Impacts and uncertainties of climate change on streamflow of the Johor River Basin, Malaysia using a CMIP5 General Circulation Model ensemble
Mou Leong Tan, Darren L. Ficklin, Ab Latif Ibrahim and Zulkifli Yusop

ABSTRACT

The impact of climate change and uncertainty of climate projections from general circulation models (GCMs) from phase 5 of the Coupled Model Intercomparison Project (CMIP5) on streamflow in the Johor River Basin, Malaysia was assessed. Eighteen GCMs were evaluated, and the six that adequately simulated historical climate were selected for an ensemble of GCMs under three Representative Concentration Pathways (RCPs; 2.6 (low emissions), 4.5 (moderate emissions) and 8.5 (high emissions)) for three future time periods (2020s, 2050s and 2080s) as inputs into the Soil and Water Assessment Tool (SWAT) hydrological model. We also quantified the uncertainties associated with GCM structure, greenhouse gas concentration pathways (RCP 2.6, 4.5 and 8.5), and prescribed increases of global temperature (1–6°C) through streamflow changes. The SWAT model simulated historical monthly streamflow well, with a Nash–Sutcliffe efficiency coefficient of 0.66 for calibration and 0.62 for validation. Under RCPs 2.6, 4.5, and 8.5, the results indicate that annual precipitation changes of 1.01 to 8.88% and annual temperature of 0.60–3.21°C will lead to a projected annual streamflow ranging from 0.91 to 12.95% compared to the historical period. The study indicates multiple climate change scenarios are important for a robust hydrological impact assessment.

Key words | climate change, Johor River, Malaysia, streamflow, SWAT, uncertainty

INTRODUCTION

Increases in air temperature are expected to accelerate the global hydrological cycle (Oki & Kanae 2006). Precipitation and evapotranspiration are the most affected components that will influence regional water availability (e.g. Milly et al. 2005). The Intergovernmental Panel on Climate Change (IPCC) emphasized that current water management systems cannot cope with the impacts of climate change, and that large drought and flood damages are expected to occur (Bates et al. 2008). Therefore, the expected changes of local-to-regional-scale hydrological changes are essential to develop adaptations to current water resource systems.

Generally, there are three approaches for developing future climate scenarios: using past climatic data to project the future climate with a statistical approach, using synthetic climate scenarios, and using output from general circulation models (GCMs). Wilby & Harris (2006) concluded that using output from GCMs models provide the most reliable results compared to other methods and is therefore the focus of this work. The fifth phase of the Coupled Model Project (CMIP5) has replaced the CMIP3 in the IPCC Fifth Assessment Report (AR5) that was released in 2014. The CMIP5 will include newer and more comprehensive GCMs including finer spatial resolution, associated with more complex orography of the region and different greenhouse gases emission scenarios (Taylor et al. 2012).

A new set of greenhouse gas scenarios called Representative Concentration Pathways (RCPs), RCP 2.6, 4.5, 6.0 and 8.5, has been released to replace the earlier emission scenarios (A2, B1, etc.) from the Special Report on Emission
Scenarios (SRES) in the IPCC AR4. The RCPs were named based on their concentration pathway that approximates the level of radiative forcing (Wm \(^{-2}\)) at the end of the 21st century (Meinshausen et al. 2011). Compared to SRES scenarios, RCPs were designed to support research on the impact of potential policy and adaptation strategic in reduction of climate change effects (Moss et al. 2010; Van Vuuren et al. 2011a). Alkama et al. (2013) applied RCP 8.5 to evaluate the global streamflow variation for Central America, North America, South America, Africa, South Asia, North Asia, South Europe, North Europe, while Kim et al. (2013) investigated the impact of future land use and climate changes under RCP 4.5 and 8.5 on streamflow in the Hoeya River Basin, South Korea. No hydrological impact studies have been performed in Malaysia, which is the region assessed in this study, using RCPs, and therefore this study attempts to fill that research gap.

GCM-projected precipitation and temperature data are often used as input to a calibrated hydrological model to simulate the future hydrological cycle (Dessu & Melesse 2013). The selection of the appropriate hydrological model should include several criteria: flexible for testing different climate conditions and spatial scales, easily amendable with different data sets, and easily calibrated and able to evaluate the sensitivity of study area from projected climate changes (Xu 1999). The Soil and Water Assessment Tool (SWAT) (Arnold et al. 2012) has been verified as an effective tool to evaluate the effects of climate change on streamflow around the world (Bouraoui et al. 2002; Perazzoli et al. 2012; Zeng et al. 2012; Ficklin et al. 2013).

The output of GCMs cannot directly be used in hydrological studies due to their coarse resolution (around 200 km), so a spatial downscaling procedure is necessary. Dynamic and statistical downscaling are the most common approaches used to downscale GCMs and the choice of the method depends on the objective of the study (Wilby & Wigley 1997). Dynamic downscaling uses regional climate models (resolution approximately 50 km) with output from a GCM (Fowler et al. 2007). Statistical downscaling uses empirical or statistical relationships between GCM variables and observation station data. The statistical downscaling approach such as delta approach is often applied in hydrological impact studies due to its simplicity, flexibility and low computation cost (Wilby et al. 2002).

