Hydrol. Earth Syst. Sci. Discuss., 9, 1783–1825, 2012 www.hydrol-earth-syst-sci-discuss.net/9/1783/2012/ doi:10.5194/hessd-9-1783-2012 © Author(s) 2012. CC Attribution 3.0 License.



This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

High-resolution projections of surface water availability for Tasmania, Australia

J. C. Bennett^{1,2,3,*}, F. L. N. Ling³, D. A. Post⁴, M. R. Grose², S. C. Corney², B. Graham⁵, G. K. Holz², J. J. Katzfey⁶, and N. L. Bindoff^{1,2,6}

¹Institute for Marine and Antarctic Studies (IMAS), University of Tasmania, Sandy Bay, Tasmania, Australia
²Antarctic Climate and Ecosystems Cooperative Research Centre (ACE CRC), University of Tasmania, Sandy Bay, Tasmania, Australia
³Entura, Cambridge Park, Tasmania, Australia
⁴Commonwealth Scientific and Industrial Research Organisation (CSIRO) Land and Water (LW), Black Mountain, Australian Capital Territory, Australia
⁵Department of Primary Industries, Parks, Water and Environment, New Town, Tasmania, Australia
⁶Centre for Australian Weather and Climate Research, CSIRO Marine and Atmospheric Research (MAR), Aspendale, Victoria, Australia
^{*}now at: CSIRO LW, Highett, Victoria, Australia





Received: 16 December 2011 – Accepted: 27 January 2012 – Published: 8 February 2012 Correspondence to: J. C. Bennett (james.bennett@csiro.au)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Discussion Pa		HESSD 9, 1783–1825, 2012					
per Discussion		High-resolution projections of surface water availability J. C. Bennett et al.					
Paper		Title Page					
—		Abstract	Introduction				
Disc		Conclusions	References				
ussion		Tables	Figures				
Pape		14	►I				
P		•	•				
		Back	Close				
Discussio		Full Screen / Esc Printer-friendly Version					
n Pa							
aper		Interactive Discussion					



Abstract

15

Changes to streamflows caused by climate change may have major impacts on the management of water for hydro-electric generation and agriculture in Tasmania, Australia. We present high-resolution projections of Tasmanian surface water availability

⁵ between 1961–1990 and 2070–2099. Six fine-scale (10 km) simulations of daily rainfall and potential evapotranspiration are generated with the CSIRO Conformal Cubic Atmospheric Model (CCAM), a variable-resolution regional climate model (RCM). These variables are bias-corrected with quantile mapping and used as direct inputs to the hydrological models AWBM, IHACRES, Sacramento, SIMHYD and SMAR-G to project
 ¹⁰ streamflows.

The performance of the hydrological models is assessed against 86 streamflow gauges across Tasmania. The SIMHYD model is the least biased (median bias = -3%) while IHACRES has the largest bias (median bias = -22%). We find the hydrological models that best simulate observed streamflows produce similar streamflow projections. In contrast, the poorly performing IHACRES model amplifies changes more than the other hydrological models.

There is much more variation in projections between RCM simulations than between hydrological models. This shows that it is more important to consider the range of RCM simulations than the range of hydrological models used here to adequately describe uncertainty in the projections.

We use the SIMHYD model to describe future changes to streamflow in eight rivers. Changes to streamflows are projected to vary by region. Marked decreases of up to 30 % are projected for annual runoff in central Tasmania, while runoff is generally projected to increase in the east. Daily streamflow variability is projected to increase for

²⁵ most of Tasmania, consistent with increases in rainfall intensity. Inter-annual variability of streamflows is projected to increase across most of Tasmania.

This is the first major Australian study to use high-resolution bias-corrected rainfall and potential evapotranspiration projections as direct inputs to hydrological models.





Our study shows that these simulations are capable of producing realistic streamflows, allowing for increased confidence in assessing future changes to surface water variability.

1 Introduction

- ⁵ Human-induced climate change has been shown to contribute to changes in the spatial distribution of precipitation in the 20th century (Zhang et al., 2007). In a warmer future world, understanding the local and regional implications of changes in the hydrological cycle is critical to planning for water security (Oki and Kanae, 2006). Dynamical regional climate models (RCMs) have been used successfully to assess climate change impacts on spatial distributions of rainfall (Kilsby, 2007), seasonal changes to rainfall (Kendon et al., 2010), and changes to rainfall intensity (Berg et al., 2009) and frequency (Mailhot et al., 2007) at spatial scales relevant to water managers. To assess how these complex rainfall changes affect surface water availability, RCM outputs are often coupled to hydrological models. RCMs and hydrological models can be coupled indiractly by adjusting historical changes to rainfall the future climate (Chiaw et al., 2010).
- ¹⁵ indirectly by adjusting historical observations to resemble the future climate (Chiew et al., 2009), or directly by using timeseries generated by RCMs in hydrological models (Akhtar et al., 2009; Kilsby et al., 2007; Wood et al., 2004). Fowler and Kilsby (2007) point out that indirect coupling methods often do not explicitly account for changes to rainfall variability or to changes in the sequences of wet and dry days, even though
- these are likely to have significant impacts on streamflow. Coupling RCMs directly to hydrological models has the advantage that the complex suite of rainfall changes projected by RCMs, including changes to seasonal rainfall, maximum daily precipitation, and number of rain days, will be reflected in projections of streamflow. This allows more meaningful assessment of climate change impacts on streamflow volumes and variability.

The challenge in coupling RCMs directly to hydrological models is that RCM outputs usually do not match observations accurately enough to allow hydrological models to





produce realistic streamflows (Graham et al., 2007). To address this problem, climate model outputs are often linked to hydrological models with statistical coupling methods. These range from simple scaling to more complex methods of bias-correction such as weather generators (Fowler et al., 2007; Maraun et al., 2010).

- Quantile mapping (also called quantile-quantile bias-correction; Boé et al., 2007) has been shown to be effective for coupling climate models and hydrological models (Boé et al., 2007; Wood et al., 2004). Quantile mapping corrects biases across the entire frequency distribution of a given variable, and is highly effective at removing biases from climate model outputs (Ines and Hansen, 2006; Piani et al., 2010a). Quantile
 mapping has been successfully used to couple RCMs to hydrological models in sev-
- eral northern hemisphere studies (Akhtar et al., 2009; Boé et al., 2007; Fowler and Kilsby, 2007; Wood et al., 2004), but has not been used for regional hydroclimatological studies in Australia, where indirect coupling methods based on pattern-scaling and simple perturbation of historical observations have been more popular (Charles et al., 2010; Chiaw et al., 2009; Poet et al., 2010)
- ¹⁵ 2010; Chiew et al., 2009; Post et al., 2012).

Longer-term ensemble GCM projections of rainfall change for Australia to 2100 by the Intergovernmental Panel on Climate Change (IPCC) (Christensen et al., 2007) give inconclusive results for Tasmania. Christensen et al. (2007) find little agreement in the sign and magnitude of rainfall change over Tasmania, perhaps because Tasmania sits

²⁰ midway between a region of increasing precipitation to the south-east and a region of decreasing precipitation to the north-west. About half of the 21 GCMs described by Christensen et al. (2007) project increased mean annual precipitation for Tasmania.

Tasmania's highly varied rainfall distribution is poorly replicated by GCMs, making Tasmania an ideal candidate for fine-scale modelling. Tasmania has been the subject

of a major hydroclimatological study by Post et al. (2012) that reviewed future availability of surface water in Tasmania to 2030. Post et al. (2012) used pattern scaling (Mitchell, 2003) of global climate models (GCMs) and a series of hydrological models to better replicate spatial variation in Tasmanian runoff. Post et al.'s (2012) median future scenario projected decreased mean annual runoff in Tasmania's central highlands





and north-eastern highlands of up to 30 % by 2030, with little change elsewhere. No region was projected to experience increased runoff under the median scenario by 2030. Post et al. (2012) note that there are plans to develop new irrigation infrastructure in Tasmania in light of declining agricultural yields in the Murray Darling basin and
 ⁵ south-west Western Australia. Longer-term high-resolution projections of surface water availability are needed for informed water management planning in Tasmania for the 21st century.

