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

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Abstract

This study compares the application of two distinctively different hydrologic models, conceptual (HBV) and distributed (BTOPMC), to simulate the future runoff across three unregulated catchments of the Australian Hydrologic Reference Stations (HRSs) namely Harvey catchment in Western Australia, Beardy and Goulburn catchments in New South Wales. These catchments have experienced significant runoff reduction during the last decades due to climate change and human activates. Budyko Elasticity method was employed to precisely assign the influences of human activities and climate change on the runoff variations. After estimating the contribution of climate change in runoff reduction, the downscaled future climate signals from a multi-model ensemble of eight-GCMs of the CMIP5 under the RCP4.5 and RCP8.5 scenarios were used to simulate the future daily runoff at the three HRSs for the mid (2046-2065) and late (2080-2099) of the 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 two models was relatively compatible in the overall direction of change with regard to the future streamflow, irrespective of the magnitude, and inconsistent 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 contributing catchments.

Keywords: Climate change, Human activities, Hydrologic Reference Stations, conceptual modelling, distributed modelling, CMIP5, Budyko equation, Australia.

1- 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 (Al-Safi & Sarukkalige, 2017b, 2017c and 2017d; Chiew et al., 2009; McFarlane et al., 2012; Silberstein et al., 2012; Teng et al., 2012; Vaze & Teng, 2011). These variations in runoff are believed to be due to impacts of climate change and human activities. Accordingly, it is important to investigate the influences of climate change and human activities on catchment hydrology and water resources to properly managing for the long-term runoff reduction (Liu et al., 2017).

Two popular methods, hydrologic modelling and Budyko Elasticity method, can be used to attribute the effects of climate change and human activities on runoff change. Previous research suggests that at shorter study period, such as daily or monthly periods, hydrologic models are better tools in investigating the hydrological response of a catchment. Budyko framework, on the other hand, is a competent method for the long-term cases (Dooge, 1992; Hu et al., 2012; Huang et al., 2016; Li et al., 2012; Liu et al., 2017; Xu et al., 2014; Zeng et al., 2015; Zheng et al., 2009). Moreover, unlike hydrologic models, Budyko method is an efficient approach which does not need sophisticated parameterization and large input data (Liu et al., 2017). Therefore, in this study, in line with the hydrologic modelling procedure, the Budyko method is used to define the quotas of impacts of climate change and human activities.

A wide range of hydrologic studies has investigated the combined effect of climate change and human interaction on runoff variations. For instance, Fan et al (2010) analysed the contribution of climate change and human impact on runoff variation in Mian River Basin in North China using the SWAT model. The results indicated that human activities have the dominant influence on runoff variation rather than climate change. Wang et al (2013) used Budyko method to assess the impact of climate change and human activities on runoff in the Haihe River basin in China. They concluded that human activities were responsible for more than 50% of the runoff reduction in the basin. Patterson et al (2013) also used the Budyko equation to study the impact of both climate and human interactions on the mean annual streamflow in the South Atlantic region in the USA. They concluded that human activities were estimated to influence 27% of basins in South Atlantic. This has been attributed to the agricultural land expansion and dam constructions in these areas which has significantly affected runoff. Wu et al (2017) compared the applications of the SWAT model and Budyko equation to examine runoff reduction in the Yanhe Basin in China. They found that the decline in runoff of the Yanhe River basin was dominantly related to the climate change rather than human interaction. Climate change was estimated to account for 46.1%–60.8% (mean 54.1%) of the total decrease in runoff, whereas human activities accounted for 39.1%–53.9% (mean 45.9%).

After apportioning of climate and human impacts on runoff variation, the next step is to predict future hydrological alterations resulting from climate change. Hydrological modelling is a widely used procedure to study the impact of changing climate conditions on runoff. This has a 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 (Al-Safi & Sarukkalige, 2018a; Blöschl & Montanari, 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 hydrologic modelling research area on whether physically based distributed models better capture recorded streamflow than conceptual lumped models approach does. Blöschl and Montanari (2010) point out 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 hydrological 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 HRSs. The detailed application of these two models across the three catchments has been done in two separate studies (Al-Safi and 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 hydrological 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.

2- Study area (the unregulated catchments of the Australian HRSs)

The Australian HRSs 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 (Figure 1). Three main motivations were behind the selection of the study area. Firstly, 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. Secondly, Beardy and Harvey Rivers basins support biodiversity of environmental and ecological communities. Lastly, 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.

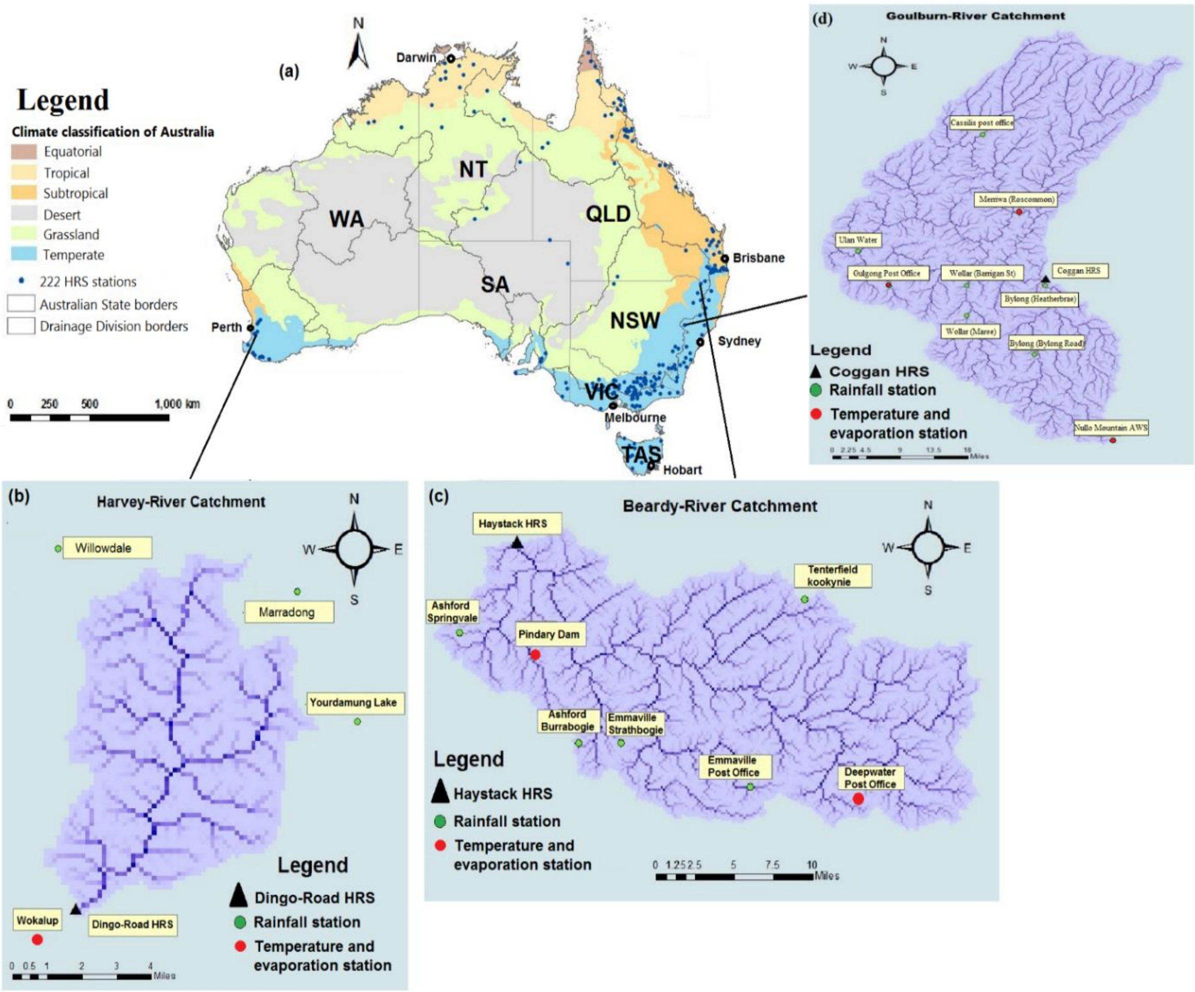


Figure 1 (a) HRSs network sites within the Australian states (b) Harvey River catchment with the weather stations (c) Beardy River catchment with the weather stations (d) Goulburn river catchment with the weather stations (Al-Safi & Sarukkalige, 2018a)

2.1 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 km^2. 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 tend to be hot-dry, the average daily minimum and maximum temperature fluctuates between 18°C–28°C and sometimes reaches 40°C and a winter season tends to be cool-wet, with an average daily minimum and maximum temperature range between 10°C and 18°C (Peel-Harvey Catchment Council, 2012). The period between April and October nearly holds 90% of the total annual rainwater with an approximate annual mean rainfall of 900 mm (Peel- Harvey Catchment Council, 2012). The annual mean potential evaporation (ET) across the catchment is normally going above the annual mean precipitation and it approximately reaches 1,460 mm. Harvey River drains directly to the Peel-Harvey estuary. The Peel-Harvey estuarine system has a considerable ecological, recreational, commercial and scientific importance in south Western 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 133 km^2) 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).

