Hydrologic response of arid and semi-arid river basins in Iraq under a changing climate

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ABSTRACT

An assessment of the total hydrologic response of arid and semi-arid river basins to various scenarios of climate change by considering evapotranspiration, streamflow, and snowmelt is essential for sustainable management of water resources. The Diyala River Basin in Iraq has been chosen as a typical case study of dozens of river basins in arid and semi-arid regions. Here, the LARS-WG, the Soil and Water Assessment Tool (SWAT), and the SWAT Calibration and Uncertainty Program (CUP) were used to evaluate the total response by considering three Representative Concentration Pathways (RCPs); RCPs 2.6, 4.5, and 8.5 over three periods, 2021–2040, 2041–2061, and 2061–2080, were considered. The results indicate that by the year 2080, the basin will experience a temperature increase by 6.6, 10.1, and 16.6% for RCP 2.6, RCP 4.5, and RCP 8.5, respectively. The corresponding reduction in precipitation will be 3.2, 6.4, and 8.7%, resulting in 38.8, 47.9, and 52.8% fall in streamflow for RCPs 2.6, 4.5, and 8.5, respectively. Due to the increase in temperature, an earlier and less contribution of snowmelt is expected in the projected streamflow. Our findings provide a useful reference and a guide to decision makers for developing adaption plans to sustainably manage water resources in the Diyala River Basin and other similar basins in arid and semi-arid regions.

Key words: adaptation, arid and semi-arid regions, climate change, Diyala River, LARS-WG, SWAT

HIGHLIGHTS

• The study provides valuable information on possible future changes in streamflow under a changing climate.
• LARS-WG, SWAT, SWAT-CUP, and three RCP scenarios to predict the hydrologic response of a river basin are used.
• Precipitation is predicted to decrease, resulting in a reduction in streamflow.
• This study supports the sustainable use of water resources in a changing climate.
• This study serves the development of adaptation plans to climate change and its effects.

GRAPHICAL ABSTRACT

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INTRODUCTION

Climate change is now affecting almost every inhabited region worldwide, with human activities contributing to many recorded extreme weather and climate events (Intergovernmental Panel on Climate Change (IPCC) 2018). Climate change is altering the frequency, severity, spatial extent, duration, and timing of extreme weather and climate episodes (Naqi et al. 2021). Extreme drought and flood events are becoming more commonplace and more prolonged due to climate change (Elsner et al. 2010). The projected weather in Middle East and North Africa (MENA) suggests that the region will tend to become drier and hotter, with the associated streamflow declining by 20–30% (Milly et al. 2005). Lelieveld et al. (2012) reported that the MENA region is greatly impacted by climate change, putting significant strain on the already scarce water and agriculture resources. The expanded fifth phase of the Coupled Model Intercomparison Project Phase 5 (CMIP5) considers policy issues that simulate greenhouse emissions based on four Representative Concentration Pathways (RCPs 2.6, 4.5, 6, and 8.5) (Taylor et al. 2012).

Numerous works have evaluated the response of some climate and/or hydrologic variables to various greenhouse emissions. Zarghami et al. (2011) predicted that the temperature will increase by 2.3 °C and precipitation will decline by 3% in the middle of the current century in the East of Iran. Salman et al. (2018) projected the temperature of Iraq over the period of 2070–2099 using the Model for Interdisciplinary Research on Climate-Earth System Model (MIROC-ESM), Model for Interdisciplinary Research on Climate-version 5 (MIROC5), Hadley Centre Global Environment Model-version 2-Atmosphere-Ocean (HadGEM2-AO), and Hadley Centre Global Environment Model-version 2-Earth System (HadGEM2-ES) General Circulation Model (GCM). The findings of these models suggested that the increase in the maximum temperature falls within the range of 1.7–2.9, 1.8–4.4, and 1.5–4.9 °C, and the corresponding ranges for the minimum temperature are 1.5–2.4, 1.6–5.6, and 1.3–6.2 °C for RCP 2.6, RCP 4.5, and RCP 8.5, respectively. Osman et al. (2019) modeled the impact of climate change on streamflow of the Great Zab River, Iraq, using projected precipitation and temperature generated by the Long Ashton Research Station Weather Generator (LARS-WG). The results showed that streamflow tends to decline by 25–60% during the current century. Using the Soil and Water Assessment Tool (SWAT) model, Al-Mukhtar et al. (2014) found a decline in the projected annual streamflow of the Spree River, Germany, by 39 and 43% for the periods 2021–2030 and 2041–2050, respectively, under medium greenhouse emissions (A1B). Al-Khafaji & Al-Chalabi (2019) evaluated the impact of climate change on the Diyala River Basin (DRB) under the A1B scenario. They reported that by 2050, there will be a decrease in the inflow to the Darbandikhan and Hemrin Dams by 49 and 43.7%, respectively. Ayalew et al. (2021) indicated a decline in streamflow modeled by the SWAT under RCP 4.5 (RCP 8.5) of greenhouse emissions from 42.8 to 40.24 m³/s (37.58 m³/s) in the Lake Tana Basin, Ethiopia. Zaredar et al. (2021) projected the future rainfall over the Karkheh River Basin, Iran, till the year 2040 using the LARS-WG. Their results indicated that an increasing frequency of spring droughts is expected.