This paper's primary aim is to quantify seasonal and spatial changes in Tasmanian streamflows by 2100 using high-resolution RCM simulations. This is the first highresolution study of changes in Tasmanian streamflows by the end of the 21st century. To better understand future changes in streamflow variability, we project streamflows using bias-corrected RCM projections as direct inputs to hydrological models. Ours is the first Australian study to use this method to produce basin-scale surface water projections, and accordingly we aim to demonstrate that our method credibly replicates historical streamflows.

Finally, this paper aims to understand whether uncertainty in the streamflow projections comes more from the RCM simulations than from the hydrological modelling. The practice of using ensembles of climate models to describe uncertainty in projections is well established. Using ensembles of hydrological models to quantify uncertainty in projections is less common, even though uncertainties in hydrological modelling may contribute significantly to uncertainties in climate change impact studies (Bastola et al., 2011). To find if the RCM simulations are a greater source of uncertainty than the hydrological models, we couple an ensemble of RCM simulations to an ensemble of hydrological models.

25 2 Study area: Tasmania

Tasmania is Australia's smallest (~70000 km²) and most southerly state, in addition to being Australia's only island state. Tasmania is mountainous, with mountain ranges





in the north-east (Ben Lomond Plateau), centre (central highlands), west and south all exceeding 1000 m in elevation. Tasmania lies in the path of the "Roaring Forties" winds (Fig. 1), and the prevailing westerly weather combines with mountains in western Tasmania to make the western part of Tasmania one of the wettest areas in Australia.

- Mean annual rainfalls exceed 2000 mm for much of the west and rise to more than 4000 mm on some mountain peaks (Fig. 2a). Rainfall in the west is highest in the austral winter (June-July-August – JJA) and lowest in summer (December-January-February – DJF). Snowfalls are common on Tasmanian mountains, however snow typically melts within a few weeks and seasonal snowmelt is not an important component
- ¹⁰ of Tasmanian streamflows. The central, western and south-western mountains are of high conservation value and much of this unpopulated region is listed as a UNESCO world heritage area.

Tasmanian mean annual rainfall follows a sharp gradient from west to east, with the central midlands and eastern lowlands averaging less than 600 mm (Fig. 2a). In

- ¹⁵ contrast to the winter dominant rainfall in the west and north-west, rainfall in the east does not show a strong seasonal cycle. Low pressure systems off the east coast cause occasional high-intensity rain storms over the east of the Tasmania. Despite the low and less reliable rainfall, agriculture is an important industry in the lowlands of the east. Mean annual areal potential evapotranspiration (APET) is highest (>1100 mm) in the
- ²⁰ central north of Tasmania and declines to <850 mm in the south and west (Fig. 2b). These patterns of APET and rainfall combine to give Tasmania a very steep west-to-east gradient in mean annual runoff, from >3000 mm on the western mountains to <100 mm in some eastern areas (Fig. 2c). An exception to this west-to-east gradient is the small, mountainous Ben Lomond plateau in the north-east of Tasmania, where high mean annual runoff (>1200 mm) occurs.





3 Data and methods

3.1 Regional climate modelling

Regional climate simulations are produced for 1961–2100 by downscaling GCMs with the CSIRO Conformal Cubic Atmospheric Model (CCAM) (McGregor and Dix, 2008). CCAM is a global atmospheric model that uses a stretched grid to increase the resolution over Tasmania. CCAM has no lateral boundaries and accordingly does not suffer from the problems associated with lateral boundaries in limited area RCMs (Fox-Rabinovitz et al., 2008). Variable resolution global atmospheric models have been shown to simulate rainfall and related processes realistically at a range of scales and locations (Berbery and Fox-Rabinovitz, 2003; Boé and Terray, 2007; Zou et al., 2010). CCAM has been used for regional climate studies in Australia (Charles et al., 2007; Chiew et al., 2010; Post et al., 2012) and internationally (Engelbrecht et al., 2009; Lal et al., 2008). For this study. CCAM is configured to be forced only by GCM sea surface tem-

For this study, CCAM is configured to be forced only by GCM sea surface temperatures (SSTs) and sea ice concentration. CCAM has been successfully used with this configuration to generate high-resolution regional climate projections over southern Africa (Engelbrecht et al., 2009). Simulations from six GCMs under the SRES A2 emissions scenario (Nakićenović and Swart, 2000) from stage 3 of the coupled model intercomparison project (CMIP3) (Meehl et al., 2007) are downscaled:
20 CSIRO-Mk3.5, ECHAM5/MPI-OM, GFDL-CM2.0, GFDL-CM2.1, MIROC3.2(medres) and UKMO-HadCM3. For convenience, each RCM simulation will be referred to by the CCM used to force downscaling biases in the CCM cSTs (Dependent et al.).

the GCM used to force it. Before downscaling, biases in the GCM SSTs (Randall et al., 2007) are removed using a simple additive bias-correction (Katzfey et al., 2009) to Reynolds (1988) SSTs. The downscaling is carried out in two stages. The first stage is forced only with the bias-corrected GCM SSTs and sea-ice concentration, and achieves an approximate horizontal resolution of 50 km (0.5°) over Australia. The second stage is forced using the same bias-corrected GCM SSTs and sea-ice concentration, along with spectral nudging (Thatcher and McGregor, 2009) of the atmosphere





1791

from the corresponding 50 km simulations, achieving an approximate horizontal resolution of $10 \text{ km} (0.1^{\circ})$ over Tasmania.

3.2 Quantile mapping

Two inputs are required for the hydrological models: daily rainfall and daily APET. We use quantile mapping to align daily rainfalls and APET to 0.1° (~10 km) gridded observations aggregated from the 0.05° (~5 km) SILO dataset (Jeffrey et al., 2001). Rainfall is a direct output from the SILO dataset, while APET is calculated from base variables (vapour pressure, temperature and solar radiation) according Morton's (1983) method for wet environments.

¹⁰ We calculate 'quantile mapping factors' independently at each grid cell for each RCM simulation:

$$F_{i} = \begin{cases} \frac{P_{i} \text{ (Obs)}}{P_{i} \text{ (RCM)}} : P_{i} \text{ (RCM)} > 0\\ 1 : P_{i} \text{ (RCM)} = 0 \end{cases} \text{ and } i = \{0.5, 1.5, \dots, 98.5, 99.5\}$$

where *F_i* is the quantile mapping factor at the *i*-th percentile, and *P_i* (Obs) and *P_i* (RCM) are the *i*-th percentiles of observation and RCM outputs, respectively. This is similar
to the method of Li et al. (2010) in that we independently correct moments of the frequency distribution, however we calculate corrections from empirical frequency distributions. When RCM outputs are zero for Eq. (1), we do not calculate a quantile mapping factor (*F_i* = 1). Quantile mapping factors are calculated for each percentile from 0.5 to 99.5 (0.5th, 1.5th, ..., 98.5th, 99.5th percentiles). Percentiles are calculated independently at each grid cell for the seasons DJF, March-April-May (MAM), JJA, and September-October-November (SON) for the training period 1961–2007.

We force any rain day with rainfall of less than 0.2 mm to zero in both observed and modelled rain time series. The threshold of 0.2 mm is chosen because it is the lower



(1)



resolution limit of the Bureau of Meteorology rain gauges that are the basis of the SILO dataset.

