Comparative study of conceptual versus distributed hydrologic modelling to evaluate the impact of climate change on future runoff in unregulated catchments

Hashim Isam Jameel Al-Safi, Hamideh Kazemi and P. Ranjan Sarukkalige

ABSTRACT

The application of two distinctively different hydrologic models, (conceptual-HBV) and (distributed-BTOPMC), was compared to simulate the future runoff across three unregulated catchments of the Australian Hydrologic Reference Stations (HRSs), namely Harvey catchment in WA, and Beardy and Goulburn catchments in NSW. These catchments have experienced significant runoff reduction during the last decades due to climate change and human activities. The Budyko-elasticity method was employed to assign the influences of human activities and climate change on runoff variations. After estimating the contribution of climate change in runoff reduction from the past runoff regime, the downscaled future climate signals from a multi-model ensemble of eight global climate models (GCMs) of the Coupled Model Inter-comparison Project phase-5 (CMIP5) under the Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios were used to simulate the future daily runoff at the three HRSs for the mid-(2046–2065) and late-(2080–2099) 21st-century. Results show that the conceptual model performs better than the distributed model in capturing the observed streamflow across the three contributing catchments. The performance of the models was relatively compatible in the overall direction of future streamflow change, regardless of the magnitude, and incompatible regarding the change in the direction of high and low flows for both future climate scenarios. Both models predicted a decline in wet and dry season’s streamflow across the three catchments.

Key words | Budyko equation, climate change, conceptual modelling, distributed modelling, human activities, hydrologic reference stations

INTRODUCTION

The past few decades have seen noticeable changing climate conditions across many parts of Australia, particularly rainfall reduction and temperature increase (Al-Safi & Sarukkalige 2017a, 2018a). The vast majority of hydrological impact studies showed reduction tendencies in future rainfall and runoff across many Australian local catchments especially in the south-eastern and south-western parts of the continent (Chiew et al. 2009; Vaze & Teng 2011; McFarlane et al. 2012; Silberstein et al. 2012; Teng et al. 2012; Al-Safi & Sarukkalige 2017b, 2017c, 2017d). These variations in runoff are believed to be due to impacts of climate change and human activities.

Climate change and, more precisely, global warming, change the quantity and patterns of precipitation and temperature which in return affects runoff and streamflow (Schaake 1990; Teng et al. 2012). Humans, on the other hand, manipulate water resources’ cycles by the construction of dams, water withdrawals for industrial and domestic uses or agricultural purposes (Haddeland et al. 2014). Some studies show human influences on water resources including runoff can be as effective or even more destructive than the average climate change (Haddeland et al. 2014; Guyennon et al. 2017). Variation of
runoff, especially runoff reduction, needs extensive investigation and action to understand the influences of climate change and human activities on catchment hydrology and water resources. It is critical for organizations in charge to take this into account and look for management plans for the long-term runoff reduction (Teng et al. 2012; Liu et al. 2017a, 2017b).

Researchers have employed many models to investigate the contribution of climate changes and human activities on runoff variations in almost every part of the world (Teng et al. 2012). Two popular methods, hydrologic modelling and the Budyko elasticity method, can be used to attribute the effects of climate change and human activities on runoff change (Sankarasubramanian et al. 2001; Fu et al. 2007; Hu et al. 2012). Hydrologic modelling is usually a detailed sophisticated simulation, which according to the recent literature is a competent tool for shorter study periods, such as daily or monthly periods. The Budyko framework, on the other hand, is a simple model developed based on the climate elasticity concept (Teng et al. 2012). It is a popular method, especially in long-term studies (Dooge 1992; Zhang et al. 2008; Potter & Zhang 2009; Zheng et al. 2009; Donohue et al. 2011; Roderick & Farquhar 2011; Hu et al. 2012; Li et al. 2012; Tang et al. 2014; Xu et al. 2014; Zeng et al. 2015; Huang et al. 2016; Liu et al. 2017a, 2017b). For instance, Wang et al. (2013) used the Budyko method to assess the impact of climate change and human activities on runoff decrease in the Haihe River basin in China. Based on their research, human activities were responsible for more than 50% of the reduction.

Patterson et al. (2013) also used the Budyko equation to allocate the impact of climate and human interactions on the mean annual streamflow in the South Atlantic region in the USA. The study area has experienced agricultural land expansion and dam constructions. The influence of human activities in the basins was correctly diagnosed by the Budyko method. In another example, Wu et al. (2017) studied runoff reduction in the Yanhe Basin in China using Budyko equations. They detected a changing point in the runoff trend and divided the study period into two periods of before and after change. Based on this study, the decline in the runoff trend was predominantly related to climate change rather than human interaction. Climate change was estimated to account for 54.1% of the total decrease in runoff, whereas human activities accounted for 45.9%.

Unlike hydrologic models, the Budyko method is an efficient approach which does not need sophisticated parameterization and large input data, although the basic hypothesis of this approach assumes the water cycle is static and water storage change is almost zero (Liu et al. 2017a, 2017b). Therefore, in this study, in line with the hydrologic modelling procedure, the Budyko method is used to investigate the involvement of climate change and human activities in variations of runoff trends in three unregulated Australian catchments.

After apportioning of climate and human impacts on runoff variation, the next step is to predict future hydrological alterations resulting from climate change. Hydrologic modelling is a widely used procedure to study the impact of changing climate conditions on runoff. This has considerable importance for sustainable water resources management, developed plans for the economy, agriculture and other water-related sectors in the studied catchments to overcome the expected economic and population developments in the near and long-term future. Local-scale hydrologic modelling based on climate predictions normally involves many sources of uncertainty (Blöschl & Montanari 2010; Al-Safi & Sarukkalige 2010). These sources could be linked to the different scenarios of global climate models (GCMs), parameter uncertainties resulting from different structures of hydrologic models and approximations in solution (Brown & Heuvelink 2005) and the selection of the downscaling procedure.

There is a continuing debate in the area of hydrologic modelling research as to whether physically based distributed models better capture recorded streamflow than the conceptual lumped models approach does. Blöschl & Montanari (2010) point out that complex models are not necessarily better for climate change impact analysis because of higher model uncertainty caused by a larger number of parameters. In this study, the ability of two characteristically different hydrologic models, a conceptual lumped model and a physically based distributed model (Hydrologiska Byrans Vattenbalansavdelning, HBV and BTOPMC), was assessed to represent the observed streamflow and to simulate the impact of future climate changes on the hydrological behaviour of three unregulated local catchments of the Australian Hydrologic Reference Stations.
(HRSs). The detailed application of these two models across the three catchments was carried out in two separate studies (Al-Safi & Sarukkalige 2018a, 2018b). The selected catchments also represent a range of climatic conditions and biophysical characteristics (e.g. latitude, longitude, elevation, land use type and soil type) across Australia. Therefore, it is highly valuable to assess the applicability of both models to represent the observed discharge and to simulate the future runoff at the HRSs. To fairly compare the behaviour of the two hydrologic models, precisely the same forcing data applied to the distributed model was used to force the conceptual model but as lumped input. It is no doubt true that the forcing data has a significant effect on model performance, regardless of the kind of model structure. Hence, the quality of the observed data has been checked carefully, and the regression relationships between the neighbouring stations were used to fill the very few missing data. This study mainly aims at comparing and evaluating the outcome of the application of two different modelling concepts and interprets the results of these two models in different hydrological environments.

