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Identifying Model Structure using Catchment Characteristics

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Abstract: Currently, there are many rainfall-runoff models available, but no single model can account for the uniqueness and variability of all catchments. While there has been great progress in developing frameworks for optimal model selection, the process currently selects a range of model structures *a priori* rather than starting from the hydrological data and processes. In this study, six hydrological signatures and two catchment characteristics from 108 catchments were extracted for two 7-year time periods: (1) wet and; (2) dry. The data was modelled using the GR4J model to explore the relationship between model performance, catchment features and identified parameters. The assumption is that the hydrological signatures reflect catchment behaviour, and therefore will lead to distinct parameters. Results show that during the wet period, smaller catchment areas, a greater high flow value and greater autocorrelation in the flow data were related to better calibration performance, while smaller area, greater mid flow values and peak distribution determined better performance in the dry period. Catchments also performed better in the wet period compared to the dry period. This resulted in variability in model parameters between the periods, with the soil moisture accounting parameter greatly varying in the dry period, and greater losses of groundwater in the dry period. This study is provides a foundation to optimise and improve model selection in catchments based on their unique characteristics. Overall, it suggest that the specific model structure of GR4J is more suited to modelling wet catchments with smoother flow signals.

***Keywords**:* Model behaviour; hydrological signatures; data based; GR4J.

1 INTRODUCTION

A model can be seen as a simplistic representation of a systems composed of different variables and functional relationships that can help explain system functioning. In hydrology, there is a plethora of models within different types and classifications of models (Pechlivanidis et al., 2014). While these models differ in how they explain, describe and represent hydrological functions and features, their main elements might not be very different (Fenicia et al., 2011). In the end, most modelling still depends on calibration as a test of performance (Hrachowitz et al., 2013). The calibration process aims to create a set of reasonable parameters that reflects dominant catchment processes under varying climatic conditions. However, this assumes stationary catchment behaviour (response to rainfall) for a given period of interest, and recently, there has been a shift (Wagener and Montanari, 2011) towards catchments being ever changing (Montanari et al., 2013). For example, if hydrologic conditions change due to natural and anthropogenic causes, it is reasonable to expect a change in catchment behaviour, and simulation models should be able to capture this.

This has more recently led to the consideration of models as hypotheses describing hydrological systems (Clark et al., 2011; de Boer-Euser et al., 2017). Flexible approaches to catchment modelling can test competing hypotheses for catchments, using models that have different internal process representations (de Boer-Euser et al., 2017). A common element in many studies is that model structures are selected a priori, followed by a Monte-Carlo type selection process, based on model parameter optimization and model output performance. This generates multiple possible structures based on existing model components. The “best model” is subsequently based on the best output performance after calibration (de Boer-Euser et al., 2017). These flexible approaches can help assess competing model hypotheses, but are not necessarily efficient. As a result there is a limited number of potential model structures that is generally generated for the analysis. Finally, the best model is often identified using calibration performance, which does not avoid issues around parameter equifinality.

This study starts from the data end, acknowledging the fact that all catchments are different and unique in terms of their physical features and dominant hydrological processes and this is summarized by the streamflow. Catchment characteristics are based on hydrological signatures (McMillan et al., 2017), reflecting behaviour of a catchment and the underlying processes (e.g. Wagener and Montanari, 2011). Therefore, these hydrological signatures are potential indicators of model structure, and certain signatures are expected to match better (or worse) with a specific model structure. The objective of this study is identify which catchment characteristics best match the structure of a specific rainfall-runoff model. In this study, we concentrate on the model GR4J, but the methodology is easily expanded to include other models. We also compare wet and dry periods for an Australian dataset to investigate whether the strong non-linearity affects the methodology, and whether this allows drawing conclusions about the generality of the hydrological signature – model structure match.