In arid and semi-arid river basins, the total response of evapotranspiration, streamflow, and snowmelt to various scenarios of greenhouse emissions and the interaction between these hydrologic elements were not inclusively considered in previous works, which need a deeper understanding. Therefore, this paper targets the DRB shared between Iran and Iraq and located in arid and semi-arid regions to evaluate future hydrologic characteristics of the basin in response to various climate change scenarios. This evaluation includes the expected trends in evapotranspiration, streamflow, and snowmelt of the DRB in response to projected precipitation and temperature. The DRB is comparable to a large number of shared river basins in arid and semi-arid climatic zones that are experiencing challenges in sustainable water resource management (Al-Faraj & Scholz 2014). The future trends in precipitation and temperature are investigated over three periods, P1: 2021–2040, P2: 2041–2060, and P3:2061–2080, by applying five GCMs under RCP 2.6, RCP 4.5, and RCP 8.5 climate change scenarios in the LARS-WG. The findings will contribute to a better understanding of the impacts of climate change on water resource availability, especially for the downstream country, where there is a notable imbalance between available water and growing water demands. These will assist water managers and decision makers in arid and semi-arid regions for planning future water projects and managing water resources in a sustainable manner.

MATERIALS AND METHODS

Study area

The Diyala River is one of the shared rivers between Iraq and Iran and is one of the principal tributaries of the Tigris River. The river originates in the Zagros Mountains of western Iran and joins the Tigris River in Iraq, south of Baghdad, and is 445-
km long. The DRB drains an area of 32,600 km² located between the coordinates: latitudes 33.216°N and 35.833°N and longitudes 44.500°E and 46.833°E. About 43% of the DRB is located in Iraq and the remainder (57%) in Iran (Al-Faraj & Scholz 2014). The river basin is divided into three segments. The upper segment with a drainage area of 16,750 km² (also called the Darbandikhan Dam Watershed (DDW)) is located between its source in the Zagros Mountains in the upper riparian country (Iran) and the Darbandikhan Dam in the lower riparian country (Iraq), the middle segment lies between the Darbandikhan Dam and the Hemrin Dam in Iraq with a drainage area of 12,822 km² (also called the Hemrin Dam Watershed (HDW)), and the lower segment (3,028 km²) is located between the Hemrin Dam and the confluence point with the Tigris River, south of Baghdad, in Iraq. The DDW and the HDW of the DRB are shown in Figure 1.

The DRB is characterized by an arid to semi-arid climate, that is cool wet winters and hot dry summers. The majority of the streamflow volume is generated between November and May. The rainy season usually starts from October or November every year and lasts till April or May depending on the rainfall pattern for that year. The non-rainy season spans from June to September.

About 90% of the rainfall falls between November and April. The long-term mean annual rainfall ranges between 970 mm in the upper portion of the basin in Iran and 100 mm in the lower segment of the basin in Iraq with a mean value of about 500 mm. The potential evapotranspiration values range between 1,550 mm in the upper part of the basin in Iran and 2,650 mm in the lower segment of the basin in Iraq. The river basin in Iran is largely dammed and is characterized by hydraulic diversions, inter-basin water transfer schemes, and extensive agriculture activities. The river basin in Iraq is dammed by three cascade dams, which are Darbandikhan, Hemrin, and the Diyala weir, which mainly serve the purposes of flood control, hydropower generation, and agriculture. The upstream large-scale human-induced activities associated with the impacts of climate change in Iran have become a major concern for water management decision makers in the lower riparian country (Iraq), where there is a considerable gap between available water and growing water demands (Al-Faraj & Tigkas 2016).