An uncertainty assessment is often used to quantify the feasible threshold of anticipated future hydro-climatic conditions (Dessu & Melesse 2013). Such information is important to ensure sustainable development of water related projects in the basin. In general, uncertainty in GCMs is evaluated by using multiple GCMs with different emission scenarios as input into a hydrological model (Sufle & Tullos 2013). The Quantifying and Understanding the Earth System – Global Scale Impacts (QUEST-GSI) methodology (Todd et al. 2011) represents an advance compared to other uncertainty assessment approaches due to: (1) a unification of impact and uncertainties climate scenarios for better comparison between various study sites and (2) use of prescribed warming scenarios to inform mitigation policy. The QUEST-GSI methodology has been applied in various parts of the world such as North America (Thorne 2011), South America (Nobrega et al. 2011), Asia (Kingston et al. 2011; Xu et al. 2011) and Africa (Hughes et al. 2011). However, the previous QUEST-GSI methodologies used the CMIP3 GCMs and SRES emission scenarios in climate scenarios development. Hence, another goal of this study is to attempt to update the QUEST-GSI methodology by replacing the outdated climate scenarios with CMIP5 GCMs and RCPs

Malaysia is well endowed with water throughout the year with average annual precipitation greater than 2,000 mm. Water plays a vital role in the agriculture sector because oil palm productivity largely depends on water availability (Carr 2011) and palm oil exportation is one of the main national incomes. Additionally, floods are a severe natural disaster in Malaysia, with 29.800 km\(^2\) (9% of Malaysia) land area and 4.82 million (22% of Malaysian population) people affected by floods (Kia et al. 2012). By the end of the 21st century, mean air surface temperature over Malaysia is expected to increase by 3–5°C from the historical average (Tangang et al. 2012). These changes would affect the availability of water resources in Malaysia, impacting oil palm productivity and potentially bringing more intense and frequent flood events. Lack of scientific knowledge related to climate change in Malaysia limits the understanding of the impacts of climate changes, especially on water resources. In Malaysia, climate change policy is still developing and most of the climate change knowledge is based on IPCC Fourth Assessment Report (AR4) and national documents (Al-Amin...
et al. 2013). However, IPCC AR4 provides a comprehensive evaluation of the climate changes at the global scale and therefore regional and local knowledge is still narrow (Tangang et al. 2012). The only impact of climate change on future hydrology was conducted by Shaaban et al. (2011) using the Canadian Centre for Climate Modelling and Analysis (CCCma) GCM under the ‘business as usual’ IS92a emission scenario to investigate the climate change effects on major basins of Peninsular Malaysia for the 2025–2034 and 2041–2050 periods. However, application of updated emission scenarios are essential due to the update of economic, technologic, and environmental strategies that should be reflected in a climate impact assessment (Moss et al. 2010). In addition, application of a single GCM in a hydrological impact study has less ‘predictive’ skill in seasonal climate projection compare to multi-model assessments (Palmer et al. 2008). This study is conducted to fill this Malaysian-research gap.

The motivation of this study, then, is to attempt to apply the most up-to-date climate knowledge, GCMs of CMIP5 under RCP scenarios, to investigate the hydrological impact of climate change in Malaysia. The main objective of this study is to investigate the impacts of climate change on streamflow of the Johor River Basin (JRB) using an ensemble of six GCMs selected from 18 GCMs under RCP 2.6, 4.5 and 8.5 scenarios for the period of 2006–2035 (2020s), 2036–2065 (2050s) and 2066–2095 (2080s). The more specific objectives are to: (1) validate the performance of SWAT in streamflow simulation in the JRB, (2) evaluate the changes of projected precipitation and temperature against the baseline, 1975–2004 (1990s), (3) modify the QUEST-GSI methodology by adding latest GCMs, emission scenarios and (4) quantify the uncertainty in projection of climate scenarios on streamflow by the modified QUEST-GSI methodology. The findings of this study can be used as a reference to develop better national climate change policies related to water resources.

DATA AND METHODOLOGY

Study area

The JRB was chosen because it represents a typical Malaysian climate and geographical conditions. The Johor River is one of the main rivers in Malaysia and acts as an important source of water for the Johor and Singapore populations. As Malaysia is one of the largest oil palm producers, the JRB is dominated by oil palm regions due to its fertile soil and climate conditions. In the 1970s, huge areas of forest in the JRB were cleared following land development projects (palm oil and rubber) by the Federal Land Development Authority (FELDA) and South East Johore Development Authority (KEJORA).

Flooding is one of the main natural disasters in Malaysia. The JRB is one of the regions in Malaysia where floods occur annually, either in small or large events. Historically, there have been six major devastating flood events in the JRB that destroyed infrastructure and properties and caused loss of lives. The most destructive events were the floods that occurred between December 2006 and January 2007, leading to the evacuation of more than 100,000 people and 18 deaths and a total estimated loss of 0.5 billion US dollars (Kia et al. 2012).

The JRB has a watershed area of 1,652 km², and is located in the southern region of Peninsular Malaysia, between the latitudes of 1 30’–2 10’ N and longitudes of 103 20’–104 10’ E (Figure 1). Elevation in the JRB ranges between 3–977 m above the mean sea level. The basin covers four major districts of Johor state including Johor Bahru, Kluang, Kota Tinggi and Mersing with a total population of 500,000 people and 70,000 households as estimated by the Department of Statistics Malaysia in 2010. The Johor River is the main river of the JRB and has a total length of 122.7 km. The river flows south from Gunung Belumut (north; second highest mountain in Johor) and then south-west into the Strait of Johor. The major tributaries of the Johor River are the Sayong River, Belitong River, Penggeli River, Jengeli River and Linggiu River.