Before the bias-correction is implemented, we detrend each season in the uncorrected simulation (1961–2100) by subtracting a 30-year moving average to remove any long-term changes in rainfall regimes. Each day from this detrended series is consigned to a percentile "bin" between integer percentiles (i.e. percentile bins of 0–1, 1–2, ..., 98–99, 99–100), and assigned a rank that accords to the bin. These ranks are then transferred to the original (undetrended) simulation. Bias-corrected RCM outputs are calculated for each day for the entire simulation by

10
$$\operatorname{RCM}_{b}^{\prime} = F_{i} \cdot \operatorname{RCM}_{b}$$
 : $i = \{0.5, 1.5, \dots, 98.5, 99.5\}$ and $\begin{cases} \{i - 0.5 \le b > i + 0.5\} : b < 99.5 \\ \{i - 0.5 \le b \ge i + 0.5\} : b = 99.5 \end{cases}$ (2)

where RCM_{b} and RCM_{b}' are the uncorrected and corrected simulations, respectively, falling in percentile bin b. The other terms are as described for Eq. (1). Equation (2) applies the quantile mapping factors calculated at the 0.5th percentile to the 0–1 percentile bin, the factor for the 1.5 percentile is matched to the 1–2 percentile bin, and so on up to the factor for the 99.5th percentile, which is applied to the 99–100 percentile bin.

Finally, bias-corrected RCM outputs are regridded from the 10 km RCM grid to a 5 km grid to be compatible with the hydrological models.

3.3 Hydrological modelling

15

- We use the five hydrological models calibrated by Viney et al. (2009b): AWBM (Boughton, 2004), IHACRES (Post and Jakeman, 1999), Sacramento (Burnash et al., 1973), SIMHYD (Chiew et al., 2002) with Muskingum routing (Tan et al., 2005), and SMAR-G (Goswami et al., 2002). The hydrological models are simple conceptual models that use a variety of algorithms to partition available water into baseflows and guickflows which are then combined to represent observed bydrographs. IHACRES is
- quickflows, which are then combined to represent observed hydrographs. IHACRES is distinguished from the other models by (i) employing a rainfall scaling parameter and





(ii) by characterising streamflow using a unit-hydrograph. Viney et al. (2009b) used a log-bias objective function (Viney et al., 2009a) to automate the calibration of the five hydrological models to 90 streamflow records for 1975–2007 for catchments around Tasmania. The stream records Viney et al. (2009b) chose were from catchments that had negligible human influence on streamflows. For four catchments, streamflow

records were augmented with estimates of irrigation extractions to simulate natural streamflows. The hydrological models produce runoff timeseries at a daily time step distributed on a 0.05° grid covering all of Tasmania. To achieve Tasmania-wide coverage with the five hydrological models, Viney et al. (2009b) assigned model parameters to ungauged catchments from their nearest gauged neighbour.

We aggregate runoff to eight river catchments (Fig. 3). Operation of storages, diversions and water extractions in these catchments are accounted for based on practices current at 31 December 2007 (Bennett et al., 2010). The eight rivers are chosen as they represent different climatic regions of Tasmania, and all have >20-year, high-quality streamflow records.

Descriptions of streamflow changes in a further 70 Tasmanian rivers, 12 large irrigation storages and the Tasmanian hydro-electric system are given by Bennett et al. (2010).

Changes are described between a baseline period, 1961–1990, and a future period, 20 2070–2099.

4 Results

5

15

4.1 Performance of hydrological modelling

4.1.1 Hydrological model performance under a changing climate

Performance of a hydrological model may not remain consistent under a changing cli-²⁵ mate (Merz et al., 2011). Vaze et al. (2010) found that performance of the IHACRES,





Sacramento, SIMHYD and SMAR-G models declined sharply in periods where mean annual rainfall was more than 15% lower or more than 20% greater than mean annual rainfall in the calibration period. Differences between simulated mean annual rainfall and SILO mean annual rainfall during the calibration period (1975–2007) are between

5 -15% and +20% for most of Tasmania for all six RCM simulations presented here (Bennett et al., 2010), suggesting that the hydrological models should perform adequately during the baseline (1961–1990) and future (2070–2099) periods.

4.1.2 Comparisons of biases of hydrological models

Performance of hydrological models forced with RCM inputs (RCM-runoff) is assessed
 at 86 streamflow gauges for all data available for 1961–2007. The 86 catchments range in size from 8 km² to >2000 km², and give good coverage of Tasmania (Fig. 4). Performance is assessed by calculating biases of RCM-runoff against observed streamflows. To isolate the effects of the RCM inputs on hydrological model performance, biases are also calculated for RCM-runoff against streamflows modelled with hydrological models
 forced by SILO (SILO-runoff). Biases are calculated as:

bias =
$$\frac{\sum_{t=1}^{T} Q_m - \sum_{t=1}^{T} Q_o}{\sum_{t=1}^{T} Q_o} \times \%$$

where $Q_{\rm m}$ is streamflow modelled with RCM-runoff and $Q_{\rm o}$ is either observed streamflow or streamflow modelled with SILO-runoff.

Figure 5 shows biases of mean annual streamflows, biases of 5th percentile (Q_5) streamflows and biases of 95th percentile (Q_{95}) streamflows at 86 sites. Biases vary much more between hydrological models than between RCM simulations (Fig. 5). Low variation between RCM simulations is caused in part by the bias-correction of GCM SSTs before downscaling, which forces GCM SSTs to be similar to observations



for 1961 to 1990 (Corney et al., 2010). Low variation between RCM simulations is also consistent with the use of a single RCM for all the simulations. Because the performance of hydrological models tends not to vary greatly between RCM simulations, we focus on describing hydrological model biases for the mean of the six RCM simulations from here on.

5

Flows modelled with AWBM, SIMHYD and SMAR-G show similar characteristics to observed mean annual and Q_{95} streamflows for 1961–2007 (Fig. 5, Table 1). AWBM, SIMHYD and SMAR-G replicate observed streamflows well, with biases smaller than ±10% for more than 40% of catchments and biases smaller than ±25% for more than 85% of catchments. SIMHYD has the smallest median biases (median bias for mean annual streamflows = -3.2%) and smallest interquartile ranges of biases of any hydrological model for annual and seasonal streamflows (Table 1). AWBM, SIMHYD and SMAR-G show a tendency to underpredict observed annual streamflows (underpredicted in >60% of catchments) and a strong tendency to underpredict observed Q_{95} streamflows (underpredicted in >80% of catchments). IHACRES is least like observed streamflows (median bias for mean annual streamflows = -22.3%), and Sacramento

biases are second largest after IHACRES. IHACRES shows a very strong tendency to underpredict observed mean and Q_{95} streamflows (Fig. 5), and has the largest median biases and largest interquartile ranges of biases against observed annual and ²⁰ seasonal streamflows (Table 1).

RCM-runoff biases are generally smaller against SILO-runoff than against observations for mean streamflows and *Q*₉₅ streamflows (Fig. 5). This is expected as biases calculated against observations add errors in the RCM inputs to errors inherent in the hydrological models, while biases calculated against SILO-runoff reflect differences only between the RCM inputs and SILO variables. In general, RCM-runoff tends to underpredict SILO-runoff. The bias-correction aligns frequency distributions of modelled and observed rainfalls, however it does not account for spatial correlations of rainstorms (how daily rainfalls in all grid cells in a catchment behave together) nor for temporal correlations of rainfall (how rainfalls behave in a multi-day rainstorm). The





bias-corrected RCM rainfalls tend to overestimate large daily rainstorms over large areas (Bennett et al., 2011). Underestimation of streamflows is therefore most probably caused by inadequate replication of the temporal characteristics of rainstorms by the bias-corrected RCM inputs.

⁵ All RCM-runoff simulations tend not to replicate Q_5 streamflows as well as higher streamflows (Table 1, Fig. 5). Poor replication of low streamflows is a common problem in hydrological modelling. Figure 5 shows that low streamflows generated from SILO-runoff do not replicate observations well. That is, many of the deficiencies in low streamflows emanate from the hydrological models.

10 4.1.3 SIMHYD model performance

SIMHYD exhibited the lowest biases of the hydrological models, and accordingly we focus on SIMHYD projections to report changes to future streamflows. We describe several additional performance tests of the SIMHYD model here.

