Quantifying the uncertainty in future groundwater recharge simulations from regional climate models

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Abstract
This study aims to show how future groundwater recharge (GR) simulations in arid areas respond to uncertainty in climatic parameters—a question, if explored, that bridges a gap in water resources management plans. To this aim, eight regional climate models (RCMs) under two representative concentration pathways (RCP4.5 and RCP8.5) projected four climatic parameters [surface air temperature, precipitation, wind speed, and potential evapotranspiration (PET)] over Qatar during the period of 2071–2100. Using topographic and groundwater data, a physically based water balance model was built to simulate future GR under these 16 scenarios. Results show high uncertainty in climatic parameters. Relative to the reference period (1976–2005), values varied under RCP4.5 (RCP8.5) from +1.8 to +3.4 (+3.8 to +5.6) °C for average temperature, −48% to +15% (−60% to +6%) for annual precipitation, −0.23 to +0.1 (−0.27 to +0.04) m/hour for wind speed, and from −5.7 to +12.8 (+4.3 to +17) mm for annual PET. Uncertainty in climatic parameters caused great uncertainty in future GR estimations. During the late 21st century, GR simulations varied from −67% to +64% with an average value of −20% under RCP4.5, and from −81% to +8% with an average value of −36% under RCP8.5. The greatest uncertainty resulted from the driving model, whereas the choice of emission scenario had a secondary impact. Since GR is a critical component of feeding arid aquifers, the study’s findings emphasize the importance of both considering the uncertainty associated with climatic parameters and the regional climatic information chosen.

KEYWORDS
climate change, groundwater recharge, uncertainty analysis, urbanization, water-balance model, Qatar

1 | INTRODUCTION

Minimal rainfall and lack of surface water continue to be significant concerns in arid areas, often making aquifers the primary source of potable and agricultural water. Therefore, it is vital, to manage aquifers to achieve socioeconomic and ecosystem sustainability. This management becomes a top priority if aquifers are put under immense pressure by climate change and anthropogenic activities such as population growth, rapid urbanization, and overexploitation. However, aquifers’ sustainability cannot be achieved without a precise estimation of groundwater recharge (GR). Therefore, an accurate assessment of GR under varying climatic and environmental conditions is necessary for water resources management, climate change mitigation, and adaptation plans (Anibas et al., 2016; Pozdniakov et al., 2020; Xie...
et al., 2018). In contrast, unreliable GR assessment may make integrated water resource management impossible, leading to a significant deficit in water requirements, disruption in soil conditions, and land degradation (Moiwio et al., 2010; Xie et al., 2018).

Direct measurements (e.g., lysimeters, tensiometers, and time domain reflectometry probes) are optimum ways to calculate accurate GR in arid areas. However, these measurements are elaborate and expensive, which limits their accessibility in several countries. Additionally, these measurements are only locally applicable. Some arid areas have karst aquifers. Karst aquifers have their unique hydrogeological composition (e.g., heterogeneous permeability of aquifer matrix and conduits, heterogeneous hydraulic conductivity), making extrapolating local and wide range GR estimations untrustworthy (Martos-Rosillo et al., 2015). Further, arid environments mostly get heterogeneous, intense, short-duration rainfall (Ajjur & Al-Ghamdi, 2021a; IPCC, 2021). Such rainfall characteristics hinder determining soil moisture capacity, making the runoff and infiltration rain distributions uncertain. To overcome these issues, some other techniques are used for regional GR evaluation. These techniques include soil water balance, energy water balance, chloride mass balance, and inverse calibration in numerical modelling. All these techniques generally depend on climate, surface, and groundwater components as inputs. Uncertainty in these components can lead to significant uncertainty in GR estimations (Kurylyk & MacQuarrie, 2013; Martos-Rosillo et al., 2015).