LARS-WG

The LARS-WG is a stochastically based weather generator model used for downscaling the current and future weather simulations at a single site. The simulation in the LARS-WG requires four weather variables, which are precipitation, minimum
temperature (Tmin), maximum temperature (Tmax), and solar radiation. The LARS-WG uses a Semi-Empirical Distribution (SED) to predict the durations of precipitation, solar radiation, and the occurrence of dry and wet events. Precipitation is simulated by rotating dry and wet series, where wet days considered with precipitation are >0 mm. The model selects the temporal extent of dry and wet series randomly from SED for the month in which the series starts. The LARS-WG simulates solar radiation in the same way as it does for precipitation by utilizing an independent SED that describes solar radiation on wet and dry days. Also, an autocorrelation coefficient is considered by models that are assumed to be constant during the year of simulation.

The prediction of Tmin and Tmax is processed stochastically by utilizing daily mean and standard deviation based on day conditions and dry or wet status. For this purpose, the LARS-WG model implements finite Fourier series of order 3 to generate seasonal series of mean and standard deviation. By defined location and historical weather records including precipitation, temperature, and solar radiation, the LARS-WG is able to project weather data optionally from the year 2011 to 2100 by considering different climate change scenarios (RCPs) for different projects such as the CMIP5 (Semenov & Barrow 2002).

The LARS-WG has many features that make it more suitable for weather projections. Together with the SWAT model, these features include an assessment of risk in hydrological or agricultural applications, the creation of multiple-year climate change scenarios at the daily time scale, better simulation of monthly precipitation extremes, risk analysis of extreme precipitation, easy in transformed data format with the SWAT, and simulation of temperature and precipitation at single climate stations under RCPs 2.6, 4.5, 6, and 8.5 scenarios of greenhouse emissions (Yang et al. 2021).

### SWAT and SWAT-CUP

The SWAT is a semi-distributed hydrologic model developed by the United States Department of Agricultural (USDA) to simulate streamflow, sedimentation, groundwater, and pollution for watersheds under different land management and forecasting scenarios (Gassman et al. 2007). The SWAT divides an entire watershed into sub-basins based on the topographic condition. For the purposes of simplification, the SWAT further divides the watershed into hydrologic response units (HRUs), which have a unique slope, land cover and land use (LCLU), and soil type. The streamflow for each HRU is calculated by using a balance equation as shown in the following equation (Neitsch et al. 2011).

\[
SW_i = SW_0 + \sum_{i=1}^{t} (R_{\text{day}} + Q_{\text{sur}} - E_a - W_{\text{seep}} - Q_{\text{gw}})
\]

where \(SW_i\) is the final soil water content (mm); \(SW_0\) is the initial soil water content on day \(i\) (mm); \(R_{\text{day}}\) is the amount of precipitation on day \(i\) (mm); \(Q_{\text{sur}}\) is the amount of surface runoff on day \(i\) (mm); \(E_a\) is the amount of evapotranspiration (ET) on day \(i\) (mm); \(W_{\text{seep}}\) is the amount of water entering the vadose zone from the soil profile on day \(i\) (mm); \(Q_{\text{gw}}\) is the amount of return flow on day \(i\) (mm); and \(t\) is the time (day).

The SWAT simulates snowmelt based on air and accumulated snow temperature. If snow is present, it is melted on days when the maximum temperature exceeds 0 °C. The contribution of snowmelt to simulated runoff is estimated by the model assuming a uniformly melted snow for a 24-h duration, and the rainfall energy is set to zero.

The SWAT Calibration and Uncertainty Program (SWAT-CUP) is an automatic software developed for sensitivity analysis, calibration, and validation for the SWAT model (Abbaspour 2011). The SWAT-CUP contains five programs, namely, Sequential Uncertainty Fitting-2 (SUFI2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC). The SWAT-CUP is designed to capture most of the observed data within 95% of prediction using iteration processes. Abbaspour et al. (2004) suggested two factors to represent the quality of the calibration process, which are the \(p\)-factor and the \(r\)-factor. The \(p\)-factor is the percentage of observed data included inside the simulation envelope and ranges from 0 to 1 and the \(r\)-factor is the ratio of the width of the simulation envelope and standard deviation of observed data, and the value of the \(r\)-factor is <1.5 and is in an acceptable range.