2 METHODS

2.1. Study Area

This study focuses on a range of catchments around Australia, located in areas with varying geologies, topographies, climates and climatic regions, vegetation and land use (Figure 1). The streamflow data of the study catchments vary in quality, with some catchments in Northern Australia and South-Eastern Australia having lower quality streamflow data (Figure 1). There is no missing data in the record as they have been gap filled using the GR4J model (BOM, 2018a).

The time periods were separated into: (1) Wet period 1990-1996; and (2) Dry period 2000-2006 (van Dijk et al., 2013) to investigate whether this has an impact on model performance. Seven years of data was chosen to account for various high and low flow events. Wet and dry period years were determined using annual rainfall anomalies from south-eastern Australia, where most of the catchments are located (BOM, 2018b). The dry years were deliberately chosen within the millennium drought to capture catchments of low or very low flow. Of the 222 catchments, the final set of catchments chosen for the study met the two following criteria: 1) Had available streamflow data in the time periods; and 2) Over 90% of the daily streamflow data had the highest quality code (Quality code A), which indicates that the streamflow value was produced with the best available technology, techniques and monitoring objectives. The final data set included 108 catchments, which are predominantly located in Victoria and Queensland. The catchment areas range from 4.5 km^2 to 119033.6 km^2 with a median of 322.55 km^2. Daily rainfall and daily maximum temperature (in lieu of Potential ET (Croke and Jakeman, 2007)) were extracted from SILO Data Drill (https://www.longpaddock.qld.gov.au/silo/datadrill/) (Jeffrey et al., 2001) at the location of the catchments, consisting of interpolated estimates from the 0.05^o x 0.05^o stored grid.

2.2. Hydrological signatures and Catchment Characteristics

Six hydrological signatures and two physical catchment characteristics were used in this study. The physical catchment characteristics used in this study are Area and River Type (Type). Rivers were classified into ephemeral and perennial rivers as a broad classification between catchments. A perennial catchment is defined as having 0 flow ≤ 1% of the time and an ephemeral catchment as 0 flow > 1% of the time. This essentially divides groundwater driven systems from surface water driven systems.

The hydrological signatures used in this study include: low flow (FDC.Low), mid flow (FDC.mid), high flow (FDC.high), autocorrelation (AC), peak distribution (Peaks) and cumulative flow (CF). The signatures are based on previous studies (Sawicz et al., 2011; Euser et al., 2013) (Table 1). The low flow, mid flow and high flow signatures are single quantities reflecting flow at the 90th, 50th, and 1st quantiles respectively. The autocorrelation (AC) represents a lag-1 autocorrelation coefficient, which is the correlation between two daily flows of the hydrograph and is useful in understanding the timing of the peaks (Winsemius et al., 2009; Euser et al., 2013):

$$\mathrm{AC} = \frac{\Sigma(\mathrm{Q_i}-\bar{\mathrm{Q}})(\mathrm{Q_{i+24}}-\bar{\mathrm{Q}})}{\Sigma((\mathrm{Q_i}-\bar{\mathrm{Q}})^2} \quad (1)$$

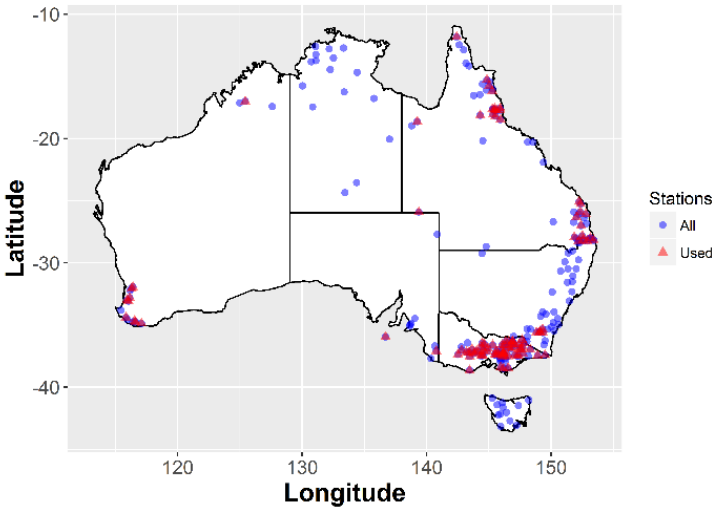

Figure 1. Map of the initial 222 Hydrological Reference Station catchments used in this study

