Review comments from Bettina Schaefli

**Comment #1.1.** This manuscript proposes a new method to correct forecasted streamflows based on the forecast error of the previous time step. The method represents a modification of the commonly applied autoregressive correction. The paper is well written, the method and the results concisely presented and discussed. However, the presented results did not convince me that the new method really outperforms the reference method; this might easily be improved by showing more details of the performed tests.

Response: Thank you very much for the time and effort you have taken to carefully review this manuscript. We feel your comments are very valuable for us to improve the quality of the manuscript considerably. We appreciate your positive feedback. We have paid serious attention to your suggestions and have attempted to address all your concerns, especially on the model performance comparison. Please refer to specific responses to your comments below.

My suggestion for moderate revisions of this paper are:
General comment on used terms

**Comment #1.2.** I would carefully revise the used wording to clearly distinguish between "forecast" (prediction of the system state at a given moment in time) from the more general "prediction". At the moment, the two terms are used interchangeably, which might sometimes be misleading, especially because the discussed streamflow correction only applies to forecasting.

Response: We have now used the word *forecast* throughout the paper, and have removed the word *prediction*. We occasionally use the word 'simulation' to differentiate instances where forecast rainfalls would never be used to force a rainfall runoff model, and make the distinction in the text, as follows:

"Our study is aimed at streamflow forecasting applications, so we preserve the distinction between observed and forecast forcings by referring to streamflows modelled with observed rainfall as *simulations* and those modelled with forecast rainfall as *forecasts*. As the forecast rainfall we use is observed rainfall, the terms *forecast* and *simulation* are interchangeable." Lines 198-203

Intro

**Comment #1.3.** As far as I see, the Kavetski et al. 2003 reference does not discuss forecasting and thus also not updating procedures but parameter estimation. Please give here references for papers that actually use streamflow correction / updating in a forecast setting.

Response: Thanks for the suggestion. We now use Morawietz et al., 2011 in the revision as a reference for updating procedures used in the context of streamflow forecasting.

**Comment #1.4.** In the general discussion of streamflow prediction errors, you might want to add the recent reference by Pianosi, F., and Raso, L.: Dynamic modeling of predictive uncertainty by regression on absolute errors, Water Resources Research, 48, W03516, 10.1029/2011wr010603, 2012.

Response: Thanks. We have added Pianosi and Raso (2012) as a reference for heteroscedastic prediction errors.

Method, section 2 and 5

**Comment #1.5.** Eq. 2 as well as following eqs. does not show the involved parameters

Response: We have carefully revised all equations and notations. The corresponding new equation comes with the definitions of the parameters involved.

**Comment #1.6.** Eq. 4: which part of the equation does result in the "median value"? should be corrected;

Response: Thanks for reading the manuscript so closely. We provide the proof in Appendix A to show why the updated streamflow is the median.

**Comment #1.7.** Reference for max. likelihood formulations in eq. 6 , 7?

Response: we add Li et al. (2013) as a reference for the likelihood formulations.

**Comment #1.8.** In general, I think the superscript notation is not nice to read, why not use two different variable names and subscripts for the parameters?

Response: Thanks for the suggestion. We have carefully and thoroughly revised the notations to increase the readability. For example, we don't use complex superscripts any more.

**Comment #1.9.** I am not convinced by the current structure with section 5 presenting the new approach; instead of having an "idea-flow" paper structure (method - result 1 - new method - result 2), I would introduce the new method in section 3.
Response: This suggestion is really valuable to improve the presentation of this manuscript. We have followed the suggestion to change the structure of the manuscript.

**Comment #1.10.** Eq. 8: the same variable name is used for something new, to avoid, what is QM?
Response: We have updated the notations completely and avoided the duplication of variable names.

**Comment #1.11.** P. 6045 last line: word missing
Response: In the revision, the estimation of all three models is described in Section 2.2. We don't need this sentence any more.

**Comment #1.12.** P. 6046 first paragraph: would be useful before eq. 8
Response: We have re-worded the motivation/idea behind the RAR-Norm model and placed this paragraph before the definition as suggested by you.

**Comment #1.13.** Likelihood formulation of the new approach?
Response: We have added the likelihood formulation.

Case study
**Comment #1.14.** The GR4J model: do any specificities of the model influence the obtained results? (to be mentioned in results section?)
Response: There may be. GR4J may be more prone to fluctuations in base hydrological model performance than other models, as pointed out by our other reviewer. We have added the following discussion of this matter:

"We note that the poor performance of the hydrological model may be specific to the GR4J model, and many not occur in other hydrological models. Evin et al. (2014) estimated hydrological model and error model parameters jointly using GR4J and another hydrological model, HBV, for the three US catchments tested here. While they did not assess the performance of the base hydrological models, they found that HBV tended to perform more robustly when combined with different error models. It is possible that we may have achieved more stable base model performance had we used HBV or another hydrological model. We note, however, that our conclusions can probably be generalised to other hydrological models that do not offer robust base model performance under joint parameter estimation (e.g. GR4J). Because the RAR-Norm model essentially limits the range of updating that can be applied through the AR-Norm model, it will tend to rely more heavily on the base hydrological model, and therefore will tend to favour parameter sets that encourage good stand-alone performance of the base model. For those hydrological models that already produce robust base model performance under joint parameter estimation (perhaps HBV), RAR-Norm is unlikely to undermine this performance for the same reasons. We see some evidence of this in our experiments with GR4J: when the performance of the base hydrological model is already strong relative to the updated forecasts for the AR-Norm and AR-Raw models (e.g. the Tarwin, Mitta Mitta, or Guadalupe catchments), the RAR-Norm model base hydrological model also performs strongly." (Lines 418-437)

**Comment #1.15.** P. 6041, line 21: "we then predict streamflow": not clear here whether in prediction or in forecast mode

Response: We agree – see responses to comments 1.2 and 1.16. This sentence now reads:
"We then generate streamflow forecasts in that year (1999) with model parameters estimated from the remaining data."

**Comment #1.16.** The use of "simulation" and "prediction" is confusing; I recommend using the term "forecast" for simulations with forecasted rainfall and the term "simulation" in the other case
Response: Thanks for this – we agree this makes things clearer. We have now changed the terms we use, as described in response to comment #1.2.

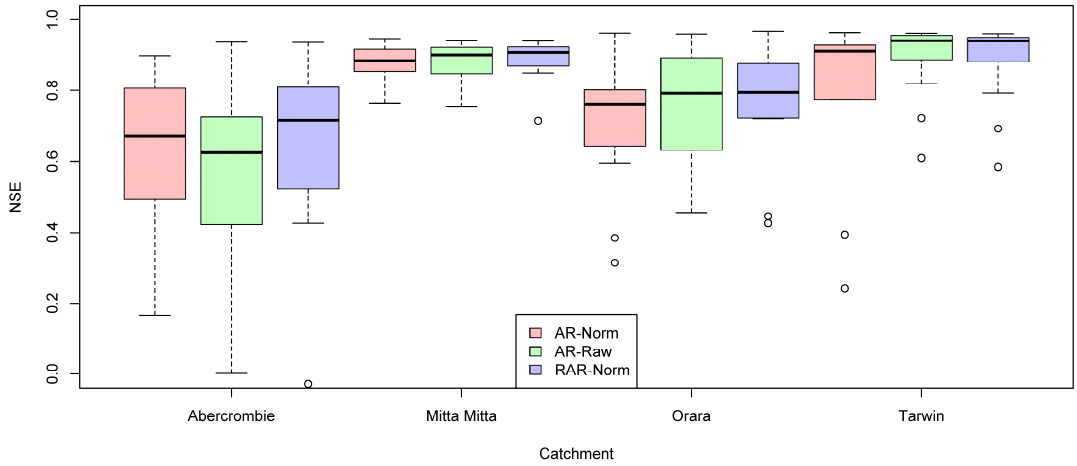
Results

**Comment #1.17.** I suggest a new results section presenting all the results
Response: Thank you for your valuable recommendation. We have followed your suggestion and made all results into two sections: Section 4). All methods are now described before results are documents.

**Comment #1.18.** In any case, the results of the new method require a separate section (now part of section 5 presenting also the method)
Response: We have followed your suggestion and presented all results in Section 4 (See Comment #1.17)
**Comment #1.19.** P. 6047, line 13: "notable better performance": as far as I see, only 2 out of 4 cases show a slightly better performance; from fig. 7, the improvement of RAR over AR-raw is not evident
Response: We have made several additions to demonstrate the performance of our RAR-Norm model:

1) We now assess our model on three additional US catchments, and these confirm our results
2) We use a greater range of metrics and analyses, including assessing the performance of AR models on all instances where streams are i) rising and ii) receding. This demonstrates the general tendency of AR-Norm models to perform least well when flows are rising, as well as the general tendency of the AR-Raw model to perform least well when streamflows are receding. The RAR-Norm model tends to combine the best aspects of the AR-Norm and AR-Raw models.
3) We have chosen a different example that more clearly shows the problem of over-correction of receding flows by the AR-Raw model.
4) We have changed the structure of the paper, following your suggestions, to group all results together. In doing this, we are better able to present that the RAR-Norm model outperforms both other models (see also response to Comment 1.21)

**Comment #1.20.** The NSE results are aggregated, how do they look like for individual cross-validation experiments? Are the NSE samples really significantly better with RAR (different distributions with higher mean) or is this pure chance?
Response: We show box-plots of the NSE values from each cross-validation period for the four Australian catchments below (note that for display purposes we have limited the vertical axis to [0, 1] and this means some of the outliers are not displayed). .These support our contention that the RAR-Norm model generally leads to better performing forecasts in two ways: 1) the means of the box plots are similar or higher than the next best performing model and 2) The distributions NSE scores of RAR-norm tend to be as narrow or narrower than the next best performing model, indicating that the performance of RAR-norm model is more robust under cross-validation.




