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Detecting and attributing drought-induced changes in catchment hydrological behaviors using data assimilation method

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Abstract

It is widely recognized that multi-year drought can induce changes in catchment hydrological behaviors. However, at present, our understanding about multi-year, drought-induced changes in catchment hydrological behaviors and its driving factors at the process level is still very limited. This study proposed a new approach using a data assimilation technique with a process-based hydrological model to detect multi-year drought-induced changes in catchment hydrological behaviors and to identify driving factors for the changes in an unimpaired Australian catchment (Wee Jasper) which experienced prolonged drought from 1997 to 2009. Modelling experiments demonstrated that the multi-year drought caused a significant change in the catchment rainfall-runoff relationship, indicated by significant step changes in the estimated time-variant hydrological parameters SC (indicating catchment active water storage capacity) and C (reflecting catchment evapotranspiration dynamics), whose average values increased 23.4% and 10.2%, respectively, due to drought. The change in the rainfall-runoff relationship identified by the data assimilation method is consistent with that arrived at by a statistical examination. The proposed method provides insights about the drivers of the changes in the rainfall-runoff relationship at the processes level. Declining groundwater and deep soil moisture depleted by persistent evapotranspiration of deep-rooted woody vegetation during drought are the main driving factors for the catchment behaviors change in the Wee Jasper catchment. The new method proposed in this study was found to be an effective technique for detecting both the change of hydrological behaviors induced by prolonged drought and its driving factors at the process level.

Detecting and attributing drought-induced changes in catchment hydrological behaviors using a data assimilation method

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Abstract: It is widely recognized that multi-year drought can induce changes in catchment hydrological behaviors. However, at present, our understanding about multi-year, drought-induced changes in catchment hydrological behaviors and its driving factors at the process level is still very limited. This study proposed a

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new approach using a data assimilation technique with a process-based hydrological model to detect multi-year drought-induced changes in catchment hydrological behaviors and to identify driving factors for the changes in an unimpaired Australian catchment (Wee Jasper) which experienced prolonged drought from 1997 to 2009. Modelling experiments demonstrated that the multi-year drought caused a significant change in the catchment rainfall-runoff relationship, indicated by significant step changes in the estimated time-variant hydrological parameters SC (indicating catchment active water storage capacity) and C (reflecting catchment evapotranspiration dynamics), whose average values increased 23.4% and 10.2%, respectively, due to drought. The change in the rainfall-runoff relationship identified by the data assimilation method is consistent with that arrived at by a statistical examination. The proposed method provides insights about the drivers of the changes in the rainfall-runoff relationship at the processes level. Declining groundwater and deep soil moisture depleted by persistent evapotranspiration of deep-rooted woody vegetation during drought are the main driving factors for the catchment behaviors change in the Wee Jasper catchment. The new method proposed in this study was found to be an effective technique for detecting both the change of hydrological behaviors induced by prolonged drought and its driving factors at the process level.

Keywords: multi-year drought; rainfall-runoff; nonstationary; data assimilation; Particle filter; Australia Millennium drought

Introduction

Drought is one of the most frequently occurring environmental disasters, and both historical observations and future climate projections show increasing frequency of drought worldwide (Dai, 2013; Feng & Fu, 2013; Trenberth et al., 2013). Droughts are mostly triggered by a reduction in seasonal or annual precipitation (Mishra & Singh, 2010). Droughts can have devastating impacts on regional food production, water resources management, drinking water supply, and even the stability of governments (Mishra & Singh, 2010; Dai, 2011; Zhang, Zhang, Cui, & Zeng, 2011). Although drought usually has dire environmental and socio-economic consequences, drought prediction is still a grand challenge (Dai, 2011; Mishra & Singh, 2011; Chiew et al., 2014). Drought involves complex interactions amongst different dimensions including meteorological conditions, vegetation water demand, hydrological conditions,*etc* . (Wang, Basia, & Arie, 2003; Nalbantis & Tsakiris, 2009; Dai, 2011; Zhang et al., 2011; Buttafuoco, Caloiero, & Coscarelli, 2015) hat can induce shifts in regional hydrological regime or rainfall-runoff relationship, leading to failures in predicting the onset, duration, severity, and termination of drought (Guardiola-Claramonte et al., 2011; Mishra & Singh, 2011; Zhang et al., 2011; Chiew et al., 2014; Huijgevoort, Lanen, Teuling, & Uijlenhoet, 2014; Yang et al., 2017).

Determining whether drought can lead to shifts in catchment hydrological behaviors is critical for future accurate hydrological prediction (Huijgevoort et al., 2014; Saft, Western, Zhang, Peel, & Potter, 2015). Previously, many studies have reported that drought can violate the assumption of stationarity in the catchment rainfall-runoff relationship (Conway et al., 2004; Guardiola-Claramonte et al., 2011; Cheng et al., 2012; Hughes, Petrone, & Silberstein, 2012; Chiew et al., 2014). Chiew et al. (2014) found that the rainfall-runoff relationship during drought periods was simulated poorly and overestimated significantly (up to 150%) by a hydrological model previously calibrated under normal period. Petrone, Hughes, Niel, & Silberstein (2010) found a significant decline in the runoff coefficient and a shift in hydrological regime in the headwater regions of southwest Western Australia after a long-term decline in rainfall from the mid-1970s to 2008. Based on the long-term rainfall-runoff observations of 228 catchments in south-eastern Australia, Saft et al. (2015) showed that prolonged drought during 1997-2009 led to a statistically significant shift in the rainfall-runoff relationship in about 46% of the studied catchments. Although many studies have statistically demonstrated that long-term drought can lead to shifts in catchment hydrological regimes based on observations and modelling, there is still great uncertainty in detecting and predicting whether drought can induce changes in catchment hydrological behaviors and in understanding why the rainfall-runoff relationship can change at the process level.

Insights into this challenge can be gained by combining a data assimilation method with process-based hydro-

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logical models. This approach accounts for hydrological non-stationarity in the rainfall-runoff relationship for capturing shifts in the flow regime induced by long-term drought. It also accounts for time-variant parameters in the hydrological model. Accounting for both factors leads to identification of possible mechanisms that cause the changes in catchment hydrological behaviors. Parameters in a process-based hydrological model represent catchment functional properties, and thus can be used to detect catchment hydrological behaviors and their changes (Pathiraja, Marshall, Sharma, & Moradkhani, 2016). Parameters in hydrological models are traditionally assumed to be stationary (*i.e.,* time-invariant), and are calibrated against observed runoff (Coron et al., 2012). There is an accumulated body of literature showing that hydrological systems can be non-stationary, and that parameters in hydrological models should be time-variant. This is because substantial anthropogenic changes of climate have occurred outside of the historically measured mode of natural variability, and direct alteration of local water cycles has occurred as a result of land and water management practices including deforestation (Destouni, Jaramillo, & Prieto, 2013; Lima et al., 2014; Cheng et al., 2017; Guimberteau et al., 2017), groundwater extraction (Kinal & Stoneman, 2012; Miguez-Macho & Fan, 2012), and damming of rivers for hydroelectricity (Botter, Basso, Porporato, Rodrigueziturbe, & Rinaldo, 2010; Xue, Liu, & Ge, 2011). Recent studies have recognized that models with time-variant parameters can reasonably account for shifts in the catchment rainfall-runoff relationship or catchment behaviors under changing environments (Merz, Parajka, & Blöschl, 2011; Chiew et al., 2014; Deng, Liu, Guo, Li, & Wang, 2016). Based on time-variant parameters obtained by a data assimilation method, not only can changes in the catchment rainfall-runoff relationship can be detected (Deng et al., 2016), but also the causes of the changes can be identified from hydrological parameters (Pathiraja et al., 2016; Xiong et al., 2019). For example, (Deng et al., 2016) combined a two-parameter monthly water balance model to obtain time-variant hydrological parameters, and successfully detected the impacts of land-use changes on catchment water storage capacity in the Wudinghe Basin, which led to changes in the catchment rainfall-runoff relationship. Pathiraja et al. (2016) demonstrated that land cover changes can lead to significant step changes in estimated parameters in hydrological models using an ensemble Kalman filter with a locally evolutionary linear parameter in two paired experimental catchments in the Western Australia. They identified changes in the excess runoff generation process that resulted from land use changes. Based on previous successful studies for detecting and understanding hydrological non-stationarity under changing environments using a data assimilation method, we employed a similar methodology to investigate the non-stationarity in hydrological behavior induced by long-term drought.