In this study, ArcSWAT 2012 connected with ArcGIS 10.3 was implemented for hydrologic simulation. The following methods were used in the processes: Soil Conservation Service Curve Number (SCS-CN) for streamflow, the Penman–Monteith method for evapotranspiration, and variable storage for flow routing and SUFI2 by maximizing the Nash–Sutcliffe efficiency (NSE) for calibration. Other optional methods were kept as default settings.
Data

The daily precipitation data (daily Pcp) for the period from 1/1/1990 to 31/12/2019 were made available by the General Directorate of Weather Forecasting and Seismic Observation, Iraq (GDWFSO), for two meteorological stations in the HDW and by the Climate Forecast System Reanalysis (CFSR) for two meteorological stations located within the DDW. Other weather data, including wind speed, relative humidity, solar radiation, and Tmin and Tmax, were harvested from the CFSR (Fuka et al. 2014). The locations and long-term records of these stations are given in Table 1. The CFSR data are available until 31/7/2014. These data were extended to 31/12/2019 using the SWAT weather generator, and the results of simulated streamflow were evaluated based on the findings of Arnold et al. (2012). The filling of missing data in hydrologic modeling is conventionally used by Nkuna & Odiyo (2011), Mwale et al. (2012), and Tan & Yang (2020).

The SWAT model requires spatial data, including the Digital Elevation Model (DEM), LCLU, and soil data. The DEM was obtained from the Shuttle Radar Topography Mission (SRTM) with 90 m of spatial resolution, and the data were downloaded from http://glcf.umd.edu/data/srtm/. The Moderate Resolution Imaging Spectroradiometer (MODIS) LCLU of 500 m spatial resolution for the year 2000 was used in the SWAT (Al-Khafaji et al. 2020). The data were downloaded from http://gdxcr.usgs.gov/gdex/. The soil data provided by the Food Agricultural Organization (FAO) were used for implementing the SWAT model. These data are available in vector form with 1:50,000 of spatial scale and contain two soil layers: 0–30 and 30–100 cm. The FAO soil database, which includes the soil characteristics required for the SWAT, was incorporated into the SWAT database. The FAO soil data were downloaded from https://www.fao.org.

A 30-year time series of daily inflows to the Darbandikhan and Hemrin Dams was provided by the National Center for Water Resources Management, Iraq (NCWRM), for the period from 1/1/1990 to 31/12/2019. These data were used in the calibration and validation processes of the SWAT model.

Methodology

For streamflow simulation, two watersheds were considered (the DDW and the HDW). These watersheds were modeled independently using the SWAT model. The DEM-based method was used to define stream locations and watershed boundaries. The HRUs were generated using four slope classes (according to slope variation) with 0–10, 10–15, 15–20, and >20 for the DDW and 0–2, 2–5, 5–10, and >10 for the HDW. The LCLU and soil data were reclassified in the HRU definition window to