Where $\bar{Q}$ is the average flow, $\mathrm{Q_i}$ is the discharge at a time step i. Based on Euser et al. (2013), the peak distribution measures the relative height between peak discharges in the hydrograph. The calculation uses the 50th and 10th quantiles in order to construct a slope. The signature is a measure of this slope whereby a high value represents a large peak height:

$$Peaks = \frac{Q_{10}-Q_{50}}{0.9-0.5} \quad (2)$$

Cumulative flow the total streamflow of the catchment over the six year period. It was used to determine whether the amount of water flowing in the catchment affected the performance of the model calibration. This characteristic does not take into account temporal variability of streamflow.

Table 1 Summary of the signatures and characteristics used in this study.

	Unit	Description
Signature		
FDC.low	mm	90th quantile of flow
FDC.mid	mm	50th quantile of flow
FDC.high	mm	1st quantile of flows
AC	-	Correlation coefficient between 2 points – 1 day
Peaks	-	Calculates different between the height of peak events
CF	mm	Total flow across the time period
Characteristic		
Area	km^2	
River Type	-	Perennial or Ephemeral Perennial: no flow ≤ 1% of the time Ephemeral: no flow > 1 of the time

2.3. Rainfall-Runoff Model

A daily lumped conceptual rainfall-runoff model, GR4J, was chosen for this study because it is a parsimonious model with few parameters and is computationally efficient. GR4J has been widely used in research over hundreds of catchments (Oudin et al., 2008; Perrin et al., 2003) with varying climatic conditions (Perrin et al., 2007) . A description of the model parameters and the minimum and maximum ranges used in the calibration are in Table 2. The ranges were selected in order to cover the variability of a wide range of catchments, and have been extended beyond the 80% confidence intervals described in Perrin et al. (2003). The model uses a warm-up period of 100 days in order to account for unknown initial conditions that may impact model performance. This study uses the Viney objective function, which is a weighted combination of the Nash-Sutcliffe efficiency and the logarithmic function of the relative bias (Viney et al., 2009). The calibrations and model simulations were run using the R-package Hydromad (Andrews et al., 2011) and calibrated to optimise the Viney objective function using 1000 sample parameter sets.

Table 2 GR4J parameter description and set ranges

Parameter	Units	Description	Range
x1	mm	Size of production reservoir	50 – 2000
x2	mm	Water exchange coefficient	-10 – 10
x3	mm	Capacity of routing store	5 – 500
x4	day	Unit hydrograph time base	0.5 - 10

2.4. Statistical Analysis

Principal component analysis (PCA) was used to explore the correlation between the hydrological signatures, the catchment characteristics and the objective function values. Biplots were created to examine the magnitude and direction of the vectors. A longer vector signifies higher loadings and a greater influence on the analysis. A simple multiple linear regression was used to relate the Viney objective function value and the hydrological signatures and catchment characteristics. The assumptions were tested prior and post-regression and accounted for through log-transformation if necessary. The fitted model was:

$$Viney = a_0 + a_1 \ln(Area) + a_2 \ln(CF) + a_3 \ln(FDC.low) + a_4 \ln(FDC.mid) + a_5 \ln(FDC.high) + a_6 AC + a_7 \ln(Peaks) + a_8 \ln(Slope) + a_9 Type \quad (3)$$

Where $a_{0\ldots9}$ represents the estimated coefficients from the linear regression. The Akaike's information criterion (AIC) (Akaike, 1974) was used as a performance measure to reduce the number of predictors and create a more parsimonious model.

