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Comparison of runoff modelled using rainfall from different downscaling methods for historical and future climates

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SUMMARY

This paper: (i) assesses the rainfall downscaled from three global climate models (GCMs) using five downscaling models, (ii) assesses the runoff modelled by the SIMHYD rainfall–runoff model using the downscaled daily rainfall, and (iii) compares the modelled changes in future rainfall and runoff characteristics. The modelling study is carried out using rainfall and streamflow data from eight unimpaired catchments near the headwaters of the Murray River in south-east Australia. The downscaling models used, in increasing order of complexity, are a daily scaling model, an analogue statistical downscaling model, GLIMCLIM and NHMM parametric statistical downscaling models, and CCAM dynamic downscaling model. All the downscaling models can generally reproduce the observed historical rainfall characteristics. The rainfall–runoff modelling using downscaled rainfall also generally reproduces the observed historical runoff characteristics. The future simulations are most similar between the daily scaling, analogue and NHMM models, all of them simulating a drier future. The GLIMCLIM and CCAM models simulate a smaller decrease in future rainfall. The differences between the modelled future runoff using the different downscaled rainfall can be significant, and this needs to be further investigated in the context of projections from a large range of GCMs and different hydrological models and applications. The simpler to apply daily scaling and analogue models (they also directly provide gridded rainfall inputs) can be relatively easily used for impact assessments over very large regions. The parametric downscaling models offer potential improvements as they capture a fuller range of daily rainfall characteristics.

Introduction

Global warming could lead to changes in future runoff characteristics that may require a significant planning response or a change in the way water resources are currently managed. There are numerous studies in the literature on the modelling of climate change impact on runoff. In most of these studies, the hydrological model is first calibrated against historical data, and then driven with a future climate series usually with the same optimised parameter values, and the modelled future and historical runoff are compared to estimate the climate change impact on runoff (Schaake, 1990; Xu, 1999; Chiew and McMahon, 2002; Chiew et al., 2009). Rainfall is the key driver in these hydrological modelling studies and a change in rainfall is generally amplified as a larger percent change in runoff (Wigley and Jones, 1985; Sankarasubramaniam et al., 2001; Chiew, 2006).

The future climate series is usually obtained by analysing results from global climate models (GCMs) that simulate global and regional climate systems (IPCC, 2007). However, GCMs provide information at a resolution that is too coarse to be used directly in hydrological modelling. Various methods have been used to obtain catchment-scale climate series, informed by GCM simulations for the future and current climates, to drive hydrological models. Three commonly used methods are explored in this paper. The first is a daily scaling method that scales the observed historical point or catchment-scale daily rainfall series to obtain a future daily rainfall series by considering changes in the seasonal means and daily rainfall distribution simulated by a GCM (Chiew et al., 2009; Mpelasoka and Chiew, 2009). The second method uses three statistical downscaling techniques that relate synoptic large-scale atmospheric predictors to catchment-scale rainfall (gridded rainfall or point rainfall at multiple sites) based on analysis of historical data, and the relationship is then used to downscale future atmospheric predictors simulated by a GCM to obtain future catchment-scale rainfall. The three statistical downscaling techniques used here are: (i) an analogue technique (Timbal, 2004; Timbal

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et al., 2009); (ii) an implementation of the Generalised LInear Model for daily CLIMate (GLIMCLIM) software package (Chandler, 2002) and (iii) a Non-homogeneous Hidden Markov Model (NHMM) (Hughes et al., 1999). The third method is a dynamic downscaling method that uses a high resolution regional atmospheric model with boundary conditions and far-field nudging provided by a GCM. Fowler et al. (2007) provide a thorough review of downscaling methods with an emphasis on hydrological applications, and Wood et al. (2004), Haylock et al. (2006) and Timbal et al. (2008) provide comparative analysis of future rainfall obtained using statistical and dynamic downscaling methods.

The aims of this paper are to: (i) assess the historical runoff characteristics modelled by a rainfall–runoff model using daily rainfall series obtained from the above downscaling methods against the observed historical runoff characteristics and (ii) compare the future runoff characteristics modelled using future daily rainfall obtained from the different downscaling methods informed by three GCMs. The modelling is carried out using data from south-east Australia. The focus of this paper is mainly on the runoff simulations, and a related paper by Frost et al. (submitted for publication) describes the downscaling methods and discusses the verification of rainfall simulations against historical rainfall in more detail.

The paper is organised as follows. The streamflow, rainfall, reanalysis and GCM data used in the study are first described. This is followed by a description of the downscaling methods, rainfall–runoff modelling and the modelling experiments. The modelling results are then presented followed by a discussion of the relative differences between the downscaling methods and rainfall–runoff simulations and the implications on climate change impact studies.

Data

Study area and streamflow data

The study area is in south-east Australia near the headwaters of the Murray River. Daily streamflow data from eight relatively unimpaired catchments are used (Fig. 1). The catchment areas range between 100 and 1600 km^2. Most of the catchments have less than 1% missing data over the model calibration period of 1986–2005. The mean annual rainfall in the catchments ranges from 500 to 1300 mm and the proportion of mean annual rainfall that becomes runoff ranges from 5% to 50% (Fig. 1). Most of the runoff is generated in the winter half (May–October) of the year.

Observed rainfall

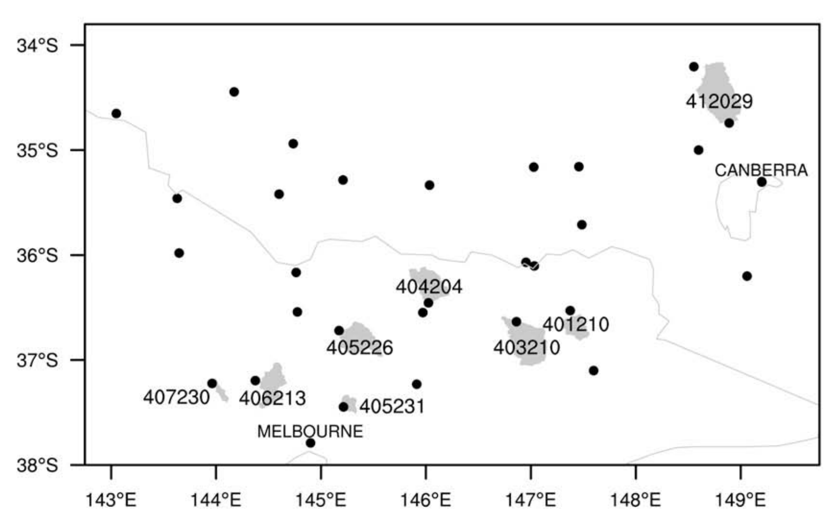
Two types of observed daily rainfall data (recorded as 24-h accumulations to 0900) from 1961–2005 are used. The first is point rainfall from 30 locations (Fig. 1) with high quality daily rainfall data observed by the Australian Bureau of Meteorology over the model calibration period of 1986–2005 (Frost et al., submitted for publication). The second is daily rainfall over 0.05° grids from the 'SILO Data Drill' of the Queensland Department of Natural Resources and Water (http://www.nrw.qld.gov.au/silo; Jeffrey et al., 2001). The SILO Data Drill provides surfaces of daily rainfall and other climate data for 0.05° grids across Australia, interpolated from point measurements made by the Australian Bureau of Meteorology. The gridded rainfall data are used with the CCAM dynamic downscaling model outputs and the point rainfall data are used with the other downscaling methods.

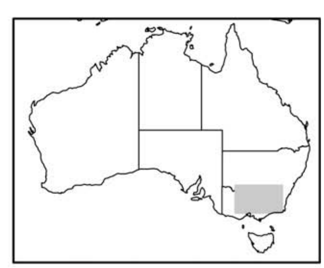
Reanalysis data for atmospheric predictors

The atmospheric predictor data for 1986–2005 used to calibrate the downscaling methods come from the NCEP/NCAR reanalysis data at 2.5° grids (Kalnay et al., 1996; http://www.cdc.noa.gov/cdc/reanalysis/). The ten candidate predictors considered are mean sea level pressure, geopotential heights at 500, 700 and 850 hPa, dew point temperature depression at 500, 700 and 850 hPa, and specific humidities at 500, 700 and 850 hPa. Daily values of the predictors, averaged over 24 h are used to be consistent with the 24-h observed daily rainfall data.

GCM data

Daily simulations of rainfall and the above atmospheric predictors from three GCMs (GFDL 2.0, CSIRO MK3.5 and MRI) for 1961–2000 and 2046–2065 are used. The GCM data are extracted from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) website (http://www-pcmdi.llnl.gov) and interpolated to the 2.5° NCEP/NCAR reanalysis data grid. The 2046–2065 data used is for the SRES A2 greenhouse gas emission scenario (IPCC, 2007).





