Utilising hydrological signatures to improve baseflow estimation

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Abstract: Baseflow separation is a common exercise in hydrology. Recursive digital filters are often used to estimate baseflow by utilising the streamflow hydrograph. Calibration of these filters is noted for requiring subjective decisions. This study extended previous research by Su et al. (2016a). The utility of the signatures identified by Su et al. (2016a) was explored for the case of real world catchments. The output of a numerical experiment to determine parameters for hydrograph separation were compared to the default calibration technique as well as tracer-based baseflow estimates. It was found that hydrological signatures could be utilised to determine a set of parameters for the Eckhardt (2005) recursive digital filter from real streamflow data. The outcome of this process provided a range of baseflow values. This range demonstrated the uncertain nature of estimating baseflow and could be used as a more robust and reproducible method of hydrograph separation. However, areas of further research were also identified.

1 Introduction

Baseflow separation is a common exercise in hydrology. Distinguishing between types of flow within the hydrograph enables flood frequency analysis, understanding hydrological processes as well as providing information regarding water supply, irrigation, and quality in resources management (Su et al., 2016b; Tallaksen, 1995). Additionally, groundwater discharge into streams supports continued flow during dry periods. Effective river basin management is important for food production, economic benefit and environmental protection. It is particularly important in Australia due to water scarcity, seasonal variability and the changing climate.

Although hydrograph separation is not necessarily dichotomous, it is common practice to reduce the hydrograph to two distinct components: storm runoff and baseflow (Su et al., 2016b) or quickflow and slowflow (Schwartz, 2007). There is no fixed boundary between these components. Flow paths that are sensitive to rain events are considered quickflow (Schwartz, 2007). Quickflow includes not only surface or near-surface runoff, but also groundwater in near saturated conditions. The remaining flow is considered baseflow and is dominated by groundwater discharge (Chapman, 1999). This definition of baseflow will be adopted herein.

Hydrograph separation employs continuous streamflow records which are widely available for many catchments. However, it is difficult to monitor baseflow physically at the catchment scale (Costelloe et al., 2015). For this reason, many authors have contributed to improving and refining methods of determining baseflow within a catchment. Many methods for hydrograph separation have been proposed in recent history. One commonality with many baseflow separation techniques is a lack of objectivity in separation selection or parameter determination (Eckhardt, 2005; Rimmer & Hartmann, 2014; Schwarz, 2007; Tallaksen, 1995; etc.). Although physical reasoning is utilised to perform hydrograph separation, Nathan and McMahon (1990) note that the “quantitative elements of separation techniques are essentially arbitrary” (p. 1468). Therefore, improving reproducibility and objectivity in baseflow separation techniques is a valuable exercise.
This study applied research previously performed by Su et al. (2016a) by exploring the utility of their proposed hydrological signatures when used on real-world catchments. Independent estimates of baseflow from tracer studies as well as current hydrograph separation practices were compared to the method described by Su et al. (2016a). These analyses were performed with the aim of executing plausible and reproducible hydrograph separation that also captured the uncertainty surrounding baseflow estimation techniques.

2 Literature Review

2.1 Hydrograph Separation

Hydrograph separation can be performed using numerous techniques. Separation methods can include graphical manipulation (Linsley et al., 1988; Pettyjohn & Henning, 1979), single input, one parameter numerical models (Lyne & Hollick, 1979; Chapman, 1991), or multiple input, many parameter conceptual models (Furey & Gupta, 2001; Huyck et al., 2005). This study focussed on the application of the Eckhardt (2005) baseflow separation method.

The Eckhardt (2005) recursive digital filter (RDF) estimates baseflow by applying a low-pass filter across the stream hydrograph (Cartwright et al., 2014). This technique aims to attenuate the high-frequency response of storm runoff generated by rainfall events. The resultant curve is considered to be the baseflow component of the hydrograph.