In this study, the Particle filter (PF) data assimilation technique was combined with a two-parameter monthly water balance model (TWBM) to obtain time-variant parameter series, and then to identify changes caused by drought at the process level. The PF data assimilation technique is one of a general class of ensemble-based statistical data assimilation methods that is more suitable for nonlinear data assimilation problems and retaining the water balance (Arulampalam, Maskell, Gordon, & Clapp, 2002; Moradkhani & Weihermüller, 2011; Field, Tavrisov, Brown, Harris, & Kreidl, 2016) , and thus was selected in this study. The TWBM model is a widely used monthly hydrological model that has been successfully applied to simulate the catchment rainfall-runoff relationship in a wide range of climates, soils, and vegetation conditions (Guo, Wang, Xiong, Ying, & Li, 2002; Guo et al., 2005; Xiong & Guo, 2012; Shuai, Xiong, Dong, & Zhang, 2013; Zhang, Liu, Liu, & Bai, 2013; Xiong, Yu, & Gottschalk, 2015). The specific objectives of this study were to (1) demonstrate whether the PF data assimilation method can be used to detect changes in catchment hydrological behaviors induced by drought; (2) detect whether prolonged drought can cause changes in the catchment rainfall-runoff relationship; and (3) identify the mechanisms responsible for drought induced changes in catchment hydrological behavior at the process level.

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Methodology

Two-parameter monthly water balance model

The TWBM was applied in this study to simulate the catchment rainfall-runoff relationship. The TWBM was developed by Xiong & Guo (1999) and has been widely applied worldwide to simulate monthly runoff (Guo et al., 2005; Zhang et al., 2013; Deng et al., 2016). The model inputs are potential evapotranspiration (PET) and precipitation (P), both of which are readily available or can be estimated from routine meteorological observations (Xiong & Guo, 1999).

Monthly actual evapotranspiration (E_i) is estimated in TWBM as:

$$E_i = C \times \mathrm{PET}_i \times tanh(\frac{P_i}{\mathrm{PET}_i}) \quad (1)$$

where C is an empirical parameter and the subscript $i$indicates the time step. The parameter C was originally proposed as an empirical coefficient. Essentially, C accounts for time scale effects by applying a Budyko-type equation to a monthly time scale, *i.e.,* secondary influences of dynamics in soil water storage rather than P and PET on catchment E .

Monthly runoff (Q_i) in TWBM is estimated from catchment water content (S_i) as:

$$Q_i = S_i \times tanh(\frac{S_i}{\mathrm{SC}}) \quad (2)$$

where SC is a parameter in mm. SC can be regarded as catchment active water storage capacity, which regulates the response of catchment monthly runoff to rainfall.

By combining TWBM with the PF data assimilation method, monthly time-variant series of SC and C were obtained, reflecting the dynamic variation of catchment hydrological behaviors to climate variability. Shifts in C reflect the changes in catchment evapotranspiration mechanisms resulting from the impacts of drought on catchment water and the energy balance. Trends and/or step changes in SC indicate the influences of drought on catchment water yields through the control of catchment soil water dynamics (e.g., groundwater storage, interaction between surface water and groundwater, *etc.*) on runoff generation.

The Particle filter

PF was used in this study to trace the variation of C and SC. It is a sequential data assimilation method, using many independent random samples, called particles, to simulate posterior distribution (Arulampalam et al., 2002; Moradkhani & Weihermüller, 2011). PF was selected for two main reasons in this study: superiority in handling non-linear processes (Moradkhani, Hsu, Gupta, & Sorooshian, 2005; Moradkhani, 2008) and capacity in retaining the water balance (Pan & Wood, 2006; DeChant & Moradkhani, 2012; Moradkhani, DeChant, & Sorooshian, 2012). Two equations (*i.e.,* state-transition and measurement equations) were the fundamental equations of PF at each time step t_k (k = 0, 1, 2, . . .) (Moradkhani et al., 2005).

The state-transition equation is:

$$x_{k+1} = f(x_k, v_k) \quad (5)$$

where $x_k \in R^{n_x}$ is an n_x-dimensional vector representing the system states at time step t_k (k = 0, 1, 2, . . .). R^{n_x} represents n_x-dimensional real space; variable v_k is ann_v-dimensional vector representing a white noise sequence with independent and identical distribution; f_k:$R^{n_x} \times R^{n_v}$represents a nonlinear function transiting

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the system from timet_k to time t_{k+1} in response to the model input vector.

The general measurement equation can be written as:

$$z_k = h(x_k, w_k) \quad (6)$$

where $z_k \in R^{n_z}$ is an observation vector withn_z dimension; h is a measurement function representing the relationship between the states and observations; w_k is the measurement noise sequence, which is generally considered as an independent and random vector.

With the state-transition equation (5) and the measurement equation (6), PF recursively estimates system states at each time when an observation becomes available. For the initial time, the PF estimate process can be divided into four steps. First, PF uses the given initial distribution to create N equally-weighted samples, called particles. These particles are generally represented by$\{x_0^i\}_{i=1}^N$. Second, the weights of all particles are updated by comparing the simulated measurement$z_0^i = h(x_0^i, n_k)$ to the observed z_0. The particle whose agreement between simulation and observation is higher will be given a larger weight. Third, the estimated state$\hat{x_0}$ will be calculated. The collection of weighted particles$\{(x_0^i, \omega_0^i)\}_{i=1}^N$can approximate the posterior distribution of the state variable under the condition of the given observation by normalizing the updated weights. The estimated state $\hat{x_0}$ is calculated as (Moradkhani et al., 2005):

$$\hat{x_0} = \sum_{i=1}^N \omega_0^i x_0^i \quad (7)$$

The last step is resampling. Resampling is conducted in PF to reduce the particle degeneracy problem (Arulampalam et al., 2002). The basic idea of resampling is to eliminate the low-weighted particles in favor of concentrating on high-weighted particles. The resampling particles are generated by the system dynamic function$x_1^i = f(x_0^i, v_0)$. The obtained new collection of equally-weighted particles $\{x_1^i\}$is used for another reweighting under the condition of subsequent observation y_1. As the procedure continues at time step k (k =1, 2, 3. . . .), the subsequent estimated states$\hat{x_1}$, $\hat{x_2}$, $\hat{x_3}$,. . . will be obtained analogously to Equation (7) until the final observation is used. A more detailed description of the PF method can be found in Arulampalam et al. (2002).

Derivation of time-variant parameters

In this study, the Particle filter is combined with hydrological model (*i.e.* , TWBM), to estimate the soil moistures S , parameter$C$ and parameter SC at each time step. The state vector$x_k = [SC, C, S\ ]'$, includes both state and parameters. The observed runoff is the observation in the Particle filter. The parameters C and SC are set to range from 0.2-2.0 and 100-4000 (mm), respectively. The system state-transition equation for the SC, C and S are as follows:

$$\mathrm{SC}_{k+1} = \mathrm{SC}_k + v_k \quad (8)$$

$$C_{k+1} = C_k + \xi_k \quad (9)$$

$$S_{k+1} = S_k + P_k - E_k - Q_k + \eta_k$$

where v_k, ξ_k and η_k are the independent white noise for the state-transition equation; v_k, ξ_k andη_k are all the Gaussian distribution with zero mean.

The measurement equation is as follow:

$$Q_{k+1} = TWBM(\mathrm{SC}_{k+1},\ C_{k+1},\ S_{k+1},\ P_{k+1},\ \mathrm{EP}_{k+1}) +\ w_{k+1} \quad (11)$$

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Where $TWBM$ represents the two-parameter monthly water balance model; w_{k+1} represents the observation error, following a Gaussian distribution with zero mean; P_{k+1} is the precipitation at time k +1; EP_{k+1} is the potential evapotranspiration at time k +1; Q_{k+1} is the observed runoff at time k +1.

