Calibration of hydrological models for medium-term streamflow prediction in a changing climate

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Abstract Prediction of medium-term (1–10 years) streamflow has become more challenging under climate change conditions. This paper presents results from a modelling study carried out to evaluate the performance of conceptual rainfall–runoff models in predicting medium-term streamflow using parameter values from model calibration against different periods of observed historical data. Four rainfall–runoff models are calibrated using the past 1 year, 2 years, 5 years, 10 years, 20 years and the entire historical daily climate and streamflow data for 20 catchments in southeastern Australia. The calibrated models are then used to predict the next 1 year, 2 years, 5 years and 10 years of streamflow. Calibrating hydrological models against the more recent data may give better medium-term streamflow predictions because the more recent data are likely to be of better quality, and they represent the current hydroclimate state and current land use and development. The results indicate that at least 10 years of data are needed for the model calibration to properly capture the range of hydroclimate variability. However, the modelling experiments here show little difference in the streamflow prediction results using parameter values from model calibrations against the past 10 or 20 years of data or the entire historical record.

Key words streamflow prediction; rainfall–runoff model; model calibration; southeastern Australia

BACKGROUND

Medium-term streamflow forecasts or predictions (1–10 years ahead) are important for water resources management and planning. The reliability of the streamflow predictions is dependent on the ability to predict the climate drivers of streamflow (mainly precipitation), as well as the ability to model the streamflow response to the climate drivers. Seasonal climate forecasts, and to a lesser extent streamflow forecasts, are now routinely provided in many countries (e.g. www.bom.gov.au/weather; http://weather.noaa.gov). Although climate prediction skills beyond one or two years are still relatively poor, there is considerable effort globally to develop medium-term and decadal climate prediction systems (www.metoffice.gov.uk/climatechange/science/hadleycentre; http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch8.html).

The hydrological models used to predict streamflow are usually developed for specific locations and modelling objectives. Most studies calibrate these models using historical climate and streamflow data. This approach is generally robust as the models are used to predict only the near-term future. However, with decadal hydroclimate variability and climate change, it is worth asking whether the streamflow predictions should be modelled using hydrological models calibrated against long historical records or against only the more recent data. The use of long historical records allows different hydroclimate regimes to be represented in the model calibration. The use of only the more recent data may better represent the current hydroclimate state or regime. This can be important for regions like southeastern Australia, which has recently experienced a severe and prolonged drought lasting more than a decade. In addition, the more recent data is likely to be of better quality. The recent data also represents current land use and development conditions.

This paper addresses this question by carrying out a modelling experiment using climate and streamflow data from southeastern Australia. The modelling experiment evaluates the performance of four conceptual rainfall–runoff models in predicting medium-term streamflow (next 1, 2, 5 and 10 years) when using parameter values from model calibration against the past 1, 2, 5, 10, 20 years and all years of observed historical data.

DATA

Daily streamflow data from 20 upland catchments in southeastern Australia, ranging in size from 300 km^2 to 1000 km^2, are used (Fig. 1). The catchments are largely unregulated and have less than 10% missing data from 1960 onwards. The streamflow data were obtained from the respective state water agencies and have been quality assessed as part of another project (Vaze *et al.*, 2011a). For this study, data since the start of record (which varies from 1930 to 1960) to 2008 are used to calibrate the rainfall–runoff models and assess the model forecasts/simulations.

This study uses daily precipitation and climate data aggregated to the catchment scale from the SILO Data Drill (Jeffrey *et al.*, 2001). The SILO Data Drill provides surfaces of daily rainfall and other climate data interpolated from point measurements made by the Australian Bureau of Meteorology. The daily potential evaporation is calculated from solar radiation, maximum and minimum temperatures and actual vapour pressure data using Morton's wet environment or equilibrium evaporation formulation (Morton, 1983).