2.2 Beardy River at Haystack HRS (site ID 416008)

Beardy catchment is located in the far northeastern part of New South Wales (Figure 1) with the latitude of 29.11° to 29.30°S and longitude of 151.18° to 151.50° E and area of 908 km^2. The actual vegetation cover of the catchment is mainly evergreen broadleaf forest, shrublands, woody savannas, croplands and natural vegetation mosaic (USGS, 2011). The climate of the catchment is temperate with a relatively warm dry summer, the temperature approximately ranges between 27°C–30°C and cool moderate winter, the temperature nearly ranges between 19°C–20°C (Commonwealth Scientific and Industrial Research Organisation and Australian Bureau of Meteorology, 2007). The rainfall distribution over the catchment is extremely seasonal in which the summer season holds the maximum rainwater volumes due to the activity of summer storm, 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 mean PE in the catchment is higher than the annual mean precipitation with a spatial variation over the catchment ranged 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 south-eastern 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).

2.3 Goulburn River at Coggan HRS (site ID 210006)

The corresponding catchment extends over 3,402 km^2 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 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 relatively located 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 in which the summer is the wettest season in the year (December to February) and the annual potential evaporation normally exceeds the annual rainfall to reach more than 1,300 mm and it varies with temperature variations (Krogh et al., 2013).

3- Dataset and hydrologic models

3.1 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 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.

Table 1 Sources and details of data used in the BTOPMC model application for the three contributing catchments

Data Type	Data Description	Original Spatial Resolution	Data Source	Remarks
Physical data	Digital Elevation Map (DEM)	3”x3” (90mx90m)	Jarvis et al. (2008)	Global Shuttle Radar Topography Mission data by the CGIAR Consortium for Spatial Information (http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp)
	Soil Map	3”x3” (90mx90m)	FAO (2012)	Harmonized world soil database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
	Soil properties (texture)	----------		
	Land Cover Map	30”x30” (1km x 1km)	USGS (2011)	Global Land Cover Characteristics Database (Version 2.0) (http://landcover.usgs.gov/landcoverdata.php)
Vegetation data	Normalized Difference Vegetation Index NDVI	30”x30” (1km x 1km)	Tucker et al. (2010)	Global monthly data by Distributed Active Archive Center—Global Inventory Modelling and Mapping Studies (DAAC- ISLSCP II GIMMS) (https://daac.ornl.gov/ISLSCPII/guides/gimms_ndvi_monthly_xdeg.html), input for the Shuttleworth-Wallace model
Meteorological data	Rainfall (mm)	Point data	Australian Bureau of Meteorology	Three stations for Harvey Catchment, Daily scale data (1982-2014). Five stations for Beardy Catchment and seven stations for Goulburn Catchments. Daily scale data (1975-2014).
	Mean Temperature ^oC			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)
	Potential Evaporation (mm)			Long-term monthly scale. One station for Harvey Catchment (1982-2014), two stations for Beardy Catchment and three stations for Goulburn Catchments (1975-2014)
	Cloud cover (tenth)	0.5 x 0.5 degree (50 x 50 km)	CRU 2.0 data sets from IPCC (2011)	Global monthly data used for potential evaporation calculation, input for the Shuttleworth-Wallace model (http://www.ipcc-data.org/obs/get_30yr_means.html)
	Daylight duration (h)			
	Diurnal temperature range ^{o} C			
	Extraterrestrial radiation (MJ day^{-2} m^{-2})			
	Vapour pressure (kPa)			
	Wind speed (m/s)			
Hydrological Data	Daily observed streamflow	Gauged	Australian Bureau of Meteorology	Dingo-Road HRS for Harvey Catchment at a daily scale (1982-2014). Haystack HRS for Beardy Catchment and Coggan HRS for Goulburn Catchment at a daily scale (1975-2014)

3.2 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 (RCP4.5 and RCP8.5). 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 (https://www.climatechangeinaustralia.gov.au/en/support-andguidance/faqs/eight-climate-models-data/). The mid (2046-2065) and late (2080-2099) of the current century were selected to represent the future climate status. A 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 the one hand and the observed and simulated discharges on the other hand.

Table 2 The 8-GCMs used in this study to predict the future rainfall and temperature

CMIP5 model ID	Institute	Global average Atmosphere resolution (km)
ACCESS1.0	CSIRO-BOM, Australia	210×130
CanESM2	CCCMA, Canada	310×310
CNRM-CM5	CNRM-CERFACS, France	155×155
GFDL-ESM2M	NOAA, GFDL, USA	275×220
CESM1-CAM5	NSF-DOE-NCAR, USA	130×100
HadGEM2-CC	MOHC, UK	210×130
MIROC5	JAMSTEC, Japan	155×155
NorESM1-M	NCC, Norway	275×210

A Statistical Downscaling Model developed by the Australian Bureau of Meteorology (BoM-SDM) using an analogue approach (Timbal et al., 2008) 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 a distributed data with final spatial and temporal resolutions of 5 × 5 km (approximately 0.05° × 0.05°) 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 skilled in capturing inter-annual variability as well as long-term observed climatic trends (Timbal et al., 2008). 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, therefore, the detailed explanation of the downscaling procedure is not provided in the current version and can be found in (Timbal et al., 2008).

For the conceptual modelling procedure, the modified Blaney-Criddle method (Equation 1) (Doorenbos and 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 the potential evaporation by utilizing the daily mean temperature (T_{mean}) and daily mean proportion of annual daylight hours (P).

$$ET = C\,[D\,(0.46\,T_{mean} + 8)] \qquad (1)$$

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_{mean} refers to the downscaled daily mean temperature (°C).

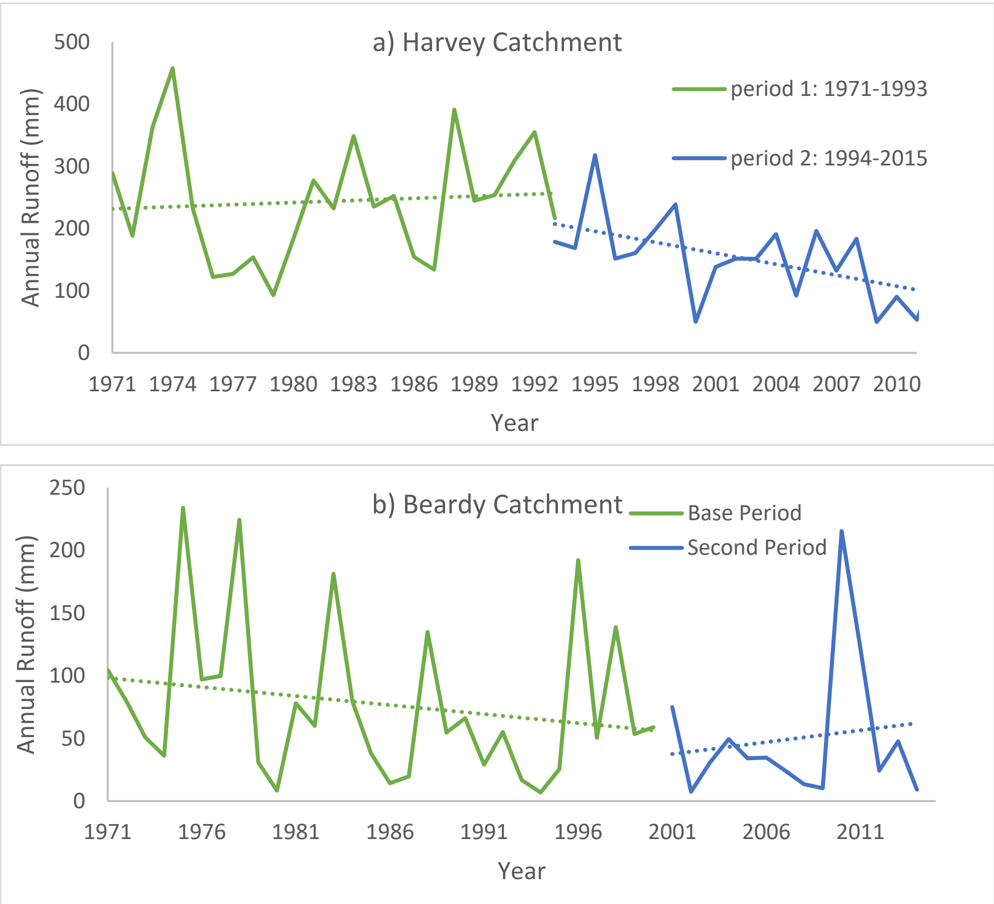
While for the distributed modelling approach, the global monthly data was adopted to force the Shuttleworth-Wallace model (Shuttleworth and Wallace, 1985) to calculate the spatially distributed monthly average ET values.

3.3 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 and 2018b).

