Assessment of climate change impacts in a semi-arid watershed in Iran using regional climate models
Hamid R. Solaymani and A. K. Gosain

ABSTRACT
This paper aims to summarize in detail the results of the climate models under various scenarios by temporal and spatial analysis in the semi-arid Karkheh Basin (KB) in Iran, which is likely to experience water shortages. The PRECIS and REMO models, under A2, B2 and A1B scenarios, have been chosen as regional climate models (RCMs). These regional climate models indicate an overall warming in future in KB under various scenarios. The increase in temperature in the dry months (June, July and August) is greater than the increase in the wet months (January, February, March and April). In order to perform climate change impact assessment on water resources, the Arc-SWAT 9.3 model was used in the study area. SWAT (Soil and Water Assessment Tool) model results have been obtained using present and future climate data. There is an overall reduction in the water yield (WYLD) over the whole of the KB. The deficit of WYLD is considerable over the months of April to September throughout KB due to the increase in average temperature and decrease in precipitation under various emission scenarios. Statistical properties in box-and-whisker plots have been used to gain further understanding relevant to uncertainty analysis in climate change impacts. Evaluation of uncertainty has shown the highest uncertain condition under B2.

Key words | climate change, impact assessment, RCMs, SWAT, uncertainty analysis

INTRODUCTION
Climate change has the potential to affect fundamental drivers of the hydrological cycle, and consequently may have a large impact on the water sector. Increased global population can be assumed to have an increased climatic impact on the Earth. About 23% of the total anthropogenic carbon dioxide (CO₂) emissions arise from land-use change (Pepper et al. 1992), which makes it an important driving force for climatic changes. Due to the consumption of fossil fuels, anthropogenic emissions of CO₂ and other greenhouse gases have increased (IPCC 2009). Natural as well as anthropogenic factors can be responsible for the change in the greenhouse gas content of the atmosphere. A higher concentration of these gases in the atmosphere has caused global warming, which reduces the proportion of solar radiation hitting the Earth that is reflected back into space (Kalany & Cai 2003). According to the IPCC (Intergovernmental Panel on Climate Change) range of emission scenarios report, CO₂ concentrations are expected to increase from the current concentration of approximately 350 ppmv (part per million by volume) to approximately 550 ppmv in the 2030s and 660 ppmv in the 2050s (IPCC 2009).

Nearly all regions of the world are expected to experience a net negative impact of climate change on water resources and freshwater ecosystems (IPCC 2007). The frequency of floods and droughts are certain to increase in much of the world (Cuo et al. 2009; Nunes et al. 2009). There is no doubt whatsoever that climate change is going to impact many other sectors that are vulnerable to changes in water resources (Arnell 1999; Dirnböck et al. 2003; Calanca et al. 2006; Fu et al. 2007; Thomas et al. 2007). Societies are vulnerable to extreme climate-related events (Serrat et al. 2007). Reducing societal vulnerability to changes in climate depends upon our ability to bridge the
gap between climate science and the implementation of scientific management of the water sector (Gosain et al. 2006). Climate data, analysis and forecasts, and regional vulnerability assessments assist water resource managers in mitigating the effects of extreme events such as droughts and floods through the use of climate information and the related decision-support resources such as geographic information systems (GIS) (Sharma & Gosain 2010).

It is also important to emphasize that no individual weather event can be attributed to climate change and the instrumental records for such events are not long enough to help characterize how extreme future events could be. Climate change refers to the change in state of the climate that can be associated with the changes in the mean and/or variability of its properties that persist over an extended period of decades, or longer. The United Nations Framework Convention on Climate Change (UNFCCC 1992) defines climate change as ‘a change of climate which is attributed directly or indirectly to human activity, that alters the composition of the global atmosphere and which is, in addition to natural climate variability, observed, over comparable time periods’. It is crucial to develop a better understanding of the impact of such a change. This paper aims to present the results of the climate change impact assessment on the water resources of Karkheh Basin (KB) in Iran using the SWAT model. The uniqueness of the study is its implication of the impacts of climate change in heterogeneous KB (which is more susceptible to flooding (peak flows) and base flows; hence, subsequent water resources planning and management becomes a top priority) using SWAT. The analysis also uses the regional climate models (RCMs) in KB for the first time.

**MATERIAL AND METHODS**

**Study area**

The KB is located in the western part of Iran (Figure 1). The drainage area of the basin is about 50,764 km², out of which 80% falls in the Zagros mountain ranges. The topography depicts large spatial variation with elevations ranging from 3 to more than 3,000 masl (metres above sea level). The elevation of about 60% of the basin area is between 1,000 and 2,000 masl and about 20% is below 1,000 masl. The population living in the basin is about 4 million (in 2002), of which about one third resides in the rural areas (JAMAB Consulting Engineers 1999; Ashrafi et al. 2004). Hydrological features of the KB are complex and heterogeneous because of its diverse topography and natural settings of geology, climate and ecology.