Previous literature in arid areas focused on GR uncertainty associated with surface and groundwater components. Xie et al. (2018) randomly sampled vegetation parameters in semi-arid southeast Australia, generating 10,000 realizations of long-term GR using energy and water balance modelling. The resulted annual GRs varied between 7 and 144 mm despite all these realizations having the same climatic inputs. Martos-Rosillo et al. (2015) reviewed GR assessment in 51 carbonate aquifers in southern Spain. They found six estimation methods in semi-arid regions to have significant uncertainty. Both studies (Martos-Rosillo et al., 2015; Xie et al., 2018) provided no evidence on how GR simulations will change in response to climatic uncertainty. Jackson et al. (2011) used a distributed recharge model to investigate the GR uncertainty resulting from climatic components in Chalk aquifers. They noticed that temperature and precipitation uncertainty in 13 global climate models (GCMs) could result in significant uncertainty in future GR estimations in a temperate climate in central-southern England. Similarly, Serrat-Capdevila et al. (2007) used a 3D transient groundwater-surface water flow model to study GR uncertainty in the San Pedro Basin. They found that precipitation uncertainty in GCMs could considerably change future GR simulations. Though, recent improvements in the climate arena have advanced regional climate downscaling techniques, producing regional climate models (RCMs) that are supposed to reduce the uncertainty in climatic projections, leading to more accurate future GR simulations. Little effort has been devoted to defending this statement. Therefore, there is a pressing need to quantify the uncertainty in future GR simulations resulting from RCMs projections.

This study is comprised of two objectives: (1) quantifying the uncertainty that GR projections in arid areas are exposed to due to changes in climatic components, specifically the changes in precipitation, air temperature, wind speed, and potential evapotranspiration (PET); and (2) estimating future GRs in Qatar during the late 21st century. To this end, the study obtained climatic projections from eight RCMs participating in the COordinated Regional climate Downscaling Experiment (CORDEX) under two Representative Concentration Pathways (RCP4.5 and RCP8.5). Accompanied by topographic and groundwater data, these components were utilized in a physically based water balance model (WetSpass) to simulate GR during historical and future periods. The period between 1976 and 2005 was considered a reference, while 2071–2100 represented the late 21st century.

2 | CLIMATE AND HYDROGEOLOGICAL DESCRIPTION

Qatar is a hyper-arid country covering 11,500 km² in the eastern Arabian Peninsula (Figure 1). Qatar’s surface is almost flat, with an elevation that varies between 0 and 92 m above mean sea level (AMSL). There is no surface water, and agricultural activities entirely depend on aquifers (Baalousha, 2016; Baalousha et al., 2018).

2.1 | Historical climate

Qatar has an extremely long, hot summer and a mild winter (Ajjur & Al-Ghamdi, 2021a, 2021b). The trends of average, maximum, and minimum air temperatures, precipitation, and wind speeds from 1976 to 2005 are depicted in Figure S1. The trends at six meteorological stations distributed throughout Qatar (Figure 1a) were available through the Qatar Meteorological Department (QMD), Civil Aviation Authority. As the QMD said, all records were screened for accuracy and consistency. No systematic changes in stations’ location or measurement methods occurred over this period. The influence of each station on the whole country was weighted using the inverse distance weighted (IDW) interpolation technique in ArcGIS.

Qatar had an average temperature of 27.1°C, a maximum temperature of 35.1°C, a minimum temperature of 20.1°C, a wind speed of 4.1 m/h, and 76.6 mm/year precipitation, during the period of 1976–2005. The most rain fell from December to March, accounting for 81% of the annual rainfall. While the maximum temperature trend decreased, the minimum temperature over Qatar increased. On average, an increase of +1°C was observed in the average temperatures between 1976 and 2005. The direction of rainfall was unclear, though there was a minor decrease in annual rainfall values ($R^2 = 0.02$). The wind speed trend also decreased. Figure S2 depicts the mean spatial distribution of climatic parameters over Qatar during the reference period (2071–2100). It shows evidence of significant spatial variability in climatic components, especially for maximum temperature and rainfall. For example, the mean historical maximum temperature of the six
stations varied between 29.5 and 34.6°C, while the mean historical annual rainfall varied between 54.9 and 84.1 mm.