SIMHYD RCM-runoff tends to underestimate the daily variance (measured as the
 coefficient of variation, CV) of observed streamflows at the 86 gauge sites (Fig. 6a).
 However, when daily CV of SIMHYD RCM-runoff is compared to daily CV of SIMHYD
 SILO-runoff at the same sites, there is strong agreement (Fig. 6b). This implies that
 the tendency of SIMHYD RCM-runoff to underestimate daily CV of observed runoff is
 not caused by the RCM or the bias-correction, but rather by the SILO dataset or the
 SIMHYD hydrological model. The bias-corrected RCM inputs reproduce a similar level
 of variability to that present in SILO rainfalls for the purposes of hydrological modelling.
 SIMHYD RCM-runoff matches observed seasonal streamflows reasonably well
 (Fig. 7). Seasonal streamflows are particularly closely matched in northern and west ern and southern catchments (Nive, Franklin and Huon Rivers) SIMHYD RCM-runoff

tends to underpredict gauged streamflows from September to December. This difference is also present in the SIMHYD SILO-runoff (black line in Fig. 7), indicating that it is caused by hydrological model calibration or the SILO rainfalls rather than the





bias-corrected RCM inputs. SIMHYD RCM-runoff varied much more between RCM simulations in the drier eastern catchments (South Esk, Little Swanport and Clyde rivers) than in the wetter western and southern catchments (Black River, Franklin River and Huon River). This is consistent with the higher variability of rainfall in eastern Tasmania. The summer (DJF) yields of the Clyde River are difficult to replicate as the upper reaches of this catchment are impounded (Lake Crescent/Sorell) and regulated for irrigation.

The effects of the bias-corrected RCM inputs on hydrological performance are more easily seen in streamflow duration curves (Fig. 8). In general, SIMHYD RCM-runoff underestimates larger streamflows modelled with SIMHYD SILO-runoff. This is most 10 probably caused by the inadequate replication of the temporal characteristics of rainstorms by the bias-corrected RCM outputs, already described. In catchments with high rainfalls SIMHYD SILO-runoff tends to underestimate large (exceedance probabilities <10%) observed streamflows (Black River, Nive River, Franklin River, Huon River),

- and this tendency is exacerbated in SIMHYD RCM-runoff. Despite this, larger stream-15 flows generated by SIMHYD SILO-runoff are reasonably well replicated by SIMHYD RCM-runoff in several of the wetter catchments (Black River, Nive River, Huon River). In catchments where SIMHYD SILO-runoff overestimates larger observed streamflows (South Esk River, Clyde River), the SIMHYD RCM-runoff offers a closer match to ob-
- served streamflows than SIMHYD SILO-runoff. In all catchments, SIMHYD SILO-runoff 20 medium streamflows (exceedance probabilities of 10-80%) are reasonably well replicated by SIMHYD RCM-runoff. Differences between medium observed streamflows and SIMHYD RCM-runoff are largely caused by the hydrological models, and not by the bias-corrected RCM inputs. Overall, SIMHYD RCM-runoff replicates the range of observed streamflows and SIMHYD SILO-runoff reasonably well. 25

4.2 Projected changes in rainfall and APET

Projected changes in rainfall and APET from 1961–1990 to 2070–2099 calculated from the mean of the six RCM simulations are shown in Fig. 9. Changes in mean annual





rainfall vary spatially. Reductions in mean annual rainfall are projected for the mountainous centre (up to -15%), but marked increases (up to +30%) are projected in the east. The increases in the east tend to occur at lower elevations. An increase in mean annual rainfall is also projected along the south-west coast. The simulations agree strongly on the sign of change in the lower-lying parts of the east coast, and at high elevations in the mountainous centre (Fig. 9a).

Mean annual APET is projected to increase across Tasmania, with the highest increases in the western mountains (Fig. 9c). Increases in APET are small compared to changes in mean annual rainfall, with mean annual APET increases always less than 2%. All DOM simulations project Technology with increases in APET by 0070, 0000

 7 %. All RCM simulations project Tasmania-wide increases in APET by 2070–2099. Mean daily rainfall intensity is projected to increase over most of Tasmania (Fig. 9b). The largest proportional increases occur in the east (>15 %). RCM simulations show strong agreement on the sign of change in mean daily rainfall intensity for much of Tasmania by 2070–2099 (Fig. 9b). The general tendency of rain to fall in fewer, more intense events as the climate warms is a robust feature of theory, simulations and observations (Allen and Ingram, 2002; Pall et al., 2007; Petheram et al., 2009) and is at least partly consistent with an increase in atmospheric moisture (Hegerl et al., 2004; Stephens and Hu, 2010).

4.3 Projected changes in runoff and streamflows

²⁰ In describing projections we distinguish between "runoff", defined as gridded outputs from the hydrological models, and "streamflows", calculated by aggregating runoff to river catchments.

4.3.1 Variation between hydrological models and RCMs

Projected changes to future runoff vary much more between RCM simulations than between hydrological models. For a given RCM simulation, future changes to mean annual runoff projected with AWBM, Sacramento, SIMHYD and SMAR-G are very similar





(Fig. 10). Using the downscaled GFDL-CM2.1 simulation as an example, AWBM, Sacramento, SIMHYD and SMAR-G agree strongly on the spatial features of runoff change (Fig. 10). The four hydrological models show drying in central and north-west Tasmania, little change in the south-west, and wetting in the east. AWBM, Sacramento,

- SIMHYD and SMAR-G are also consistent in seasonal projections and at projections of low and high streamflows (not shown). IHACRES consistently projects more intense and more widespread wetting than other hydrological models for all RCM simulations. In the downscaled GFDL-CM2.1 example, IHACRES projects more intense wetting in the east and stronger wetting in the west and south-west than the other hydrological
- ¹⁰ models. The high sensitivity of IHACRES to changes in inputs renders suspect the projections of Tasmanian runoff from IHACRES with bias-corrected RCM inputs.

4.3.2 Projections from the SIMHYD hydrological model

In many areas, the projected changes to rainfall are amplified in changes to runoff. Where mean annual rainfall in central Tasmania decreases by up to 15% (Fig. 9a), runoff decreases by more than 30% (Fig. 11a). In eastern Tasmania, rainfall increases of <20\% (Fig. 9a) are projected to increase runoff by >60\% (Fig. 11a).

Low runoff events generally decrease more than mean runoff, while high runoff events increase similarly to mean runoff. The RCM simulations agree strongly on a decrease in low runoff (here represented by 25th percentile runoff, Q_{25}) over most of

- ²⁰ Tasmania (Fig. 11d). Q_{25} runoff decreases more and over a wider area than decreases to mean runoff (Fig. 11d). Increases in high runoff (represented by 99th percentile runoff, Q_{99}) are more widespread and show similar proportional increases to mean runoff (Fig. 11e). The RCM simulations agree strongly on an increase in Q_{99} runoff over the west coast, north and east. Because Q_{99} runoff events are larger than mean
- ²⁵ runoff events, a proportional change in Q_{99} runoff equates to a much greater increase in streamflow than the same proportional change to mean runoff.





Changes in seasonal streamflow projected with SIMHYD at the eight study catchments are shown in Fig. 12. Projected changes to streamflows vary considerably by season. DJF runoff decreases markedly in the west (Fig. 11b), however these seasonal decreases have little effect on annual streamflows in the Black and Franklin rivers as

⁵ DJF runoff makes a small contribution to streamflow in these rivers. Similar seasonal changes are also projected in the Huon River in the south-west. The Rubicon River in the central north of Tasmania is projected to experience increases in streamflows in all seasons, particularly JJA (Fig. 12).

Projections for rivers in the drier regions, including the north-east (South Esk River),
 east (Little Swanport River) and centre (Clyde River), are characterised by a high degree of variation between RCM simulations. The South Esk River and Little Swanport River are projected to experience increases in streamflow (Fig. 12), largely during February to April.