4- Methodology

In order to assign climate change and human activities influences on runoff change, the first step is to find the change point/s in the temporal trend of runoff during the period of study. Any runoff reduction/increase before that point is supposed to be due to climate change, while from that changing point (year) onward, the human has involved in the variation of runoff, too (Dey & Mishra, 2017; Xiangyu Xu et al., 2014). The usual method to define the change point is defined by Mann- Kendall statistic (MMK) test (Ashofteh et al., 2016; Fan et al., 2017; Li et al., 2012; Liu et al., 2017) which is applied here as well. The application of the Mann-Kendall trend test finds that 1993, 2000 and 1978 are the years in which the runoff trends have changed for the Harvey, Beardy and Goulburn catchments, respectively (Figure 2). These years are also stated as the breaking points by the Australian Bureau of Meteorology (BOM, 2018).



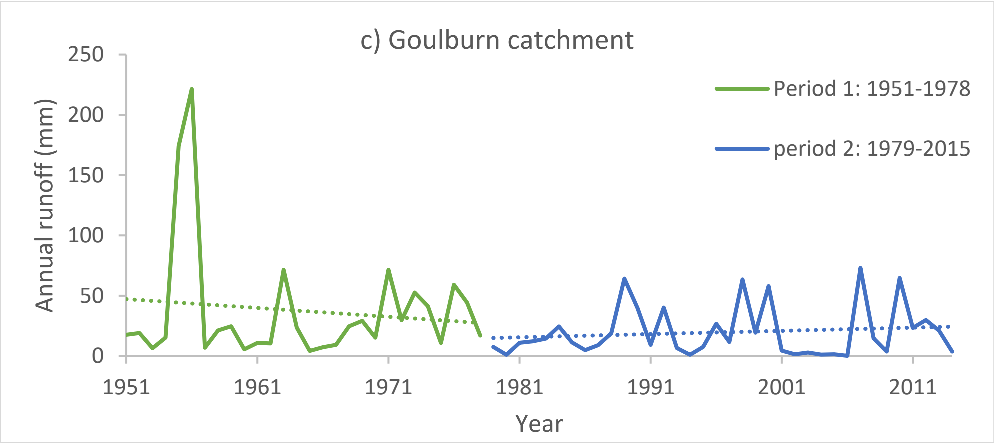


Figure 2 Annual runoff trend and the change point at a) Harvey catchment, b) Beardy catchment and c) Goulburn catchment

4.1 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 (Alimohammadi, 2012; Budyko, 1974).

$$ET = f(P, ET_0) \qquad (2)$$

where ET_0 is the potential evapotranspiration [mm/day] and p is precipitation [mm/ day]. He later introduced his equation (Equation 3) which present a relationship between mean annual evaporation ratio and mean annual potential evaporation ratio (drought index) (McMahon et al., 2013; Wang et al., 2016):

$$\frac{ET}{P} = \left[\frac{ET_0}{P}\tanh\left(\frac{ET_0}{P}\right)^{-1}(1-\exp(\frac{ET_0}{P}))\right]^{0.5} \qquad (3)$$

Later Choudhury (1999) proposed a generalized form for Budyko equation (Liang et al., 2015; Wang et al., 2016; Xu et al., 2014):

$$\frac{ET}{P} = \frac{1}{(1+\left(\frac{P}{ET_0}\right)^n)^{1/n}} \qquad (4)$$

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., 2013). In Choudhury, for a given P and ET0, the higher n value signifies a higher ET which means a lower streamflow (Q) value (Xu et al., 2014).

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., 2013):

$$obj = min \sum_i \left\{ \frac{ETi}{Pi} - \left\{ \frac{1}{(1+\left(\frac{Pi}{ET_0 i}\right)^n)^{1/n}} \right\} \right\}^2 \qquad (51)$$

A large basin can have multiple characteristic parameter values depending on its major land use types (such as grassland, forest, urban,…) (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 3, catchment characteristic parameters for each case study has shifted on the Budyko curves vertically and horizontally. The horizontal change is believed to be as a result of climate change impacts while the vertical movement is imposed by human activities.

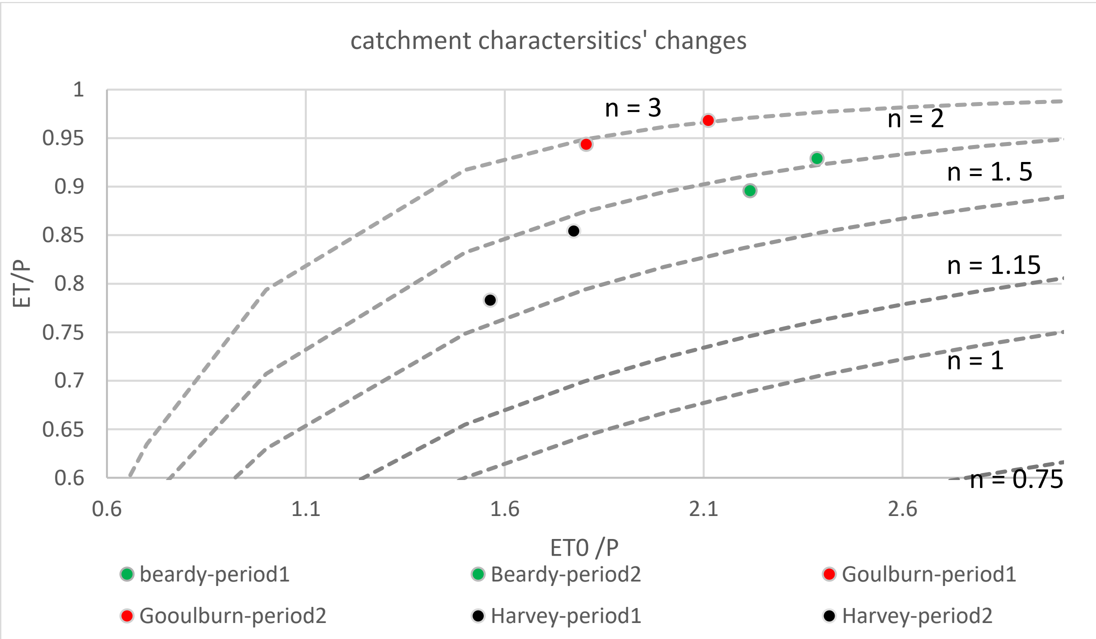


Figure 2 catchment characteristic parameters in the three HRS stations

In Budyko type model the variation of water storage is considered to be negligible at long-term time scale; therefore, actual evapotranspiration (ET) can be estimated using Equation 5 (Xu et al., 2013).

$$\bar{P} = \overline{ET} + \bar{Q} + \Delta S \qquad (6)$$

$$Q = P - ET \qquad (7)$$

The total variation of runoff (ΔQ) is, in fact, a combined change of the runoff influenced by both climate change (ΔQ_{cc}) and Human activities (ΔQ_{HA}) (Li et al., 2012; Liang et al., 2015).

$$\Delta Q = \Delta Qcc + \Delta Q_{HA} \qquad (8)$$

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

$$dQ_{CC} = \frac{\partial f}{\partial P} dP + \frac{\partial f}{\partial ET_0} dE0 \qquad (9)$$

Equation 10 can be derived considering the definition of elasticity ($\varepsilon X = \frac{dQ/Q}{dX/X}$), (Liang et al., 2015; Yang & Yang, 2011):

$$\frac{dQ_{CC}}{Q} = \varepsilon_P \frac{dP}{P} + \varepsilon_{ET_0} \frac{dET_0}{ET_0} \qquad (10)$$

where ε_P and ε_{ET_0} are the P elasticity and ET_0 elasticity of Q, respectively. ε_P and ε_{ET_0} are derived by equation 10 and 11 (Liang et al., 2015; Yang & Yang, 2011)

$$\varepsilon_P = \left\{1 - 1/\left[1 + (\frac{P}{ET_0})^n\right]^{1+1/n}\right\} / \left\{1 - 1/\left[1 + (\frac{P}{ET_0})^n\right]^{1/n}\right\} \qquad (11)$$

And $$\varepsilon_{ET_0} = -\frac{1}{\left[1+\left(\frac{ET_0}{P}\right)^n\right]^{1+\frac{1}{n}}} \cdot \frac{1}{\frac{1}{ET_0/P} \frac{1}{\left[1+\left(\frac{ET_0}{P}\right)^n\right]^{\frac{1}{n}}}} \qquad (12)$$

where *n* is the catchment characteristic.

The runoff variation (Q) due to climate variation can be derived as follows:

$$\Delta Q_{CC} = \varepsilon_P \frac{\Delta P}{\bar{P}} \bar{Q} + \varepsilon_{ET_0} \frac{\Delta ET_0}{\overline{ET_0}} \bar{Q} \qquad (13)$$

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

Finally, using Equations 8 the impact of human activity on runoff change can be calculated. Here, runoff variations induced by climate change and human activities in the three catchments are calculated based on the Elasticity method which has been derived from Choudhury equation.