The precipitation (P) pattern depicts large spatial and intra- and inter-annual variability across the basin. The mean annual precipitation ranges from 150 mm/yr in the lower arid plains to 750 mm/yr in the mountainous parts (JAMAB Consulting Engineers 1999). According to this variability, KB can be divided into three major sub-basins: Upper B (UKB), Middle KB (MKB) and Lower KB (LKB). On average, the MKB receives higher P than the Upper and Lower parts as illustrated by the records of Kermanshah (450 mm/yr), Khorramabad (510 mm/yr) and Ahwaz (230 mm/yr) synoptic stations situated in these sub-basins, respectively (JAMAB Consulting Engineers 1999 and Figure 2). In the mountainous parts the winter P falls as snow because temperatures often fall below 0 °C. The temperature shows large intra-annual variability, with January being the coolest and July the hottest month. The potential evapotranspiration (ETP) largely follows a pattern similar to the temperature (T) with the highest ETP in the southern arid plains and the lowest in the mountainous semi-arid region. There is a large gap between ETP and P in most of the months, which widens as we move from upper northern semi-arid regions to the lower southern arid parts of the basin. The hydrological analysis and impact assessment of water resources in such semi-arid to arid regions with high climatic variability is a challenging task compared with humid areas where P exceeds the ETP in most of the months (Sutcliffe 2004).

The water resources of the KB comprise both surface water and groundwater. The volume of water generated on account of average annual rainfall in the basin is 24.9 bm³ (billion cubic metres), of which 5.1 bm³ is surface water, 3.4 bm³ infiltrates to ground and the remaining 16.4 bm³ is lost to the atmosphere through evapotranspiration (JAMAB Consulting Engineers 2006). The quality of river water is generally good, though it varies both seasonally and along the path downstream, reaching up to 5 dsrm⁻¹ (decisieemens per metre) near the final outlet. The KB
comprises five sub-basins: the Gamasiab, Qarasu, Seymureh, Kashkan and south-Karkheh (JAMAB Consulting Engineers 1999; Figure 1). Basic characteristics of these five sub-basins are given in Table 1.

**Climate change models**

The IPCC Data Distribution Centre has used data from 23 general circulation models (GCMs) in preparing the Fourth Assessment Report (IPCC 2007). Of these models, one from the Hadley Centre for Climate Prediction and Research, referred to as HadCM3, and one from the Max Planck Institute für Meteorologie, referred to as ECHAM5, are more widely applied in climate change studies in Iran. Resolution of the two models differs substantially. The atmospheric component of HadCM3 has 19 levels with a horizontal resolution of 2.5 degrees of latitude by 3.75 degrees of longitude, which produces a global grid of 96 × 73 grid cells. This is equivalent to a surface resolution of about 417 km × 278 km at the Equator, reducing to 295 km × 278 km at 45 degrees of latitude. ECHAM5 also uses a vertical resolution of 19 layers, but the horizontal
resolution produces $128 \times 64$ grid points. The third-generation Hadley Centre Regional Climate Model ‘RCM’ (HadRM3 or PRECIS) and fifth-generation Max Planck Institute ‘REMO’ (ECHAM5) based on the respective GCMs, namely HadCM3 and ECHAM5, have been used. They have a horizontal resolution of $50 \text{ km} \times 50 \text{ km}$ with 19 levels in the atmosphere (from the surface to 30 km in the stratosphere) and four levels in the soil. The advantages of RCMs are as follows:

- Simulate current climate more realistically.
- Predict climate change with more detail and with regional differences.
- Represent smaller islands.
- RCM are much better at simulating and predicting changes to extremes of weather.
- RCM can simulate cyclones and hurricanes.
- RCM data can be used to drive other models (for example, a tropical cyclone, such as a vortex in the Bay.

Figure 2 | Locations of rain gauge and stream flow gauges in KB.
of Bengal, simulated by a RCM, the output from which was used as input to a coastal model to produce a map of water level in the Bay).

Moreover, the domains of RCM data belonging to different GCMs are not available for all places in the world. In this research, REMO with scenario A1B and PRECIS with A2 and B2 scenarios have been used.

Data

The REMO and PRECIS have been configured for Iran using a domain extending from about 44 N to 66 N and 24 E to 44 E. IPCC A1B, A2 and B2 scenarios for the time slices of present (1970–1999) and end century (2070–2099) have been obtained from Max Planck Institute für Meteorologie-Germany and Climatological Research Institute-Iran, respectively. In KB, there is a well-distributed network of meteorological gauging stations (Figure 2). Time series weather data (1969–2005) has been collected from Iran Meteorological Organization and the Ministry of Energy. Processing of RCM scenarios input data on precipitation and temperature for KB has been taken up before using them as inputs to the hydrological model.