Catchment	Area (km^2)	Mean annual rainfall (mm)	Mean annual runoff (mm)
401210	416	1049	516
403210	1238	1257	406
404204	748	586	46
405226	818	557	83
405231	187	1188	227
406213	644	742	130
407230	161	588	65
412029	1540	726	71

Fig. 1. Study area showing locations of catchments, rainfall stations and 1986–2005 mean annual rainfall and runoff.

Method

Rainfall downscaling models and model calibration

Five rainfall downscaling models are used to obtain the point or gridded daily rainfall: (i) daily scaling model; (ii) analogue statistical downscaling model; (iii) GLIMCLIM statistical downscaling model; (iv) NHMM statistical downscaling model; and (v) CCAM dynamic downscaling model.

The analogue model used here (Timbal, 2004; Timbal et al., 2009) defines a daily weather type by relating large-scale atmospheric predictors to observed point or gridded rainfall. For a given future daily weather type simulated by a GCM, the observed historical rainfall on a day that best matches this future daily weather type is used as the daily rainfall. This analogue model has been used to successfully downscale point and gridded rainfall across Australia (Timbal et al., 2009) and to study rainfall trends across south-east and south-west Australia (Timbal et al., 2006; Timbal and Jones, 2008). The GLIMCLIM and NHMM models use parametric equations to relate the atmospheric predictors to point rainfall at multiple sites. Both the GLIMCLIM (Chandler, 2002; Chandler and Wheater, 2002; Yang et al., 2005) and NHMM (Bates et al., 1998; Hughes et al., 1999; Charles et al., 2003, 2004, 2007) models have been used widely to downscale rainfall including for hydrological applications.

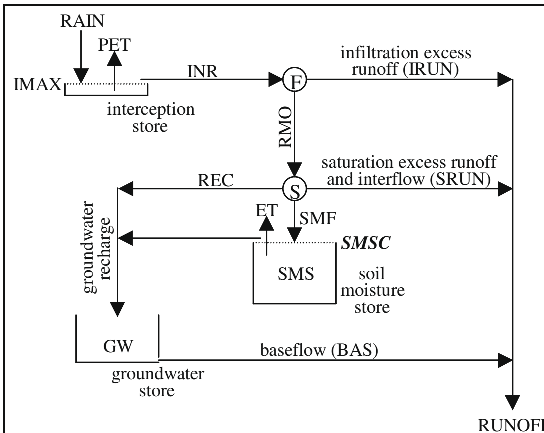
For the GLIMCLIM and NHMM models, the daily atmospheric predictors from the NCEP/NCAR reanalysis and the daily rainfall data from the 30 locations over the 1986–2005 calibration periods are used to develop the downscaling relationships. For the analogue model, the data used are the same but the optimisation is done using data from a larger number of rainfall stations covering the southern parts of the Murray–Darling Basin (Timbal et al., 2009). The calibration of the three statistical downscaling models and the predictors selected are described in more detail in Frost et al. (submitted for publication).

The daily scaling model and the dynamic downscaling model are not 'calibrated' like the three statistical downscaling models. The daily scaling model scales the historical point rainfall series by the relative difference between GCM rainfall simulations for future and historical periods to provide a future point rainfall series, and this is described in more detail later. The CSIRO conformal-cubic atmospheric model (CCAM) used here is a global climate model, formulated using a conformal-cubic grid that covers the whole globe but stretched to provide higher resolution simulations over the area of interest (McGregor, 2005; McGregor and Dix, 2008; Nguyen and McGregor, 2009). The CCAM resolution over the study area is 0.15°, and the model is far-field forced by a CSIRO MK3.0 GCM simulation.

Rainfall-runoff modelling and model calibration

The lumped conceptual daily rainfall–runoff model, SIMHYD (Chiew et al., 2002), with Muskingum routing (Tan et al., 2005), is used to model runoff in the eight catchments. The model simulates daily runoff from input data of daily rainfall and potential evapotranspiration. The SIMHYD model structure, parameters and algorithms used to model the rainfall–runoff processes are shown in Fig. 2. SIMHYD has been used widely including for climate change impact on runoff studies (Chiew and McMahon, 2002; Zhang and Chiew, 2009; Chiew et al., 2009; Reichl et al., 2009).

The rainfall–runoff modelling is carried out in two ways. In the first, point rainfall from the closest rainfall station is used to drive the rainfall–runoff model (except for Catchment 412029 where the Thiessen average of the two closest rainfall stations is used). In the second, SILO rainfall aggregated to 0.15° resolution close to the



PET = areal potential evapotranspiration (input data)
IMAX = lesser of {***INSC***, PET}
INT = lesser of {IMAX, RAIN}
INR = RAIN - INT
RMO = lesser of {***COEFF*** exp (-***SQ*** x SMS/***SMSC***), INR}
IRUN = INR - RMO
SRUN = ***SUB*** x SMS/***SMSC*** x RMO
REC = ***CRAK*** x SMS/***SMSC*** x (RMO - SRUN)
SMF = RMO - SRUN - REC
POT = PET - INT
ET = lesser of {10 x SMS/***SMSC***, POT}
BAS = ***K*** x GW
[Runoff is routed to the catchment outlet using Muskingum routing]

Model parameters

INSC interception store capacity (mm)
COEFF maximum infiltration loss (mm)
SQ infiltration loss exponent
SMSC soil moisture store capacity (mm)
SUB constant of proportionality in interflow equation
CRAK constant of proportionality in groundwater recharge equation
K baseflow linear recession parameter
DELAY delay parameter in Muskingum routing (days)
X storage weight parameter in Muskingum routing

In the model application in this study, ***COEFF***, ***SQ*** and ***X*** are set to 150, 2 and 0 respectively, leaving six model parameters to be optimised in the model calibration.

Fig. 2. Structure of the daily lumped conceptual rainfall–runoff model SIMHYD.

catchment centroid is used to drive the rainfall–runoff model. The first rainfall–runoff model application is used together with all the rainfall downscaling models except CCAM. The second application is used with CCAM to be consistent with the CCAM resolution of 0.15°. Mean monthly values of potential evapotranspiration (one value for each of the 12 months), estimated using Morton's areal evapotranspiration algorithms (Morton, 1983; Chiew and McMahon, 1991), are used for the rainfall–runoff modelling experiments throughout this study.

The SIMHYD rainfall–runoff model is calibrated against 1986–2005 observed runoff, with six parameters (Fig. 2) optimised to reproduce the observed daily runoff series. Specifically, the parameters are optimised to maximise the Nash–Sutcliffe efficiency, NSE (Nash and Sutcliffe, 1970), of daily runoff with a constraint used to ensure that the total modelled runoff is within 5% of the total observed runoff. The model is calibrated using the shuffled complex evolution global optimisation method (Duan et al., 1993) followed by a local optimisation method (Rosenbrock, 1960), with multiple starting parameter sets to increase the likelihood of locating the global optimum. The model calibration is generally satisfactory, with the model reproducing reasonably the observed monthly runoff series (NSE greater than 0.7 in most catchments) and observed daily runoff series (NSE greater than 0.6 in most catchments). The rainfall–runoff model calibration results are discussed further in the 'Modelling results' section.

Modelling rainfall and runoff for calibration period (1986–2000)

The analogue, GLIMCLIM and NHMM rainfall downscaling models are used with each of the three GCMs to obtain daily rainfall series at the 30 locations for 1986–2000. Although the calibration period described earlier extends to 2005, the GCM downscaled simulations end in 2000 because the archived GCM data for the 20th century ends in 2000. The statistical downscaling relationships developed from observed data described earlier are used to downscale the 1986–2000 GCM atmospheric predictors to obtain point rainfall at the 30 locations representative of the 1986–2000 climatology. For the analogue model, a single daily rainfall series is obtained. For the GLIMCLIM and NHMM models, 100 stochastic replicates of daily rainfall series are generated. Rainfall for the 30 locations are generated and used for the rainfall comparative study in Frost et al. (submitted for publication), whilst this study focuses only on the results at the eight catchments.

Prior to downscaling, bias corrections are used to remove errors in the GCM atmospheric predictors relative to the NCEP/NCAR reanalysis data. The bias is different for the different GCMs and predictor variables, with some GCMs/variables showing significantly different distributional shape compared to the reanalysis data. The different bias correction methods used for the different models are described in Frost et al. (submitted for publication).

For the dynamic downscaling, the daily rainfall series from the CCAM simulations for 1986–2000 are used directly. The daily rainfall series from these four rainfall downscaling models are then used to drive the SIMHYD rainfall–runoff model and the modelled runoff characteristics are compared in the 'Modelling results' section.

