the objective to ensure the availability and sustainable management of water resources. The objective of SDG-6 can only be achieved through proper management and policy that uses precautionary approaches and appropriate attention. During the last few years, numerous works have been carried out to help stakeholders achieve various targets addressed in SDG-6, such as conserving water quality [1, 2], efficiency of water use [2, 3], and integrated water resources management at all levels [2, 4].

Despite its critical role, recent studies show that the sustainability of global groundwater resources has been threatened by climate change and anthropogenic activities [5–9]. Due to increasing surface water fluctuation under climate change, groundwater demand is expected to grow. Moreover, with the current trend of climate change (continuously increasing atmospheric CO_2), returning to paleoclimatic conditions such as the Cretaceous period is possible [10]. In addition to climate change, population growth would increase groundwater abstraction and use, particularly for irrigation purposes, resulting in anthropogenic stress on water supplies. Without active and sustainable management of groundwater resources, the factors mentioned above might threaten natural ecosystem function and human livelihoods.

Assessing groundwater risk status could serve as a preliminary step for decision-makers as part of the sustainable management of groundwater resources. Groundwater risk

✉ Arya Pradipta
arprdipta@gmail.com

[1] Department of Geosciences, College of Petroleum Engineering and Geosciences, King Fahd University of Petroleum and Minerals, 31261 Dhahran, Saudi Arabia

[2] Interdisciplinary Research Center for Membranes and Water Security, King Fahd University of Petroleum and Minerals, 31261 Dhahran, Saudi Arabia

can be defined as a probability of an entity experiencing a deleterious water-related event caused by either natural conditions (e.g., hydrogeology of a specific basin), anthropogenic activities, or both [11]. Due to this definition, the groundwater risk status could serve as the basis of decision-making to ensure groundwater sustainability. The term groundwater risk should not be used interchangeably with water scarcity and groundwater stress. While water scarcity refers to volumetric availability, groundwater stress represents the ability of the system to satisfy the water demand of human and ecological sectors. Together, both scarcity and stress might inform the understanding of risk due to basin or natural conditions [11].

The existing developed water indicators to facilitate assessing the behavior of groundwater systems have focused primarily on scarcity and stress conditions. These developed water indicators range from simple to sophisticated approaches, such as Falkenmark index [12], water poverty index [13], green–blue water scarcity [14], and cumulative abstraction-to-demand ratio [15]. A sophisticated approach typically incorporates more water indicators, like soil moisture and environmental flow requirement [16]. In addition, several index-based water indicators also existed, for instance DRASTIC [17], GOD [18], SINTACS [19], and PI [20]. Despite being recognized as a suitable tool to assess groundwater system, index-based water indicator has lacuna in the form of subjective weighting and rating [21, 22]. Moreover, unlike previous water indicators, DRASTIC, GOD, SINTACS, and PI mainly focus on qualitative measurement of deleterious event such as groundwater contamination.

To date, the number of water indexes measuring risk is still limited [23]. Comprehensive risk assessment might require the involvement of anthropogenic parameters as a source of risk could come from both natural and human activities. The inclusion of anthropogenic factors in the water index has been demonstrated by prior studies, mainly for qualitative assessment [22, 24, 25].

The groundwater risk index (GRI) is one of the techniques based on a composite index to evaluate groundwater risk by integrating hydrogeological data and anthropogenic parameters at a regional scale [23]. The composite index has been increasingly used as it can summarize multidimensional issues and provides the big picture for numerous fields, such as environment, economy, and society [26]. The variable of the proposed index involves groundwater storage changes, groundwater reserves, the governance level, food security, and groundwater extraction cost. The robustness of selected indicators, choice of normalization, and aggregation method of GRI have been tested through sensitivity analysis and provide reliable results [27]. In addition, the structural flexibility of GRI (equal weighting and linear additive aggregation) will allow other users to modify its index components that represent the distinctive characteristic of groundwater sustainability in semi- to hyper-arid regions [23].

In arid environments, groundwater serves as a main water source to supply water demand; therefore, this limited resource should be evaluated against all possible risk factors. This study adopts and modifies GRI to measure the groundwater risk within the Arabian Basin of Saudi Arabia. Groundwater quantity is known as the major concern in arid regions; moreover, the availability of these data is more abundant and accessible than qualitative data [28]; thereby, this study intends to focus on quantity factor.

The application of GRI at a national scale might require some modifications on its variables, particularly anthropogenic parameters since the original anthropogenic datasets (governance level and food security) are usually provided at a national scale that leads to homogenization of spatial dimensions. Therefore, by considering that the biggest consumer of groundwater in Saudi Arabia is irrigated agriculture practices, this study replaced governance level, food security, and extraction cost with total cropland area and its expansion. The expectation of this study is to highlight the areas that are at critical risk of groundwater storage and guide the local authorities to develop better management to sustain the limited water resources in Saudi Arabia.