2.2 | Geological description

As Figure 1b shows, Qatar’s soils are generally lithosols; they are composed of thin, calcareous, sandy loams (10–30 cm) covered by limestone debris and bedrock (Eccleston et al., 1981). These lithosols are not suitable for agriculture except in depression areas where colluvial soils have accumulated up to 150 cm depths, overlaying limestone debris and bedrock. The colluvial deposits are accumulated from calcareous loam, sandy loam, and sandy clay loam. These deposits form three types of soil: farm soil, sabkha soil, and sandy soil. Farm soil, locally called roda, is the main agricultural soil in Qatar and is composed of silty clay and sandy loam. Sabkha is a
saline soil located along coastal areas comprised of gypsiferous soil and sandy clay loam. Finally, sandy soils are composed of calcareous loam and sand and are located throughout the country (Schlumberger Water Services, 2009).

Qatar’s land-use patterns can be classified in three ways: bare areas, urban areas, and agricultural areas. Bare areas constitute the majority of Qatar, where there are exposed rocks and sand dunes. Urban areas include built-up surfaces like buildings, roads, construction sites, and industrial communities. This class is mainly found in metropolitan Doha (the central-eastern part of the country) and small communities in the south and north. Finally, agricultural areas are generally spread throughout the northern part of the country.

Qatar has three principal aquifers: the northern basin, the southern basin, and the southwest basin (Eccleston et al., 1981; Schlumberger Water Services, 2009). Figure 3 depicts the location of these aquifers and groundwater levels. The primary aquifer is the northern basin since it receives higher rainfall and thus has higher recharge. The northern basin contains fresh groundwater lenses sitting on top of brackish and saline groundwater. The depth to groundwater level is up to 49 m from the ground surface, and its quality is better than that of the other aquifers (Southern and Southwest). Most farms are concentrated in the northern aquifer. The northern aquifer includes approximately two-third of all wells, whereas the southern basin contains 28% (Schlumberger Water Services, 2009). These aquifers are karst carbonate heterogeneous (Baalousha et al., 2018; Schlumberger Water Services, 2009). During the last two decades, aquifers have been extremely overexploited due to anthropogenic and climate change stressors. The country’s population has risen fivefold, and per-capita water consumption has reached an unprecedented rate (World Bank, 2020). The main groundwater-associated problems are water table decline, storage reduction, quality degradation, and seawater intrusion. Eccleston et al. (1981) stated that GR occurred in Qatar under two circumstances: directly by intense rainfall (>10 mm/day) and indirectly by rain flow accumulating in land depressions (indirect recharge). Indirect recharge occurs five times more than intense rainfall (Schlumberger Water Services, 2009).

3 | METHODS

3.1 | Regional climate models

Future climatic simulations, including precipitation; average, minimum, and maximum air temperature; and wind speed, were obtained from eight RCMs participating in the CORDEX. The CORDEX uses regional downscaling methods to provide climate data at the regional scale. It has 14 geographic domains, and four of them include Qatar. These domains are Africa, Middle East and North Africa, South Asia, and Central Asia. This study selected all RCMs in a 0.44° resolution that comprise the r1i1p1 ensemble that runs through the year 2100 under the RCP4.5 and RCP8.5. Table 1 shows the eight RCMs in two CORDEX domains (Africa and MENA). More information about the CORDEX project can be found at www.cordex.org.

The PET was calculated from RCMs data by implementing Hargreaves and Samani (1985) temperature-based equation, an equation widely used to estimate PET for agriculture, water resources, and climate impact studies (Folberth et al., 2016). Although using a standard physically based method, such as the Penman–Monteith equation, has maximum climatic variables coverage and may better estimate PET, the Penman–Monteith equation requires extensive inputs that are neither fully available at QMD stations nor from CORDEX simulations. Further, several studies reported comparable, reliable results of the Hargreaves and Samani (1985) method to those obtained using the Penman–Monteith equation in various environments (Kurylyk & MacQuarrie, 2013; Martos-Rosillo et al., 2015). Therefore, the Hargreaves and Samani (1985) equation was used to calculate the daily PET as follows:

\[
\text{PET} = AHC R_\text{g} (T + 17.8) \sqrt{T_{\text{max}} - T_{\text{min}}} 
\]

