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Discussions

Evaluating a landscape-scale daily water balance model to support spatially continuous representation of flow intermittency throughout stream networks

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Abstract

There is a growing interest globally in the spatial distribution of intermittently flowing streams and rivers, and how their spatial extent varies in relation to climatic factors. However, deriving consistent information on the extent of flow intermittency within river networks is hampered by the fact that streamflow gauges are often sparsely distributed and more often located within the most perennial parts of the river network. Here, we developed an approach to quantify catchment-wide streamflow intermittency over long timeframes and in a spatially explicit manner, using readily accessible and spatially contiguous daily runoff data from a national-scale water balance model. We examined the ability of the water balance model to simulate streamflow in two hydro-climatically distinctive (subtropical and temperate) regions in Australia, with a particular focus on low flow simulations. We also evaluated the effect of model time step (daily vs. monthly) on flow intermittency estimation to inform future model selection. The water balance model showed better performance in the temperate region characterised by steady baseflow than in the subtropical region with flashy hydrographs and frequent cease-to-flow periods. The model tended to overestimate low flow magnitude due to both overestimation of gains (e.g. groundwater release to baseflow) and underestimation of losses (e.g. transmission losses) during low-flow periods. Modelled patterns of flow intermittency revealed highly dynamic behaviour in space and time, with intermittent flows affecting between 29 % and 80% of the river network over the period of 1911-2016. The daily flow model did not perform better than the monthly flow model in quantifying flow intermittency, and model selection should depend on the intended application of the model outputs. Our general approach to quantifying spatio-temporal patterns of flow intermittency is transferable to other parts of the world, and can inform hydro-ecological understanding and management of intermittent streams where limited gauging data are available.

Keywords: AWRA-L model, flow regime, river routing, Australia, temporary streams

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1 Introduction

Intermittent streams that cease to flow for some period of most years are prevalent within river networks globally (Acuña et al., 2014;Datry et al., 2014). Their spatial extent is projected to increase in regions experiencing drying trends related to climate change and water extraction for human uses (Larned et al., 2010). Intermittent streams have seen increasing research interest over the past decade (e.g. Costigan et al., 2016; Fritz et al., 2013; Gallart et al., 2017; Leigh et al., 2016), and there is a growing interest in conserving these unique ecosystems. The scarcity of spatially-explicit information on flow intermittency has been identified as one of the key issues confronting intermittent stream management (Acuña et al., 2017). Improved understanding of temporal and spatial patterns in flow intermittency is fundamentally important for effective river management. Flow intermittency exerts primary control on the transfer of energy, materials and organisms by surface water through river networks (Jaeger et al., 2019) and is a key driver of riverine ecosystems (Stanley et al., 1997;Datry et al., 2017;Poff et al., 1997).

Previous studies have predominantly relied on the use of gauged streamflow data to make inferences about the distribution of intermittent streams in many regions, including France (Snelder et al., 2013), Australia (Kennard et al., 2010;Bond and Kennard, 2017), Spain and North America (de Vries et al., 2015). However, spatial biases in the distribution of stream gauges used in such studies may give misleading impressions of spatial patterns and extent of streamflow intermittency (Snelder et al., 2013). Alternative methods for quantifying the extent of intermittent flow include citizen-observation networks supported by regular reports from trained volunteers (Datry et al., 2016;Turner and Richter, 2011), the use of electrical arrays by measuring electrical conductivity of the streambed (Jaeger and Olden, 2012), development of predictive models for intermittent streams (González-Ferreras and Barquín, 2017), and deployment of unmanned aerial systems (Spence and Mengistu, 2016). These alternatives are generally appropriate over small spatial extents and short time frames, but are difficult to scale up to larger areas to quantify flow intermittency in space and time. Satellite remote sensing-based quantification of flow intermittency (Hou et al., 2019) can cover larger spatial extents, but for now remains applicable only to relatively large rivers (> 30 m in the case of Landsat imagery) and can be affected by factors such as vegetation and cloud obstruction.

Spatially contiguous runoff data derived from water balance models provide another potential alternative to quantify spatio-temporal variations in flow intermittency. For example, Yu et al. (2018) used runoff simulations obtained from a water balance model (Raupach et al., 2009) to generate spatially explicit and catchment-wide estimates of streamflow intermittency, but only at a relatively coarse monthly time step. Depending on the application, flow simulations at a finer temporal scale (e.g. daily) may be necessary to capture the dynamic aspects of hydrological processes. These kind of simulations are important to understand the causes of flow intermittency at multiple spatial scales better, potentially enabling more ecologically-relevant characterisation of hydrology, such as the magnitude, frequency, duration, and change of rate of ecologically important high or low flow events. However, there are few examples of studies quantifying spatial and temporal variation in flow intermittency across river networks using spatially contiguous daily flow data. That is partly because streamflow simulation is more

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challenging at a daily versus monthly time step due to higher uncertainties in input data at this finer temporal scale (Wang et al., 2011).

Water balance models at a daily time step have been increasingly developed around the world (Lin et al., 2019;Bierkens et al., 2015). One prominent regional example is the Australian Water Resource Assessment Landscape (AWRA-L) model (van Dijk, 2010). The AWRA-L model has been developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Australian Bureau of Meteorology (BoM) to simulate the terrestrial water balance across Australia at a daily time step (van Dijk, 2010;Frost et al., 2016). The model yields spatially contiguous daily water availability values gridded at a spatial resolution of 0.05 arc-degree spatial resolution (approximately 5 × 5 km) (Frost et al., 2016). The development of such water balance models in Australia and other parts of the world provides the potential to quantify spatial and temporal variation in runoff, and hence flow intermittency, at a daily time step. However, this requires an effective and efficient conversion process to translate gridded runoff estimates to accumulated streamflow estimates down the river network. This is especially challenging for large study areas due to lags in runoff, which can influence the timing of flow peaks and rates of recession. Additionally, many national-scale water balance models, including AWRA-L, were calibrated on a large domain that covers multiple climate conditions (Viney et al., 2015), providing a best "average" response but potentially inconsistent accuracy of runoff simulations within particular climate domains. As the predictive performance for ungauged basins strongly depends on climate settings, this compromise raises the question as to whether such models can be used to quantify flow intermittency over multiple climate conditions. Although substantial efforts have been made in evaluating hydrological models in different climate conditions (Do et al., 2019;Gudmundsson et al., 2012;Zaherpour et al., 2018;Lin et al., 2019), a limited number of such studies have focused particularly on model performance during low flow conditions, which is particularly important for flow intermittency quantification.

In this study, we sought to apply spatially contiguous daily runoff outputs from the AWRA-L water balance model to quantify the spatial extent and temporal patterns of flow intermittency. To assess the accuracy of the AWRA-L model for daily flow simulations, we first developed a simple but effective technique to convert runoff to streamflow for two hydro-climatically distinctive regions. The translation of gridded runoff to aggregated streamflow/discharge on vector river flow lines make AWRA-L outputs more accessible to fluvial geomorphologists and ecologists, who may intend to relate daily hydrologic characteristics of rivers to a broad range of physical and ecological phenomena. We further assessed the uncertainty of the AWRA-L model in capturing patterns of flow intermittency. Lastly, we evaluated the effect of time step (daily vs. monthly) on the relative performance of the model in replicating observed patterns of cease to flow periods at reference gauges. A previous study conducted at the monthly time step (Yu et al., 2018) was used to benchmark flow intermittency estimated from the daily model.

2 Study areas

This research was conducted in two hydro-climatically distinctive regions: South-east Queensland and the Tamar River catchment in Tasmania (Fig.1). The South-east Queensland (SEQ) region is located in the eastern part of Australia (Fig.1a) and comprises five major coastal river basins with a total area of 21,331 km^2 (Fig.1b) (Australian Bureau of Statistics, 2011). SEQ has 7,229 stream segments and their corresponding sub-catchments according to the Australian Hydrologic Geospatial Fabric (Geofabric). SEQ is a region of transitional temperate to subtropical climate (Fig. 1a) with substantial inter- and intra-annual variation in rainfall. The majority of rainfall and streamflow usually occur in the summer months of January to March, often followed by a second minor discharge peak between April and June, but high and low flows may occur at any time of year (Kennard et al., 2007). Thus, there are a range of flow regimes with many streams being intermittent to varying degrees. The Tamar River catchment (Tamar) is located in Tasmania, an island state off Australia's south coast (Fig.1a, c). It drains a catchment area of approximately 11,215 km^2, comprising over one fifth of Tasmania's land mass and is located in north-east and central Tasmania. Tamar is characterized by a temperate climate condition, of which rainfall is relatively evenly distributed throughout the year and most months receive very similar averages, according to climate data from BoM (http://www.bom.gov.au/climate/data).

[Figure 1 is about here]

3 Data and Methodology

3.1 Streamflow gauge data

Observed streamflow data were sourced from the BoM water data website (http://www.bom.gov.au/waterdata). Based on streamflow data availability, a total of 25 gauges in SEQ and 15 gauges in Tamar were selected (Fig.1b, c). All gauges have less than 0.5 % missing values over the period from 01/01/2005 to 31/12/2017. The gauges were dispersed throughout each study area and encompassed a range of stream sizes and flow regime types. Daily flow data for the study period were used to validate flow simulations and test flow intermittency estimates.