SWAT model

The SWAT (Soil and Water Assessment Tool) (Arnold et al. 1998) water balance model is one of the best known models for simulation of watershed hydrology. In SWAT, a watershed is divided into multiple sub-watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the sub-watershed area and are not identified spatially within a SWAT simulation. Alternatively, a watershed can be subdivided into only sub-watersheds that are characterized by dominant land use, soil type, and management. It is a semi-physically, semi-distributed and GIS coupled model, which is a computationally efficient simulator of hydrology and crop growth at various scales. The model simulates the hydrologic cycle at any chronological time steps (e.g. annually, monthly, daily and sub-daily). SWAT is a continuous, hydrological model with an Arc-GIS interface. The interface is used for pre- and post-processing of the data and outputs. The model is physically based, rather than incorporating regression equations to describe the relationship between input and output variables. Another unique specification of the model is its ability to incorporate water management practices (Neitsch et al. 2011). Since water management affects the hydrologic balance, it is critical that the model is able to accommodate a variety of management practices. The model has been successfully used in many international applications (Gassman et al. 2007).

The resulting units, referred to as HRUs, are used as the basis of the water balance calculations. Water, sediment, and nutrient transformations and losses are determined for each HRU, aggregated at the sub-basin level, and then routed to the associated reach and catchment outlet through the channel network. SWAT represents the local water balance through four storage volumes: snow, soil profile (0–2 m), shallow aquifer (2–20 m), and deep aquifer (>20 m). The soil water balance equation is the basis of hydrological modelling. The simulated processes include surface runoff, infiltration, evaporation, plant water uptake, lateral flow, and percolation to shallow and deep aquifers. Surface runoff is estimated by a modified Soil Conservation Service curve number equation using the daily precipitation data based on soil hydrologic group, land use and land cover characteristics, and antecedent soil moisture. A more detailed description of the model is given by Neitsch et al. (2011). Climate change impacts can be simulated directly in

Table 1 | Basic characteristics of five sub-basins of the KB

<table>
<thead>
<tr>
<th>Sub-basins</th>
<th>Total area (km²)</th>
<th>Average annual rainfall (mm)</th>
<th>Mean annual discharge (MCM/y)</th>
<th>Irrigated area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamsasiab</td>
<td>11,500</td>
<td>465</td>
<td>1,080</td>
<td>1,360</td>
</tr>
<tr>
<td>Qarasu</td>
<td>5,350</td>
<td>435</td>
<td>722</td>
<td>276</td>
</tr>
<tr>
<td>Kashkan</td>
<td>8,960</td>
<td>390</td>
<td>1,639</td>
<td>543</td>
</tr>
<tr>
<td>Seymareh</td>
<td>16,400</td>
<td>350</td>
<td>5,827</td>
<td>490</td>
</tr>
<tr>
<td>south-Karkheh</td>
<td>8,590</td>
<td>260</td>
<td>5,153</td>
<td>1,110</td>
</tr>
</tbody>
</table>

Source: JAMAB Consulting Engineers (2006). Details on the study basin can be found in Sutcliffe & Carpenter (1968).
SWAT using climate change projections generated by GCMs or GCMs coupled with RCMs. More than 100 papers have been published concerning hydrologic aspects of climate change based on the SWAT literature database (www.card.iastate.edu/swat_articles/index.aspx) in peer-reviewed journals from 2002 to 2012. Stone et al. (2001), Gosain et al. (2006), Muthiah & Wurbs (2002), Nearing et al. (2005), Krysanova et al. (2005, 2007), Ryu et al. (2011), and Susmita et al. (2012) used SWAT for impact assessment in climate change. According to the above capabilities and applications, the Arc-SWAT (version 9.3) model has been used for KB.

Model setup

The Shuttle Radar Topography Mission (SRTM, http://www2.jpl.nasa.gov/srtm/) Digital Elevation Model of 90 m resolution was used for sub-basin definition. A threshold of 500 km² was used for the delineation of sub-basins. This threshold was interactively selected to divide the study area into a reasonable number (49 in the present case) of sub-basins. The HRUs were defined based on information on land use, soil and slope. The land use/land cover map was prepared using fine resolution Landsat ETM+ image 2002 (Mirqasemi & Pauw 2007). It distinguishes 18 land use/land cover classes, with rain-fed farming (33%), forest (23%), rangelands (18%), and bare lands (15%) constituting about 90% of the study area. The soil map was obtained from the global soil map of the Food & Agriculture Organization of the United Nations (1995), which provides data for 5,000 soil types comprising two layers (0−30 and 30−100 cm depth) at a spatial resolution of 10 km. The five categories of slope were defined to be used in the HRU definition: (a) 0−5%; (b) 5−10%; (c) 10−20%; (d) 20−30%; and (e) >30%. Finally, the HRUs were defined using the land use, soil and slope information. A threshold value of 5% for land use, soil and slope was used in the HRU definition. A threshold value of 5−10% is commonly used in HRU definitions to avoid small HRUs, reduce total number of HRUs and improve the computational efficiency of the model (Starks & Moriasi 2009). Daily climatic data for the period from January 1982 to December 2005 were used for the model simulations. Precipitation and temperature data from 10 synoptic stations were available (Figure 2).