STUDY AREA (THE UNREGULATED CATCHMENTS OF THE AUSTRALIAN HRSS)

The Australian HRS network, 222 sites in total, represents an important source of high-quality continuous streamflow data across the continent that enables better analysis of the long-term streamflow trends (Zhang et al. 2016). In this study, three HRSs corresponding to three catchments of three rivers were selected, including Harvey River at Dingo Road station in Western Australia, Beardy River at Haystack and Goulburn River at Coggan stations in New South Wales as shown in Figure 1. There are three main motivations behind the selection of the study area. First, despite the diverse environment and ecology of the catchments, the selected rivers have received less attention in investigating their hydrological response to future climate changes. Second, the Beardy and Harvey river basins support biodiversity of environmental and ecological communities. Last, Harvey and Goulburn Rivers represent the main tributaries of the surface water supply system in their catchments. Hence, assessing the impacts of future climate changes and human activities on the hydrological system of these rivers is a significant task to draw efficient and sustainable water management strategies in their contributing catchments.

Harvey River at Dingo Road HRS (site ID 613002)

The corresponding catchment of this station is located around 130 km south of Perth City (Figure 1). It stretches between the latitude of 32.55°–33.05°S and longitude of 116.02°–116.26°E with an entire drainage area of 148 km². The actual vegetation cover of the catchment is mainly evergreen broadleaf forest and woody savannas (USGS 2011). The catchment has a temperate climate with a summer season which tends to be hot-dry, the average daily minimum and maximum temperature fluctuates between 18 and 28 °C and sometimes reaches 40 °C, and the winter season tends to be cool-wet, with an average daily minimum and maximum temperature range between 10 and 18 °C (Peel-Harvey Catchment Council 2012). The period between April and October accounts for nearly 90% of the total annual rainwater with an approximate annual mean rainfall of 900 mm (Peel-Harvey Catchment Council 2012). The mean potential evaporation (ET) across the catchment is normally above the annual mean precipitation and it reaches approximately 1,460 mm (BOM 2018). Harvey River drains directly to the Peel-Harvey estuary. The Peel-Harvey estuarine system has a considerable ecological, recreational, commercial and scientific importance in southwestern Australia. Its fringing environment comprises ecologically important wetlands and lakes that have been placed on the list of wetlands of international importance (Environmental Protection Authority 2008). The estuary is an internationally important habitat for waterbirds and migratory wading birds, in which tens of thousands of waterbirds gather annually with more than 80 species (Environmental Protection Authority 2008). The depth of the Peel-Harvey estuarine system (total area of 135 km²) is relatively shallow (up to 2 m for the deepest point) and more than 50% of its area has a depth of only 0.5 m (Kelsey et al. 2010).

Beardy River at Haystack HRS (site ID 416008)

Beardy catchment is located in the far north-eastern part of New South Wales (Figure 1) with the latitude of
29.11°–29.30°S and longitude of 151.18°–151.50°E and area of 908 km². The actual vegetation cover of the catchment is mainly evergreen broadleaf forest, shrublands, woody savannas, croplands and natural vegetation mosaic (USGS 2014). The climate of the catchment is temperate with a relatively warm dry summer, in which the temperature approximately ranges between 27 and 30 °C, while in the cool moderate winter, the temperature ranges between 19 and 20 °C (Commonwealth Scientific and Industrial Research Organisation and Australian Bureau of Meteorology 2011). The rainfall distribution over the catchment is extremely seasonal, with the summer season holding the maximum rainwater volumes due to the activity of summer storms, while the other seasons of the year hold the minimum amounts of rainfall. The average monthly summer precipitation is around 100 mm and it decreases to 40–50 mm during the period between April and September (Green et al. 2012). The annual potential evaporation in the catchment is higher than the annual mean precipitation with a spatial variation over the catchment ranging between 1,200 and 2,000 mm (Green et al. 2012). Beardy River, which is an important perennial river that is part of the Murray–Darling basin, is located in the New England region of New South Wales, Australia. The Murray–Darling
basin is a large geographical area in the interior of southeastern Australia. The basin, which drains around one-seventh of the Australian land mass, is one of the most significant agricultural areas in Australia (Pigram 2007).

Goulburn River at Coggan HRS (site ID 210006)

The corresponding catchment extends over a 3,402 km² area (Bureau of Meteorology 2017) (the majority are national parks, forest and wasteland areas) (Figure 1). It also forms the whole western part of the Hunter River catchment (the largest coastal catchment in NSW). The Goulburn River is a major branch of the Hunter River which drains around 50% of the Hunter catchment and donates nearly a quarter of the mean Hunter River flow (NSW Department of Infrastructure Planning and Natural Resources 2002). The Goulburn River catchment stretches from 31°48’ to 32°51’ southern latitude and from 149°40’ to 150°36’ eastern longitude. The climate of the catchment is subhumid to temperate and varies with elevation and ocean proximity (Krogh et al. 2013). As the Goulburn River catchment is located relatively far away from the ocean, it receives the lowest annual rainfall (around 620 mm) compared to the eastern part of the Hunter catchment which receives around 1,600 mm. The rainfall in the catchment is seasonally distributed with the summer being the wettest season in the year (December–February) and the annual potential evaporation normally exceeds the annual rainfall to reach more than 1,300 mm, varying with temperature fluctuations (Krogh et al. 2013). Figure 2 shows statistical characteristics of mean monthly precipitation in the study areas, such as the first and third quartiles, and mean maximum and minimum precipitation.

DATASET AND HYDROLOGIC MODELS

Observed climate data

Different datasets were collected from various sources and used as input into the HBV and BTOPMC models, as illustrated in Table 1. Observed hydro-meteorological data including the daily scale rainfall, temperature, and discharge and the long-term monthly mean potential evaporation from the contributing catchments of the three HRSs were obtained from the Australian Bureau of Meteorology. Weather stations (Figure 1 and Table 1) were selected within the contributing catchments and nearby locations considering the availability of long-term data. The temporal distribution of the hydro-meteorological data is presented in Table 1 and is used to calibrate and validate the two models before the streamflow projection. Spatial distribution of rainfall and temperature data was implemented by the two models by applying the Thiessen polygon method.