Modelling rainfall and runoff for a future period (2046–2065) relative to a historical period (1961–2000)

As in the above 1986–2000 modelling, the calibrated analogue, GLIMCLIM and NHMM rainfall downscaling models are used with the atmospheric predictors from each of the three GCMs for 1961–2000 and for 2046–2065 to obtain daily rainfall series at the 30 locations for a future (2046–2065) climate and a historical (1961–2000) climate. Likewise, the rainfall simulations from the CCAM dynamic downscaling model for 1961–2000 and for 2046–2065 are used directly.

In the daily scaling model, the relative difference between the 2046–2065 GCM rainfall and the 1961–2000 GCM rainfall is used to scale the 1961–2000 observed point daily rainfall series to obtain the future (2046–2065) point daily rainfall series. The different daily rainfall amounts are scaled differently, as indicated by the relative difference between the future (2046–2065) and historical (1961–2000) GCM daily rainfall distributions at the different ranked daily rainfall percentiles. Each of the four seasons (DJF, MAM, JJA, SON) is considered separately in applying the daily scaling method. The future point rainfall series is then rescaled such that the point mean seasonal rainfall is the same as the relative difference between the GCM future and historical mean seasonal rainfall. Unlike the other four rainfall downscaling models, the future (2046–2065) point daily rainfall series in the daily scaling model has the same sequence as the historical (1961–2000) point daily rainfall series, but with scaled amounts. The daily scaling model is described in more detail in Chiew et al. (2009) and Mpelasoka and Chiew (2009).

The historical (1961–2000) daily rainfall series and the future (2046–2065) daily rainfall series from the five downscaling models are then used to drive the SIMHYD rainfall–runoff model to simulate historical and future runoff, and the modelled future runoff characteristics relative to the modelled historical runoff characteristics from the different modelling runs are compared in the 'Modelling results' section.

Modelling results

Rainfall-runoff model calibration over 1986–2000

Fig. 3 compares the modelled and observed key runoff characteristics that are assessed in subsequent sections of the paper. The modelled runoff in Fig. 3 is from the SIMHYD rainfall–runoff modelling using observed daily rainfall data over 1986–2000. The eight points in each of the plots are results for the eight catchments. The key runoff characteristics assessed are mean annual runoff, mean summer (December–January–February) runoff, mean winter (June–July–August) runoff, inter-annual variability of annual runoff (shown as the coefficient of determination of annual runoff (Cv) defined as the standard deviation of annual runoff divided by mean annual runoff), extreme high daily runoff (shown as daily runoff that is exceeded 1% of the time, Q_1), and a low flow characteristic (shown as number of days when runoff is less than 0.1 mm – many metrics can be used to describe low flow characteristics (see Smakhtin, 2001; Tallaksen and van Lanen, 2004) and the criteria used here simply provides an example). Fig. 4 compares the modelled and observed daily runoff distributions in the eight catchments, presented as exceedance plots. The results for modelling using point rainfall and using 0.15° aggregated rainfall are similar, with Figs. 3 and 4 showing results for the former.

The comparisons indicate that the SIMHYD model reproduces the annual and seasonal mean runoff, in part due to the constraint used in the model calibration to ensure that the total modelled runoff is within 5% of the total observed runoff. SIMHYD underestimates the very high daily runoff (except in Catchment 403210), which is expected because any model optimisation that reduces overall error variance tends to result in some underestimation of high runoff and some overestimation of low runoff (despite the calibration against NSE which places more importance on the simulation of high runoff) (Q_1 in Fig. 3 and runoff distributions in Fig. 4). It should be noted that the discernible difference between the modelled and observed daily runoff in Fig. 4 mainly occurs only for daily runoff that is exceeded less than 1% of the time, but is accentuated in the plots because of the linear scale on the *y*-axis and normal probability scale on the *x*-axis. A different model calibration strategy could be used to improve the simulation of the very high runoff (at the expense of other runoff characteristics), but this is not important in the context of this paper.

Fig. 3 also shows that the rainfall–runoff modelling slightly underestimates the inter-annual variability of annual runoff, and can generally reproduce the observed number of days when runoff is less than 0.1 mm. The comparisons here provide context for subsequent assessments of future rainfall and runoff projections, where the uncertainties associated with the rainfall downscaling models and rainfall–runoff modelling can be considered relative to the errors in the rainfall–runoff model calibration.

Modelled rainfall and runoff over the calibration period (1986–2000)

Figs. 5 and 6 compare the modelled and 'observed' rainfall and runoff characteristics respectively over the 1986–2000 calibration period. The 'observed' runoff characteristics discussed here are for modelled runoff using the observed rainfall presented earlier (which in the case of the mean annual and seasonal runoff are very similar to the observed values). Each point in the plots shows the modelled value versus observed value for each of the eight

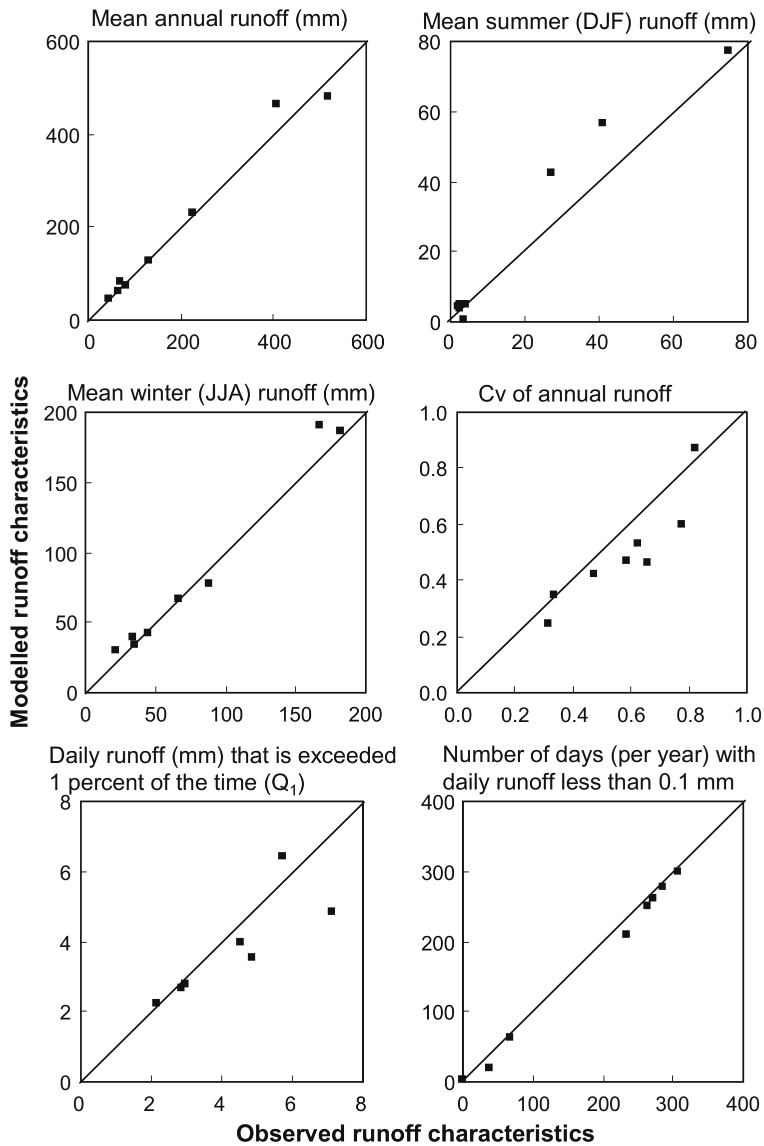


Fig. 3. Comparison of modelled (by the SIMHYD rainfall–runoff model) and observed runoff characteristics over the 1986–2000 period (one point for each of the eight catchments).

catchments for each of the four rainfall downscaling models (all except the daily scaling model, which does not require calibration like the other models) for the three GCMs that are downscaled. The CCAM dynamic downscaling model results are shown in the middle column, together with results for the CSIRO GCM whose boundary conditions are used by CCAM. There are 100 stochastic replicates for the GLIMCLIM and NHMM downscaling models, and the median results are shown in Figs. 5 and 6.

Fig. 7 compares the modelled and observed daily rainfall and runoff distributions, presented as exceedance plots for Catchment 403210 (catchment with the second highest runoff). For the GLIMCLIM and NHMM models with 100 replicates, the plots show the median values at each of the ranked daily rainfall and runoff percentiles. Fig. 8 shows the spatial daily runoff correlations between all pairs of the eight catchments for the analogue, GLIMCLIM and NHMM rainfall models.

Fig. 5 shows that the analogue model underestimates the mean annual rainfall and mean summer rainfall and generally reproduces the observed mean winter rainfall. The GLIMCLIM model generally reproduces the observed mean rainfall except when used with the MRI GCM where it overestimates the mean annual rainfall and mean summer rainfall. The NHMM model generally reproduces the observed mean annual and seasonal rainfall. The CCAM model slightly underestimates the mean annual and winter rainfall and overestimates the mean summer rainfall.