In this study, the uncertainties in output and input (*i.e.* v, ξ, η and w in the Equation 8, Equation 9, Equation 10 and Equation 11, respectively) are important to the performance of Particle filter in assimilating the parameters (*i.e.* SC and C). The uncertainties (*i.e.* v, ξ, η and w in the Equation 8, Equation 9, Equation 10 and Equation 11, respectively) are specified empirically to follow a Gaussian distribution with zero mean and specified deviation following previous studies(Moradkhani et al., 2005; Wang, Chen, & Cai, 2009; Xie & Zhang, 2010; Deng et al., 2016). The deviation of C is set as 0.05. Both the deviation of SC and$S$ is assumed to be proportional to the forecasted SC and S(*i.e.* obtained from state-transition equation), respectively, at each time. The proportional factors are both set as 0.05. The deviation of observed error is assumed to be proportional to the observed runoff. The proportional factor is set as 0.15. The Particle filter is run 100 times account the possible uncertainty in assimilated parameters and the ensemble mean of the 100 times estimated parameters is considered as the final estimated parameters.

Pettitt's test for step change detection

In this paper, the Pettitt's test (Pettitt, 1979) is used to detect significant change in the average value for the assimilated times series of SC and C. The test employs a statistic $U_{t,\ N}$, to verify whether there is a single change-point between two samples x_1,. . . x_t andx_{t+1},. . . ,x_N. The test statistic for each time$t$ (t= 1, 2 . . . , N) is calculated by:

$$U_{t,N} = U_{t-1,N} + \sum_{j=1}^{N} sgn(x_t - x_j) \qquad (12)$$

The Pettitt's test is proposed of H: the N variables follow one or more distribution with same location parameter (no change) against$A$: a change point exists. The statistic K_t used in significance testing is given by:

$$K_t = \mathrm{Max}_{1 \leq t \geq N} |U_{t,N}| \qquad (13)$$

The probabilities associated with K_t are calculated as:

$$p \cong 2exp\{-6(K_t)^2/(N^3 + N^2)\} \qquad (14)$$

The value of $p < 0.05$ means the time series divided by this point (t) into two series have different distributions, which suggest there is a significant step change point. Here, hydrological behavior of the catchment is regarded as changed or shifted if the step change point is identified in either SC or C time series with $p < 0.05$.

Evaluation of model performance

The Nash-Sutcliffe efficiency (NSE) (Nash & Sutcliffe, 1970) and water balance bias (BIAS) were used to evaluate model performance and were calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^{n} (Q_{obs,i} - Q_{\mathrm{obs}})^2} \qquad (15)$$

$$BIAS = \frac{\sum_{i=1}^{n} Q_{sim,i} - \sum_{i=1}^{n} Q_{obs,i}}{\sum_{i=1}^{n} Q_{obs,i}} \qquad (16)$$

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where $Q_{sim,i}$ and $Q_{obs,i}$ are the simulated and observed runoff at the i -th time step, respectively; theQ_{obs} is the mean observed runoff.

Study area

Southeastern Austrilian has experienced the Millennium drought (1997-2009), which was the worst drought period occurring from 1900 to 2010 (CSIRO, 2012; van Dijk et al., 2013). This drought has caused a severe decrease in agriclutural production and great depletion of water storage. The Wee Jasper catchment has experinced the Millenium drought (Saft et al., 2015), and was chosen as a case study catchment for this study (see Figure 1). It is located in southeastern Austrilia and has an area of 990 km^2. The latitude and longitude of the catchment gauging station are 35.17°S and 148.69°E, respectively. This catchment is an unimpaired catchment with almost no human impacts on streamflow, such as reservoirs, land-use changes, irrigation systems,*etc* . Irrigation has not been reported in this catchment.

[Please insert Figure 1 here]

Climate of the Wee Jasper catchmet is winter-dominated rainfall regime. Mean annual rainfall (P) of the Wee Jasper catchment is 1002 mm and mean annual potential evapotransipiration (PET) is 1221 mm over the study period. The inter-annual varaibility of P is very large. The coefficient of varaition of annual P during the study period (1970-2014) is about 0.25. The long-term average runoff is 279 mm with a runoff coefficient of 0.28 during the study period. February and March are the driest months with P less than 60 mm/month. July is the wettest month with mean monthly P of 121 mm. However, monthly PET shows an opposite seasonal pattern, which varies from 26 mm in July to 206 mm in January. Therefore, catchment evapotranpiration is generally limited by available water in summer ($P <$ PET), and is limited by available energy in winter ($P >$ PET).

In this study, daily rainfall, potential evaporation, runoff, and other climate variables were collected from the dataset of Zhang et al. (2013). Figure 2 presents the anomalies of rainfall, runoff, and temperature in the Wee Jasper catchment from 1970 to 2014. The Wee Jasper catchment experienced extremely dry conditions during the Millenium drought period (1997-2009). During this period, all years experienced below average rainfall (averaged from 1970 to 2014) except for 1999, 2000, and 2005 when annual rainfall was slightly above the long-term mean. All years from 1997 to 2009 experienced below average annual runoff except 2000. All years from 1997 to 2009 had above average annual temperature.

[Please insert Figure 2 here]

Results

Rainfall-runoff relationships during pre- and post-drought periods

In order to verify whether there was a change in the rainfall-runoff relationship in the Wee Jasper catchment due to multi-year drought, a statistical examination used by Saft et al. (2015) was employed. The observed annual rainfall-runoff relationships for the Wee Jasper catchment during the pre- and post-drought periods are shown in Figure 3. The entire study period (1970-2014) was divided into the pre- and post-drought periods using the beginning year of the Millennium drought (1997) (CSIRO, 2012), as the catchment behaviors were assumed to change during the Millennium drought and to not recover in the more normal last five years (2010-2014). The runoff data were transformed by the Box-Cox transformation (Box & Cox, 1964) to make them follow an approximately normal distribution and to become approximately linear with rainfall data as done by (Saft et al., 2015). Figure 3 demonstrates that during the pre-drought period, the slope and intercept of the rainfall-runoff relationship are 0.016 and 4.35, respectively. During the post-drought period, the slope was the same (0.016), but the intercept was 2.19. The significant decrease in the intercept ($p < 0.05$) suggests

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that the rainfall-runoff relationship between the pre- and post-drought periods were significantly different. The small intercept means that the reduction in runoff with decreasing rainfall during the post-drought period was smaller than expected for the same reduction of rainfall during the pre-drought period.

[Please insert Figure 3 here]

Simulated runoff by combining a data assimilation method with a hydrological model

Observed and simulated monthly runoff are shown in Figure 4. The simulated monthly runoff was calculated by TWBM with ensemble mean parameters from 100 runs using the PF data assimilation method. Figure 4 shows that the simulated monthly runoff agreed well with observed monthly runoff over the entire period from 1970 to 2014 except March 2012. The NSE between the simulated and observed runoff was 0.94. High NSE values indicated that the simulated runoff was almost the same as the observed runoff at every time step. The BIAS between the simulated and observed runoff was -0.05, which indicated that the total volume of simulated runoff was slightly less than the volume of observed runoff. Both NSE and BIAS values suggested that the long-term monthly rainfall-runoff relationship of the Wee Jasper catchment was well captured by the combination of the PF data assimilation method with TWBM. Thus, assimilated time-variant parameters of the hydrological model (*i.e.,* SC and C) can be used to infer the long-term dynamic state of the catchment hydrological behavior.

[Please insert Figure 4 here]

Changes in the state variables (SC and C)

Anomalies of the annual values of SC and C from 1970 to 2014 are shown in Figure 5. The anomalies were calculated using ensemble mean parameters from 100 runs using the PF data assimilation method. Annual anomalies of SC (Figure 5a) were generally seen to increase from negative to positive over the 1970-2014 period, with some variability. Annual anomalies of SC varied from -40.7% around 1976 to 22.4% around 2004. The entire study period can be divided into three different but consecutive periods (1970-1984, 1985–1992, 1993–2014) by the three-year moving window curve. The three-year moving window of SC anomalies was negative during the 1st period (1970-1984). The moving window curve alternated between negative and positive values during the 2nd period (1985–1993). And moving window curve was all positive during the 3rd period (1994–2014) except for 2013. The Millennium drought period (1997–2009) lies in the 3rdperiod (1994–2014), indicating that during the Millennium drought period, SC was larger than the mean SC value cacluated over the entire study period (1970-2014).