5- Results and Discussion

5.1 Observed hydrological changes in the study areas

Considering the long-term annual runoff and application of the Mann-Kendall test to specify the temporal points, in which the mean annual runoff has changed dramatically. Based on Figure 2 and Table 3, the annual runoff in all catchments has experienced a significant reduction during the last decades. In these catchments, annual runoff has been reduced from 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 have either increased or didn't experienced a dramatic reduction.

Table 3 climate parameters variation during the base period and the second period

	Variables	1971-1993 (mm)	1994-2015 (mm)	Changes (mm)	Rate of Change
Harvey	Annual $\overline{Q}$	244	148	-96	-39%
	Annual $\overline{P}$	1124	1017	-107	-9.5%
	Annual $\overline{ET_0}$	1758	1804	46	2.6%
	Variables	1971-2000 (mm)	2001-2015 (mm)	Changes (mm)	Rate of Change
Beardy	Annual $\overline{Q}$	77	50	-27	-35%
	Annual $\overline{P}$	740	700	-40	-5%
	Annual $\overline{ET_0}$	1641	1668	27	2%
	Variables	1951-1978 (mm)	1979-2015 (mm)	Changes (mm)	Rate of Change
Goulburn	Annual $\overline{Q}$	41	17	-15	-37%
	Annual $\overline{P}$	723	615	-108	-15%
	Annual $\overline{ET_0}$	1305	1298	-7	-0.5%

Further analysis of the runoff changes shows the significant difference between the minimum runoff statistics (Q25), mean runoff statistics (Q50) and maximum runoff statistics (Q95) of the base period comparing 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% -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 Beardy catchment are 6% for the base period, which has increased to 14% of the days in the second period. Goulburn catchment did not experience days with the zero-flow frequency.

Table (4) runoff statistics variation during the base period and the second period

	Variables	1971-1993 (mm)	1994-2015 (mm)	Rate of Change
Harvey	Q25	30	20	-33%
	Q50	12.36	5.63	-54%
	Q75	4.8	1.5	- 68%
	Variables	1971-2000 (mm)	2001-2015 (mm)	Rate of Change
Beardy	Q25	7.2	4.7	-34%
	Q50	1.3	0.7	-48%
	Q75	0.2	0.13	-36%
	Variables	1951-1978 (mm)	1979-2015 (mm)	Rate of Change
Goulburn	Q25	2	1.3	-35%
	Q50	0.83	0.4	-51%
	Q75	0.4	0.1	-68%

5.2 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 $\varepsilon(ET0)$ which 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 comparing to the evapotranspiration elasticities', which means that the runoff change is more sensitive to rainfall than to ET0.

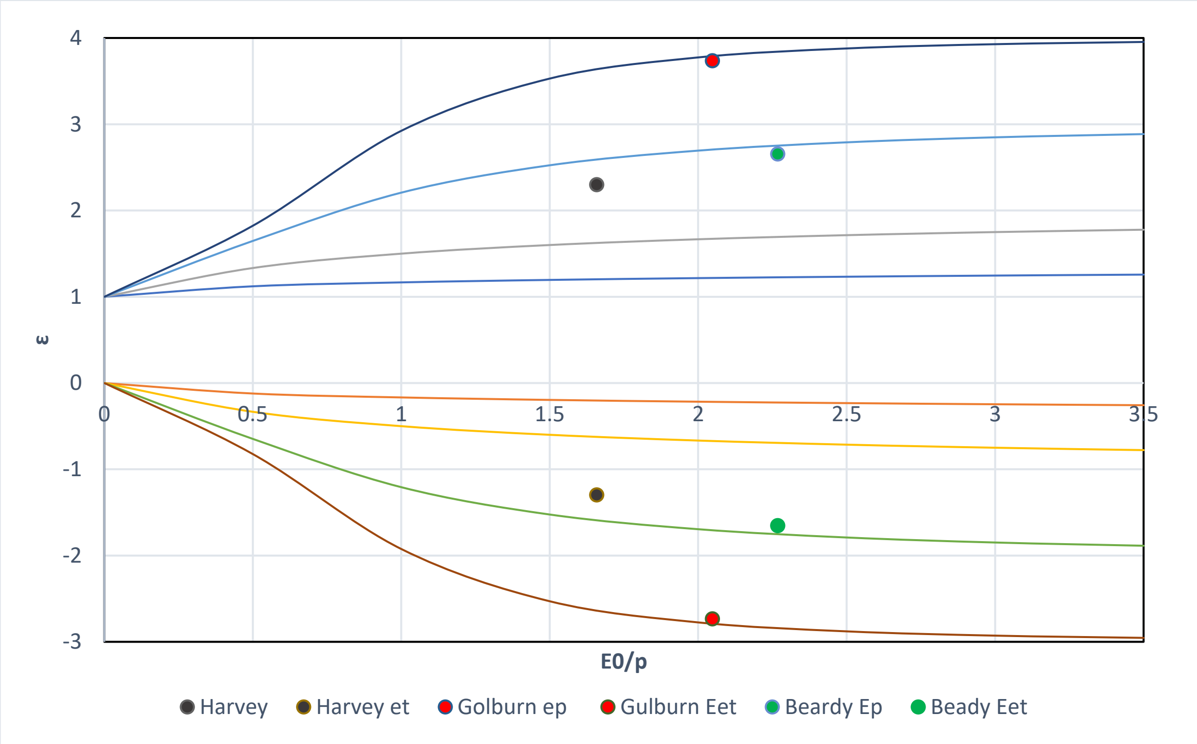


Figure 4 εp and εET_0 based on aridity index

The impacts of Climate change and human activities are estimated using equations 7 to 13 (Table 5). The results suggest that the main factor of runoff reduction in each catchment is different. In 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 mostly affected by human activities. In 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.

Table 5 contribution of climate change and human activities on streamflow reduction in the contributing catchments based on the proposed methods

Catchment	ΔQ(mm)	εp	εET_0	$\Delta Q_{CC}\ (mm)$	$\Delta Q_{HA}\ (mm)$	$\Delta Q_{CC}\ (\%)$	$\Delta Q_{HA}\ (\%)$
Harvey	96	2.3	-1.3	52	42	55	45
Beardy	27	2.65	-1.65	12	15	44	56
Goulburn	21	3.73	-2.73	14.5	6.5	69	31

Now that 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 hydrological models are employed for this step.

5.3 Modelling performance of the two hydrological models

To evaluate the performance of the two hydrological models, HBV and BTOPMC, across the studied catchments, 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 hydrological 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 hydrological models. At Dingo-Road HRS, the model was calibrated for 22 years (1983–2004) and validated for the rest of the recorded period (2005–2014). While at Haystack and Coggan HRSs, the HBV-model was calibrated for a 29-year period (1976–2004) and validated for the rest 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 models, four criteria were used. Nash-Sutcliffe efficiency (NSE), relative volume error (VE) and the coefficient of determination (R^2) (Equations 14, 15 and 16) were used in the conceptual modelling. While NSE and Volume Ratio (VR) (Equations 14 and 17) were used in the distributed modelling. Model parameters were optimised 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 hydrological 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 hydrological models at the three HRSs (for a specified period of two-years each). The visual inspection 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).

$$NSE = 1 - \frac{\sum (\boldsymbol{QC} - \boldsymbol{QR})^2}{\sum (\boldsymbol{QR} - \boldsymbol{QR}_{\boldsymbol{mean}})^2} \tag{14}$$

$$VE = \frac{\sum (\boldsymbol{QR} - \boldsymbol{QC})}{\sum (\boldsymbol{QR})} X\,100 \tag{15}$$

$$R^2 = \frac{[\sum_{i=1}^{n}(\boldsymbol{QR} - \boldsymbol{QR}_{\boldsymbol{mean}})(\boldsymbol{QC} - \boldsymbol{QC}_{\boldsymbol{mean}})]^2}{\sum_{i=1}^{n}(\boldsymbol{QR} - \boldsymbol{QR}_{\boldsymbol{mean}})^2 \ . \ \sum_{i=1}^{n}(\boldsymbol{QC} - \boldsymbol{QC}_{\boldsymbol{mean}})^2} \tag{16}$$

$$\mathrm{VR} = \frac{\sum \boldsymbol{Qc}}{\sum \boldsymbol{QR}} \text{ x } 100 \tag{17}$$