Fig. 6 shows that the mean annual and summer runoff modelled using daily rainfall from the analogue model downscaled from the CSIRO GCM are also underestimated, consistent with the underestimation of the mean annual and summer rainfall. However, the mean annual runoff modelled using daily rainfall from the analogue model downscaled from the GFDL and MRI GCMs is generally similar to the observed mean annual runoff despite the analogue model underestimating the mean annual rainfall. This is because the analogue model generally overestimates the extreme high daily rainfall amounts that generate significant runoff (Fig. 7 and Q_1 in Fig. 6).

The modelled mean annual and seasonal runoff results for the GLIMCLIM model are consistent with the mean annual and seasonal rainfall results. The modelled mean rainfall and runoff for GLIMCLIM are generally similar to the observed values when

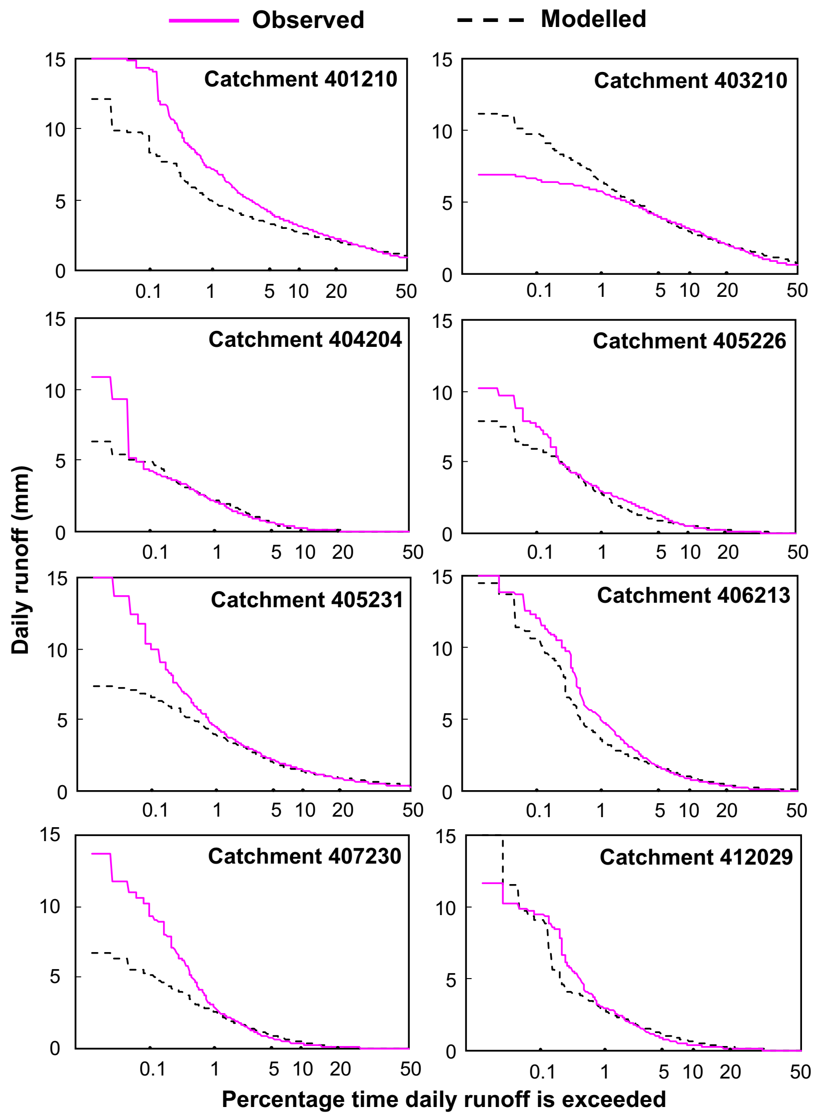


Fig. 4. Comparison of modelled (by the SIMHYD rainfall–runoff model) and observed daily runoff distributions over the 1986–2000 period.

downscaled from the GFDL and CSIRO GCMs, but are higher than the observed values when downscaled from the MRI GCM (first three rows of Figs. 5 and 6). The mean annual and seasonal runoff modelled using daily rainfall from the NHMM model are slightly lower than the observed values, despite the NHMM model generally reproducing the observed mean rainfall and the daily rainfall and runoff distributions (Figs. 5–7).

The modelled daily rainfall and runoff distributions from the NHMM model are remarkably similar to the observed daily rainfall and runoff distributions (NHMM results for all the eight catchments are similar to the plots in Fig. 7). The analogue and GLIMCLIM models generally overestimate the very high daily rainfall and runoff (the results for most of the other catchments are generally similar to the results for Catchment 403210 shown in Fig. 7). The CCAM dynamic downscaling model underestimates considerably the high and medium daily rainfall (rainfall that is exceeded less than 5% of the time) in all the eight catchments (note that: (i) Fig. 7 shows observed point rainfall while CCAM simulates 0.15° rainfall, and (ii) comparisons not shown here also indicate that CCAM underestimates the high and medium daily 0.15° rainfall, but not as poorly as shown in Fig. 7). This and the slight underestimation of mean annual and winter rainfall in CCAM translate to a considerable underestimation in the modelled mean annual and winter runoff.

All the four rainfall downscaling models generally reproduce the observed inter-annual rainfall variability (the modelled Cv is generally within 0.1 of the observed Cv), although there is a consistent underestimation in the downscaling from the GFDL GCM and the analogue model considerably overestimates the inter-annual rainfall variability when downscaled from the CSIRO GCM (Fig. 5). This overestimation in the inter-annual rainfall variability from the analogue model when downscaled from the CSIRO GCM translates to an overestimation in the inter-annual runoff variability (Fig. 6). Apart from this, the inter-annual runoff variability modelled using daily rainfall from the four downscaling models is generally similar to or slightly higher than the observed inter-annual runoff variability (the modelled Cv is generally within 0.2 of the observed Cv).

The number of days with modelled runoff less than 0.1 mm using rainfall from all four downscaling models is remarkably similar to the observed value (last row of Fig. 6). This suggests that the downscaling models can generally reproduce the rainfall characteristics important for modelling this low runoff characteristic. The analogue and CCAM models generally reproduce the observed spatial rainfall and runoff correlations, and the GLIMCLIM and