3.2 Conversion from spatially contiguous runoff to streamflow

Simulated daily runoff from the AWRA-L model (version 5) were downloaded from BoM (http://www.bom.gov.au/water/landscape). These data are in gridded format and require conversion to streamflow for each sub-catchment by aggregating the gridded runoff data with a hierarchically nested catchment to simulate streamflow throughout river networks. The conversion process may or may not need to use a river routing model to propagate streamflow through river networks, partly depending on the size of the catchment of interest (Robinson et al., 1995). If streamflow can be simulated at an acceptable accuracy without a routing model, the conversion process is more efficient and the readily available runoff data can be more accessible for potential applications, such as flow characterisation for ungauged stream segments. In addition, a conversion process involving a routing model can be computationally-intensive and usually requires parallel computing to speed up the calculations (David et al., 2011b). Therefore, in this study we applied two approaches to determine an effective and efficient runoff-streamflow conversion. The first approach coupled a river routing model to the water balance model, and its effects on flow simulations are compared to the model performance of a lumped model, which was operated without any river routing. As the conversion process was achieved using the "*catchstats*" package (https://github.com/nickbond/catchstats) in the R programming language (R Development Core Team, 2017), so the second approach was to speed up the conversion process by incorporating parallel algorithm to exiting functions of that package. The conversion process was run on a Griffith University High Performance Computing node with 12 cores and RAM 12 GB.

The hierarchically nested catchment dataset used in this study was sourced from the Geofabric dataset (Stein et al., 2014), which provides a fully connected and directed stream network and associated catchment hierarchy at the national scale. The routing model applied in this study was the Routing Application for Parallel Computation of Discharge (RAPID) model (David et al., 2011b). RAPID solves the matrix-based Muskingum equation to route flow through each stream of the river network and performs streamflow computation for every stream segment of a river network, including ungauged streams. Various water balance models have been used in combination with RAPID (Follum et al., 2017;Lawrence et al., 2011;Lin et al., 2019).

To test the effects of river routing, we first calculated summary flow metrics describing the critical components of hydrological variation across average, high- and low-flow conditions (Table 1) for flow simulations from both the lumped and coupled models. Then we conducted Student's *t*-test for each flow metric to identify whether the inclusion of river routing can improve model accuracy based on a significance level of 5 %. We used the 10th and 90th percentiles of daily flows to respectively describe low-flow and high-flow thresholds (Leigh and Datry, 2016;Gudmundsson et al., 2019). The calculation process was conducted with the "*hydrostats*" package in the R language (Bond, 2016).

[Table 1 is about here]

3.3 Accuracy assessment of modelled streamflow

To evaluate overall model performance in streamflow simulations, we calculated the modified Kling-Gupta efficiency (KGE) (Kling et al., 2012) between the observed and modelled streamflow for all gauges in SEQ and Tamar. KGE is an integrated skill metric, which measures the Euclidean distance between a point and the optimal point that has the maximum correlation coefficient, zero variability error and zero bias error between the simulated and observed streamflow (Kling et al., 2012;Gupta et al., 2009). KGE takes values from -1 to 1: KGE = 1 indicates perfect agreement between simulations and observations, and KGE < -0.41 indicates that the mean of observations provides better estimates than simulations (Knoben et al., 2019). We also calculated each summary flow metric (Table 1) for observed and modelled streamflow data at all gauges in SEQ and Tamar and visually compared their frequency distributions.

Furthermore, considering that this study aims to apply flow simulations to quantify flow intermittency, the model accuracy of low flow simulation is particularly important. A preliminary analysis showed that AWRA-L modelled streamflow was very sensitive to rainfall events, relative to the response of observed flow (Fig.2). This finding indicates that over-responsiveness of AWRA-L to rainfall may potentially contribute to overestimation of low flow. We hypothesized that this over-responsiveness is partly due to overestimation of "*in situ*" gains to low flow discharge (e.g. groundwater release to baseflow) as well as underestimation of transmission losses (e.g. depression filling and evapotranspiration) during water movement through various flow paths in the stream network (Davison and van der Kamp, 2008). Given that we do not have access to the underlying models to directly adjust model parameters, we instead compared the observed and modelled low flow magnitude at all gauges in the two study areas along the gradient of their catchment areas (22-3,881 km^2 in SEQ; 33-3,294 km^2 in Tamar) to test this hypothesis. We expect that 1) if the difference in low flow magnitude occurs at all gauges, then low flow overestimation can be at least attributed to the overestimation of gains to low flow discharge. Alternatively, 2) if the difference in low flow magnitude occurs towards the downstream of the catchment, then low flow overestimation may be related to underestimation of transmission losses.

[Figure 2 is about here]

3.4 Quantifying flow intermittency using spatially contiguous flow simulations

Due to the fact that water balance models often over-predict the magnitude of very low flows (Ye et al., 1997), we adopted the same method used in Yu et al. (2018) to estimate a threshold of zero flow from the model that correlated with measured cease to flow duration at each gauge. This involved three steps.

1) We used linear regression to model the cease to flow duration at each gauge as a function of catchment environment variables. The environmental variables were the same as those in Yu et al. (2018), and included variables related to climate (annual daily maximum temperature), catchment geology topography (catchment area, catchment average slope, and catchment average elevation), and catchment soil properties (catchment average saturated hydraulic conductivity).
2) We then used the predictive models to extrapolate estimates of overall flow permanency (in terms of the proportion of days with flow) to each segment in the entire river network.
3) For each segment, the time-series of daily runoff was truncated (flows below the threshold were set to "0") by adopting an appropriate threshold for 'zero flows' that preserved the proportion of days with flow as estimated at Step 2.

This truncation was only conducted in SEQ as most gauges in the Tamar catchment had perennial flow. Based on the modelled daily streamflow from AWRA-L, we calculated annual flow intermittency as the number of zero-flow days per year over the period of 2005-2016. In examining the model outputs, we also compared the patterns of cease to flow from the daily AWRA-

L model, with those derived by aggregating daily outputs to a monthly time step (termed "monthly-aggregated AWRA-L" hereafter), as well as results from the AWAP water balance model, which operates only at a monthly time step. For the monthly-aggregated AWRA-L outputs, all days in a month had to have zero flow for the flows for that month to be zero. The AWAP model was developed at the Australian continental scale by CSIRO and BoM with a similar model structure to AWRA-L (Raupach et al., 2018), and has been used to quantify flow intermittency in SEQ in our previous research (Yu et al., 2018). Modelled flow intermittency from all three sources (i.e. daily and monthly-aggregated AWRA-L, and monthly AWAP) was also tested against the measured flow intermittency derived respectively from daily and monthly observed streamflow data at gauged locations in SEQ.

Taking the advantage of the modelled long-term runoff data from AWRA-L over the period of 1911-2016, we further quantified spatial and temporal dynamics of flow intermittency for every stream segment within SEQ, and compared the results with those from the AWAP model over the same period (Yu et al., 2018). The spatial pattern of flow intermittency was represented by the mean annual number of zero flow days across the period of 1911-2016 for the AWRA-L and by the mean annual number of calendar months for the AWAP. The temporal pattern of flow intermittency was expressed as the proportion of streams with flow intermittency > 30 days or 1 month (termed "intermittent streams" hereafter) for the AWRA-L and AWAP models, respectively.

4 Results

4.1 Negligible effects of river routing on daily flow simulations

The lumped and coupled (i.e. with routing) models using AWRA-L simulated runoff were run in both SEQ and Tamar and produced similar values for various flow metrics between the lumped and coupled in both regions (Fig.3; *p* values were greater than 0.50 for most flow metrics based on *t*-test results). There were noticeable differences for three flow metrics related to low flows (the variability in timing, the frequency and the duration of low flow spells), but these differences were not statistically significant at the 5 % level. These results suggested that the routing algorithm has negligible effects on flow simulations in our study areas, which is reasonable because of the small size of the two watersheds. Therefore, in the subsequent analysis, we only used the results from the AWRA-L lumped model as it is less computationally intensive and was able to maintain a comparable model performance to that of the coupled model taking into account the routing effect.

[Figure 3 is about here]

4.2 Accuracy assessment of modelled streamflow in SEQ and Tamar

The overall accuracy of streamflow estimated by AWRA-L lumped model (referred to as "modelled streamflow" in this section) was evaluated for 25 gauges in SEQ and 15 gauges in Tamar. Results suggested a fair to good explanatory value across all gauges (Fig.4). The KGE values varied across the 25 gauges in SEQ, ranging from -0.19 (Gauge No. 145103) to 0.76 (143901), with a median value of 0.42, while the model performed generally better in Tamar and the KGE values ranged from 0.11 (18219.1) to 0.71 (852.1) across 15 gauges, with a median value of 0.47 (Fig.4). However, no significant difference was found in the overall model performance between the two hydro-climatically distinctive regions, according to the two-sample Student's *t*-test (t = -1.46, p = 0.15).

[Figure 4 is about here]

The modelled streamflow in SEQ revealed a generally good match with the observed streamflow across all high-flow metrics and the magnitude of average flow, but the model tended to overestimate the variation in the magnitude of average flow (almost two times higher on average), report earlier timing of low flows, overestimate the frequency (48 % higher), and underestimate the duration (74 % lower) of low flows (Fig.5). Compared to the model performance in SEQ, the flow simulations in Tamar showed slightly better performance, predicting well not only for the high-flow metrics but also for the metrics related to average flows (Fig.5). However, flow simulations in Tamar also exhibited slightly earlier estimations for the timing of low flow spells (13 % earlier), overestimations for low flow spell frequency (92 % lower on average) and underestimation for low flow spell duration (58 % lower) (Fig.5).