2 Materials and Methods

2.1 Study Area

The Arabian basin of Saudi Arabia is characterized by low annual precipitation, limited renewable groundwater storage, and the presence of deep aquifers [29]. The delineation of the Arabian Basin is provided by World-wide Hydrogeological Mapping and Assessment Programme (WHYMAP). This basin encompasses several provinces in Saudi Arabia, such as Jauf, Tabuk, Northern Border, Hail, Qassim, Riyadh, Eastern, and Najran provinces (Fig. 1). This basin is the home of several large primary aquifers that supply daily water demand for various sectors across the Kingdom.

2.2 Groundwater Reserves

Groundwater is considered as the main water source in arid regions such as Saudi Arabia. A number of primary aquifers in Saudi Arabia that are considered as good aquifers providing adequate water supply involve Saq, Wajid, Tabuk, Minjur, Wasia-Biyadh, Umm er Radhuma, Dammam, and Neogene aquifers [30]. These primary sedimentary aquifers lie within the Arabian Basin and covering two-thirds of Saudi Arabia. The aforementioned aquifers were used to estimate groundwater storage capacity in the study area.

Fig. 1 Location of the study area with administrative boundaries

Geometry (area and aquifer thickness) and hydrogeological features of aquifer (specific yield and storativity) are the two main factors of groundwater storage calculation. In this study, groundwater storage was estimated differently based on the type of aquifer: unconfined and confined aquifers. The following equation was used to calculate groundwater storages of unconfined and confined aquifers, respectively:

$$V_u = A_u \times H \times S_y \quad (1)$$

$$V_c = A_c \times H \times S \quad (2)$$

where V_u is groundwater reserves of unconfined aquifer, A_u is extent of unconfined aquifer, H is aquifer thickness, S_y is specific yield, V_c is groundwater reserves of confined aquifer, A_c is extent of confined aquifer, and S is storativity. The extent of both confined and unconfined aquifers, aquifer thickness, specific yield, and storativity were obtained from existing literatures [30–34]. In particular, the thickness of each aquifer was estimated based on the average values across the range of thickness estimates derived from various literatures (Table 1).

Table 1 Range of the thickness of each aquifer derived from various literatures

Aquifer	Thickness Range (m)
Tabuk	200–500
Saq	400–928
Wajid	200–900
Minjur	185–400
Wasia-Biyadh	600
UER	300–700
Dammam	90–130
Neogene	20–200

2.3 Groundwater Storage Changes

Traditionally, groundwater resource variations have been monitored using the availability of local well measurement data. However, it is difficult to monitor at a large scale where the gauged measurements are limited. To overcome these issues, satellite-based observations could be incorporated due to its recent improvement. Since it was launched in 2002, NASA's Gravity Recovery and Climate Experiment (GRACE) has been widely applied for numerous groundwater studies. GRACE offers unprecedented techniques to make direct observation of water stored variations above and below the earth surface, including snow, surface water, soil moisture, and groundwater at global, regional, and basin scales [35]. This approach has been widely used due to some advantages, such as long duration, wide coverage, free to public, and most importantly providing valuable insight for regions where ground-based observations are inaccessible.

The groundwater storage variations can be assessed by removing the contribution of soil moisture (SM), snow water equivalent (SWE), and surface water (SW) from terrestrial water storage (TWS) change quantified by GRACE. The effect of SW is negligible due to the fact that Saudi Arabia is located in an arid environment with lack of perennial rivers. The same condition is applied for SWE as well. Therefore, for the context of this study area, the relationship between groundwater (GW), TWS and SM can be expressed from Eq. (1)

$$\Delta \mathrm{GW} = \Delta \mathrm{TWS} - \Delta \mathrm{SM} \tag{3}$$

TWS in this study was calculated using the mass concentration block (mascon) solution released by the Center of Space Research at The University of Texas at San Austin (CSR UT-TEXAS) with a resolution of 0.5 × 0.5 from January 2010 to December 2020 and can be downloaded from https://www2.csr.utexas.edu/grace/ [36, 37]. This solution reduces the effect of leakage and measurement errors and does not require scaling factor to restore the possible signal losses during postprocessing. The monthly TWS anomalies were generated after constructing the baseline from 2004 to 2009. The missing dataset due to battery problem of GRACE satellite was computed by performing simple linear interpolation.

SM variations in this study were simulated from land surface model (LSM) developed by Global Land Data Assimilation System (GLDAS). GLDAS utilizes ground measurement and space-based observation to model global land surface states and fluxes in near real-time [38]. Three different LSM from Noah, Variable Infiltration Capacity (VIC), and catchment land surface model (CLSM) were utilized to avoid any bias coming from one model solely. The averaged value from different simulations of SM is assumed to represent a realistic model due to the limitation of the in situ dataset in the study area. In order to make it consistent with GRACE TWS anomalies, the simulated SM was converted into anomalies by subtracting monthly average of the same baseline as GRACE from observed value in each month.