where \(T\), \(T_{\text{max}}\), and \(T_{\text{min}}\) represent daily mean, maximum, and minimum temperature in °C, respectively; \(R_\text{g}\) represents the water equivalent of extraterrestrial radiation in mm/day; and the AHC is the adjusted Hargreaves coefficient, equal to 0.0023. Extraterrestrial radiation is computed from latitude and day data of the year (Allen et al., 1998). We

| RCM | CORDEX Domain | Diving model/GCM run | Model ID | Institution | Institution name |
|-----|----------------|----------------------|----------|-------------|------------------|
| 1   | MNA-44         | CNRM-CERFACS-CM5     | RCA4_v1  | SMHI        | Swedish Meteorological and Hydrological Institute, Norrkoping, Sweden |
| 2   | GFDL-ESM2M     | ICHEC-EC-EARTH       |          |             |                   |
| 3   | CNRM-CERFACS-CM5 | ICHEC-EC-EARTH     | CCLM4-8-17_v1 | CLMcom | Climate Limited-area Modeling Community |
| 4   | AFR-44         | CNRM-CERFACS-CM5     | REMO2009_v1 | MPI-CSC | Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Planck Institute for Meteorology |
| 5   | HadGEM2-ES     | ICHEC-EC-EARTH       |          |             |                   |
| 6   | MPI-M-ESM-LR   |                      |          |             |                   |
| 7   | MPI-M-ESM-LR   |                      |          |             |                   |
| 8   | CCLM4-8-17_v1  | CLMcom               |          |             |                   |

Abbreviations: GCM, global climate model; RCM, regional climate model.
multiplied PET by the number of days ($N_d$) in each specific month. Monthly PETs were then aggregated to get a yearly PET.

Figure 2 depicts the differences among the eight RCMs when simulating the mean Qatar climate during the late 21st century. All RCMs (except RCM5) agreed on temperature increases under both RCPs. However, there are some variations among RCMs, when quantifying this increase. Data varied from $+1.8$ to $+3.4^\circ C$ for the average temperature, $+1.2$ to $+4.5^\circ C$ for the maximum temperature, and from $+0.5$ to $+3.4^\circ C$ for the minimum temperature under RCP4.5. The previous projections evolved significantly under RCP8.5, with the most growth in RCM6. RCM6 projected an increase of $+5.6^\circ C$ in average temperature; $+7^\circ C$ in maximum temperature; and $+6.1^\circ C$ in minimum temperature. Unexpectedly, RCM5 only projected a slight growth of $+0.5$ ($+0.8$) $^\circ C$ in minimum (maximum) temperature, whereas it projected that the average temperature would increase by $+4.4^\circ C$. On average, the ensemble of RCMs projected an increase of

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**FIGURE 2**  Mean projected changes, among RCMs, for the average, minimum, and maximum air temperature; wind speed; annual precipitation; and PET over Qatar during the period from 2071 to 2100, relative to 1976–2005. Changes are shown (a) under RCP4.5 and (b) RCP8.5. PET, potential evapotranspiration; RCM, regional climate model.
2.4°C (4.3°C) in average temperature; 2.4°C (4.2°C) in maximum temperature; and 2.1°C (4.2°C) in minimum temperature under RCP4.5 (RCP8.5).

The RCMs ensemble projected that, relative to the reference period, precipitation would decrease by −16% and −26% under RCP4.5 and RCP8.5, respectively. Nevertheless, RCMs show discrepancies in precipitation projections, which is not surprising considering the poorly resolved precipitation in GCMs over the Middle East (Ajjur & Al-Ghamdi, 2021a). While three RCMs projected a precipitation increase of up to +10.4 mm/year (+15%), five RCMs projected a significant decrease (−37.9 mm/year [−39%] under RCP4.5). The differences among RCMs were more considerable for rainfall projections under RCP8.5. The uncertainty among RCMs was also apparent for wind speed projections. Blue circles in Figure 2 represent this uncertainty. The RCMs ensemble shows no change in wind speed under RCP4.5, while a reduction of −0.06 m/h is projected under RCP8.5. While the RCMs ensemble projected a mean increase in PET of +4.4 mm/year and +9.1 mm/year under RCP4.5 and RCP8.5, respectively, the uncertainty in temperature projections led to uncertainty in PET estimations. The PET estimations varied in magnitude and direction among RCMs (see olive stars in Figure 2). Under RCP4.5, PET increased up to 12.8 mm/year according to RCM6 and declined by −1.4 mm/year and −5.7 mm/year under RCM4 and RCM5, respectively. All RCMs projected a PET increase (between +4.3 and +17 mm/year) during the late 21st century. To conclude, among RCMs, there is significant uncertainty in climatic projections during the late 21st century. This uncertainty illustrates that uncertainty may develop in future GR simulations. RCMs, therefore, can best address the questions of this study.