Sensitivity analysis

Sensitivity analysis refers to the identification of parameters that have important effects in the model for the basin in question. It is a desirable step prior to model calibration. It demonstrates the impact that a change to an individual input parameter has on the model response and can be performed using a number of different methods. The method in the Arc-SWAT Interface combines the Latin Hypercube and One-factor-At-a-Time (OAT) sampling. The sensitivity analysis tool in Arc-SWAT has the capability of performing two types of analyses. The first type of analysis uses only modelled data to identify the impact of adjusting a parameter value on some measure of simulated output, such as average stream-flow. The second type of analysis uses measured data to provide overall ‘goodness of fit’ estimation between the modelled and the measured time series. The first analysis may help to identify parameters that improve a particular process or characteristic of the model, while the second analysis identifies the parameters that are affected by the characteristics of the study watershed and those to which the given project is most sensitive (Veith & Ghebremichael 2009). The description of parameters obtained after sensitivity analysis and their relative sensitivity is presented in Table 2. In this research, sensitivity analysis was performed based on both the approaches, with and without observed data. The parameters were ranked based on their sensitivities. For example, curve number for wetting condition II (CN2) ranked first in both approaches; this means CN2 is the most responsive parameter in KB compared with other parameters.

Model calibration and validation

Calibration involved tuning of model parameters based on checking model results against observations over time. This involves comparing the model results, generated with the historical meteorological data, to the recorded stream flows. In this process, model parameters are varied until recorded flow patterns are accurately simulated. For this study, two approaches have been used for calibration: (i) manual; and (ii) auto-calibration. The model was calibrated by removing the dams and
irrigated agriculture, and subsequently the stations that were affected by the dams. This was necessary as future land use changes and dam operation could not be predicted with any accuracy. The OAT sampling has been used for manual calibration. The Sequential Uncertainty Fitting (SUFI-2) algorithm in the SWAT-CUP program was used for parameter optimization. The evaluation of calibration was done using Graphical Procedure, Nash–Sutcliffe Efficiency (NSE), Percent Bias (PBIAS) and root mean square error (RMSE)-observations standard deviation ratio (RSR).

NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. NSE ranges between $-\infty$ and 1, where NSE $= 1$ is the optimal value. According to Moriasi et al. (2007), NSE values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values lower than 0.0 indicate that the mean observed value is a better predictor than the simulated value which indicates unacceptable performance. NSE is computed as shown in Equation (1):

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{i}^{\text{obs}} - Q_{i}^{\text{sim}})^2}{\sum_{i=1}^{n} (Q_{i}^{\text{obs}} - Q_{i}^{\text{mean}})^2}$$

where $Q_{i}^{\text{obs}}$ is the $i$th observation for the constituent being evaluated, $Q_{i}^{\text{sim}}$ is the $i$th simulated value for the constituent being evaluated, $Q_{i}^{\text{mean}}$ is the mean of observed data for the constituent being evaluated, and $n$ is the total number of observations. PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed values (Moriasi et al. 2007). Positive values indicate model underestimation bias, and negative values indicate overestimation bias (Gupta et al. 1999), the optimal value of PBIAS being zero. PBIAS is

<table>
<thead>
<tr>
<th>No</th>
<th>Parameter</th>
<th>Description</th>
<th>Initial value</th>
<th>Rank no. a</th>
<th>Rank no. b</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ALPHA_BF</td>
<td>Baseflow alpha factor (days)</td>
<td>0–50</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>CANMX</td>
<td>Maximum canopy storage (mm H$_2$O)</td>
<td>0–10</td>
<td>10</td>
<td>16</td>
</tr>
<tr>
<td>3</td>
<td>CH_K2</td>
<td>Channel effective hydraulic conductivity</td>
<td>0–150</td>
<td>4</td>
<td>15</td>
</tr>
<tr>
<td>4</td>
<td>CH_N2</td>
<td>Manning coefficient for channel</td>
<td>0.01–0.3</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>CN2</td>
<td>Initial SCS runoff curve number for wetting condition-2</td>
<td>$\pm$ 20%</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>EPCO</td>
<td>Plant uptake compensation factor</td>
<td>0–1</td>
<td>14</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
<td>0–1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>GW_DELAY</td>
<td>Ground water delay time</td>
<td>0–50</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>9</td>
<td>GW_REVAP</td>
<td>Ground water ‘REVAP’ coefficient</td>
<td>0.02–0.2</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>10</td>
<td>GWQMN</td>
<td>Threshold depth for shallow aquifer for flow</td>
<td>0–5,000</td>
<td>13</td>
<td>2</td>
</tr>
<tr>
<td>11</td>
<td>RCHRG_DP</td>
<td>Deep aquifer percolation factor</td>
<td>0–1</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>12</td>
<td>REVAPMN</td>
<td>Threshold depth of water in shallow aquifer for ‘REVAP’</td>
<td>0–500</td>
<td>16</td>
<td>18</td>
</tr>
<tr>
<td>13</td>
<td>SFTMP</td>
<td>Snowfall temperature (°C)</td>
<td>–5–5</td>
<td>20</td>
<td>6</td>
</tr>
<tr>
<td>14</td>
<td>SLOPE</td>
<td>Slope steepness (m/m)</td>
<td>0–0.6</td>
<td>9</td>
<td>13</td>
</tr>
<tr>
<td>15</td>
<td>SMFMN</td>
<td>Melt factor for snow December 21 (mm H$_2$O/°C-day)</td>
<td>0–10</td>
<td>20</td>
<td>8</td>
</tr>
<tr>
<td>16</td>
<td>SMFMX</td>
<td>Melt factor for snow June 21 (mm H$_2$O/°C-day)</td>
<td>0–10</td>
<td>20</td>
<td>11</td>
</tr>
<tr>
<td>17</td>
<td>SMTMP</td>
<td>Snow melt base (°C)</td>
<td>–5–5</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>18</td>
<td>SOL_AWC</td>
<td>Soil available water capacity</td>
<td>0.01–0.5</td>
<td>20</td>
<td>14</td>
</tr>
<tr>
<td>19</td>
<td>SURLAG</td>
<td>Surface runoff lag time</td>
<td>0–10</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>20</td>
<td>TIMP</td>
<td>Snow pack lag temperature lag factor</td>
<td>0–1</td>
<td>12</td>
<td>9</td>
</tr>
</tbody>
</table>