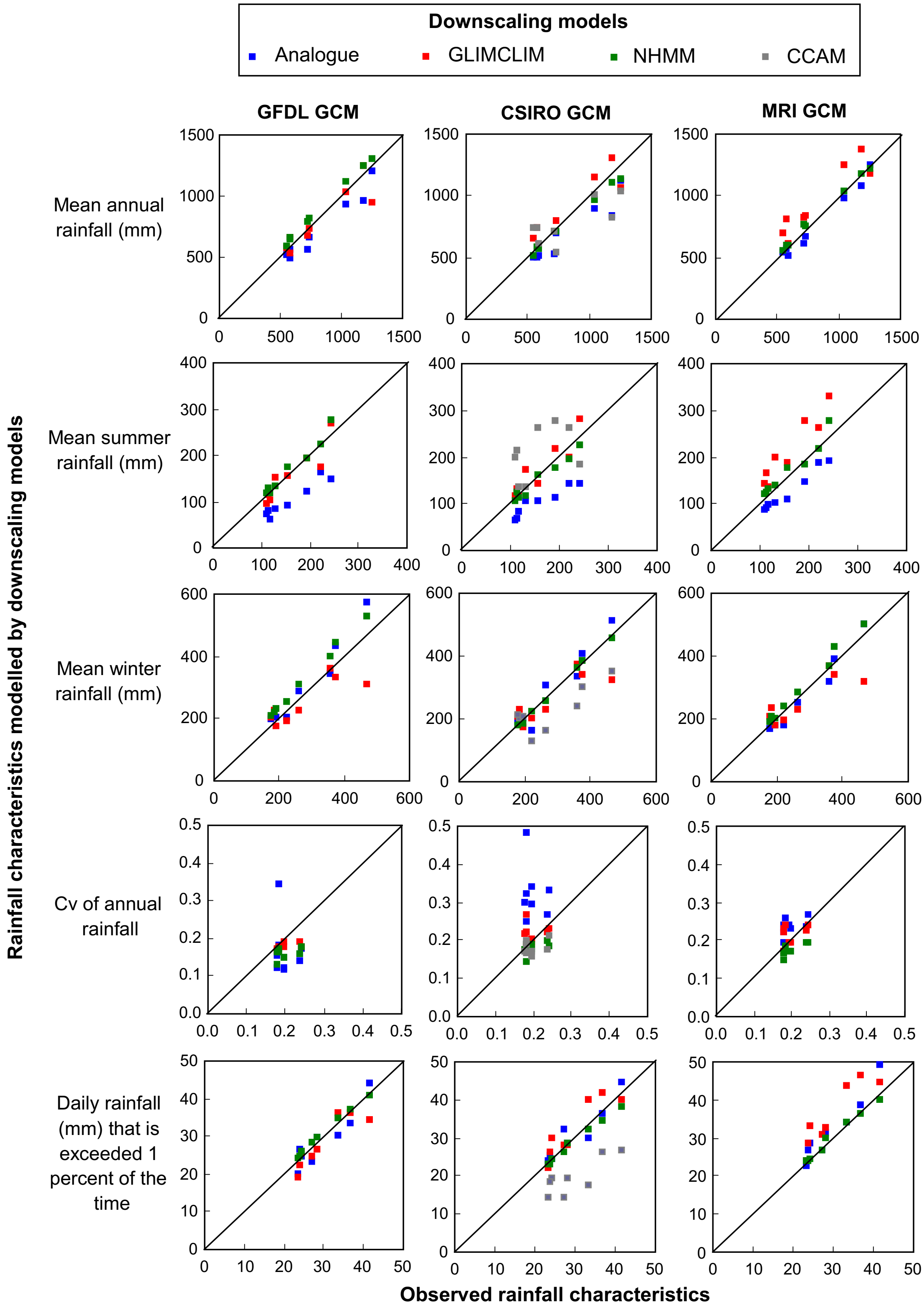


Fig. 5. Comparison of rainfall characteristics downscaled from three GCMs by the four downscaling models with the observed rainfall characteristics over the 1986–2000 period.

NHMM models slightly underestimate the spatial rainfall and runoff correlations. Fig. 8 compares the observed and modelled daily runoff correlations (CCAM results are not shown), and the results are similar for all the daily and annual rainfall and runoff spatial correlations.

Modelled changes in future rainfall and runoff (2046–2065 relative to 1961–2000)

Fig. 9 shows the percentage changes in the rainfall characteristics for the future period (2046–2065) relative to the historical period

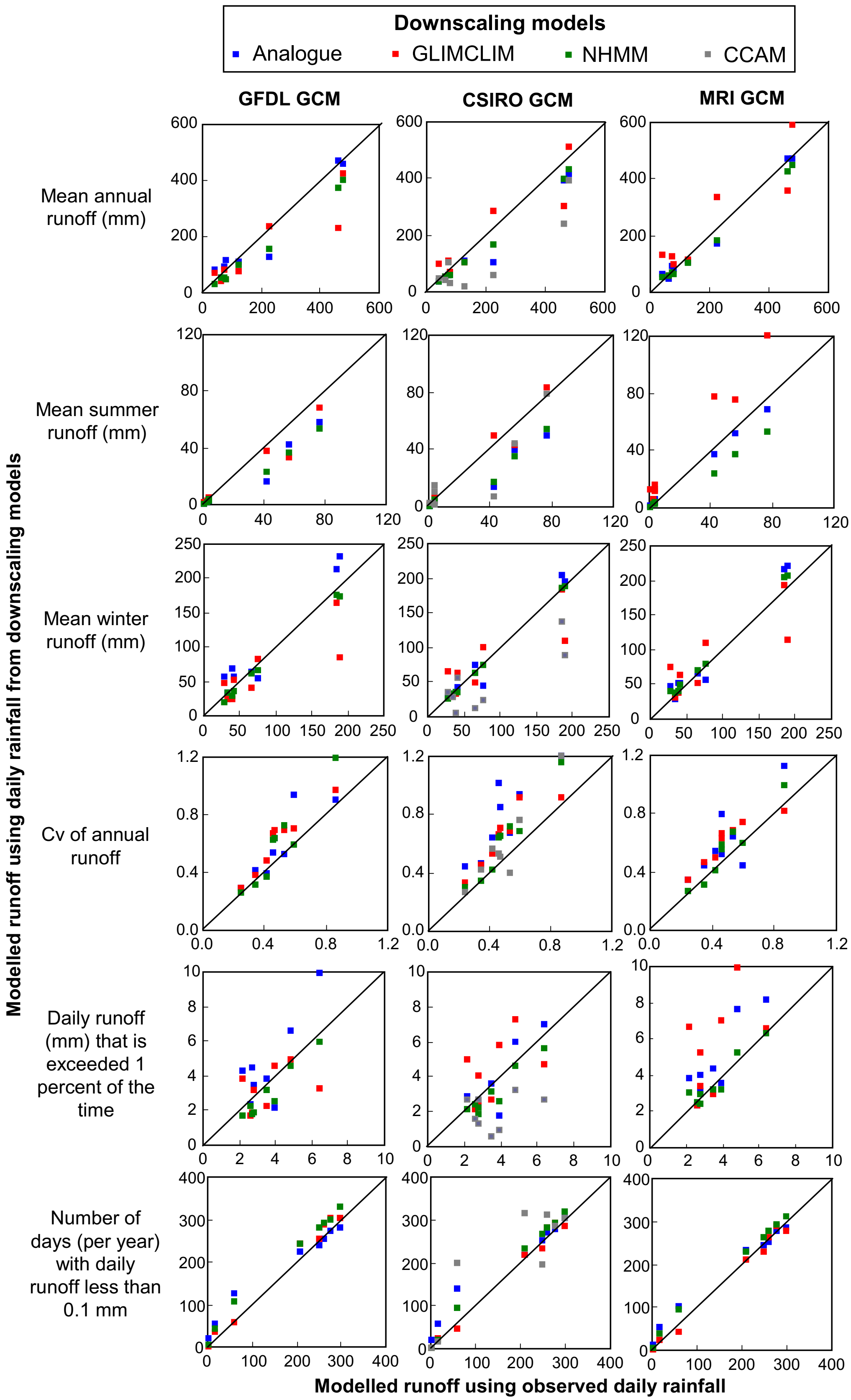


Fig. 6. Comparison of runoff characteristics from SIMHYD rainfall–runoff modelling using daily rainfall from the four downscaling models with the runoff modelled using observed daily rainfall over the 1986–2000 period.

(1961–2000) for all the five downscaling models (including the daily scaling model) and all three GCMs. Fig. 10 shows the percentage changes in the runoff characteristics modelled by SIMHYD using daily rainfall from the downscaling models for the future period relative

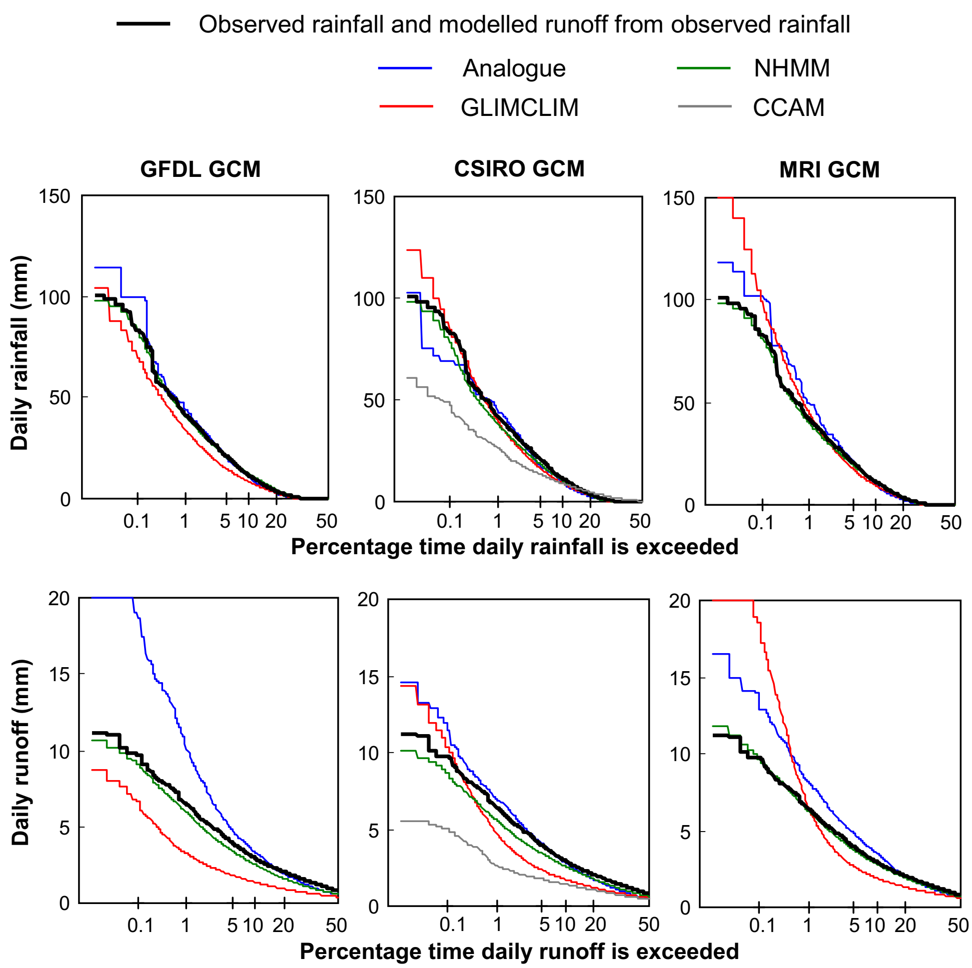


Fig. 7. Comparison of modelled and observed daily rainfall distributions and comparison of daily runoff distributions modelled using downscaled rainfall and using observed rainfall for Catchment 403210.

to the historical period. Unlike the 1986–2000 modelling where results from all the eight catchments are shown, Figs. 9 and 10 show only the weighted result from the eight catchments. The results are weighted by the 1961–2000 values in the eight catchments and are therefore dominated by the catchments with higher rainfall and runoff (except for the low flow characteristic).