Figure 5b shows inter-annual fluctuations of the anomalies of C . Annual anomalies of C showed a similar increasing time trend as seen for SC. Basically, anomalies of C were negative at the beginning of the study period, and mostly positive at the end of study period. The C anomaly fluctuated more frequently and had shorter and more consecutive positive and negative periods than seen for SC (Figure 5a). Annual anomalies ranged from -23.5% to 21.7%, and could be divided into three periods (1970-1979, 1980-1997, 1998-2014) using the three-year moving window curve. The three-year moving window of C anomalies was always negative during the 1stperiod (1970-1979). It then alternated between negative and positive values during the 2nd period (1980-1997), similar to what was observed for SC, but with more fluctuation cycles. The three-year moving window of C anomalies was always positive during the 3rd period (1997-2014) except for 2013. The Millennium drought period (1997–2009) fell in the 3rdperiod (1997–2014), during which the three-year moving window of C anomalies were all positive, indicating the during the Millennium drought period C was larger than the mean Cvalue calculated for the entire study period (1970-2014).

Figure 6 presents of SC and C at the monthly time scales over the 1970-2014 study period with the 5.0%–95.0% prediction uncertainty range (grey ribbon) estimated from 100 model runs. Step changes in the time-variant series of SC and C were detected using the Pettitt-test and are also shown in Figure 6 (red

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dashed line). In Figure 6a, the step change for SC was identified as occurring in April 1997. The average values of SC before and after the step change were 2606.4 and 3217.4 mm, respectively. The average value of SC increased 23.4% after the step change. The estimated monthly time series of C is shown in Figure 6b. The step change for C was identified as occurring in November 1996. The average values of C before and after the step change point were 1.08 and 1.19, respectively. The mean C value increased about 10.2% after the step change. Figure 6 shows that TWBM parameters shifted significantly around the beginning of the Millennium drought (*i.e.,* 1997), which is consistent with the statistical examination described in Section 4.1, and indicates a significant shift in the rainfall-runoff relationship in the Wee Jasper catchment due to the prolonged drought.

[Please insert Figure 5 here]

[Please insert Figure 6 here]

Discussion

Changes in rainfall-runoff relationship induced by drought

Figure 3 and Figure 6 both show the consistent result that there was a shift in the rainfall-runoff relationship during the post-drought period (1997-2014) compared with the relationship during the historical period (1970–1996). In this study, the increase in the catchment water storage capacity and the decrease in soil moisture are considered to be the main causes that induced the observed change in the hydrological process in terms of the increase of parameters SC and C . The decline in soil moisture means decreased groundwater recharge (Western, Grayson, & Bloschl, 2002) leading to a decline in groundwater level and reduced discharges to stream networks. Increased catchment water storage capacity may also lead to a larger initial rainfall loss during the drought and result in smaller runoff coefficient (Saft et al., 2016). The increase in catchment water storage capacity may be caused by the decline in groundwater level, which will be discussed in Section 5.2. Many previous studies (Petrone et al., 2010; Petheram, Potter, Vaze, Chiew, & Zhang, 2011; Hughes et al., 2012; Chiew et al., 2014) also reported that declining groundwater level and deep soil moisture could lead to changes in the rainfall-runoff relationship during the Millennium drought in southeastern Australia. The pre-drought groundwater level was close to the soil surface, and could amplify the generation of surface runoff. However, this effect will be diminished during drought with lower groundwater level and drier deep soil, resulting in less rainfall becoming runoff.

Estimated time-variant model parameters

SC represents the active water storage capacity (Xiong & Guo, 1999), which is not a constant, but rather is a time-variant parameter in contrast to the original parameter definition. There is also a difference in the physical meaning of C compared with the original definition given by Xiong & Guo (1999). In this study, a change in C can reflect a change in the ratio between rainfall and soil moisture in supplying actual evapotranspiration. The higher C value means that the ratio of rainfall to soil moisture is smaller with regards to supplying actual evapotranspiration. That result is due to Equation (1) of TWBM being based on the Budyko framework (Xiong & Guo, 1999), where the mean variation of soil water content is assumed to be zero on a multi-year scale. However, at a monthly scale, the rainfall is sometimes not enough to provide water availability for evapotranspiration, and soil water content in the deeper soil layer is used to sustain evapotranspiration during drought (Cheng, Xu, Wang, & Cai, 2011). If evapotranspiration is calculated using equation (1) when TWBM is combined with the PF data assimilation method, then C is calculated optimally at each time step rather than over the entire study period. The time-variant parameter C reflects the variation of the ratio of rainfall to soil moisture at each time step. Thus, the increase in C can be attributed to the decrease of water supply (including rainfall and soil moisture) available for actual evapotranspiration. This can be inferred from Figure 2, which also suggests that the Wee Jasper catchment

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experienced a wet period from 1983 to 1996). Average PET and precipitation were approximately equal during this wet period. The PET and precipitation were 1174 mm and 1105 mm, respectively. However, during the period of 1997-2009, the average PET became 403 mm larger than average precipitation. Due to changes in the ratio of PET to precipitation (i.e., aridity index), more soil moisture could be evaporated (Western et al., 2002) during period of 1997-2009. In addition, Figure 2 shows, the rainfall in this period became lower. With higher evaporation of soil moisture and lower rainfall, the ratio of rainfall to soil moisture in supplying actual evapotranspiration was smaller.

More evaporated water from soil may come from deeper soil layers. During prolonged drought, trees can access deep soil moisture and thereby sustain transpiration. Loeb, Wang, Liang, Kato, & Rose (2017) found that during the Millennium drought, the moisture in the top soil layer stopped declining in 2002, while in the lower soil layer the moisture continually declined until 2008 in central Australia, indicating that the deep soil layer was capable of consistently supplying water for evapotranspiration. The decrease in deep soil moisture may be due to the transpiration of vegetation with deep roots during dry periods (Gao et al., 2014; Loeb et al., 2017). The capacity of deep soil moisture to consistently supply evapotranspiration is consistent with the characteristics of the estimated parameter C time series.C maintained a higher value for a long time after the step change point in the Millennium drought period (1997-2009) (see Figure 5).

Groundwater decline was considered to be the main reason for the shift in SC. SC represents the active water storage capacity, which exhibited large fluctuations at the monthly scale (Figure 6). The average inter-monthly variation of SC was 43 mm. The large fluctuation of SC indicated that it is sensitive to meteorological factors at the monthly scale. Typically, there are two main factors that can lead to changes in catchment water storage capacity, i.e., groundwater and soil properties. Groundwater is considered to be the main factor because of the quicker responses of groundwater to meteorological factors compared with responses of soil properties (Hughes et al., 2012). Groundwater can also vary at a monthly time scale (Jackson, Meister, & Prudhomme, 2011; Adams et al., 2012). Relative to the interdecadal variation of soil properties, such as hydraulic conductivity, water repellence, and preferential flow pathways, groundwater is more sensitive to meteorological factors in impacting catchment water storage capacity (Saft, Peel, Western, & Zhang, 2016). Hughes et al. (2012) also found that groundwater level declined about 3 m or more during the Millennium drought in many catchments in southern Australia, including at the Del Park, Bates, Lewis, Gordon, Cameron West, and Cameron Central catchments. Many researchers also reported that the catchment groundwater level dropped significantly during the Millennium drought in southern Australia (Petrone et al., 2010; Petheram et al., 2011; Kinal & Stoneman, 2012; Gao et al., 2014). Significant declines in groundwater levels reported by these literature sources are consistent with the findings in this study that SC was larger during the Millennium drought period (1997-2009) than at other times (Figure 5 and Figure 6).

Data assimilation method for detecting drought impacts

Many studies have reported that drought can alter catchment rainfall-runoff relationships (Conway et al., 2004; Guardiola-Claramonte et al., 2011; Petheram et al., 2011; Chiew et al., 2014). However, reasons for changes in the relationship are still unclear, especially regarding the driving factors at the process level. In this study, a new method involving the combining of a data assimilation technique (PF) with a process hydrological model (TWBM) was employed to detect and attribute drought induced changes to the rainfall-runoff relationship in the Wee Jasper catchment, which had experienced a 13-year prolonged drought. Shifts in hydrological parameters adequately accounted for the change in the rainfall-runoff relationship, as they represented functional properties of hydrological behaviors. This new method not only confirmed the fact that prolonged drought altered the rainfall-runoff relationship, but also determined that increased catchment water storage capacity and decreased soil moisture induced by deep soil moisture depletion through persistent evapotranspiration of deep-rooted woody vegetation during drought were the main factors changing the rainfall-runoff relationship during the Millennium drought in the Wee Jasper catchment. The results of this study demonstrated that combining data assimilation with a process-level hydrological model is an effective

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method for detecting and attributing drought impacts.