Future climate data

The global-scale monthly mean climate outputs were extracted from a multi-model ensemble of eight GCMs (Table 2) of the Coupled Model Inter-comparison Project phase-5 (CMIP5) under two Representative Concentration Pathways (RCP 4.5 and RCP 8.5). According to CSIRO and BoM (2015), the used GCMs are the best amongst the 40 GCMs of the CMIP5 that have been selected according to specific criteria to effectively investigate the Australian future climate, especially for the impact assessment studies (www.climatechangeinaustralia.gov.au/en/support-andguidance/faqs/eight-climate-models-data/). The mid (2046–2065) and late (2080–2099) periods of the current century were selected to represent the future climate status. Historical (baseline) climatic periods of 33 years (1982–2014) for the Harvey catchment and 40 years (1975–2014) for the Beardy and Goulburn catchments were also extracted from the multi-model ensemble. The baseline periods were selected depending on the available observed climate forcing data across the three catchments to enable a fair comparison between the observed and historical climate on one hand and the observed and simulated discharges on the other hand.

A Statistical Downscaling Model developed by the Australian Bureau of Meteorology (BoM-SDM) using an analogue approach (Timbal et al. 2008b) was employed to extract the local-scale daily rainfall and temperature from the global-scale monthly outputs of each GCM for the baseline and the future periods. For the conceptual modelling, the future climate data was extracted (downscaled) as a point-specific climate projection, while for the distributed modelling approach, the future climate data was extracted as distributed data with final spatial and temporal...
resolutions of $5 \times 5$ km (approximately $0.05 \times 0.05^2$) and 24 hours respectively, which are suitable for the local-scale impact assessment studies. The reliability and statistical characteristics of the downscaled climate data have been checked as a high priority by the Australian BoM before using them to force the calibrated models (HBV and BTOPMC) to simulate the future streamflow in this study. The daily variability is well reproduced, as captured by the day-to-day correlation between the observed and reconstructed series. In addition, the downscaling technique is highly efficient for capturing inter-annual variability as well as long-term observed climatic trends (Timbal et al.)
It was also found that the downscaled climate variables are able to reproduce the certain key characteristics of historical data such as mean monthly values, autocorrelation and duration of dry spells for rainfall (Timbal et al. 2008a). Since the main focus of the present study is to investigate the impact of climate change on future streamflow patterns at the studied catchments, the detailed explanation of the downscaling procedure is not provided in the current version and can be found in Timbal et al. (2008b).

For the conceptual modelling procedure, the modified Blaney–Criddle method (Equation (1)) (Doorenbos & Pruitt 1977) was employed to calculate the Potential Evaporation (ET) over the baseline and the future periods depending on the downscaled daily mean temperature. Palutikof et al. (1994) explained that this method computes

<table>
<thead>
<tr>
<th>Data type</th>
<th>Data Description</th>
<th>Original spatial resolution</th>
<th>Data source</th>
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<tbody>
<tr>
<td>Physical data</td>
<td>Digital Elevation Map (DEM)</td>
<td>$3 \times 3^\circ$ (90 × 90 m)</td>
<td>Jarvis et al. (2008)</td>
<td>Global Shuttle Radar Topography Mission data by the CGIAR Consortium for Spatial Information (<a href="http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp">http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp</a>)</td>
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<td></td>
<td>Soil Map</td>
<td>$3 \times 3^\circ$ (90 × 90 m)</td>
<td>FAO (2012)</td>
<td>Harmonized world soil database (FAO/IIASA/ISRIC/ISSCAS/JRC)</td>
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<td>Soil properties (texture)</td>
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<td></td>
<td>Land Cover Map</td>
<td>$30 \times 30^\circ$ (1 × 1 km)</td>
<td>USGS (2011)</td>
<td>Global Land Cover Characteristics Database (Version 2.0) (<a href="http://landcover.usgs.gov/landcoverdata.php">http://landcover.usgs.gov/landcoverdata.php</a>)</td>
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<td>Vegetation data</td>
<td>Normalized Difference Vegetation Index NDVI</td>
<td>$30 \times 30^\circ$ (1 × 1 km)</td>
<td>Tucker et al. (2010)</td>
<td>Global monthly data by Distributed Active Archive Center – Global Inventory Modelling and Mapping Studies (DAAC-ISLSCP II GIMMS) (<a href="https://daac.ornl.gov/ISLSCPII/guides/gimms_ndvi_monthly_xdeg.html">https://daac.ornl.gov/ISLSCPII/guides/gimms_ndvi_monthly_xdeg.html</a>), input for the Shuttleworth-Wallace model</td>
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<td></td>
<td>Mean temperature ($^\circ$C)</td>
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<td>One station for Harvey Catchment at a daily scale (1982–2014). Two stations for Beardy Catchment and three stations for Goulburn Catchments at a daily scale (1975–2014)</td>
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<td></td>
<td>Cloud cover (tenth)</td>
<td>$0.5 \times 0.5^\circ$ (50 × 50 km)</td>
<td>CRU 2.0 data sets from IPCC (2011)</td>
<td>Global monthly data used for potential evaporation calculation, input for the Shuttleworth-Wallace model (<a href="http://www.ipcc-data.org/obs/get_30yr_means.html">www.ipcc-data.org/obs/get_30yr_means.html</a>)</td>
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the potential evaporation by utilizing the daily mean temperature ($T_{\text{mean}}$) and daily mean proportion of annual daylight hours ($D$).

$$ET = C[D(0.46 T_{\text{mean}} + 8)]$$  \hspace{1cm} (1)

where $ET$ is the monthly average crop potential evaporation (mm/day). $C$ is a correction factor calculated based on sunshine hours, minimum relative humidity, and daytime wind speed. $D$ is the daily mean proportion of yearly daylight periods (in hours), while $T_{\text{mean}}$ refers to the downscaled daily mean temperature ($^\circ$C).

For the distributed modelling approach, the global monthly data was adopted to force the Shuttleworth–Wallace model (Shuttleworth & Wallace 1985) to calculate the spatially distributed monthly average $ET$ values.

### Hydrologic models

A full description of the two hydrologic models (HBV and BTOPMC), their structure, parameters and the calibration and validation processes can be found in Al-Safi & Sarukkalige (2018a, 2018b).

### METHODOLOGY

In order to assign the influence of climate change and human activities on runoff change, the first step is to find the change point/s in the temporal trend of runoff during the period of study (Xu et al. 2014; Dey & Mishra 2017). The usual method to define the change point is defined by the Mann–Kendall statistic (MMK) test (Li et al. 2012; Ashofteh et al. 2016; Fan et al. 2017; Liu et al. 2017a, 2017b) which is applied here as well. The Mann–Kendall test, with a statistical significance of $\alpha = 0.05$, shows 1993 and 2000 are the changing years for the Harvey and Beardy catchments, respectively. The period of study for these catchments is from 1971 to 2015. While at Goulburn catchment, for the period of 1951–2015, the year 1978 is the point in which the change of runoff trend occurred (Figure 3 and Table 3). These years are also stated as the breaking points by the Australian Bureau of Meteorology (BOM 2018).