*Without observed data.

With observed data.

**Table 2:** SWAT sensitivity analysis results for KB

---

H. R. Solaymani & A. K. Gosain | Climate change impact assessment using RCMs, Iran
Journal of Water and Climate Change | 06.1 | 2015
Downloaded from https://iwaponline.com/jwcc/article-pdf/6/1/161/375127/jwc0060161.pdf
by guest on 10 October 2019
PBIAS values lower than 25% using SWAT are considered satisfactory, less than 10% are very good and between 10 and 15% are good. RMSE is a commonly used error statistic with model performance decreasing with increasing RMSE values. According to Singh et al. (2004), RSR values can be considered low when they are less than half the standard deviation of the observed data. RSR is computed as shown in Equation (3):

\[
RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\frac{\sum_{i=1}^{n} (Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{n} (Q_{obs})^2}}} \left( \frac{\sum_{i=1}^{n} (Q_{obs}^i - Q_{avg}^i)^2}{\sum_{i=1}^{n} (Q_{obs}^i)^2} \right)
\]  

(3)

In the RSR equation, \(n\) is the number of years, months or days according to the type of time series. The study period was divided into a calibration period from 1994 to 1996 and a validation period from 1997 to 1999. A warm-up period of three years (1991 to 1993) was used to initialize the model for the calibration period. The model has been calibrated and validated using manual and auto-calibration procedures. Table 3 shows the calculated results of values for NSE, PBIAS and RMSE for both manual and auto-calibration.

In situations with conflicting performance ratings for different criteria, performance on the conservative side should be attributed. For example, if simulation for one output variable in one watershed produces performance ratings of ‘very good’ for PBIAS, ‘good’ for NSE, and ‘satisfactory’ for RSR, then the overall performance should be described conservatively as ‘satisfactory’ for that one watershed. In the present case, the values of NSE, PBIAS and RSR for manual calibration respectively are 0.71 (good), –0.24 (very good) and 0.6 (good). Therefore, the overall result for ‘Manual calibration’ for the KRB should be designated as ‘good’ and in the same manner for the validation period is ‘satisfactory’. It has been seen that the manual calibration procedure performs much better than the auto-calibration procedure. In Figure 3, the calibration and validation series is shown. Further findings have been presented related to calibration and validation of SWAT in KB by Solaymani & Gosain (2012).

### RESULTS AND DISCUSSION

**Climate change data extraction**

Data for different variables (rainfall, temperature, solar radiation, relative humidity and wind speed) on a daily time scale are the outputs of RCM available for use in the modelling of the study area. The data represents grid cells 50 km × 50 km and are available in binary (NetCDF format for REMO data and Post Processing format for PRECIS model). The Climate Data Analysis Tools (CDAT) were used to extract the relevant data using grids for the study area and converting binary format to ascii format. These data are to be used as inputs to quantify the potential impacts of climate change on water resources by performing hydrological modelling with current and future climates respectively. The RCM grids for KB are shown in Figure 4.

<table>
<thead>
<tr>
<th>NSE</th>
<th>PBIAS</th>
<th>RSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Validation</td>
<td>Calibration</td>
</tr>
<tr>
<td>Manual calibration</td>
<td>0.71 (Good)</td>
<td>–0.24 (Very good)</td>
</tr>
<tr>
<td>Auto-calibration</td>
<td>0.31 (Unsatisfactory)</td>
<td>30.7 (Unsatisfactory)</td>
</tr>
<tr>
<td></td>
<td>0.60 (Satisfactory)</td>
<td>0.96 (Very good)</td>
</tr>
</tbody>
</table>

Table 3 | Outputs for statistical parameters with manual calibration and auto-calibration at Pay-e-pol flow gauge station

Downloaded from https://iwaponline.com/jwcc/article-pdf/6/1/161/375127/jwc0060161.pdf by guest
Climate change impact

Water is involved in all components of the climate system (atmosphere, hydrosphere, cryosphere, land surface and biosphere). Therefore, climate change affects water through a number of mechanisms. Climate warming observed over the past several decades is consistently associated with changes in a number of components of the hydrological cycle and hydrological systems such as: changing precipitation patterns, intensity and extremes, widespread melting of snow and ice, increasing atmospheric water vapour, increasing evaporation, and changes in soil moisture and runoff. It has been decided to discuss observations of recent changes in water-related variables, and projections of future changes to account for temperature, precipitation, evapotranspiration, water yield and runoff.