3. RESULTS

From the 108 catchments modelled in both the wet and dry periods, two catchments from the wet period and five catchments from the dry period did not converge in the optimisation. Catchment A0020101 was also removed from the analysis for both wet and dry periods, as its large size (119033.6 km^2) greatly skewed the statistical analysis, resulting in 105 catchments in the wet period and 102 in the dry period. Figure 2 highlights the exceedance probability of the Viney objective function values. Clearly, the wet period has relatively a higher objective function value than the dry period. Over 50% of catchments exceeded a value of 0.8 in the wet period and 0.72 in the dry period. A summary of the hydrological signatures indicated that mean and median low, mid and high flows values were lower in the dry period than the wet period. With the exception of AC, the relative differences between the mean and median values for all other signatures indicated positive skewness. Low median mid flow values in both periods suggests varying hydrological regimes around Australia. In terms of catchment size, only four catchments have an area above 5000 km^2. In the dry period, AC is weakly correlated to FDC.high (0.21, Pearson's correlation) compared to the wet period (-0.0003, Pearson's correlation). Between the FDC.low and FDC.mid signatures, AC is also weakly correlated, with a 0.36 and 0.41 Pearson's correlation for the wet and dry periods.

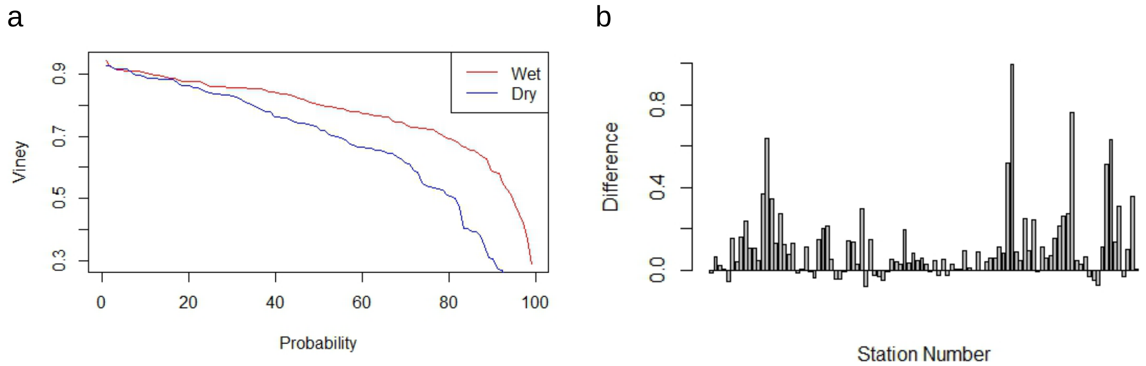

Figure 2. a) Exceedance probability of the Viney objective function value for both wet and dry periods for all catchments b) Difference in objective function values between the wet and dry periods (wet – dry).

Figure 3 was created using log-transformed values of all signatures except for AC to reduce the influence of high leverage on the analysis. The "Area" predictor was also log-transformed. The PCA was also scaled because the signatures and catchment characteristics are not measured on the same scale and have variable ranges. The PC1 and PC2 of the wet period explain 57.52% and 15.66% of the variance, respectively, and the PC1 and PC2 of the dry period explain 62.02 and 14.61% of the variance. In the both periods, Peaks, CF, FDC.mid and FDC.high dominated PC1, and AC and Area dominated PC2. In general this suggests that the second principal component explains the memory and storage of the catchments, while the first principal component is more related to floods and high flow. Area has more emphasis in the dry period. Figure 3 shows there is a clear separation between ephemeral and perennial river types, with vectors in the direction of perennial rivers. All signatures are positive in PC1 for both periods with the exception of Area. In the dry period, all variables except Area and AC are highly correlated. There is more variability in the relationship between hydrological signatures in the wet period, particularly for FDC.low and FDC.mid, where these values show a larger difference in the wet period compared to the dry period. Negative PC1 indicates less high flow and peaks, negative PC2 indicates less memory, as highlighted above.