The Eckhardt (2005) filter was developed to improve upon and extend previous RDFs proposed by Lyne and Hollick (1979), Chapman (1991) and Chapman and Maxwell (1996). The filter contained two parameters that could be defined using real catchment characteristics. Firstly, $\alpha$ was defined by Chapman (1991) as the recession constant. This parameter was calculated using a process called recession analysis, which is discussed in the next section. Eckhardt (2005) introduced a new parameter: $\text{BFImax}$. This was defined as the long-term fraction of baseflow to streamflow (Eckhardt, 2005). The filter was defined by the equation

$$\hat{b}_n = \frac{(1 - \text{BFImax})\alpha\hat{b}_{n-1} + (1 - \alpha)\text{BFImax}y_n}{1 - \alpha\text{BFImax}}$$

subject to the condition

$$\hat{b}_n \leq y_n.$$  \hspace{1cm} (1')

where $\hat{b}$ is the baseflow estimate and $y$ is streamflow.

This filter improved on Lyne and Hollick (1979) and Chapman and Maxwell (1996) as both parameters are physically based. However, Eckhardt (2008) noted that more research needed to be done to reduce the subjectivity in choosing $\text{BFImax}$. In practice, there has been some success in calibrating the Eckhardt filter with tracer data (Eckhardt, 2008; Lott & Stewart, 2016). However, the uncertainty in these estimations is rarely captured in the resultant hydrograph.

The Eckhardt (2005) filter has shown popularity in the literature as a preferred choice RDF (Collischonn & Fan, 2013; Gonzales et al., 2009; Costelloe et al., 2015; Su et al., 2016a; etc.). For this reason, it was the target filter to test the ABC analysis (discussed in Section 4.2) technique in this study.

2.2 Recession Analysis

The Eckhardt (2005) filter assumes that groundwater discharge is linearly proportionate to the groundwater storage available. For recession periods where flow is equal to baseflow, Equation (1) reduces to:
where \( T_R \) represents recession periods in excess of five days. Nathan and MacMahan (1990) and Wittenberg (1995) observe that the linear storage model is problematic. Physical realities like the depth of the channel, the thickness of aquifers, and varying recharge patterns introduce nonlinearity into the system (Nathan & MacMahan, 1990). Wittenberg (1995) argued that the linear model of recession was a poor approximation for longer durations of recession. However, Chapman (1999) demonstrated that the linear storage model was sufficiently accurate for recession periods less than ten days.

One method to determine the recession constant is to plot all values \( y_{t+1} \) against \( y_t \) for those flow values that occur during recession periods (Eckhardt, 2008). The slope of the linear upper bound of this plot is taken to be the recession constant. The argument is that the upper-bound represents streamflow that is entirely made up of baseflow as recession periods longer than five days presumably occur only when quickflow is absent. The recession constant can be a useful guide for appropriate values for the \( \alpha \)-parameter in performing baseflow separation with the Eckhardt (2005) filter. In this way, recession analysis could be used as a method to observe how hydrological signatures performed relative to current calibration techniques.

2.3 Tracer Estimation

Studies of dissolved geochemical tracers offer one of very few means to volumetrically separate flow into its constituent pathways within a catchment. Fundamentally, tracer studies utilise mass-balance equations to determine various fluxes within a catchment (Cartwright et al., 2014). For mass-balance to be suitable, there must be a large difference in tracer concentration between groundwater and surface waters (McCallum et al., 2012). Additionally, there needs to be the same number of suitable tracers as there are unknowns in any mass-balance. For this reason, studies measuring multiple tracers have become prevalent in the literature (Eg: Cartwright et al., 2011; Costelloe et al., 2015; Atkinson et al., 2015). Although implemented in different ways, the aim was to improve the accuracy for various flow paths by combining the results of multiple tracer-based estimates.

Similar to baseflow filters, tracer studies estimate flow path fluxes with large amounts of uncertainty (Cartwright et al., 2015; Atkinson et al., 2015; Costelloe et al., 2015; Cartwright et al., 2011). Additionally, the utility of tracer studies for estimates of baseflow has been questioned (Cartwright et al., 2014). Cartwright et al. (2014) conclude that many sources of delayed flow are geochemically similar to surface runoff. This ambiguity means baseflow is likely to be underestimated in catchments with water stored in floodplains or comprised of bank storage return. However, in this way, tracer studies yield a minimum expected value for baseflow.