Climate in the JRB is characterized by the Asian–Australian monsoon system with a summer/dry (May–August) and winter/wet monsoon (November–February) (Webster et al. 1998). The seasonal system of the JRB is divided into January–March (JFM), April–June (AMJ), July–September (JAS) and October–December (OND). Based on Tangang et al. (2007), the OND (AMJ) and JFM (JAS) represents the early and late stages of the winter (summer) monsoon, respectively. The average annual rainfall over the JRB is
2,500 mm and annual mean temperature is approximately 26 °C. The average annual flow at the Rantau Panjang station (sub-basin 12; Figure 1) is 37.7 m$^3$s$^{-1}$. Figure 2 shows the average total monthly precipitation and average monthly streamflow from 1975 to 2002. The major land use in the JRB was oil palm plantation (60.9%), followed by forest (19.5%), rubber plantation (4.3%), urban (3.4%) and water bodies (3.2%).
**SWAT model**

The SWAT is a continuous time and spatially distributed hydrological model developed by the United States Department of Agriculture (USDA) to evaluate the impact of land management practices on water, sediment and contaminant transport at the basin scale (Arnold et al. 1998). SWAT operates at daily, monthly, or annual time step. In SWAT, a basin is divided into multiple sub-basins, which are then divided into unique land use and soil group called hydrologic response units (HRUs). The water balance is then estimated on each HRU. In this study, the SWAT model used the SCS curve number (CN) procedure (USDA-SCS 1972) to estimate surface runoff. Additionally, for this work SWAT estimates evapotranspiration (ET) using the Hargreaves approach (Hargreaves et al. 1985) that requires only air temperature data. Flows are summed from all HRUs to the sub-watershed level, and then routed through the streamflow system using the Muskingum routing method (Chow 1959). See Neitsch et al. (2011) for a detailed description of SWAT and its model components.

**Input data**

The main data sets required for SWAT modelling are a digital elevation model (DEM), land use map, soil map and hydro-climatic data. In this study, the daily precipitation, minimum and maximum temperature from 1975 to 2004 are available at Kluang and Senai stations (Figure 1) while daily precipitation data are available at seven rainfall stations as listed in Table 1 and shown in Figure 1. These data were obtained from the Malaysia Meteorological Department (MMD) and are categorized as good climate data sets in Malaysia because they are well maintained. Missing data and gaps in long series precipitation data were filled with nearby station data. If there are no rainfall data on the nearby station for that particular period, the corresponding days of previous year data were used to fill the gap. The observed monthly streamflow data at Rantau Panjang station, which is located at the outlet of sub-basin 12 from 1980 to 1991, were obtained from the Department of Irrigation and Drainage Malaysia (DID). Other stations’ data were not available due to missing data or lack of maintenance, and therefore only the Rantau Panjang station data were used for calibration and validation of SWAT.

A DEM is used for drainage pattern generation and basin delineation. A 90 m resolution DEM was obtained from the National Aeronautics and Space Administration Shuttle Radar Topography Mission (SRTM) with an accuracy of ±16 m (Reuter et al. 2007). It is freely available at http://srtm.csi.cgiar.org/. Land use data (1,250,000), collected in 2002, were acquired from the Ministry of Agriculture and Agro-based Industry Malaysia (MOA). Soil data (1,350,000) were obtained from the MOA. Soil properties (e.g. soil texture and soil depth) were extracted from a report prepared by Pushparajah & Amin (1977).

**Model setup, calibration and validation**

The SWAT-CUP tool, a public domain program that was developed for sensitivity analysis, calibration and validation of SWAT models, was used. Sequential Uncertainty Fitting algorithm (SUFI-2), a semi-automatic inverse modelling procedure within SWAT-CUP, was selected because of its capability in handling and analysing many parameters in the smallest number of model runs (Yang et al. 2008). In this study, the global sensitivity analysis approach was
used to test the 10 most sensitive parameters (Table 2) with 500 runs (different combination of parameters for each run) running parallel with calibration. The new parameters obtained from calibration were then applied in the SWAT model for validation.

The SWAT model performance was evaluated using statistical analyses to compare reliability and quality of simulated discharge against the observed data. In this study, the statistical approaches applied included the coefficient of determination ($R^2$), Nash–Sutcliffe coefficient (NSE) (Nash & Sutcliffe 1970), percent bias (PB) (Gupta et al. 1999) and ratio of the root mean square error (RMSE) to the standard deviation of the measured data (RSR) (Moriasi et al. 2007). These statistics are calculated as shown below

$$R^2 = \left( \frac{\sum_{i=0}^{n}(o - \bar{o})(p - \bar{p})}{\sum_{i=0}^{n}(o - \bar{o})^2\sum_{i=0}^{n}(o - \bar{p})^2} \right)^2$$

$$NSE = 1 - \frac{\sum_{i=0}^{n}(o - p)^2}{\sum_{i=0}^{n}(o - \bar{o})^2}$$

$$PB = \frac{\sum|o - p|}{\sum o} \quad (100)$$

$$RSR = \frac{\sqrt{\sum_{i=0}^{n}(o - p)^2/n}}{\sqrt{\sum_{i=0}^{n}(o - \bar{o})^2}}$$