2.4 Cultivated Area and its Expansion

In arid regions, the extent of cultivated area is strongly associated with groundwater variability since their water demand is mainly supplied by fossil water. It should be noted that land use is one of factors that can affect the dynamic of freshwater resources in a short period [39–41]. Therefore, this variable should be considered as a possible risk factor for groundwater sustainability.

The global land use and land cover dataset (LULC) named the Climate Change Initiative Land Cover (CCI-LC) dataset developed by the European Space Agency (ESA) was used to estimate the cultivated area and its expansion over the study period (2010–2020). ESA CCI-LC was launched to provide land cover datasets for the climate modeling community. This product has a spatial resolution of 300 m covering a one-year interval from 1992 to 2020 [42]. The ESA CCI-LC dataset was pre-processed for radiometric, geometric, and atmospheric corrections. In this dataset, land covers are classified separately using a combination of supervised and unsupervised methods from the Medium Resolution Imaging Spectrometer (MERIS). The capability of ESA CCI-LC to monitor cropland areas accurately has been demonstrated by prior studies [43–45]

2.5 Groundwater Risk Index

The risk of groundwater resources in the study area was determined by integrating groundwater storage change, groundwater reserves, cultivated area, and its expansion over the study period into a final composite index (Fig. 2). The list of all datasets used in this study is depicted in Table 2. In order to integrate aforementioned variables, a min–max transformation was performed to normalize data as described in equation below:

$$Xi_{0-100} = \frac{X_i - X_{\max}}{X_{\max} - X_{\min}} \times 100 \tag{4}$$

where $Xi_{0\text{-}100}$ is normalized value, while X_i, $X_{\max}$ and $X_{\min}$ represent the original, the maximum, and the minimum values of each indicator, respectively. Each parameter is assumed to have the same influence for calculating GRI; hence, equal weighting is applied during the aggregation step in this study. Assigning the relative importance to parameter that determine measured phenomenon is considered difficult and subjective bias [27]. Moreover, subjective weighting schemes could make it difficult for those who have diverse backgrounds to reach a consensus [46]. The aggregation of each input variable into a final composite index was performed using a simple additive arithmetic mean.

2.6 Sensitivity Analysis

The choice of individual indicators for the index might rely on subjective judgments. Therefore, their selections would not be free from any criticism. The robustness of the developed index can be evaluated using sensitivity analysis. In this study, the sensitivity test was conducted to assess the influence of individual input parameters on the index through the inclusion/exclusion of each indicator following Milewski et al. [27]. Then, the difference of region ranks between the original and modified GRI (after the exclusion of input parameter) can be explored through equation below:

$$\Delta \mathrm{rank_r} = \mathrm{rank_{original,r}} - \mathrm{rank_{exclude\ q,r}} \tag{5}$$

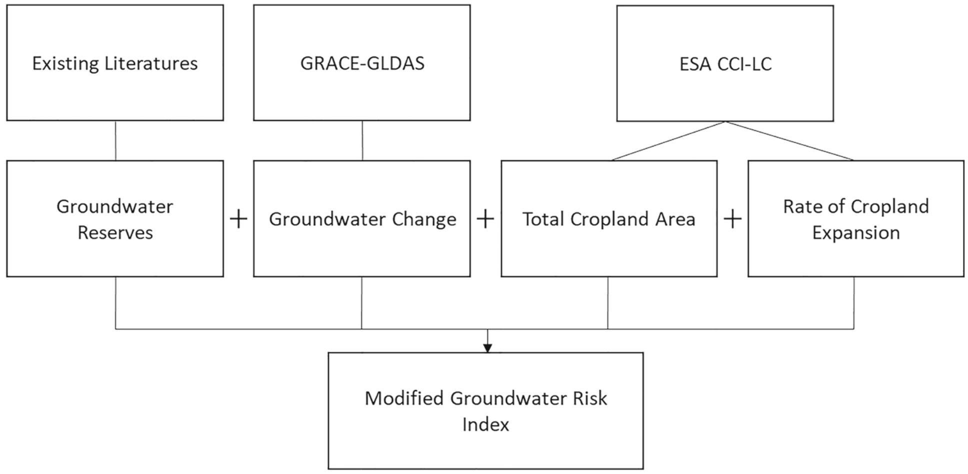

Fig. 2 Primary steps involved in creating the groundwater risk index

Table 2 List of all datasets used in this study

Datasets	Temporal resolution	Spatial resolution	Sources
GRACE-RL05-Mascon	Monthly	0.5 ° × 0.5 °	https://www2.csr.utexas.edu/grace/
GLDAS-NOAH v2.1	Monthly	0.25° × 0.25 °	https://disc.gsfc.nasa.gov/
GLDAS-CLSM v2.1	Monthly	1° × 1°	
GLDAS-VIC v2.1	Monthly	1 ° × 1°	
ESA CCI-LC	Yearly	300 m	https://www.esa-landcover-cci.org/
Geometry and hydrogeological data of primary aquifers			[30–34]

where Δrank_r represents rank change of region r, $\text{rank}_{\text{original},r}$ is the original rank of region r, $\text{rank}_{\text{exclude } q,r}$ denotes the modified GRI after implementing sensitivity test.