| Table 1 | Long-term weather records for the DRB |
|---------|-------------------------------------|
|         | HDW Latitude 34.329°E               | DDW Latitude 35.144°E               |
|         | Longitude 45.379°N                  | Longitude 45.700°N                  |
| Month   | Pcp (mm)   Tmin (°C)   Tmax (°C)  | Pcp (mm)   Tmin (°C)   Tmax (°C)  |
| Jan     | 42.9       5.3            14.8    | 72.8       2             10.8    |
| Feb     | 29.1       5.6            15.7    | 80.2       2             11      |
| Mar     | 29.3       8.3            20      | 86.7       4.3           15.5    |
| Apr     | 14.6       13.2           26.6    | 83.4       8.4           22      |
| May     | 2.7        19              33.7    | 32.4       13.8          29.3    |
| Jun     | 0.1        23.3           39.4    | 0.2        18.1           35.5    |
| Jul     | 0          25.9           43.5    | 4.5        21.5           40.3    |
| Aug     | 0          26.8           44.3    | 0.9        22.3           41      |
| Sep     | 0.1        24.5           41.1    | 0.4        19.5           37.4    |
| Oct     | 12.2       20.5           35      | 17.5       15.7           31.4    |
| Nov     | 28.2       13.8           26      | 53.7       9.9            22.5    |
| Dec     | 37.9       8.5            18.4    | 66.9       5.4            15      |
| Av.     | 16.2       29.9           28.4    | 11.9       26             9.3      |
| Sum     | 197.1      560             499.5   | 532.5      |
match with those of the SWAT database. The streamflow simulated by the SWAT was calibrated for the period 1/1/1990–31/12/2009 and validated for the period 1/1/2010–31/12/2019 against the observed streamflow records using the SWAT-CUP with the SUFI2 algorithm. Using the recorded outflow water from the Darbandikhan Dam, the streamflow contribution of the DDW was separated from the streamflow of HDW in order to simulate only the natural streamflow generated inside the HDW. The most sensitive parameters were extracted by using sensitivity analysis, and the parameters suggested by Abbaspour et al. (2015) were used as the initial calibrated parameters. Subsequently, the PcP, TmIn, and solar radiation data used in the SWAT for the referenced period (1990–2019) were reincorporated into the LARS-WG model to generate future PcP, TmIn, and Tmax for the three projected periods, P1, P2, and P3.

The commonly used GCMs available in LARS-WG version 6 were run under the RCP 2.6, RCP 4.5, and RCP 8.5 scenarios, which are named the Beijing Climate Centre Institute of Atmospheric Physics (BCC-CSM1), the Canadian Earth System second generation Model (CanESM2), Australia’s Commonwealth Scientific and Industrial Research Organization (CSIRO-MK36), Hadley Centre Global Environment Model-version 2 (HadGEM2-ES), and the Norwegian Earth System Model (NorESM1). Furthermore, the calibrated SWAT model was run again under the same future periods, scenarios, and PcP, TmIn, and Tmmax modeled by the LARS-WG. Finally, the results from the LARS-WG and SWAT model were analyzed, plotted, and displayed for both watersheds.

RESULTS AND DISCUSSIONS

Sensitivity analysis

The global sensitivity analysis method provided by the SWAT-CUP introduced the most sensitive hydrologic parameters for both watersheds based on t-Stat and P-value. The results are given in Tables 2 and 3. The results revealed that the Curve Number-2 (CN2, mgt) and the baseflow parameters (GW_DELAY.gw, ALPHA_BF.gw, and GWQMN.gw) are the most sensitive parameters in the DDW and the HDW. However, streamflow was found to be sensitive to the snow parameters (SFTMP.bsn and SMTMP.bsn) in the DDW because of the lower temperature in the upper segments of the DDW.

Calibration and validation

Two statistical goodness-of-fit measures (the Nash–Sutcliffe efficiency, NSE, and the coefficient of determination, $R^2$) were used to evaluate the performance of the validation of the LARS-WG and calibration and validation of the SWAT model. The average NSE ($R^2$) given in Table 4 for the considered stations was found in the range of 0.96 and 0.98 (0.97) for both watersheds, whereas, for TmIn and Tmmax, the NSE and $R^2$ were found to be 0.99.

Table 5 shows the NSE, $R^2$, p-factor, and r-factor during the calibration of the DDW with 0.69, 0.72, 0.57, and 0.61, respectively. The corresponding values during the validation were obtained as 0.64, 0.73, 0.58, and 0.82, respectively. For the HDW, the NSE ($R^2$) were 0.70 (0.71) and 0.72 (0.73) for the calibration and validation processes, respectively. The p-factor (r-factor)

