

Storage in south-eastern Australian catchments

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Key Points:

- Storage is poorly understood and under-studied in hydrology
- We adopt a multi-method and multi-catchment approach to estimate storage in south-eastern Australia
- The results highlight that the methods available to broadly derive storage at the catchment scale are inadequate

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11 **Abstract**

12 Storage and subsequent release of water is a key function of catchments that moderates
13 the impact of meteorological and climate extremes. Despite the fact that many key hy-
14 drological processes depend upon storage, there are relatively few studies that focus on
15 storage itself. Storage is difficult to quantify due to catchment heterogeneity and the paucity
16 of data on key catchment characteristics that largely determine storage, such as soil, hy-
17 drogeology, and topography. We adopt a multi-method approach to estimate the dynamic
18 and extended dynamic storages using hydrometric data in 69 catchments in the Murray-
19 Darling Basin in south-eastern Australia. We test relationships between the derived catch-
20 ment storages and hydrological and physical characteristics that potentially control stor-
21 age. The study catchments tended to have small dynamic storages relative to the extended
22 dynamic storage; proportionally the dynamic storages were all less than 10% of the ex-
23 tended dynamic storage. While storage estimates produced by the different methods and
24 study catchments varied, the order in which they ranked was consistent. Correlations
25 between catchment characteristics and estimates of storage were inconsistent; however,
26 the results indicated that greater storage is strongly associated with steeper catchments
27 and smoother hydrographs. This study highlights limitations in the current methodol-
28 ogy to derive storage and the quality of widely applied hydrometric data. We reinforce
29 the need to collect data that can validate storage estimates and call for new approaches
30 that can broadly estimate storage at the catchment scale.

31 **1 Introduction**

32 The hydrological system is perhaps best characterized by the volume of water stored
33 within a catchment (McNamara et al., 2011). Storage directly influences the runoff re-
34 sponse (Spence, 2007), stream water chemistry (Kirchner & Neal, 2013; Hrachowitz et
35 al., 2015), drought severity (Van Loon & Laaha, 2015), and transpiration behavior (Dawson,
36 1996; Jackson et al., 2000). The seminal variable source area work of Hewlett and Hi-
37 bbert (1967) highlighted the importance of storage, but the topic has been mostly ne-
38 glected by hydrologists. Instead, much of the work on understanding the hydrological
39 system has focused on quantifying catchment fluxes (Soulsby et al., 2009). Much of the
40 neglect stems from the elusive nature of storage. Storage is difficult to characterize or
41 observe at the catchment scale (Seyfried et al., 2009), owing to its large spatial hetero-

42 geneity and the limited inference that can be drawn from individual observations (Soulsby
43 et al., 2008).

44 An improved sense of how, and how much, water is retained in catchments will in
45 turn provide a greater understanding of how water is released from catchments (McNamara
46 et al., 2011). As an example, a major goal of catchment hydrologists has been to accu-
47 rately predict streamflow for scenario analysis and forecasts. However, to achieve good
48 model performance, the water balance and other hydrological processes are often mis-
49 represented (Kirchner, 2006) which results in a poor simulation of the temporal storage
50 and release of water. This is exemplified in the study by Fowler et al. (2020), which showed
51 five conceptual models failing to reproduce long-term declines in water storages over an
52 extended drought. Rather, the models prioritize seasonal cycles of water storage in a more
53 dynamic fashion. Beyond water yield from catchments, storage also strongly controls wa-
54 ter quality. Many biogeochemical reactions depend on subsurface contact time (Hornberger
55 et al., 2001; Kirchner, 2003) and this subsequently affects the persistence of pollutants
56 (Hrachowitz et al., 2016).

57 More recently, the role of storage within the hydrological cycle has received greater
58 attention (e.g., Spence, 2007, 2010; Soulsby et al., 2009; McNamara et al., 2011; Tetzlaff
59 et al., 2011; Buttle, 2016; Fan, 2019). This recognizes that storage is under-studied (Soulsby
60 et al., 2009), but recent interest is also driven by novel methods that describe catchment
61 storage, such as through recession analysis (Kirchner, 2009), tracer applications (Soulsby
62 et al., 2009; Gleeson et al., 2016) and remote sensing methods at a larger scale (Ramillien
63 et al., 2008). McNamara et al. (2011) proposed using standardized methods and com-
64 parative investigations of storage across a range of environments to obtain insights into
65 relationships between catchment processes and storage dynamics. Since then, a few stud-
66 ies have employed multi-method and multi-catchment approaches to investigate storage
67 (e.g., Sayama et al., 2011; Peters & Aulenbach, 2011; Staudinger et al., 2017), however
68 globally such studies are still sparse.

69 Much of the current research has been devoted to understanding storage in head-
70 water catchments. Headwater catchments are often located in mountainous regions and
71 provide high volumes of river flows to lowland areas, such that they are considered the
72 “water towers of the world” (Viviroli et al., 2007). These flows are important for main-
73 taining hydrologic connectivity and ecological integrity of regional hydrologic systems

(Freeman et al., 2007) and are important sources of water for downstream human water demands. Headwater catchments in montane areas are particularly vulnerable to climate change and other anthropogenic developments (Viviroli et al., 2011; Immerzeel et al., 2020) and a lack of a deep understanding of catchment storage threatens global water security. In the south-east of Australia, forested catchments along the Great Dividing Range are responsible for large inflows into the Murray-Darling Basin, which is Australia’s largest food bowl (Wheeler, 2014) and a region of significant ecological importance. In Australia, as well as in other temperate to semi-arid regions across the globe, droughts are a frequent phenomenon and are often severe (Leblanc et al., 2009; van Dijk et al., 2013). Water stored and later released by headwater catchments serve as a buffering mechanism that can reduce the impacts of drought and understanding the role catchment storage plays in sustaining streamflows and evapotranspiration is therefore crucial.

In this study, we build on past multi-method and multi-catchment approaches and estimate storage in catchments spread across the Murray-Darling Basin. We are interested in whether landscape and climate factors are indeed related to derived storage, such that specific catchments can be protected and managed effectively. Catchment characteristics may also reveal common controls on catchment storage (Wagener et al., 2007; Geris et al., 2015; Saft et al., 2016). More specifically, our aims are to (1) Estimate and evaluate the dynamic storage and extended dynamic storage of catchments in the Murray-Darling Basin (2) Determine if there are robust relationships with catchment characteristics; and (3) Evaluate if the comparative approach is useful to gain insights into catchment storage.

2 Materials and Methods

2.1 Study catchments and data

Catchments located within the Murray-Darling Basin were selected from the Australian Bureau of Meteorology (BOM) Hydrological Reference Station (HRS) project (X. S. Zhang et al., 2016). HRS are unregulated catchments with high-quality streamflow records that are in areas with minimal land use change and impacts of water resource development. As such, they are ideal for long-term analysis. The study period focuses on 1990-2018. This time range includes both distinct wet and dry periods. The 1990s, early 2010s, and

104 2016 were notably wet, while the Millennium Drought (van Dijk et al., 2013) was a se-
 105 vere drought that extended over much of the 2000s.

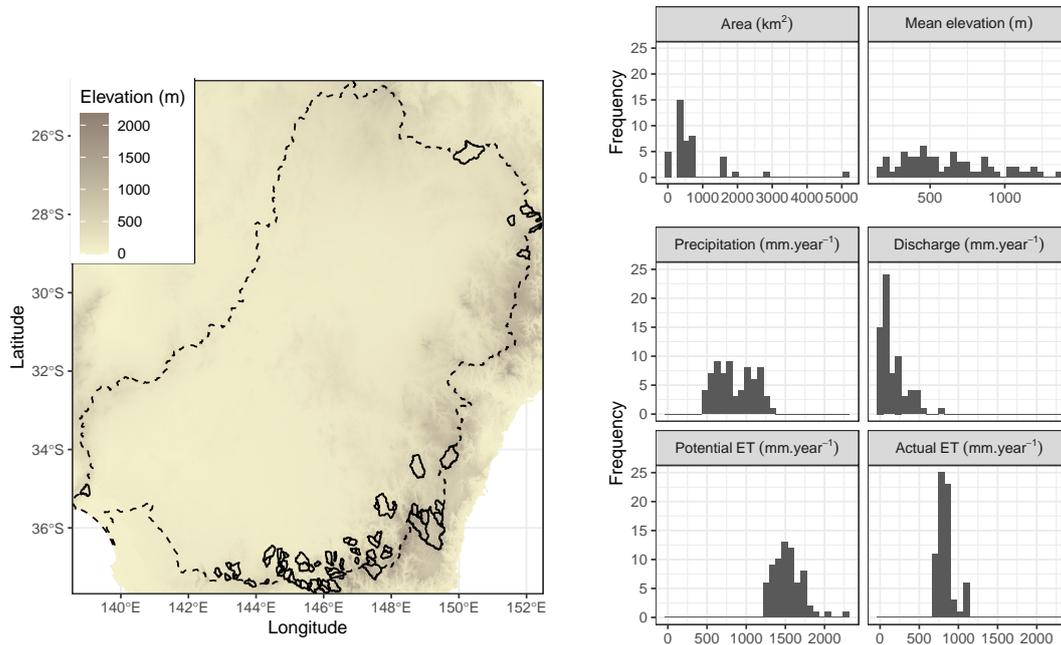


Figure 1. Catchments included in this study and histograms of key hydrological and physical variables. The solid lines are the boundaries of the catchments, and the dashed line is the boundary of the Murray-Darling Basin. Potential and actual evapotranspiration (ET) are calculated using Morton’s models. Other key catchment characteristics are summarized in Table 1.

106 Streamflow data were obtained from the BOM HRS portal (<http://www.bom.gov.au/water/hrs/>).
 107 There is no missing data in the records as the BOM gap fills the data using the GR4J
 108 model. Gauges selected for the study needed to have more than 70% of data classified
 109 as containing the best available data (quality code A) or good data (quality code B) over
 110 the study period. After data quality filtering, 69 catchments remained for analysis (Fig-
 111 ure 1). Area weighted daily catchment means of precipitation, maximum temperature,
 112 minimum temperature, and Morton’s potential and actual evapotranspiration (Morton,
 113 1983) were extracted from the SILO gridded database (Jeffrey et al. (2001); www.longpaddock.qld.gov.au/silo/).
 114 The choice of Morton’s models was motivated by the suitability of the models to calcu-
 115 late catchment water balances and in rainfall-runoff modeling (McMahon et al., 2013).

116 A summary of the main catchment hydrological forcings is presented in Figure 1.
 117 Mean annual precipitation (P) ranges from 473 to 1341 mm.year⁻¹. Mean annual catch-

118 ment streamflows (Q) ranges from 19 to 804 mm.year⁻¹ and are highly variable, where
119 the annual coefficient of variation of Q (Q_{cv}), defined as the ratio of the standard de-
120 viation to the mean of annual flows, ranges from 0.23 to 1.72 (Table 2). Morton’s mean
121 annual potential evapotranspiration (PET) for the catchments ranges from 1244 and 2298
122 mm.year⁻¹ and vastly exceeds Morton’s actual transpiration (AET) which ranges from
123 717 to 1124 mm.year⁻¹, indicating most catchments are water limited.