[Figure 5 is about here]

Varying degrees of difference in the magnitude of low flow between the observed and modelled were found at nearly all gauges. At the same time, there appeared to be a tendency toward larger differences with increasing catchment area in both SEQ and Tamar (Fig.6). The models appeared to both over-estimate "*in situ*" gains to low flow in some reaches, while also under-estimating transmission losses; these both contribute to the overall overestimation of low flow in downstream catchments.

[Figure 6 is about here]

4.3 Quantifying flow intermittency using flow simulations

We calculated annual flow intermittency at gauged locations in SEQ using three sources of modelled flow (daily and monthly-aggregated AWRA-L, and monthly AWAP). Annual flow intermittency calculated using daily AWRA-L flow was tested against the observed data (Fig.7a). The AWRA-L model displayed the potential to be used to estimate flow intermittency at a daily time step, with a good match with the observed flow intermittency (R^2= 0.56) in SEQ. Nonetheless, the model tended to overestimate flow intermittency for gauges located in relatively wet areas (e.g. ≤ 40 days of flow intermittency) while underestimating for gauges located in relatively dry areas (Fig.7a).

Annual flow intermittency calculated using monthly-aggregated AWRA-L flow and monthly AWAP flow were also compared with the observed (Fig.7b). The AWAP model showed much more accuracy than the monthly-aggregated AWRA-L model in estimating flow intermittency (R^2 = 0.53 and 0.32, respectively for the two models). More specifically, the AWAP model displayed a similar estimation pattern as the daily AWRA-L model: overestimation in relatively wet areas while underestimation in relatively dry areas. By contrast, the monthly-aggregated AWRA-L model underestimated flow intermittency at nearly all gauges (Fig.7b).

[Figure 7 is about here]

The spatial patterns of flow intermittency derived from the daily and monthly flow simulations aligned well only for the main stems and some coastal streams, which were predicted to flow for most of the time (Fig.8). There was a noticeable difference for inland streams, especially those lower order streams. More specifically, in the western Brisbane River catchment and the South Coast River catchment, most inland streams were predicted by the daily model to flow for longer period than by the monthly model; while in the Pine River catchment and the Logan-Albert River catchment, many inland streams were predicted by the daily model to flow for a shorter period (Fig.8a). Compared to the AWAP model, fewer streams were predicted to experience extremely long dry events. But more streams on average (60 % vs. 49 % for the AWRA-L and AWAP model, respectively) were predicted to flow intermittently (> 30 days or > 1 month) to varying degrees in SEQ, which suggested that flow intermittency was prevalent in SEQ.

[Figure 8 is about here]

Temporally, the daily model estimated that the proportion of intermittent streams in SEQ varied from 29 % to 80 % over the study period (1911-2016), while the monthly model estimated the range to be from 3 % to 80 % estimated during the same time span (Fig.9). The two temporal patterns were temporally correlated (r = 0.71) and similar predictions with higher proportions of intermittent streams were estimated for the dry years by both models. Compared to dry years, the two models exhibited greater differences in predictions for the wet years, where the daily model tended to predict more proportion of intermittent streams. Overall, the daily model suggested a drier history in SEQ in terms of flow intermittency than the monthly model. The models successfully identified the extensive drying associated severe drought periods. Notably, the Widespread drought (1914-1920), WWII drought (1939-1946) and Millennium drought (2001-2009) were all visible in both two sets of model predictions.

[Figure 9 is about here]

5 Discussion

The scarcity of information on the spatial and temporal extent of flow intermittency has been identified as a major barrier for ecologists and managers to understand and protect intermittent stream ecosystems (Acuña et al., 2017). This barrier has been partly overcome in previous studies by using statistical models relating flow intermittency to surrounding environmental variables (Snelder et al., 2013;Jaeger et al., 2019;González-Ferreras and Barquín, 2017;Bond and Kennard, 2017), but most of these studies focused on only the spatial variations in flow intermittency, except for Jaeger et al. (2019), overlooking its temporal aspects. This issue becomes particularly urgent in the time when flow regimes of streams are changing worldwide, mainly in response to climate change and water extraction for human uses (Jaeger et al., 2014;Chiu et al., 2017). Monthly runoff data have been recently used to quantify flow intermittency for entire river networks (Yu et al., 2018), and the current study takes one step further to use daily runoff data in flow intermittency estimation, which is especially needed for studies aimed at quantifying ecological responses to short term flow events (e.g. frequent zero flow events within a month). In this study, we comprehensively examined the ability of a daily water balance model to simulate streamflow, with a particular focus on low flow simulations. We also investigated how to better choose water balance models to estimate flow intermittency by answering the question that whether daily flow models outperform monthly flow models at both daily and monthly scales. Our study can not only inform the estimation of the spatial distribution of intermittent flow, but also reveal the temporal dynamics of intermittent streams over long timeframes.

5.1 Efficient runoff-streamflow conversion for eco-hydrological research

Effects of river routing on daily flow simulations were found negligible in SEQ and Tamar, most probably due to the relatively small size of the two catchments and the relatively short length of even the longest streams (Cunha et al., 2012). By following the formula for calculating time of concentration proposed by Pilgrim and McDermott (1982) that has been widely used in Australia, we found time of concentration in SEQ is around 33 hours, only slightly more than a daily time step (24 hours). This illustrates why it is difficult for a daily time-step routing model to effectively capture routing lags in our study domain. Negligible effect of river routing on flow simulations was also observed in previous studies (David et al., 2011a). Robinson et al. (1995) found that catchment size is a primary factor to determine which process, the hillslope or the channel network transport component, characterize lags in catchment runoff down the river network. In areas such as SEQ and Tamar that have a relatively small catchment size, the inclusion of channel network transport contributes little to the improvement of flow simulations. The negligible effect of river routing in SEQ and Tamar allowed us to simplify the simulation of daily flows without coupling with a river routing model. Hence we were able to use existing runoff outputs from the daily AWRA-L model. Arguably, similar opportunities exist in other small catchments.

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5.2 Accuracy assessment of modelled daily streamflow in two hydro-climatically distinctive regions

Daily streamflow estimates showed a fair to good overall alignment with the observed flows in both SEQ and Tamar, with all gauges showing that flow simulations were better estimates than the mean of observations (KEG ≥ -0.41 at all gauges). Interestingly, although streamflow was more accurately simulated in the Tamar than in SEQ (the median values of KEG were 0.47 and 0.42, respectively), the differences between the two hydro-climatically distinctive regions were relatively small. Despite ongoing efforts to calibrate AWRA-L against a set of reference scales distributed across the continent (Viney et al., 2015), this finding was reassuring given the much higher variability in rainfall and soil moisture in SEQ, factors that typically can lead to a more nonlinear streamflow response to rainfall (Poncelet et al., 2017), which possibly undermines the ability of water balance models to reliably predict runoff (Sheng et al., 2017). These results hence bode well for the application of AWRA-L outputs across diverse hydroclimatic regions.

When looking into the model performance for specific components of the flow regime, average- and high-flow metrics were both modelled well in Tamar, while only high-flow metrics were modelled well in SEQ. However, in both regions the AWRA-L model showed poor performance in low flow metrics: overestimating the frequency and underestimating the duration of low flows, consistent with previous studies (Costelloe et al., 2005;Ivkovic et al., 2014;Ye et al., 1997). This suggests that the AWRA-L model is a generally robust model in predicting average- and high-flows, but still needs some improvement to better simulate low flows. The uncertainty of AWRA-L in low flow simulations can be linked to its over-responsiveness to rainfall, caused by both overestimation of "in situ" gains and underestimation of transmission losses to low flow discharge. Previous studies found that lateral flow exchange between grid cells of land surface models (e.g. AWRA-L) plays a significant role in redistributing soil water (Kim and Mohanty, 2016), and thus may improve "in situ" surface/subsurface runoff simulations (Lee and Choi, 2017). On the other hand, hydrological process involved in transmission losses have been extensively discussed (Jarihani et al., 2015;Konrad, 2006), and recently many studies have developed methods to calculate transmission losses for better flow simulations (Lange, 2005;Costa et al., 2012). Therefore, low flow simulations by AWRA-L can possibly be improved by incorporating lateral flow exchange algorithms and better accounting for hydrological process such as evapotranspiration from riparian vegetation and infiltration into channel beds. This improvement is made more likely as AWRA-L has been released as a Community Modelling System (https://github.com/awracms/awra_cms), which allows co-development by the research community.

5.3 Choose appropriate water balance models to quantify spatio-temporal dynamics of flow intermittency

To mitigate the overestimation of low flow simulations, we identified segment-specific zero-flow thresholds and used the corrected runoff estimates to quantify flow intermittency. The daily AWRA-L flow showed promise for estimating flow intermittency at a daily time step, while the monthly AWAP model was better than the monthly-aggregated AWRA-L model in flow intermittency estimation at a monthly time step. This suggests that monthly flow models can sometimes outperform daily flow models in quantifying flow intermittency, depending on the intended resolution of the analysis. For example, daily flow models may be appropriate for studies aimed at quantifying ecological responses to short term flow events, while monthly flow models are more suitable for research requiring the average degree of flow intermittency at a large spatial or temporal scale, such as examining the effect of flow intermittency on aquatic/streamside vegetation or species distributions (Stromberg et al., 2005).