### Table 2 | DDW calibrated parameters

| Rank | Parameter name | Definition | t-Stat | P-value | Initial range | Final range |
|------|----------------|------------|--------|---------|---------------|-------------|
| 1    | CN2.mgt        | SCS-CN     | −21.05 | 0.00    | −0.5, 0.5     | −0.28, −0.03 |
| 2    | GW_DELAY.gw    | Groundwater delay | 0.39   | 0.69    | 0, 450        | 8.4, 88     |
| 3    | ALPHA_BF.gw    | Baseflow alpha factor | 1.08   | 0.28    | 0, 1          | 0.53, 0.74  |
| 4    | GWQMN.gw       | Threshold depth of water in the shallow aquifer required for return flow | −0.49  | 0.62    | 0, 100        | 50.3, 83.7  |
| 5    | SOL_AWC(…).sol| Soil available water capacity | 0.38   | 0.70    | −0.5, 0.5     | −0.15, 0.05 |
| 6    | SFTMP.bsn      | Snowfall temperature | 1.31   | 0.19    | −0.5, 0.5     | −2.7, 0.65  |
| 7    | SMTMP.bsn      | Snow melt base temperature | 1.00   | 0.32    | −0.5, 0.5     | 4.18, 9     |
| 8    | SLSUBBSN.hru   | Average slope length | −0.88  | 0.38    | −0.5, 0.5     | −0.06, 0.44 |
| 9    | ESCO.hru       | Soil evaporation compensation factor | −0.56  | 0.57    | −0.5, 0.5     | 0.42, 0.65  |
were found to be 0.56 (0.63) and 0.54 (0.43), respectively, as given in Table 5. These results are within the acceptable range suggested by Arnold et al. (2012).

**Future trends in precipitation and minimum and maximum temperatures**

Figure 2 shows the trend of precipitation over the DRB. For the RCP 2.6 scenario, a decrease in the mean annual precipitation can be noticed, reaching 518, 511, and 507 mm for P1, P2, and P3, respectively. A higher decrease is detected for the RCP 4.5 (RCP 8.5) scenario with a mean annual precipitation of 513 (501), 496 (488), and 490 (478) mm for P1, P2, and P3, respectively. It can also be perceived that the rate of decrease in precipitation is not the same over the DRB. This is especially clear in scenario RCP 8.5 over the period 2061–2080, where the decrease rate reaches about 13% in the east-northern zone compared with 7% in the west and west-southern zones of the watershed.

The results indicate an increase in the projected Tmin and Tmax over the DRB compared with the recorded data of the reference period. Figure 3 displays an increase in Tmin of +1.6, +2.4, and +3.8 °C for RCP 2.6, RCP 4.5, and RCP 8.5, respectively, by the year 2080. Moreover, the average of Tmin, which ranges between 19 and 20 °C, is expected to extend over the
The southern part of the DRB with <0.5, 0.5, and 24% of the entire DRB under RCPs 2.6, 4.5, and 8.5, respectively. Moreover, the average Tmin <10 °C is expected to be excluded in the DRB due to climate change for all scenarios.

The results show that by 2080, the mean Tmax will be characterized by an increase of +1.6, +2.5, and +4.2 °C for RCPs 2.6, 4.5, and 8.5, respectively (Figure 4). A rapid increase can be observed on the mean Tmax for RCP 8.5, where the temperature
ranges between 33 and 34 °C will cover 27% of the DRB, which was never recorded in the reference period (Al-Mukhtar & Qasim 2019). Moreover, the results show that temperature will increase, on average, by 2.69 °C by 2080 or by 0.45 °C/decade.

Streamflow analysis

Streamflow in the reference period

The average monthly streamflow for the reference period (1990–2019) is presented in Figure 5(a) and 5(b) for the DDW and the HDW, respectively. For the DDW, in spite of a peak in precipitation occurring in March with 89.3 mm, the peak streamflow recorded in April was 288 m³/s. This is because snow is dominated as precipitation in March fall in snow form due to low temperatures in high altitudes; therefore, snowmelt has a considerable contribution of streamflow in April as a start of the spring season. Also, the sensitivity analysis procedures confirmed that the DDW is sensitive to snow parameters (Table 2).

However, the peak discharge of the HDW for the reference period was recorded in February, reaching 72 m³/s as shown in Figure 5(b). The difference between the peaks in the DDW and the HDW is attributed to the higher temperature in the HDW compared with that in DDW. This makes all precipitation (minus losses) transformed to surface streamflow and no considerable amount of snowmelt contribution in HDW streamflow.

Moreover, in the HDW, the peak of recorded precipitation in the reference period is the same in January and February with 52 mm for both months, while the peak of streamflow can be observed in February; this is because the soil in the HDW becomes more saturated in February. It is noteworthy that the soil available water capacity parameter is one of the sensitive hydrologic parameters to the simulated streamflow in the HDW (see Table 3).