Based on Figure 3 and Table 3, the annual runoff in all catchments has experienced a significant reduction during the last decades (35 to almost 40%). The precipitation has also suffered a considerable decrease from the base period (period 1) to the second period (after change) while the values for evapotranspiration did not experience a dramatic fluctuation.

Further analysis of the runoff changes shows the significant difference between the minimum runoff statistics (Q25), mean runoff statistics (Q50) and maximum runoff statistics (Q75) of the base period compared to the second period in all catchments (Table 4). The Q25s in all catchments have decreased by more than 33%, Q50s have almost reduced by 54% and Q75s have experienced a significant reduction between 36 and 68%. For the Harvey catchment, the zero-flow frequency was 6%, which almost never happened in the first period. The values of zero frequency for the Beardy catchment are 6% for the base period, which has increased to 14% of the days in the second period. The Goulburn catchment did not experience days with a zero-flow frequency.

### Attribution of climate change impacts on runoff variation by means of Budyko elasticity method

Budyko (1974) claimed that there is a link between available water and available energy and potential evaporation in a hydrological system (Budyko 1974; Alimohammadi 2012):

$$ET = f(P, ET_0)$$  \hspace{1cm} (2)
where $ET_0$ is the potential evapotranspiration (mm/day) and $P$ is precipitation (mm/day). He later introduced his equation (Equation (3)) which presents a relationship between mean annual evaporation ratio and mean annual potential evaporation ratio (drought index) (McMahon et al. 2013; Wang et al. 2016):

$$\frac{ET}{P} = \left[ \frac{ET_0}{P} \tanh \left( \frac{ET_0}{P} \right)^{-1} \left( 1 - \exp \left( \frac{ET_0}{P} \right) \right) \right]^{0.5}$$

(3)

\[
ET = \frac{P}{1 + \left(\frac{P}{ET_0}\right)^n} \quad (4)
\]

where \( n \) is an empirical parameter called the catchment characteristic parameter, representing soil properties, slope, land use, and climate seasonality (Liang et al. 2015). This parameter also defines the Budyko curve shape (Li et al. 2015). In Choudhury, for a given \( P \) and \( ET_0 \), the higher \( n \) value signifies a higher ET which means a lower streamflow (Q) value (Xu et al. 2017).

To find the parameter \( n \) for a catchment, a curve fitting procedure is applied. The objective function can be obtained by minimizing the mean squared errors between the calculated annual evapotranspiration ratios (\( ET/P \)) and the observed ratios (Equation (4)) (Li et al. 2015):

\[
obj = \min \sum \left\{ \frac{ET}{P_i} - \frac{1}{\left(1 + \left(\frac{P_i}{ET_0}\right)^n\right)^{1/n}} \right\}^2
\]

A large basin can have multiple characteristic parameter values depending on its major land use types (such as grassland, forest, urban, etc.) (Zhang & Chiew 2012). This parameter can change temporally, too. It means that by changing the land cover over the years and decades, catchment characteristic parameters experience different values. As represented in Figure 4, catchment characteristic parameters for each case study have shifted on the Budyko curves vertically and horizontally. The horizontal change is believed to be due to climate change impacts while the vertical movement is imposed by human activities.

In the Budyko type model the variation of water storage is considered to be negligible at the long-term time scale;
therefore, for catchments with steady state conditions in which the only mean of water loss is evapotranspiration, the following equations are applicable:

Water balance relation can be written as Equation (6) (Xu et al. 2013):

\[ P = ET + Q + \Delta S \]  

where \( \Delta S \) is assumed to be almost zero, the equation can be rewritten as:

\[ Q = P - ET \]  

Actual evapotranspiration (\( ET \)) can be estimated using Equation (4) (Xu et al. 2013).

The total variation of runoff (\( \Delta Q \)) is believed to be due to both climate change (\( \Delta Q_{cc} \)) and human activities (\( \Delta Q_{HA} \)) as illustrated in Equation (8) (Li et al. 2012; Liang et al. 2015):

\[ \Delta Q = \Delta Q_{cc} + \Delta Q_{HA} \]  

By assuming \( P \) and \( ET_0 \) in Equation (2) are independent variables, Sankarasubramanian et al. (2001) and Fu et al. (2007) developed a method called the elasticity method to distinguish the impact of human activities and climate change on runoff variation in a catchment (Equation (9)) (Yang & Yang 2011; Liang et al. 2015):

\[ dQ_{cc} = \frac{\partial f}{\partial P} dP + \frac{\partial f}{\partial ET_0} dET_0 \]  

Taking the definition of elasticity \( \varepsilon = \frac{dQ/Q}{dX/X} \) into account, Equation (10) is presented (Yang & Yang 2011; Liang et al. 2015):

\[ dQ_{cc} = \varepsilon_P \frac{dP}{P} + \varepsilon_{ET_0} \frac{dET_0}{ET_0} \]  

where \( \varepsilon_P \) and \( \varepsilon_{ET_0} \) are the \( P \) elasticity and \( ET_0 \) elasticity of \( Q \), respectively. \( \varepsilon_P \) and \( \varepsilon_{ET_0} \) are derived by Equations (11) and (12) (Yang & Yang 2011; Liang et al. 2015):

\[ \varepsilon_P = \frac{1}{\left(1 + \left(\frac{ET_0}{P}\right)^n \right)^{1/n}} \left\{ 1 - \frac{1}{\left(1 + \left(\frac{ET_0}{P}\right)^n \right)^{1/n}} \right\} \]  

and

\[ \varepsilon_{ET_0} = - \frac{1}{\left[ 1 + \left(\frac{ET_0}{P}\right)^n \right]^{1/n}} \cdot \frac{1}{\left[ 1 + \left(\frac{ET_0}{P}\right)^n \right]^{\frac{1}{n}}} \]  

where \( n \) is the catchment characteristic.

With some rearrangement in Equation (10), the contribution of climate variation in changing the runoff (\( \Delta Q_{cc} \)) can be derived as follows:

\[ \Delta Q_{cc} = \varepsilon_P \frac{\Delta P}{P} Q + \varepsilon_{ET_0} \frac{\Delta ET_0}{ET_0} Q \]  

where \( Q, P, \) and \( ET_0 \) are the long-term mean annual runoff, precipitation, and potential evapotranspiration, respectively.