Temperature

The HADCM3 and ECHAM5 simulation downscaled with PRECIS and REMO models indicate overall warming with enhanced greenhouse gas concentration in KB. Mean daily temperature from the REMO and PRECIS models simulation of the A1B, A2, and B2 scenarios are given in Table 4.

Mean daily temperature is projected to rise significantly under the REMO and PRECIS in A1B, A2, and B2 scenarios, respectively. Positive change indicates warming in future. The increase in temperature in the dry months (e.g. June, July and August) is greater than that in the wet months (January, February, March and April). The maximum enhancement in the temperature is expected in the LKB followed by the Upper and MKB, respectively. Some anomalies have been observed during the cold season mainly under B2 and A2. An increase in temperature was expected for all months, whereas there has been a decrease in November, December, January, and February. Some researchers reported similar results (Myneni et al. 1997; Vaghefi et al. 2013) due to the seasonal circulation of CO2. Benjamin et al. (2006) reported that the CO2 variability is relatively strong during the cold season and weak during the warm season in the northern hemisphere.

Precipitation

Most of the precipitation (about 65%) falls during the winter months from December to March and almost no precipitation during the summer season (June to September in KB). The mean monthly and annually simulated precipitation by REMO and PRECIS models are shown in Table 5. Under all three scenarios, rainfall is projected to decrease. Mean annual precipitation decrease is 93, 328 and 367.7 mm in LKB under A1B, A2, and B2, respectively.

The precipitation reduction in Upper KB is 249, 220, and 272 mm under A1B, A2, and B2 scenarios, respectively. Almost all the months during the rainy season show considerable reduction in rainfall for all the
sub-basins of KB except for the month of November for MKB where an increase in rainfall by 64.8, 42.9, and 7.7 mm has been predicted under A1B, A2, and A1B scenarios, respectively.

**Evapotranspiration, water yield and surface flow**

Precipitation is more highly correlated with total water yield than the other hydro-climatic variables. Rain and snowfall supply all the water available for the hydrologic cycle; thus, the magnitude of precipitation strongly influences the magnitude of water yield. Increased precipitation also increases available soil moisture to fulfil potential evapotranspiration (ETp). On the other hand, a decrease in precipitation reduces the available water supply and hence can have detrimental effects on plant productivity and stream-flow, especially in arid and semi-arid regions. The SWAT model accounts for this through simulation of all

---

**Figure 4 | REMO and PRECIS grids for KB.**
these processes of ET, soil moisture and water yield (WYLD).

The Penman–Monteith equation used for ET directly accounts for alterations of stomatal conductance by adjusting the leaf conductance of each plant type for variations in atmospheric CO₂. Leaf conductance, radiation, vapour pressure, soil heat flux, and leaf-area-index are the major components of the Penman–Monteith equation. When CO₂ in the atmosphere is increased, the stomatal openings decrease to maintain the CO₂ flux necessary for the plant.
processes; consequently, the amount of water transpired from the plant through these openings is decreased leaving more water available for other processes. Temperature and relative humidity are used in the aerodynamic component of the Penman–Monteith equation. Temperature is used to determine the saturation vapour pressure in the atmosphere, which is then adjusted by the relative humidity to determine the actual vapour pressure at the boundary layer of the plant/atmosphere system. The difference between the saturation and actual vapour pressures is termed the vapour pressure deficit and is the driving factor of the aerodynamic component. Increased air temperature increases the saturation vapour pressure and consequently the vapour pressure deficit causing a significant increase in potential ET (Stoniefeet al. 2000).

Changes in relative humidity will also affect the vapour pressure deficit; for example, an increase in relative humidity will decrease the vapour pressure deficit thus decreasing ET. The change in ET will have an inverse effect on surface runoff and WYLD. Total amount of water leaving the subbasin and contributing to the main stream during the time step is called water yield (SWAT 2009). With SWAT it is possible to give the output of WYLD at HRUs scales and/or sub-basins scales. Radiation is used in the energy balance component of the Penman–Monteith equation. The net radiation for the energy balance is determined from the direct short-wave radiation from the sun, the long-wave radiation from the atmosphere, the long-wave radiation emitted by the Earth’s surface, and the surface albedo. Increased CO2 increases the long-wave radiation from the atmosphere and consequently increases the total net radiation received on the surface of the Earth. This increase in net radiation increases the energy balance component of the equation, which increases ET causing a decrease in surface runoff and WYLD. Results of the SWAT run present and future climate data have been compiled for WYLD and ET for the whole of KB and have been presented on a long-term mean monthly basis in Table 6.