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter name</th>
<th>Min</th>
<th>Max</th>
<th>Fitted value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CN2 (Initial SCS CN II value)</td>
<td>-0.20</td>
<td>0.20</td>
<td>-0.14</td>
</tr>
<tr>
<td>2</td>
<td>ESCO (Soil evaporation compensation factor)</td>
<td>0.80</td>
<td>1.00</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>GW_REVAP (Groundwater ‘revap’ coefficient)</td>
<td>0</td>
<td>0.20</td>
<td>0.08</td>
</tr>
<tr>
<td>4</td>
<td>SOL_AWC (Available water capacity)</td>
<td>-0.20</td>
<td>0.40</td>
<td>0.23</td>
</tr>
<tr>
<td>5</td>
<td>CH_N2 (Manning’s value for main channel)</td>
<td>0</td>
<td>0.30</td>
<td>0.22</td>
</tr>
<tr>
<td>6</td>
<td>GWQMN (Threshold water depth in the shallow aquifer for flow)</td>
<td>0</td>
<td>2.00</td>
<td>1.88</td>
</tr>
<tr>
<td>7</td>
<td>GW_DELAY (Groundwater delay)</td>
<td>30.00</td>
<td>450.00</td>
<td>48.06</td>
</tr>
<tr>
<td>8</td>
<td>ALPHA_BNK (Baseflow alpha factor for bank storage)</td>
<td>0</td>
<td>1.00</td>
<td>0.45</td>
</tr>
<tr>
<td>9</td>
<td>ALPHA_BF (Baseflow alpha factor)</td>
<td>0</td>
<td>1.00</td>
<td>0.65</td>
</tr>
<tr>
<td>10</td>
<td>CH_K2 (Channel effective hydraulic conductivity)</td>
<td>5.00</td>
<td>130.00</td>
<td>24.88</td>
</tr>
</tbody>
</table>

The SWAT model performance was evaluated using statistical approaches to compare reliability and quality of simulated discharge against the observed data. In this study, the statistical approaches applied included the coefficient of determination ($R^2$), Nash–Sutcliffe coefficient (NSE) (Nash & Sutcliffe 1970), percent bias (PB) (Gupta et al. 1999) and ratio of the root mean square error (RMSE) to the standard deviation of the measured data (RSR) (Moriasi et al. 2007). These statistics are calculated as shown below

$$R^2 = \left( \frac{\sum_{i=0}^{n}(o - \bar{o})(p - \bar{p})}{\sum_{i=0}^{n}(o - \bar{o})^2\sum_{i=0}^{n}(o - \bar{p})^2} \right)^2$$

$$NSE = 1 - \frac{\sum_{i=0}^{n}(o - p)^2}{\sum_{i=0}^{n}(o - \bar{o})^2}$$

$$PB = \frac{\sum|o - p|}{\sum o} \quad (100)$$

$$RSR = \frac{\sqrt{\sum_{i=0}^{n}(o - p)^2/n}}{\sqrt{\sum_{i=0}^{n}(o - \bar{o})^2}}$$

where $o$ and $p$ are observed and simulated streamflow, respectively; $n$ is the number of measured streamflow.

The NSE is widely applied in hydrograph assessment in order to measure ‘goodness-of-fit’ by indicating how well the plot between simulated and observed streamflow fits a 1:1 line (Nash & Sutcliffe 1970). The NSE value between 0 to 1 (ideal) is known as acceptable performance while $-\infty$ to 0 represents an unacceptable performance. $R^2$ can be used to evaluate the correlation between two different variables and range from −1 to 1 (perfect). The optimal value for PB is 0. A negative value shows overestimation of bias while a positive value indicates an underestimation of bias of the simulated variable compared to the observed variable (Gupta et al. 1999). RSR is a popular error index statistic that varies from 0 to a large positive value, the lower RSR indicates a better modelling performance. Based on Moriasi et al. (2007), SWAT modelling performance is categorized as satisfactory if NSE > 0.5, PB < ±25 and RSR ≤ 0.7.

Rantau Panjang station monthly streamflow from 1980 to 1985 and 1986 to 1991 were used for streamflow calibration and validation, respectively.

**GCM performance evaluation**

The GCMs were chosen based on a set of criteria including: (1) availability of daily precipitation, minimum and maximum temperature data in CMIP5, (2) combination of GCMs that underestimate, overestimate and accurately capture annual data, (3) various models sources from different countries and institutions and (4) ability to capture observed seasonal variability (Dessu & Melesse 2013).

The capability of GCMs in simulating historical monthly precipitation from 1975 to 2004 were evaluated for a grid cell in middle JRB by area average of monthly total precipitation (mm) between stations 48679, 47144 and 47146 shown in Figure 1. The statistics used to analyse the
performance of GCMs were mean error (ME) and RMSE (Nyeko-Ogiramoi et al. 2010; Khoi & Suetsugi 2012)

\[
ME = \frac{1}{k} \sum (G_{p,j}^{bas} - O_{p,i})
\]  
(5)

\[
RMSE = \sqrt{\frac{1}{k} \sum (G_{p,j}^{bas} - O_{p,i})^2}
\]  
(6)

where \( O_{p,i} \) is the time series of observed precipitation, \( G_{p,j}^{bas} \) is the corresponding period of GCM precipitation, \( k \) can be either 12 using monthly data or number of years using annual data. ME and RMSE are further divided by sample mean of \( G_p \) to obtain the normalized RMSE (NRMSE) and normalized ME (NME), respectively. NRMSE and NMR are unitless and related to the observed RMSE divided by mean of observations (ObsCV). The smaller the NRMSE and NME values, the closer the GCM simulation to observed data. Good performance of GCMs should have a NME value within \( \pm 2^{*}\text{ObsCV} \) uncertainty bounds (Nyeko-Ogiramoi et al. 2010).

Climate scenarios

RCPs are a set of greenhouse gas concentration and emission pathways developed to support climate change impacts research (Moss et al. 2010). The three greenhouse gas concentration trajectories, RCP 2.6 (Van Vuuren et al. 2011b), 4.5 (Thomson et al. 2011) and 8.5 (Riahi et al. 2011), were named based on a possible range of radiative forcing values of +2.6 (low), +4.5 (medium-low) and +8.5 (high) \( \text{Wm}^{-2} \), respectively in the year 2100.