Due to a lack of long-term groundwater and soil moisture observations, at this location, the relationship between the change in hydrological parameters (SC and C) and observed groundwater and/or deep soil moisture was not presented. Long-term groundwater data for such long-term drought impact studies are typically very rare (Saft et al., 2016). However, the decline of groundwater and deep soil moisture can still be inferred from the meaning of the hydrological parameters, as described in Section 5.2. This is one of the advantages of using time-variant parameters to detect changes in the rainfall-runoff relationship (Deng et al., 2016; Pathiraja et al., 2016).

The relationship between the hydrological parameters and runoff is non-linear in TWBM. To obtain the parameters more accurately, the data assimilation used in this study must be capable of handling a non-linear system. For the capacity of retaining water balance, in contrast to the to the Kalman filter-based recursive method, PF upgrades the probability distributions of system states rather than changing the state ensemble members, and thereby retains the water balance law of the hydrological model. Therefore, PF was viewed as a suitable method for estimating the hydrological parameters in this study.

However, in this study, modeling experiments were not carried out to demonstrate the superiority of PF and/or TWBM compared with other data assimilation methods and/or physical hydrological models. This study can be viewed as an exploratory approach for detecting and attributing changes in the rainfall-runoff relationship induced by prolonged drought rather than a determination of the best combination of a data assimilation method with a hydrological model. PF was selected because of its ability to handle the non-linear characteristic (Arulampalam et al., 2002; Moradkhani et al., 2005; Dumedah & Coulibaly, 2013) of the rainfall-runoff relationship, which is widely recognized as a non-linear type of function. TWBM was selected because of its successful application with data assimilation (Deng et al., 2016) and its capability to simulate the catchment rainfall-runoff relationship across a wide range of climates, vegetation, and soil conditions. Because of the limited number of parameters involved, combining TWBM with PF does not afford the opportunity to obtain more information of impacted hydrological behaviors. In the future, a more complex process-based hydrological model with more parameters could be employed to detect the impacted hydrological behaviors in a prolonged drought situation in order to obtain a better understanding of the stationarity of the catchment rainfall-runoff relationship, although this will likely involve more uncertainties and/or computational costs.

Conclusions

A few previous studies using statistical approaches have reported that multi-year drought can induce a shift in the catchment rainfall-runoff relationship, but rarely have studies provided process-level interpretation of such shifts. Consistent with the results of previous research, the current study demonstrated that a change in the rainfall-runoff relationship was detected after the beginning of a prolonged drought period (1997) in the Wee Jasper catchment in New South Wales, Australia. However, the new analysis approach proposed in this study found that the change in the rainfall-runoff relationship is induced by an increase of catchment active storage capacity and a decrease in soil moisture resulting from persistent evapotranspiration of deep-rooted woody vegetation during the drought, leading to a decline in groundwater level and deep soil moisture.

This study concluded that the combination of data assimilation and a hydrological model was a suitable approach for detecting the hydrological non-stationarity caused by prolonged drought. This approach not only can detect changes in rainfall-runoff relationships, but also can identify the driving factors for such changes at the process-level. The method used in this study can provide assistance in developing strategies and management practices to mitigate the negative effects of prolonged drought, and in developing preparedness and adaptation strategies for the challenges of climate change which will likely increase the frequency and severity of drought in the future.

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Data Availability Statement

The data that support the findings of this study are openly available in the CSIRO Research Publications Repository at*https://publications.csiro.au/rpr/home*, which is published by Zhang et al. (2013). The data can also be obtained on request from the corresponding author.

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References

Adams, H.D., Luce, C.H., Breshears, D.D., Allen, C.D., Weiler, M., Hale, V.C.,... Huxman, T.E., 2012. Ecohydrological consequences of drought- and infestation- triggered tree die-off: insights and hypotheses.*Ecohydrology* , *5* (*2*): 145-159. http://dx.doi.org/10.1002/eco.233.

Arulampalam, M.S., Maskell, S., Gordon, N. & Clapp, T., 2002. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Ieee Transactions On Signal Processing* ,*50* (*2*): 174-188. http://dx.doi.org/10.1109/78.978374.

Botter, G., Basso, S., Porporato, A., Rodrigueziturbe, I. & Rinaldo, A., 2010. Natural streamflow regime alterations: damming of the Piave river basin (Italy). *Water Resources Research* , *46* (*6*): 1896-1911. http://dx.doi.org/10.1029/2009WR008523.

Box, G.E.P. & Cox, D.R., 1964. An analysis of transformations. *Journal of the Royal Statistical Society* , *26* (*2*): 211-252. http://dx.doi.org/10.2307/2343934.

Buttafuoco, G., Caloiero, T. & Coscarelli, R., 2015. Analyses of drought events in Calabria (Southern Italy) using standardized precipitation index. *Water Resources Management* ,*29* (*2*): 557-573. http://dx.doi.org/10.1007/s11269-014-0842-5.

Cheng, L., Xu, Z., Wang, D. & Cai, X., 2011. Assessing interannual variability of evapotranspiration at the catchment scale using satellite-based evapotranspiration data sets. *Water Resources Research* , *47* (*9*): W09509. http://dx.doi.org/10.1029/2011WR010636.

Cheng, L., Yaeger, M., Viglione, A., Coopersmith, E., Ye, S. & Sivapalan, M., 2012. Exploring the physical controls of regional patterns of flow duration curves - Part 1: Insights from statistical analyses. *Hydrology and Earth System Sciences* ,*16* (*11*): 4435-4446. http://dx.doi.org/10.5194/hess-16-4435-2012.

Cheng, L., Zhang, L., Chiew, F.H.S., Canadell, J.G., Zhao, F., Wang, Y.,... Lin, K., 2017. Quantifying the impacts of vegetation changes on catchment storage-discharge dynamics using paired-catchment data.*Water Resources Research* , *53* (*7*): 5963-5979. http://dx.doi.org/10.1002/2017WR020600.

Chiew, F.H.S., Potter, N.J., Vaze, J., Petheram, C., Zhang, L., Teng, J.,... Post, D.A., 2014. Observed hydrologic non-stationarity in far south-eastern Australia: implications for modelling and prediction.*Stochastic Environmental Research and Risk Assessment* ,*28* (*1*): 3-15. http://dx.doi.org/10.1007/s00477-013-0755-5.

Conway, D., Persechino, A., Ardoinbardin, S., Hamandawana, H., Dieulin, C. & Mahe, G., 2004. Rainfall and water resources variability in sub-Saharan Africa during the twentieth century. *Journal of Hydrometeorology* ,*10* (*1*): 41-59. http://dx.doi.org/10.1175/2008JHM1004.1.

Posted on Authorea 31 Jul 2020 — The copyright holder is the author/funder. All rights reserved. No reuse without permission. — https://doi.org/10.22541/au.159620885.50825175 — This a preprint and has not been peer reviewed. Data may be preliminary.

Coron, L., Andreassian, V., Perrin, C., Lerat, J., Vaze, J., Bourqui, M.,... Hendrickx, F., 2012. Crash testing hydrological models in contrasted climate conditions: An experiment on 216 Australian catchments. *Water Resources Research* , *48* (*5*). http://dx.doi.org/10.1029/2011WR011721.

CSIRO, 2012. *Climate and water availability in south-eastern Australia: A synthesis of findings from Phase 2 of the South Eastern Australian Climate Initiative (SEACI)* . CSIRO, Australia, 41 pp.

Dai, A., 2011. Drought under global warming: A review. *Wiley Interdisciplinary Reviews-Climate Change* , *2* (*1*): 45-65. http://dx.doi.org/10.1002/wcc.81.