124 **2.2 Defining catchment storage**

125 Water storage can be considered the sum of the individual stores of water that ex-
126 ist within catchments. These individual stores may include groundwater, soil moisture,
127 vegetation, surface water, and snow. The term storage is used inconsistently in hydrol-
128 ogy and may include or omit some of these features due to the diverse applications and
129 various domains of hydrological studies (McNamara et al., 2011; Condon et al., 2020).
130 We follow the suggestion of McNamara et al. (2011) and use standardized methods to
131 investigate the relationship between storage dynamics and catchment processes. Staudinger
132 et al. (2017) created a scheme that distinguishes different conceptual catchment storages
133 (Figure 2). The different conceptual storages are total storage, immobile storage, mo-
134 bile storage, extended dynamic storage, and dynamic storage. The partitions are based
135 on specific methodologies that derive them and are of practical interest. Total storage
136 is the sum of all water stored in the catchment and includes all mobile and immobile wa-
137 ter. Total storage can be estimated through an aggregation of hydrogeological assess-
138 ment of aquifers, groundwater, soil moisture information, and aboveground storage (e.g.,
139 snow). In reality, total storage cannot be precisely quantified. Immobile water is water
140 that does not participate in the hydrological cycle and may be found in bedrock with
141 poor permeability (Staudinger et al., 2017). Mobile water is water that participates in
142 the hydrological cycle and is connected to catchment fluxes. Mobile water can include
143 water with a variety of ages, such as soil moisture (young), shallow groundwater, and
144 deep groundwater (old) passing through fractured rock systems. Estimates of mobile wa-
145 ter can be obtained using tracer methods (Birkel et al., 2011; Cartwright & Morgenstern,
146 2016; Howcroft et al., 2018) or through hydrological transport models (van der Velde et
147 al., 2012; Rinaldo et al., 2015).

148 Dynamic storage is the storage that controls streamflow dynamics (Spence, 2007;
149 Kirchner, 2009; Birkel et al., 2011). Dynamic storage can be estimated from streamflow

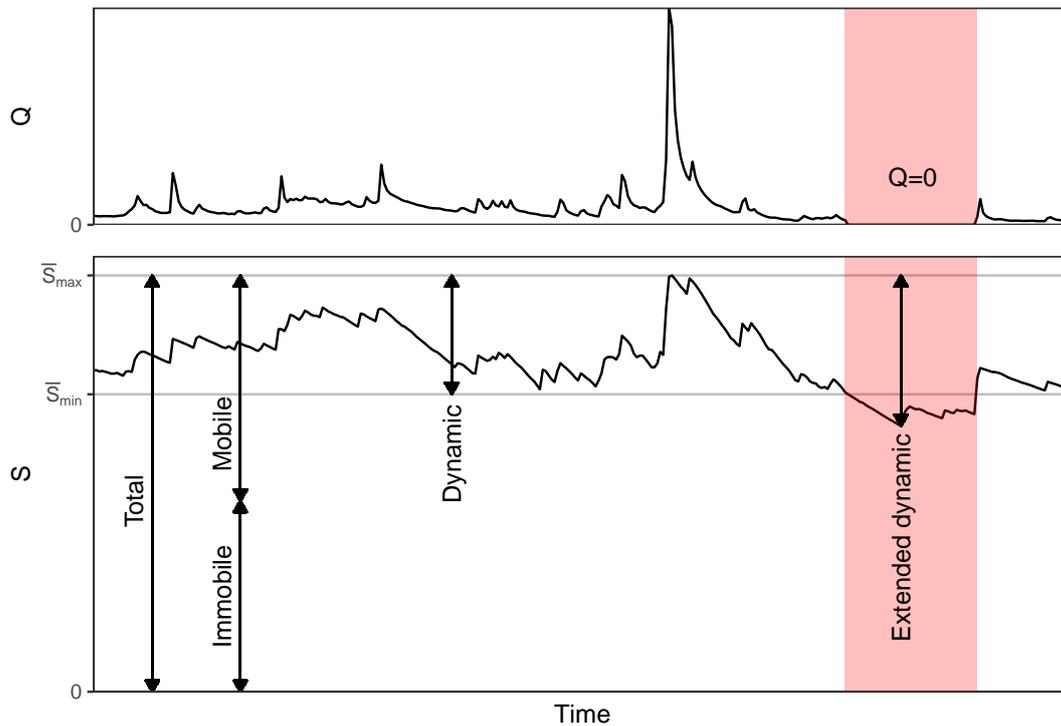


Figure 2. Illustration of different conceptual ideas of storage within a catchment, as adapted from Staudinger et al. (2017; Figure 1). The top panel shows catchment streamflow (Q) and the bottom panel catchment storage (S) through time. The red shaded area indicates a period when streamflow ceases yet catchment storage still decreases.

150 data alone using, for example, streamflow recession analysis (Kirchner, 2009) or by hydro-
 151 dromological modeling (Staudinger et al., 2017; Fowler et al., 2020). For non-perennial streams,
 152 such as intermittent or ephemeral streams, there are periods when there is no stream-
 153 flow, yet storage continues to decrease due to subsurface water flow and evapotranspi-
 154 ration (Carrer et al., 2019). Extended dynamic storage is defined by Staudinger et al.
 155 (2017) as this hydrologically dynamic storage that is a result of precipitation, discharge,
 156 evapotranspiration, and groundwater. Extended dynamic storage can be estimated us-
 157 ing hydrological models or the cumulative water balance. In this study, we focus on dy-
 158 namic and extended dynamic storages as they are readily estimated from available hy-
 159 drometric data. While we use different methods to derive dynamic and extended dynamic
 160 storages, we expect that the estimates obtained from each method should be reasonably
 161 comparable to other studies that have used the same definitions of storage (e.g., McNa-
 162 mara et al., 2011; Buttle, 2016; Staudinger et al., 2017; Cooke & Buttle, 2020).

163 **2.3 Storage methods**

164 The methods used to estimate storage in this study are introduced in the subsec-
165 tions below. A summary of the methods is presented in Table 1.

166 **2.3.1 Dynamic storage: Storage-discharge relationship**

167 The first method uses the storage-discharge (SD) relationship to estimate dynamic
168 storage. The storage-discharge relationship is derived by examining the relationship of
169 streamflow recession ($-dQ/dt$) and discharge (Q) during minimal flux periods of precip-
170 itation (P) and evapotranspiration (ET). Kirchner (2009) showed that during these pe-
171 riods, storage is theoretically a function of discharge (i.e., $S = f^{-1}(Q)$) and several stud-
172 ies have estimated storage using the method (Teuling et al., 2010; Ajami et al., 2011; Birkel
173 et al., 2011; Staudinger et al., 2017; Yeh & Huang, 2019). Dynamic storage was estimated
174 as the difference between maximum (S_{max}) and minimum storage (S_{min}) correspond-
175 ing to some maximum (Q_{max}) and (Q_{min}) discharge rates. We estimated dynamic stor-
176 age using the means of the annual maxima and minima of flows for each catchment, as
177 done by Kirchner (2009).

178
$$S_{max} - S_{min} = \int_{Q_{min}}^{Q_{max}} \frac{1}{g(Q)} dQ \quad (1)$$

179 where $g(Q)$ is:

180
$$g(Q) = \frac{dQ}{dS} = \frac{dQ/dt}{dS/dt} \approx \frac{-dQ/dt}{Q} \Big|_{P \ll Q, ET \ll Q} \quad (2)$$

181 Daily data were used to estimate the storage-discharge relationships and only mea-
182 sured (i.e., not gap-filled) streamflow data classified in the top two quality codes were
183 used. While hourly data were used in the original study, Kirchner (2009) also demon-
184 strated that daily data could yield similar estimates of storage with a sufficient amount
185 of data points. Kirchner (2009) selected days in the recession where P and ET were less
186 than 10% of discharge. In south-east Australia, the latter condition of ET being less than
187 10% of discharge is rarely met as high rates of ET are possible even in cooler seasons.
188 This resulted in an insufficient amount of data points to calculate robust storage-discharge
189 relationships. Instead, to minimize the effect of catchment fluxes on the storage-discharge
190 relationships, we excluded days with precipitation and one day after, and restricted anal-

191 yses to only include data from the winter months between June and August. This ap-
 192 proach may underestimate the size of dynamic storage due to the effects of ET and this
 193 will be discussed later.

194 **2.3.2 Extended dynamic storage: water balance**

195 The second method uses the cumulative water balance to calculate the extended
 196 dynamic storage:

$$197 \quad \Delta S(t) = \sum_{i=1}^{i=t} P_i - Q_i - AET_i \cdot s_{ET} \quad (3)$$

198 where $\Delta S(t)$ is the extended dynamic storage increase or decrease from timestep
 199 $t = 1$ to timestep $t = t$, P is precipitation, Q is streamflow, AET is actual evapotran-
 200 spiration, and s_{ET} is the evapotranspiration scaling factor. P , Q , and AET are in mm
 201 per timestep, which is daily. The term $\Delta S(t)$ is used as some initial storage (S_0), and
 202 the total storage (S) cannot be determined using the water balance method (Sayama et
 203 al., 2011). AET was scaled for each catchment using a scaling factor s_{ET} to ensure the
 204 water balances closed over the study period (equivalent to f_{WB} in equation 2 Staudinger
 205 et al., 2017). s_{ET} is calculated as:

$$206 \quad s_{ET} = \frac{\bar{P} - \bar{Q}}{\overline{AET}} \quad (4)$$

207 where \bar{P} , \bar{Q} , and \overline{AET} are mean annual precipitation, discharge, and actual evap-
 208 otranspiration, respectively. Extended dynamic storage was calculated as the difference
 209 between the maximum and minimum values of ΔS observed over the study period (1990-
 210 2018). Using long study periods to derive storage using this method is critical to sat-
 211 isfy the steady-state assumption, especially in more arid regions (Han et al., 2020).

212 **2.3.3 Extended dynamic storage: Budyko framework**

213 A second estimate of extended dynamic storage was obtained using the Budyko frame-
 214 work (Budyko, 1974). We used the framework to obtain an alternate estimate of actual
 215 evapotranspiration and subsequently the water balance. The Budyko framework relates
 216 the index of dryness (PET/P) and the evaporative index (AET/P) on the basis that wa-
 217 ter availability and atmospheric demand are the primary constraints on the equilibrium

218 water balance (J. Y. Zhang et al., 2008). The Budyko curve, therefore, captures the in-
 219 teractions and feedbacks between the atmosphere, vegetation, and soil within the hydro-
 220 logical cycle (van der Velde et al., 2014). A generic form of the Budyko-like equation is
 221 the Fu-Zhang equation (Fu, 1981; L. Zhang et al., 2004) and is defined as:

$$222 \quad \frac{\overline{AET}}{\overline{P}} = 1 + \frac{\overline{PET}}{\overline{P}} - \left[1 + \left(\frac{\overline{PET}}{\overline{P}} \right)^w \right]^{1/w} \quad (5)$$

223 where w is an adjustable catchment parameter. The implementation of the w pa-
 224 rameter allows for the representation of the geographical variation of the Budyko curve
 225 and the integrated effects of vegetation cover, soil properties, and catchment topogra-
 226 phy (L. Zhang et al., 2004). Equation (5) is normally solved over mean annual timescales
 227 and AET is usually assumed to equal $\overline{AET} = \overline{P} - \overline{Q}$, which also inherently assumes
 228 negligible storage change (i.e., $\Delta S = 0$).

229 The approach in equation (5) yields the average annual evapotranspiration, but we
 230 needed finer-scale temporal estimates to calculate the water balance and derive storage.
 231 AET is limited by water availability and energy, but water availability can be carried
 232 through time via storage and is not simply a result of annual precipitation. Zeng and
 233 Cai (2015) showed that the water balance (ΔS) can be integrated into the Fu-Zhang equa-
 234 tion to obtain finer-scale estimates of AET:

$$235 \quad AET_i = P'_i \left[1 + \frac{PET_i}{P'_i} - \left[1 + \left(\frac{PET_i}{P'_i} \right)^w \right]^{1/w} \right] \quad (6)$$

236 where i is the timestep, $P'_i = P_i + \Delta S_{i-1}$, and w adopts a similar definition to
 237 the optimized catchment parameter in equation (5). We first optimized w in equation
 238 (6) using annual data to define the overall relation between water, energy, and integrated
 239 catchment characteristics. Optimization of w was performed over the range $1 < w \leq$
 240 10 using the least-squares approach. We then calculated the water balance for each catch-
 241 ment using monthly P , Q , and estimates of AET obtained using equation (6) with the
 242 optimized catchment value of w . The extended dynamic storage was then estimated as
 243 the difference between the maximum and minimum observed level of ΔS , as in section
 244 2.3.2.

