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# Comparing flow duration curve and rainfall–runoff modelling for predicting daily runoff in ungauged catchments

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SUMMARY

Predicting daily runoff time series in ungauged catchments is both important and challenging. For the last few decades, the rainfall–runoff (RR) modelling approach has been the method of choice. There have been very few studies reported in literature which attempt to use flow duration curve (FDC) to predict daily runoff time series. This study comprehensively compares the two approaches using an extensive dataset (228 catchments) for a large region of south-eastern Australia and provides guidelines for choosing the suitable method. For each approach we used the nearest neighbour method and two weightings – a 5-donor simple mathematical average (SA) and a 5-donor inverse-distance weighting (5-IDW) – to predict daily runoff time series. The results show that 5-IDW was noticeably better than a single donor to predict daily runoff time series, especially for the FDC approach. The RR modelling approach calibrated against daily runoff outperformed the FDC approach for predicting high flows. The FDC approach was better at predicting medium to low flows in traditional calibration against the Nash–Sutcliffe-Efficiency or Root Mean Square Error, but when calibrated against a low flow objective function, both the FDC and rainfall–runoff models performed equally well in simulating the low flows. These results indicate that both methods can be further improved to simulate daily hydrographs describing the range of flow metrics in ungauged catchments. Further studies should be carried out for improving the accuracy of predicted FDC in ungauged catchments, including improving the FDC model structure and parameter fitting.



## 1. Introduction

Predicting catchment runoff time series is still a challenging task in surface water hydrology since many catchments around the world are ungauged or poorly gauged (Sivapalan et al., 2003). Therefore, the International Association of Hydrological Sciences launched a decade-long initiative, Predictions in Ungauged Basins (PUB) (http://www.iahs-pub.org/) in 2003, which has been the subject of great interest by hydrologists around the world.

Predicting catchment runoff time series in ungauged catchments has direct practical applications. It can be used for designing characteristics of spillways and embankments, managing water resource for irrigation, human and industrial water use, hydropower operation and environmental flow estimates (Parajka et al., 2013). It can also be used for risk management, such as flood and drought forecasting, water quality simulations and predictions. When combined with climate change scenarios, it can be used to predict climate change impact on water availability (Vaze and Teng, 2011; Li et al., 2014b). Furthermore, it can provide parameter set(s) for hydrological modelling to investigate land use and land cover change impacts on hydrological processes.

Numerous approaches have been developed for predicting runoff time series in ungauged catchments, the major one being the use of hydrological modelling (Parajka et al., 2013). The rainfall–runoff (RR) modelling approach has been widely used for predicting runoff times series in ungauged catchments in Europe (Bardossy, 2007; Goswami et al., 2007; McIntyre et al., 2005; Merz and Bloschl, 2004; Oudin et al., 2008; Parajka et al., 2006, 2007; Samaniego et al., 2010a, 2010b), the U.S.A. (Bai et al., 2009; Kokkonen et al., 2003; Singh et al., 2011; Wagener and McIntyre, 2005), Australia (Petheram et al., 2012; Post and Jakeman, 1999; Reichl et al., 2009; Vaze et al., 2010a, 2011; Zhang and Chiew, 2009), Canada (Samuel et al., 2011), Central America (Caballero et al., 2013), South America (Allasia et al., 2006), Africa (Kim and Kaluarachchi, 2008), and the Tibetan Plateau (Li et al., 2014a). It has also been used to predict climate change impact on runoff (Chiew and Siriwardena, 2005; Chiew et al., 2009; Vaze et al., 2010b; Wang et al., 2011) and land use

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change impact on runoff (Hundecha et al., 2008; Li et al., 2012, 2013; Tuteja et al., 2007; Zhou et al., 2013).

Various regionalisation methods have been used in hydrological models to transfer calibrated parameters obtained from gauged to ungauged catchments (Bloschl and Sivapalan, 1995). Most studies have used entire sets of parameter values from a donor catchment to model runoff in the target ungauged catchment, with choice of the donor catchment based on similarities to the target ungauged catchment and/or spatial proximity to it. Many studies have shown that the geographically closest catchment (i.e. spatial proximity) to the target ungauged catchment is often the best donor catchment (Bardossy, 2007; McIntyre et al., 2005; Merz and Bloschl, 2004; Oudin et al., 2008; Parajka et al., 2005; Zhang and Chiew, 2009). Parameter regression method is used in some studies to transfer parameters, in which the calibrated parameter sets are related to catchment attributes to obtain empirical relationships that are used to estimate model parameters in ungauged catchments (Kokkonen et al., 2003; Merz and Bloschl, 2004; Oudin et al., 2008; Parajka et al., 2005). Some comparison studies show that the spatial proximity performs better than the parameter regression for regions with dense networks of gauging stations, such as Austria and France (Oudin et al., 2008; Parajka et al., 2005), and for the less dense stream-gauge network in Canada (Samuel et al., 2011). The spatial proximity is chosen in this study to select the catchment to transfer parameters to predict runoff time series, which are compared to those obtained using flow duration curve (FDC) approach.