Dai, A., 2013. Increasing drought under global warming in observations and models. *Nature Climate Change* , *3* (*1*): 52-58. http://dx.doi.org/10.1038/nclimate1633.

DeChant, C.M. & Moradkhani, H., 2012. Examining the effectiveness and robustness of sequential data assimilation methods for quantification of uncertainty in hydrologic forecasting. *Water Resources Research* ,*48* (*4*). http://dx.doi.org/10.1029/2011WR011011.

Deng, C., Liu, P., Guo, S., Li, Z. & Wang, D., 2016. Identification of hydrological model parameter variation using ensemble Kalman filter.*Hydrology and Earth System Sciences* , *22* (*5*): 1-39. http://dx.doi.org/10.5194/hess-2015-407.

Destouni, G., Jaramillo, F. & Prieto, C., 2013. Hydroclimatic shifts driven by human water use for food and energy production. *Nature Climate Change* , *3* (*3*): 213-217. http://dx.doi.org/10.1038/nclimate1719.

Dumedah, G. & Coulibaly, P., 2013. Evaluating forecasting performance for data assimilation methods: The ensemble Kalman filter, the particle filter, and the evolutionary-based assimilation. *Advances in Water Resources* , *60* (*8*): 47-63. http://dx.doi.org/10.1016/j.advwatres.2013.07.007.

Feng, S. & Fu, Q., 2013. Expansion of global drylands under a warming climate. *Atmospheric Chemistry and Physics* , *13* (*19*): 10081-10094. http://dx.doi.org/10.5194/acp-13-10081-2013.

Field, G., Tavrisov, G., Brown, C., Harris, A. & Kreidl, O.P., 2016. Particle filters to estimate properties of confined aquifers.*Water Resources Management* , *30* (*9*): 3175-3189. http://dx.doi.org/10.1007/s11269-016-1339-1.

Gao, H., Hrachowitz, M., Schymanski, S.J., Fenicia, F., Sriwongsitanon, N. & Savenije, H.H.G., 2014. Climate controls how ecosystems size the root zone storage capacity at catchment scale. *Geophysical Research Letters* , *41* (*22*): 7916-7923. http://dx.doi.org/10.1002/2014GL061668.

Guardiola-Claramonte, M., Troch, P.A., Breshears, D.D., Huxman, T.E., Switanek, M.B., Durcik, M.,... Cobb, N.S., 2011. Decreased streamflow in semi-arid basins following drought-induced tree die-off: A counter-intuitive and indirect climate impact on hydrology. *Journal of Hydrology* ,*406* (*3-4*): 225-233. http://dx.doi.org/10.1016/j.jhydrol.2011.06.017.

Guimberteau, M., Ciais, P., Ducharne, A., Boisier, J., Aguiar, A., Biemans, H.,... Poveda, G., 2017. Impacts of future deforestation and climate change on the hydrology of the Amazon Basin: a multi-model analysis with a new set of land-cover change scenarios. *Hydrology and Earth System Sciences* , *21* (*3*): 1455-1475. http://dx.doi.org/10.5194/hess-21-1455-2017.

Guo, S., Chen, H., Zhang, H., Xiong, L., Liu, P., Pang, B.O.,... Wang, Y., 2005. A semi-distributed monthly water balance model and its application in a climate change impact study in the middle and lower Yellow River basin. *Water International* , *30* (*2*): 250-260. http://dx.doi.org/10.1080/02508060508691864.

Guo, S., Wang, J., Xiong, L., Ying, A. & Li, D., 2002. A macro-scale and semi-distributed monthly water balance model to predict climate change impacts in China. *Journal of Hydrology* , *268* (*1*): 1-15. http://dx.doi.org/10.1016/S0022-1694(02)00075-6.

Hughes, J.D., Petrone, K.C. & Silberstein, R.P., 2012. Drought, groundwater storage and stream flow decline in southwestern Australia.*Geophysical Research Letters* , *39* (*3*): 41-59.

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http://dx.doi.org/10.1029/2011GL050797.

Huijgevoort, M.H.J.V., Lanen, H.A.J.V., Teuling, A.J. & Uijlenhoet, R., 2014. Identification of changes in hydrological drought characteristics from a multi-GCM driven ensemble constrained by observed discharge.*Journal of Hydrology* , *512* (*9*): 421-434. http://dx.doi.org/10.1016/j.jhydrol.2014.02.060.

Jackson, C.R., Meister, R. & Prudhomme, C., 2011. Modelling the effects of climate change and its uncertainty on UK Chalk groundwater resources from an ensemble of global climate model projections. *Journal of Hydrology* , *399* (*1-2*): 12-28. http://dx.doi.org/10.1016/j.jhydrol.2010.12.028.

Kinal, J. & Stoneman, G.L., 2012. Disconnection of groundwater from surface water causes a fundamental change in hydrology in a forested catchment in south-western Australia. *Journal of Hydrology* ,*472-473* (*2012*): 14-24. http://dx.doi.org/10.1016/j.jhydrol.2012.09.013.

Lima, L.S., Coe, M.T., Filho, B.S.S., Cuadra, S.V., Dias, L.C.P., Costa, M.H.,... Rodrigues, H.O., 2014. Feedbacks between deforestation, climate, and hydrology in the Southwestern Amazon: implications for the provision of ecosystem services. *Landscape Ecology* ,*29* (*2*): 261-274. http://dx.doi.org/10.1007/s10980-013-9962-1.

Loeb, N.G., Wang, H., Liang, L., Kato, S. & Rose, F.G., 2017. Surface energy budget changes over Central Australia during the early 21st century drought. *International Journal of Climatology* ,*37* (*1*): 159-168. http://dx.doi.org/10.1002/joc.4694.

Merz, R., Parajka, J. & Bloschl, G., 2011. Time stability of catchment model parameters: Implications for climate impact analyses. *Water Resources Research* , *47* (*2*): W02531. http://dx.doi.org/10.1029/2010WR009505.

Miguez-Macho, G. & Fan, Y., 2012. The role of groundwater in the Amazon water cycle: 1. Influence on seasonal streamflow, flooding and wetlands.*Journal of Geophysical Research-Atmospheres* ,*117* (*D15*): D15113. http://dx.doi.org/10.1029/2012JD017539.

Mishra, A.K. & Singh, V.P., 2010. A review of drought concepts. *Journal of Hydrology* , *391* (*1-2*): 202-216. http://dx.doi.org/10.1016/j.jhydrol.2010.07.012.

Mishra, A.K. & Singh, V.P., 2011. Drought modeling-A review.*Journal of Hydrology* , *403* (*1*): 157-175. http://dx.doi.org/10.1016/j.jhydrol.2011.03.049.

Moradkhani, H., 2008. Hydrologic remote sensing and land surface data assimilation. *Sensors* , *8* (*5*): 2986-3004. http://dx.doi.org/10.3390/s8052986.

Moradkhani, H. & Weihermuller, L., 2011. Hydraulic parameter estimation by remotely - sensed top soil moisture observations with the particle filter.*Journal of Hydrology* , *399* (*3*): 410-421

Moradkhani, H., DeChant, C.M. & Sorooshian, S., 2012. Evolution of ensemble data assimilation for uncertainty quantification using the particle filter-Markov chain Monte Carlo method. *Water Resources Research* ,*48* (*12*). http://dx.doi.org/10.1029/2012WR012144.

Moradkhani, H., Hsu, K., Gupta, H. & Sorooshian, S., 2005. Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter. *Water Resources Research* ,*41* (*5*). http://dx.doi.org/10.1029/2004WR003604.

Nalbantis, I. & Tsakiris, G., 2009. Assessment of hydrological drought revisited.*Water Resources Management* , *23* (*5*): 881-897. http://dx.doi.org/10.1007/s11269-008-9305-1.

Nash, J.E. & Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology* , *10* (*3*): 282-290. http://dx.doi.org/10.1016/0022-1694(70)90255-6.

Pan, M. & Wood, E.F., 2006. Data assimilation for estimating the terrestrial water budget using a constrained ensemble Kalman filter. *Journal of Hydrometeorology* , *7* (*3*): 534-547.

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http://dx.doi.org/10.1175/JHM495.1.