245 **2.3.4 Extended dynamic storage: conceptual model**

246 The last approach estimates extended dynamic storages using a conceptual hydro-
247 logical model. We used the same approach as (Staudinger et al., 2017, section 3.3) and
248 used the Hydrologiska Byråns Vattenbalansavdelning (HBV) model. In this method, the
249 values of model parameters control the sizes of the storage state variables in the model.
250 The state variables within HBV that store water are snow depth, soil moisture, upper
251 groundwater storage, and lower groundwater storage. The extended dynamic storage was
252 estimated as the sum of the maximum size of the HBV state variables within the study
253 period. The parameter ranges used in calibration are presented in supporting informa-
254 tion S1 Table S1. The full study period (1990-2018) was used to calibrate the model for
255 each catchment and the model is run on a daily timestep. An adaptation of the HBV-
256 light model as described in Seibert and Vis (2012) was used within the R package hy-
257 dromad (Andrews et al., 2011). The HBV method to calculate AET was used (Seibert
258 and Vis (2012); equation 4) and Morton’s estimates of daily PET were input directly into
259 the model routine (i.e., the mean daily temperature and long-term PET approach was
260 not used). The HBV model parameters were calibrated using the Shuffled Complex Evo-
261 lution - University of Arizona (SCE-UA) algorithm (Duan et al., 1992) and the Nash-
262 Sutcliffe Efficiency objective function (Nash & Sutcliffe, 1970) with the Lindström penalty
263 for volume error (R_V^2) (Lindström, 1997). Model calibration for each catchment was re-
264 peated 10 times to capture the effect of parameter uncertainty on simulated storage sizes
265 due to parameter equifinality. Extended dynamic storage was calculated independently
266 for each calibrated catchment model and then averaged.

267 **2.4 Catchment characteristics**

268 Several catchment physical characteristics are used to explore the controls on catch-
269 ment storage. We selected characteristics that have demonstrated relations to storage,
270 including soil properties (Western et al., 1999; Geroy et al., 2011), bedrock type (Tague
271 & Grant, 2004; Pfister et al., 2017), topographic attributes (Sayama et al., 2011). The
272 BOM Geofabric V2.1 product (<http://www.bom.gov.au/water/geofabric/>), a stream and
273 nested catchment framework for Australia (Stein et al., 2014), was used to extract sev-
274 eral characteristics including mean elevation, elevation range, stream density, stream length,
275 slope, and the proportion of catchment grid cells that are valley bottoms (henceforth named
276 PVB). Three geological attributes were also extracted: the catchment areal proportion

Table 1. A summary of the storage estimation methods used in this study. Dynamic storage is the storage that controls streamflow dynamics, while extended dynamic storage includes all measurable fluxes. Note: P is precipitation, Q is discharge, PET and AET are potential and actual evapotranspiration, respectively, T_{avg} is average daily temperature, and S is storage

Storage term name	Method	Method type	Timestep	Data	Estimation summary
Dynamic	Storage discharge	Streamflow recession	Daily	P, Q	Using the storage-discharge relationship obtained through the Kirchner (2009) method, storage is estimated using the means of annual maxima and minima of flows.
Extended dynamic	HBV	Conceptual model	Daily	P, Q, PET, T_{avg}	The sum of the maximum size of the conceptual model stores (snow, soil moisture, groundwater).
	Water balance	Water balance	Daily	P, Q, AET	The difference between the maximum and minimum values of the change in storage (ΔS).
	Budyko	Water balance	Monthly	P, Q, PET	The difference between the maximum and minimum values of the change in storage (ΔS).

277 of igneous rocks, sedimentary rocks, and metamorphic rocks. The catchment average of
278 the Silica Index (Gray et al., 2016), a broad classification of soil parent material that fo-
279 cuses on chemical composition rather than the formation process, is an additional mea-
280 sure that was included to evaluate the effect of lithology on storage. Catchment aver-
281 age soil depth and clay content in the top meter of soil were extracted from the Soil and
282 Landscapes Grid of Australia (Grundy et al., 2015).

283 Additional catchment characteristics were calculated using hydrometric data: the
284 coefficient of annual streamflow variability (Q_{cv}), the runoff ratio (Q/P), the mean an-
285 nual aridity index (P/PET), the baseflow index (BFI), and the lag-1 day autocorrela-
286 tion coefficient (AC) (Winsemius et al., 2009). The BFI has been shown to represent the
287 storage and release properties of catchments (Salinas et al., 2013; Van Loon & Laaha,
288 2015) and was calculated using the `lfstat` R package (Koffler & Laaha, 2013). The lag-
289 1 autocorrelation is a measure of smoothness of the hydrograph and can provide insights
290 into water release properties of a catchment, where a higher autocorrelation coefficient
291 indicates a slower release of water from the catchment. It is also considered one of the
292 key hydrological signatures (Euser et al., 2013).

293 The study catchments cover a wide range of catchment physical properties and char-
294 acteristics (Table 2). The catchment areas range from 25 to 5158 km² and the median
295 catchment area is 304 km². The distribution of catchment areas is also presented in Fig-
296 ure 1. Igneous and sedimentary rocks are the most common underlying geologies of the
297 catchments. Soils are moderately deep (mean depth is 0.73 to 1.14 m) with a range of
298 clay fractions (22 to 44%).

299 Spearman’s *rho* statistic (ρ) was used to evaluate the association between the dif-
300 ferent storage estimates and catchment properties. Significance ($P < 0.05$) of the re-
301 lationship was evaluated using Spearman’s rank correlation test Algorithm AS 89 (Best
302 & Roberts, 1975).

303 In our study catchments, we hypothesize that catchment storage will be greater
304 in catchments with greater elevation and greater mean slope, based on other findings that
305 high topographic gradients lead to increased deeper infiltration of water (Jasechko et al.,
306 2016; Hayashi, 2020). Since flatter catchments will have lower topographic gradients, this
307 also means that the runoff ratio should be lower and allow for greater evaporation, at
308 least in the study region which is not energy limited. We also hypothesize that catch-

Table 2. Numerical summary of the catchment characteristics.

Characteristic	Min	1st quartile	Median	Mean	3rd quartile	Max
Area (km ²)	25.05	147.74	303.82	516.73	560.01	5157.96
Elev mean (m)	156.02	379.53	546.27	612.65	822.41	1351.42
Elev range (m)	142.70	478.61	682.75	775.77	1030.00	1629.49
Slope (°)	0.60	3.36	5.52	6.39	9.58	14.98
Soil depth (m)	0.73	0.90	0.94	0.94	1.01	1.14
Clay (%)	23.43	28.25	30.56	31.02	33.11	46.18
Stream length (km)	0.28	1.52	2.09	2.70	3.63	9.76
Stream density (km/km ²)	0.58	0.74	0.83	0.83	0.90	1.14
PVB (%)	0.00	0.00	0.89	4.29	4.44	31.23
Silica Index	49.00	67.09	68.00	67.13	69.55	74.73
Igneous rocks (%)	0.00	8.45	26.68	35.54	56.36	99.98
Sedimentary rocks (%)	0.00	18.67	46.41	45.10	68.69	99.03
Metamorphic rocks (%)	0.00	0.00	0.00	6.50	0.00	90.63
Qcv	0.32	0.61	0.84	0.90	1.16	1.72
P/PET	0.26	0.40	0.53	0.58	0.76	1.00
Q/P	0.03	0.07	0.11	0.16	0.23	0.74
BFI	0.01	0.19	0.40	0.39	0.60	0.79
AC	0.25	0.52	0.65	0.67	0.83	0.96

Note

PVB: percent valley bottoms

Qcv: coefficient of variation of annual flow

P/PET: aridity index where P is precipitation and PET is potential evapotranspiration

Q/P: annual runoff ratio

BFI: baseflow index

AC: lag-1 day autocorrelation coefficient

309 ments with greater baseflow and smoother hydrographs, as indicated by the BFI and AC,
310 respectively, will be indications of greater storage. Similarly, deeper soils and greater clay
311 content are expected to indicate greater soil storage. Bedrock permeability has been found
312 to exert a large influence on storage characteristics (Hale et al., 2016; Pfister et al., 2017).
313 If significant relationships are discovered between rock types and storage estimates, it
314 may relate to more permeable rock types, such as sedimentary sandstone, or the pres-
315 ence of fractured metamorphic or igneous bedrocks. However, a simple relationship be-
316 tween bedrock type and storage may not be found, as a regional study found that the
317 bedrock type alone does not simply control storage and release properties (Howcroft et
318 al., 2018).

319 **3 Results**

320 **3.1 Storages**

321 Robust storage-discharge relationships were found for all catchments. The mean
322 and standard deviation of the coefficient of determination was $R^2 = 0.92 \pm 0.06$. The
323 minimum R^2 was 0.68. Storage values for the SD method ranged from 3 to 158 mm (Fig-
324 ure 3) and had a median storage value of 22 mm. Recession plots and plots of the storage-
325 discharge relationships are presented in supporting information S1 Figure S2 and Fig-
326 ure S3, respectively.

327 All HBV models obtained reasonable calibration scores (median $R_V^2 = 0.71$). All
328 catchments obtained a score above 0 (minimum $R_V^2 = 0.32$), which is often used to dis-
329 tinguish good and bad NSE performance (Knoben et al., 2019) as a score of 0 indicates
330 the model can only simulate mean Q. Variability of calibration scores across the 10 cal-
331 ibration trials for each catchment was low, where the maximum standard deviation of
332 a catchment's R_V^2 score was 0.04. HBV extended dynamic storage estimates covered a
333 range from 147 to 1012 mm with a median value of 402 mm.

334 Budyko curve derived water balance storage estimates ranged between 97 to 841
335 mm and had a median value of 343 mm. The distribution of storage values derived us-
336 ing the Budyko method are broadly comparable to the HBV method (Figure 3). The
337 mean absolute difference between the HBV estimates and Budyko estimates of extended
338 dynamic storage was 108 mm. The w parameter had a mean and standard deviation of
339 2.78 ± 0.66 across all catchments and the relationship of w to storage is discussed later.

340 Extended dynamic storages estimated by the water balance method ranged from
 341 536 to 1802 mm and had the highest median value of 1061 mm. The water balance scal-
 342 ing factor, s_{ET} , had a mean and standard deviation of 0.83 ± 0.17 , which highlights that
 343 most catchments required a reduction in actual evapotranspiration to close the water bal-
 344 ance. The relation of s_{ET} to storage is described later. Extended dynamic storage sizes
 345 estimated by this method were greater compared to the HBV and Budyko methods. The
 346 mean absolute difference of extended dynamic storage between the water balance method
 347 and the HBV method was 631 mm.

348 The size of dynamic storage, as estimated by the SD method, relative to extended
 349 dynamic storage varied from 0.3% to 59.1% depending on the catchment and the method.
 350 The median ratio of dynamic storage to extended dynamic storage was 5.2%, 6.6%, and
 351 2.0% for the HBV, Budyko, and water balance methods, respectively.

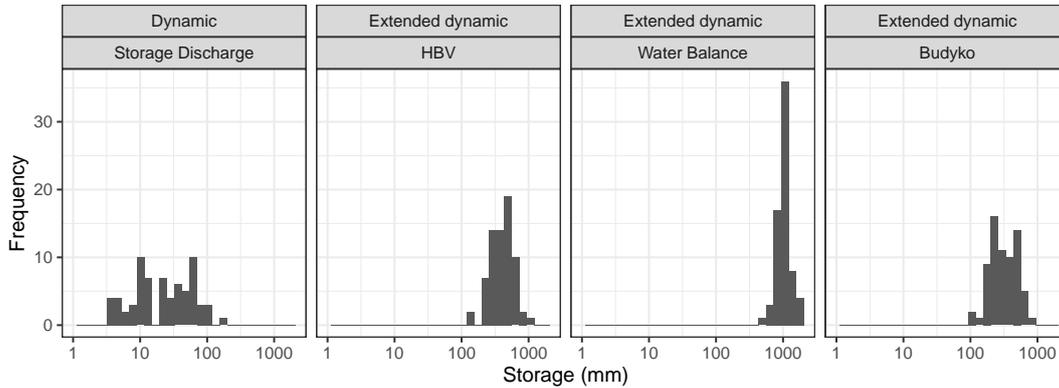


Figure 3. Distributions of storage values for each method.