2.4 Hydrological Signatures

Hydrological signatures are the patterns that arise in hydrology that can be quantitatively described (Su et al., 2016a). Signatures relevant to the objective of hydrograph separation were considered. Su et al., (2016a), on which this report extends, tested numerous hydrological signatures for joint calibration of the Eckhardt (2005) filter. Their study used synthetic catchments to determine the suitability of hydrological signatures. This study extended these hydrological signatures to real world catchments.

Su et al. (2016a) identified two metrics that performed well in calibrating \( \alpha \) and \( \text{BFI}_{\text{max}} \). The highest performing hydrological signature attempted to encourage low-frequency variations across a seasonal timescale. The signature was defined as:

\[
S_{\text{low}} = \frac{E[(\bar{b} - y_{\text{low}})^2]}{\text{var}(y_{\text{low}})},
\]
where $y_{\text{low}}$ is the median of streamflow along a 6-month moving window, $E(o)$ is expectation and $\text{var}(o)$ is the variance across the data.

The relationship between streamflow flashiness and BFI was another signature that also performed well. A high flashiness index is an attribute of streams with high event flow and low baseflows (Baker et al., 2004). This disparity means that a stream with a high flashiness is likely to correspond with a low BFI. The calibration metric in Equation (4) was defined by this relationship. It implemented the Richards-Baker flashiness index ($F_{RB}$) as an a priori estimate of the baseflow index where $BFI \sim 1 - F_{RB}$.

$$S_{BFI} = \left| \frac{E(h)}{E(y)} - \max(0, 1 - F_{RB}) \right|. \quad (4)$$

These signatures were paired with the commonly accepted property that baseflow is equal to streamflow during recession periods to prevent trivial answers. The signature associated with recession periods was defined:

$$S_{\text{rec}} = \frac{E_{TR} \left[ (h - y)^2 \right]}{\text{var}_{TR}(y)}. \quad (5)$$

By combination of the signatures in Equations (3), (4) and (5), Su et al. (2016a) developed the following metrics to calibrate the Eckhardt (2005) filter parameters:

$$\rho_1 = \max(S_{\text{rec}}, S_{\text{low}}) \quad (6)$$

$$\rho_2 = \max(S_{\text{rec}}, S_{BFI}) \quad (7)$$

In addition, a third metric was constructed for examination based on the signatures identified above:

$$\rho_3 = \max(S_{\text{rec}}, S_{\text{low}}, S_{BFI}) \quad (8)$$

These metrics were selected for experimentation within this study.

### 2.5 Summary

Standard practice for baseflow separation with the Eckhardt (2005) filter continues to rely on the independent calibration of its two parameters. Additionally, calibration of $BFI_{\text{max}}$ as Eckhardt (2008) described requires information regarding physical catchment and aquifer properties. Further, Eckhardt (2008) noted that his proposed method is not likely to produce reliable results. However, calibration of the Eckhardt (2005) filter using tracer estimates has shown promise. This indicates that there may be potential for further development of calibration techniques with the Eckhardt (2005) filter. Su et al. (2016) demonstrated that joint calibration of the Eckhardt (2005) filter parameters was possible with the use of hydrological signatures. However, their research explored joint calibration using synthetic catchment data with known baseflow values. For this reason, there was an opportunity to explore the potential for hydrological signatures to be applied to real-world catchments. In doing so, it was hoped that improved baseflow estimation could be achieved with commonly available streamflow data without the need for costly tracer studies or rainfall data that is difficult to be applied across a catchment scale reliably.
3 Methodology

This study applied the signatures identified by Su et al. (2016a) in a numerical experiment using streamflow data from real world catchments. The results from the experiment were then compared to results from existing baseflow estimation techniques within the literature. In this way, the utility of signatures to eliminate subjective parameter selection, as well as demonstrating the uncertainty in hydrograph separation, could be explored.