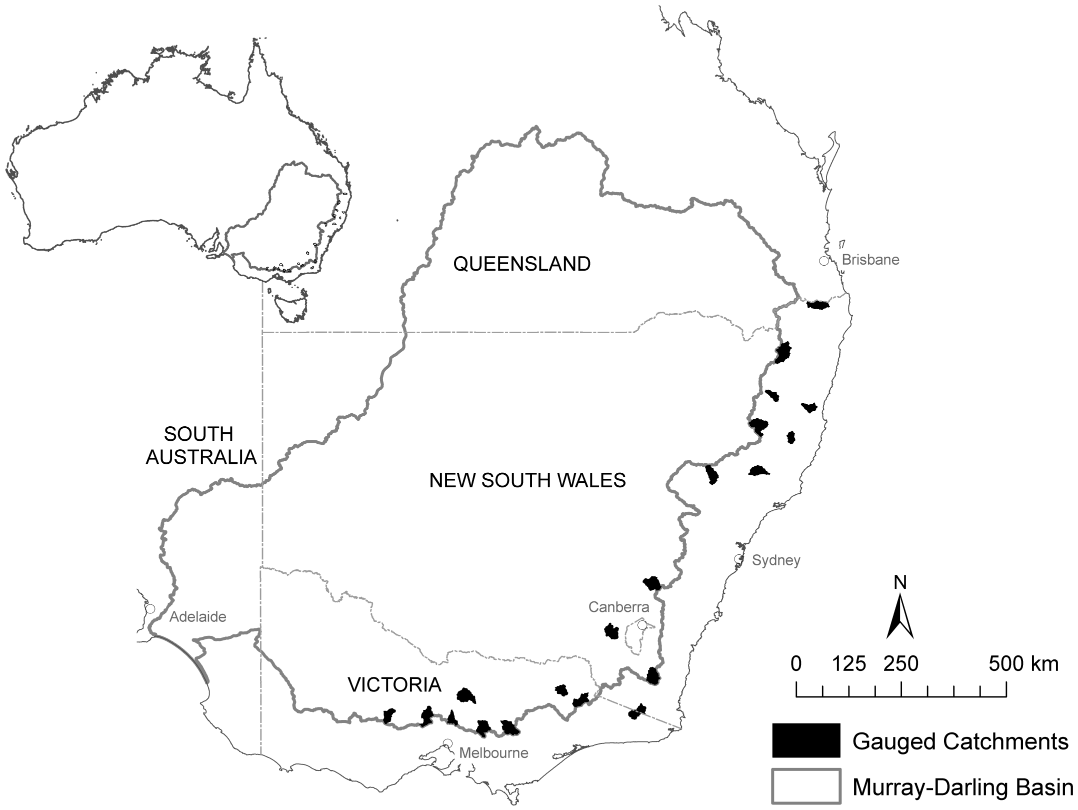

Fig. 1 Study area and catchment boundaries.

METHODOLOGY

Rainfall–runoff models

Four lumped conceptual daily rainfall–runoff models: Sacramento (Burnash *et al.*, 1973), SIMHYD (Chiew *et al.*, 2002), SMARG (Vaze *et al.*, 2004) and IHACRES (Croke *et al.*, 2006) are used in this study. For the application here, the number of parameters calibrated are 14 for Sacramento, six for SIMHYD, eight for SMARG, and seven for IHACRES. The input data to the models are daily rainfall and potential evaporation, and the models simulate daily streamflow. The models are typical of lumped conceptual rainfall–runoff models, with interconnected storages and algorithms that mimic the hydrological processes used to describe movement of water into and out of the storages. The Sacramento and SIMHYD models are widely used by water agencies, research organisations and consultants for local and regional water resources assessments throughout south-eastern Australia.