- A major feature of these projections is reduced runoff over Tasmania's central mountains in all seasons (Fig. 11a–c). This contrasts with projected increases in mean annual runoff in many low-elevation areas in the east and in coastal areas (Fig. 11). The high-elevation Nive River catchment is projected to experience decreases in streamflow year round, particularly in May and June (Fig. 12). Catchments in central Tasmania that span both high and low elevations (e.g. Clyde River) show complex responses. The
- ²⁰ Clyde River is projected to experience year-round streamflow decreases in high elevation areas (not shown), but these decreases are offset by projected increases at lower elevations, particularly during MAM, resulting in increased mean annual streamflow at the catchment outlet. A similar elevation-sensitive streamflow response is observed for the South Esk River in the north-east.
- Variance in daily and annual runoff is projected to increase in many areas of Tasmania. Increases in the variance of daily runoff occur in the northern two-thirds of Tasmania (Fig. 13), and the RCM simulations agree strongly on projected increases in CV of daily runoff over much of Tasmania. The most marked increases in daily variance occur in the lowlands of the central east, which is consistent with an increase in





mean daily rainfall intensity (Fig. 9). Variance in annual runoff increases over most areas, with the most notable increases projected for the north-west and central highlands (Fig. 13).

Overall, the projections suggest that there will be a greater variability of streamflows, ⁵ with rivers rising to higher peaks and experiencing longer periods of low streamflow.

5 Discussion and conclusions

Our study demonstrates that quantile mapping can directly couple RCM outputs to hydrological models to produce realistic streamflows. Direct coupling makes the most of the high spatial and temporal resolution of RCMs. The dynamical downscaling emloployed in this study includes changes resulting from fundamental shifts in the climate drivers of rainfall. Where the RCM projects changes to the frequency distributions of rainfall or the sequences in which rain falls, these are realised in the runoff projections. Perturbation of historical datasets with pattern scaling or other simple scaling techniques based on global temperature change do not have the capacity to address future the number or sequence of rain days.

We note that the period chosen to train the quantile mapping may affect the projections (Li et al., 2010). This was tested by Bennett et al. (2011), who showed that quantile mapping factors are not constant when different and shorter training periods are applied to the projections presented in this paper. Crucially, however, varying the training period has little effect on projected changes to mean annual rainfall (Bennett

- training period has little effect on projected changes to mean annual rainfall (Bennett et al., 2011). This is very likely because the corrections applied are usually small due to the high skill of the uncorrected RCM rainfall simulations (Corney et al., 2010). The high RCM skill is due to the bias-correction of GCM SSTs before downscaling, as well as the very fine horizontal resolution of the outputs used in this study. If larger quantile
- ²⁵ mapping corrections are required, projected changes to rainfall may vary more substantially with choice of training period (Piani et al., 2010b). Greater variation in quantile mapping factors and projections could also be expected if we had used more than





one RCM for our study. Replication of our method with another RCM would strengthen our conclusions.

The IHACRES hydrological model does not replicate observed runoff as realistically as the other hydrological models with bias-corrected RCM inputs. Further, IHACRES gives different projections of change. Viney et al. (2009a) found that IHACRES was the best performed model when calibrated, but performed worst under spatial crossvalidation tests. They attributed this drop in performance to the IHACRES parameter that scales rainfall. In contrast, Vaze et al. (2010) found that IHACRES was not particularly sensitive to changes in inputs when calibrated to a range of wet and dry conditions for catchments on continental Australia. We conclude that for studies using bias-corrected RCM variables as direct inputs to hydrological models for impact studies, it is important to test a hydrological model for sensitivity to changes in inputs as a precursor to generating stable, plausible runoff projections, even if the model has been

¹⁵ Projected changes in Tasmanian runoff vary far more between RCM simulations than between hydrological models. This finding is accentuated if we exclude the poorly performing IHACRES model from the projections. For our study, therefore, it is more important to consider the range of RCM simulations than the range of hydrological models to adequately describe uncertainty in projections of surface water availability. This

shown to be effective for climate studies elsewhere.

finding supports several other studies that have shown climate models to be a more significant source of uncertainty than hydrological models for surface water projections (Prudhomme and Davies, 2009; Teng et al., 2011; Wilby and Harris, 2006).

Our fine-scale simulations project future changes to Tasmanian runoff to vary considerably by region, in contrast to near-uniform spatial changes projected by GCMs

(Christensen et al., 2007). Of note are the year-round decreases in runoff projected for the central mountains, as Tasmania relies on streamflows from this region to generate hydro-electric power and to supply irrigators. The projected decrease in runoff over the central mountains of Tasmania reported here has seasonal dependence. For winter in the future, the air is warmer and moister as it approaches the west coast of





Tasmania. This causes an increase in rainfall along the west coast, which leads to increased upward motion along the western slopes of the mountains. After reaching the highest elevations, the air descends, and at a greater rate in the future as a response to the increased upward motion further west. This tendency for subsidence

- ⁵ causes a slight decrease in rainfall in the central plateau region. In the other seasons, the decreased westerly airflow projected in the future results in weaker upward motion, and rainfall, along the western slopes. This decrease in rainfall extends to the central mountains. In addition, with decreased clouds and warmer temperatures, the surface dries out relative to the current climate (see APET changes). As a result, less moisture
- is available locally for evaporation. Thus for all seasons, runoff is projected to decrease in the central mountains relative to the lower-lying areas. Reduced streamflows from Tasmania's central mountains will reduce Tasmania's hydro-electric power generation capacity (Bennett et al., 2010).

The projected increases in runoff in eastern Tasmania reported contrast with Post et al. (2012), whose median future scenario showed either no change or decreases in runoff in eastern Tasmania by 2030. This difference in sign may be attributed to the increased resolution of land-ocean boundaries in CCAM in comparison to the GCM projections used by Post (2012). The increases in eastern rainfall projected by CCAM result from a tendency for increased atmospheric blocking, southward extension of the

- East Australian Current, and the formation of a small but significant mean sea level pressure anomaly in the Tasman Sea that enhances the onshore winds in this region (Grose et al., 2010). The pattern in the GCMs is similar but displaced further offshore to the south and east due to the coarser grid size of GCMs (Grose et al., 2011). Notwithstanding increased variability of streamflows (discussed below), increased sur-
- ²⁵ face water availability in Tasmania's east may present opportunities for future agricultural production.

Changes in seasonal runoff are an important feature of these projections. The projected decreases in DJF runoff over western Tasmania are caused by a reduction in the mean westerly circulation (Grose et al., 2010), associated with an expansion of





the Hadley cell and a poleward movement of the mid-latitude storm tracks (Yin, 2005), including a poleward movement and strengthening of the subtropical ridge of high pressure and an increase in the high phase of the southern annular mode (Kushner et al., 2001). Even though reduced DJF streamflows in the west have little impact on annual streamflow volumes, these changes are likely to have deleterious effects on endemic

freshwater fish (Morrongiello et al., 2011).

Increased runoff variability could have as great an impact on Tasmanian water management practices as changes to seasonal runoff. Projected increases to inter-annual variability in streams fed by the central highlands and western mountains could mean

- that the large hydropower and irrigation storages situated in these areas may not be able to buffer periods of low inflows as effectively in future as they have in the past. Projected increases in runoff occur largely in the east in lowland areas, where water is presently stored mostly in small farm dams. Small dams may not be able to buffer the projected increases in annual variability, even if there is more water available on aver-
- age. In short, the projected increases in runoff may not easily be captured by current infrastructure.

The implications for Tasmanian surface water availability and storage illustrate the virtue of using an ensemble of high-resolution RCM projections as direct inputs to hydrological models to understand the nature of future surface water changes in a warmer

- ²⁰ world. These implications cannot easily be addressed through the more common approach of perturbing historical climate data that assumes that rainfall variability is unchanged in the future. A large amount of effort has been expended in Australia in recent years building complex series of hydrological models to assess climate change impacts from pattern scaling of GCMs (Charles et al., 2010; Chiew et al., 2009; Petheram et al., 2009; Petheram et al., 2010; Chiew et al., 2010; Chiew et al., 2009; Petheram et al., 2010; Chiew et al., 2009; Petheram et al., 2010; Chiew et al., 2010; Chiew et al., 2009; Petheram et al., 2010; Chiew et al., 2009; Petheram et al., 2010; Chiew et al., 2010; Chiew et al., 2009; Petheram et al., 2010; Chiew et al., 2010; C
- al., 2009). Our paper has shown that there is the potential to update these studies using high-resolution RCM simulations when these become available for other regions of Australia.





