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Assessment of the internal dynamics of the Australian Water Balance Model under different calibration regimes

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ABSTRACT

Conceptual rainfall runoff models are used extensively in practice, as they provide a good balance between transparency and computational and data requirements. However, the degree to which they are able to represent underlying physical processes is poorly understood. This is because the performance of such models is generally assessed based on their ability to match total streamflow, rather than component processes. In this paper, the ability of the Australian Water Balance Model (AWBM) to represent baseflow and quickflow is assessed for 66 synthetic catchments with different physical characteristics and hydrological inputs under seven calibration regimes utilising a shuffled complex evolution (SCE) algorithm. The "observed" total-, base- and quick-flow hydrographs for these catchments are generated using HydroGeoSphere. The results indicate that while AWBM is generally able to match total streamflow well, the same does not apply to baseflow and quickflow, suggesting that these processes are not represented well by AWBM.

1. Introduction

Modelling approaches for estimating runoff from rainfall and evapotranspiration (ET) can be traditionally classified into three main groups: black box models, physical process based models and conceptual rainfall runoff (CRR) models (Beven, 2005). While all of these approaches have been shown to be able to predict total streamflow successfully, the degree to which they are able to represent underlying streamflow generating mechanisms is highly variable (Chen and Adams, 2006; Ferket et al., 2010; Refsgaard and Knudsen, 1996).

Black box modelling approaches, such as artificial neural networks (Abrahart et al., 2012; Maier et al., 2010; Wu et al., 2014), are at one end of the spectrum, while physically based approaches are at the other end. Black box models produce streamflow outputs solely as a function of their inputs and transfer characteristics, without any knowledge or understanding of the underlying physical processes. However, they are generally computationally efficient and can be developed using limited data. Physically based approaches attempt to simulate the detailed mechanisms of the component physical processes within the hydrologic cycle using well-established physical laws, with numerical solutions of the mathematical representation of these processes (Jayatilaka et al., 1998). Such approaches include fully integrated surface water/groundwater (SW/GW) models, such as InHM (VanderKwaak and Loague, 2001), MODHMS (HydroGeoLogic, 2000), HydroGeoSphere (HGS) (Therrien et al., 2009) and SHE (Abbott et al., 1986). However, there are problems with the application of these models in practice due to the difficulties and expense associated with obtaining the data required (e.g. due to limitations of existing instrumentation and intrinsic uncertainty in measurements), as well as their high computational demands.

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CRR models represent a compromise between the high data and computational requirements of physical process based models and the lack of transparency of black-box models. They are more computationally efficient and less data intensive than process based models, as they do not attempt to represent all physical processes explicitly. However, they are more transparent than black-box models, as they represent the assumed underlying physical processes in a conceptual manner, generally in the form of a number of interconnected storages that are linked with empirical mathematical equations to conceptualise the movement of water into, between the storages of and out of a catchment. Many different CRR models have been proposed in the literature, such as the Australian Water Balance Model (AWBM) (Boughton, 1993, 2004), the Soil Moisture and Accounting Model (SMAR) (Tuteja and Cunnane, 1999), SIMHYD (Chiew et al., 2002) and GR4J (Oudin et al., 2005), for example. These models have been able to capture enough of the dynamics of rainfall runoff simulation time series to be useful in water resources assessments.

Among the different rainfall–runoff modelling approaches mentioned above, CRR models are the most widely utilised in practice, due to their relatively simple structure, small number of parameters and production of generally acceptable results. A common feature of CRR models is that some of their model parameters have limited physical interpretation (Delleur, 1982; Troutman, 1985), due to the fact that many complex catchment physical processes are lumped together. In addition, although some of the CRR model parameters, representing the physical properties of the catchment (e.g. catchment area, surface slope), are usually measurable, there are some physical parameters, such as hydraulic conductivity and porosity, which are measurable in theory, but difficult to measure in practice. Therefore, such CRR model parameters are generally estimated by calibration, by comparing the modelled total streamflow time series with the corresponding observed data until an acceptable fit to the objective function, or an acceptable trade-off between objective functions in cases where multi-objective optimisation is used (e.g. Ahmadi et al., 2014; Gibbs et al., 2012), has been obtained. Significant research effort has been directed towards obtaining a well-defined optimal parameter set, including local-type direct search optimisation methods and globally based optimisation methods (Duan et al., 1992). However, because CRR models are usually calibrated using only observed total streamflow time series, while internally they calculate a number of additional states and fluxes, such as baseflow and quickflow, there may be many combinations of parameter values that give similar objective function values. This phenomenon is called ‘equifinality’ (Beven, 1993), and is caused by problems such as over-parameterisation of models, data limitations and structural faults in the model. As a result, even though the structure of CRR models is based on a conceptual representation of underlying physical processes, how well these processes are represented by calibrated models is generally unknown, as a good match to total streamflow does not necessarily mean that the component processes are modelled accurately. For example, similar total streamflow time series can be obtained with very different combinations of baseflow and quickflow, without consideration of the appropriateness of their quantities and dynamics.