The models are calibrated against observed historical daily streamflow data in the 20 catchments. A one-year warm-up period is used in model calibrations. The optimised model parameter values are then used with the climate data to simulate the medium-term streamflow, and the simulated streamflow is compared with the observed streamflow to quantify the ability of the calibrated models in predicting the streamflow. In the model calibration, the model parameters are optimised to maximize the NSE-bias objective function, which is a weighted combination of the daily Nash-Sutcliffe efficiency (NSE) (Nash & Sutcliffe, 1970) and a logarithmic function of bias given by:

$$OBJ = NSE - 5\,|\ln(1 + B)|^{2.5}$$

where NSE is the Nash-Sutcliffe efficiency of daily streamflow and B is the bias (total modelled error divided by observed total streamflow). The coefficients of this equation control the severity and shape of the bias constraint penalty. The coefficients above are chosen such that the models are calibrated predominantly to optimise NSE, while ensuring a relatively low bias in the total streamflow (Viney *et al.*, 2009). The Shuffled Complex Evolution global optimisation method (Duan *et al.*, 1993) followed by a local optimisation method (Rosenbrock, 1960), with multiple starting parameter sets, are used to calibrate the model parameters.

Modelling experiments

For each of the 20 catchments, the four rainfall–runoff models are calibrated using the past 1, 2, 5, 10 and 20 years, and all years, of historical daily climate and streamflow data. The calibrated models are then used to predict the following 1, 2, 5 and 10 years of streamflow. Table 1 provides an example of the calibration and simulation strategy for one run. In run 1, the rainfall–runoff model is calibrated against: (i) all available streamflow data up to 1980, (ii) the past 20 years of streamflow data (1961–1980), (iii) the past 10 years data (1971–1980), (iv) the past 5 years data (1976–1980), (v) the past 2 years data (1979–1980), and (vi) the past 1 year data (1980). The calibrated parameter values from each of the six calibrations are then used to simulate streamflow for the next 1, 2, 5 and 10 years from 1981. The procedure is then repeated in run 2 with the calibration end year and simulation start year moved forward by one year (1981 and 1982 respectively, Table 1). These runs are continued until the calibration end year of 1998 is reached.

Each future simulation is therefore assessed by comparing 19 simulated and observed streamflow values. For simulation for the next 1 year, the simulation of 1981, 1982, … , up to 1999 streamflow values are assessed. For simulation for the next 2 years, the simulation of 1981–1982 total streamflow, 1982–1983 total streamflow, …, up to 1999–2000 total streamflow values are assessed. For simulation for the next 5 years, the simulation of 1981–1985 total streamflow, 1982–1986 total streamflow, …, up to 1999–2004 total streamflow values are assessed. For simulation for the next 10 years, the simulation of 1981–1990 total streamflow, 1982–1991 total streamflow, …, up to 1999–2008 total streamflow values are assessed. We are therefore assessing the ability of the models to predict total streamflow over the period of interest (next 1, 2, 5 and 10 years, respectively).

RESULTS AND DISCUSSION

The modelling results are summarised in Fig. 2. Each panel shows results for each rainfall–runoff model for each future simulation period (the next 1 year, 2 years, 5 years and 10 years). Each box and whisker plot in the panels shows the range of NSE values assessing the streamflow predictions for the 20 catchments (5th, 25th, median, 75th and 95th percentile values) using parameter values from model calibrations against each of the past 1, 2, 5, 10, 20 years and all years of historical data. All the NSE values reported in Fig. 2 assess how well the 19 predicted total streamflow values compare with the 19 observed total streamflow values (see last paragraph of modelling experiments above).

Table 1 Example of model calibration and simulation strategy. Catchment 1– observed streamflow from 1930 to 2008).