352 To determine if there were consistent storage size differences between the methods,
 353 we ranked the sizes of the estimated storage for each catchment. From smallest to largest,
 354 the rankings were consistently ordered for the SD, Budyko, HBV, and the water balance
 355 methods (Table 3) with only a few exceptions.

356 **3.2 Physical characteristics**

357 Significant Spearman correlations ($P < 0.05$) were found for several character-
 358 istics across all storage methods (Table 4). Greater mean catchment elevation, elevation
 359 range, and slope were strongly associated with greater storage. This result is reflected
 360 with PVB, where the greater the proportion of valley bottoms in catchments indicated

Table 3. Rankings of the storage size across all catchments and methods. Rank 1 represents the smallest storage and Rank 4 the largest storage.

Storage	Method	Rank			
		1	2	3	4
Dynamic	Storage-discharge	69	0	0	0
Extended dynamic	HBV	0	5	64	0
	Budyko	0	64	5	0
	Water Balance	0	0	0	69

361 less storage. No significant relationship was found between the size of the catchment and
 362 any of the estimated storages. Greater soil depth, unsurprisingly, indicated greater wa-
 363 ter storage. This is despite percent clay content, the particle size fraction that has the
 364 greatest water storage capacity, had no significant correlation with storage. No geolog-
 365 ical variables had consistent and strong relationships to the different estimates of stor-
 366 age. Catchments with lower mean annual flow variance were found to have greater stor-
 367 age capacity. Significant relationships between the runoff ratio and the aridity index in-
 368 dicated that wetter catchments have greater storage potential. Limited inference can be
 369 made with these variables, however, as the variables are part of the equations used to
 370 derive storage. The BFI had strong positive correlations with all storage methods, sug-
 371 gesting the digital low pass filter captures some aspect of storage and release properties.
 372 AC also had significant correlations with all storage estimates. Combined, these two vari-
 373 ables support our initial hypothesis that smoother and slower releases of water are re-
 374 lated to greater storage capacity.

375 3.3 HBV partitioning

376 The HBV model has conceptual stores for snow, soil water, and groundwater and
 377 can provide insights into the simulated partitioning of water storage in the study catch-
 378 ments. The calibrated models show that soil storage was simulated as the largest stor-
 379 age for most catchments (Figure 4). Groundwater storage was the next largest storage,
 380 but the distribution was long-tailed, and some catchments have large simulated ground-
 381 water storages. Snow storage was minimal with most catchments having zero simulated

Table 4. Spearman correlation coefficients between storage estimates and the catchment characteristics. Bolded values are significant ($P < 0.05$) correlations.

Characteristic	Dynamic	Extended dynamic		
	SD	HBV	WB	Budyko
Area (km ²)	-0.2	-0.2	-0.19	-0.2
Elev mean (m)	0.63	0.47	0.28	0.51
Elev range (m)	0.65	0.66	0.51	0.71
Slope (°)	0.81	0.75	0.54	0.8
Soil depth (m)	0.44	0.53	0.43	0.55
Clay (%)	-0.06	-0.18	-0.18	-0.19
Stream length (km)	-0.25	-0.1	-0.28	-0.16
Stream density (km/km ²)	-0.03	-0.22	0.05	-0.08
PVB (%)	-0.77	-0.73	-0.46	-0.76
Silica Index	0.07	0.15	0.26	0.21
Igneous rocks (%)	0.26	0.09	0.03	0.19
Sedimentary rocks (%)	-0.1	0.01	0.01	-0.1
Metamorphic rocks (%)	0.06	0.3	0.22	0.26
Qcv	-0.75	-0.78	-0.62	-0.83
P/PET	0.87	0.83	0.59	0.87
Q/P	0.9	0.76	0.55	0.83
BFI	0.83	0.82	0.54	0.84
AC	0.64	0.6	0.4	0.62

382 snowfall. The size of conceptual stores for each catchment can be viewed in supporting
 383 information S1 Figure S3. The correlations between the physical characteristics and the
 384 HBV conceptual storages are presented in supporting information S1 Table S2. Aside
 385 from snow storage, there are few differences across the conceptual stores. Overall, the
 386 results match the HBV method in Table 4, where more varied topography, greater slope,
 387 deeper soils, and a smoother hydrograph, as indicated by the BFI and AC, had greater
 388 catchment storage.

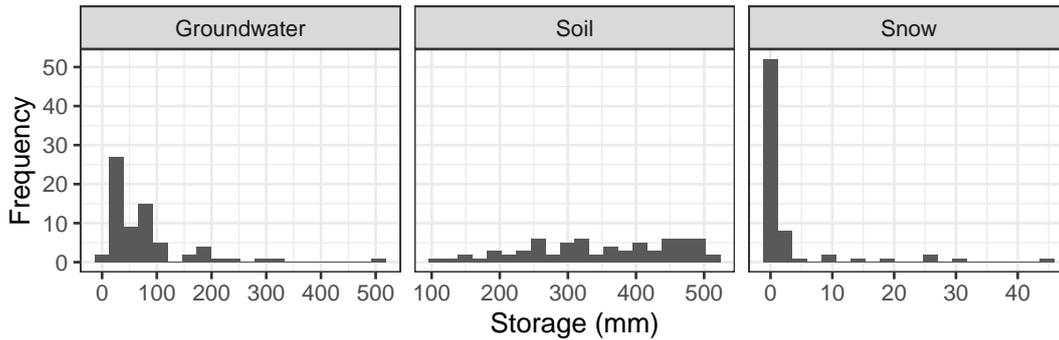


Figure 4. Distributions for each HBV conceptual storage component derived from the extended dynamic storage method.

389 3.4 Water balance

390 The water balances were scaled using the scaling factor s_{ET} to force the water bal-
 391 ances to close over the study period. As mentioned, s_{ET} had a mean and standard de-
 392 viation of 0.83 ± 0.17 . Indeed, in 66 out of the 69 catchments, the scaling factor was less
 393 than 1, indicating that Morton’s model systematically overestimates AET, and/or that
 394 there are errors in the values of P and Q.

395 We planned to evaluate whether s_{ET} had any relationships to catchment charac-
 396 teristics to determine if the scaling factor was representative of any characteristics (sup-
 397 porting information S1 Table S3). However, s_{ET} had a significant positive correlation
 398 with water balance derived storage estimates ($\rho = 0.49, r = 0.51$), which suggests that
 399 larger storages tend to either have smaller observational errors or lower overestimation
 400 of AET.

3.5 Budyko approach

The distribution of points in Figure 5 shows the catchments respected the Budyko water and energy limits. Fitting a w parameter for all catchments in the study by minimizing the sum of squared error resulted in a value of 2.77, which is close to the mean value of the individual fits. This number is comparable to the values of 2.84 and 2.55 found by L. Zhang et al. (2004) for forested and grass covered Australian catchments, respectively.

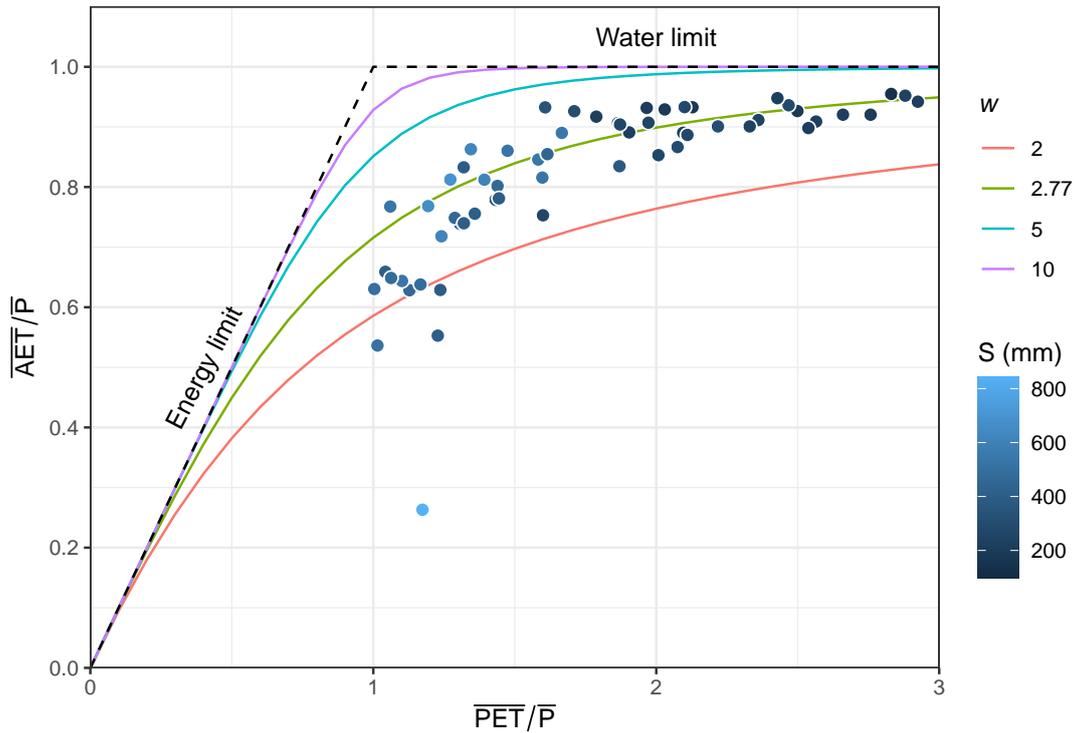


Figure 5. Ratio of the dryness index ($\overline{PET}/\overline{P}$) and evaporative index ($\overline{AET}/\overline{P}$) and Fu-Zhang curves. Each point represents one catchment.

The relationship of catchment storages and the calibrated Fu-Zhang curve parameters w in the Budyko space are presented in Figure 5. There appears to be a general trend that catchments that have a lower index of dryness and a lower evaporative index have greater storage. However, the w parameters have no significant correlation with storage ($\rho = -0.04$) and the parameter does not strongly represent physical characteristics that may be associated with storage (supporting information S1 Table S3).

4 Discussion

4.1 Storage and catchment characteristics

Our study catchments had small dynamic storages and relatively large extended dynamic storage. Across all the study catchments, the mean and one standard deviation of the dynamic storage as a proportion of extended dynamic storage is $5.1 \pm 4.8\%$. Dynamic storage represents the storage that directly contributes to streamflow and the fact the storages were estimated to be small reflects the study environment, where evapotranspiration dominates catchment losses. The difference between the sizes of dynamic and extended dynamic storage sizes can be interpreted that a large proportion of catchment storage is “reserved” for evapotranspiration (Brooks et al., 2010; Carrer et al., 2019). While the dynamic storages are small, the fact that the headwater catchments along the south-east of Australia continue to flow in prolonged dry periods and have long travel times (Cartwright et al., 2020) suggests that these stores are deeper in the subsurface and are connected to long groundwater flowpaths (Howcroft et al., 2018).

We tested several physical catchment characteristics hypothesized to act as controls on catchment storage, as well as to assess if the storage estimation methods possess physical realism. As we hypothesized, storages were strongly linked with topographic characteristics. Catchments with greater slopes were positively correlated with storage and catchments with a lower percentage of valley bottoms were negatively correlated to storage across all methods. These characteristics together express a physical system where water can readily drain to subsurface stores and supports prior findings that catchment topographic characteristics are pivotal to water storage (Jencso & McGlynn, 2011; Berghuijs et al., 2014). Soil storage was found to be important, with soil depth positively correlated to all the storage estimates. This was also highlighted in the simulated partitioning of water by the HBV model, where soil water represented the greatest store for most catchments.