Quantity-temporal distribution of streamflow

An analysis of streamflow characteristics showed that climate change alters the magnitude and timing of peak streamflow. For the DDW, the projected peaks tend to reduce and form earlier in future. From Figure 6, the peaks under RCP 2.6 (RCP 4.5) will gradually reduce in magnitudes by 216.3 (200.4), 202.4 (191.7), and 197.8 (182.5) m³/s for P1, P2, and P3, respectively. For RCP 8.5, there is a significant decrease in peaks with 192, 155, and 134.6 m³/s. It is worth noting that the observed peak of streamflow in the reference period was 288 m³/s (Figure 5).

An analysis of peak timing for the DDW shown in Figure 6 indicates that the peak of future streamflow will occur in March instead of April. The figure demonstrates that peak streamflow temporally moves forward under all RCPs and the projected
periods. This can be attributed to the integrated impacts of: first, an increase in temperature in the future leading to earlier snowmelt. Rottler et al. (2021) found a similar result in the Rhine River; they confirmed that the earlier snowmelt due to a rise in temperature shifts forward the peak flood and indicated that peak flood decreases due to a decrease in snowmelt contribution in streamflow. The results of this research also agree with the results of Sharif et al. (2012), where they indicated that the effects of climate change on the magnitude and timing of the Indus streamflow hydrograph could be testified by a change in the peak of snowmelt and variation in seasonal temperature. Secondly, the thin snow cover over the DDW will melt earlier in the future as the temperature will increase in the DDW. Finally, the increase in temperature (Figures 3 and 4) will lead to an increase in evapotranspiration, consequently reducing the surface streamflow. Berghuijs et al. (2014) argued that reduction in streamflow addressed to decline in the fraction of precipitation as snowfall. From Figure 6, it can be noticed that some GCMs such as in RCPs 2.6 (P1), 4.5 (P1 and P3), and 8.5 (P2 and P3) have unshifted peaks, but the effects of these GCMs are eliminated by those of other GCMs; therefore, the resultant peaks extracted from an average of overall GCMs resemble shifted peaks. For the HDW, Figure 7 shows a change in the magnitude of peak streamflow with a negative trend, and there is no significant change in the timing of this peak. This is because there is no snowmelt contribution in streamflow and most of the precipitation falls over the HDW in the form of rainfall so that the watershed is sensitive only to reduction in rainfall. The recorded peak streamflow will reduce under RCP 2.6 from 71.1 to 43.3 m³/s, 42.3, and 41.4 m³/s for P1, P2, and P3, respectively. In the same context, peak reduction is significant for RCP 4.5 (RCP 8.5) with 37.6 (34.3), 35.4 (33.4), and 34.1 (23.8) m³/s for P1, P2, and P3, respectively. From the results, it can be noticed that the increase in temperature denotes an increase in evapotranspiration, which is considered as another factor leading to a decrease in streamflow in addition to a decrease in precipitation.

Trends of future evapotranspiration and streamflow
The variation in the performance of GCMs shown in Figures 6 and 7 was accommodated by using the ensemble average of the five GCMs in the analysis of projected streamflow and evapotranspiration (Tan et al. 2014). For the DDW and the HDW, Figure 8(a) and 8(b) show the results of projected evapotranspiration. It can be noticed that the evapotranspiration will increase to 1,941 (2,091), 1,964 (2,135), and 2,037 (2,175) mm/year at the end of 2080 for RCPs 2.6, 4.5, and 8.5, respectively, compared with 1,718 (2,006) mm/year earlier in the 1990s. By combining the increase in evapotranspiration and reduction in precipitation, the response of the DRB in terms of streamflow is expected to decrease, as shown in Figure 9. This figure indicates that the future streamflow in the DDW and the HDW is expected to decline at the end of periods P1, P2, and P3 with a maximum reduction rate associated with RCP 8.5.
For the DDW (HDW), the RCP 2.6 scenario offers a gradual reduction in the annual projected streamflow with 90.7 (17.6), 83.7 (17.25), and 82.1 (17) m³/s at the end of the periods P1, P2, and P3, respectively. The observed annual flows are 160 and 44.7 m³/s for the DDW and the HDW, respectively, in the early 1990s. Under RCP 4.5, the projected streamflow shows more decline in the future than under RCP 2.6. Furthermore, the projected annual flows for the DDW are 82.8, 70, and 69.7, at the end of P1, P2, and P3, respectively, and those for HDW are 14.34, 12.95, and 12.49 m³/s at the end of P1, P2, and P3, respectively. On the other hand, RCP 8.5 shows a significant fall in the streamflow of the DDW, with 77.79, 67.9, and 56.66 m³/s at the end of the years 2040, 2060, and 2080, respectively. In addition, for the HDW, the projected flows are 12.73, 10.8, and 10.5 m³/s at the end of 2040, 2060, and 2080, respectively.