3.2 Groundwater recharge modelling

This study calculates annual GR using the WetSpass model (Batelaan & De Smedt, 2007). WetSpass is a physically based, spatially distributed model that utilizes water balance at each grid to calculate GR, actual evapotranspiration (AET), and runoff. WetSpass results are validated through error maps, which constitute a part of the model outputs. Error maps measure the modelling error in seasonal (summer and winter) and annual water balance simulations. This error (±) should be zero, or very close to zero. WetSpass has been extensively tested, and its reliability has been proven in many regions worldwide (Gebreyohannes et al., 2013; Moiwo et al., 2009; Moiwo et al., 2010). WetSpass requires a set of climatic data (temperature, precipitation, wind speed, and PET), topographic data (topography, slope, soil type, and land use), and groundwater data (the depth to water table; Figure S3).

For each grid cell in October, there are four parts representing the non-uniformity of the land cover. These are vegetated, bare soil, open water, and impervious surfaces. For example, for the vegetated area, the water balance is calculated using a raster cell as follows:

$$P = S + T + I + GR$$

where P is the precipitation, S is the surface runoff, T is the transpiration, and I is the interception fraction. AET is the sum of two components (Equation 3):

$$AET = T + E$$

where E is the evaporation. The surface runoff (S) is related to rainfall characteristics (amount and intensity), the interception fraction, and the soil infiltration capacity. The interception fraction depends on the land cover and represents a constant percentage of annual rainfall. The GR is the residual term of the water balance. All components are measured with the unit of mm year$^{-1}$. Similar approaches are followed for the water balance in bare soil, open-water, and impervious surfaces. Though, interception and transpiration terms are omitted for the bare soil, open-water, and impervious surfaces.

In this study, WetSpass analysis was performed for two seasons. These are summer (from April to September) and winter (from October to March). Geological and groundwater maps were prepared and resampled into a 30 m grid. This study obtained groundwater levels from 313 wells from fieldwork done by Schlumberger Water Service (see Figure 3). To incorporate the changes of storage on a seasonal basis, ground measurements of water level depths were used for each season (winter and summer). Next, mean values of seasonal

![FIGURE 3](image-url) 

**FIGURE 3** The groundwater level map for the shallow aquifers in Qatar includes the location of 313 monitored wells used in this study. Levels are presented in metres below the natural ground.
climatic variables during the historical period were computed by averaging monthly temperature and wind speed. Precipitation records were aggregated to get a seasonal sum then averaged to get a seasonal mean. Next, seasonal climatic maps were also resampled into a standard 30 m grid. The land use and soil type maps were connected with WetSpass model as attribute tables. The supplementary materials in the online system include these tables for the land use (Table S2), Soil type (Table S3), and runoff coefficient for different raster cells (Table S4). The reader can refer to more information about WetSpass computation, calibration, and validation in Batelaan and De Smedt (2007). After simulating seasonal GRs using the WetSpass model, the two seasons were summed to obtain yearly values. In similar, future GR simulations were conducted using inputs from 16 climatic scenarios (see Section 3.2). We created these simulations to examine how GR would change in response to differences in climatic parameters and quantify GR uncertainty.