The FDC approach is widely used for water resource assessments (Vogel and Fennessey, 1995), such as hydropower design schemes, reliability of water supply and water quality assessments. However, there are only limited studies reported to use the FDC to predict runoff time series in ungauged catchments, mainly reported in North America (the U.S.A. and Canada) (Bloeschl and Montanari, 2010; Shu and Ouarda, 2012). The FDC approach first establishes cumulative distribution functions in gauged catchments, and then estimates the FDC (exceedance probabilities (EP) of daily runoff) for an ungauged catchment. Several cumulative distribution functions have been used to present FDC in last several decades. Among them lognormal distribution was widely used since this distribution applies several parameters whose values can be estimated as functions of readily available catchment climate and physical properties (Cutore et al., 2007; Fenicia et al., 2011; Fernandez et al., 2000; Goswami et al., 2007; Gupta et al., 2009; Li et al., 2010). The final step is to obtain the daily runoff time series using the estimated FDC and EP in the ungauged (target) catchment. The EP on any given day is estimated according to that observed in the neighbouring (donor) catchment (s) on that day (Shu and Ouarda, 2012).

Numerous approaches have been developed for predicting FDCs in ungauged catchments in last several decades (Blöschl et al., 2013; Booker and Snelder, 2012; Ganora et al., 2009; Hope and Bart, 2012; Li et al., 2010; Mohamoud, 2008; Shu and Ouarda, 2012). These approaches can be grouped into spatial interpolation methods (Castiglioni et al., 2009; Chokmani and Ouarda, 2004; Shu and Ouarda, 2012) and index flow methods (Castellarin et al., 2004, 2007; Li et al., 2010; Rianna et al., 2011; Shao et al., 2009). The spatial interpolation methods predict a FDC for the target ungauged catchment using observations from its neighbouring gauged catchments that are put on same or different weights. The index flow methods estimate FDCs in ungauged catchments using relationships between each parameter of a FDC model and the catchment's climatic and physical characteristics. The index flow methods become more and more favourable since some FDC parameters are physically meaningful, such as mean annual runoff (Castellarin et al., 2007; Smakhtin, 1997) and standard deviation of daily runoff (Li et al., 2010). The index flow methods are found being superior to the spatial interpolation methods for predicting FDC in south-eastern Australia (Li et al., 2010; Zhang et al., 2014). The FDC model developed by Li et al. (2010) and the index flow model developed by Zhang et al. (2014) are chosen in this study to predict FDCs in ungauged catchments.

The EP required in the FDC approach for predicting runoff time series is obtained using various regionalisation approaches (Booker and Snelder, 2012; Ganora et al., 2009; Hope and Bart, 2012; Li et al., 2010; Mohamoud, 2008; Shu and Ouarda, 2012). This is similar to those applied to the RR modelling, as foreshadowed. Therefore, the regionalisation approach – spatial proximity – is chosen in this study to select donor catchment (s) for predicting the EP in ungauged catchments.

To predict runoff for an ungauged catchment, the FDC and RR modelling approaches can be used not only with the nearest donor but also with several neighbouring donors. Several studies have shown that the Simple mathematical Average (SA), i.e. using the same weight for each donor to predict runoff, reduced uncertainty of RR modelling in ungauged catchments (McIntyre et al., 2005; Oudin et al., 2008; Zhang and Chiew, 2009). However, recent studies have shown that SA is often not the best solution. Inverse Distance Weighting (IDW) is found to perform better than SA in predicting daily runoff time series (Shu and Ouarda, 2012). This study investigates the performance of a single donor and multiple donors that were weighted using SA and IDW, respectively.

Studies on runoff predictions in Australia have been intensively carried out in the last several decades. Surprisingly, the hydrological modelling is almost used in all studies, and no attempts have been reported to use the FDC approach to predict runoff time series. Is there any possibility of successfully applying the FDC approach in this country? Is the FDC approach comparable to the RR modelling for predicting high flows and/or medium to low flows?

To answer these questions, this study comprehensively compares the FDC and RR modelling for predicting runoff time series using a large dataset (228 unregulated catchments) in south-eastern Australia. To achieve this objective, following models and modelling experiments are selected, and following comparisons are designed, including

(1) Selecting the three-parameter FDC model developed by Li et al. (2010) and a parsimonious RR model, GR4J (Perrin et al., 2003).
(2) Choosing donor catchments using three regionalisation schemes: the nearest neighbour, 5-donor SA, and 5-donor IDW.
(3) Designing two objective functions for calibrating the GR4J model: one for predicting high daily flows, another for predicting medium to low daily flows.
(4) Compared the FDC and RR modelling approaches for predicting both high daily flows, and medium to low daily flows, respectively.

It is expected that the findings from this study will provide guidelines for checking suitability of the FDC approach in Australia, and stimulate similar studies to be carried in other regions where climatic conditions are different.

## 2. Study area and data

The study area is located in south-eastern Australia and includes New South Wales, Victoria, part of South Australia, and part of Queensland (Fig. 1), and covers the most populated and important agricultural region of Australia, the Murray Darling Basin. The area is also of interest because of its low runoff