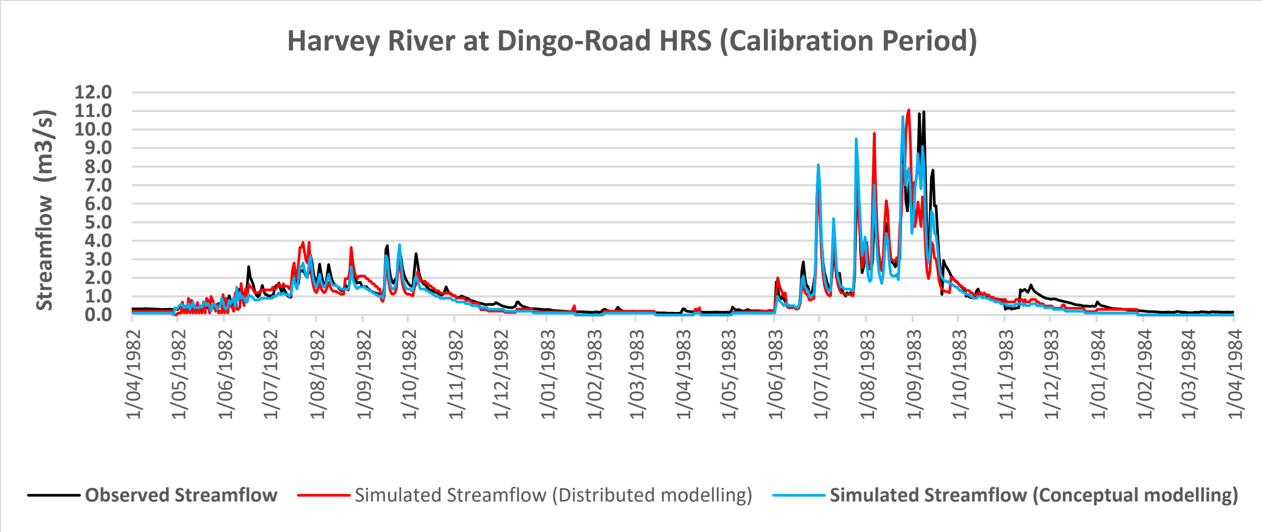
Table (6) HBV model parameters and their optimal values for the calibration period at the three contributing catchments

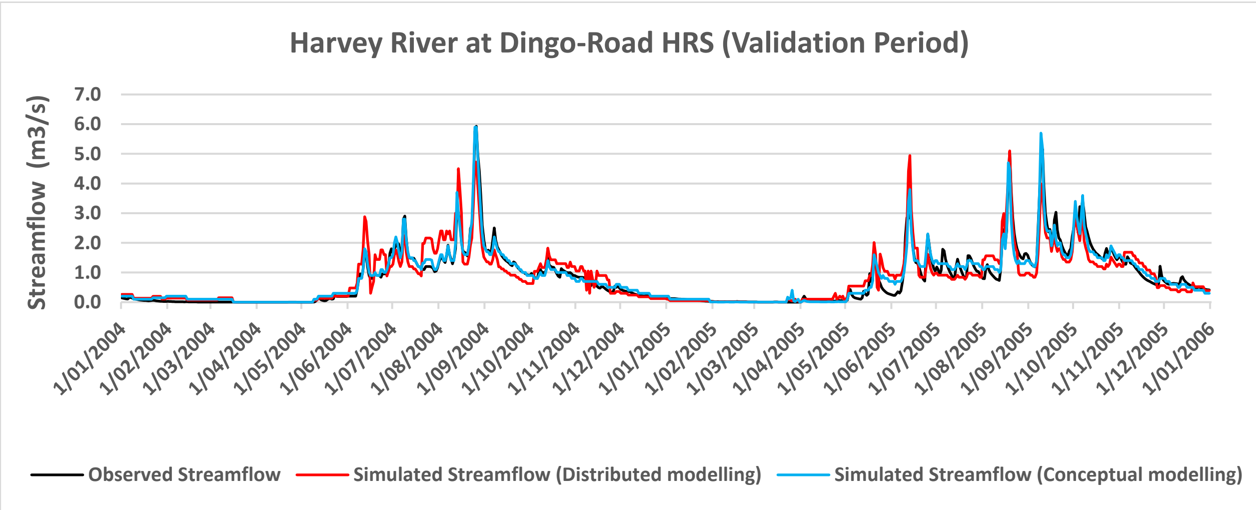
	Parameter	Symbol	Unit	Optimal value Harvey catchment	Optimal value Beardy catchment	Optimal value Goulburn catchment
Conceptual Modelling	**Rainfall correction factor**	rfcf	-	0.8	0.9	0.8
	Elevation correction factor for precipitation	pcalt	1/100m	0.1	0.1	0.1
	Temperature lapse	tcalt	º C/100m	0.6	0.6	0.6
	Maximum of soil moisture zone	FC	mm	400	500	250
	Limit for potential evaporation	Lp	-	0.7	0.5	0.8
	Shape coefficient	Beta	-	1.5	2	3
	General correction factor for potential evaporation	ecorr	-	0.9	0.9	0.85
	Recession coefficient for upper response box	Khq	1/day	0.25	0.8	0.9
	Recession coefficient for lower response box	K4	1/day	0.04	0.09	0.07
	Maximum percolation capacity	Perc	mm/day	1.1	0.9	0.9
	Routing parameter	Maxbaz	day	0.07	1.1	0.5
Distributed Modelling	**Groundwater Dischargeability**	D_o	m/day	Sand = 0.1 Silt = 0.05 Clay = 0.05	Sand = 0.12 Silt = 0.06 Clay = 0.07	Sand = 0.14 Silt = 0.05 Clay = 0.06
	Decay factor of transmissivity	m	-----	0.1	0.075	0.073
	Block average Manning's coefficient	n_o	-----	0.01	0.014	0.019
	Maximum root zone storage	S_{rmax}	m	0.25	0.3	0.32
	Drying function parameter	α	-----	5	6	6.5

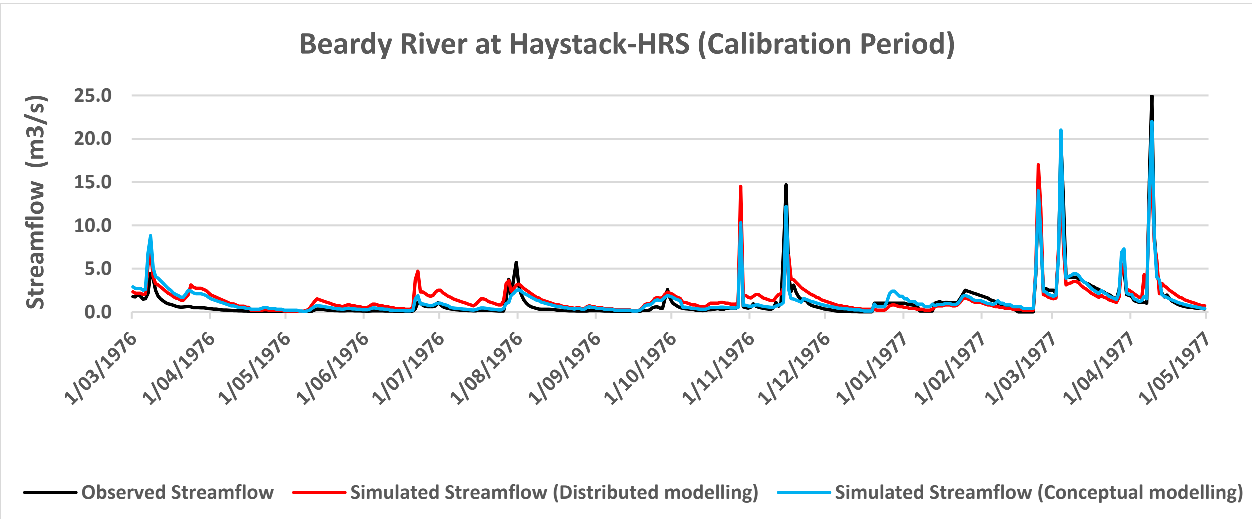
Table 7 Modelling performance during the calibration and verification periods at the three HRS based on the two modelling approaches

	Hydrologic Reference Stations	**Calibration**			**Validation**		
		NSE	**VE (%)**	**R^2**	**NSE**	**VE (%)**	**R^2**
Conceptual modelling approach	Harvey River at Dingo Road	0.87	-4.2	0.83	0.85	4.4	0.81
	Beardy River at Haystack	0.92	-3.9	0.91	0.90	-4.1	0.89
	Goulburn River at Coggan	0.9	3.8	0.85	0.88	4.2	0.82

	Hydrologic Reference Stations	**Calibration**		**Validation**	
		NSE	**VR (%)**	**NSE**	**VR**
Distributed modelling approach	Harvey River at Dingo Road	0.76	96.2	0.74	114.3
	Beardy River at Haystack	0.79	97.6	0.77	109.3
	Goulburn River at Coggan	0.83	102.4	0.8	107.6


Harvey River at Dingo-Road HRS (Calibration Period)
Streamflow (m3/s)
Observed Streamflow
Simulated Streamflow (Distributed modelling)
Simulated Streamflow (Conceptual modelling)


Harvey River at Dingo-Road HRS (Validation Period)
Streamflow (m3/s)
Observed Streamflow
Simulated Streamflow (Distributed modelling)
Simulated Streamflow (Conceptual modelling)


Beardy River at Haystack-HRS (Calibration Period)
Streamflow (m3/s)
Observed Streamflow
Simulated Streamflow (Distributed modelling)
Simulated Streamflow (Conceptual modelling)