3 Results and Discussion

3.1 State of Groundwater Storage

The estimated groundwater storage for each region within the Arabian basin is summarized by Fig. 3. Qassim is classified as the area with the least storage, while the highest groundwater reserve is estimated in Riyadh. Compared to other areas, Riyadh has more major productive aquifers, ranging from Saq, Wajid, Minjur, and Wasia-Biyadh [30, 31], therefore it is not surprising that this region has the biggest estimated groundwater reserves. In particular, the groundwater storage in Riyadh accounted for 36% of the total groundwater reserves in the study area. Qassim, Hail, and Tabuk have the same two major aquifers: Saq and Tabuk aquifers. However, among them, Qassim has the smallest area; hence, this factor contributes to Qassim's least groundwater reserves. Generally, Qassim, Hail, Jouf, and Northern Border have smaller groundwater storage capacities than Riyadh, Najran, Tabuk, and Eastern Province. The number of productive aquifers and total area of each region are not the only variables contributing to the volume of groundwater storage. For instance, Najran has only one productive aquifer (Wajid aquifer). Moreover, its total area is smaller than Eastern Province, Jouf, or Northern Border. However, Najran's groundwater reserves are estimated as the second highest throughout the study area. This is due to the higher specific yield value of Wajid aquifer than other aquifers.

Assessing the validity of estimated groundwater reserves is quite difficult due to the lack of in situ data in the study area. Hence, the uncertainty in groundwater storage calculation cannot be avoided. The adopted approach used to estimate groundwater storage is based on the assumption that the entire sediment column is saturated by water. Thus, it might lead to over-calculation of groundwater storage. The limit of acceptable saturated sediment thickness and the use of specific yield instead of effective porosity were introduced by previous studies to constrain the volume of groundwater storage [46, 47].

Despite those limitations, the groundwater storage capacity estimated by this study is still smaller than those by

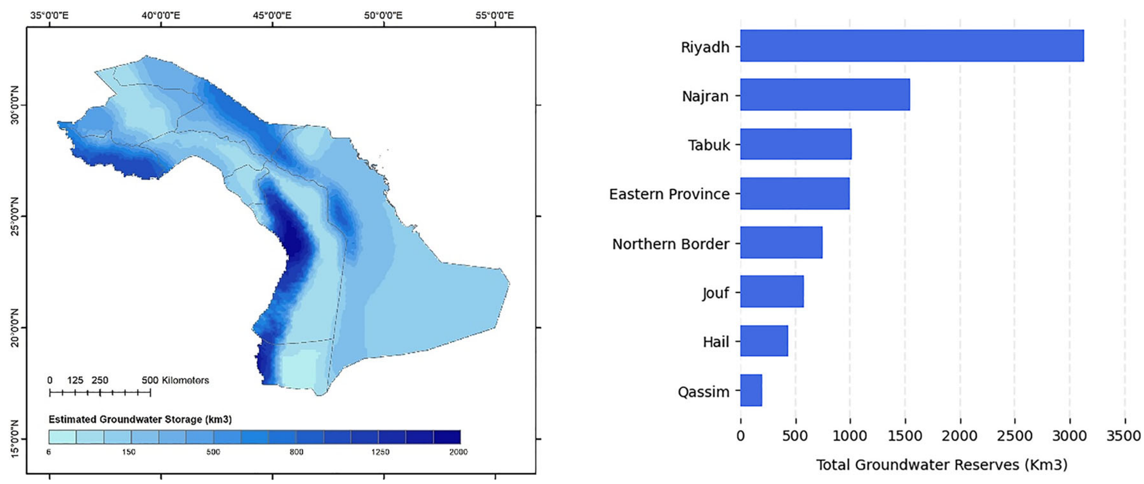

Fig. 3 Estimated groundwater reserves within the study area

Lezzaik and Milewski [46] and Richey et al. [47]. Several factors contribute to this discrepancy. First, this study used aquifer geometries and their hydrogeological features based on available hydrogeological reports and data to calculate groundwater reserves, while Lezzaik and Milewski [46] used the global gridded dataset consisting by depth of water table, sediment thickness, effective porosity, and lithology. Second, Richey et al. [47] used specific yield that represents storage coefficient of unconfined aquifer to calculate groundwater reserves. In this study, storage coefficients of both confined and unconfined aquifers were incorporated since the extent of these two types of aquifers was already determined. The value of storage coefficient of confined aquifers generally is smaller than unconfined aquifers. Therefore, this approach led to smaller estimates of groundwater storage capacity.