The BFI and stream AC also significantly correlated to water storage, in line with other studies that have found the BFI captures storage and release properties of catchments (Salinas et al., 2013). A greater BFI relates to higher stream autocorrelation and, for the study catchments, there is a strong Pearson’s correlation between the two characteristics. A physical interpretation of this result is that greater autocorrelation, and

445 therefore greater memory in the streamflow signal, suggests a slower storage release, slower
446 flow paths, and therefore greater storage.

447 The bedrock characteristics were not found to be a strong indication of storage,
448 with no consistent correlations across the storage estimates from the different methods.
449 This may be a result of the coarseness of the parent data (1:1M) and the uncertainty of
450 spatial mapping of bedrock type. Bedrock and the soil-bedrock interface are important
451 for hydrological storage (Sklash & Farvolden, 1979; Sophocleous, 2002; Jencso & McG-
452 lynn, 2011; Pfister et al., 2017); however, other evidence has shown that the physical ar-
453 rangement of these features (e.g., McGuire et al. (2005)) is more important than the sim-
454 ple bedrock constituencies. Staudinger et al. (2017) also did not find a significant rela-
455 tionship between their geological indicator (average quaternary depth) and derived stor-
456 age. This raises a broader issue of what the ideal geological indicators and measures are
457 when determining broad-scale storage controls.

458 **4.2 Methodology**

459 The methods we applied all yielded different results, but like Staudinger et al. (2017)
460 we found that the methods had similar rankings. That is, the methods consistently es-
461 timated relatively smaller or larger storages for the same catchment. Moreover, the multi-
462 method and multi-catchment approach demonstrated the difficulty of quantifying catch-
463 ment storage. The strong correlations with the physical characteristics show the meth-
464 ods captured some aspect of catchment storage behavior that match conceptual ideas
465 of catchment storage; however, the inconsistencies of the correlations to some of the meth-
466 ods raises doubt if simple rules about the controls on catchment storage can be estab-
467 lished. A potential source of this inconsistency is the fact that, despite using the most
468 up-to-date sources of data that covered the study region, many of the physical charac-
469 teristics are spatially modeled values derived from other landscape-level data.

470 Each of the methods have their relative strengths (and weaknesses) and are dis-
471 cussed in subsections below. A general problem that applies to all the methods in this
472 study is that none of the methods are direct observations of storage, rather they have
473 been inferred from catchment fluxes. Without some direct measure of storage, there is
474 a reciprocal problem: it is difficult to define storage without defining it from fluxes when
475 storage itself is defining or controlling those processes.

476 **4.2.1 Storage-discharge**

477 The SD method provides a clever way of estimating the dynamic storage size by
478 analyzing times when streamflow is a function of storage. This behavior can be observed
479 during low flux hours, i.e., when there is negligible precipitation and evapotranspiration,
480 and the stream is in recession. This proved challenging to implement in this study us-
481 ing daily data and it is likely to always be an issue in drier regions. An additional com-
482 plication is that catchments in Australia tend to be larger due to the flatter topography.
483 This typically results in low yields of water, and it is rarely the case that streamflow is
484 substantially larger than evapotranspiration.

485 The effects of P and ET are minimized in this study by removing days with pre-
486 cipitation and the day after from analysis and limiting the analysis to cooler months of
487 June to August. However, ET can still be considerable during these months in south-
488 eastern Australia and there is almost certainly an effect on the calculated dynamic stor-
489 age sizes. Improperly excluding ET results in underestimation storage of storage (Kirchner,
490 2009) and this is a caveat of the results. Nevertheless, it is clear that dynamic storage
491 is likely to be much smaller than extended dynamic storage in most catchments in our
492 study region. The use of hourly data is one opportunity to improve the reliability of stor-
493 age estimates using this method. This comes with other challenges, including (1) long
494 timeseries of hourly data for many catchments are not widely available (2) nocturnal tran-
495 spiration can still be considerable in the Australian environment (Buckley et al., 2011).

496 **4.2.2 HBV**

497 As Staudinger et al. (2017) identified, the HBV model can consider different sources
498 of storage and their relative contributions to extended dynamic storage. These storages
499 are simulated and are not based on any real observations of groundwater, soil water, or
500 snow storage. While they are simulated storages, our results show these conceptual stores
501 were significantly correlated to many physical characteristics that are representative of
502 these stores. Model structure and the choice of the objective function are likely to have
503 an impact on the partitioning of water and model performance (Knoben et al., 2020).
504 This source of uncertainty was not assessed in this study, but it could be examined by
505 comparing the results of multiple conceptual models and objective functions to evalu-
506 ate the consistency of water partitioning and storage size. Additionally, there is always

507 uncertainty that derives from the chosen initial parameter ranges and model calibration
 508 routine (Butts et al., 2004). We used parameter ranges that are consistent with the lit-
 509 erature (Seibert, 1997; Lidén & Harlin, 2000; Seibert & Vis, 2012) and we repeated the
 510 calibration trials 10 times for each catchment to capture parameter equifinality. The val-
 511 ues of parameters can have a large effect on the partitioning of water between the dif-
 512 ferent stores. The ranges of calibrated parameters did not indicate that there was lim-
 513 iting behavior that prevented further increases or decreases of the sizes of storages. There
 514 were limited cases where parameters were poorly identified across the 10 calibration tri-
 515 als for catchments, but the variation in the size of the conceptual storages was low across
 516 calibration trials for each catchment.

517 **4.2.3 Water balance**

518 The water balance approach should theoretically provide the optimal measure of
 519 extended dynamic catchment storage as it tries to directly relate changes in storage with
 520 fluxes. However, a clear source of uncertainty for the water balance approach is the use
 521 of the scaling factor s_{ET} . The use of this scaling factor was necessary as, without this
 522 factor, sensible water balances could not be computed with the data for most catchments.
 523 Despite the apparent suitability of Morton’s estimates of evapotranspiration to calcu-
 524 late the water balance (McMahon et al., 2013), Morton’s estimates of evapotranspira-
 525 tion do not factor in effects from wind, which can cause large differences in PET and AET
 526 calculations (Donohue et al., 2010). Most catchments had a s_{ET} of less than 1, indicat-
 527 ing that the catchment losses to ET are less than what is estimated by Morton’s actual
 528 areal evapotranspiration. A few possibilities that may explain this result include the poor
 529 estimation of actual evapotranspiration, inaccurate spatial estimation of precipitation,
 530 or inaccurate gauging of streamflow. Small errors in any of those variables accumulate
 531 over time and cause the water balance not to close. This raises a broader issue in that
 532 we cannot close the water balance from the best datasets we have available. Moreover,
 533 despite the ubiquity of the cumulative water balance equation (i.e., $\Delta S = P - Q -$
 534 ET) in hydrology, the equation excludes other losses, such as inter-catchment flows which
 535 are often (and potentially falsely) assumed to be negligible (Bouaziz et al., 2018; Fan,
 536 2019). This also gives rise to another common assumption, employed here, that long-term
 537 average AET can be estimated using $\overline{AET} = \overline{P} - \overline{Q}$. This term could be considered
 538 the mean loss term that excludes Q, as any losses to other sources are attributed to ET.

539 While this assumption does have utility, recent studies have highlighted that there are
540 cases where steady-state may not be reached even in reasonably long (30-year) windows
541 (Han et al., 2020) and there is evidence of ecohydrological feedbacks with storage (Rice
542 & Emanuel, 2019). As such, careful consideration should be given when using the hy-
543 drological steady-state assumption in studies of storage and future storage assessment
544 frameworks should explicitly incorporate tests of the assumption.

545 **4.2.4 Budyko**

546 The Budyko approach simplifies the complex processes and interactions and ex-
547 presses the controls of actual evapotranspiration by the availability of energy and wa-
548 ter and has been validated globally (Koster & Suarez, 1999; Choudhury, 1999; L. Zhang
549 et al., 2001). We added this method due to the limitations of the water balance approach,
550 where it was suspected poor evapotranspiration estimates may hinder an accurate sim-
551 ulation of the water balance. We defined the w parameter using annual data to capture
552 the overall long-term relationship between AET/P and PET/P. Extrapolating Budyko
553 relationships to the monthly scale, while commonly done in the literature (e.g., Zeng &
554 Cai, 2015; Du et al., 2016), creates some uncertainty because the relationship between
555 AET/P and PET/P may not be consistent seasonally. Since the main long-term rela-
556 tionship is represented, this may mean that the extremes of the change in storage are
557 reduced and there could be an underestimation of extended dynamic storage.

558 We hypothesized that w may relate to some physical characteristics related to stor-
559 age, as the parameter is widely believed to represent the integrated effects of soil, veg-
560 etation, and topography (L. Zhang et al., 2004). The fact that w parameter did not strongly
561 relate to many physical characteristics likely indicates that w does integrate many char-
562 acteristics and it is unlikely to have simple relationships to due catchment heterogene-
563 ity.

564 **4.3 Implications and future research**

565 This study builds on the global push to understand water storages in catchments
566 by using common storage definitions (McNamara et al., 2011) and estimation methods
567 (Staudinger et al., 2017). In our study catchments, the multi-method and multi-catchment
568 approach did not tightly constrain the sizes of extended dynamic storages. A key lim-

569 itation was that the uncertainties of the hydrometric input data, which ultimately lim-
570 ited how well we could constrain the size of storages. Quantifying the uncertainty of the
571 hydrometric data should be a focus of further work. Further research is also required to
572 obtain physical estimates of storage to validate storage estimation methods using hydro-
573 metric data. This includes, and is not limited to, using tracers to characterize mobile stor-
574 age, and using satellite products, groundwater level data, or local scale gravimetry (e.g.,
575 Creutzfeldt et al., 2014) to study dynamic and extended dynamic storage. Hydromet-
576 ric methods are currently the only viable way to assess storage broadly at the catchment
577 scale, and as such it is critical that improvements are found so that storage can be eas-
578 ily and rapidly estimated.

579 Many of the results here indicated that groundwater and slow storage release are
580 important to water storage and release from catchments. Hydrological models poorly sim-
581 ulate these features and are likely a reason why performance outside calibration windows
582 is reduced. Our results reinforce the call to improve conceptual models to better account
583 for slow flow processes (e.g., Fowler et al. (2020)). It is likely a complete understanding
584 of the underlying mechanisms cannot be attained without grasping the mobile storage.
585 Much of the underlying hydrological processes likely occur in the mobile storage domain
586 where there is an important distinction between particle velocities and celerities (McDonnell
587 & Beven, 2014; Beven & Davies, 2015). Mobile storage was not assessed as it cannot be
588 determined from hydrometric data alone. Rather, it is usually inferred with the assis-
589 tance of tracers. Several studies have evaluated MTTs using tracer data within the study
590 region, and these could be pooled to evaluate mobile storage. However, the physical con-
591 trols on MTTs in some of these catchments have not been readily identified (Howcroft
592 et al., 2018; Cartwright et al., 2020) and the estimates of MTTs often carry consider-
593 able uncertainty due to the assumptions required to estimate recharge rates (e.g., Li et
594 al. (2019)). Despite the clear challenges, further work focusing on water age behavior
595 could lead to breakthroughs in the understanding of the controls on catchment storage.

596 Changes in interannual catchment storage volumes are often assumed to be neg-
597 ligible, even though this assumption is widely acknowledged as being unrealistic (Rice
598 & Emanuel, 2019). This assumption was applied in this study to derive storage from the
599 long-term water balance. It is likely that dynamic and extended dynamic storages in our
600 study region behave non-linearly, as indicated by the research by Saft et al. (2015) and
601 Saft et al. (2016), who showed that drought induces changes to the land system that are

602 likely to influence water storage and release properties. Recent research by Peterson et
603 al. (2021) has also shown that several catchments in south-eastern Australia have not
604 recovered from the Millennium Drought, which may indicate permanent changes in their
605 capacity to store water. Analysis of distinct wet and dry periods may reveal changes in
606 storage behavior and should be a focus of further work. A similar phenomenon has been
607 observed in regions with Mediterranean climates, where the sharp seasonal differences
608 in precipitation and temperature in combination with drought resulted in complex runoff,
609 evapotranspiration, and storage partitioning behavior (Hahm et al., 2019; Feng et al.,
610 2019; Avanzi et al., 2020). Progress in this area is critical, as hydrological models also
611 frequently perform poorly under changing climate scenarios (e.g., Fowler et al., 2016; Dueth-
612 mann et al., 2020; Avanzi et al., 2020) and more realistic concepts of storage and release
613 behavior need to be integrated into model structures (Fowler et al., 2020).