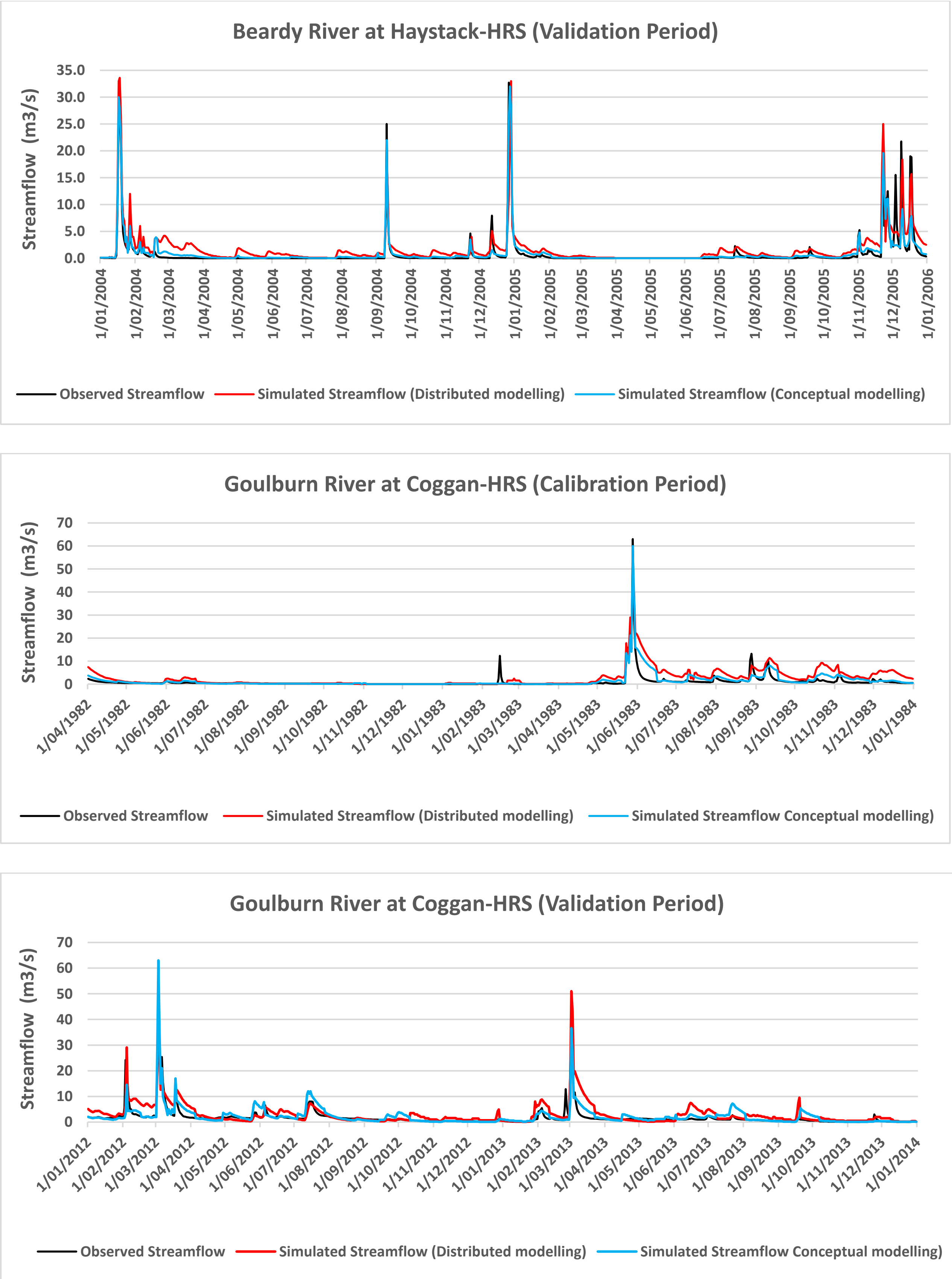


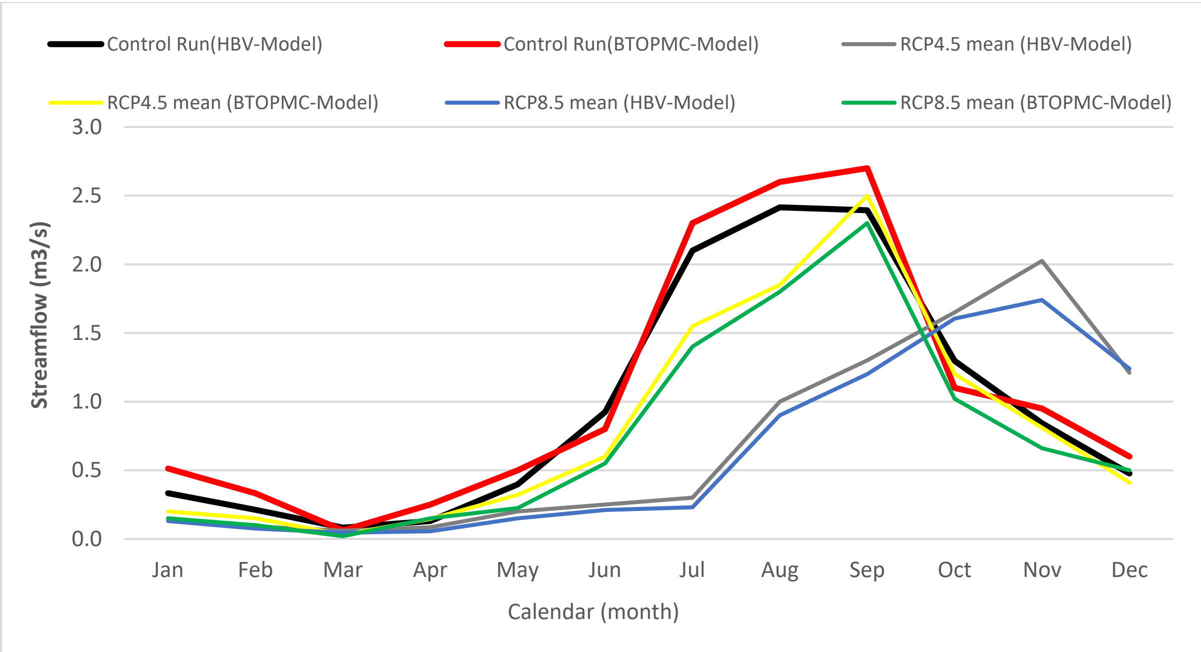
Figure (5) Daily observed and simulated streamflow (from the two hydrological models) at the three HRSs for the calibration and validation periods

However, the modelling results from Table 4 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 hydrological modelling. The results also specified that the peak and low discharges are well 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 hydrological models that are requiring 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.

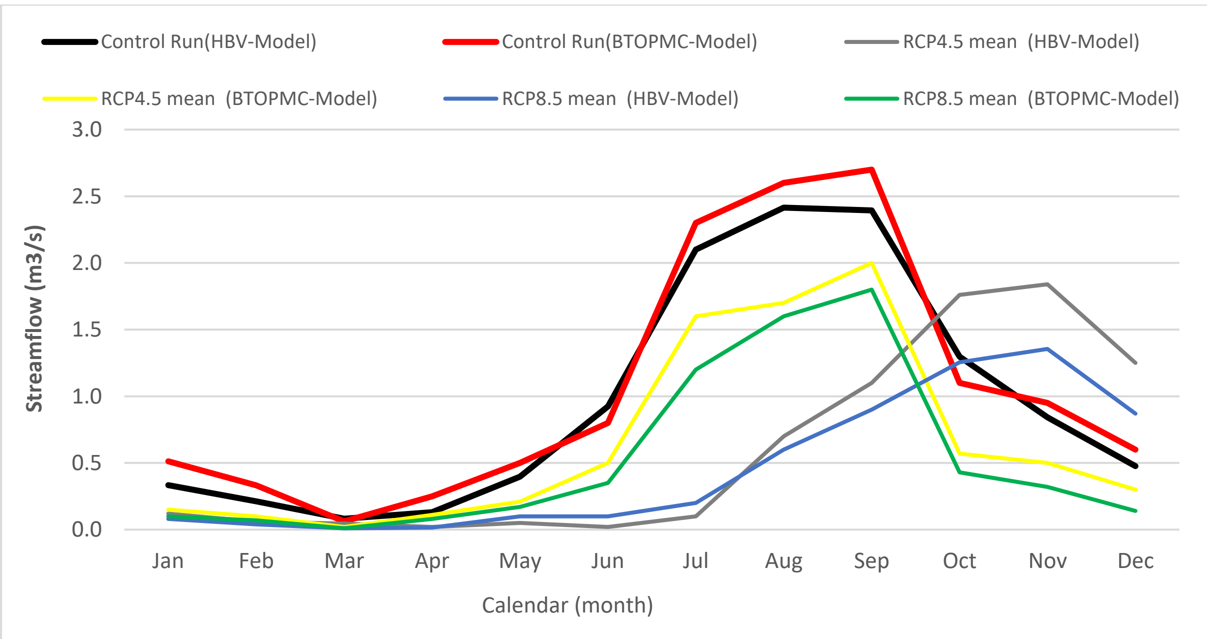
Based on the above analysis, the general performance of the two models was relatively sensible in simulating the historical runoff volume at the three HRSs. The analysis of the results shows that there are no large differences in the modelling performance of the two models. On the basis of model performances, it seems that the conceptual and distributed hydrological models almost perform similarly across the studied catchments. Therefore, both hydrological 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.