While there have been many studies comparing the performance of CRR models using total streamflow time series (Ferket et al., 2010; Knapp et al., 1991; Post et al., 2007; Ranatunga et al., 2008), very few attempts have been made to use baseflow or quickflow estimates for CRR model internal dynamic performance assessment, due to the difficulty of accurately measuring baseflow or quickflow in the field (Dukic, 2006; McCallum et al., 2010). Recently, Ferket et al. (2010) use baseflow estimated from a physically-based digital filter (Furey and Gupta, 2001) to validate the internal dynamics of two CRR models (HBV and PDM) for a subcatchment of the Dender catchment in Belgium. As part of the study, two optimisation algorithms (SCE-UA and MWARPE) are used to calibrate the models by matching total streamflow to observations. They conclude that no clear picture emerges of which model produces the best results of simulating total streamflow, but that the MWARPE calibration algorithm and the HBV model lead to the best baseflow estimates, giving the best internal model dynamics, at least when compared with the results obtained using the Furey and Gupta filter (Furey and Gupta, 2001).

This study builds on the research by Ferket et al. (2010) by assessing (i) how well the Australian Water Balance Model, which is a commonly used CRR, is able to represent total-, base- and quick-flow for 66 synthetic catchments with different catchment characteristics and hydrological inputs and (ii) the impact of seven different calibration regimes that take internal model dynamics into account in different ways on the accuracy of total-, base- and quick-flow hydrograph prediction. While the methodology is illustrated for a particular case study, its generic nature means it could easily be adapted and applied to other CRR models around the world. The remainder of this paper is organised as follows. The methodology is given in Section 2, followed by the results and discussion in Section 3 and summary and conclusions in Section 4.

2. Methodology

The underlying premise of the proposed methodology for assessing the internal dynamics of CRR models is that fully integrated SW/GW models can be used to obtain reasonably accurate estimates of actual total streamflow, quickflow and baseflow (see Partington et al., 2012; Li et al., 2013, 2014), thereby providing a benchmark against which the internal dynamics of CRR models can be assessed (e.g. whether flow components that make up total streamflow are predicted accurately). This is a reasonable assumption, as fully integrated SW/GW models provide a rigorous representation of the underlying physical processes of hydrologic systems (Brookfield et al., 2009; Furman, 2008; Partington et al., 2012; Sulis et al., 2010; Therrien and Sudicky, 1996). They typically represent 3D variably saturated subsurface flow with the Richards' equations, and 1D and 2D surface flow with the diffusion wave approximation to the St. Venant equations. A unique feature is that such models can simulate the partitioning of rainfall into different components, including overland flow, streamflow, evaporation, infiltration and recharge, as well as subsurface discharge to surface water features (e.g. lakes and streams), in a physically realistic fashion (Therrien et al., 2009). All of the governing flow equations implemented by fully integrated SW/GW models are solved simultaneously to obtain total streamflow, baseflow and quickflow, making them ideal candidates for assessing the internal dynamics of CRR models.

While it is acknowledged that fully integrated SW/GW models are in themselves an approximation of the actual processes in real catchments, they provide the best means of quantifying the absolute volume of the flow components (e.g. baseflow and quickflow) currently available (see Partington et al., 2012; Li et al., 2013, 2014). In addition, they can be used to obtain estimates of different flow components for catchments with different characteristics (see Partington et al., 2013). Therefore they are able to provide the first step towards being able to assess the internal dynamics of CRR models under a range of physical conditions in a controlled manner.

The steps in the methodology adopted for assessing the internal dynamic performance of AWBM are given in Fig. 1. As shown, initially synthetic total streamflow (q_T^{obs}), baseflow (q_B^{obs}) and quickflow (q_Q^{obs}) hydrographs are generated using a fully integrated SW/GW model for a number of catchments with different physical properties and hydrological inputs in order to ensure the results are as generic as possible. Next, AWBMs are developed for the same catchments by using the same hydrological inputs, but different calibration methods. Finally, the performance of the AWBMs calibrated using the different methods is compared in terms of the ability to predict total-, base- and quick-flow hydrographs accurately, thereby providing a means of assessing the performance of the internal dynamics of AWBM (e.g. whether flow components that make up total streamflow are predicted accurately). Details of each step in the methodology are given in subsequent sections. It should be noted that while the AWBM is used as the CRR model in this study, the same approach should also be used to test the internal dynamic performance of other CRR models.

2.1. Catchment characteristics and hydrological inputs

The 66 synthetic catchments with different physical characteristics and hydrological inputs developed by Li et al. (2014) are used. These catchments have drainage areas ranging from 6 to 192 km^2 and are loosely based on a benchmarked integrated surface–subsurface hydrology problem, the V-catchment test case, as shown in