Fig. 11 shows the modelled future (2046–2065) daily rainfall and runoff distributions from the five rainfall downscaling models and three GCMs and the observed historical daily rainfall distribution (1961–2000) and modelled runoff distribution using historical daily rainfall data (1961–2000) for Catchment 403210. The results for most of the other catchments are generally similar to the results presented for Catchment 403210.

All the three GCMs indicate that the 2046–2065 period will be drier than the 1961–2000 period, consistent with the projections of a drier future in south-east Australia by a large majority of the IPCC 4AR GCMs (CSIRO and BoM, 2007). The GCM rainfall model output (i.e. rainfall simulated directly by the GCM rather than rainfall downscaled from atmospheric predictors simulated by the GCM) can be inferred from the results of the daily scaling model which scales the historical daily rainfall series by the relative difference between the future and historical mean seasonal rainfall simulated by the GCMs. The GFDL, CSIRO and MRI GCMs simulations (and the daily scaling model) indicate that the 2046–2065 mean annual rainfall will be 23%, 19% and 5% lower respectively than the 1961–2000 mean annual rainfall (Fig. 9).

The results from the five rainfall downscaling models range from −30% to +5%, −20% to −5% and −10% to 0% change in the 2046–2065 mean annual rainfall relative to 1961–2000 for the GFDL, CSIRO and MRI GCMs respectively (Fig. 9). The GLIMCLIM and CCAM models simulate the wettest future. GLIMCLIM is the only model that shows a rainfall increase downscaling from the GFDL GCM, GLIMCLIM simulates the smallest decrease downscaling from the MRI GCM, and CCAM and GLIMCLIM show the smallest decrease downscaling from the CSIRO GCM. The NHMM model simulates the biggest decrease in future rainfall downscaling from the GFDL and MRI GCMs, and the analogue model simulates the biggest decrease in future rainfall downscaling from the CSIRO GCM. The daily scaling model (and therefore also the rainfall simulated by the GCMs) simulates the second biggest decrease in future rainfall for all the GCMs. The mean winter rainfall results are similar to the mean annual rainfall results (this region is dominated by winter rainfall and runoff) and the mean summer rainfall results show a larger variation.

The range of future rainfall projections are amplified in the runoff results. The future simulations are most consistent for the MRI GCM, with the −10% to 0% change in future mean annual rainfall translating to a −15% to −5% change in future mean annual runoff. The relatively small range of −20 to −5% change in future mean annual rainfall for downscaling from the CSIRO GCM translates to a −40% to −15% change in future mean annual runoff. The −30% to +5% change in future mean annual rainfall for downscaling from the GFDL GCM translates to a −40% to +10% change in future mean annual runoff.

As for rainfall, the highest future runoff comes from the rainfall–runoff modelling using rainfall from the GLIMCLIM model

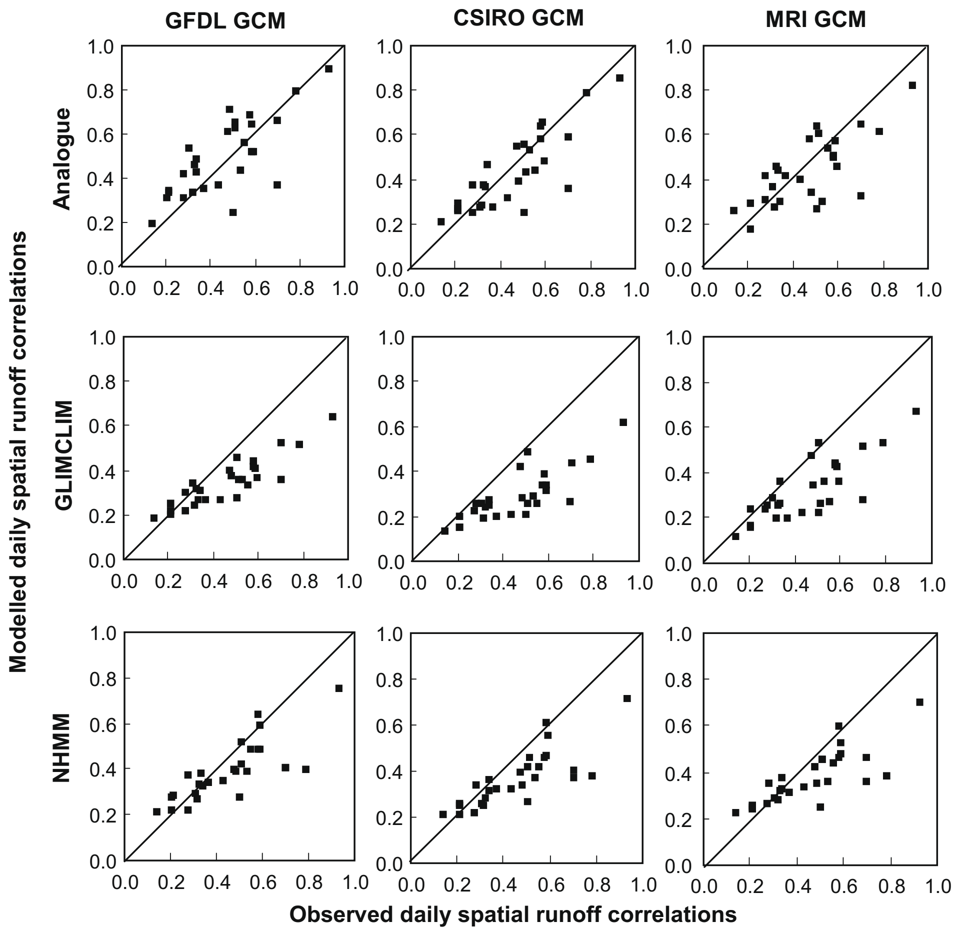


Fig. 8. Comparison of modelled versus observed daily spatial runoff correlations.

(Fig. 10). Although CCAM simulates the smallest decrease in future rainfall for downscaling from the CSIRO GCM, the CCAM future mean annual runoff result is within the range of future mean annual runoff results from the other four downscaling models. This is mainly because CCAM also simulates a considerable reduction in the more intense rainfall that generates significant runoff (Fig. 11). The largest decrease in future runoff modelled using rainfall downscaled from the GFDL GCM is from the daily scaling model (42% decrease) followed by the analogue model (25% decrease). The largest decrease in future runoff modelled using rainfall downscaled from the CSIRO GCM is from the analogue model (42% decrease) followed by the daily scaling model (34% decrease). The decrease in future runoff modelled using rainfall downscaled from the MRI GCM is similar in the daily scaling, analogue and NHMM models (15% decrease).

It is difficult to attribute the differences in the future rainfall and runoff simulations from the different downscaling models because of the complex changes to the various modelled daily rainfall characteristics (amounts, distribution and sequencing) and the non-linear modelled runoff response to the changes in daily rainfall. Nevertheless, the wetter future simulated by GLIMCLIM compared to the other downscaling models may be in part due to the large increase in the very extreme daily rainfall and runoff (rainfall and runoff that is exceeded less than 0.5% of the time) simulated by GLIMCLIM (Fig. 11). The similarities in the future runoff results in the daily scaling and analogue models may be due to both models using the historical daily rainfall directly (scaling the historical rainfall series in the daily scaling model and resampling from the historical rainfall in the analogue model).

It is difficult to interpret inter-annual variability changes because of the short length of data used (20 years for the future period). Nevertheless, there appears to be relatively little difference in the inter-annual rainfall and runoff variability between the future and historical periods from Figs. 9 and 10, with the daily scaling model results generally falling within the range of the other downscaling model results (the daily scaling model scales the historical rainfall series and therefore would have a similar inter-annual rainfall variability in the future and historical periods). It is interesting that the runoff modelled using rainfall from the daily scaling model shows that the number of days when runoff is less than 0.1 mm (low runoff days) will increase in the future, while the runoff modelled using rainfall from the other downscaling models indicate that the number of days when runoff is less than 0.1 mm will decrease in the future (consistently similar results in the four downscaling models) (Fig. 10). The daily scaling model is limited to using the historical rainfall sequence (but different amounts) to represent the future, while the future and historical rainfall sequences from the other downscaling models will be different and will depend on the sequences of atmospheric predictors simulated by the GCMs.