5.4 Application of Hydrological models to predict the future runoff variation in the HRSs

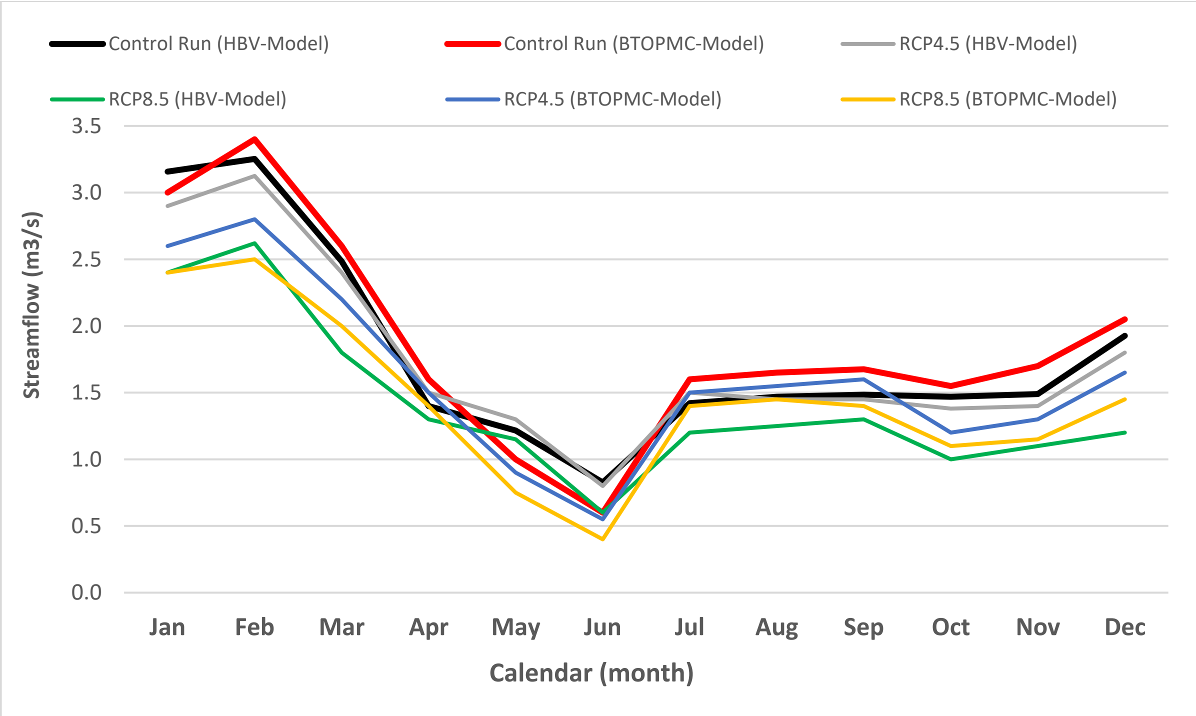
To reduce the uncertainties in the GCMs projections, the ensemble mean of the downscaled climate data was derived and used as input into the HBV and BTOPMC models to simulate the future daily streamflow at the three HRSs. To study the hydrologic behaviour of the three contributing catchments under the 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 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 of the century with the control run (Figure 6). Furthermore, the changes in annual mean streamflow statistics of the future climate scenarios (RCP4.5 and RCP8.5) relative to the control run at the three HRSs were also compared and presented in Table (8). 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.



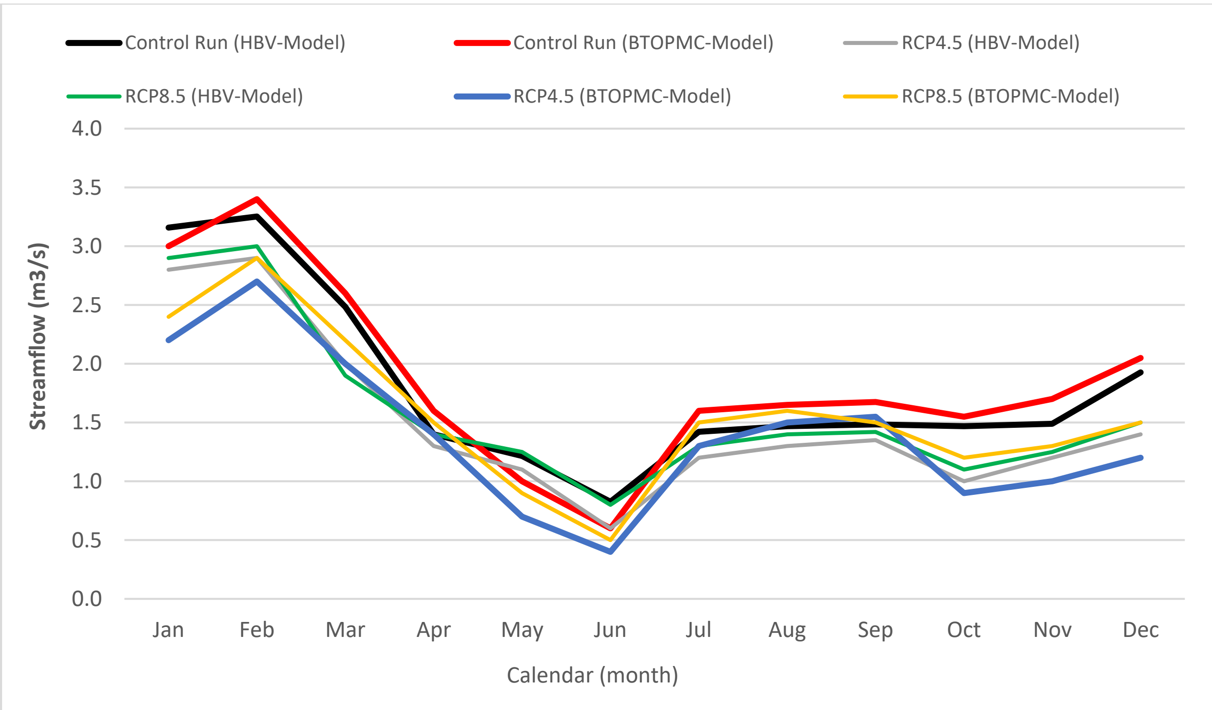
(a) Harvey catchment at Dingo-Road HRS (Mid-century)



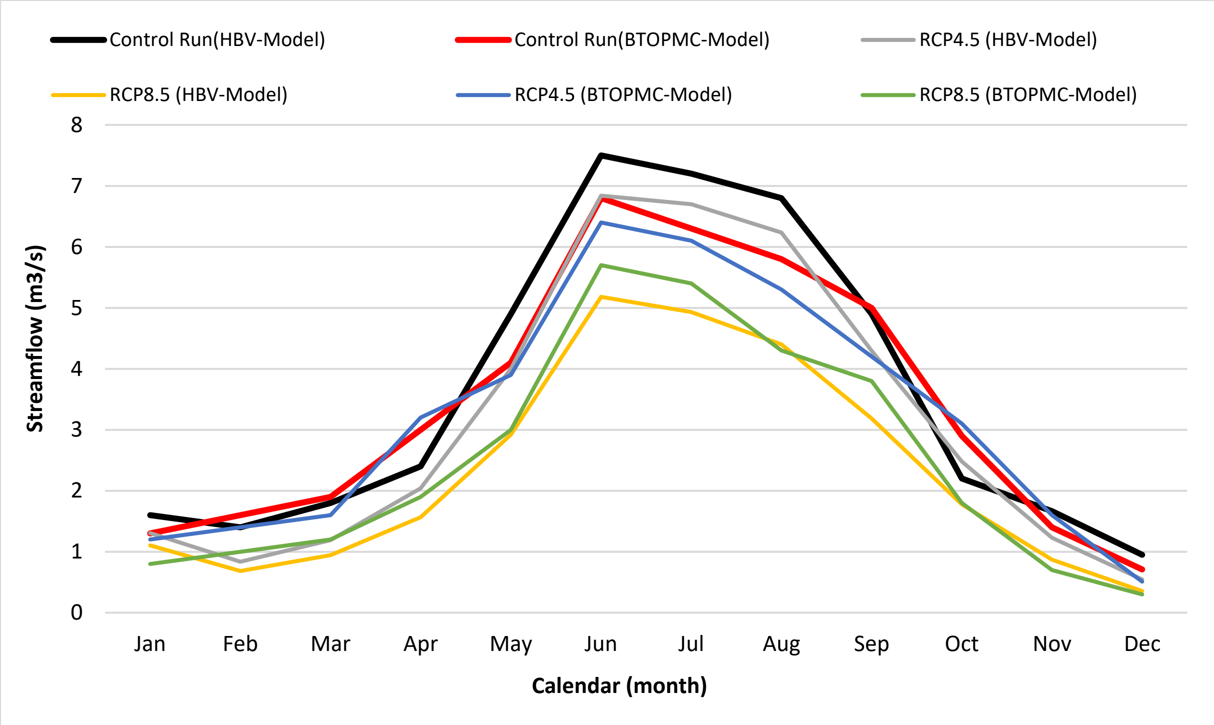
(b) Harvey catchment at Dingo-Road HRS (Late-century)