Spatially contiguous runoff data were used in this study as an alternative method to quantify spatial and temporal dynamics of flow intermittency, shedding light on the temporal aspect of flow intermittency that has been often overlooked in previous studies. Annual flow intermittency was shown to vary significantly from year to year, ranging from 29 % to 80 % for the AWRA-L model. Although there is difference in the temporal patterns of estimated flow intermittency between the AWRA-L and AWAP models, neither model estimated intermittency to have a clear trend over the past century. However, there is still the concern about the potential shift of some perennial streams to intermittent streams due to climate change and intense human activities, as it has been evident in several regions where the number of low-flow and/or no-flow days is increasing (King et al., 2015;Ruhí et al., 2016;Sabo, 2014). Jaeger et al. (2014) investigated the effect of climate change on flow intermittency patterns and found that annual zero-flow days frequency were projected to increase by 27 % by mid-century in the Lower Colorado River Basin of United States. Research looking into projected changes in regional climate regimes can provide insights into future scenarios people may face, but research of similar types is still scarce.

6 Conclusions

In this study, we presented an approach to quantifying spatially explicit and catchment-wide flow intermittency over long timeframes based on spatially contiguous daily runoff data from a readily accessible water balance simulation. This research builds upon previous studies using monthly runoff data, and paves the way for ecological research looking for metrics of flow intermittency at a daily time step. By testing this approach in eastern Australia, we not only confirmed our previous finding that intermittent flow conditions prevailed in the majority of streams, but also provided more detailed information on their spatio-temporal variability at short time frames. The proposed approach has the potential applicability to other catchments globally, but our results also highlighted some complexities that future research should address to help improve the reliability of model outputs.

Data availability

The data used in this study are available publicly online and the access websites have been listed in the main text where they were first mentioned.

Competing interests

The authors declare that they have no conflict of interests.

Author contribution

AvD, HXD, MK and SY designed the research, and SY and HXD carried it out. SY wrote the original draft, and HXD, AvD, PL, NB and MK contributed to writing of subsequent drafts.

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References

Acuña, V., Datry, T., Marshall, J., Barceló, D., Dahm, C., Ginebreda, A., McGregor, G., Sabater, S., Tockner, K., and Palmer, M.: Why should we care about temporary waterways?, Science, 343, 1080-1081, 2014.

Acuña, V., Hunter, M., and Ruhí, A.: Managing temporary streams and rivers as unique rather than second-class ecosystems, Biological Conservation, 211, 12-19, 2017.

Bierkens, M. F. P., Bell, V. A., Burek, P., Chaney, N., Condon, L. E., David, C. H., de Roo, A., Döll, P., Drost, N., Famiglietti, J. S., Flörke, M., Gochis, D. J., Houser, P., Hut, R., Keune, J., Kollet, S., Maxwell, R. M., Reager, J. T., Samaniego, L., Sudicky, E., Sutanudjaja, E. H., van de Giesen, N., Winsemius, H., and Wood, E. F.: Hyper-resolution global hydrological modelling: what is next?, Hydrological Processes, 29, 310-320, 10.1002/hyp.10391, 2015.

Bond, N. R., and Kennard, M. J.: Prediction of Hydrologic Characteristics for Ungauged Catchments to Support Hydroecological Modeling, Water Resources Research, 53, 8781-8794, 10.1002/2017wr021119, 2017.

Chiu, M.-C., Leigh, C., Mazor, R., Cid, N., and Resh, V.: Chapter 5.1 - Anthropogenic Threats to Intermittent Rivers and Ephemeral Streams, in: Intermittent Rivers and Ephemeral Streams, edited by: Datry, T., Bonada, N., and Boulton, A., Academic Press, 433-454, 2017.

Costa, A. C., Bronstert, A., and de Araújo, J. C.: A channel transmission losses model for different dryland rivers, Hydrology and Earth System Sciences, 16, 1111-1135, 10.5194/hess-16-1111-2012, 2012.

Costelloe, J. F., Grayson, R. B., and McMahon, T. A.: Modelling stream flow for use in ecological studies in a large, arid zone river, central Australia, Hydrological processes, 19, 1165-1183, 2005.

Costigan, K. H., Jaeger, K. L., Goss, C. W., Fritz, K. M., and Goebel, P. C.: Understanding controls on flow permanence in intermittent rivers to aid ecological research: integrating meteorology, geology and land cover, Ecohydrology, 9, 1141-1153, 10.1002/eco.1712, 2016.

Cunha, L. K., Mandapaka, P. V., Krajewski, W. F., Mantilla, R., and Bradley, A. A.: Impact of radar-rainfall error structure on estimated flood magnitude across scales: An investigation based on a parsimonious distributed hydrological model, Water Resources Research, 48, 10.1029/2012wr012138, 2012.

Datry, T., Larned, S. T., and Tockner, K.: Intermittent Rivers: A Challenge for Freshwater Ecology, BioScience, 64, 229-235, 10.1093/biosci/bit027, 2014.

Datry, T., Pella, H., Leigh, C., Bonada, N., and Hugueny, B.: A landscape approach to advance intermittent river ecology, Freshwater Biology, 61, 1200-1213, 10.1111/fwb.12645, 2016.

Datry, T., Bonada, N., and Boulton, A. J.: Chapter 1 - General Introduction, in: Intermittent Rivers and Ephemeral Streams, edited by: Datry, T., Bonada, N., and Boulton, A., Academic Press, 1-20, 2017.

David, C. H., Habets, F., Maidment, D. R., and Yang, Z.-L.: RAPID applied to the SIM-France model, Hydrological Processes, 25, 3412-3425, 10.1002/hyp.8070, 2011a.

David, C. H., Maidment, D. R., Niu, G. Y., Yang, Z. L., Habets, F., and Eijkhout, V.: River Network Routing on the NHDPlus Dataset, Journal of Hydrometeorology, 12, 913-934, 10.1175/2011jhm1345.1, 2011b.

Davison, B., and van der Kamp, G.: Low-flows in deterministic modelling: a brief review, Canadian Water Resources Journal, 33, 181-193, 2008.

de Vries, S. B., Hoeve, J., Sauquet, E., Leigh, C., Bonada, N., Fike, K., Dahm, C., Booij, M. J., and Datry, T.: Characterizing spatial and temporal patterns of intermittent rivers, EGU General Assembly Conference Abstracts, 2015,

Do, H. X., Zhao, F., Westra, S., Leonard, M., Gudmundsson, L., Chang, J., Ciais, P., Gerten, D., Gosling, S. N., Schmied, H. M., Stacke, T., Stanislas, B. J. E., and Wada, Y.: Historical and future changes in global flood magnitude – evidence from a model-observation investigation, Hydrology and Earth System Sciences Discussions, 1-31, 10.5194/hess-2019-388, 2019.

Follum, M. L., Tavakoly, A. A., Niemann, J. D., and Snow, A. D.: AutoRAPID: A Model for Prompt Streamflow Estimation and Flood Inundation Mapping over Regional to Continental Extents, JAWRA Journal of the American Water Resources Association, 53, 280-299, 10.1111/1752-1688.12476, 2017.

Fritz, K. M., Hagenbuch, E., D'Amico, E., Reif, M., Wigington, P. J., Leibowitz, S. G., Comeleo, R. L., Ebersole, J. L., and Nadeau, T.-L.: Comparing the Extent and Permanence of Headwater Streams From Two Field Surveys to Values From Hydrographic Databases and Maps, JAWRA Journal of the American Water Resources Association, 49, 867-882, doi:10.1111/jawr.12040, 2013.

Frost, A. J., Ramchurn, A., and Smith, A.: The Bureau's Operational AWRA Landscape (AWRA-L) Model. Bureau of Meteorology Technical Repor, Melbourne, 47, 2016.

Gallart, F., Cid, N., Latron, J., Llorens, P., Bonada, N., Jeuffroy, J., Jimenez-Argudo, S. M., Vega, R. M., Sola, C., Soria, M., Bardina, M., Hernandez-Casahuga, A. J., Fidalgo, A., Estrela, T., Munne, A., and Prat, N.: TREHS: An open-access software tool for investigating and evaluating temporary river regimes as a first step for their ecological status assessment, Sci Total Environ, 607-608, 519-540, 10.1016/j.scitotenv.2017.06.209, 2017.

González-Ferreras, A. M., and Barquín, J.: Mapping the temporary and perennial character of whole river networks, Water Resources Research, 53, 6709-6724, 10.1002/2017wr020390, 2017.

Gudmundsson, L., Tallaksen, L. M., Stahl, K., Clark, D. B., Dumont, E., Hagemann, S., Bertrand, N., Gerten, D., Heinke, J., Hanasaki, N., Voss, F., and Koirala, S.: Comparing Large-Scale Hydrological Model Simulations to Observed Runoff Percentiles in Europe, Journal of Hydrometeorology, 13, 604-620, 10.1175/jhm-d-11-083.1, 2012.

Gudmundsson, L., Leonard, M., Do, H. X., Westra, S., and Seneviratne, S. I.: Observed Trends in Global Indicators of Mean and Extreme Streamflow, Geophysical Research Letters, 46, 756-766, 10.1029/2018gl079725, 2019.

Gupta, H. V., Kling, H., Yilmaz, K. K., and Martinez, G. F.: Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling, Journal of Hydrology, 377, 80-91, 10.1016/j.jhydrol.2009.08.003, 2009.

Hou, J., van Dijk, A. I. J. M., Renzullo, L. J., Vertessy, R. A., and Mueller, N.: Hydromorphological attributes for all Australian river reaches derived from Landsat dynamic inundation remote sensing, Earth Syst. Sci. Data, 11, 1003-1015, 10.5194/essd-11-1003-2019, 2019.

Ivkovic, K., Croke, B., and Kelly, R.: Overcoming the challenges of using a rainfall–runoff model to estimate the impacts of groundwater extraction on low flows in an ephemeral stream, Hydrology Research, 45, 58-72, 2014.