3.2 Trend of GRACE Observations

The spatial variability of yearly groundwater storage changes derived by GRACE-GLDAS in the study area during 2010–2020 is displayed by Fig. 4. This map was developed by solving Eq. (1) and representing the change of groundwater storage relative to the GRACE baseline (2004–2009). In general, all regions exhibited a declining trend in groundwater storage over the study period. The significant groundwater depletion was certainly more pronounced in the northwestern part of the Arabian basin, particularly Jouf and Hail, while the southern, eastern, and northeastern parts showed lower groundwater changes. This finding is in line with results from earlier studies conducted in the same area [48, 49], proving the feasibility of this study's result despite the lack of ground-based observation for validation. Moreover, this assumption is supported by a number of studies reporting the high correlation coefficient of GRACE product with field monitoring data [50–52].

These results indicate that freshwater withdrawal for irrigation purposes is the dominant factor driving groundwater variations in this area. Most irrigated agriculture is distributed in areas where higher groundwater depletion was observed. Meanwhile, the southern, eastern, and northeastern parts of the study area are dominated by bare land (desert) with minimum anthropogenic activities. Hence, no wonder these regions have lower groundwater depletion compared to northwestern areas. This assumption is supported by agricultural production being the biggest groundwater consumer in the Kingdom as shown in Table 3.

3.3 Cropland Area and its Expansion

The cropland area of each region was determined for the period of 2020 while the rate of cropland expansion from 2010 to 2020 was estimated by using the linear least square regression method (Fig. 5). According to ESA CCI-LC's results, Riyadh and Najran are regarded as the regions with the largest and smallest total cropland areas with total area of 655,589 ha and 2356 ha, respectively.

Since 2010, four regions, including Tabuk, Jouf, Hail, and Riyadh showed an increasing trend of cropland expansion. Among them, Jouf has the biggest expansion with a rate of 1086 ha/year, followed by Hail, Riyadh, and Tabuk. The rate of cropland expansion in Jouf is three times higher than in Hail and Riyadh. After the implementation of the Eighth Development Plan 2005–2009 by the government to suspend agricultural expansion, no clear alternative crops were presented to the farmers to replace wheat, hence, alfalfa, and other fodder crops began to be planted [53]. Consequently, cropland areas increased significantly since alfalfa was one of the most developed crops from 2010 [54]. Despite showing an increasing trend, the rate of cropland expansion started to

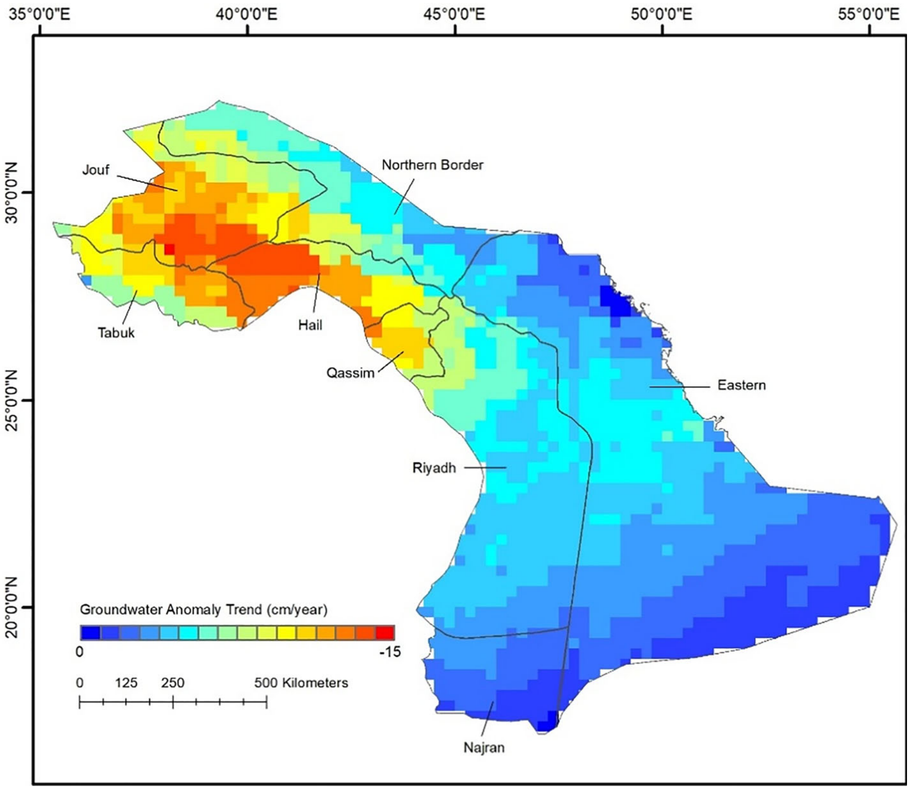

Fig. 4 The groundwater anomaly trend derived from GRACE-GLDAS for the period from 2010 to 2020