Run 1						
Calibration end year 1980	Calibration 1	Calibration 2	Calibration 3	Calibration 4	Calibration 5	Calibration 6
Calibration period	(1930–1960)–1980 (all)	1961–1980 (20 years)	1971–1980 (10 years)	1976–1980 (5 years)	1979–1980 (2 years)	1980 (1 year)
Simulation period	Use Calibration 1 parameter values to simulate stream flow for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)	Use Calibration 2 parameter values to simulate stream flow for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)	Use Calibration 3 parameter values to simulate stream flow for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)	Use Calibration 4 parameter values to simulate stream low for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)	Use Calibration 5 parameter values to simulate stream-flow for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)	Use Calibration 6 parameter values to simulate stream-flow for next one (1981), two (1981–1982), five (1981–1985) and 10 years (1981–1990)
Run 2						
Calibration end year 1981	Calibration 1	Calibration 2	Calibration 3	Calibration 4	Calibration 5	Calibration 6
Calibration period	1930–1981 (all)	1962–1981 (20 years)	1972–1981 (10 years)	1977–1981 (5 years)	1980–1981 (2 years)	1981 (1 year)
Simulation period	Repeat the same experiment as in Run 1 above and simulate streamflow for 1, 2, 5 and 10 years ahead starting from 1982 using calibrated parameter values from calibrations 1, 2, 3, 4, 5 and 6 in Run 2.					
Continue these runs until calibration end at 1998.						

The shorter-term streamflow predictions (next 1 or 2 years) are generally considerably better than the longer term predictions (next 5 or 10 years). This can be expected because the model storage levels (from the model's perspective) are likely to be best simulated at the start of the prediction period (the end of the calibration period). The modelling errors then accumulate over the simulation period, therefore resulting in poorer longer-term total streamflow predictions.

The results indicate that at least 10 years of data are needed for the model calibration to properly capture the range of hydroclimate variability. This is particularly so for the IHACRES model, where the streamflow predictions are very poor when less than 10 years of data are used to calibrate the model. For the other three rainfall–runoff models, the model simulations using parameter values from model calibration against the past 5 years of data, and to a lesser extent the past 2 years of data for the shorter-term predictions, are often not much poorer than the streamflow predictions using parameter values from model calibration against the past 10 or more years of data.

It is difficult to distinguish between the streamflow prediction results from model calibrations against the past 10 years, past 20 years and all years of data, except for IHACRES where the streamflow predictions improve when longer records are used to calibrate the model. Nevertheless, for the Sacramento model, which is used by water agencies for operational river system modelling and water resources planning across much of southeastern Australia (Vaze *et al.,* 2011b), the best median streamflow prediction result (from the 20 catchments, see Fig. 2) come from using parameter values from model calibration against the past 10 years of data. For the SIMHYD model, which is used for the recent large-scale water resources assessment across southeastern Australia (www.csiro.au/partnerships/MDBSY.html; www.seaci.org), the best median streamflow prediction result for the next 5 years and next 10 years also come from using parameter values from model calibration against the past 10 years of data, and the best median streamflow prediction result for the next 1 year and next 2 years come from using parameter values from model calibration against the past 20 years of data.

CONCLUSION

A modelling study is carried out using data from 20 catchments in southeastern Australia to evaluate the performance of four lumped conceptual rainfall–runoff models in predicting medium-