Jaeger, K. L., and Olden, J. D.: Electrical Resistance Sensor Arrays as a Means to Quantify Longitudinal Connectivity of Rivers, River Research and Applications, 28, 1843-1852, 10.1002/rra.1554, 2012.

Jaeger, K. L., Olden, J. D., and Pelland, N. A.: Climate change poised to threaten hydrologic connectivity and endemic fishes in dryland streams, Proceedings of the National Academy of Sciences, 111, 13894-13899, 2014.

Jaeger, K. L., Sando, R., McShane, R. R., Dunham, J. B., Hockman-Wert, D. P., Kaiser, K. E., Hafen, K., Risley, J. C., and Blasch, K. W.: Probability of Streamflow Permanence Model (PROSPER): A spatially continuous model of annual streamflow permanence throughout the Pacific Northwest, Journal of Hydrology X, 2, 100005, 10.1016/j.hydroa.2018.100005, 2019.

Jarihani, A. A., Larsen, J. R., Callow, J. N., McVicar, T. R., and Johansen, K.: Where does all the water go? Partitioning water transmission losses in a data-sparse, multi-channel and low-gradient dryland river system using modelling and remote sensing, Journal of Hydrology, 529, 1511-1529, 10.1016/j.jhydrol.2015.08.030, 2015.

Kennard, M. J., Olden, J. D., Arthington, A. H., Pusey, B. J., and Poff, N. L.: Multiscale effects of flow regime and habitat and their interaction on fish assemblage structure in eastern Australia, Canadian Journal of Fisheries and Aquatic Sciences, 64, 1346-1359, 10.1139/f07-108, 2007.

Kennard, M. J., Pusey, B. J., Olden, J. D., Mackay, S. J., Stein, J. L., and Marsh, N.: Classification of natural flow regimes in Australia to support environmental flow management, Freshwater Biology, 55, 171-193, 10.1111/j.1365-2427.2009.02307.x, 2010.

https://doi.org/10.5194/hess-2020-10
Preprint. Discussion started: 4 February 2020

Kim, J., and Mohanty, B. P.: Influence of lateral subsurface flow and connectivity on soil water storage in land surface modeling, Journal of Geophysical Research: Atmospheres, 121, 704-721, 10.1002/2015jd024067, 2016.

King, A. J., Townsend, S. A., Douglas, M. M., and Kennard, M. J.: Implications of water extraction on the low-flow hydrology and ecology of tropical savannah rivers: an appraisal for northern Australia, Freshwater Science, 34, 741-758, 2015.

Kling, H., Fuchs, M., and Paulin, M.: Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios, Journal of Hydrology, 424-425, 264-277, 10.1016/j.jhydrol.2012.01.011, 2012.

Knoben, W. J. M., Freer, J. E., and Woods, R. A.: Technical note: Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores, Hydrology and Earth System Sciences Discussions, 1-7, 10.5194/hess-2019-327, 2019.

Konrad, C. P.: Longitudinal hydraulic analysis of river-aquifer exchanges, Water Resources Research, 42, W08425, 10.1029/2005wr004197, 2006.

Lange, J.: Dynamics of transmission losses in a large arid stream channel, Journal of Hydrology, 306, 112-126, 10.1016/j.jhydrol.2004.09.016, 2005.

Larned, S. T., Datry, T., Arscott, D. B., and Tockner, K.: Emerging concepts in temporary-river ecology, Freshwater Biology, 55, 717-738, 10.1111/j.1365-2427.2009.02322.x, 2010.

Lawrence, D. M., Oleson, K. W., Flanner, M. G., Thornton, P. E., Swenson, S. C., Lawrence, P. J., Zeng, X., Yang, Z.-L., Levis, S., Sakaguchi, K., Bonan, G. B., and Slater, A. G.: Parameterization improvements and functional and structural advances in Version 4 of the Community Land Model, Journal of Advances in Modeling Earth Systems, 3, M03001, doi:10.1029/2011MS00045, 2011.

Lee, J., and Choi, H.: Improvements to Runoff Predictions from a Land Surface Model with a Lateral Flow Scheme Using Remote Sensing and In Situ Observations, Water, 9, 10.3390/w9020148, 2017.

Leigh, C., Boulton, A. J., Courtwright, J. L., Fritz, K., May, C. L., Walker, R. H., and Datry, T.: Ecological research and management of intermittent rivers: an historical review and future directions, Freshwater Biology, 61, 1181-1199, 10.1111/fwb.12646, 2016.

Leigh, C., and Datry, T.: Drying as a primary hydrological determinant of biodiversity in river systems: a broad-scale analysis, Ecography, 40, 487-499, 10.1111/ecog.02230, 2016.

Lin, P., Pan, M., Beck, H. E., Yang, Y., Yamazaki, D., Frasson, R., David, C. H., Durand, M., Pavelsky, T. M., Allen, G. H., Gleason, C. J., and Wood, E. F.: Global Reconstruction of Naturalized River Flows at 2.94 Million Reaches, Water Resources Research, 10.1029/2019wr025287, 2019.

Pilgrim, D., and McDermott, G.: Design floods for small rural catchments in eastern New South Wales, First National Local Government Engineering Conference 1981: Reprints of Papers, 1982, 138,

Poff, N. L., Allan, J. D., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R. E., and Stromberg, J. C.: The Natural Flow Regime, BioScience, 47, 769-784, 10.2307/1313099, 1997.

Poncelet, C., Merz, R., Merz, B., Parajka, J., Oudin, L., Andréassian, V., and Perrin, C.: Process-based interpretation of conceptual hydrological model performance using a multinational catchment set, Water Resources Research, 53, 7247-7268, 10.1002/2016wr019991, 2017.

Raupach, M., Briggs, P., Haverd, V., King, E., Paget, M., and Trudinger, C.: Australian water availability project (AWAP): CSIRO marine and atmospheric research component: final report for phase 3, Centre for Australian weather and climate research (bureau of meteorology and CSIRO). Melbourne, Australia, 67, 2009.

Raupach, M., Briggs, P., Haverd, V., King, E., Paget, M., and Trudinger, C.: Australian Water Availability Project, Data Release 26m, CSIRO Oceans and Atmospheric, <http://www.csiro.au/awap>, 2018.

Robinson, J. S., Sivapalan, M., and Snell, J. D.: On the relative roles of hillslope processes, channel routing, and network geomorphology in the hydrologic response of natural catchments, Water Resources Research, 31, 3089-3101, 10.1029/95wr01948, 1995.

Ruhí, A., Olden, J. D., and Sabo, J. L.: Declining streamflow induces collapse and replacement of native fish in the American Southwest, Frontiers in Ecology and the Environment, 14, 465-472, 2016.

Sabo, J. L.: Predicting the river's blue line for fish conservation, Proceedings of the National Academy of Sciences, 111, 13686-13687, 2014.

Sheng, M., Lei, H., Jiao, Y., and Yang, D.: Evaluation of the Runoff and River Routing Schemes in the Community Land Model of the Yellow River Basin, Journal of Advances in Modeling Earth Systems, 9, 2993-3018, 10.1002/2017ms001026, 2017.

Snelder, T. H., Datry, T., Lamouroux, N., Larned, S. T., Sauquet, E., Pella, H., and Catalogne, C.: Regionalization of patterns of flow intermittence from gauging station records, Hydrology and Earth System Sciences, 17, 2685-2699, 2013.

Spence, C., and Mengistu, S.: Deployment of an unmanned aerial system to assist in mapping an intermittent stream, Hydrological Processes, 30, 493-500, 2016.

Stanley, E. H., Fisher, S. G., and Grimm, N. B.: Ecosystem expansion and contraction in streams, BioScience, 47, 427-435, 1997.

Stein, J. L., Hutchinson, M. F., and Stein, J. A.: A new stream and nested catchment framework for Australia, Hydrology and Earth System Sciences, 18, 1917-1933, 10.5194/hess-18-1917-2014, 2014.

Stromberg, J. C., Bagstad, K. J., Leenhouts, J. M., Lite, S. J., and Makings, E.: Effects of stream flow intermittency on riparian vegetation of a semiarid region river (San Pedro River, Arizona), River Research and Applications, 21, 925-938, 10.1002/rra.858, 2005.

Turner, D. S., and Richter, H. E.: Wet/dry mapping: using citizen scientists to monitor the extent of perennial surface flow in dryland regions, Environmental management, 47, 497-505, 2011.

https://doi.org/10.5194/hess-2020-10
Preprint. Discussion started: 4 February 2020

Wang, Q. J., Pagano, T. C., Zhou, S. L., Hapuarachchi, H. A. P., Zhang, L., and Robertson, D. E.: Monthly versus daily water balance models in simulating monthly runoff, Journal of Hydrology, 404, 166-175, 10.1016/j.jhydrol.2011.04.027, 2011.

Ye, W., Bates, B. C., Viney, N. R., Sivapalan, M., and Jakeman, A. J.: Performance of conceptual rainfall-runoff models in low-yielding ephemeral catchments, Water Resources Research, 33, 153-166, 10.1029/96wr02840, 1997.

Yu, S., Bond, N. R., Bunn, S. E., Xu, Z., and Kennard, M. J.: Quantifying spatial and temporal patterns of flow intermittency using spatially contiguous runoff data, Journal of Hydrology, 559, 861-872, 10.1016/j.jhydrol.2018.03.009, 2018.