Discussion and conclusions

This paper: (i) assesses the rainfall downscaled from three GCMs using five downscaling models against observed historical rainfall characteristics, (ii) assesses the runoff modelled by the SIMHYD daily rainfall–runoff model using the downscaled daily rainfall against observed historical runoff characteristics and (iii) compares the modelled changes in future rainfall and runoff

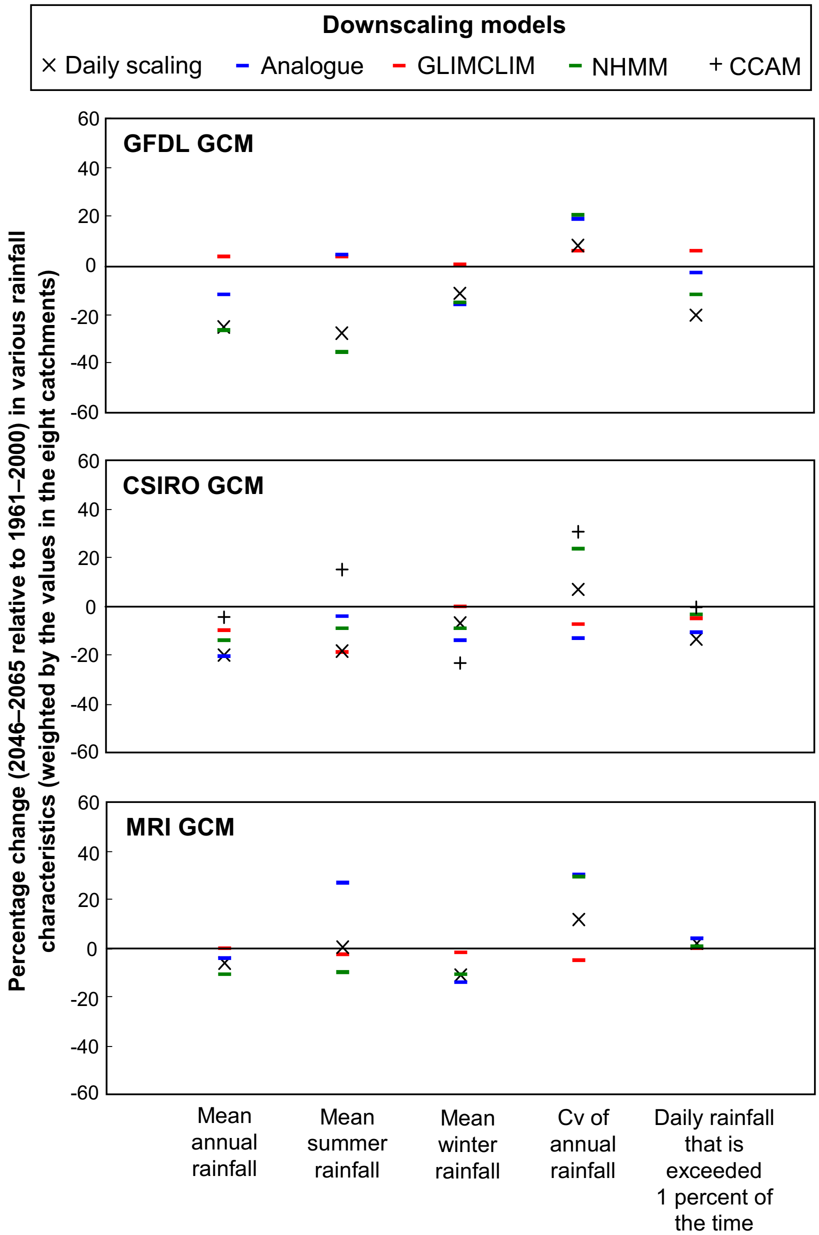


Fig. 9. Percent change in rainfall characteristics for the future period (2046–2065) relative to the historical period (1961–2000).

characteristics (2046–2065 relative to 1961–2000). The modelling study is carried out using rainfall and streamflow data from eight unimpaired catchments near the headwaters of the Murray River in south-east Australia.

The five rainfall downscaling models used, in increasing order of complexity, are the daily scaling model, the analogue downscaling model, the GLIMCLIM and NHMM statistical downscaling models and the CCAM dynamic downscaling model. The daily scaling model scales the observed historical daily rainfall series by considering the changes in the future seasonal means and daily rainfall distribution simulated by a GCM. By scaling the historical daily rainfall series to represent the future, the daily scaling model does not consider potential changes to other rainfall characteristics including the sequencing and timing of rainfall events. The analogue model accounts for changes to a greater range of rainfall characteristics by considering the daily weather types and their sequencing as simulated by a GCM. The analogue model resamples the observed historical rainfall on a day with the most similar daily weather type simulated by a GCM, and uses an inflation factor to allow projection of rainfall values outside the range of past observations (Timbal et al., 2009).

The GLIMCLIM and NHMM parametric statistical downscaling models downscale from synoptic large-scale atmospheric (and oceanic) predictors simulated by the GCMs to multi-site daily point rainfall. The GCMs can simulate the large-scale atmospheric predictors better than the large-scale rainfall, and by downscaling directly from the atmospheric predictors, the statistical downscaling models directly account for changes to many rainfall characteristics. However, subjective expert judgements are required to calibrate the statistical downscaling relationships and to bias correct GCM predictors. While possible, to date these more complicated statistical downscaling models have not been applied to gridded hydrological applications over very large regions. They need further development to generate gridded rainfall (or co-development with rainfall interpolation methods) over very large regions across different climates (e.g., in the climate change impact on runoff

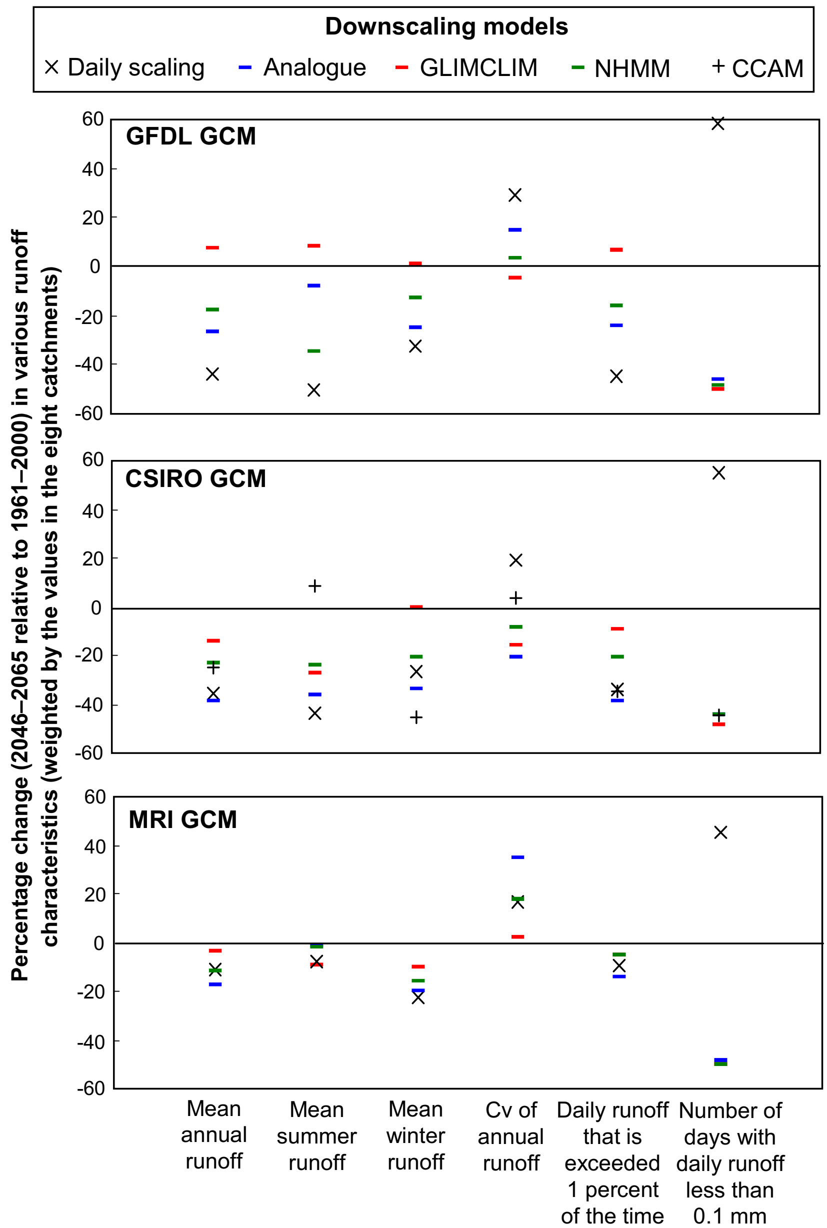


Fig. 10. Percent change in runoff characteristics for the future period (2046–2065) relative to the historical period (1961–2000).

modelling by Chiew et al. (2009) over 50,000 0.05° grid cells across south-east Australia). High resolution dynamic downscaling can directly produce the gridded daily rainfall required for hydrological applications. However, dynamic downscaling requires long computer run times and the rainfall parameterisation for the region of interest often involves many modelling experiments to properly capture the drivers for rainfall in the region.