4 | RESULTS

4.1 | Historical groundwater recharge estimation

Figure 4 depicts the spatial distribution of mean annual GR during the historical period (1976–2005), while error maps for the summer, winter and annual water balance are shown in Figures S4–S6 (errors are very close to 0). The groundwater table is below the root zone as Qatar has no wetland areas (Figure 3). Negative GR values have then resulted from high AET losses in summer, but high winter GRs compensated the negative summer GRs. In general, the WetSpass simulates a mean annual total GR of 31 Million m$^3$ during the period from 1976 to 2005. However, GR distribution is nonuniform; it varies throughout the country. Significantly changing over regions, the annual GR varied up to 16 mm. Generally, southern parts of Qatar receive less GR than northern parts, mainly because hydraulic conductivity is higher in the northern aquifer, and it receives more precipitation than the southern aquifer (Baalousha et al., 2018; Schlumberger Water Services, 2009). Higher rates of GR were also associated with clay soil, which covers farm areas. On the other hand, less water is recharged to aquifers in regions covered by lithosols. Urbanization also affects the spatial distribution of GR. Built-up urban areas, such as those in metropolitan Doha, limit flow from recharging the aquifers.

4.2 | Future groundwater recharge projections

After projecting climatic components from each RCM, WetSpass was run, and the changes in future GR simulations during the late 21st century were investigated. The same topographic and groundwater maps were used for the 16 scenarios, enabling us to quantify the uncertainty associated with each RCM. Figure 5 depicts GR projections during the late 21st century under RCP4.5. There was some consistency between the spatial distribution of GR projections and the GR simulations during the reference period. According to the data, the northern aquifer and depression regions are the primary sources of GR, and some urban areas have higher values of GR because they receive higher precipitation in RCM projections. There is also an apparent discrepancy among GR simulations from RCMs. The maximum value of GR simulations varied up to 37.1 mm/year in RCMs 1–5. At the same time, the maximum value of GR simulations from other RCMs (RCM 6–8) did not exceed 4.8 mm/year.

Another apparent discrepancy was noticed among future GR simulations under RCP8.5. Figure 6 portrays the spatial distribution of GR projections during the late 21st century under RCP8.5. Consistent with the reference period simulation and future simulations under RCP4.5, GR varied over the country, with higher values in the northern aquifer and depression areas. Nevertheless, the more significant projected decrease in precipitation values (up to ~60%), as well as the increase in average temperature (up to 5.6°C) and PET (up to 17 mm/year), led to a significant simulated decline in GR when compared with RCP4.5 simulations. Maximum values of GR were found in RCM3 (10.8 mm) and RCM2 (11.9 mm). Other RCMs projected that future GR would not exceed 7.6 mm, with urban areas receiving negligible GR values (less than 1 mm).
To better quantify the changes in GR projections among RCMs, we computed the volume of GR using ArcGIS spatial analyst tools. Figure 7 shows the future changes in annual GR during the late 21st century in each RCM, relative to the corresponding historical average. Bars show changes in Mm³, while labels show changes in percentages. Under RCP4.5, RCMs do not agree on the direction of GR change; six simulate a decline in future GR while two (RCM1 and RCM3) simulate an increase. The simulated changes in annual GR range from $-24$ to $+23.1$ Mm³, with an average value of $-7.4$ Mm³. In other words, the GR projections range from $-67\%$ to $+64\%$, with an average percentage of $-20\%$, relative to 1976–2005. The GRs simulated using RCM2 and RCM4 inputs were like the GR simulated using the RCMs ensemble.

All simulations (except RCP3) generated decreases in GR during the late 21st century, relative to 1976–2005. Under RCP8.5, an average decline in future GR projections was estimated to be $-13.2$ Mm³ ($-36\%)$. However, the differences between RCMs were larger under RCP8.5 than RCP4.5. Future GR simulations ranged from $-29$ Mm³ to $+2.7$ Mm³ ($-81\%$ to $+8\%$). The GR simulated using RCM5 was the closest to that simulated by the RCMs ensemble. Interestingly, the RCM7 projected the highest decline in GR under both RCPs.