Zaherpour, J., Gosling, S. N., Mount, N., Schmied, H. M., Veldkamp, T. I. E., Dankers, R., Eisner, S., Gerten, D., Gudmundsson, L., Haddeland, I., Hanasaki, N., Kim, H., Leng, G., Liu, J., Masaki, Y., Oki, T., Pokhrel, Y., Satoh, Y., Schewe, J., and Wada, Y.: Worldwide evaluation of mean and extreme runoff from six global-scale hydrological models that account for human impacts, Environmental Research Letters, 13, 10.1088/1748-9326/aac547, 2018.

Hydrology and Earth System Sciences
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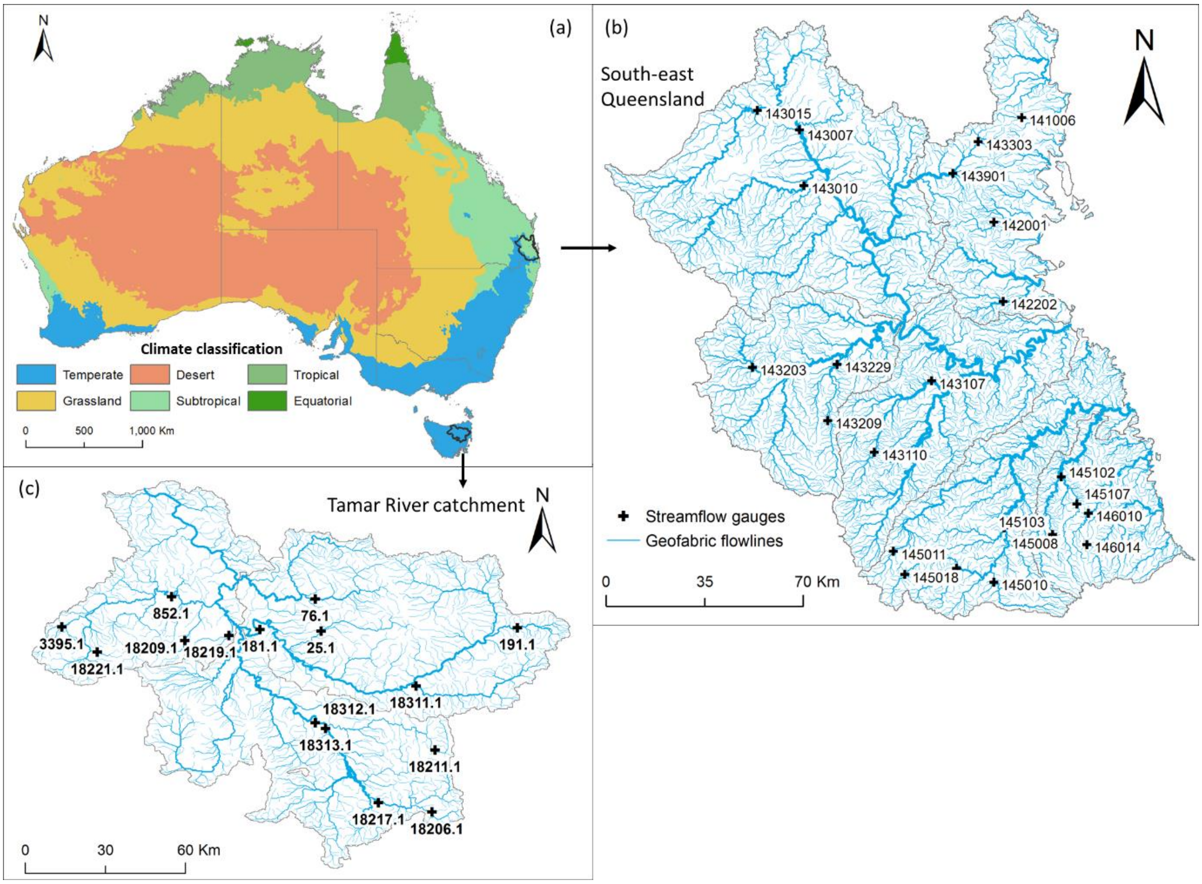

520 **Figure 1. Locations of the two climatically and hydrologically distinctive regions in Australia (a): South-east Queensland (SEQ)(b) and the Tamar River catchment (Tamar)(c) with Geofabric river networks and selected stream gauges (25 and 15 gauges for SEQ and Tamar, respectively). The climate classification in (a) is based on the Köppen classification system (Australian Bureau of Meteorology, 2014).**

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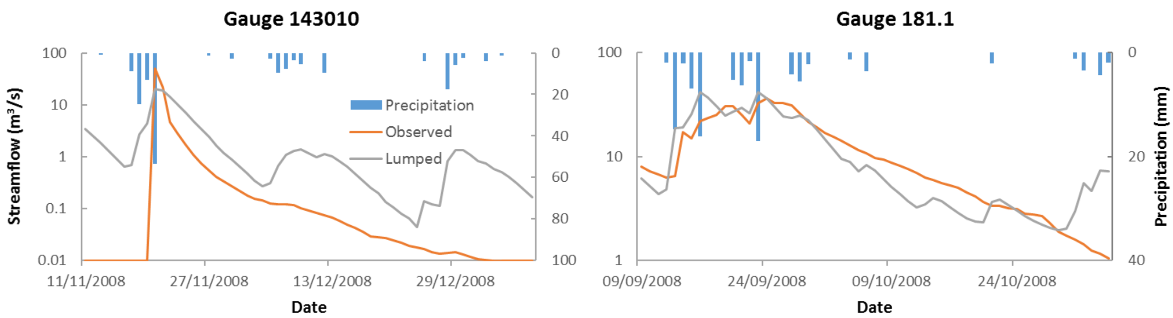
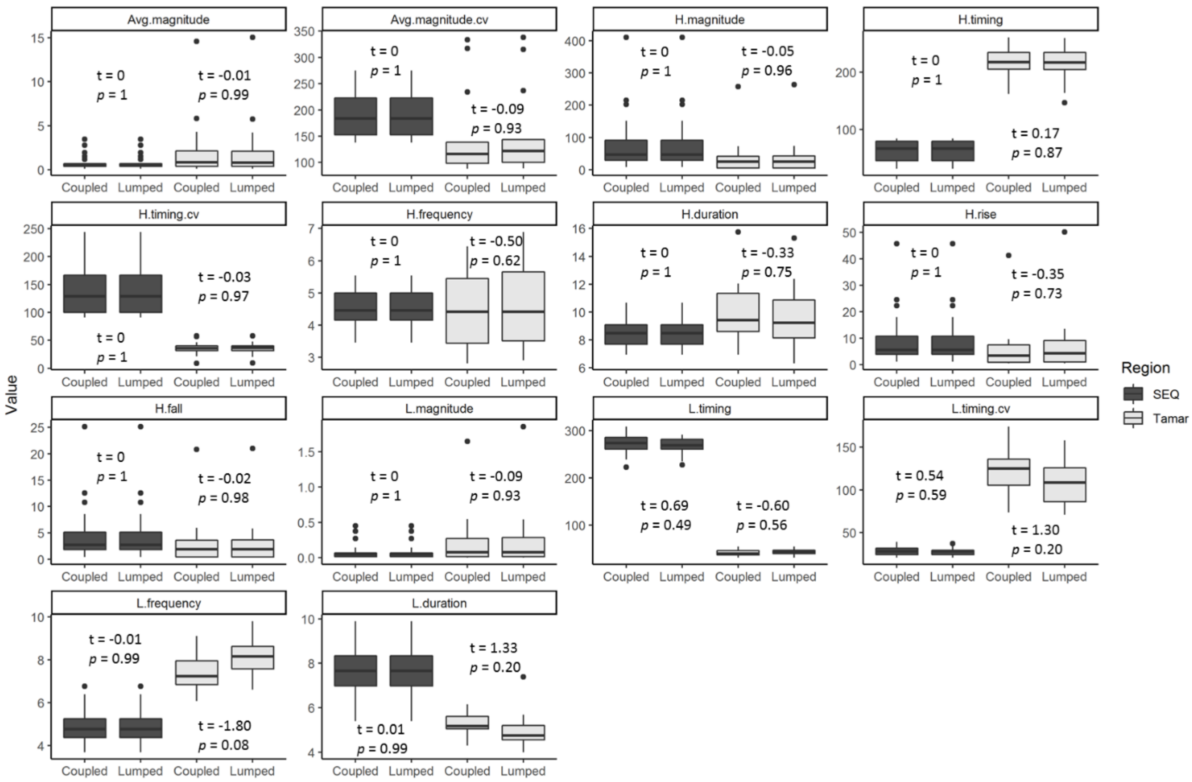


525 **Figure 2. Comparison of the observed and modelled hydrograph with the rainfall time series at gauges 143010 in SEQ and 181.1 in Tamar. The over-responsiveness of the model to rainfall is illustrated in the dramatic increase in modelled streamflow when a rainfall event occurred, while there is no obvious increase in observed streamflow. Rainfall data were sourced from the AWRA-L input.**



530 **Figure 3. Comparison of hydrological characteristics between the lumped and coupled models in SEQ and Tamar. Refer to Table 1 for description and units of measurement for each flow metric. Metrics are grouped according to average (Avg), high (H) and low (L) flow conditions. The values of *t* statistic and associated *p* values are also shown to indicate whether there is any significant difference between the coupled and lumped simulations.**