614 **5 Conclusions**

615 Storage sits at the intersection of the main hydrological processes and advances in
616 the understanding of catchment storage will provide greater insight into catchment func-
617 tioning. While in hydrology the focus is often on the fluxes, flux behavior can be more
618 precisely quantified within hydrological boundary conditions if that boundary can be es-
619 tablished. With impending challenges that will be faced globally, such as climate change
620 and large-scale land use change, it is critical to understand water storage and availabil-
621 ity from a water resource perspective. This is particularly the case for our study region,
622 the Murray-Darling Basin, given the recent findings of Peterson et al. (2021) that demon-
623 strated clear changes in storage and release patterns after severe drought.

624 We performed a broad and comprehensive analysis of storage across 69 catchments
625 in the Murray-Darling Basin. In relation to our original aims (1) we successfully esti-
626 mated dynamic and extended dynamic storages across our study area. While the differ-
627 ent methods were generally ranked consistently, the estimates of dynamic and extended
628 dynamic storage could vary substantially depending on the catchment. (2) It was dif-
629 ficult to determine robust catchment characteristics that control storage, but several key
630 characteristics highlighted the nature of the storage. Our results indicate that topogra-
631 phy and hydrograph characteristics are the better indicators of storage in the study re-
632 gion. The geological characteristics used in the study did not strongly relate to the stor-
633 age estimations and further work is required to identify useful geological measures that

634 relate to storage. (3) The multi-method and multi-catchment approach, as applied in
635 this study, has been proposed as a clear way to advance our understanding of storage
636 (e.g., Staudinger et al., 2017; McNamara et al., 2011). Our results highlight that in the
637 absence of high-quality hydrometric data, it is difficult to precisely quantify storage. This
638 poses a wider challenge, given that there is currently no other way to effectively assess
639 storage broadly at the catchment scale. We propose that the uncertainty of hydromet-
640 ric data needs to be addressed and we call for new methods that can robustly and eas-
641 ily estimate storage at the catchment scale.

642 **Acknowledgments**

643 The authors acknowledge the three anonymous reviewers and the associate editor,
644 whose valuable feedback greatly improved the quality of this study. Alexander Buzacott
645 acknowledges the support of the Research Training Program scholarship provided by the
646 Australian Government. This study was conducted with the support of the Australian
647 Research Council (LP130101183). The authors acknowledge the Sydney Informatics Hub
648 and The University of Sydney’s high performance computing cluster Artemis for pro-
649 viding the high performance computing resources that have contributed to the research
650 results reported within this paper. Rainfall, temperature, and evapotranspiration data
651 are from the SILO project (Jeffrey et al., 2001), www.longpaddock.qld.gov.au/silo/. Stream-
652 flow data were from the BOM Hydrologic Reference Station project website (<http://www.bom.gov.au/water/hrs/>)
653 and BOM Geofabric products were retrieved from <http://www.bom.gov.au/water/geofabric/>.
654 The Soil and Landscape Grid of Australia (Grundy et al., 2015) can be retrieved from
655 <https://www.clw.csiro.au/aclep/soilandlandscapegrid/index.html>. The analysis code for
656 this study is available on GitHub (<https://github.com/buzacott/StorageSEAus>).

657 **References**

- 658 Ajami, H., Troch, P. A., Maddock, T., Meixner, T., & Eastoe, C. (2011). Quan-
659 tifying mountain block recharge by means of catchment-scale storage-
660 discharge relationships. *Water Resources Research*, *47*(4), W04504. doi:
661 10.1029/2010WR009598
- 662 Andrews, F. T., Croke, B. F. W., & Jakeman, A. J. (2011). An open software en-
663 vironment for hydrological model assessment and development. *Environmental*
664 *Modelling & Software*, *26*(10), 1171–1185. doi: 10.1016/j.envsoft.2011.04.006

- 665 Avanzi, F., Rungee, J., Maurer, T., Bales, R., Ma, Q., Glaser, S., & Conklin, M.
 666 (2020, September). Climate elasticity of evapotranspiration shifts the water
 667 balance of Mediterranean climates during multi-year droughts. *Hydrology and*
 668 *Earth System Sciences*, *24*(9), 4317–4337. doi: 10.5194/hess-24-4317-2020
- 669 Berghuijs, W. R., Sivapalan, M., Woods, R. A., & Savenije, H. H. G. (2014). Pat-
 670 terns of similarity of seasonal water balances: A window into streamflow
 671 variability over a range of time scales. *Water Resources Research*, *50*(7),
 672 5638–5661. doi: 10.1002/2014WR015692
- 673 Best, D. J., & Roberts, D. E. (1975). Algorithm AS 89: The upper tail probabili-
 674 ties of Spearman’s rho. *Journal of the Royal Statistical Society. Series C (Ap-*
 675 *plied Statistics)*, *24*(3), 377–379. doi: 10.2307/2347111
- 676 Beven, K., & Davies, J. (2015). Velocities, celerities and the basin of attraction in
 677 catchment response. *Hydrological Processes*, *29*(25), 5214–5226. doi: 10.1002/
 678 hyp.10699
- 679 Birkel, C., Soulsby, C., & Tetzlaff, D. (2011). Modelling catchment-scale water
 680 storage dynamics: Reconciling dynamic storage with tracer-inferred passive
 681 storage. *Hydrological Processes*, *25*(25), 3924–3936. doi: 10.1002/hyp.8201
- 682 Bouaziz, L., Weerts, A., Schellekens, J., Sprokkereef, E., Stam, J., Savenije, H.,
 683 & Hrachowitz, M. (2018). Redressing the balance: Quantifying net inter-
 684 catchment groundwater flows. *Hydrology and Earth System Sciences*, *22*(12),
 685 6415–6434. doi: 10.5194/hess-22-6415-2018
- 686 Brooks, J. R., Barnard, H. R., Coulombe, R., & McDonnell, J. J. (2010). Ecohy-
 687 drologic separation of water between trees and streams in a Mediterranean
 688 climate. *Nature Geoscience*, *3*(2), 100–104. doi: 10.1038/ngeo722
- 689 Buckley, T. N., Turnbull, T. L., Pfautsch, S., & Adams, M. A. (2011). Nocturnal
 690 water loss in mature subalpine *Eucalyptus delegatensis* tall open forests and
 691 adjacent *E. pauciflora* woodlands. *Ecology and Evolution*, *1*(3), 435–450. doi:
 692 10.1002/ece3.44
- 693 Budyko, M. (1974). *Climate and Life* (D. H. Miller, Ed.). New York: Academic
 694 Press.
- 695 Buttle, J. M. (2016). Dynamic storage: A potential metric of inter-basin differences
 696 in storage properties. *Hydrological Processes*, *30*(24), 4644–4653. doi: 10.1002/
 697 hyp.10931

- 698 Butts, M. B., Payne, J. T., Kristensen, M., & Madsen, H. (2004). An evalua-
699 tion of the impact of model structure on hydrological modelling uncertainty
700 for streamflow simulation. *Journal of Hydrology*, *298*(1), 242–266. doi:
701 10.1016/j.jhydrol.2004.03.042
- 702 Carrer, G. E., Klaus, J., & Pfister, L. (2019). Assessing the catchment storage func-
703 tion through a dual-storage concept. *Water Resources Research*, *55*(1), 476–
704 494. doi: 10.1029/2018WR022856
- 705 Cartwright, I., & Morgenstern, U. (2016). Using tritium to document the mean
706 transit time and sources of water contributing to a chain-of-ponds river sys-
707 tem: Implications for resource protection. *Applied Geochemistry*, *75*, 9–19.
708 doi: 10.1016/j.apgeochem.2016.10.007
- 709 Cartwright, I., Morgenstern, U., Howcroft, W., Hofmann, H., Armit, R., Stewart,
710 M., ... Irvine, D. (2020). The variation and controls of mean transit times in
711 Australian headwater catchments. *Hydrological Processes*, *34*(21), 4034–4048.
712 doi: 10.1002/hyp.13862
- 713 Choudhury, B. (1999). Evaluation of an empirical equation for annual evaporation
714 using field observations and results from a biophysical model. *Journal of Hy-*
715 *drology*, *216*(1), 99–110. doi: 10.1016/S0022-1694(98)00293-5
- 716 Condon, L. E., Markovich, K. H., Kelleher, C. A., McDonnell, J. J., Ferguson, G., &
717 McIntosh, J. C. (2020). Where is the bottom of a watershed? *Water Resources*
718 *Research*, *56*(3), e2019WR026010. doi: 10.1029/2019WR026010
- 719 Cooke, C. D., & Buttle, J. M. (2020, April). Assessing basin storage: Comparison of
720 hydrometric- and tracer-based indices of dynamic and total storage. *Hydrologi-*
721 *cal Processes*, *34*(9), 2012–2031. doi: 10.1002/hyp.13731
- 722 Creutzfeldt, B., Troch, P. A., Güntner, A., Ferré, T. P. A., Graeff, T., & Merz, B.
723 (2014). Storage-discharge relationships at different catchment scales based on
724 local high-precision gravimetry. *Hydrological Processes*, *28*(3), 1465–1475. doi:
725 10.1002/hyp.9689
- 726 Dawson, T. E. (1996). Determining water use by trees and forests from isotopic,
727 energy balance and transpiration analyses: The roles of tree size and hydraulic
728 lift. *Tree Physiology*, *16*(1-2), 263–272. doi: 10.1093/treephys/16.1-2.263
- 729 Donohue, R. J., McVicar, T. R., & Roderick, M. L. (2010). Assessing the ability
730 of potential evaporation formulations to capture the dynamics in evaporative

- 731 demand within a changing climate. *Journal of Hydrology*, 386(1), 186–197.
732 doi: 10.1016/j.jhydrol.2010.03.020
- 733 Du, C., Sun, F., Yu, J., Liu, X., & Chen, Y. (2016). New interpretation of the role
734 of water balance in an extended Budyko hypothesis in arid regions. *Hydrology
735 and Earth System Sciences*, 20(1), 393–409. doi: 10.5194/hess-20-393-2016
- 736 Duan, Q., Sorooshian, S., & Gupta, V. (1992). Effective and efficient global op-
737 timization for conceptual rainfall-runoff models. *Water Resources Research*,
738 28(4), 1015–1031. doi: 10.1029/91WR02985
- 739 Duethmann, D., Blöschl, G., & Parajka, J. (2020, July). Why does a conceptual
740 hydrological model fail to correctly predict discharge changes in response to
741 climate change? *Hydrology and Earth System Sciences*, 24(7), 3493–3511. doi:
742 10.5194/hess-24-3493-2020
- 743 Euser, T., Winsemius, H. C., Hrachowitz, M., Fenicia, F., Uhlenbrook, S., &
744 Savenije, H. H. G. (2013). A framework to assess the realism of model struc-
745 tures using hydrological signatures. *Hydrology and Earth System Sciences*,
746 17(5), 1893–1912. doi: 10.5194/hess-17-1893-2013
- 747 Fan, Y. (2019). Are catchments leaky? *WIREs Water*, 6(6), e1386. doi: 10.1002/
748 wat2.1386
- 749 Feng, X., Thompson, S. E., Woods, R., & Porporato, A. (2019). Quantifying
750 Asynchronicity of Precipitation and Potential Evapotranspiration in Mediter-
751 ranean Climates. *Geophysical Research Letters*, 46(24), 14692–14701. doi:
752 10.1029/2019GL085653
- 753 Fowler, K. J. A., Knoben, W. J. M., Peel, M. C., Peterson, T. J., Ryu, D., Saft, M.,
754 ... Western, A. W. (2020). Many commonly used rainfall-runoff models lack
755 long, slow dynamics: Implications for runoff projections. *Water Resources
756 Research*, 56(5), e2019WR025286. doi: 10.1029/2019WR025286
- 757 Fowler, K. J. A., Peel, M. C., Western, A. W., Zhang, L., & Peterson, T. J. (2016).
758 Simulating runoff under changing climatic conditions: Revisiting an apparent
759 deficiency of conceptual rainfall-runoff models. *Water Resources Research*,
760 52(3), 1820–1846. doi: 10.1002/2015WR018068
- 761 Freeman, M. C., Pringle, C. M., & Jackson, C. R. (2007). Hydrologic connectivity
762 and the contribution of stream headwaters to ecological integrity at regional
763 scales. *Journal of the American Water Resources Association*, 43(1), 5–14.