The main principal components (Figure 3) are reflected in the outcome of the regression analysis (Table 3), with Area, FDC.mid, FDC.high and AC significant in the wet period, and Area, FDC.mid, and Peaks significant in the dry period. Log-transformed values were used to reduce the leverage of outliers and to reduce the effect of autocorrelation in the residuals (Saft et al., 2015). Many variables are co-linear, for example, cumulative flow has a correlation of 0.96 with FDC.high**.** Variance inflation factors (VIFs) were used to quantify the impact of collinearity**.** Variables with VIFs above a cut-off of value of 4 (Craney and Surles, 2002) were dropped.

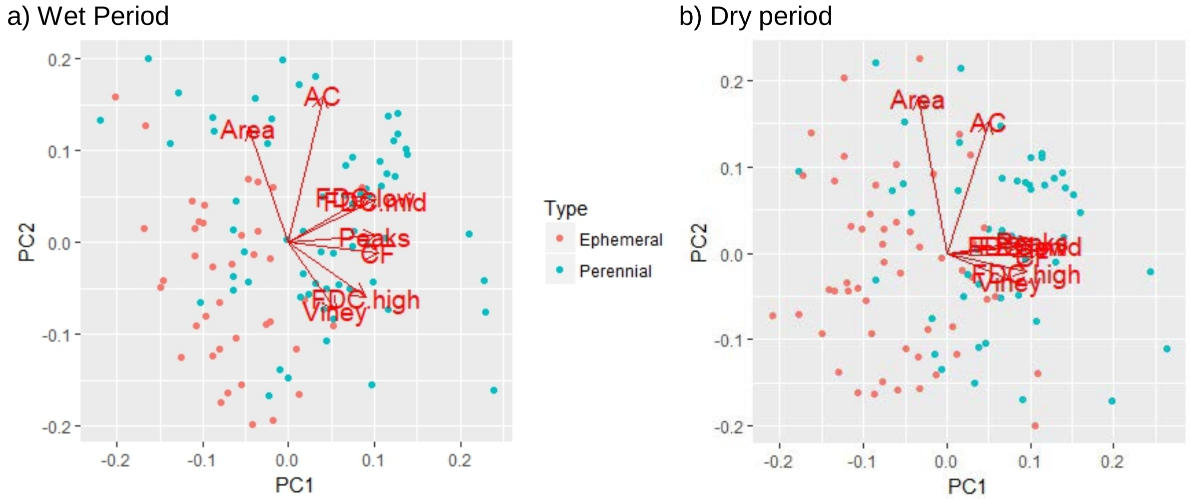

Figure 3. Biplots of the catchment characteristics in the: a) wet and b) dry period. The PCs are plotted against river type. Perennial is classified as no flow ≤ 1% of the time and Ephemeral is classified as no flow > 1% of the time.

Table 3 Summary of multilinear regression between Viney's objective function and catchment characteristics in the wet period (r^2 = 0.27, left), and in the dry period (r^2 = 0.50, right). All variables significant at $p < 0.01$.

Wet period			Dry Period		
Variable	VIF	Coefficient	Variable	VIF	Coefficient
Intercept		0.52	Intercept		0.64
ln(Area)	1.25	-0.035	ln(Area)	1.08	-0.038
ln(FDC.mid)	2.82	-0.062	ln(FDC.mid)	3.93	-0.14
ln(FDC.high)	2.04	0.12	ln(Peaks)	3.85	0.18
AC	1.60	0.30			