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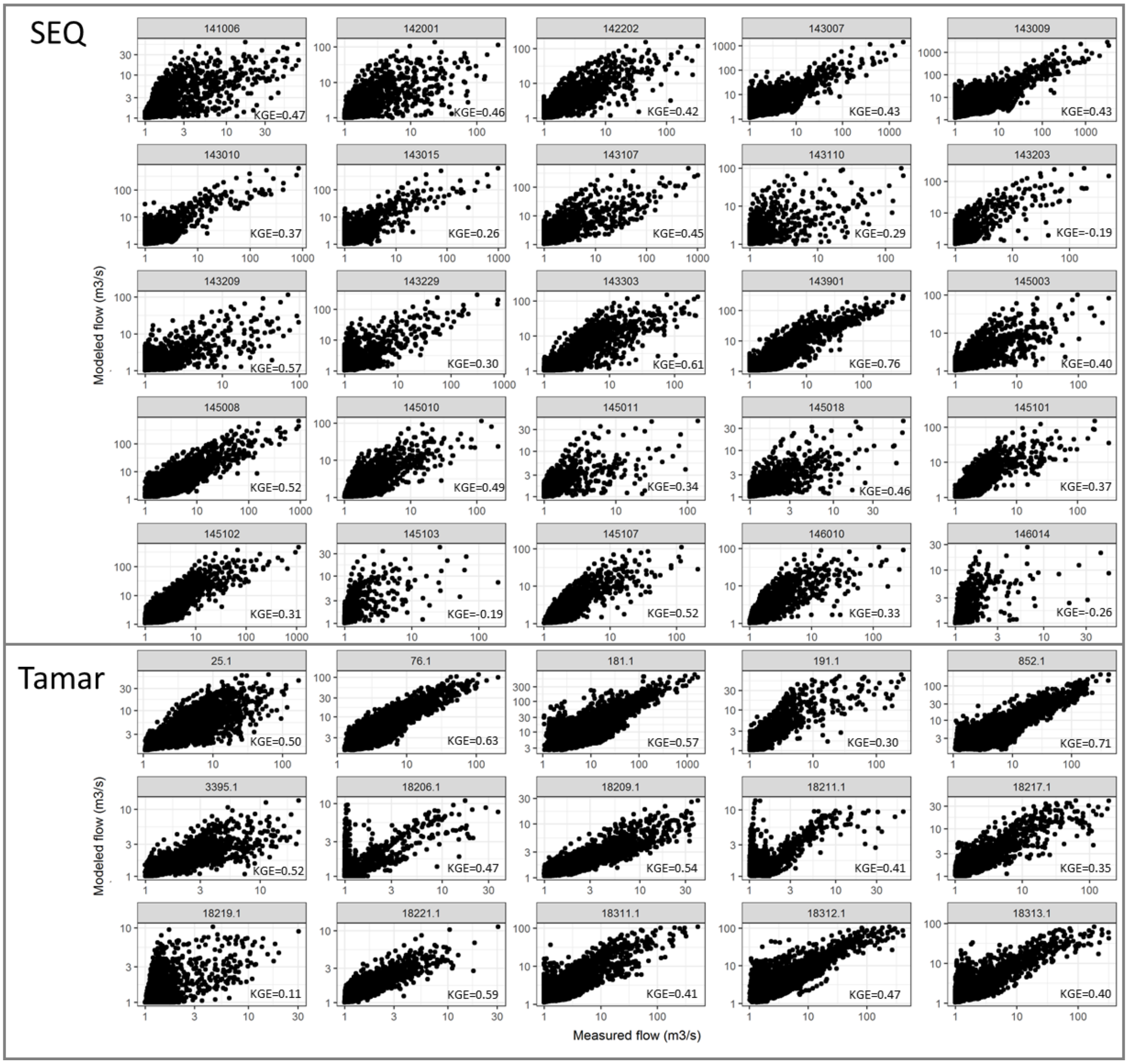
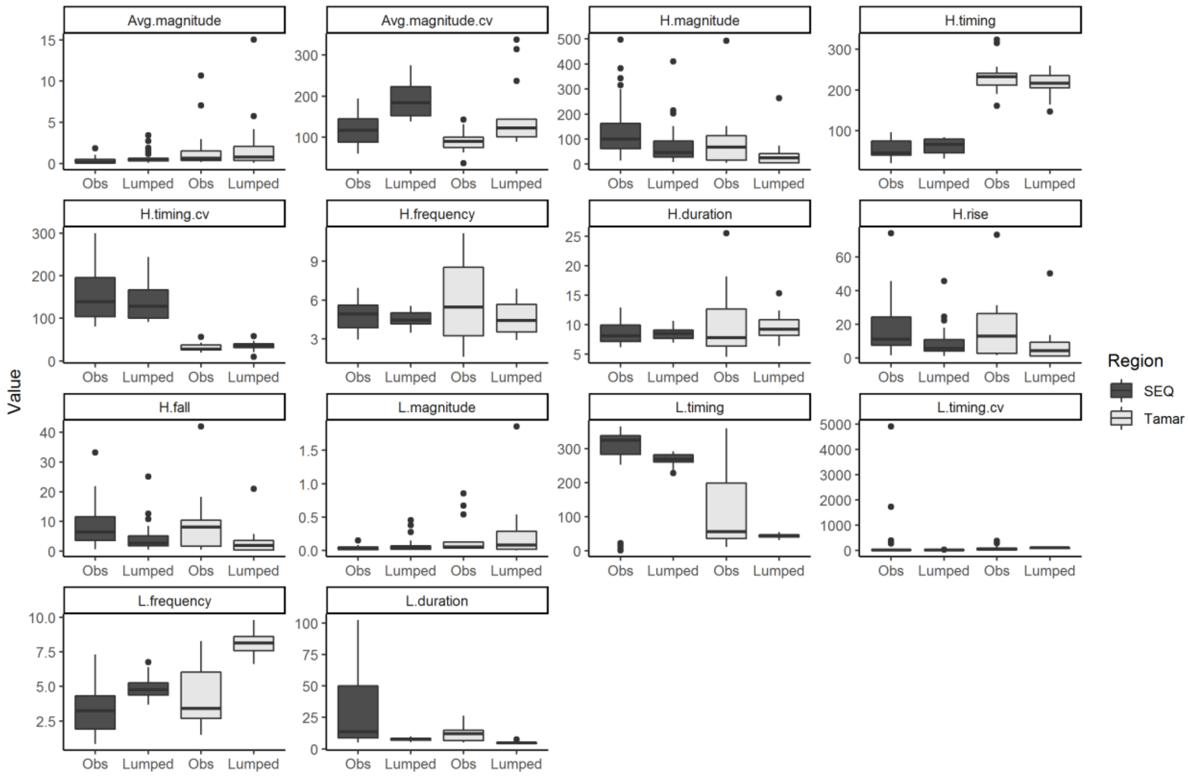
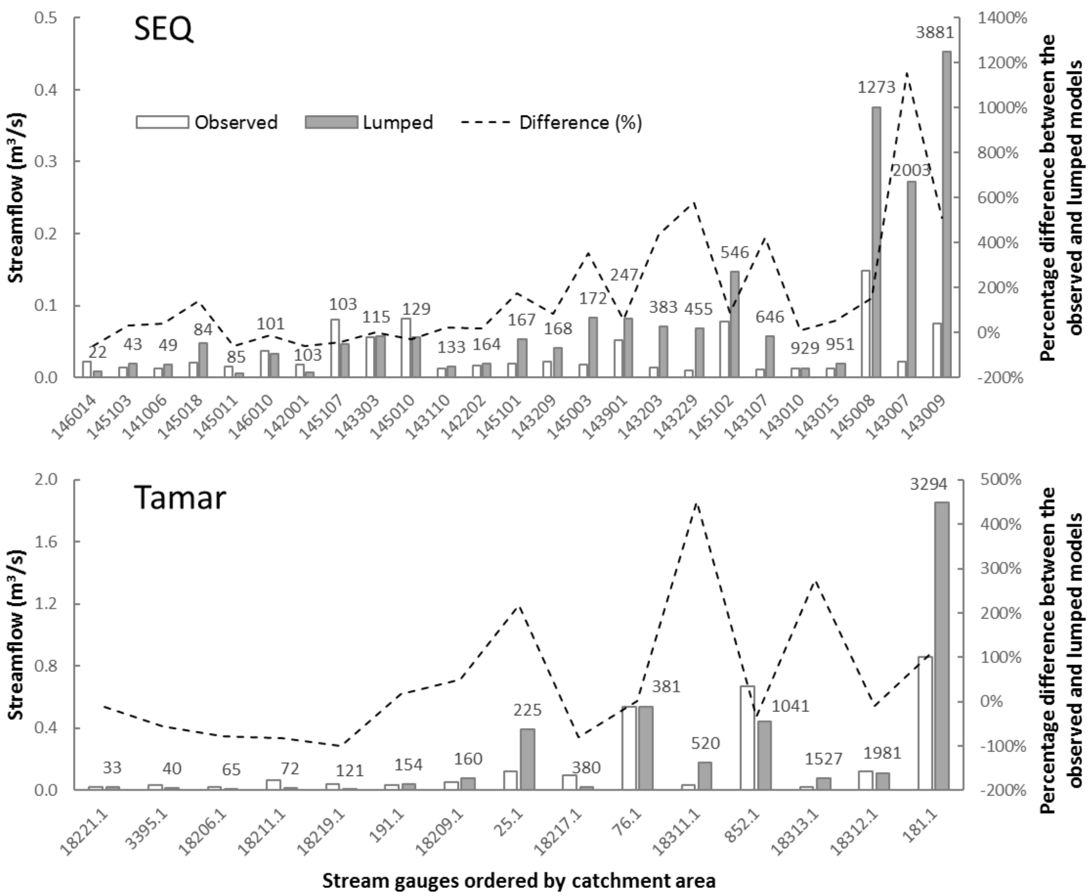


Figure 4: Scatter plots of the measured and modelled (lumped) streamflow for each gauge station in SEQ and Tamar. The modified Kling-Gupta efficiency (KGE) is presented in each panel. The x and y axes are log transformed ($\log_{10}(x+1)$) to aid interpretation.