Eighteen CMIP5 GCMs were obtained from http://cmip-pcmdi.llnl.gov/cmip5/index.html and are shown in Table 3. The climate uncertainty assessment used in this study is

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Institution</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1-0</td>
<td>Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia</td>
</tr>
<tr>
<td>BCC-CSM1-1</td>
<td>Beijing Climate Center, China Meteorological Administration</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>College of Global Change and Earth System Science, Beijing Normal University</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research</td>
</tr>
<tr>
<td>CESM1-CAM5</td>
<td>Community Earth System Model Contributors</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique</td>
</tr>
<tr>
<td>CSIRO-MK3-6-0</td>
<td>Commonwealth Scientific and Industrial Research Organization, Queensland Climate Change Centre of Excellence</td>
</tr>
<tr>
<td>EC-EARTH</td>
<td>EC-Earth consortium, representing 22 academic institutions and meteorological services from 10 countries in Europe</td>
</tr>
<tr>
<td>FGOALS-g2</td>
<td>Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, and Center for Earth System Science, Tsinghua University</td>
</tr>
<tr>
<td>GFDL-CM3 GFDL-ESM2M</td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Met Office Hadley Centre (additional HadGEM2ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)</td>
</tr>
<tr>
<td>INM-CM4</td>
<td>Institute for Numerical Mathematics</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies</td>
</tr>
<tr>
<td>MIROC5</td>
<td>Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>Meteorological Research Institute</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>Norwegian Climate Centre</td>
</tr>
</tbody>
</table>
based on the QUEST-GSI methodology (Todd et al. 2011) with some modification. QUEST-GSI is a coordinated and systematic project of global scale climate impact analysis on water resources by unifying a set of climate scenarios for uncertainty evaluation. Table 4 indicates 27 climate scenarios developed for climate impact and uncertainty analysis. In this study, we replaced the CMIP3 GCMs and SRES scenarios that applied in QUEST-GSI methodology with the CMIP5 GCMs and RCP scenarios, respectively. In addition, the QUEST-GSI methodology has been improved by applying a CMIP5 GCM ensemble (climate scenarios ID 1 to 15) instead of single GCM, which was previously the Hadley Centre Coupled Model, version 3 (HadCM3).

In general, climate scenarios of the modified QUEST-GSI methodology for impact and uncertainty assessment were categorized into four groups: (1) climate scenarios (RCP 2.6, 4.5 and 8.5) using an ensemble of six GCMs (ensemble_6), (2) prescribed increases in global mean temperature (1–6 °C) using ensemble_6, (3) GCM structures (CESM-CAM5, CNRM-CM5, HadGEM-2, MIROC-ESM, MRI-CGCM2 and NorESM1-M) under RCP 4.5, and (4) prescribed warming of 2 °C using CESM-CAM5, CNRM-CM5,

Table 4  | Climate scenarios for SWAT input (Ensemble_6 is the average of six selected GCMs)

<table>
<thead>
<tr>
<th>ID</th>
<th>Model</th>
<th>Scenario</th>
<th>Period</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ensemble_6</td>
<td>2.6</td>
<td>2006–2035</td>
<td>Hydrological impact assessment</td>
</tr>
<tr>
<td>2</td>
<td>Ensemble_6</td>
<td>2.6</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Ensemble_6</td>
<td>2.6</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Ensemble_6</td>
<td>4.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Ensemble_6</td>
<td>4.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Ensemble_6</td>
<td>4.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Ensemble_6</td>
<td>8.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Ensemble_6</td>
<td>8.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Ensemble_6</td>
<td>8.5</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Ensemble_6</td>
<td>4.5/+1 °C</td>
<td>2006–2035</td>
<td>Prescribed temperature increase</td>
</tr>
<tr>
<td>11</td>
<td>Ensemble_6</td>
<td>4.5/+2 °C</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Ensemble_6</td>
<td>4.5/+3 °C</td>
<td>2006–2035</td>
<td></td>
</tr>
<tr>
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<td>2006–2035</td>
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<td>Observed data set</td>
<td>Baseline</td>
<td>1975–2004</td>
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HadGEM-2, MIROC-ESM, MRI-CGCM2 and NorESM1-M. Prescribed global mean temperature of a 2 °C increase using six different CMIP 5 GCMs experiment is used to investigate the impact of ‘dangerous’ climate change because 2 °C is often thought as the threshold for significant impacts.

The resolution of raw GCMs are too coarse for regional impact assessment study, so downscaling must be performed before applying GCM output into the SWAT model. The daily precipitation, minimum and maximum temperature from 1975 to 2100 were extracted from grid cells covering the basin. The output was statistically downscaled using the delta method station by station (Lenderink et al. 2007; Dessu & Melesse 2013).

\[
T_{\text{delta,daily}} = T_{\text{obs,daily}} + (T_{\text{fut}} - T_{\text{bas}})_{\text{monthly}}
\]

\[
P_{\text{delta,daily}} = P_{\text{obs,daily}} \times (P_{\text{fut}} / P_{\text{bas}})_{\text{monthly}}
\]

where \( T_{\text{delta,daily}} \) is the delta downscaled daily temperature, \( T_{\text{fut,daily}} \) is the raw future daily temperature, \( T_{\text{obs}} \) is the average monthly of observed temperature, \( T_{\text{bas}} \) is the average monthly of GCM output of the baseline period, \( P_{\text{delta,daily}} \) is the delta downscaled daily precipitation, \( P_{\text{fut,daily}} \) is raw future daily precipitation, \( P_{\text{obs}} \) is the average monthly of observed precipitation and \( P_{\text{bas}} \) is the average monthly of GCM output of the baseline period.