4 Methods

4.1 Field Data

Six previous studies were identified in the literature to provide tracer baseflow estimate data for a range of catchments in Australia. Each catchment was paired with streamflow data sourced from the Bureau of Meteorology. This selection provided a variety of catchment types in which results from the experiment could be compared to both default parameter selection as well as tracer-based estimates of baseflow.

Table 1: Summary of catchments selected for the study.

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Catchment Size</th>
<th>Median Flow</th>
<th>Study Coverage</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gellibrand River, Victoria</td>
<td>250 km²</td>
<td>97 ML/day</td>
<td>Perennial</td>
<td>Costelloe et al., 2015</td>
</tr>
<tr>
<td>Nambucca River, NSW</td>
<td>431 km²</td>
<td>105 ML/day</td>
<td>Perennial</td>
<td>McCallum et al., 2012</td>
</tr>
<tr>
<td>Richmond River, NSW</td>
<td>≈7000 km²</td>
<td>84 ML/day</td>
<td>Perennial</td>
<td>Atkins et al., 2016</td>
</tr>
<tr>
<td>Deep Creek, Victoria</td>
<td>≈450 km²</td>
<td>1.5 ML/day</td>
<td>Ephemeral</td>
<td>Cartwright et al., 2015</td>
</tr>
<tr>
<td>King River, Victoria</td>
<td>≈750 km²</td>
<td>282 ML/day</td>
<td>Perennial</td>
<td>Cartwright et al., 2014</td>
</tr>
<tr>
<td>Dalrymple Creek, Queensland</td>
<td>≈240 km²</td>
<td>93 ML/day</td>
<td>Ephemeral</td>
<td>Martinez et al., 2015</td>
</tr>
</tbody>
</table>

Figure 1: Map showing locations of selected study catchments.
4.2 Computation of Eckhardt (2005) Filter Parameters

Approximate Bayesian Computation (ABC) was used to determine acceptable parameters for the Eckhardt (2005) filter for a given catchment. Put simply, ABC is a sampling technique that tests various candidate combinations of filter parameters and determines their suitability based on a given cost function, or functions (Vrugt & Sadegh, 2013). The acceptance function used was based on the metrics described in Equation (6), (7) and (8). A parameter pair will be accepted if:

\[
\rho_n(\alpha, BFI_{\text{max}}) \leq \varepsilon, \tag{9}
\]

where \(\varepsilon\) is the error threshold of the acceptance function. This was then used to determine a set of acceptable parameters for the Eckhardt (2005) filter.

Parameter pairs for the streamflow gauges from the identified catchments were generated with the method outlined by Vrugt (2016). Contrary to the method outlined by Vrugt (2016) however, convergence on a set of parameter pairs was not achieved by increasing the length of the analysis. Instead, a brute force approach was taken to increase \(\varepsilon\) in small increments until convergence was achieved. In this way, the lowest value of \(\varepsilon\) was sought that would provide a valid set of parameter pairs. This alternative was chosen as it was thought that the metrics are not naturally convergent and could not be relied upon to converge with increasing computation time.

Once accepted parameter pairs for the Eckhardt (2005) filter were identified, a baseflow timeseries was calculated for each parameter pair. These timeseries could then be used to determine a range for the baseflow component of the streamflow hydrograph.

Analysis was performed for each combination of three variables:

- Metric tested \((\rho_1, \rho_2, \rho_3)\)
- Whole streamflow record or post-2010
- Flow threshold on or off (Equation 1')