The statistical downscaling models assessed here generally perform reasonably well when downscaling from the three GCMs for the historical climate. The modelled rainfall and runoff results (annual and seasonal means and daily distributions) from the NHMM model are very similar to the observed values. The GLIMCLIM model also generally reproduces the observed historical mean annual and seasonal rainfall and runoff, but generally overestimates the very high daily rainfall and runoff amounts. The analogue model slightly underestimates the mean annual rainfall but reproduces the observed mean annual runoff because the underestimation in the mean annual rainfall is compensated by an overestimation of the high daily rainfall that generates significant runoff. The modelled mean annual runoff using rainfall from the CCAM dynamic downscaling model is lower than the observed mean annual runoff because of the slight underestimation of mean annual rainfall and considerable underestimation of the high daily rainfall in CCAM.

All the downscaling models also generally reproduce the low rainfall and runoff characteristics. The analogue and CCAM models reproduce the observed spatial rainfall correlations (the analogue model resamples from the historical rainfall data), while the GLIMCLIM and NHMM models slightly underestimate the spatial daily and annual rainfall and runoff correlations. The above observations result from the way the models are applied here, including the spatial and temporal biases in the GCM predictors. The models (and the bias corrections of GCM predictors) can be recalibrated to better reproduce any of the observed rainfall and runoff characteristics, at some expense of other characteristics.

The future downscaled simulations show a generally consistent reduction in projected future rainfall and runoff, which is also

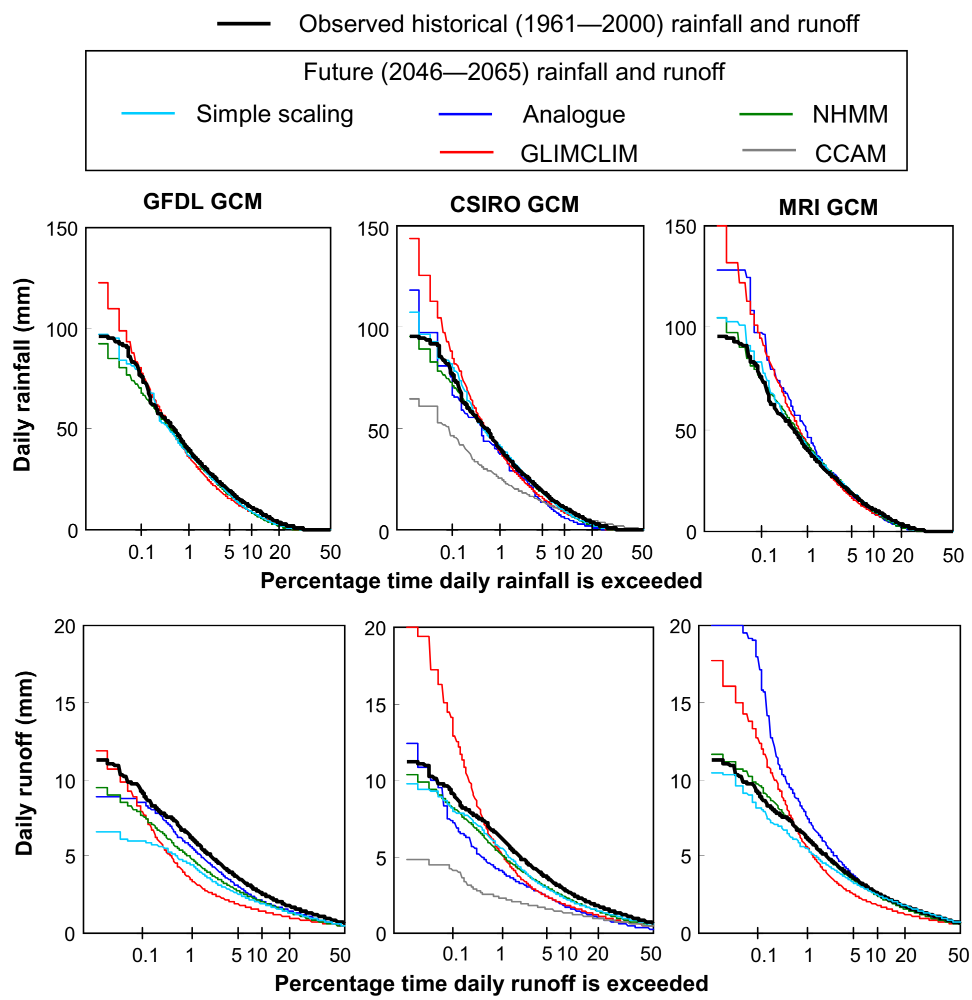


Fig. 11. Comparison of modelled future (2046–2065) daily rainfall and runoff distributions and observed historical daily rainfall distribution (1961–2000) and modelled runoff distribution using historical daily rainfall (1961–2000) for Catchment 403210.

consistent with the projections of a drier future in south-east Australia by a large majority of the IPCC 4AR GCMs. The range of rainfall projections across the GCMs and different downscaling models is quite significant, and they translate to a larger range of results in the modelled runoff. The daily scaling, analogue and NHMM models give the most similar results in mean annual rainfall, showing a −30% to −10%, −20% to −15% and −10% to 0% change in future mean annual rainfall (2046–2065 relative to 1961–2000) when downscaled from the GFDL, CSIRO and MRI GCMs respectively. The corresponding range of runoff results are −40% to −20%, −40% to −25% and −15% to −10% change in mean annual runoff for modelling using rainfall downscaled from the GFDL, CSIRO and MRI GCMs respectively. The GLIMCLIM model shows a wetter result, simulating a slight increase in future mean annual rainfall and runoff when downscaled from the GFDL GCM and a smaller decrease in future mean annual rainfall and runoff compared to the daily scaling, analogue and NHMM models when downscaled from the CSIRO and MRI GCMs. Overall there is much more consistency in winter downscaled rainfall and the resulting runoff projections compared to summer for all models, which is consistent with other studies that have found similar limitations in downscaling summer rainfall (e.g., Haylock et al., 2006).

It is difficult to determine which of the downscaling models give more realistic future rainfall projections for hydrological applications. It is difficult to differentiate between them given the significant differences in downscaled results obtained from the different GCMs. There is at least one downscaling model that simulates a future annual rainfall change more than the rainfall change simulated by the GCM directly and at least one simulating a change less than the GCM directly. Nevertheless, the range of results for the daily scaling, analogue and NHMM models, whilst significant, is generally smaller than the range of future projections from the IPCC 4AR GCMs (CSIRO and BoM, 2007; Chiew et al., 2009) where future mean annual rainfall from daily scaling and the resultant runoff projections for this region were found to differ by up to 20% and 50% respectively (Chiew et al., 2009).

The results suggest that the simpler to apply daily scaling method can be used for hydrological impact assessment studies over very large regions, particularly when the main considerations are changes to seasonal and annual catchment water yield. The analogue model is also relatively simple, but unlike the daily scaling method which can be used directly with GCM rainfall simulations over historical and future periods, the analogue model requires definition of weather types conditioned on large-scale predictors. Both the daily scaling and analogue models can be applied widely because they use the observed historical rainfall data directly, and they can directly provide gridded daily rainfall inputs required for hydrological applications over large regions. They can therefore be relatively easily used with many GCMs and global warming scenarios to represent the large range of uncertainty in future climate projections.

Nevertheless, the parametric statistical downscaling models (GLIMCLIM and NHMM) offer potential improvements in capturing a fuller range of daily rainfall characteristics, particularly when used with GCMs that adequately simulate the required atmospheric predictors. As they are stochastic models, they can also provide many realisations, allowing Monte Carlo type analysis of hydrological sensitivity to projected rainfall changes. However, considerable research is required to optimise atmospheric predictor selections (both in terms of the predictors that relate to rainfall as well as predictors that can be simulated adequately by GCMs) and improve bias correction of the GCM predictor simulations, as well as further development for robust application over large regions. The performance presented here may vary when the downscaling models are used with other GCMs and applied to other regions, and when different hydrological models are used to model runoff and other hydrological system characteristics, and these will be investigated in a subsequent study.

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