Pathiraja, S., Marshall, L., Sharma, A. & Moradkhani, H., 2016. Detecting non-stationary hydrologic model parameters in a paired catchment system using data assimilation. *Advances in Water Resources* ,*94* (*2016*): 103-119. http://dx.doi.org/10.1016/j.advwatres.2016.04.021.

Petheram, C., Potter, N., Vaze, J., Chiew, F. & Zhang, L., 2011. Towards better understanding of changes in rainfall-runoff relationships during the recent drought in south-eastern Australia. *19th International Congress on Modelling and Simulation (MODSIM)* , *26* (*1*): 3622-3628

Petrone, K.C., Hughes, J.D., Niel, T.G.V. & Silberstein, R.P., 2010. Streamflow decline in southwestern Australia, 1950-2008.*Geophysical Research Letters* , *37* (*11*): 141-150. http://dx.doi.org/10.1029/2010GL043102.

Pettitt, A.N., 1979. A non-parametric approach to the change-point problem.*Journal of the Royal Statistical Society* , *28* (*2*): 126-135. http://dx.doi.org/10.2307/2346729.

Saft, M., Peel, M.C., Western, A.W. & Zhang, L., 2016. Predicting shifts in rainfall-runoff partitioning during multiyear drought: Roles of dry period and catchment characteristics. *Water Resources Research* ,*52* (*12*): 9290-9305. http://dx.doi.org/10.1002/2016WR019525.

Saft, M., Western, A.W., Zhang, L., Peel, M.C. & Potter, N.J., 2015. The influence of multiyear drought on the annual rainfall-runoff relationship: An Australian perspective. *Water Resources Research* , *51* (*4*): 2444-2463. http://dx.doi.org/10.1002/2014WR015348.

Shuai, L., Xiong, L., Dong, L. & Zhang, J., 2013. Effects of the Three Gorges Reservoir on the hydrological droughts at the downstream Yichang station during 2003-2011. Hydrol Process. *Hydrological Processes* ,*27* (*26*): 3981-3993. http://dx.doi.org/10.1002/hyp.9541.

Trenberth, K.E., Dai, A., Schrier, G.V.D., Jones, P.D., Barichivich, J., Briffa, K.R.,. . . Sheffield, J., 2013. Global warming and changes in drought. *Nature Climate Change* , *4* (*1*): 17-22. http://dx.doi.org/10.1038/nclimate2067.

van Dijk, A.I.J.M., Beck, H.E., Crosbie, R.S., de Jeu, R.A.M., Liu, Y.Y., Podger, G.M.,. . . Viney, N.R., 2013. The Millennium Drought in southeast Australia (2001-2009): Natural and human causes and implications for water resources, ecosystems, economy, and society.*Water Resources Research* , *49* (*2*): 1040-1057. http://dx.doi.org/10.1002/wrcr.20123.

Wang, D., Chen, Y. & Cai, X., 2009. State and parameter estimation of hydrologic models using the constrained ensemble Kalman filter.*Water Resources Research* , *45* (*11*): 2471-2481. http://dx.doi.org/10.1029/2008WR007401.

Wang, W., Basia, V. & Arie, A., 2003. Plant responses to drought, salinity and extreme temperatures: towards genetic engineering for stress tolerance. *Planta* , *218* (*1*): 1-14. http://dx.doi.org/10.1007/s00425-003-1105-5.

Western, A.W., Grayson, R.B. & Bloschl, G., 2002. Scaling of soil moisture: A hydrologic perspective. *Annual Review of Earth and Planetary Sciences* , *30* (*1*): 149-180. http://dx.doi.org/10.1146/annurev.earth.30.091201.140434.

Xie, X. & Zhang, D., 2010. Data assimilation for distributed hydrological catchment modeling via ensemble Kalman filter. *Advances in Water Resources* , *33* (*6*): 678-690. http://dx.doi.org/10.1016/j.advwatres.2010.03.012.

Xiong, L. & Guo, S., 1999. A two-parameter monthly water balance model and its application. *Journal of Hydrology* , *216* (*1-2*): 111-123. http://dx.doi.org/10.1016/S0022-1694(98)00297-2.

Xiong, L. & Guo, S., 2012. Appraisal of Budyko formula in calculating long-term water balance in humid watersheds of southern China.*Hydrological Processes* , *26* (*9*): 1370-1378. http://dx.doi.org/10.1002/hyp.8273.

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Xiong, L., Yu, K.X. & Gottschalk, L., 2015. Estimation of the distribution of annual runoff from climatic variables using copulas. *Water Resources Research* , *50* (*9*): 7134-7152. http://dx.doi.org/10.1002/2013WR015159.

Xiong, M., Liu, P., Cheng, L., Deng, C., Gui, Z., Zhang, X.,... Liu, Y., 2019. Identifying time-varying hydrological model parameters to improve simulation efficiency by the ensemble Kalman filter: A joint assimilation of streamflow and actual evapotranspiration. *Journal of Hydrology* , *568* (*2019*): 758-786. http://dx.doi.org/10.1016/j.jhydrol.2018.11.038.

Xue, Z., Liu, J. & Ge, Q., 2011. Changes in hydrology and sediment delivery of the Mekong River in the last 50 years: connection to damming, monsoon, and ENSO. *Earth Surface Processes and Landforms* , *36* (*3*): 296-308. http://dx.doi.org/10.1002/esp.2036.

Yang, Y., McVicar, T.R., Donohue, R.J., Zhang, Y., Roderick, M.L., Chiew, F.H.S.,... Zhang, J., 2017. Lags in hydrologic recovery following an extreme drought: Assessing the roles of climate and catchment characteristics. *Water Resources Research* , *53* (*6*): 4821-4837. http://dx.doi.org/10.1002/2017WR020683.

Zhang, D., Liu, X., Liu, C. & Bai, P., 2013. Responses of runoff to climatic variation and human activities in the Fenhe River, China. *Stochastic Environmental Research and Risk Assessment* ,*27* (*6*): 1293-1301

Zhang, Q., Zhang, L., Cui, X. & Zeng, J., 2011. Progresses and challenges in drought assessment and monitoring. *Advances in Earth Science* ,*26* (*7*): 763-778. http://dx.doi.org/10.1016/B978-0-444-53599-3.10005-8.

Zhang, Y., Viney, N., Frost, A., Oke, A., Brooks, M., Chen, Y.,... Campbell, N., 2013. Collation of Australian modeller's streamflow dataset for 780 unregulated Australian catchments. *Australia: CSIRO* . http://dx.doi.org/10.4225/08/58b5baad4fcc2.

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Figure 1 . Rainfall deciles during the Millennium Drought (1997 to 2009) in eastern Australia (a), and the river networks of the Wee Jasper catchment (b) in New South Wales, Australia. The rainfall deciles subplot (a) shows that mean annual precipitation in the region of the Wee Jasper catchment during the Millennium Drought ranged from very much below average to lowest on record. Subplot (a) was accessed from the Bureau of Meteorology of Australia (http://www.bom.gov.au). The green open circle indicates the location of the Wee Jasper catchment.

Figure 2 . Annual rainfall, runoff, and temperature anomalies for the Wee Jasper catchment, New South Wales, Australia (expressed as a percentage of mean annual rainfall, runoff, and temperature over the period of 1970-2014). The bars in cyan and red indicate annual rainfall, runoff, and temperature values larger and lower, respectively, than the mean values. The solid black lines are the three-year moving averages.

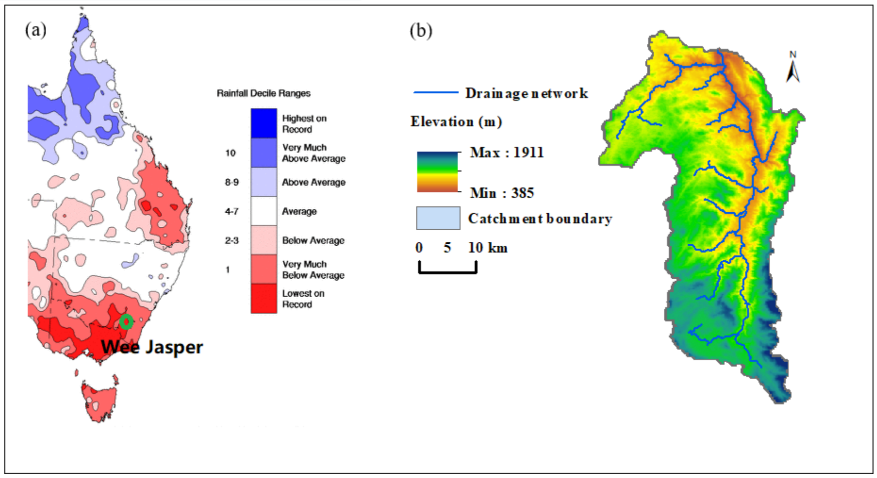
Figure 3 . Linear relationship between annual rainfall and runoff in the Wee Jasper catchment, New South Wales, Australia transformed by the Box-Cox method during two different periods, *i.e* ., before (red line) and after (cyan line) 1997.