The impact and uncertainties of climate change on streamflow were evaluated based on annual, seasonal and monthly changes of each individual climate scenarios (ID 1–27) against the baseline scenarios (ID 28). Flow duration curves were also plotted to offer a different perspective of hydrological response of Johor River in the future. Flow exceeded 5%/high flow (Q5) and 95%/low flow (Q95) of the time changes between each climate scenarios and baseline were also assessed.

RESULTS AND DISCUSSION

SWAT calibration and validation

Table 2 presents the initial sensitive parameter ranges and the fitted values. Figure 3 shows observed and simulated monthly streamflow at Rantau Panjang station for the calibration (1980–1985) and validation period (1986–1991). \( R^2 \), NSE, PB and RSR for the calibration time period were 0.67, 0.66, −3.90% and 0.58, and 0.68, 0.62, −15.9% and 0.61 for the validation time period. Based on the work of Moriasi et al. (2007), the NSE values of the SWAT modelling for this study were deemed a ‘good’ performance rating for the calibration period and a ‘satisfactory’ performance rating for the validation period. A ‘good’ rating indicates better performance compared to a ‘satisfactory’ rating. The SWAT performance rating table was developed by Moriasi et al. (2007) and widely used by researchers for SWAT model applications. The validation statistics are lower because of the extreme flood events that occurred in early 1984 and end of 1991 where SWAT poorly matched the peak flow. The lower statistics might also be due to sparse distribution of
climate monitoring stations and spatial distribution of precipitation (Bardossy & Das 2008). Additionally, the land use data used in this work were from 2002, which was outside of the calibration and validation time periods. Major land use changes such as reservoir development and conversion to oil palm plantations have been observed since 1990. However, the statistical tests indicate that the calibrated SWAT model is applicable for JRB.

GCM performance evaluation

The capability of 18 raw outputs of GCMs to reproduce historical annual and monthly precipitation (1975–2004) over the study area were evaluated by NME and NRMSE statistical analysis (Figures 4 and 5). At the annual scale, the NRMSE and percentage bias values ranged from 0.16–0.50 and −1.43–60.18%, respectively, with smallest values found for the NorESM1-M GCM. The historical performance of GCMs over southern Peninsular Malaysia varied, with an underestimation of annual precipitation for seven models (CanESM2, CNRM-CM5, EC-EARTH, FGOAL-g2, INM-CM4, MIROC5 and MRI-CGCM3) and an overestimation for the rest. Four of the 18 models (CanESM2, CSIRO-Mk3-6-0, GFDL-ESM2M and MIROC5) displayed poor performance at the annual scale with the NME value exceeding the uncertainty bounds of ±0.23.

At the monthly scale, only four GCMs (CNRM-CM5, HadGEM-2, MIROC-ESM and NorESM1-M) have NME
values within the uncertainty bounds for all months. The results indicate that GCMs have difficulty in projecting extreme precipitation events in this region, especially in December and January. One of the reasons is because of the difficulty of GCMs in simulating precipitation processes compared to other climate variables (Juneng et al. 2010). In addition, these results could be due to coarse spatial resolution of models that are unable to capture complex local topography which influence the winter monsoon circulation (Chang et al. 2005). Based on criteria described in the section methodology and statistical analyses, six GCMs (CESM-CAM5, CNRM-CM5, HadGEM-2, MIROC-ESM, MRI-CGCM2 and NorESM1-M) were selected for hydrological impact assessment, and are now termed as ‘Ensemble_6’. Each individual GCM within Ensemble_6 was downscaled using the previously described delta method.

Future climate projections

Figure 6 displays the Ensemble_6 changes in annual precipitation and maximum temperature at the Kluang and Senai station for the 2020s, 2050s and 2080s under three RCPs compared to the baseline period (1990s). The results show an increase in the average annual temperature, ranging from 0.60 to 3.21°C. Generally, the maximum and minimum temperatures trend similarly. The annual maximum temperature changes of the three future time periods for the Kluang (Senai) station range between 0.62°C–0.68°C (0.60–0.64°C), 0.84–1.78°C (0.83–1.76) and 1.01–3.21°C.
(0.99–3.15 °C) for RCP 2.6, 4.5 and 8.5 scenarios, respectively. Annual precipitation is projected to increase for all time periods. The annual precipitation change of Kluang and Senai station for all time periods ranged between 1.01–8.88%. The greatest changes (8.88%) occurred during the 2080s period under RCP 4.5 at the Kluang station. Furthermore, the increase of annual precipitation at the Senai station is lowest during the 2050s period compared to the other time periods under the three RCPs. The results indicate that precipitation changes in the upper basin is greater compared to the middle and lower basins. This phenomenon might be due to their difference in geographical location, local meteorological condition, land-sea distribution (Kripalani & Kulkarni 1998) and uncertainty in GCMs model projections (Xu et al. 2013).