It may be observed in Table 6 that maximum increase in evapotranspiration (ET) in Upper KB is 24.3 mm under A1B in November and the maximum decrease in ET is 13.8 mm under B2 in March. The maximum increase in the water yield (WYLD) is 8.2 mm under A2 in August whereas the maximum reduction is 78.3 mm under B2 in January. A similar trend was observed in the MKB and LKB. It may also be noticed that as far as annual WYLD is concerned a net reduction is predicted in the future for all sub-basins of KB. The deficit in WYLD is observed for most of the months across the sub-basins of KB except for a marginal increase in the month of October. The pattern of the monthly change is highly correlated with the variability of monthly precipitation and temperature. Similar variation has also been observed for evapotranspiration. The reduction of evapotranspiration has been observed for the majority of the months due to the decrease in precipitation. Spatial variation of ET and WYLD for two seasons, autumn (OND) and winter (JFM), under present and future scenarios for all the sub-basins of KB are depicted under A1B in Figure 5.

The changes are calculated using the differences between the averages of future (2070–2099) periods with respect to the average of the present (1970–1999) period. While the A1B scenario shows general reduction in the WYLD and ET in the whole of the KB, there are deviations for the MKB and LKB. There can be large increases in the WYLD in the LKB during the autumn.

It may be observed from Figure 6 that consequent to changes in temperature, precipitation and evapotranspiration, stream flow decreases considerably from January to September but increases from October to December under the A1B scenario at both of the discharge stations of KB. The reduction in discharge at Jelogir is 53, 49, and 92% under A1B, A2, and B2 in February respectively and there is an increase in discharge of 226% from 183 to 414 m$^3$/s for the month of December under A1B. A similar trend is depicted for the Pay-e-Pol station.

Uncertainty in climate change projections

Uncertainties in climate change projections in the hydrologic system originate from internal variability of the climate system, uncertainty in future greenhouse gas emissions, the addressing of these emissions into climate change by GCMs, and uncertainty in hydrological models. Döll et al. (2003) and Arnell (2004) highlighted that the uncertainties in impact of climate change projection on water resources are mainly a result of the uncertainty in climate model inputs and less because of
the uncertainties in greenhouse gas emissions. It was also emphasized when assessing uncertainty in the impact of climate change on water resources that multi-model application approaches are more desirable than using the output of only one climate model (Arnell 2003; Jasper et al. 2003). There are two main reasons for most of the uncertainties in the many relevant studies on water resources and climate change projections (Arnell 2003):

- The mismatch between spatial scales of GCMs and hydrological process. Techniques for dynamical rather than statistical downscaling have been developed.
- Acknowledge that uncertainties originate from climate scenarios. For example, in those studies, time series of observed climate values were adjusted with the computed change in climate variable to obtain scenarios which are consistent with present conditions.

To determine future uncertainty relevant to climate change impact, further understanding could be gained using statistical properties in box-and-whisker plots (Frigge et al. 1988). The box-and-whisker plot may seem more primitive than the other methods but it has some advantages (e.g. it takes up less space and is therefore particularly useful for

<table>
<thead>
<tr>
<th>Table 6</th>
<th>Changes of the mean daily ET and WYLD (mm) under A1B, A2, and B2 scenarios (base: 1970–1999, future: 2070–2099)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Jan</td>
</tr>
<tr>
<td>Upper KB</td>
<td></td>
</tr>
<tr>
<td>ET-Base</td>
<td>16.44</td>
</tr>
<tr>
<td>ET-A1B</td>
<td>10.75</td>
</tr>
<tr>
<td>ET-A2</td>
<td>23.27</td>
</tr>
<tr>
<td>ET-B2</td>
<td>5.38</td>
</tr>
<tr>
<td>WYLD-Base</td>
<td>78.32</td>
</tr>
<tr>
<td>WYLD-A1B</td>
<td>18.39</td>
</tr>
<tr>
<td>WYLD-A2</td>
<td>15.00</td>
</tr>
<tr>
<td>WYLD-B2</td>
<td>0.01</td>
</tr>
<tr>
<td>Middle KB</td>
<td></td>
</tr>
<tr>
<td>ET-A1B</td>
<td>12.56</td>
</tr>
<tr>
<td>ET-A2</td>
<td>24.63</td>
</tr>
<tr>
<td>ET-B2</td>
<td>5.56</td>
</tr>
<tr>
<td>WYLD-Base</td>
<td>35.16</td>
</tr>
<tr>
<td>WYLD-A1B</td>
<td>19.47</td>
</tr>
<tr>
<td>WYLD-A2</td>
<td>16.83</td>
</tr>
<tr>
<td>WYLD-B2</td>
<td>0.02</td>
</tr>
<tr>
<td>Lower KB</td>
<td></td>
</tr>
<tr>
<td>ET-Base</td>
<td>21.06</td>
</tr>
<tr>
<td>ET-A1B</td>
<td>14.40</td>
</tr>
<tr>
<td>ET-A2</td>
<td>13.14</td>
</tr>
<tr>
<td>ET-B2</td>
<td>8.32</td>
</tr>
<tr>
<td>WYLD-Base</td>
<td>25.19</td>
</tr>
<tr>
<td>WYLD-A1B</td>
<td>15.16</td>
</tr>
<tr>
<td>WYLD-A2</td>
<td>18.43</td>
</tr>
<tr>
<td>WYLD-B2</td>
<td>0.10</td>
</tr>
</tbody>
</table>
Figure 5 | Spatial variation of the WYLD (a) and ET (b) between historic and future climate conditions in KB. This comparison is visualized based on the averages of data periods 2070–2099 (end century) and the average of 1970–1999 (present) in two seasons, winter (JFM) and autumn (OND).
comparing distributions between several groups or sets of data). This plot is designed on a scatter plot. The box often indicates median (50th percentile) and 25th and 75th percentiles, the whiskers 10th and 90th percentiles, but could equally well be average, $\pm 1$ and 2 standard deviations, or 90 and 95% confidence intervals or whatever is meaningful for the statistic.