Acknowledgements. This work was part of the Climate Futures for Tasmania project (CFT) (www.acecrc.org.au/Research/ClimateFutures). CFT was made possible through funding and research support from a consortium of state and national partners. The work was supported by the Australian government's Cooperative Research Centres Program through the ACE CRC.

- ⁵ We acknowledge J. L. McGregor (CSIRO MAR) for assisting in running the RCM simulations.
 C. J. White (Bureau of Meteorology), W. F. Budd (ACE CRC) and S. Wotherspoon (IMAS) provided advice and assistance. J. Teng (CSIRO LW) provided the evapotranspiration algorithms.
 A. Yang (CSIRO LW) provided hydrological modelling software and assistance. K. Michael (IMAS) provided useful comments on an earlier draft.
- We acknowledge the modelling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, US Department of Energy.

References

- Akhtar, M., Ahmad, N., and Booij, M. J.: Use of regional climate model simulations as input for hydrological models for the Hindukush-Karakorum-Himalaya region, Hydrol. Earth Syst. Sci., 13, 1075–1089, doi:10.5194/hess-13-1075-2009, 2009.
 - Allen, M. R. and Ingram, W. J.: Constraints on future changes in climate and the hydrologic cycle, Nature, 419, 224–232, doi:10.1038/nature01092, 2002.
- Bastola, S., Murphy, C., and Sweeney, J.: The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments, Adv. Water Resour., 34, 562–576, doi:10.1016/j.advwatres.2011.01.008, 2011.
 - Bennett, J. C., Ling, F. L. N., Graham, B., Corney, S. P., Holz, G. K., Grose, M. R., White, C. J., Post, D. A., Gaynor, S. M., and Bindoff, N. L.: Climate Futures for Tasmania: water and catchments, Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart,
- and catchments, Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart, 2010.
 - Bennett, J. C., Grose, M. R., Post, D. A., Ling, F. L. N., Corney, S. P., and Bindoff, N. L.: Performance of quantile-quantile bias-correction for use in hydroclimatological projections, MODSIM2011 International Congress on Modelling and Simulation, Perth, December 2011.





Berbery, E. H. and Fox-Rabinovitz, M. S.: Multiscale Diagnosis of the North American Monsoon System Using a Variable-Resolution GCM, J. Climate, 16, 1929–1947, doi:10.1175/1520-0442(2003)016j1929:MDOTNA¿2.0.CO;2, 2003.

Berg, P., Haerter, J. O., Thejll, P., Piani, C., Hagemann, S., and Christensen, J. H.: Seasonal

- characteristics of the relationship between daily precipitation intensity and surface temperature, Geophys. Res. Lett., 114, D18102, doi:10.1029/2009JD012008, 2009.
 - Boé, J. and Terray, L.: A Weather-Type Approach to Analyzing Winter Precipitation in France: Twentieth-Century Trends and the Role of Anthropogenic Forcing, J. Climate, 21, 3118– 3133, doi:10.1175/2007JCLI1796.1, 2007.
- Boé, J., Terray, L., Habets, F., and Martin, E.: Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies, Int. J. Climatol., 27, 1643–1655, 2007.
 Boughton, W. C.: The Australian water balance model, Environ. Model. Softw., 19, 943–956, doi:10.1016/j.envsoft.2003.10.007, 2004.

Burnash, R. J. C., Ferral, R. L., and McGuire, R. A.: A generalized streamflow simulation

- system-conceptual modeling for digital computers, Joint Federal and State River Forecast Center, Sacramento, 204 pp., 1973.
 - Charles, S. P., Bari, M. A., Kitsios, A., and Bates, B. C.: Effect of GCM bias on downscaled precipitation and runoff projections for the Serpentine catchment, Western Australia, Int. J. Climatol., 27, 1673–1690, doi:10.1002/joc.1508, 2007.
- ²⁰ Charles, S. P., Silberstein, R., Teng, J., Fu, G., Hodgson, G., Gabrovsek, C., Crute, J., Chiew, F. H. S., Smith, I. N., Kirono, D. G. C., Bathols, J. M., Li, L. T., Yang, A., Donohue, R. J., Marvanek, S. P., McVicar, T. R., Van Niel, T. G., and Cai, W.: Climate analyses for southwest Western Australia. A report to the Australian Government from the CSIRO South-West Western Australia Sustainable Yields Project, CSIRO, Australia, 2010.
- ²⁵ Chiew, F. H. S., Peel, M. C., and Western, A. W.: Application and testing of the simple rainfallrunoff model SIMHYD, in: Mathematical models of small watershed hydrology and applications, edited by: Singh, V. P. and Frevert, D. K., Water Resources Publications, Littleton, USA, 335–367, 2002.

Chiew, F. H. S., Teng, J., Vaze, J., Post, D. A., Perraud, J. M., Kirono, D. G. C., and

³⁰ Viney, N. R.: Estimating climate change impact on runoff across southeast Australia: Method, results and implications of the modeling method, Water Resour. Res., 45, W10414, doi:10.1029/2008WR007338, 2009.



- Chiew, F. H. S., Kirono, D. G. C., Kent, D. M., Frost, A. J., Charles, S. P., Timbal, B., Nguyen, K. C., and Fub, G.: Comparison of runoff modelled using rainfall from different downscaling methods for historical and future climates, J. Hydrol., 10–23, doi:10.1016/j.jhydrol.2010.03.025, 2010.
- ⁵ Christensen, J. H., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, I., Jones, R., Kolli, R. K., Kwon, W.-T., Laprise, R., Magaña Rueda, V., Mearns, L., Menéndez, C. G., Räisänen, J., Rinke, A., Sarr, A., and Whetton, P.: Regional Climate Projections, in: Climate Change 2007: The Physical Science Basis, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, Cambridge, UK and New York, NY, USA, 2007.
- Corney, S. P., Katzfey, J. J., McGregor, J. L., Grose, M. R., White, C. J., Holz, G. K., Bennett, J. C., Gaynor, S. M., and Bindoff, N. L.: Climate Futures for Tasmania: methods and results on climate modelling, Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart, 2010.
- Engelbrecht, F. A., McGregor, J. L., and Engelbrecht, C. J.: Dynamics of the Conformal-Cubic Atmospheric Model projected climate-change signal over southern Africa, Int. J. Climatol., 29, 1013–1033, doi:10.1002/joc.1742, 2009.
 - Fowler, H. J. and Kilsby, C. G.: Using regional climate model data to simulate historical and future river flows in northwest England, Climatic Change, 80, 337–367, doi:10.1007/s10584-006-9117-3, 2007.

20

Fowler, H. J., Blenkinsop, S., and Tebaldi, C.: Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling, Int. J. Climatol., 27, 1547–1578, doi:10.1002/joc.1556, 2007.

Fox-Rabinovitz, M., Côté, J., Dugas, B., Déqué, M., McGregor, J. L., and Belochitski, A.:

- Stretched-Grid Model Inter-comparison Project: decadal regional climate simulations with enhanced variable and uniform-resolution GCMs, Meteorol. Atmos. Phys., 100, 159–177, doi:10.1007/s00703-008-0301-z, 2008.
 - Goswami, M., O'Connor, K. M., and Shamseldin, A. Y.: Structures and performances of five rainfall-runoff models for continuous river-flow simulation, 1st Biennial Meeting of Interna-
- tional Environmental Modeling and Software Society, Lugano, Switzerland, 2002. Graham, L. P., Hagemann, S., Jaun, S., and Beniston, M.: On interpreting hydrological change from regional climate models, Climatic Change, 81, 97–122, doi:10.1007/s10584-006-9217-0, 2007.