After calibration the relationship between model parameter outputs, signatures and characteristics of the observed data was investigated. Parameters x1, x3, and x4 have been transformed to reduce the leverage of outliers in the analysis. In Figure 4, PC1 of the wet period explains 46.82% of the variation in the dataset and PC2 explains 16.54%. In the dry period, PC1 explains 47.48% and PC2 14.23% of the variation in the dataset. In PC1 of the wet period, the dominant variables are CF, FDC.mid, and Peaks (~0.39) and in PC2, the dominant variables are x4 and AC (>0.5). Interestingly, in the dry period, all variables except x4 and area are negatively correlated. In terms of magnitude, Peaks, CF, and FDC.mid dominate PC1, similar to the wet period. In PC2, the trend is similar to the wet period with x4 and area dominating. In the wet period, the production store (x1) is negatively correlated to x2 and area. The routing storage capacity (x3) is moderately correlated to CF, FDC.low, FDC.high (not shown). The time based unit (x4) is moderately negatively correlated to x2, x3, and the flow signatures with the exception of AC. Generally, the relationships between the model parameters and the signatures is similar in both periods, although the magnitude of the relationship may differ.

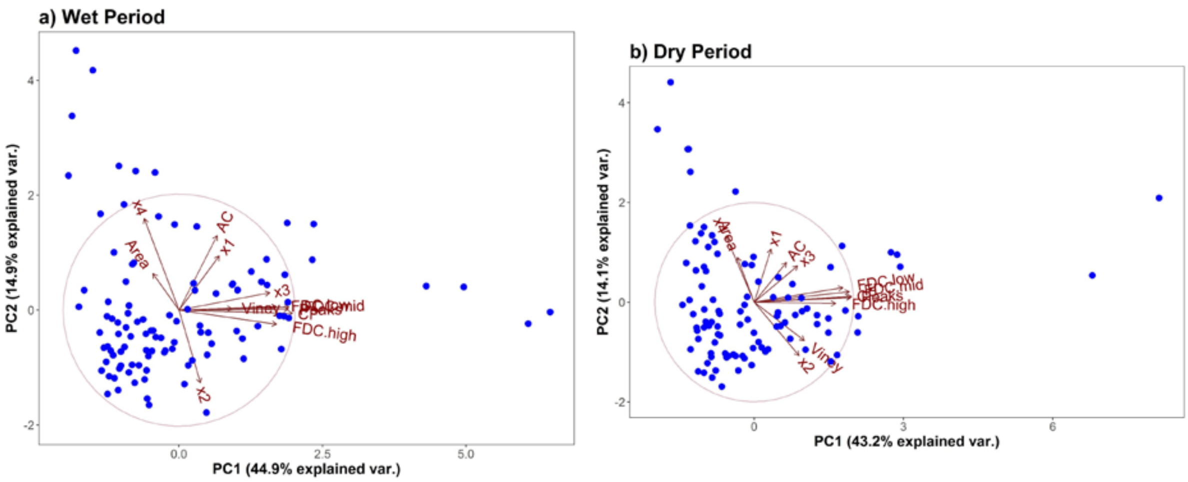

Fig. 4: Biplots of the model parameter outputs, hydrological signatures and other characteristics for both: (a) wet; and (b) dry periods

There was little difference in the distribution of the values for the x1, x3, and x4 parameters, but for individual catchments values appear to be quite different between both periods. The dry period has more outliers for x1 and a smaller spread of values, suggesting the soil moisture store in this period is fitted to a lower capacity than in the wet periods. In terms of x2, the dry period has more negative values fitted compared to the wet period, meaning that to close the water balance, the model “lost” more water from the catchments.

4. DISCUSSION

Larger catchments were found to be more difficult to calibrate in both time periods, with Area negatively correlated to the Viney objective function value, confirming that GR4J is less suitable for such catchment sizes. For the same catchments, variability in climate and hydrological regime can affect calibration performance for a particular model. In the wet period, the hydrological signatures explain less of the variance in the objective function (r^2 = 0.35) compared to the dry period (r^2 = 0.50). In the wet period, catchments with greater high flow, autocorrelation (AC, memory) and more mid flows contribute to higher Viney objective function values. In the dry period, catchments with a greater peak distribution had greater objective function values, which is strongly correlated to FDC.high (0.91 Pearson’s Correlation). FDC.mid also strongly correlates to Peaks (0.86 Pearson’s Correlation), but was not removed because the VIF did not exceed 4 (Table**.** 4**).** Therefore, it seems that even during the dry period, catchments with greater high flows had higher objective function values.