Table 3 Water consumption by sector in Saudi Arabia (million m^3) obtained from Ministry of Environment, Water and Agriculture Statistical Book 2021

Sectors	Year										
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Municipal	2284	2423	2527	2731	2874	3025	3129	3150	3392	3493	3629
Industrial	753	800	843	890	930	977	1015	1000	1400	1400	1680
Agricultural	14,410	15,970	17,514	18,639	19,612	20,831	19,789	19,200	21,200	10,500	8500

decrease from 2018 in these regions as a result of new regulation in 2018 to stop the cultivation of alfalfa [55]. Meanwhile, the cropland areas in Eastern Province, Qassim, and Northern Border have declined during the same period with rates of − 205 ha/year, − 199 ha/year, and − 2 ha/year, respectively. The declining trend of cropland in these areas could be a consequence of the implementation of the Eighth Development Plan 2005–2009.

On the other hand, the development of cropland area in Najran derived from ESA CCI-LC remains constant over the study period. This can be explained as ESA CCI-LC is known for having a spatial resolution of 300 m, which could be too coarse in detecting small-scale changes in agricultural development in Najran. Additionally, most cropland areas in Najran are located within the Arabian Shield, in particular along the valley surrounded by the basement rocks [56], while the focus area of this study is limited to the sedimentary basin; hence, those areas were excluded from ESA CCI-LC observation. The area and expansion rate of cropland in the Arabian basin are summarized in Table 4.

3.4 Groundwater Risk in the Arabian Basin

The relative groundwater risk in the Arabian basin within the time span of 2010–2020 was evaluated using modified GRI based on hydrogeology and anthropogenic parameters. Figure 6 illustrates the final composite index and spatial pattern of relative groundwater risk across the Arabian Basin. The integration between these parameters can be considered as an integrated approach to determine how risky one area is compared to other areas. Hence, modified GRI developed in this study could help the decision-maker to prioritize groundwater resource management in high-risk areas. Low and high-risk areas were classified based on score on a 0–100