Grose, M. R., Barnes-Keoghan, I., Corney, S. P., White, C. J., Holz, G. K., Bennett, J. C., Gaynor, S. M., and Bindoff, N. L.: Climate Futures for Tasmania: general climate, Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart, 2010.

Grose, M. R., Corney, S. P., Katzfey, J. J., Bennett, J. C., and Bindoff, N. L.: Improving projections of rainfall trends through regional climate modeling and wide-ranging assessment,

- 5 MODSIM2011 International Congress on Modelling and Simulation, Perth, December 2011. Hegerl, G. C., Zwiers, F. W., Stott, P. A., and Kharin, V. V.: Detectability of anthropogenic changes in annual temperature and precipitation extremes, J. Climate, 17, 3683-3700, doi:10.1175/1520-0442(2004)017;3683:DOACIA;2.0.CO;2,2004.
- Ines, A. V. M. and Hansen, J. W.: Bias correction of daily GCM rainfall for crop simulation 10 studies, Agr. Forest Meteorol., 138, 44–53, doi:10.1016/j.agrformet.2006.03.009, 2006.
- Jeffrey, S. J., Carter, J. O., Moodie, K. M., and Beswick, A. R.: Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environ. Model. Softw., 16. 309-330. doi:10.1016/S1364-8152(01)00008-1. 2001.
- Katzfey, J. J., McGregor, J., Nguyen, K. C., and Thatcher, M.: Dynamical downscaling tech-15 niques: impacts on regional climate change signals, 18th World IMACS Congress and MOD-SIM09 International Congress on Modelling and Simulation, Cairns, July, 2009.

Kendon, E. J., Rowell, D. P., and Jones, R. G.: Mechanisms and reliability of future projected changes in daily precipitation, Clim. Dyn., 35, 489-509, doi:10.1007/s00382-009-0639-z, 2010.

20

25

- Kilsby, C. G.: Context and aims, Hydrol. Earth Syst. Sci., 11, 1065–1068, 2007, http://www.hydrol-earth-syst-sci.net/11/1065/2007/.
- Kilsby, C. G., Tellier, S. S., Fowler, H. J., and Howels, T. R.: Hydrological impacts of climate change on the Tejo and Guadiana Rivers, Hydrol. Earth Syst. Sci., 11, 1175–1189, doi:10.5194/hess-11-1175-2007. 2007.
- Kushner, P. J., Held, I. M., and Delworth, T. L.: Southern Hemisphere Atmospheric Circulation Response to Global Warming, J. Climate, 14, 2238-2249, doi:10.1175/1520-0442(2001)014;0001:SHACRT; 2.0.CO; 2, 2001.

Lal, M., McGregor, J. L., and Nguyen, K. C.: Very high-resolution climate simulation over Fiji using a global variable-resolution model, Clim. Dynam., 30, 293-305, doi:10.1007/s00382-30 007-0287-0, 2008.

Li, H., Sheffield, J., and Wood, E. F.: Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant





quantile matching, J. Geophys. Res., 115, D10101, doi:doi:10.1029/2009JD012882, 2010.
Mailhot, A., Duchesne, S., Caya, D., and Talbot, G.: Assessment of future change in intensityduration-frequency (IDF) curves for Southern Quebec using the Canadian Regional Climate Model (CRCM), J. Hydrol., 347, 197–210, doi:10.1016/j.jhydrol.2007.09.019, 2007.

- ⁵ McGregor, J. L. and Dix, M. R.: An updated description of the conformal-cubic atmospheric model, in: High Resolution Numerical Modelling of the Atmosphere and Ocean, edited by: Hamilton, K. and Ohfuchi, W., Springer, New York, 51–76, 2008.
 - Meehl, G., Covey, A. C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., Stouffer, R. J., and Taylor, K. E.: The WCRP CMIP3 multi-model dataset: A new era in climate change research. B. Am. Meteorol. Soc., 88, 1383–1394. doi:10.1175/BAMS-88-9-1383. 2007.
- research, B. Am. Meteorol. Soc., 88, 1383–1394, doi:10.11/5/BAMS-88-9-1383, 2007. Merz, R., Parajka, J., and Blöschl, G.: Time stability of catchment model parameters: implications for climate impact analyses, Water Resour. Res., 47, W02531, doi:10.1029/2010WR009505, 2011.

Mitchell, T.: Pattern Scaling, Climatic Change, 60, 217–242, doi:10.1023/A:1026035305597,

15 2003.

25

30

- Morrongiello, J. R., Beatty, S. J., Bennett, J. C., Crook, D. A., Ikedife, D. N. E. N., Kennard, M. J., Kerezsy, A., Lintermans, M., McNeil, D. G., Pusey, B. J., and Rayner, T.: Climate change and its implications for Australia's freshwater fish, Mar. Freshwater Res., 62, 1082–1098, doi:10.1071/MF10308, 2011.
- Morton, F. I.: Operational estimates of areal evapotranspiration and their significance to the science and practice of hydrology, J. Hydrol., 66, 1–76, doi:10.1016/0022-1694(83)90177-4, 1983.

Nakićenović, N., and Swart, R.: Special Report on Emissions Scenarios, A Special Report of Working Group III of the Intergovernmental Panel on Climate Change, Cambridge, UK, 599, 2000.

Oki, T. and Kanae, S.: Global hydrological cycles and world water resources, Science, 313, 1068–1072, doi:10.1126/science.1128845, 2006.

Pall, P., Allen, M. R., and Stone, D. A.: Testing the Clausius-Clapeyron constraint on changes in extreme precipitation under CO₂ warming, Clim. Dynam., 28, 351–363, doi:10.1007/s00382-006-0180-2, 2007.

Petheram, C., Hughes, D., Rustomji, P., Smith, K., Van Neil, T., and Yang, A.: River modelling for Northern Australia. A report to the Australian Government from the CSIRO Northern Australia Sustainable Yields Project, Australia, 2009.





- Piani, C., Haerter, J., and Coppola, E.: Statistical bias correction for daily precipitation in regional climate models over Europe, Theor. Appl. Climatol., 99, 187–192, doi:10.1007/s00704-009-0134-9, 2010a.
- Piani, C., Weedon, G. P., Best, M., Gomes, S. M., Viterbo, P., Hagemann, S., and Haerter, J. O.:
 Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models, J. Hydrol., 395, 199–215, doi:10.1016/j.jhydrol.2010.10.024, 2010b.
 - Post, D. A. and Jakeman, A. J.: Predicting the daily streamflow of ungauged catchments in SE Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model, Ecol. Model., 123, 91–104, doi:10.1016/S0304-3800(99)00125-8, 1999.
- Post, D. A., Chiew, F. H. S., Teng, J., Viney, N. R., Ling, F. L. N., Harrington, G., Crosbie, R. S., Graham, B., Marvanek, S., and McLoughlin, R.: A robust methodology for conducting largescale assessments of current and future water availability and use: A case study in Tasmania, Australia, J. Hydrol., 412–413, 233–245, doi:10.1016/j.jhydrol.2011.02.011, 2012.

10

- Prudhomme, C. and Davies, H.: Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK, Part 1: baseline climate, Climatic Change, 93, 177–195, doi:10.1007/s10584-008-9464-3, 2009.
 - Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Shukla, A. P. J., Srinivasan, J., Stouffer, R. J., Sumi, A., and Taylor, K. E.: Climate models and
- their evaluation, in: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, Cambridge, UK, New York, NY, USA, 2007.
- Reynolds, R. W.: A real-time global sea surface temperature analysis, J. Climate, 1, 75–86, 1988.
 - Stephens, G. L. and Hu, Y.: Are climate-related changes to the character of global-mean precipitation predictable?, Environ. Res. Lett., 5, 025209, doi:10.1088/1748-9326/5/2/025209, 2010.
- Tan, K. S., Chiew, F. H. S., Grayson, R. B., Scanlon, P. J., and Siriwardena, L.: Calibration of a daily rainfall-runoff model to estimate high daily flows, MODSIM 2005 International Congress on Modelling and Simulation, Melbourne, December 2005.





surface water **Discussion** Paper availability J. C. Bennett et al. **Title Page** Introduction Abstract **Discussion** Paper Conclusions References **Figures Tables** 14 Close Back **Discussion** Paper Full Screen / Esc **Printer-friendly Version** Interactive Discussion



Teng, J., Vaze, J., Chiew, F. H. S., Wang, B., and Perraud, J.-M.: Estimating the relative uncertainties sourced from GCMs and hydrological models in modelling climate change impact on runoff, J. Hydrometeorol., doi:10.1175/JHM-D-11-058.1, in press, 2011.