FDC.low had not much impact on the objective function, possibly due to co-linearity, at least while using Viney as an objective function. The fact that Viney’s objective function includes the NSE, might bias the calibration towards high flows. In addition, 99 of the 102 catchments had an FDC.mid under 1 mm during the dry period so it is not surprising that it is strongly correlated to FDC.flow (0.96 Pearson’s correlation). This suggests the 50th quantile may not be a good cut-off to capture mid flow. As all FDC flow signatures are positive, and strongly correlated in some cases, alternative hydrologic signatures that can better capture low, mid and high flows should be considered. Other studies have used the 95% quantile (Laaha and Blöschl, 2006) and the $\widehat{Q}_{7,10}$ low flow statistic (Eng and Milly, 2007) as a low flow signatures. Incorporating other low flow hydrological signatures can further extend this work (e.g. Pfannerstill et al., 2014).

In the regression analyses performed in this study, not all the model residuals strictly follow the assumption of linearity, despite the log-transformation of the flow signatures and characteristics. Skewness may create high leverage points that may negatively influence parameter estimates. The fact that the data was filled in using GR4J (BOM, 2018a) might have influenced the goodness of fit in some of the catchments. However, as the infilling is minor (given the high quality data used), we don't think this has influenced the results in a major way.

Perrin et al. (2007) found that wetter years produce more robust results during the calibration of model parameters. Between the wet and dry years, the major differences between the parameter estimates is the size of the x2 parameter, the groundwater exchange coefficient. The mean and median value in the wet period is -1.53 and -0.32 respectively compared to -3 and -1.58 in the dry period. A negative x2 represents a loss of water from the routing store. In the wet period, approximately 56% of catchments had a negative x2, suggesting some "leaking" of the catchment whereas in the dry period, approximately 65% of the catchments have a negative x2. This implies that Australian catchments have inter-catchment groundwater exchanges occurring, which may or may not be justified. It could be that x2 would be replacing water loss due to evaporative processes and should be set to 0 even if this degrades goodness of fit (Hughes et al., 2015). Hughes et al. (2012) found that there was a strong linkage between groundwater storage and streamflow in South Western Australia, and acting as "memory" for the catchment. Saft et al. (2015) also found that long dry periods can shift rainfall-runoff relationships in catchments by up to 46%. Finally, persistent dry conditions can modify groundwater interactions so gaining systems become less so and losing systems become dominant (Kinal and Stoneman, 2012).

The Viney objective function might also be an issue, as relatively poor models can provide a high values (Jain and Sudheer, 2008). Fenicia et al. (2007) argues that the use of a single objective function can create unrealistic hydrograph representations and bias certain signals at the expense of others and suggests using two objective functions can be more realistic to reproduce observations.

5. CONCLUSION

Many of the hydrological signatures used were quite correlated and there was variability in the usefulness of these signatures and characteristics in explaining the calibration performance of catchments with varying climates. The performance in the wet periods were best explained through the high flows (FDC.high), Area, mid flows (FDC.mid) and the autocorrelation (AC) signatures. During the dry period the mid flows and peak distribution (Peaks) were most usefulness in explaining the variance in performance the dry period. However co-linearity between predictors showed that high flows and autocorrelation were equally as useful, with higher memory (AC) leading to higher performance. The signatures and catchment characteristics explained more of the variance in performance in the dry period than the wet period, but the wet period provided better results in terms of the objective function. Potential future research would include other hydrological signatures. Further studies may also include other models, as well as multiple-objective functions.

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