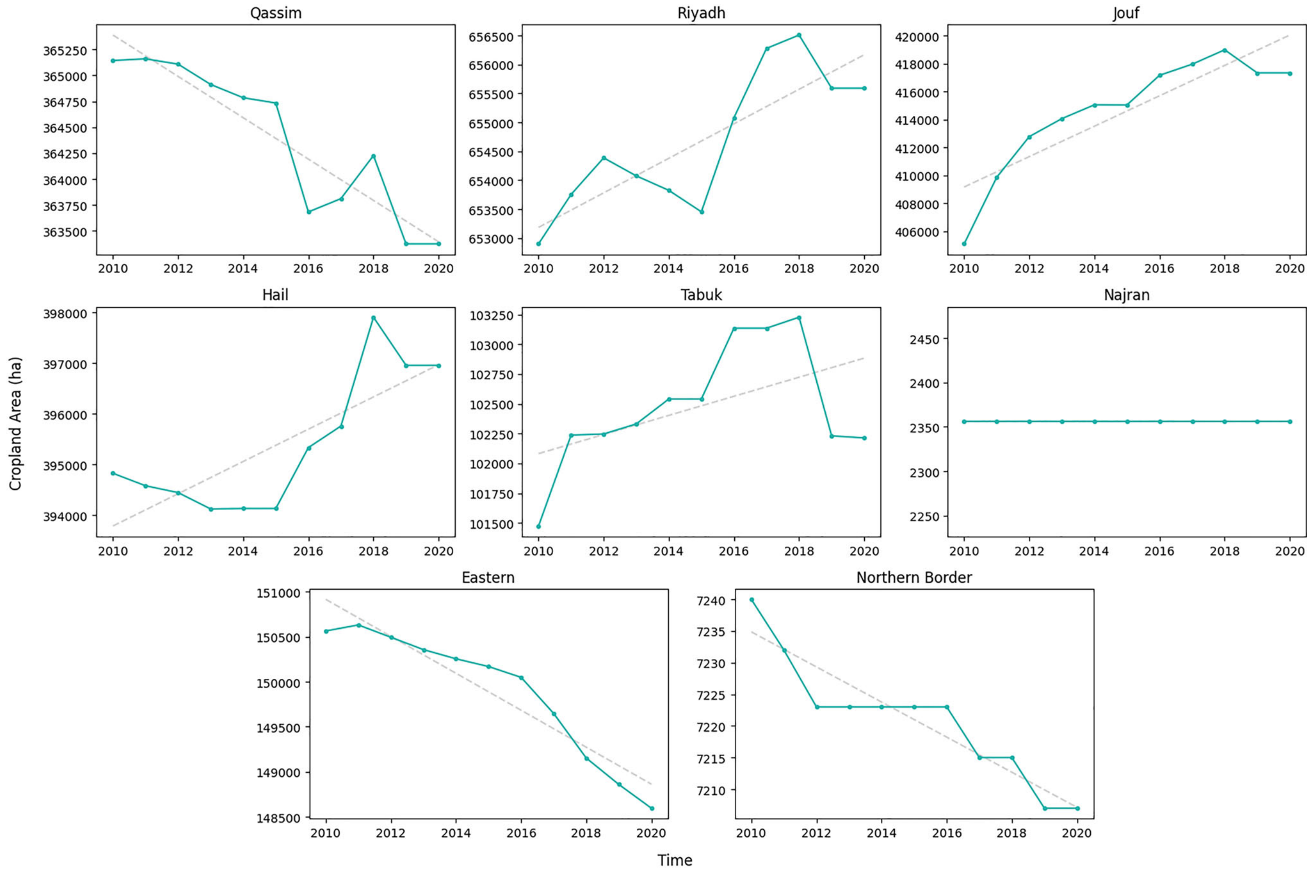

Fig. 5 Time series of cropland expansion along with their linear regression obtained by ESA CCI-LC from 2010 to 2020

Table 4 Cropland area and rate of change between 2010 and 2020 observed by CCI-LC

	Regions							
	Tabuk	Jouf	Hail	Qassim	Riyadh	Eastern	Northern Border	Najran
Total area (ha)	102,214	417,330	396,956	363,376	655,589	148,596	7207	2356
Rate of expansion (ha/year)	80	1086	317	− 199	298	− 205	− 2	0

scale and ranking of region. A higher index score denotes a lower risk area. For example, the lower groundwater risk area in this study is represented by a higher score on a 0–100 scale and higher ranks out of 8 regions.

The index utilized in this study indicated that Jouf and Hail are regarded as the most risk regions compared to other areas with a score of 17/100 and 31/100, respectively. Some estimated parameters are responsible for their low scores. First, Jouf was observed as the area with the highest cropland expansion over the study period with a rate of 1086 ha/year, followed by Hail at a rate of 317 ha/year. These cropland expansions can be largely attributed to the continually increasing irrigation water demand. Subsequently, both regions have the largest groundwater depletion observed by GRACE throughout the study area. Besides groundwater depletion, agricultural sprawls occurred in Jouf have been reported to trigger several land-deformation features such as sinkholes, fissures, and subsidences [57, 58]. The last parameter contributing to their low scores is the total cropland area. According to ESA CCI-LC dataset, Jouf and Hail are classified as the second and third-largest cropland areas in KSA, respectively. As irrigation activities are the largest groundwater consumer in the Kingdom, without active water resources management, the groundwater system in Jouf and Hail surely will be exacerbated in the future.

Having a large groundwater reserve is not a guarantee to be classified as a region with a high index score. This applies to Riyadh which has the largest groundwater storage capacity, yet this region is still categorized as the third risk region with an index score of 36/100. Irrigated agricultural areas

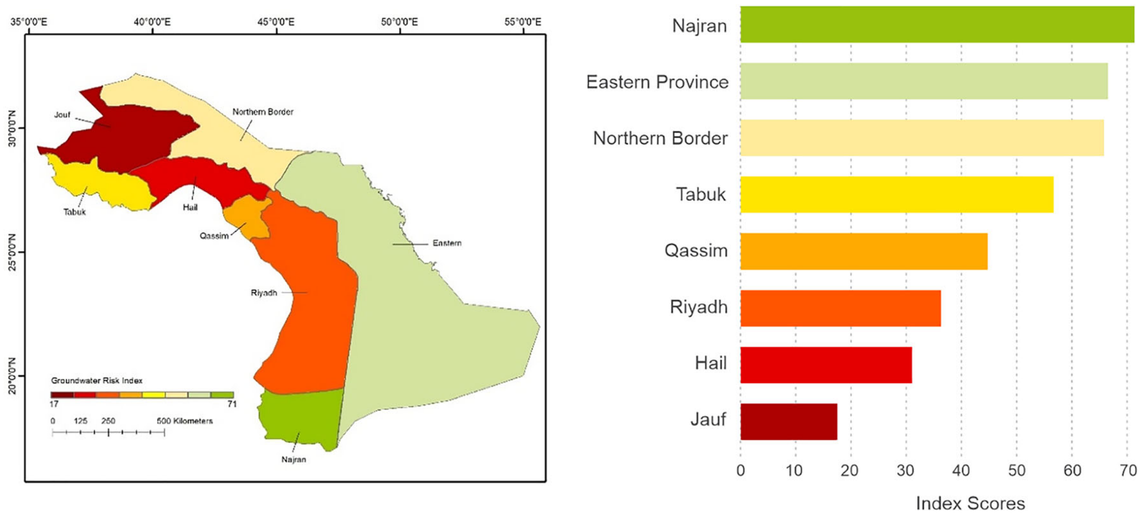

Fig. 6 The final composite index represents relative groundwater risk in the Arabian Basin, Saudi Arabia. The high score and low score represent the low-risk region and high-risk region, respectively

and their expansion is believed to be the determining factor of Riyadh's low score. Riyadh is known as the biggest cropland area throughout the Arabian Basin, accounting for 31% of the total cultivated area in the study area. Moreover, Riyadh has experienced cropland expansion with a rate of 298 ha/year which consequently puts Riyadh on a low score. These revealed that groundwater reserves indeterminate groundwater risk.