Monthly changes of precipitation and maximum temperature under the three RCPs for 2020s, 2050s and 2080s against the baseline period are shown in Figure 7. The increase of maximum temperature is more significant at the monthly scale for the Kluang and Senai station, with a range of 0.30–1.24 °C and 0.59–1.15 °C (RCP2.6), 0.44–1.91 °C and 0.50–1.83 °C (RCP4.5) and 0.41–3.58 °C and 0.49–3.36 °C (RCP8.5), respectively. Under the three RCPs, the seasonal maximum temperature has a larger increase in the early winter season for the 2020s and 2050s and is then shifted to the late winter
season by the end of the century. In the most severe scenario, RCP 8.5, the early winter season precipitation increase is largest for the Kluang station (51.51%) compared to the other RCPs. At the Kluang station, the summer (winter) season projected precipitation changes by 18.55, −6.57 and 30.14% (1.44, 20.84 and 7.44%) for RCP2.6, 29.65, 23.94 and 74.50% (8.99, 27.43 and 32.00%) for RCP 4.5 and 16.61, 18.48 and 68.22% (26.39, 40.78 and 27.17%) for RCP 8.5 for the 2020s, 2050s and 2080s, respectively. Monthly precipitation changes unevenly, with an increasing trend for January, May, July and December and a decreasing trend for March. The highest increment of projected monthly precipitation was found in January and December where historical major flood events frequently occur. This indicates that more severe flood events may be expected to occur more frequently in the future.

**Impact of climate change on streamflow**

Table 5 shows the results of the ensemble_6 annual streamflow changes as well as the results of the other developed climate scenarios for Rantau Panjang station. The simulated baseline annual streamflow (ID 28) is 43.76 m$^3$s$^{-1}$. The annual streamflow is projected to increase for three time periods under three RCP scenarios. The annual streamflow increased dramatically for early and end of century and only slightly in the mid-century. The increases under RCP 4.5 scenario are the largest compared to other RCP scenarios, approximately 12.95% during the 2080s period. The lowest streamflow change occurred under RCP 2.6 with an increase of 0.91% for the 2050s period. Under RCP 8.5 scenario, the annual streamflow is expected to increase by 6.72, 4.39 and 5.91% for the 2020s, 2050s and 2080s period, respectively. The increases in annual
streamflow at Rantau Panjang station are largely due to increases of precipitation. Streamflow is a measure of water availability (Milly et al. 2005), so increases of annual streamflow shows that water resources of the JRB is sufficient until the end of the century. The Q5 (high) flows increased slightly for RCP 2.6 (3.46–13.55%) and dramatically for RCP 4.5 (8.19–20.91%) and 8.5 (8.51–15.91%). Conversely, Q95 (low) flows changed unevenly by −5.73, 3.02 and −0.71% and 8.48, 3.34 and −6.13% for RCP 2.6 and 8.5 scenarios for the 2020s, 2050s and 2080s, respectively. Under RCP 4.5, Q95 flow is projected to increase from 5.51 (2020s) to 15.10% (2050s).

The projected seasonal streamflow is non-uniform with dramatic changes (up to 89.93%). Large streamflow decreases were found during the early summer, ranging from −26.50–6.61%, −2.38–23.85% and −42.58–18.88% for the RCP 2.6, 4.5 and 8.5 scenarios. Late summer and early winter seasons, on the other hand, display an increasing trend, ranging from 10.35–89.93% and −6.16–44.21%, −12.48–89.47% and 13.22–67.61% and 3.46–81.22% and 13.13–65.43% under RCP 2.6, 4.5 and 8.5 scenarios, respectively. The pattern changes of seasonal streamflow can be explained by the trend of projected precipitation over study area. These findings indicate that water availability of the early summer period in the future will be reduced and might influence the agriculture sector within and surrounding the JRB.

Figure 8 displays the monthly streamflow changes at the Rantau Panjang station under three RCP scenarios. During the 2020s, projected decreases of streamflow occur during March (−9.15 to −54.61%) and April (−1.73 to −25.47%). The largest increases can be found in January and December, and were up to 50.47%. Monthly streamflow changes less than 11% under all RCPs were found in May, Jun, October and November. By the 2050s, monthly streamflow is projected to decrease by March (−8.43–10.81%), October (−0.05 to −10.01%) and November (−1.78 to −6.68%). Monthly streamflow changes ranged from −10.09 to 28.35% for the other month. During the 2080s, decreases of projected streamflow occur during February (−0.39–11.02%), March (−16.30 to −28.09%), April (−2.65 to −21.37%), May (−5.36 to −15.65%). Non-uniform monthly streamflow trend were found in Jun (−5.75–5.62%). In addition, August and December streamflow changes are greater than 20%. Generally, future monthly streamflow is projected to increase from July to January. This phenomenon might bring more flood events, especially in December and January, and may be catastrophic if there are no flood adaptation strategic implementations.

Climate impact uncertainty assessment

Table 5 and Figures 8–10 summarize annual and monthly streamflow projected changes for the established scenarios described in Table 4. For prescribed temperature increase of
Figure 8 | (a) Annual and (b) monthly streamflow changes at Rantau Panjang station of Ensemble_6 under RCP 2.6, RCP 4.5 and RCP 8.5 for the periods of 2020s, 2050s and 2080s.

Figure 9 | Flow duration curve of the Rantau Panjang station under various climate scenarios based on RCP 4.5 for the 2020s period.

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1–6 °C scenarios, the average annual streamflow is decreased proportionally with increase in mean temperature compared to the baseline streamflow by 7.56% for a 1 °C increase to 0.97% for a 6 °C increase (Table 5). The Q5 (high) flow increased slightly (13.01–17.66%), and Q95 (low) flow decreased slightly (−6.56 to 3.20%). The monthly streamflows are projected to decrease from March to April and July to October, ranging from −3.60 (1 °C) to −19.45% (6 °C) and −1.86 (1 °C) to −16.49% (6 °C), respectively. The greatest increases of streamflow occurred for January and increased
by 49.92 (1°C) to 42.73% (6°C). Uncertainty in projected monthly stream flow for prescribed temperature scenarios varies from −10.38 to 49.93% for the 1°C scenario to the range of −19.45 to 42.75% for the 6°C scenario.