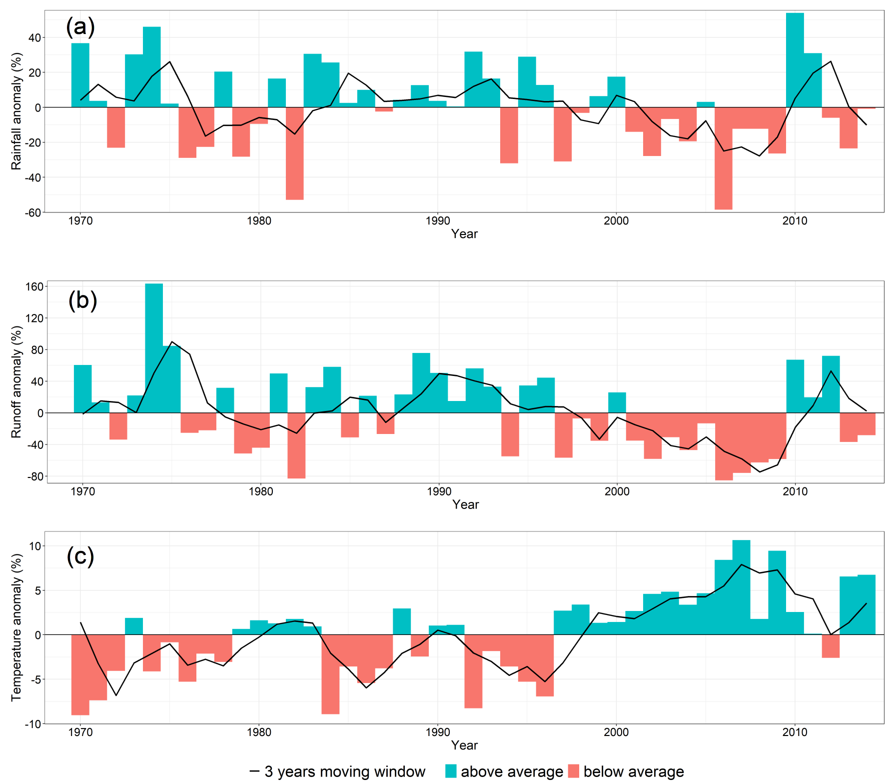
Figure 4 . Observed (red line) and simulated (cyan line) monthly runoff from 1970 to 2014 in the Wee Jasper catchment, New South Wales, Australia.

Figure 5 . Annual anomalies of the estimated values of parameters (a) SC (catchment active water storage capacity and (b) C (constant reflecting catchment evapotranspiration dynamics) of the two-parameter monthly water balance model expressed as a percentage of the mean annual value of SC or C over the period of 1970-2014. The bars in cyan and red indicate annual values of SC or C that are larger and lower, respectively, than the mean annual values. The solid black lines are the three-year moving averages of annual anomalies.

Figure 6 . Estimated monthly values of parameters SC and C from 1970 to 2014. The grey ribbon and the blue line represent the 5.0%–95.0% range and mean, respectively, of estimated monthly values of an

ensemble of 100 model runs. The red dashed line represents the mean values of SC and $C$for the periods before and after the step changes identified by the Pettitt's test.





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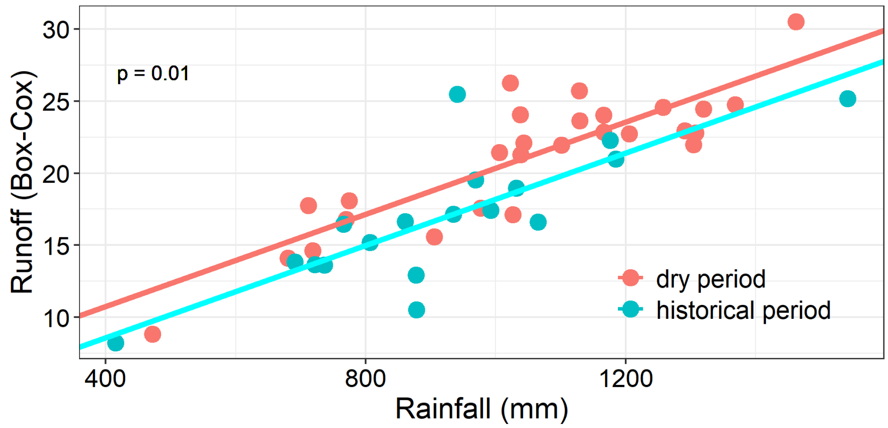

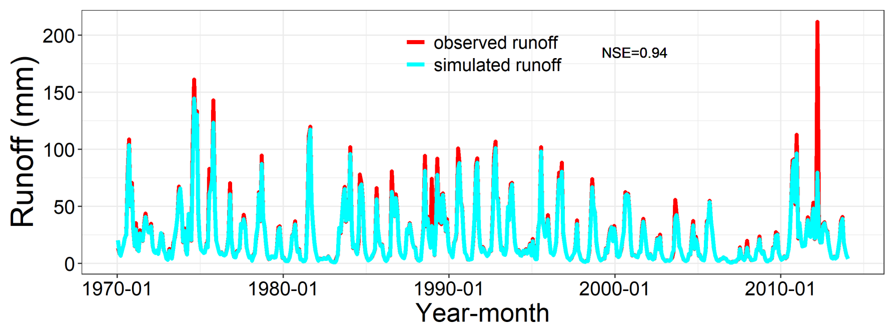

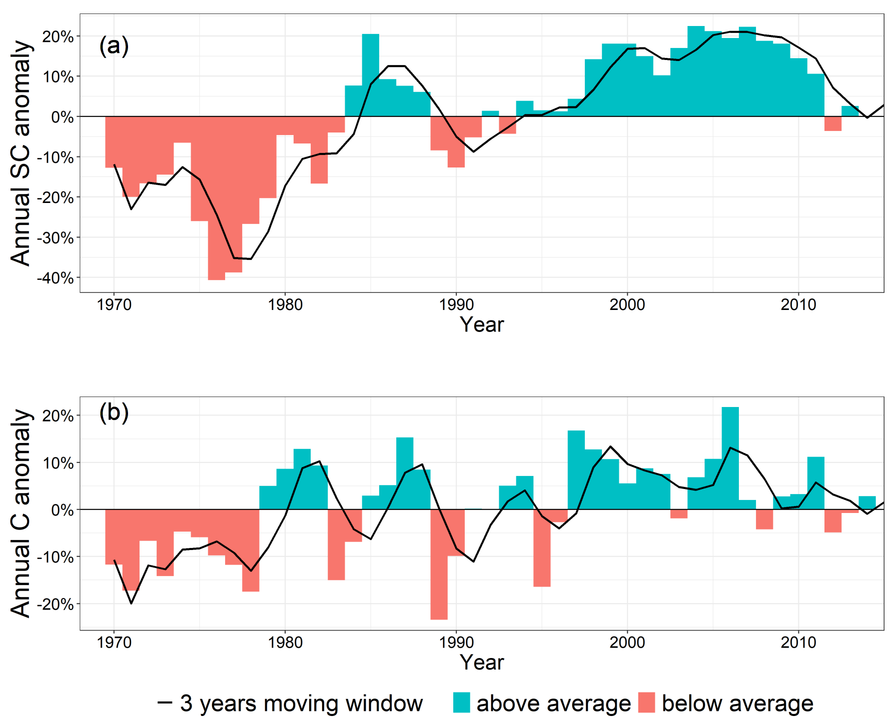

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