764 doi: 10.1111/j.1752-1688.2007.00002.x

765 Fu, B.-P. (1981). On the calculation of the evaporation from land surface. *Chinese*
766 *Journal of Atmospheric Sciences*, 5(1), 23–31.

767 Geris, J., Tetzlaff, D., & Soulsby, C. (2015). Resistance and resilience to droughts:
768 Hydropedological controls on catchment storage and run-off response. *Hydro-*
769 *logical Processes*, 29(21), 4579–4593. doi: 10.1002/hyp.10480

770 Geroy, I. J., Gribb, M. M., Marshall, H. P., Chandler, D. G., Benner, S. G., & Mc-
771 Namara, J. P. (2011). Aspect influences on soil water retention and storage.
772 *Hydrological Processes*, 25(25), 3836–3842. doi: 10.1002/hyp.8281

773 Gleeson, T., Befus, K. M., Jasechko, S., Luijendijk, E., & Cardenas, M. B. (2016).
774 The global volume and distribution of modern groundwater. *Nature Geo-*
775 *science*, 9(2), 161–167. doi: 10.1038/ngeo2590

776 Gray, J. M., Bishop, T. F. A., & Wilford, J. R. (2016). Lithology and soil relation-
777 ships for soil modelling and mapping. *Catena*, 147, 429–440. doi: 10.1016/j
778 .catena.2016.07.045

779 Grundy, M. J., Rossel, R. A. V., Searle, R. D., Wilson, P. L., Chen, C., & Gregory,
780 L. J. (2015). Soil and landscape grid of Australia. *Soil Research*, 53(8),
781 835–844. doi: 10.1071/SR15191

782 Hahm, W. J., Dralle, D. N., Rempe, D. M., Bryk, A. B., Thompson, S. E., Dawson,
783 T. E., & Dietrich, W. E. (2019). Low Subsurface Water Storage Capacity
784 Relative to Annual Rainfall Decouples Mediterranean Plant Productivity and
785 Water Use From Rainfall Variability. *Geophysical Research Letters*, 46(12),
786 6544–6553. doi: 10.1029/2019GL083294

787 Hale, V. C., McDonnell, J. J., Stewart, M. K., Solomon, D. K., Doolittle, J., Ice,
788 G. G., & Pack, R. T. (2016). Effect of bedrock permeability on stream
789 base flow mean transit time scaling relationships: 2. Process study of stor-
790 age and release. *Water Resources Research*, 52(2), 1375–1397. doi:
791 10.1002/2015WR017660

792 Han, J., Yang, Y., Roderick, M. L., McVicar, T. R., Yang, D., Zhang, S., & Beck,
793 H. E. (2020). Assessing the Steady-State Assumption in Water Balance
794 Calculation Across Global Catchments. *Water Resources Research*, 56(7),
795 e2020WR027392. doi: 10.1029/2020WR027392

796 Hayashi, M. (2020). Alpine hydrogeology: The critical role of groundwater in sourc-

- 797 ing the headwaters of the world. *Groundwater*, 58(4), 498–510. doi: 10.1111/
798 gwat.12965
- 799 Hewlett, J. D., & Hibbert, A. R. (1967). Factors affecting the response of small wa-
800 tersheds to precipitation in humid areas. In W. E. Sopper & H. W. Lull (Eds.),
801 *Forest Hydrology* (pp. 275–291). New York: Pergamon Press.
- 802 Hornberger, G. M., Scanlon, T. M., & Raffensperger, J. P. (2001). Modelling trans-
803 port of dissolved silica in a forested headwater catchment: The effect of hydro-
804 logical and chemical time scales on hysteresis in the concentration–discharge
805 relationship. *Hydrological Processes*, 15(10), 2029–2038. doi: 10.1002/hyp.254
- 806 Howcroft, W., Cartwright, I., & Morgenstern, U. (2018). Mean transit times in
807 headwater catchments: Insights from the Otway Ranges, Australia. *Hydrology
808 and Earth System Sciences*, 22(1), 635–653. doi: 10.5194/hess-22-635-2018
- 809 Hrachowitz, M., Benettin, P., van Breukelen, B. M., Fovet, O., Howden, N. J., Ruiz,
810 L., . . . Wade, A. J. (2016). Transit times—The link between hydrology and
811 water quality at the catchment scale. *WIREs Water*, 3(5), 629–657. doi:
812 10.1002/wat2.1155
- 813 Hrachowitz, M., Fovet, O., Ruiz, L., & Savenije, H. H. G. (2015). Transit time
814 distributions, legacy contamination and variability in biogeochemical $1/f\alpha$
815 scaling: How are hydrological response dynamics linked to water quality
816 at the catchment scale? *Hydrological Processes*, 29(25), 5241–5256. doi:
817 10.1002/hyp.10546
- 818 Immerzeel, W. W., Lutz, A. F., Andrade, M., Bahl, A., Biemans, H., Bolch, T., . . .
819 Baillie, J. E. M. (2020). Importance and vulnerability of the world’s water
820 towers. *Nature*, 577(7790), 364–369. doi: 10.1038/s41586-019-1822-y
- 821 Jackson, R. B., Sperry, J. S., & Dawson, T. E. (2000). Root water uptake and trans-
822 port: Using physiological processes in global predictions. *Trends in Plant Sci-
823 ence*, 5(11), 482–488. doi: 10.1016/S1360-1385(00)01766-0
- 824 Jasechko, S., Kirchner, J. W., Welker, J. M., & McDonnell, J. J. (2016). Substantial
825 proportion of global streamflow less than three months old. *Nature Geoscience*,
826 9(2), 126–129. doi: 10.1038/ngeo2636
- 827 Jeffrey, S. J., Carter, J. O., Moodie, K. B., & Beswick, A. R. (2001). Using spa-
828 tial interpolation to construct a comprehensive archive of Australian cli-
829 mate data. *Environmental Modelling & Software*, 16(4), 309–330. doi:

830 10.1016/S1364-8152(01)00008-1

831 Jencso, K. G., & McGlynn, B. L. (2011). Hierarchical controls on runoff generation:
832 Topographically driven hydrologic connectivity, geology, and vegetation. *Water*
833 *Resources Research*, *47*(11), W11527. doi: 10.1029/2011WR010666

834 Kirchner, J. W. (2003). A double paradox in catchment hydrology and geochemistry.
835 *Hydrological Processes*, *17*(4), 871–874. doi: 10.1002/hyp.5108

836 Kirchner, J. W. (2006). Getting the right answers for the right reasons: Linking
837 measurements, analyses, and models to advance the science of hydrology. *Wa-*
838 *ter Resources Research*, *42*(3), W03S04. doi: 10.1029/2005WR004362

839 Kirchner, J. W. (2009). Catchments as simple dynamical systems: Catchment char-
840 acterization, rainfall-runoff modeling, and doing hydrology backward. *Water*
841 *Resources Research*, *45*(2), 1–34. doi: 10.1029/2008WR006912

842 Kirchner, J. W., & Neal, C. (2013). Universal fractal scaling in stream chemistry
843 and its implications for solute transport and water quality trend detection.
844 *Proceedings of the National Academy of Sciences*, *110*(30), 12213–12218. doi:
845 10.1073/pnas.1304328110

846 Knoben, W. J. M., Freer, J. E., Peel, M. C., Fowler, K. J. A., & Woods, R. A.
847 (2020). A brief analysis of conceptual model structure uncertainty us-
848 ing 36 models and 559 catchments. *Water Resources Research*, *56*(9),
849 e2019WR025975. doi: 10.1029/2019WR025975

850 Knoben, W. J. M., Freer, J. E., & Woods, R. A. (2019). Technical note: Inherent
851 benchmark or not? comparing Nash–Sutcliffe and Kling–Gupta efficiency
852 scores. *Hydrology and Earth System Sciences*, *23*(10), 4323–4331. doi:
853 10.5194/hess-23-4323-2019

854 Koffler, D., & Laaha, G. (2013). LFSTAT - Low-flow analysis in R. In *EGU General*
855 *Assembly 2013* (Vol. 15). Vienna, Austria: Geophysical Research Abstracts.

856 Koster, R. D., & Suarez, M. J. (1999). A simple framework for examining the inter-
857 annual variability of land surface moisture fluxes. *Journal of Climate*, *12*(7),
858 1911–1917. doi: 10.1175/1520-0442(1999)012<1911:ASFFET>2.0.CO;2

859 Leblanc, M. J., Tregoning, P., Ramillien, G., Tweed, S. O., & Fakes, A. (2009).
860 Basin-scale, integrated observations of the early 21st century multiyear
861 drought in southeast Australia. *Water Resources Research*, *45*(4), W04408.
862 doi: 10.1029/2008WR007333

- 863 Li, Z., Jasechko, S., & Si, B. (2019). Uncertainties in tritium mass balance models
864 for groundwater recharge estimation. *Journal of Hydrology*, *571*, 150–158. doi:
865 10.1016/j.jhydrol.2019.01.030
- 866 Lidén, R., & Harlin, J. (2000). Analysis of conceptual rainfall–runoff modelling per-
867 formance in different climates. *Journal of Hydrology*, *238*(3), 231–247. doi: 10
868 .1016/S0022-1694(00)00330-9
- 869 Lindström, G. (1997). A simple automatic calibration routine for the HBV model.
870 *Hydrology Research*, *28*(3), 153–168. doi: 10.2166/nh.1997.0009
- 871 McDonnell, J. J., & Beven, K. (2014). Debates - The future of hydrological sciences:
872 A (common) path forward? a call to action aimed at understanding velocities,
873 celerities and residence time distributions of the headwater hydrograph. *Water*
874 *Resources Research*, *50*(6), 5342–5350. doi: 10.1002/2013WR015141
- 875 McGuire, K. J., McDonnell, J. J., Weiler, M., Kendall, C., McGlynn, B. L., Welker,
876 J. M., & Seibert, J. (2005). The role of topography on catchment-scale
877 water residence time. *Water Resources Research*, *41*(5), W05002. doi:
878 10.1029/2004WR003657
- 879 McMahan, T. A., Peel, M. C., Lowe, L., Srikanthan, R., & McVicar, T. R. (2013).
880 Estimating actual, potential, reference crop and pan evaporation using stan-
881 dard meteorological data: A pragmatic synthesis. *Hydrology and Earth System*
882 *Sciences*, *17*(4), 1331–1363. doi: 10.5194/hess-17-1331-2013
- 883 McNamara, J. P., Tetzlaff, D., Bishop, K., Soulsby, C., Seyfried, M., Peters, N. E.,
884 ... Hooper, R. (2011). Storage as a metric of catchment comparison. *Hydro-*
885 *logical Processes*, *25*(21), 3364–3371. doi: 10.1002/hyp.8113
- 886 Morton, F. I. (1983). Operational estimates of areal evapotranspiration and their
887 significance to the science and practice of hydrology. *Journal of Hydrology*,
888 *66*(1), 1–76. doi: 10.1016/0022-1694(83)90177-4
- 889 Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual
890 models part I — A discussion of principles. *Journal of Hydrology*, *10*(3), 282–
891 290. doi: 10.1016/0022-1694(70)90255-6
- 892 Peters, N. E., & Aulenbach, B. T. (2011). Water storage at the Panola Mountain
893 Research Watershed, Georgia, USA. *Hydrological Processes*, *25*(25), 3878–
894 3889. doi: 10.1002/hyp.8334
- 895 Peterson, T. J., Saft, M., Peel, M. C., & John, A. (2021, May). Watersheds may