Uncertainty analysis of precipitation and temperature

In this section, future precipitation and temperature under various scenarios are compared to evaluate the spread of uncertainty from the choice of the RCMs. Figure 7 shows that precipitation has been reduced dramatically during the winter months under A1B and B2 scenarios. This reduction is also observed in the A2 scenario although to a slightly smaller extent in winter. During November and December the average precipitation increased slightly in A1B. Overall, the precipitation reduction has been observed in all three scenarios in KB. These results are consistent with findings obtained from other studies in Iran (e.g. Massah 2006; Faramarzi et al. 2008; Morid & Massah 2008; Abbaspour et al. 2009). The range of uncertainty in the projections of precipitation is much bigger for both RCMs in the three scenarios compared with temperature.
According to Figures 8(a) and 8(b), T_{max} is significantly increased during summer (JJA) with the lowest changes in the winter (DJF); T_{min} changes follow the same trend with less intensity under A2. In the B2 scenario, T_{max} also increased substantially throughout the year except in December and January. T_{min} shows anomalous monthly trends in March, April, October and November where the increases are lower compared with the other months in the B2 scenario (Figures 8(c) and 8(d)). As can be observed in Figures 8(e) and 8(f), the increase in T_{max} and T_{min} is lower than that for A2 and B2. The maximum increase in T_{max} is also shown in summer and the minimum in the other months. Generally, during winter and summer, the spread of uncertainty in the temperature projections resulting from the various RCMs is higher, while it is lower during spring and autumn.

**Uncertainty analysis of ET and WYLD**

In the next step, uncertainty was evaluated in mean monthly ET. Figure 9 shows the downward trend in all projections. The lowest reduction in ET trend was observed in the A2 scenario while the maximum was observed in the A1B projection during January to May due to the substantial downward trend in precipitation in the relevant months.

Temperature as well as relative humidity of the atmosphere plays the most vital effect in simulating ET. Temperature projections also follow a similar trend whereas precipitation has a greater effect on ET than temperature in KB.

Figure 10 shows the spread of uncertainty in the WYLD projections. In the A1B emission scenario, a decidedly downward trend is observed from January to July. The substantial upward trend shown in November and December.
is due to an increase in precipitation. In both A2 and B2, the trend of WYLD is reduced throughout the year.

**CONCLUSION**

The KB represents a large, unregulated, mountain catchment in the southwest of Iran. It contains extensive areas of the Zagros mountain range with permanent snowfields that dominate the surface runoff processes. Understanding the hydrologic response to climate change for watersheds of this type is particularly important due to the dependence of major water systems on the contribution made by the stream-flow of the Karkheh River. An attempt has been made in the present study to use various available RCMs in the study area in Iran to select the one that fitted best...
to the observed data. It has been observed that the REMO simulated data under A1B was slightly close to observed data.

The SWAT model was then used to evaluate the sensitivity of annual and seasonal stream-flow from the KB to possible changes in climate. The change in precipitation had the most significant impact on the magnitude of annual water yield. Increased temperature causes a significant reduction in total stream-flow volume. As mentioned above, the pattern of the monthly change in ET, WYLD and discharge is largely governed by the combined impact of temperature and precipitation in a very complex manner. Evaluation of uncertainty in climate change impacts has also shown the most uncertain condition is relevant to the B2 scenario in both climate and hydrologic projections. It has also been observed that the most stable portions are MKB in the irrigated, cultivated areas. Surprisingly, risk of drought and heat stress is thought to increase throughout the study area. However, risk from soil erosion and flooding is perceived to be much higher in KB, where enhanced precipitation is expected in both spring and autumn, but is also mentioned as a threat in LKB. The present study presents the consequences of climate change on the water resources of KB and shall be useful in formulating the adaptation options in a sustainable manner.

ACKNOWLEDGEMENTS

We appreciate the help extended by Dr K. Achuta Rao, Associate Professor, Atmospheric Sciences Centre, IIT Delhi in using the CDAT model. We also thank Dr Pankaj Kumar, Max Planck Institute für Meteorologie, Germany, and Dr I. Babaein, Climatological Research Institute, Iran, for useful help in obtaining the REMO and PRECIS RCM data.

REFERENCES

Arnell, N. W. 1999 Climate change and global water resources. Global Environmental Change 9, 31–49.