### 5 | DISCUSSION

Previous literature showed high inconsistency in GR estimation over Qatar. Consistent with the mean value estimated by this study between 1976 and 2005 (i.e., $31$ Mm³), Kimrey (1985) estimated the annual GR at $27$ Mm³, and Eccleston et al. (1981), for only the northern aquifer, estimated $27$ Mm³. A negligible amount of GR was found for the southern aquifers, compared with the northern one (see Section 2.1), making the results obtained by Eccleston et al. (1981)
similar. However, this study had inconsistent findings compared with Baalousha (2016), who obtained an annual GR of 58.7 Mm$^3$ in 1980, and Harhash and Yousif (1985), who proposed a range between 21 and 166 Mm$^3$ (1972–1983). Although using different approaches to estimate GR may produce result variations, the variations should not be significant. Martos-Rosillo et al. (2015) reviewed GR simulations in 51 carbonate aquifers in southern Spain. They stated that semi-arid areas with <300 mm of rainfall had a GR of ~38% of rainfall. Qatar has comparable hydrogeological characteristics: carbonate karst aquifers and receives an annual rainfall of 76 mm (see Section 2.1).

The historical simulated groundwater recharge (1976–2005) was 31 Mm$^3$ (40.7%) which is similar to Martos-Rosillo et al. (2015) findings. Therefore, the estimated historical annual GR in this study is acceptable. Regarding future estimations, it may be presumed that the future mean annual GR will decrease by −20% under RCP4.5, given that only two RCMs suggested a GR increase (see Figure 5). Nevertheless, the trend of GR decrease is more evident under RCP8.5, making the −36% decline a more acceptable data point.

Few studies discuss the uncertainty associated with future GR simulations in arid areas, making assessing our results difficult. A comparison with research conducted in other environments shows some agreement and disagreement. Based on a single GCM, downscaled by two methods, under two emission scenarios, Holman et al. (2009) found an approximate range of GR uncertainty (between −14% and +37%) for loamy soil areas in East Anglia, UK. Jackson et al. (2011) quantified the GR uncertainty in a chalk aquifer in the United Kingdom based on 13 GCMs run under the A2 emissions scenario. They also reported an approximate range of uncertainty between −26% and +31%. Ali et al. (2012) concluded a range of uncertainty between −33% and +28% based on 15 GCMs downscaled under three emission scenarios in a temperate climate in southwestern Australia. The slight variations between previous studies and

![Figure 6](image)

**Figure 6** Annual GR distribution during the late 21st century simulated using RCM inputs under RCP8.5. GR, groundwater recharge; RCM, regional climate model.
our results can be attributed to variations in studied periods. To illustrate, the future periods used for GR simulations were the 2050s in Holman et al. (2009), the 2080s in Jackson et al. (2011), and the 2030s in Ali et al. (2012). Our analysis uses the late 21st century (2071–2100). Also, Holman et al. (2009) and Jackson et al. (2011) computed GR changes using the baseline period between 1961 and 1990, whereas Ali et al. (2012) compared the future GR simulations using the period between 1975 and 2007 [very similar to this study (1976–2005)].

Some previous literature documented different ranges of uncertainty in future GR projections. Considering five GCMs and two dynamically downscaled RCMs under the A2 emission scenario, Kurylyk and MacQuarrie (2013) concluded a GR uncertainty range of −6% and +58% in eastern Canada. Kurylyk and MacQuarrie (2013) study was conducted in a humid climate, which differs than the hyper-arid environment in Qatar. Similarly, Serrat-Capdevila et al. (2007) reported a higher range of uncertainty, between −100% and +35%, in the San Pedro Basin; an area that characterized by bimodal rain regime: winter rains and summer rains. Considering one emission scenario, Crosbie et al. (2011) found a much larger scale of GR uncertainty (−83% to +447%) at three locations in southern Australia between 2046 and 2065, relative to the 1981–2000 reference period used. Therefore, it can be concluded that different climates can have different ranges of uncertainty in future GR projections.