Finally, using Equation (8), the impact of human activity on runoff change can be calculated:

\[ \Delta Q_{cc} = \Delta Q - \Delta Q_{HA} \]  

RESULTS AND DISCUSSION

Quantifying impacts of climate variation and human activities on streamflow

The parameters of precipitation elasticity and evapotranspiration elasticity for each catchment are calculated by
applying annual rainfall and annual potential evapotranspiration for the study period. The values of \( \varepsilon(P) \) and \( \varepsilon(ET_0) \) suggest the runoff variation sensitivity to precipitation and evapotranspiration are derived based on Equations (11) and (12). As presented in Table 5 and Figure 4, the values of precipitation elasticity are higher compared to the evapotranspiration elasticities, which means that the runoff change is more sensitive to rainfall than to \( ET_0 \).

The impacts of climate change and human activities are estimated using Equations (7)–(13) (Table 5). The results suggest that the main factor of runoff reduction in each catchment is different. In the Harvey catchment, the impacts of climate change and human involvement were not that much different although the climate change had a higher share in this reduction. Beardy catchment, on the other hand, was most affected by human activities. In the Goulburn catchment, human activities were responsible for only 30% of the decrease in runoff. Considering the location of the Goulburn catchment, which has been less manipulated by human activities, suggests we should have expected such a result.

The elasticity method was used to estimate the runoff variations in the three catchments for the base period (period 1) and the second period (after change) by quantifying the impact of both climate change and human interaction on the runoff reduction. The next step is to predict the possible future runoff variation under different climate scenarios. Two hydrologic models are employed for this step.

**Modelling performance of the two hydrologic models**

To evaluate the performance of the two hydrologic models, HBV and BTOPMC, across the studied catchments, daily simulation results during the calibration and validation periods were assessed and compared. As mentioned earlier, the same observed hydro-meteorological data from the three contributing catchments were used to calibrate and validate the conceptual and distributed hydrologic models. The only difference between the observed forcing data is the values of potential evapotranspiration (ET). The long-term observed monthly mean values were used in the conceptual modelling, whereas the global monthly data (Table 1) was adopted to force the Shuttleworth–Wallace model to calculate the ET values in the distributed modelling. The two models were calibrated and validated over the same time periods, and the manual calibration was used to optimize the parameters of the two hydrologic models. At Dingo Road HRS, the models were calibrated for 22 years (1983–2004) and validated for the rest of the recorded period (2005–2014), while at Haystack and Coggan HRSs, the models were calibrated for a 29-year period (1976–2004) and validated for the remaining ten years (2005–2014). The calibration and validation periods were selected to represent a compromise between a longer period that would better account for climate variability and a shorter period that would better represent current catchment conditions (Vaze et al. 2011).

To assess the performance of the two models, three criteria were used including Nash–Sutcliffe efficiency (NSE), relative volume error (VE) and the coefficient of determination (R²) (Equations (15)–(17)). Model parameters were optimized manually based on the efficiency criteria and the values in Table 6 represent the best result chosen after performing several trials. The goodness-of-fit statistics resulting from comparing the observed and simulated discharges based on the optimized parameters of the two hydrologic models are illustrated in Table 7. It indicates that both models performed well with acceptable goodness-of-fit. Figure 5 also shows a graphical comparison between the observed and simulated discharges resulting from both hydrologic models at the three HRSs (for a specified period of two years each). The visual inspection

<table>
<thead>
<tr>
<th>Catchment</th>
<th>ΔQ(mm)</th>
<th>( \varepsilon(P) )</th>
<th>( \varepsilon(ET_0) )</th>
<th>( \Delta Q_{CC} )(mm)</th>
<th>( \Delta Q_{Nat} )(mm)</th>
<th>( \Delta Q_{CC} )(%)</th>
<th>( \Delta Q_{Nat} )(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harvey</td>
<td>96</td>
<td>2.3</td>
<td>-1.3</td>
<td>52</td>
<td>42</td>
<td>55</td>
<td>45</td>
</tr>
<tr>
<td>Beardy</td>
<td>27</td>
<td>2.65</td>
<td>-1.65</td>
<td>12</td>
<td>15</td>
<td>44</td>
<td>56</td>
</tr>
<tr>
<td>Goulburn</td>
<td>21</td>
<td>3.73</td>
<td>-2.73</td>
<td>14.5</td>
<td>6.5</td>
<td>69</td>
<td>31</td>
</tr>
</tbody>
</table>

Table 5 | Contribution of climate change and human activities on streamflow reduction in the contributing catchments based on the proposed methods
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Unit</th>
<th>Optimal value Harvey catchment</th>
<th>Optimal value Beardy catchment</th>
<th>Optimal value Goulburn catchment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conceptual modelling</td>
<td>rcf</td>
<td>–</td>
<td>0.8</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Rainfall correction factor</td>
<td>pcalt</td>
<td>1/100 m</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Elevation correction factor for precipitation</td>
<td>tcal</td>
<td>°C/100 m</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Temperature lapse</td>
<td>FC</td>
<td>mm</td>
<td>400</td>
<td>500</td>
<td>250</td>
</tr>
<tr>
<td>Limit for potential evaporation</td>
<td>Lp</td>
<td>–</td>
<td>0.7</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>Shape coefficient</td>
<td>Beta</td>
<td>–</td>
<td>1.5</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>General correction factor for potential evaporation</td>
<td>gere</td>
<td>–</td>
<td>0.9</td>
<td>0.9</td>
<td>0.85</td>
</tr>
<tr>
<td>Recession coefficient for upper response box</td>
<td>Khq</td>
<td>1/day</td>
<td>0.25</td>
<td>0.8</td>
<td>0.9</td>
</tr>
<tr>
<td>Recession coefficient for lower response box</td>
<td>K4</td>
<td>1/day</td>
<td>0.04</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Maximum percolation capacity</td>
<td>Perc</td>
<td>mm/day</td>
<td>1.1</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Routing parameter</td>
<td>Maxbaz</td>
<td>day</td>
<td>0.07</td>
<td>1.1</td>
<td>0.5</td>
</tr>
<tr>
<td>Distributed modelling</td>
<td>Do</td>
<td>m/day</td>
<td>Sand = 0.1</td>
<td>Sand = 0.12</td>
<td>Sand = 0.14</td>
</tr>
<tr>
<td>Groundwater dischargeability</td>
<td>Ds</td>
<td>m/day</td>
<td>Sand = 0.05</td>
<td>Silt = 0.06</td>
<td>Silt = 0.05</td>
</tr>
<tr>
<td>Silt = 0.05</td>
<td>Clay = 0.05</td>
<td></td>
<td>Sm = 0.07</td>
<td>clay = 0.07</td>
<td>clay = 0.06</td>
</tr>
<tr>
<td>Decay factor of transmissivity</td>
<td>m</td>
<td>–</td>
<td>0.1</td>
<td>0.075</td>
<td>0.073</td>
</tr>
<tr>
<td>Block average Manning’s coefficient</td>
<td>no</td>
<td>–</td>
<td>0.01</td>
<td>0.014</td>
<td>0.019</td>
</tr>
<tr>
<td>Maximum root zone storage</td>
<td>Smax</td>
<td>M</td>
<td>0.25</td>
<td>0.3</td>
<td>0.32</td>
</tr>
<tr>
<td>Drying function parameter</td>
<td>a</td>
<td>–</td>
<td>5</td>
<td>6</td>
<td>6.5</td>
</tr>
</tbody>
</table>
of the hydrographs specifies that the two models are good at producing the observed daily scale streamflow. In addition, the two models were validated using independent hydrometeorological data during the period 2005–2014, and the goodness-of-fit results were also satisfied (Table 7).