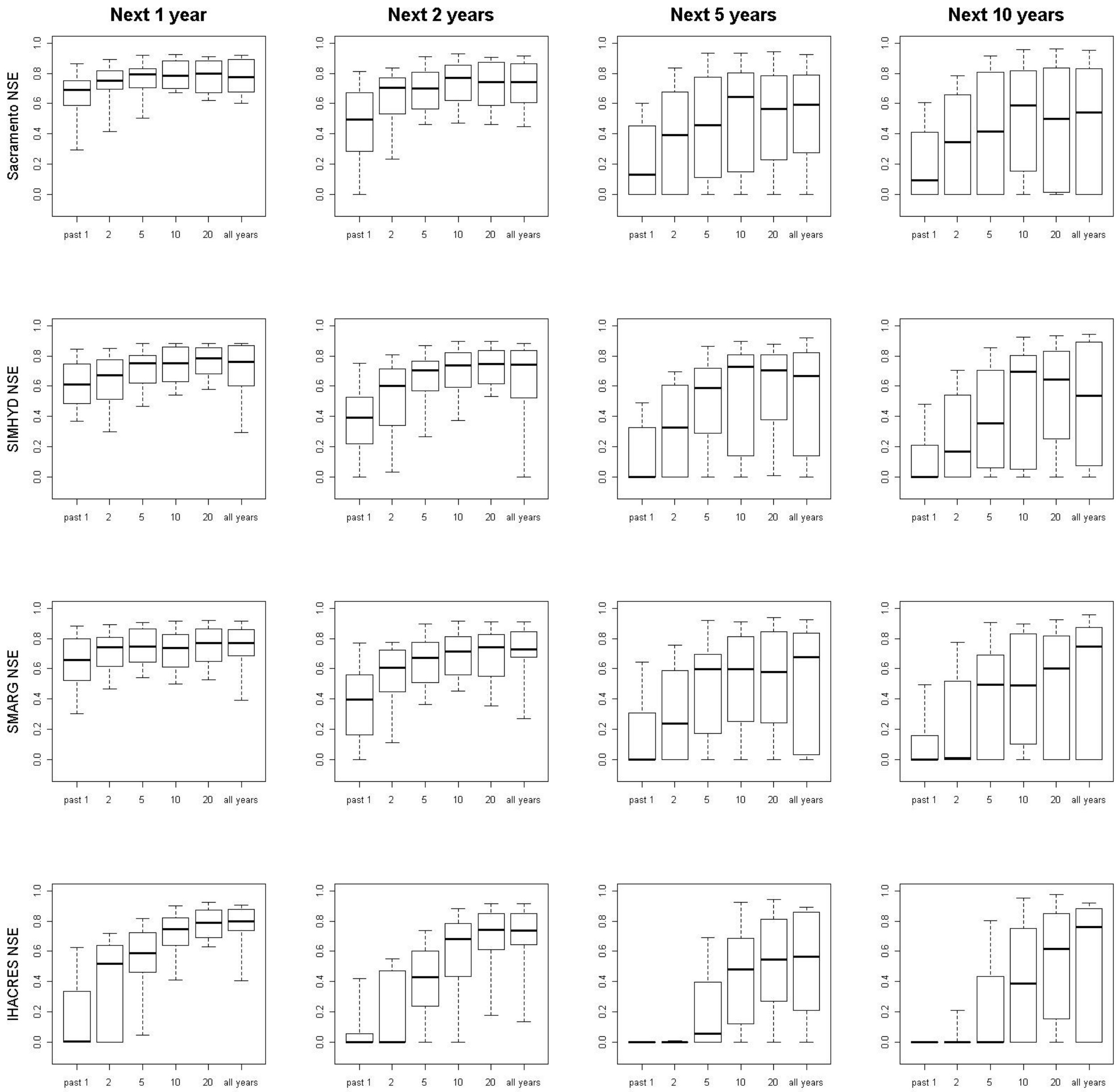

Fig. 2 NSE values summarising streamflow prediction results across all 20 catchments.

term streamflow using parameter values from model calibration against different periods of observed historical data. Calibrating hydrological models against the more recent data may give better medium-term streamflow predictions because the more recent data are likely to be of better quality and they represent the current hydroclimate state and current land use and development. The results indicate that at least 10 years of data are needed for the model calibration to properly capture the range of hydroclimate variability. However, the modelling experiments here show little difference in the streamflow prediction results using parameter values from model calibrations against the past 10 years of data, past 20 years of data, and the entire historical record.

Acknowledgements This work is supported by the CSIRO Water for a Healthy Country National Research Flagship and the South Eastern Australian Climate Initiative (SEACI). We would like to thank Jean-Michel Perraud and Biao Wang for their help with various aspects of the modelling.

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