Our analysis demonstrated that future GR simulations highly depend on the driving model and emission scenario, even under the same ensemble member and RCM version. For instance, RCA4 comprises RCM1, RCM2 and RCM3. RCM1 is driven by CNRM-CERFACS-CM5, whereas ICHEC-EC-EARTH and GFDL-ESM2-M drive RCM2 and RCM3, respectively (see Table 1). Consequently, the GR projections simulated using these inputs showed considerable changes. The changes in mean annual GR projections simulated by RCM1, RCM2, and RCM3 inputs ranged from −17% to +64% under RCP4.5 and from −24% to 8% under RCP8.5. Similarly, the CCLM4-8-17 comprises RCM4, RCM5, and RCM6 but with different driving GCMs. The changes in GR projections simulated by RCM4, RCM5, and RCM6 ranged from −23% to −57% under RCP4.5 and from −68% to −30% under RCP8.5. Therefore, significant uncertainty
in future GR simulations can be attributed to changes in the driving GCM under the same emission scenario. The analysis also demonstrated that the choice of emission scenario could largely affect GR simulation. The differences between annual GR projections under RCP4.5 and RCP8.5 were 32% in RCM1, 56% in RCM3, 45% in RCM4, 14% in RCP7, and 11% in RCP8. However, these findings cannot be generalized for all cases because the simulated GR in three RCMs (i.e., RCM2, RCM5, and RCM6) only differed slightly (<8%) among both RCPs.

Accordingly, it can be concluded that the effect of emission scenarios on GR simulations is less evident than the driving GCM effect. The findings of this study agree with Crosbie et al. (2011), who attributed the most significant cause of uncertainty in GR projection in southern Australia to GCMs, whereas the choice of downscaling approach was less critical. Kurylyk and MacQuarrie (2013) reported a similar investigation in a humid climate in eastern Canada. They found that different emission scenarios produce little uncertainty in GR simulations. Kurylyk and MacQuarrie (2013) stated that the variability in future GR simulations first arises from the downscaling approach, second from the driving model, and third from the emission scenario. Holman et al. (2009) documented that more uncertainty arises from the downscaling process chosen than the emission scenario chosen. Therefore, this study reasons that the uncertainty in GR projections, from most significant to smallest, is due to the variations in the driving GCMs and emissions scenarios.

6 | CONCLUSIONS

This study examined the uncertainty in future GR simulated using different climatic components. The study showed that climatic uncertainty arising from selecting different driving models and emission scenarios leads to uncertainty in GR simulations. As a result, the uncertainty in GR projections makes identifying the magnitude, and even the direction, of GR evolution challenging. The findings of this study suggest that future GR estimations are incompetent if climatic components are uncertain. Therefore, it is highly recommended that GR estimates be compared with ground truth measurements. Since, sometimes, ground truth measurements might be unavailable in arid areas (like this study), the simultaneous comparison might be impossible. Thus, there is a pressing need to enhance climate services at a regional scale, giving arid areas a vital opportunity to project reliable climatic simulations that reduce GR uncertainty and support sustainable water resources management. The focus of attention should be made on the greatest source of uncertainty, that is, driving GCMs. Other recommendations to improve GR analysis include considering the human impact, such as changes in groundwater abstraction, soil conditions, socioeconomic aspects, and land use. Further studies should also consider seasonal and spatial variations of GR estimations. Knowing such variations is essential to allocating abstraction projects and prioritizing augmentation schemes.

To ensure the sustainable development of Qatar aquifers, maximum abstraction should not exceed long-term recharge. Considering the projected decrease in GR, abstraction works should be minimized, and decision-makers should create and apply managed aquifer recharge projects (Ajjur & Baalousha, 2021). Additionally, the predicted decline in GR rates may imply larger runoffs under same AET losses (i.e., urban flash floods) because, in shallow aquifers, precipitation is partitioned between AET, runoff, and GR. The consequences of such results would be devastating for the built-up environment of Doha. Therefore, policymakers must implement rigid and effective regulations for effective urban planning and flood prevention.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

CRediT authorship contribution statement

Salah Ajjur: Conceptualization, Methodology, Data curation, Formal analysis, Validation, Visualization, Writing—original draft, and Writing—review & editing. Sami Al-Ghamdi: Conceptualization, Funding acquisition, Project administration, and Writing—review and editing.

DATA AVAILABILITY STATEMENT

The CORDEX data can be accessed through the Earth System Grid Federation (ESGF) nodes, for instance, esgf-data.dkrz.de.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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