Uncertainty in GCM structure under RCP4.5 for the 2020s shows that the projected annual precipitation led to increased and decreased precipitation as compared to baseline period, ranging from −4.19 to 10.47% and −4.35 to 15.80% for Kluang and Senai station, respectively. The projected annual maximum temperature increased for all GCMs with the range from 0.50 to 0.86°C (Kluang) and 0.48–0.79°C (Senai). Five GCMs (CESM1-CAM5, HadGEM2, MIROC-ESM, MRI-CGCM and Nor-ESM1M) show that annual stream flow will increase compared to the baseline, except for the CNRM-CM5 GCM, which shows a decrease of −8.79% in annual stream flow. Three GCMs (CESM1-CAM5, MRI-CGCM and Nor-ESM1M) led to large annual stream flow changes (more than 10%), whereas the other three GCMs (CNRM-CM5, HadGEM2 and MIROC-ESM) show small changes (less than 10%). Figure 10(b) shows that the projected decrease and increase of monthly stream flow changes are evenly distributed throughout the year. The MRI-CGCM model shows different seasonal trends compared to other GCMs, with an increase in stream flow during the late summer season and a decrease in early winter season. This phenomenon indicates a shift of earlier extreme flood events that normally occurs in December and January.

Projected annual stream flow changes of six GCMs for a prescribed increase of 2°C temperature at Rantau Panjang compared with the baseline time period range from −35.53 to 25.58% (Nor-ESM1M). Two GCMs (HadGEM2, MIROC-ESM) show negligible (<±6.00%) annual stream flow changes (Table 5). Uncertainty in the Q95 flow ranges from −32.58 to 11.98% and the Q5 flow ranges from −4.05 to 43.33%. At monthly scale, Nor-ESM1M shows the largest variation (−35.53–101.19%) and MIROC-ESM shows the smallest variation (−8.86–5.47%).

**SUMMARY AND CONCLUSIONS**

This paper present results for the most up-to-date and comprehensive climate change impact and uncertainties study on climate and stream flow in the JRB, Malaysia. The climate scenarios were generated from an ensemble of six GCMs selected after performance evaluation of 18 GCMs under RCP 2.6, 4.5 and 8.5 scenarios for 2020s, 2050s and 2080s period, as input into a distributed hydrological model, SWAT. Calibration and validation of SWAT model shows it can be a reliable tool for hydrology cycle simulation in Malaysia.

The capability of 18 GCMs in simulating historical precipitation were evaluated using four criteria and a statistical approach to develop a GCM ensemble for impact study. The results indicated that the CESM-CAM5, CNRM-CM5, HadGEM2, MIROC-ESM, MRI-CGCM2 and NorESM1-M models perform well in simulating annual and monthly precipitation for southern part of Peninsular Malaysia. These models can act as a reference and can be used by researchers who are interested in performing any climate change related study over this area.

The future annual precipitation and temperature are projected to increase for all time periods which results in similar trends for annual stream flow. The significant increases of projected monthly stream flow for December and January might bring more severe flood events in the future. Additionally, the dramatic decreases of monthly stream flow during March and April would lead to water shortage problems that have recently occurred in the western part of Peninsular Malaysia. The climate of the study area is becoming drier in the dry season and wetter in the wet season. This conclusion is similar to studies that have been conducted in other regions in Malaysia (Adnan & Atkinson 2011; Shaaban et al. 2011).

Uncertainty in impacts of climate change on stream flow changes were further assessed with four major elements: (1) RCP emission scenarios, (2) prescribed increase of annual temperature of 1–6°C, (3) GCM structure and (4) prescribed increase of temperature of 2°C. The annual stream flow change under RCP scenario and prescribed increase of temperature up to 6°C temperature ranged from 0.91 to 12.95% and 0.97 to 7.56%, respectively. The projected annual stream flow varied from −8.79 to 28.17% for different GCMs structure under RCP 4.5. Under the prescribed 2°C increase of temperature, the projected annual stream flow changes ranged from −11.07 to 25.58%. This study shows
that the GCM structure is the largest source of uncertainty in impacts of climate change on streamflow, which is in agreement with findings of other authors who suggest that the GCMs selection contribute to largest uncertainties in hydrological impact studies (e.g. Kingston et al. 2011; Nobrega et al. 2011). More inclusion of climate scenarios in hydrological impact studies lead to a better understanding and improve future projections.

This study shows that extreme caution should be taken on the projection result of a single GCM which may lead to misleading and mistaken management decisions. For example, an earlier shift of extreme precipitation season from mid-winter season (December and January) to end-summer season (September and October) was projected by the MRI-CGCM model, which if only used in a climate change study might lead to false conclusions about the timing of occurrences of future flood events. ±20% changes in annual streamflow or Q₅ (high) flow of the Johor River, might affect the flood hazard and vulnerability level, impacting in flood adaptation strategies planning. In addition, the changes also influence agriculture and irrigation planning water resource management and irrigation system in the oil palm region. The uncertainty in projected streamflow by different GCMs highlights the importance of application of multi-models in hydrological impact study. A single GCM or an average ensemble of GCMs are unlikely to represent the full probability of all possible climate change effects (Hughes et al. 2011). More climate scenarios should be developed in the future to better understand the range and quantify the impact of climate change on streamflow. Additionally, the ensemble GCMs procedure could be improved by applying weights to GCMs based on their performance in projection of historical climate variables. Future work is aimed at developing a better ensemble procedure to evaluate the potential impact of climate change on hydrological components in the JRB.

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