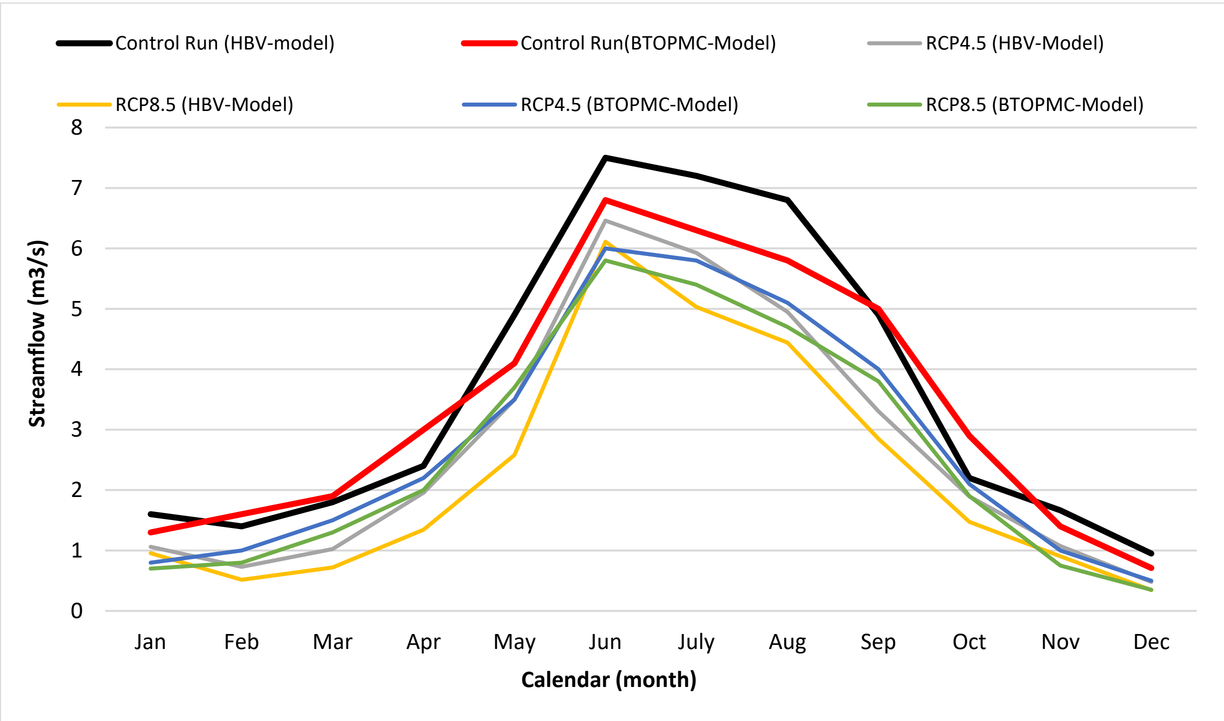
(c) Beardy catchment at Haystack HRS (Mid-century)



(d) Beardy catchment at Haystack HRS (Late-century)



(e) Goulburn catchment at Coggan HRS (Mid-century)



(f) Goulburn catchment at Coggan HRS (Late-century)

Figure 6 A comparison between the control run and the future monthly mean streamflow simulated by the two hydrological models

Table (8) changes in annual mean streamflow statistics (m^3/s) of the future climate scenarios relative to the control run at the three HRSs

HRSs		Variable	Observed streamflow (1982-2014)	Control run (1982-2014)	Changes in mean annual runoff compared to the control run (%)			
					(2046-2065)		(2080-2099)	
					RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Harvey River at Dingo Road	**Conceptual Modelling**	**Q Min.**	0.3	0.23	-13	-13	-13	-21
		Q25	0.6	0.6	-33	-33	-53	-66
		Q50	1.1	0.9	-31	-.44	-52	-61
		Q75	1.1	0.9	-30	-44	-52	-61
		Q Max.	1.8	1.7	-23	-23	-29	-35
		Q Mean	0.88	0.8	-31	-37	-48	-60
	Distributed Modelling	**Q Min.**	0.3	0.20	-10	-10	-5	-10
		Q25	0.6	0.5	-17	-30	-50	-50
		Q50	1.1	0.9	-33	-39	-44	-61
		Q75	1.1	1.2	-38	-44	-54	-62
		Q Max.	1.8	1.9	-20	-18	-26	-34
		Q Mean	0.88	0.95	-26	-32	-42	-53
			Observed streamflow (1975-2014)	**Control run (1975-2014)**	**Changes in mean annual runoff compared to the control run (%)**			
					(2046-2065)		**(2080-2099)**	
					RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Beardy River at Haystack	**Conceptual Modelling**	**Q Min.**	0.6	0.6	0	0	0	0
		Q25	0.8	0.9	-11	-11	-3	-5
		Q50	1.15	1.2	-8	-4	-6	-4
		Q75	2.025	1.9	-4	-27	-31	-4
		Q Max.	5.6	4.6	-15	-37	-28	-19
		Q Mean	1.73	1.68	-1	-24	-16	-11
	Distributed Modelling	**Q Min.**	0.6	0.5	-4	-4	-6	-6
		Q25	0.8	0.85	-6	-11	-9	-10
		Q50	1.15	1.4	-4	-14	--21	-8
		Q75	2.025	2.2	-4	-13	-32	-21
		Q Max.	5.6	6.6	-23	-39	-21	-27
		Q Mean	1.73	1.7	-10	-19	-25	-15
Goulburn River at Coggan	**Conceptual Modelling**	**Q Min.**	1.0	0.9	-11	-22	-11	-11
		Q25	1.6	2.4	-4	-54	-33	-33
		Q50	3.1	2.95	-10	-37	-36	-40
		Q75	5.1	4.3	-26	-40	-30	-53
		Q Max.	8.1	8.5	-45	-40	-49	-45
		Q Mean	3.7	3.3	-18	-39	-30	-42
	Distributed Modelling	**Q Min.**	1.0	0.8	-6	-33	-22	-28
		Q25	1.6	2.0	-28	-47	-40	-51
		Q50	3.1	2.9	-17	-41	-41	-48
		Q75	5.1	5.5	-49	-43	-49	-52
		Q Max.	8.1	7.5	-19	-42	-35	-45
		Q Mean	3.7	3.1	-6	-33	-22	-28

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 (Figure 6 a and 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%-56%) than for the BTOPMC model (-26%-53%) especially for the mid-century (Figure 6 a and 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 than the BTOPMC model. These findings specify that the uncertainty resulting from using two structurally distinctive hydrological models cannot be ignored. Therefore, even though the input data are same, different hydrological models provide different streamflow outputs because of differences in model structures. The shift in seasonal streamflow, projected by the HBV model, could be related to the shift in future rainfall patterns.

At Haystack HRS, the behaviour of the two hydrological models is almost the same and showing a clear reduction in the overall future streamflow of the wet and dry seasons (Figure 6 c and d). However, the BTOPMC model predicts slightly higher reduction tendencies than the HBV model, specifically for the RCP4.5 scenario during the mid and late of the 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 (Figure 6 c and 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 (Figure 6 e and f). In 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 models tends to follow the same temporal distribution as in the baseline period.

6- 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-hydrological processes of a catchment. Eco-hydrologic alterations resulting from changing climate conditions can alter the status of streamflow, evapotranspiration, surface storage, and soil dampness and 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 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 2m for the deepest point), and more than 50% of its area has a depth of only 0.5m (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 donates nearly 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 of the baseline period. But, at Dingo-Raod 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 (Figure 6 a and 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, as the main interest of this study is to investigate how likely the future streamflow of three Australian HRSs will be impacted due to the changes in climatological status, then, 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. Finally, the short computation time of the conceptual modelling, compared to the distributed modelling, makes it more appropriate for long-term streamflow simulation under the various scenarios of future climate.

7- Conclusion

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, 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 the climate change had impacts on runoff, but also human activities have significantly contributed to the runoff reduction. Climate change and human activities played almost the same roles in Harvey and Beardy catchments. However, for the Goulburn catchment, human interaction 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, RCP4.5 and RCP8.5, 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 prediction 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 of the current period. However, at Dingo-Raod HRS, the 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 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 extremes to improve climate change projections on hydrology and ecosystems will be useful in the sustainable management of catchment water resources in the future.

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