<table>
<thead>
<tr>
<th>Label</th>
<th>Metric</th>
<th>Equation 8’ applied</th>
<th>Part of record</th>
<th>Label</th>
<th>Metric</th>
<th>Equation X’ applied</th>
<th>Part of record</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i)</td>
<td>(\rho_1)</td>
<td>✗</td>
<td>Whole</td>
<td>(vii)</td>
<td>(\rho_1)</td>
<td>✗</td>
<td>2010-16</td>
</tr>
<tr>
<td>(ii)</td>
<td>(\rho_1)</td>
<td>✓</td>
<td>Whole</td>
<td>(viii)</td>
<td>(\rho_1)</td>
<td>✓</td>
<td>2010-16</td>
</tr>
<tr>
<td>(iii)</td>
<td>(\rho_2)</td>
<td>✗</td>
<td>Whole</td>
<td>(ix)</td>
<td>(\rho_2)</td>
<td>✗</td>
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</tr>
<tr>
<td>(iv)</td>
<td>(\rho_2)</td>
<td>✓</td>
<td>Whole</td>
<td>(x)</td>
<td>(\rho_2)</td>
<td>✓</td>
<td>2010-16</td>
</tr>
<tr>
<td>(v)</td>
<td>(\rho_3)</td>
<td>✗</td>
<td>Whole</td>
<td>(xi)</td>
<td>(\rho_3)</td>
<td>✗</td>
<td>2010-16</td>
</tr>
<tr>
<td>(vi)</td>
<td>(\rho_3)</td>
<td>✓</td>
<td>Whole</td>
<td>(xii)</td>
<td>(\rho_3)</td>
<td>✓</td>
<td>2010-16</td>
</tr>
</tbody>
</table>
4.3 Comparison

Two avenues of comparison were pursued to evaluate the effectiveness of the above computation technique: default parameter values and tracer baseflow estimates.

4.3.1 Current Practice

At present, the Eckhardt (2005) filter is suggested to be calibrated using recession analysis and assumed values for BFImax as described in Eckhardt (p.169, 2008). These methods offer a baseline for which this study can be evaluated. For this study, the accepted $\alpha$-parameters were compared to the presently used recession constant. Recession analysis as performed by Costelloe et al. (2015) was used to solve for the 50th and 98th percentile upper-bound of the recession analysis. These values provide plausible bounds for the $\alpha$-parameter derived from ABC analyses.

In addition to recession analysis, Eckhardt (2005) defined default BFImax values based on some key characteristics of the catchment. The default parameter values offered another baseline value for which comparison can be made. Further, the default parameters were applied to perform hydrograph separation on each of the catchments. The resulting hydrographs were used to compare similar timeseries data from the ABC results.

4.3.2 Tracer-based Estimates

As discussed in Section 2.3, tracers can offer an estimate of the groundwater inflow. Due to a lack of information regarding data collection, tracer estimates were applied across a week or month long period depending on the information available. A line of best fit using the power function in Microsoft Excel was then used to determine an equation that could be used to describe the relationship between streamflow and baseflow. This function was in the form $\hat{B}_n = Ay_n^B$, where $A$ and $B$ were determined by Excel’s curve fitting tool. To avoid poor confidence in the function, it was only extrapolated for streamflows up to 120% of the maximum recorded streamflow where tracers were sampled. The baseflow-streamflow relationship was used to determine a BFImax for comparison by taking the average of all BFI values that could be modelled by the power function. Additionally, the power function was used to generate a baseflow timeseries. This was compared to the timeseries produced from ABC analysis.

![Figure 2: Accepted parameter pairs from ABC analysis for the King River.](image)

5 Results

In a study of synthetic catchments, Su et al. (2016a) demonstrated that the $\rho_1$ signatures returned the closest fit to real baseflow data. The next most effective was $\rho_2$. This finding is supported in these results. However, as additional signatures beyond six month moving median ($\rho_1$) and streamflow flashiness ($\rho_2$) were not tested, it cannot be said with certainty that $\rho_2$ was the second most effective
signature. In addition, $\rho_3$ was also applied. This method was previously untested in the literature. It was found that there was very little change between results when using the whole streamflow record versus using only measurements taken post-2010. For this reason, all illustrated figures utilise whole of record streamflow data using labels defined in Table 2.