Thatcher, M. and McGregor, J.: Using a scale-selective filter for dynamical downscal-

- ing with the conformal cubic atmospheric model, Mon. Weather Rev., 137, 1742-1752, 5 doi:10.1175/2008MWR2599.1, 2009.
 - Vaze, J., Post, D. A., Chiew, F. H. S., Perraud, J.-M., Viney, N., and Teng, J.: Climate nonstationarity - Validity of calibrated rainfall-runoff models for use in climate change studies, J. Hydrol., 394, 447–457, doi:10.1016/j.jhydrol.2010.09.018, 2010.
- Viney, N. R., Perraud, J., Vaze, J., Chiew, F. H. S., Post, D. A., and Yang, A.: The useful-10 ness of bias constraints in model calibration for regionalisation to ungauged catchments, 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation, Cairns, July 2009a.

Viney, N. R., Post, D. A., Yang, A., Willis, M., Robinson, K. A., Bennett, J. C., Ling, F. L. N., and

- Marvanek, S.: Rainfall-runoff modelling for Tasmania, CSIRO Water for a Healthy Country 15 Flagship, Australia 2009b.
 - Wilby, R. L. and Harris, I.: A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK, Water Resour. Res., 42, W02419, doi:10.1029/2005WR004065, 2006.
- Wood, A., Leung, L. R., Sridhar, V., and Lettenmaier, D. P.: Hydrologic implications of dynamical 20 and statistical approaches to downscaling climate outputs, Climatic Change, 62, 189-216, doi:10.1023/B:CLIM.0000013685.99609.9e, 2004.
 - Yin, J. H.: A consistent poleward shift of the storm tracks in simulations of 21st century climate, Geophys. Res. Lett., 32, L18701, doi:10.1029/2005GL023684, 2005.
- ²⁵ Zhang, X., Zwiers, F. W., Hegerl, G. C., Lambert, F. H., Gillett, N. P., Solomon, S., Stott, P. A., and Nozawa, T.: Detection of human influence on twentieth-century precipitation trends, Nature, 448, 461–465, doi:10.1038/nature06025, 2007.
 - Zou, L., Zhou, T., Li, L., and Zhang, J.: East China Summer Rainfall Variability of 1958-2000: Dynamical Downscaling with a Variable-Resolution AGCM, J. Climate, 23, 6394-6408,
- doi:10.1175/2010JCLI3689.1.2010. 30

HESSD

Discussion Paper

9, 1783-1825, 2012

High-resolution projections of

		AWBM	IHACRES	Sacramento	SIMHYD	SMAR-G
Mean annual streamflow	Median catchment bias (%) Interquartile range of biases at all catchments (%)	-5.2 14.9	-22.6 20.5	-9.1 16.1	-3.2 11.6	-5.8 14.1
Mean November–April streamflow	Median catchment bias (%) Interquartile range of biases at all catchments (%)	-7.8 22.1	-15.6 25.1	-25.5 35.1	-6.7 25.4	-12.9 23.2
Mean May–October streamflow	Median catchment bias (%) Interquartile range of biases at all catchments (%)	-3.9 13.93	-25.6 24.9	-3.9 15.1	-2.0 14.5	-3.8 15.1
Q5 streamflows	Median catchment bias (%) Interquartile range of biases at all catchments (%)	5.5 173.3	-1.6 184.9	-11.2 448.8	-35.3 79.7	-3.9 160.9
Q95 streamflows	Median bias (%) Interquartile range of biases for all catchments (%)	-9.8 26.3	-23.4 26.8	-11.4 17.8	-11.5 20.6	-8.8 23.2

Table 1. Summary of biases of hydrological models forced by CCAM calculated at 86 stream-flow gauges from the average of the six RCM simulations.







Fig. 1. Tasmania's location (shaded) in relation to the Australian continent.







Fig. 2. Tasmanian historical climate (1961–2007) derived from the SILO climate dataset (Jeffrey et al., 2001). **(a)** Mean annual rainfall. **(b)** Mean annual Morton's (1983) wet APET calculated from SILO temperature, solar radiation and vapour pressure. **(c)** Mean annual runoff generated with the SIMHYD model using SILO variables.







Fig. 3. Catchments reported by this study.

Discussion Pa	HESSD 9, 1783–1825, 2012				
per Discussion P	High-resolution projections of surface water availability J. C. Bennett et al. Title Page				
aper					
—	Abstract	Introduction			
Disc	Conclusions	References			
ussion	Tables	Figures			
Pap	I	►I.			
θr	•	F			
	Back	Close			
iscussion	Full Screen / Esc				
Paper	Interactive Discussion				





Fig. 4. Catchments and streamflow gauges used to validate hydrological model performance.



Full Screen / Esc

Printer-friendly Version

Interactive Discussion





CC () BY

Fig. 5. Non-exceedance probabilities of streamflow biases from the hydrological models forced with the RCM at 86 streamflow gauges for 1961–2007. Left column shows biases calculated against observed streamflows, right column shows biases calculated against streamflows, right column shows biases calculated against streamflows simulated with the hydrological models forced by SILO variables. Biases are shown for mean streamflows (top panels), high (Q_{95}) streamflows (middle panels) and low (Q_5) streamflows (bottom panels). Lines show mean biases from the six RCM simulations, shaded confidence intervals show the range of biases from the six simulations. For left panels positive biases mean that RCM-forced runoff overestimate observations, and for right panels positive biases mean that RCM-forced runoff.



Fig. 6. Comparison of coefficients of variation (CV) of daily streamflows generated by SIMHYD at 86 streamflow gauges for 1961–2007. **(a)** CV of daily streamflows generated by SIMHYD forced with the RCM (RCM-runoff) and observations (OBS). **(b)** CV of daily streamflows generated by RCM-runoff and SIMHYD forced with SILO (SILO-runoff). Points show the mean of the six RCM simulations, bars show the range from the six simulations.









Fig. 7. Comparison of mean monthly modelled and gauged streamflows for 1961–2007. Blue line shows streamflows modelled with SIMHYD forced by the RCM, faint blue lines give range of the six RCM simulations, black line shows SIMHYD forced by SILO and red line shows gauged streamflows.











Fig. 9. Change in rainfall and APET from 1961–1990 to 2070–2099. **(a)** Change in mean annual rainfall. **(b)** Change in mean daily rainfall intensity for rain days > 1 mm. **(c)** Change in mean annual APET. All plots are calculated from the average of the six RCM simulations. Stippling shows regions where at least five of the six RCM simulations agree on the sign of change.















Fig. 11. Change in runoff simulated by SIMHYD from 1961–1990 to 2070–2099. (a) Change in mean annual runoff. (b) Change in mean DJF runoff. (c) Change in mean JJA runoff. (d) Change in Q_{25} runoff. (e) Change in Q_{99} runoff. Changes are calculated from the mean of the six RCM simulations. Stippling shows regions where at least five of the six RCM simulations agree on the sign of change.















Fig. 13. Changes to coefficient of variation (CV) of runoff simulated by SIMHYD from 1961–1990 to 2070–2099. (a) Changes to CV of daily runoff. (b) Changes to CV of annual runoff. Changes are calculated from the average of the six RCM simulations. Stippling shows regions where at least five of the six RCM simulations agree on the sign of change.