- 896 not recover from drought. *Science*, *372*(6543), 745–749. doi: 10.1126/science
897 .abd5085
- 898 Pfister, L., Martínez-Carreras, N., Hissler, C., Klaus, J., Carrer, G. E., Stewart,
899 M. K., & McDonnell, J. J. (2017). Bedrock geology controls on catchment
900 storage, mixing, and release: A comparative analysis of 16 nested catchments.
901 *Hydrological Processes*, *31*(10), 1828–1845. doi: 10.1002/hyp.11134
- 902 Ramillien, G., Famiglietti, J. S., & Wahr, J. (2008). Detection of continental hy-
903 drology and glaciology signals from GRACE: A review. *Surveys in Geophysics*,
904 *29*(4), 361–374. doi: 10.1007/s10712-008-9048-9
- 905 Rice, J. S., & Emanuel, R. E. (2019). Ecohydrology of Interannual Changes in Wa-
906 tershed Storage. *Water Resources Research*, *55*(10), 8238–8251. doi: 10.1029/
907 2019WR025164
- 908 Rinaldo, A., Benettin, P., Harman, C. J., Hrachowitz, M., McGuire, K. J., van der
909 Velde, Y., . . . Botter, G. (2015). Storage selection functions: A coherent
910 framework for quantifying how catchments store and release water and solutes.
911 *Water Resources Research*, *51*(6), 4840–4847. doi: 10.1002/2015WR017273
- 912 Saft, M., Peel, M. C., Western, A. W., & Zhang, L. (2016). Predicting shifts in
913 rainfall-runoff partitioning during multiyear drought: Roles of dry period and
914 catchment characteristics. *Water Resources Research*, *52*(12), 9290–9305. doi:
915 10.1002/2016WR019525
- 916 Saft, M., Western, A. W., Zhang, L., Peel, M. C., & Potter, N. J. (2015). The
917 influence of multiyear drought on the annual rainfall-runoff relationship: An
918 Australian perspective. *Water Resources Research*, *51*(4), 2444–2463. doi:
919 10.1002/2014WR015348
- 920 Salinas, J. L., Laaha, G., Rogger, M., Parajka, J., Viglione, A., Sivapalan, M., &
921 Blöschl, G. (2013). Comparative assessment of predictions in ungauged basins
922 – Part 2: Flood and low flow studies. *Hydrology and Earth System Sciences*,
923 *17*(7), 2637–2652. doi: 10.5194/hess-17-2637-2013
- 924 Sayama, T., McDonnell, J. J., Dhakal, A., & Sullivan, K. (2011). How much wa-
925 ter can a watershed store? *Hydrological Processes*, *25*(25), 3899–3908. doi: 10
926 .1002/hyp.8288
- 927 Seibert, J. (1997). Estimation of parameter uncertainty in the HBV model. *Hydrology
928 Research*, *28*(4-5), 247–262.

- 929 Seibert, J., & Vis, M. J. P. (2012). Teaching hydrological modeling with a user-
930 friendly catchment-runoff-model software package. *Hydrology and Earth System*
931 *Sciences*, *16*(9), 3315–3325. doi: 10.5194/hess-16-3315-2012
- 932 Seyfried, M. S., Grant, L. E., Marks, D., Winstral, A., & McNamara, J. (2009).
933 Simulated soil water storage effects on streamflow generation in a mountainous
934 snowmelt environment, Idaho, USA. *Hydrological Processes*, *23*(6), 858–873.
935 doi: 10.1002/hyp.7211
- 936 Sklash, M. G., & Farvolden, R. N. (1979). The role of groundwater in storm runoff.
937 *Journal of Hydrology*, *43*(1), 45–65. doi: 10.1016/0022-1694(79)90164-1
- 938 Sophocleous, M. (2002). Interactions between groundwater and surface water: The
939 state of the science. *Hydrogeology Journal*, *10*(1), 52–67. doi: 10.1007/s10040
940 -001-0170-8
- 941 Soulsby, C., Neal, C., Laudon, H., Burns, D. A., Merot, P., Bonell, M., . . . Tetzlaff,
942 D. (2008). Catchment data for process conceptualization: Simply not enough?
943 *Hydrological Processes*, *22*(12), 2057–2061. doi: 10.1002/hyp.7068
- 944 Soulsby, C., Tetzlaff, D., & Hrachowitz, M. (2009). Tracers and transit times: Win-
945 dows for viewing catchment scale storage? *Hydrological Processes*, *23*(24),
946 3503–3507. doi: 10.1002/hyp.7501
- 947 Spence, C. (2007). On the relation between dynamic storage and runoff: A discus-
948 sion on thresholds, efficiency, and function. *Water Resources Research*, *43*(12),
949 W12416. doi: 10.1029/2006WR005645
- 950 Spence, C. (2010). A paradigm shift in hydrology: Storage thresholds across scales
951 influence catchment runoff generation. *Geography Compass*, *4*(7), 819–833. doi:
952 10.1111/j.1749-8198.2010.00341.x
- 953 Staudinger, M., Stoelzle, M., Seeger, S., Seibert, J., Weiler, M., & Stahl, K. (2017).
954 Catchment water storage variation with elevation. *Hydrological Processes*,
955 *31*(11), 2000–2015. doi: 10.1002/hyp.11158
- 956 Stein, J. L., Hutchinson, M. F., & Stein, J. A. (2014). A new stream and nested
957 catchment framework for Australia. *Hydrology and Earth System Sciences*,
958 *18*(5), 1917–1933. doi: 10.5194/hess-18-1917-2014
- 959 Tague, C., & Grant, G. E. (2004). A geological framework for interpreting the low-
960 flow regimes of Cascade streams, Willamette River Basin, Oregon. *Water Re-*
961 *sources Research*, *40*(4). doi: 10.1029/2003WR002629

- 962 Tetzlaff, D., McNamara, J. P., & Carey, S. K. (2011). Measurements and modelling
 963 of storage dynamics across scales. *Hydrological Processes*, *25*(25), 3831–3835.
 964 doi: 10.1002/hyp.8396
- 965 Teuling, A. J., Lehner, I., Kirchner, J. W., & Seneviratne, S. I. (2010). Catchments
 966 as simple dynamical systems: Experience from a Swiss prealpine catchment.
 967 *Water Resources Research*, *46*(10), W10502. doi: 10.1029/2009WR008777
- 968 van der Velde, Y., Torfs, P. J. J. F., van der Zee, S. E. A. T. M., & Uijlenhoet, R.
 969 (2012). Quantifying catchment-scale mixing and its effect on time-varying
 970 travel time distributions. *Water Resources Research*, *48*(6), 1–13. doi:
 971 10.1029/2011WR011310
- 972 van der Velde, Y., Vercauteren, N., Jaramillo, F., Dekker, S. C., Destouni, G., &
 973 Lyon, S. W. (2014). Exploring hydroclimatic change disparity via the Budyko
 974 framework. *Hydrological Processes*, *28*(13), 4110–4118. doi: 10.1002/hyp.9949
- 975 van Dijk, A. I. J. M., Beck, H. E., Crosbie, R. S., de Jeu, R. A. M., Liu, Y. Y.,
 976 Podger, G. M., . . . Viney, N. R. (2013). The Millennium Drought in southeast
 977 Australia (2001–2009): Natural and human causes and implications for water
 978 resources, ecosystems, economy, and society. *Water Resources Research*, *49*(2),
 979 1040–1057. doi: 10.1002/wrcr.20123
- 980 Van Loon, A. F., & Laaha, G. (2015). Hydrological drought severity explained by
 981 climate and catchment characteristics. *Journal of Hydrology*, *526*, 3–14. doi:
 982 10.1016/j.jhydrol.2014.10.059
- 983 Viviroli, D., Archer, D. R., Buytaert, W., Fowler, H. J., Greenwood, G. B., Ham-
 984 let, A. F., . . . Woods, R. A. (2011). Climate change and mountain wa-
 985 ter resources: Overview and recommendations for research, management
 986 and policy. *Hydrology and Earth System Sciences*, *15*(2), 471–504. doi:
 987 10.5194/hess-15-471-2011
- 988 Viviroli, D., Dürr, H. H., Messerli, B., Meybeck, M., & Weingartner, R. (2007).
 989 Mountains of the world, water towers for humanity: Typology, mapping,
 990 and global significance. *Water Resources Research*, *43*(7), W07447. doi:
 991 10.1029/2006WR005653
- 992 Wagener, T., Sivapalan, M., Troch, P., & Woods, R. A. (2007). Catchment classifi-
 993 cation and hydrologic similarity. *Geography Compass*, *1*(4), 901–931. doi: 10
 994 .1111/j.1749-8198.2007.00039.x

- 1095 Western, A. W., Grayson, R. B., Blöschl, G., Willgoose, G. R., & McMahon,
1096 T. A. (1999). Observed spatial organization of soil moisture and its rela-
1097 tion to terrain indices. *Water Resources Research*, *35*(3), 797–810. doi:
1098 10.1029/1998WR900065
- 1099 Wheeler, S. A. (2014). Insights, lessons and benefits from improved regional water
1100 security and integration in Australia. *Water Resources and Economics*, *8*, 57–
1101 78. doi: 10.1016/j.wre.2014.05.006
- 1102 Winsemius, H. C., Schaefli, B., Montanari, A., & Savenije, H. H. G. (2009). On
1103 the calibration of hydrological models in ungauged basins: A framework for
1104 integrating hard and soft hydrological information. *Water Resources Research*,
1105 *45*(12), W12422. doi: 10.1029/2009WR007706
- 1106 Yeh, H.-F., & Huang, C.-C. (2019). Evaluation of basin storage–discharge sensitiv-
1107 ity in Taiwan using low-flow recession analysis. *Hydrological Processes*, *33*(10),
1108 1434–1447. doi: 10.1002/hyp.13411
- 1109 Zeng, R., & Cai, X. (2015). Assessing the temporal variance of evapotranspira-
1110 tion considering climate and catchment storage factors. *Advances in Water Re-*
1111 *sources*, *79*, 51–60. doi: 10.1016/j.advwatres.2015.02.008
- 1112 Zhang, J. Y., Wang, W. C., & Wei, J. F. (2008). Assessing land-atmosphere cou-
1113 pling using soil moisture from the Global Land Data Assimilation System and
1114 observational precipitation. *Journal of Geophysical Research: Atmospheres*,
1115 *113*(D17), D17119.
- 1116 Zhang, L., Dawes, W. R., & Walker, G. R. (2001). Response of mean annual evap-
1117 otranspiration to vegetation changes at catchment scale. *Water Resources Re-*
1118 *search*, *37*(3), 701–708. doi: 10.1029/2000WR900325
- 1119 Zhang, L., Hickel, K., Dawes, W. R., Chiew, F. H. S., Western, A. W., & Briggs,
1120 P. R. (2004). A rational function approach for estimating mean annual
1121 evapotranspiration. *Water Resources Research*, *40*(2), W02502. doi:
1122 10.1029/2003WR002710
- 1123 Zhang, X. S., Amirthanathan, G. E., Bari, M. A., Laugesen, R. M., Shin, D., Kent,
1124 D. M., ... Tuteja, N. K. (2016). How streamflow has changed across Aus-
1125 tralia since the 1950s: Evidence from the network of hydrologic reference
1126 stations. *Hydrology and Earth System Sciences*, *20*(9), 3947–3965. doi:
1127 10.5194/hess-20-3947-2016