First, the $\alpha$-parameter was compared to those that could be expected from recession analysis. Figure 3 graphically outlines the relationships between recession analysis and the parameter values accepted by the ABC analysis method. The upper green line represents the value of the recession constant that

Figure 3: Alpha parameter comparison. Box plots indicate accepted range of parameters in ABC analysis. Green lines represent the 50th and 98th percentile from recession analysis.
would commonly be used for each catchment and is defined as the 98th percentile upper-bound of the recession analysis. Within each of the assessed catchments, the ABC method for $\rho_1$ and $\rho_3$ consistently accepted $\alpha$-parameters nearer the higher values of the recession analysis. This is consistent with the current practice when choosing an $\alpha$ value. Conversely, $\rho_2$ when evaluated without the baseflow threshold applied, consistently accepted $\alpha$-parameters that were below the 50th percentile of the recession analysis. When baseflow thresholding was applied, the median $\alpha$-parameter value for each catchment was similar to the median of the recession analysis. However, the $\alpha$-parameter for this
case was poorly constrained for all catchments. This lack of constraint is illustrated in Figure 3, case iv. Additionally, the threshold case for each signature was less well constrained when compared with the non-threshold case of the same metric. It is expected that applying a baseflow threshold allows for lower constraint on parameters (in particular, for increased parameter values) as the limiting nature of the threshold prevents impossible outcomes. This outcome will be discussed further in Section 6.

Next, a comparison of BF$_{max}$-parameters was made between the current method described by Eckhardt (2005), tracer estimates and accepted values from ABC analysis. A power function for two

![Figure 5: Timeseries comparison. Green lines are the 5th to 95th quantile of the modelled baseflow from ABC. Red line is baseflow estimated using power function. Blue line is baseflow estimated using Eckhardt (2005) default value. Black line is streamflow.](image)
catchments, Nambucca River and Dalrymple Creek, could not be generated due to poorly described sampling dates and a lack of data points, respectively. Constraint was relatively poor for all signatures when baseflow thresholding was applied, in comparison to the no-threshold case. This is visualised in Figure 2. Excluding Deep Creek, BFImax values estimated using tracer data were significantly lower than the default values from Eckhardt (2005). This result was consistent with the literature where similar comparisons have been made (Cartwright et al., 2014; Collischonn and Fan, 2013; Costelloe et al., 2015; Zhang et al., 2013). Accepted BFImax-parameters from ABC analysis for King River, Richmond River and, Gellibrand River tended to deviate towards the tracer-based power function estimate. Conversely, accepted parameters for the Deep Creek catchment were further from the power function estimate than the default parameter value described by Eckhardt (2005). It should be noted, however, that the power function was developed on few data points and may not be reliable across large timescales. These findings are graphically represented in Figure 4.

Finally, a timeseries comparison was performed to visually compare the three baseflow estimation techniques employed in this study. Due to study constraints, only threshold-case baseflow estimates from $\rho_1$ and $\rho_2$ were compared. It was expected that $\rho_3$ would produce a timeseries similar to $\rho_1$ as the accepted parameter pairs have high similarity. Consistently, the baseflow range when calculated using the accepted parameters for $\rho_1$ was closer to the power function estimate than $\rho_2$ as well as the default values. Figure 5 outlines the timeseries for three streams. In order to improve the accuracy of the power function, the month plotted coincides with a tracer study sampling period.

6 Discussion

The results of this study indicate that there may be merit in applying ABC analysis techniques to hydrograph separation. In particular, $\rho_1$ fitted recession analysis well and consistently estimated baseflow values approaching similar to those derived from tracer-based estimates.

A feature of ABC is that each signature within a given metric can be weighted by setting the acceptance value ($\epsilon$) independently (Vrugt, 2016). It was noted that parameter sets for each metric with thresholding applied tended to include values such that $\alpha \rightarrow 1$, BFImax $\rightarrow 1$. This could be a symptom of not independently setting $\epsilon$. As both parameters approach 1, $\hat{b} \rightarrow q$ when a baseflow threshold is applied. This will result in $S_{\text{rec}} \rightarrow 0$ and could skew results that favour the recession signature. One option considered could have been to remove $S_{\text{rec}}$ from the signature. However, this approach was found to lead to trivial solutions (Su et al., 2016a). Additionally, it was found that a metric that combined all three streamflow signatures ($\rho_3$) resulted in accepted parameter pairs similar to the metric based on the six-month moving median streamflow ($\rho_1$). Figure 2 shows $\rho_3$ parameter sets partially eclipsing those from $\rho_1$. It is suspected that this is due to equal weighting being assigned to each of the signatures within the acceptable error function (Equation (2)). Devising a method to determine appropriate weighting to each signature was not within the scope of this study. For this reason, it cannot be concluded whether $\rho_3$ can offer an improved baseflow estimate, or not.