\[
\text{NSE} = 1 - \frac{\sum (QC - QR)^2}{\sum (QR - QR_{\text{mean}})^2}
\]

\[
\text{VE} = \frac{\sum (QR - QC)}{\sum (QR)} \times 100
\]

\[
R^2 = \frac{\left[ \sum_{i=1}^{n} (QR - QR_{\text{mean}})(QC - QC_{\text{mean}}) \right]^2}{\sum_{i=1}^{n} (QR - QR_{\text{mean}})^2 \sum_{i=1}^{n} (QC - QC_{\text{mean}})^2}
\]

However, the modelling performance results (Table 7) revealed that the conceptual model performs better than the distributed model in capturing the observed streamflow across the three contributing catchments. The values of Nash–Sutcliffe efficiency (NSE) in the conceptual modelling approach are better than those values obtained from the distributed hydrologic modelling. The results also specified that the peak and low discharges are better captured by the conceptual model than the distributed model (Figure 5). This implies that the simple structure of the HBV model, which normally requires fewer input data, can represent the hydrological behaviour of the catchments better than the more complicated structure of the BTOPMC model which usually involves more input data. An additional consideration is that simpler hydrologic models that require less complex calibration are preferred over the more complex and demanding models if only streamflow is of interest, and not the spatial patterns of runoff generating processes.

Based on the above analysis, the general performance of the two models was relatively sensible in simulating the historical runoff volume at the three HRSs. The analysis of the results shows that there are no large differences in the modelling performance of the two models. On the basis of model performances, it seems that the conceptual and distributed hydrologic models almost perform similarly across the studied catchments. Therefore, both hydrologic models can be used effectively for climate scenario quantification to assess the impacts of future climate changes on the hydrological behaviour of the corresponding catchments of the three HRSs. Hence, both models were forced with the ensemble mean of the downscaled climate outputs of rainfall and temperature from the eight GCMs of the CMIP5 model to simulate the future daily streamflow at the three HRSs.

### Application of hydrologic models to predict the future runoff variation in the HRSs

To reduce the uncertainties in the GCMs projections, the ensemble mean of the downscaled climate data was derived and used as input into the HBV and BTOPMC models to simulate the future daily streamflow at the three HRSs. To study the hydrologic behaviour of the three contributing catchments under the scenarios of climate change, the two models were forced with the same climate outputs, the ensemble mean of the eight GCMs, but as lumped and distributed modes for the HBV and BTOPMC models respectively. The key reason was to fairly compare the behaviour of the two models under changing climate conditions and to explore any changes in the future direction.

### Table 7 | Modelling performance (daily basis) during the calibration and verification periods at the three HRS based on the two modelling approaches

<table>
<thead>
<tr>
<th>Hydrologic reference stations</th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>VE (%)</td>
</tr>
<tr>
<td>Conceptual modelling approach</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Harvey River at Dingo Road</td>
<td>0.87</td>
<td>-4.2</td>
</tr>
<tr>
<td>Beardy River at Haystack</td>
<td>0.92</td>
<td>-3.9</td>
</tr>
<tr>
<td>Goulburn River at Coggan</td>
<td>0.9</td>
<td>3.8</td>
</tr>
<tr>
<td>Distributed modelling approach</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Harvey River at Dingo Road</td>
<td>0.76</td>
<td>-4.8</td>
</tr>
<tr>
<td>Beardy River at Haystack</td>
<td>0.79</td>
<td>-3.5</td>
</tr>
<tr>
<td>Goulburn River at Coggan</td>
<td>0.83</td>
<td>3.1</td>
</tr>
</tbody>
</table>
of streamflow at the studied catchments. The climate change impacts on future streamflow were analysed by comparing the future monthly mean simulations (seasonal streamflow) of the two models for the mid and late century with the control run (Figure 6). In addition, the changes in annual mean streamflow statistics of the future climate scenarios (RCP 4.5 and RCP 8.5) relative to the control run at the three HRSs were also compared and are presented in Table 8. Furthermore, Figures 7 and 8 illustrate a box plot of the annual statistics of the 25th, median and 75th streamflow percentiles at the three HRSs for the observed, baseline and future climate scenarios as simulated by the two models. It shows that the future streamflow simulated by the two models tends to decrease across the three contributing catchments under both climate scenarios, regardless of the magnitude, relative to the control run.
At Dingo Road HRS, the HBV model shows a shift in the wet season streamflow from July–September in the baseline period (control run) to October–December under the scenarios of future climate (Figures 6(a) and 6(b)), while the monthly mean streamflow simulated by the BTOPMC model tends to keep the same temporal distribution as in the baseline period. The peak flows simulated by the two hydrologic models indicate reduction tendencies for both scenarios; however, the changes are slightly higher for the HBV model (−29 to 56%) than for the BTOPMC model (−26 to 53%), especially for the mid-century (Figures 6(a) and 6(b)). The low flows, particularly the period from January to June, are also expected to decline in the future with high reduction tendencies projected by the HBV model.
Figure 6 | A comparison between the control run and the future monthly mean streamflow simulated by the two hydrologic models. (a) Harvey catchment at Dingo Road HRS (Mid-century). (b) Harvey catchment at Dingo Road HRS (Late-century). (c) Beardy catchment at Haystack HRS (Mid-century). (d) Beardy catchment at Haystack HRS (Late-century). (e) Goulburn catchment at Coggan HRS (Mid-century). (f) Goulburn catchment at Coggan HRS (Late-century). (continued).
Figure 6 | Continued
than the BTOPMC model. These findings specify that the uncertainty resulting from using two structurally distinctive hydrologic models cannot be ignored. Therefore, even though the input data are the same, different hydrologic models provide different streamflow outputs because of differences in model structures. In short, the shift in