**Figure 6** | Future quantity-temporal distribution of streamflow for the DDW.
It can be noticed from Figures 8 and 9 that the trends of evapotranspiration and streamflow under the RCP 8.5 scenario are closest to the trends in the reference period. This is because the greenhouse emissions for the reference period (1990–2019) coincide with RCP 8.5 (Intergovernmental Panel on Climate Change (IPCC) 2018).

An evaluation of the response of the DRB to climate change for the period from 2021 to 2080, shown in Figure 10, reveals that climate change alters the precipitation (temperature) over the DRB by $-5.2\%$ ($+6.6\%$), $-6.5\%$ ($+10\%$), and $-8.7\%$ ($+17\%$) under RCPs 2.6, 4.5, and 8.5, respectively. The figure shows that the evapotranspiration will increase by 6.3, 10, and 16.6% under RCPs 2.6, 4.5, and 8.5, respectively. Furthermore, the streamflow of the DRB is significantly sensitive to climate change with...
Figure 8 | Future trend of projected evapotranspiration: (a) DDW and (b) HDW.

Figure 9 | Future trend of projected streamflow: (a) DDW and (b) HDW.

Figure 10 | Response of the DRB to future trends in temperature and precipitation.
reductions by 38.8, 47.9, and 52.8% for RCPs 2.6, 4.5, and 8.5, respectively. The increase in evapotranspiration is considered as another contributing factor in the reduction of streamflow (Rottler et al. 2021).

CONCLUSIONS

In the last few decades, the DRB, which is one of the shared river basins in arid and semi-arid areas, has been significantly affected by climate change, marked by an increase in the frequency of drought, which impacted the evapotranspiration rate and the magnitude and timing of streamflow. In this paper, the future trends of precipitation and the minimum and maximum temperatures associated with climate change were investigated by considering five GCMs and three RCP scenarios in the LARS-WG model. Consequently, the hydrologic response of the DRB to these trends was evaluated using the SWAT model.

The results detected a significant change in precipitation and temperature patterns due to climate change. Due to a rise in the average temperatures by +6.6, +10.1, and +16.6% for RCP 2.6, RCP 4.5, and RCP 8.5, respectively, rainfall is expected to be dominant over the DRB and snowfall is expected to be dimensioned. However, the precipitation over the DRB is expected to decline by 3.2, 6.4, and 8.7% for RCPs 2.6, 4.5, and 8.5, respectively. Furthermore, the thickness of snow cover is expected to become less compared with that in the reference period. Therefore, the projected extent of snowfall in the DDW is expected to become less with lesser thickness. This implies that the snowmelt contribution to streamflow is expected to become less and temporally move forward with lower peaks compared with that in the reference period. Consequently, the streamflow of the DRB is significantly sensitive to climate change with reduction by 38.8, 47.9, and 52.8% for RCPs 2.6, 4.5, and 8.5, respectively.

The reduction of streamflow in arid and semi-arid river basins is largely influenced by a decrease in precipitation and an increase in the evapotranspiration rate. Here, the results demonstrated that the evapotranspiration rate is expected to increase by 6.3, 10, and 16.6% under RCPs 2.6, 4.5, and 8.5, respectively.

The study concluded that the DRB is expected to become drier and hotter by the year 2080. This suggests the importance of embedding the impacts of climate change into the management and planning of water resources at national and basin-wide scales. Moreover, increasing water-use efficiency has become imperative to adapt to the expected reduction in water resources of the Diyala River. The findings and conclusions of this study are expected to contribute to a better understanding of how the DRB will respond to various climate change scenarios. Understanding the hydrologic response under changing climatic scenarios will go a long way in supporting the sustainable management of water resources at local and basin-wide scales. The outcomes of this study can support the development of adequate climate change adaptation plans for arid and semi-arid basins.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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