It appears that generally, all separation methods tended to estimate larger baseflow volumes compared to tracer-fitted estimates. However, there were limited data points to which the power function was fitted. This reduced the confidence in the power function to reproduce accurate baseflow values across a long period. Further, a two-parameter power function was chosen due to the lack of data-points over the three-parameter function proposed by Lott and Stewart (2013) which had produced promising results when fitted to tracer data by Lott and Stewart (2016). Another limitation was caused by a lack of tracer samples available for high flow events. This meant that the power function could not be confidently applied during high flow events. An example of this can be seen in Figure 6 where the red line is discontinuous around high flow events. These issues arose due to the spatial nature of most groundwater tracer studies. Temporal changes in baseflow on a daily timescale were not relevant to the source material. Further, many reference studies were completed across a reach that did not align perfectly with surrounding streamflow gauges or lacked an upstream gauge entirely. Also, tracer-based estimation methods have additional uncertainties including identification of end members (Klaus & McDonnell, 2005) and, simplification of catchment properties (Tallaksen, 1995). These limitations affected the accuracy of tracer data in this study.
Caution should also be taken when comparing accepted parameters from ABC analysis with other methods. As previously mentioned, the two parameters in the Eckhardt (2005) filter are defined using significant assumptions. Recession analysis and long-term mean baseflow offer an intuitive point of comparison based on our understanding of each of the filter parameters. However, with a method such as ABC, compensation will occur to achieve convergence around the best fit of the target metrics. In this way, the quality of the results is determined by the signatures used instead of conscious subjective parameter selection. Further, ABC can be utilised to define and demonstrate the uncertainty surrounding filter parameters in a way that is reproducible. Current applications of baseflow separation with the Eckhardt (2005) filter fail to address uncertainty within the output hydrograph.

![Example of baseflow estimation across a one-year period modelled for Gellibrand River. Black line is streamflow. Blue line is baseflow estimated via Eckhardt (2005) default parameters. Red line is baseflow estimated via power function. Green lines are 95th, 50th (dashed), and 5th quantile baseflow estimates via ABC.](image)

**Figure 6:** Example of baseflow estimation across a one-year period modelled for Gellibrand River. Black line is streamflow. Blue line is baseflow estimated via Eckhardt (2005) default parameters. Red line is baseflow estimated via power function. Green lines are 95th, 50th (dashed), and 5th quantile baseflow estimates via ABC.

## 7 Conclusion

Parameter selection for the Eckhardt (2005) filter using an Approximate Bayesian Computation technique was compared to present parameter selection methods and tracer-based baseflow estimates. From this comparison, there is an indication that the ABC method, when applied to specific streamflow metrics, can offer a reproducible and more intuitive hydrograph separation that reflects the uncertainty surrounding baseflow estimation. A metric based on the six-month median of the streamflow ($\rho_1$) provided the best estimate of baseflow within the scope of this study. The benefit of utilising signatures present within the streamflow hydrograph is that there can be less subjective choice in parameter selection. Additionally, by accepting a large set of parameter pairs, a range of baseflow estimates can be generated. Arguably, this is a better representation of the uncertainty in estimating baseflow and thus more valuable than a single estimate. However, further investigation is required to appropriately determine the weight to apply to each of the signatures within a metric when performing ABC analysis. Additionally, little research has been performed to observe temporal measurements of baseflow. An opportunity for future research exists to further validate signature-based parameter selection with a detailed field study.
8 References


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