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(2046–2065)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>RCP 4.5</td>
</tr>
<tr>
<td>Harvey River at Dingo</td>
<td>Q Min.</td>
<td>0.3</td>
<td>0.23</td>
<td>-13</td>
</tr>
<tr>
<td>Road</td>
<td>Q25</td>
<td>0.6</td>
<td>0.6</td>
<td>-33</td>
</tr>
<tr>
<td></td>
<td>Q50</td>
<td>1.1</td>
<td>0.9</td>
<td>-31</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>1.1</td>
<td>0.9</td>
<td>-30</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>1.8</td>
<td>1.7</td>
<td>-23</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>0.88</td>
<td>0.8</td>
<td>-31</td>
</tr>
<tr>
<td>Distributed modelling</td>
<td>Q Min.</td>
<td>0.3</td>
<td>0.20</td>
<td>-10</td>
</tr>
<tr>
<td></td>
<td>Q25</td>
<td>0.6</td>
<td>0.5</td>
<td>-17</td>
</tr>
<tr>
<td></td>
<td>Q50</td>
<td>1.1</td>
<td>0.9</td>
<td>-33</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>1.1</td>
<td>1.2</td>
<td>-38</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>1.8</td>
<td>1.9</td>
<td>-20</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>0.88</td>
<td>0.95</td>
<td>-26</td>
</tr>
<tr>
<td>Beardy River at Haystack</td>
<td>Q Min.</td>
<td>0.6</td>
<td>0.6</td>
<td>0</td>
</tr>
<tr>
<td>Conceptual modelling</td>
<td>Q25</td>
<td>0.8</td>
<td>0.9</td>
<td>-11</td>
</tr>
<tr>
<td></td>
<td>Q50</td>
<td>1.15</td>
<td>1.2</td>
<td>-8</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>2.025</td>
<td>1.9</td>
<td>-4</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>5.6</td>
<td>4.6</td>
<td>-15</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>1.73</td>
<td>1.68</td>
<td>-1</td>
</tr>
<tr>
<td>Distributed modelling</td>
<td>Q Min.</td>
<td>0.6</td>
<td>0.5</td>
<td>-4</td>
</tr>
<tr>
<td></td>
<td>Q25</td>
<td>0.8</td>
<td>0.85</td>
<td>-6</td>
</tr>
<tr>
<td></td>
<td>Q50</td>
<td>1.15</td>
<td>1.4</td>
<td>-4</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>2.025</td>
<td>2.2</td>
<td>-4</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>5.6</td>
<td>6.6</td>
<td>-23</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>1.73</td>
<td>1.7</td>
<td>-10</td>
</tr>
<tr>
<td>Goulburn River at</td>
<td>Q Min.</td>
<td>1.0</td>
<td>0.9</td>
<td>-11</td>
</tr>
<tr>
<td>Coggan</td>
<td>Q25</td>
<td>1.6</td>
<td>2.4</td>
<td>-4</td>
</tr>
<tr>
<td>Conceptual modelling</td>
<td>Q50</td>
<td>3.1</td>
<td>2.95</td>
<td>-10</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>5.1</td>
<td>4.3</td>
<td>-26</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>8.1</td>
<td>8.5</td>
<td>-45</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>3.7</td>
<td>3.3</td>
<td>-18</td>
</tr>
<tr>
<td>Distributed modelling</td>
<td>Q Min.</td>
<td>1.0</td>
<td>0.8</td>
<td>-6</td>
</tr>
<tr>
<td></td>
<td>Q25</td>
<td>1.6</td>
<td>2.0</td>
<td>-28</td>
</tr>
<tr>
<td></td>
<td>Q50</td>
<td>3.1</td>
<td>2.9</td>
<td>-17</td>
</tr>
<tr>
<td></td>
<td>Q75</td>
<td>5.1</td>
<td>5.5</td>
<td>-49</td>
</tr>
<tr>
<td></td>
<td>Q Max.</td>
<td>8.1</td>
<td>7.5</td>
<td>-19</td>
</tr>
<tr>
<td></td>
<td>Q Mean</td>
<td>3.7</td>
<td>3.1</td>
<td>-6</td>
</tr>
</tbody>
</table>
seasonal streamflow projected by the HBV model is highly related to the different model structure and not to the climate scenarios (the shift in future rainfall patterns).

At Haystack HRS, the behaviour of the two hydrological models is almost the same and shows a clear reduction in the overall future streamflow of the wet and dry seasons.
However, the BTOPMC model predicts slightly higher reduction tendencies than the HBV model, specifically for the RCP 4.5 scenario during the mid and late century. The seasonal distribution of the future streamflow simulated by the two models also tends to follow the same temporal distribution as in the baseline period. Nevertheless, the decline in the wet season’s flow (October–March) is higher than the dry seasons (April–September) which show insignificant changes (Figures 6(c) and 6(d)). This indicates that the streamflow during the wet season is more sensitive to climate change than the total annual streamflow.

The attitude of the two hydrologic models is also relatively similar at Coggan HRS on Goulburn River. The wet and dry seasons stream flows are expected to decline in the future under both climate scenarios (Figures 6(e) and 6(f)). Contrary to the case of Haystack HRS, the streamflow reduction tendencies are higher as simulated by the HBV model than by the BTOPMC model. However, the seasonal distribution of the future streamflow simulated by the two

(Figures 6(c) and 6(d)). However, the BTOPMC model predicts slightly higher reduction tendencies than the HBV model, specifically for the RCP 4.5 scenario during the mid and late century. The seasonal distribution of the future streamflow simulated by the two models also tends to follow the same temporal distribution as in the baseline period. Nevertheless, the decline in the wet season’s flow (October–March) is higher than the dry seasons (April–September) which show insignificant changes (Figures 6(c) and 6(d)). This indicates that the streamflow during the wet season is more sensitive to climate change than the total annual streamflow.

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models tends to follow the same temporal distribution as in the baseline period.

**DISCUSSION**

It is expected that future climatological alterations of precipitation, temperature, evapotranspiration and the frequency of extreme weather events will affect many physical and biological processes in many Australian local watersheds (McVicar et al. 2010). Consequently, this can alter the amount and spatial and temporal distributions of water that flows into downstream rivers and estuaries. Variations of climate conditions can directly affect the vegetation, ecology and the hydrology of a watershed. As vegetation and hydrology are strongly connected, alterations in vegetation conditions themselves can also affect hydrology. Therefore, changes in climatic status can alter the hydrology both directly through the water supply demands, and indirectly through climate-induced changes in vegetation water use. Effective long-term water management strategies at local scale require an appropriate understanding of the eco-hydrologic processes of a catchment. Eco-hydrologic alterations resulting from changing climate conditions can alter the status of streamflow, evapotranspiration, surface storage, and soil dampness, directly affecting the region’s biota and habitat (Guo et al. 2014).

The results of the current study suggest that streamflow in the study areas has been significantly influenced by climate change and human activities due to land use and land cover change, water management projects and development and excess usage of groundwater which manipulate the water resources. The runoff reduction is also expected to continue in the future based on the results of hydrologic modelling. Both HBV and BTOPMC models predicted a dramatic runoff decrease in the future.