On the other hand, Najran and Eastern Province are classified as low-risk regions with scores of 71/100 and 67/100, respectively. Najran is known as the region with the smallest total cropland area within the Arabian Basin, whereas Eastern Province is regarded as the area with the highest cropland reduction since 2010. These factors have implications for their groundwater storage variabilities. Both regions have the smallest rate of groundwater depletion compared to other areas over the study period. Besides them, Northern Border, with a 66/100 score, can be considered the low-risk area, as the difference between Northern Border and the two previous high-score regions is small. Northern Border is categorized as the second region with the smallest total cropland area after Najran. Besides that, this region also experienced cropland reduction over the study period.

3.5 Indicator Sensitivity Analysis

Results of the sensitivity test associated with the input parameters selection are depicted in Table 4. It is notable that most regions exhibited no to little shift, ranging from one to two positions, in their ranking structure after the exclusion of each individual indicator (Table 5). Regions classified with high scores, such as Najran, Eastern Province, and Northern Border, consistently ranked similarly within the four-upper group with the different combinations of input indicators. This applies as well to Jouf, Hail, and Qassim who remained stable within the four-lower position.

The index sensitivity is largely influenced by groundwater storage changes, followed by total cropland area and cropland expansion with average rank changes of 1, 0.75, and 0.75, respectively, while groundwater reserves do not affect the index sensitivity. Overall, the values of average rank changes of individual input parameters indicate the robustness of the indicators selection since it did not alter the ranking structure significantly.

4 Conclusions

The modified GRI used in this study can be a valuable preliminary approach for decision-makers to observe the most risk area based on estimated parameters. This index was developed by considering all possible variables related to groundwater risk. Instead of focusing solely on hydrogeological variables, the modified GRI incorporates both hydrogeological data and anthropogenic factors. Integration of these data could offer a better understanding of the groundwater system's status. To date, there is still no consensus on which anthropogenic variables should be involved since these factors could vary for different regions. This is because each entity might interpret the term risk differently. The robustness of variable selection utilized in this study was proven through sensitivity test. Therefore, it could help local authorities to prioritize implementing sustainable groundwater management schemes in high-risk areas.

In this study, the relatively high-risk area is observed in Jouf, while Najran is classified as the least-risk area. Jouf's

Table 5 Sensitivity analysis through inclusion/exclusion of individual indicators

Regions	Original Index		Excl GWC		Excl GWR		Excl CA		Excl CE	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Najran	71	1	66	2 (− 1)	90	1	61	2 (− 1)	67	1
Eastern Province	67	2	62	4 (− 2)	86	2	63	1 (+ 1)	55	3 (− 1)
Northern Border	66	3	68	1 (+ 2)	80	3	55	3	59	2 (+ 1)
Tabuk	56	4	65	3 (+ 1)	64	4	47	5 (− 1)	46	4
Qassim	44	5	49	5	58	5	45	6 (− 1)	26	6 (− 1)
Riyadh	36	6	25	7 (− 1)	43	6	48	4 (+ 2)	28	5 (+ 1)
Hail	31	7	34	6 (+ 1)	40	7	28	7	22	8 (− 1)
Jouf	17	8	15	8	20	8	11	8	23	7 (+ 1)

GWC, GWR, CA, and CE denote groundwater storage change, groundwater reserves, total cropland area and cropland expansion, respectively

low score is mainly caused by rapid rate of groundwater withdrawal, large cropland area, and high rate of irrigated agriculture expansion. It turns out that having high groundwater storage capacity is not a guarantee to be classified as a relatively small-risk area, as happened to Riyadh. The insensitivity of groundwater reserves to groundwater risk was also revealed through sensitivity analysis. Overall, the groundwater risk status is largely affected by groundwater abstraction, followed by total cropland area and cropland expansion. It means that anthropogenic factors such as groundwater withdrawal and agricultural development should be taken into consideration by local authorities to maintain groundwater sustainability in this arid environment, particularly in areas with low scores such as Jouf and Hail. In these areas, more efficient irrigation methods such as drip and subsurface irrigation should be widely applied to reduce water losses due to evaporation and deep percolation. Another initiative is the use of treated wastewater which not only reduces groundwater extraction but can also improve soil fertility. Last, this study showed that recent advances in remote sensing have enabled valuable contributions for understanding groundwater systems.

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Declarations

Conflicts of interest The authors declare no conflict of interest.

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