535 **Figure 5. Variation in observed and modelled (lumped) hydrologic characteristics in SEQ and Tamar (n= 25 and 15 gauge locations, respectively). Refer to Table 1 for description and units of measurement for each flow metric. Metrics are grouped according to average (Avg), high (H) and low (L) flow conditions.**



540 **Figure 6. Comparison of the observed and modelled low flow magnitudes (left y-axis) at all gauges in each region, with their percentage difference shown as dashed line (right y-axis). The stream gauges are ordered by catchment area (km²), which is labelled above each column.**

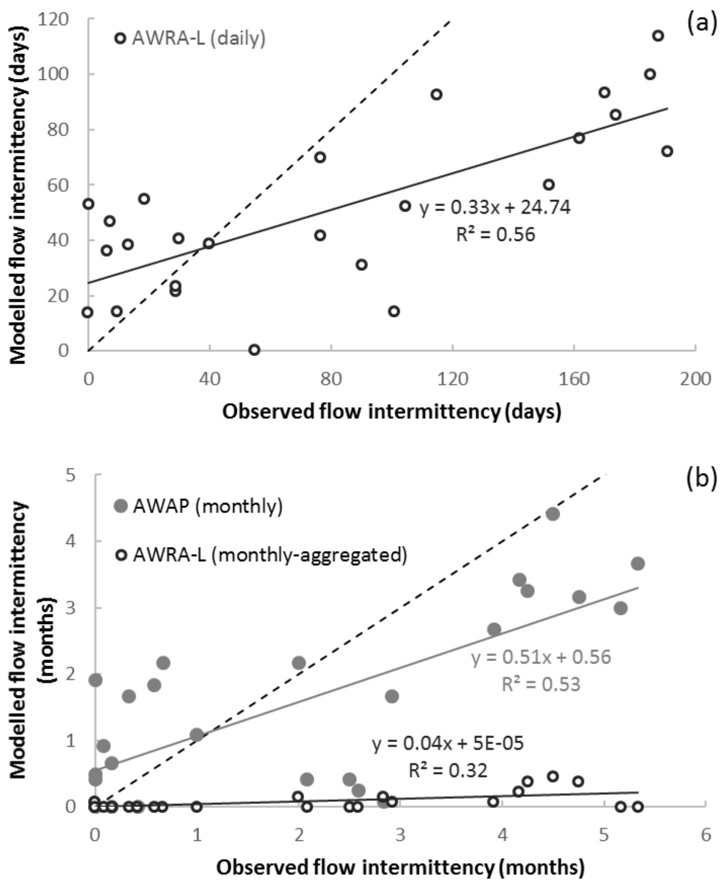


Figure 7. Scatter plots of the observed and modelled flow intermittency by the two models (AWRA-L and AWAP model) for SEQ. The solid line represents the regression line for each model. The 1:1 line (dashed line) is plotted for reference.

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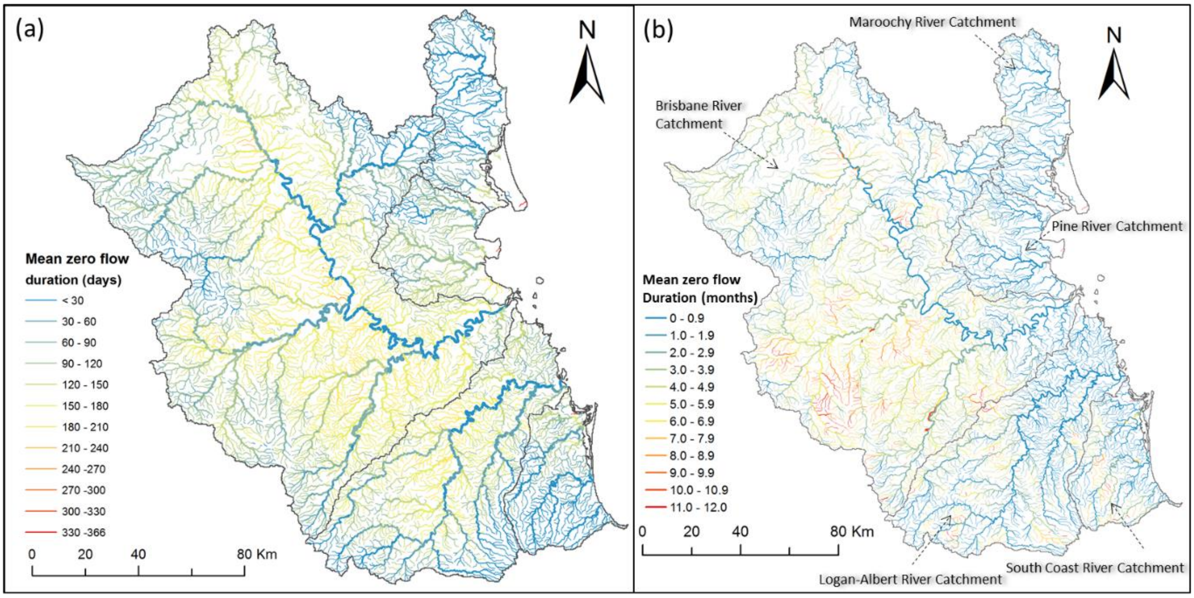
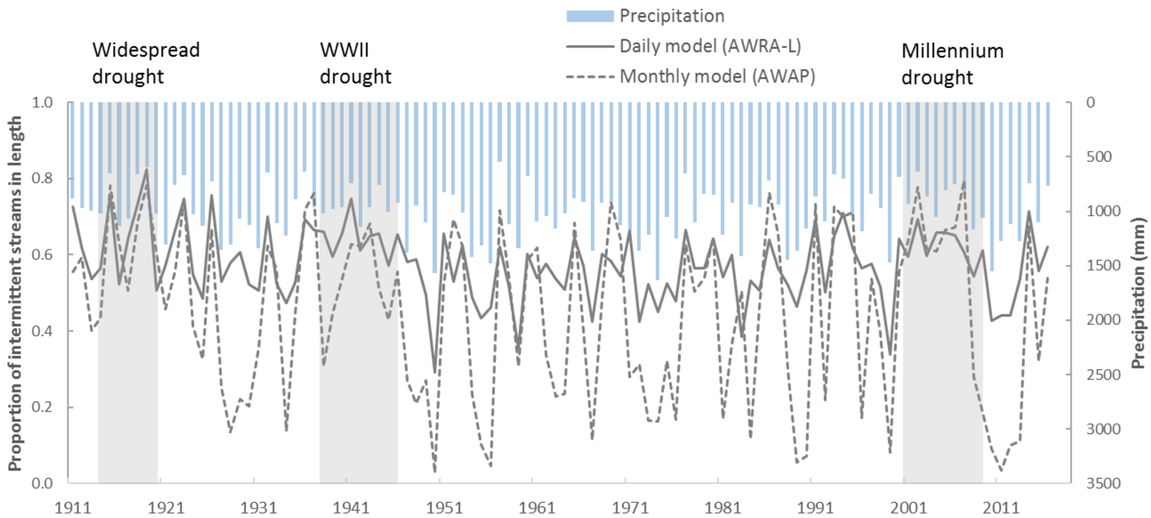
545 

Figure 8. Comparison of spatial pattern of flow intermittency in SEQ derived from (a) daily flow simulations from the AWRA-L model and (b) monthly flow simulations from the AWAP model. Stream segments in both figures are coloured using the same frame but different units. Line thicknesses show the stream orders.



550 **Figure 9. Comparison of intra-annual variation of the proportion of intermittent streams in length from 1911-2016 across SEQ, derived from stream flow simulations from the daily flow model (lumped, grey solid line) and monthly flow model (grey dash line). Three severe droughts in Australia were also presented as transparent grey rectangles: Widespread drought (1914-1920), WWII droughts (1939-1946) and Millennium droughts (2001-2009). The time series of annual mean precipitation were presented for reference and they were sourced from the AWAP model (Raupach et al., 2009, 2018).**

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Table 1. Flow metrics used to describe average-, high- and low-flow conditions across key components of hydrological variation. Note that a spell independence criteria of 5 days was applied to regard periods between spells of less than 5 days as "in spell".

Conditions	Component	Definition	Units
Average flow	Magnitude	Mean daily flow for entire period	$m^3 s^{-1}$
	Variability	Coefficient of variation in mean daily flow	%
High-flow	Magnitude	The average annual maximum flow	$m^3 s^{-1}$
	Timing	The mean Julian date of annual maximum	unitless
	Variability	Coefficient of variation in Julian date of annual maximum flow	%
	Frequency	Mean of annual count of spells above the 90^{th} percentile flow	unitless
	Duration	Mean duration of all spells above the 90^{th} percentile flow	days
	Rate of rise	Mean rate of positive changes in flow from one day to the next	$m^3 s^{-2}$
	Rate of fall	Mean rate of negative changes in flow from one day to the next	$m^3 s^{-2}$
Low-flow	Magnitude	The average annual minimum flow	$m^3 s^{-1}$
	Timing	The mean Julian date of annual minimum	unitless
	Variability	Coefficient of variation in Julian date of annual minimum flow	%
	Frequency	Mean of annual count of spells below the 10^{th} percentile flow	unitless
	Duration	Mean duration of all spells below the 10^{th} percentile flow	days