At Harvey River catchment, the expected streamflow decline, measured at Dingo Road gauging stations, would possibly reduce the flows received by the Peel–Harvey Estuary. The Harvey River discharges directly to the Harvey Estuary, therefore any reduction in the flow amount of the river will badly affect the quantities of water received by the estuary. As the depth of the estuary is quite shallow (up to 2 m for the deepest point), and more than 50% of its area has a depth of only 0.5 m (Kelsey et al. 2010), this will affect the aquatic life, habitat of waterbirds and the environmental status of the lagoon. The growing environmental and economic importance of the estuary (such as water demands for drinking and agricultural production, parasite control, commercial fishing, foreshore development and access, boat use and moorings and jetties) have placed additional burdens on the estuarine system. Furthermore, the projected reduction in the flow amount of the Harvey River would also reduce the quantities of water received by the Stirling and Harvey Reservoirs which represent the main water supply sources to the Perth Metropolitan (Al-Safi & Sarukkalige 2018c). As the population and the economic development in Perth and its outskirts is in continuous growth, this would increase the competition for the currently available water resources in the area. Therefore, options for additional water supply sources in the future would be necessary to support the economic and population development in the area.

For the Beardy River region, which is rich in rare flora and fauna, the expected streamflow reduction would adversely impact the environmental and ecological communities of the Beardy River system, particularly the Beardy River Hill Catchment. On the other hand, the Goulburn River is the right bank tributary to the Hunter River in NSW, Australia. It drains approximately 50% of the Hunter catchment and contributes nearly a quarter of the mean Hunter River flow. Water in the Hunter basin is the main source for power generation, irrigation and agriculture, stock manufacturing, coal mining and public water supplies. As the Goulburn River flow is projected to decrease due to future climate changes, this would impose further limitations on the surface water supply systems in the Hunter River basin.

Both models predicted a decline in wet and dry seasons streamflow across the three contributing catchments. At Haystack and Coggan HRSs, the future monthly mean streamflow distribution, simulated by the two models under both climate scenarios, follows the same patterns as the baseline period. However, at Dingo Road HRS, the HBV model shows a shift of the peak season from July–September in the base period to October–December for future climate scenarios (Figures 6(a) and 6(b)). The performance of the two hydrologic models in simulating the
future streamflow was relatively compatible in the overall direction of change, irrespective of the magnitude, and inconsistent regarding the change in the direction of high and low flows for both future climate scenarios. However, the conceptual HBV model could be considered more suitable than the distributed BTOPMC model for streamflow simulations as it requires fewer input data which is an advantage in data-sparse regions. Furthermore, conceptual models are preferred over the distributed models in situations when only streamflow is of interest, as in the case of this study, and not the spatial patterns of runoff generating processes. However, if the assessment of climate change impacts on water balance components is the main concern, then the impact on interflow conditions may be better described by using the physically based distributed models.

Although the main interest of this study is to investigate the likelihood of the future streamflow of three Australian HRSs being impacted due to the changes in climatological status, the priority is given to the conceptual modelling as its overall performance was highly satisfied and seems to be more robust than distributed modelling. The conceptual model properly represented the extreme events, which increase the possibility of reliable representation of future streamflow due to the shifts in extreme events of future climate. Furthermore, the more accurate and complicated calculation process of potential evapotranspiration (Shuttleworth–Wallace method) by the distributed modelling did not improve the modelling performance even in the dry periods when the volume of evaporation is highly significant in the water balance. This could also be attributed to the difference in the input values of PE for the conceptual and distributed modelling (long-term monthly mean values versus global monthly data) as discussed above under ‘Modelling performance of the two hydrologic models’. Finally, the short computation time of the conceptual modelling, compared with the distributed modelling, makes it more appropriate for long-term streamflow simulation under the various scenarios of future climate.

**CONCLUSIONS**

To estimate climate change impacts on runoff across three contributing catchments of the Australian HRSs, two hydrologic models, HBV and BTOPMC, were employed to simulate the historical streamflow and catchment hydrologic response to climate change. As a first step, the Budyko elasticity method was applied to understand the history of the hydrological variations in the catchments. The elasticity approach, by using the hydrological parameters and their variation during the recent decades, suggested not only that climate change had an impact on runoff, but also human activities have significantly contributed to the runoff reduction. Climate change and human activities played almost the same roles in the Harvey and Beardy catchments. However, for the Goulburn catchment, climate change was responsible for almost 70% of runoff decrease. The results were predictable as the Goulburn area is mostly covered by national parks and forests and has been less affected by human activities.

After assigning the impact of climate change on runoff variation, the two hydrologic models were calibrated and validated using the same observed hydro-meteorological data from the three contributing catchments. The ensemble mean of the downscaled climate scenarios, RCP 4.5 and RCP 8.5, derived from the most reliable eight GCMs of the CMIP5, was used to force the two hydrologic models to predict the future runoff changes. The results were then compared to assess the applicability of the two models in predicting future runoff under climate change scenarios. Both HBV and BTOPMC models estimated a decline in streamflow in the study areas. At Haystack and Coggan HRSs, the predicted trend of monthly mean streamflow follows the same patterns as the current period. However, at Dingo Road HRS, a shift of the peak season from July–September in the base period to October–December is predicted.

The hydrological results of this study will provide a theoretical basis to the local management authorities to make scientific and rational control measures and response plans which will allow them to manage the usage of future water resources in the study area. The impacts of climate change may influence human water use and the stability of the ecosystem. More attention and effort should be allocated to future water resources management and ecosystem planning in the study regions. Further research on feedbacks of vegetation, water balance, processes that directly influence plant performance and the ecological effects of weather changes...
extremes to improve climate change projections on hydrology and ecosystems will be useful in the sustainable management of catchment water resources in the future.

REFERENCES


Environmental Protection Authority and Australian Bureau of Meteorology 2005 Climate Change Impacts on the Harvey System – Phosphorus Management. Environmental Protection Authority, Perth, Western Australia.


FAO/IAEA/ISRIC/ISSCAS/JRC. 2012 Harmonized World Soil Database, Version 1.2. FAO, Rome, Italy. and IIASA, Laxenburg, Austria.


Guyennon, N., Salerno, F., Portoghesi, I. & Romano, E. 2017 Climate change adaptation in a Mediterranean semi-arid...


NSW Department of Infrastructure, Planning and Natural Resources 2002 Geomorphic Categorisation of Streams in the Wybong Creek Catchment. NSW Department of Infrastructure, Planning and Natural Resources. Australia.


Peel–Harvey Catchment Council 2012 *Adapting to climate change in the Peel region: Improving local government emergency management and biodiversity conservation services.* A report by Kim Byrnes to the PHCC, edited by Andrew Del Marco, Mandurah, Western Australia.


Timbal, B., Hope, P. & Charles, S. 2008a Evaluating the consistency between statistically downscaled and global
dynamical model climate change projections. *J. Climate* 21 (22), 6052–6059.


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