Box-plots of NSE values for each cross-validation period for Australian catchments. Dark lines, mean values; boxes, interquartile range; whiskers, [0.1, 0.9] intervals; points, outliers.

Discussion

**Comment #1.21.** I am not convinced that the paper shows that the new method leads to a more robust performance of the base hydrological model. This should be shown in a more convincing way by presenting some more detailed results of all the simulations.

Response: We believe the additional metrics, analyses and catchments we have added (see response to comment 1.19) add weight to our conclusion that the RAR-Norm model is an improvement over the conventional AR-Raw and AR-Norm models we test. We summarise this in the conclusion as follows:

"The RAR-Norm model is a modification of the AR-Norm: in most instances it operates as the AR-Norm model, but in instances of possible over-correction it relies on the error in untransformed streamflows at the previous time step. That is, RAR-Norm is essentially a more conservative error model than AR-Norm: in situations where streamflows change rapidly, it opts to update with whichever error (transformed or untransformed) is smaller. This forces greater reliance on the base hydrological model to simulate streamflows accurately, leading to more robust performance in the base hydrological model. The RAR-Norm model clearly outperforms the AR-Norm model in both the updated and base model forecasts, as well as ameliorating the problem of over-correcting rising streamflows. The RAR-Norm model's advantage over the AR-Raw model is less clear: both the base hydrological model and the updated forecasts produced by the AR-Raw model perform similarly to (or sometimes slightly better than) the RAR-Norm model. However, the RAR-Norm model clearly addresses the problem of over-correcting receding streamflows that occurs in the AR-Raw model. As we show, this type of over-correction can seriously distort event hydrographs, and cause forecasts of near zero flows reasonably substantial flows are observed. While these instances are not very common, the failure in the forecast is a serious one. As we note earlier, the over-correction of receding flows is likely to be exacerbated when producing forecasts at lead times of more than one time step. Accordingly, we contend that the RAR-Norm model is preferable to both AR-Norm and AR-Raw models for streamflow forecasting applications." (Lines 458-479)

# A strategy to overcome adverse effects of autoregressive updating of streamflow forecasts

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## Abstract

For streamflow forecasting applications, rainfall-runoff hydrological models are often augmented with updating procedures that correct streamflow forecasts based on the latest available observations of streamflow and their departures from model simulations. The most popular approach uses autoregressive (AR) models that exploit the "memory" in hydrological model simulation errors. AR models may be applied to raw errors directly or to normalised errors. In this study, we demonstrate that AR models applied in either way can sometimes cause over-correction of forecasts. In using an AR model applied to raw errors, the over-correction usually occurs when streamflow is rapidly receding. In applying an AR model to normalised errors, the over-correction usually occurs when streamflow is rapidly rising. Furthermore, when parameters of a hydrological model and an AR model are estimated jointly, the AR model applied to normalised errors sometimes degrades the stand-alone performance of the base hydrological model. This is not desirable for forecasting applications, as forecasts should rely as much as possible on the base hydrological model, and updating should be applied only to correct minor errors. To overcome the adverse effects of the conventional AR models, a restricted AR model applied to normalised errors is introduced. The new model is evaluated on a number of catchments and is shown to reduce over-correction and to improve the performance of the base hydrological model considerably.

## 1. Introduction

Rainfall-runoff models are widely used to generate streamflow forecasts, which provide essential information for flood warning and water resources management. For streamflow forecasting, rainfall-runoff models are often augmented by updating procedures that correct streamflow forecasts based on the latest available observations of streamflow and their departures from model simulations. Model errors reflect limitations of the hydrological models in reproducing physical processes as well as inaccuracies in data used to force and evaluate the models.

The most popular updating approach uses autoregressive (AR) models, which exploit the “memory” - more precisely the autocorrelation structure - of errors in hydrological simulations (Morawietz et al., 2011). Essentially, AR updating uses a linear function of the known errors at previous time steps to anticipate errors in a forecast period. Forecasts are then updated according to these anticipated errors. AR updating is conceptually simple and yet generally leads to significantly improved forecasts (World Meteorological Organization, 1992). AR updating has been shown to provide equivalent performance to more sophisticated non-linear and nonparametric updating procedures (Xiong and O'Connor, 2002).

In rainfall-runoff modelling, model errors are generally heteroscedastic (i.e., they have heterogeneous variance over time) (Xu, 2001;Kavetski et al., 2003;Pianosi and Raso, 2012) and non-Gaussian (Bates and Campbell, 2001;Schaefli et al., 2007;Shrestha and Solomatine, 2008). In many applications (Seo et al., 2006;Bates and Campbell, 2001;Salamon and Feyen, 2010;Morawietz et al., 2011), AR models are applied to normalised errors that are considered homoscedastic and Gaussian. Normalisation is often achieved through variable transformation by using, for example, the Box-Cox transformation (Thyer et al., 2002;Bates and Campbell, 2001;Engeland et al., 2010) or, more recently, the log-sinh transformation (Wang et al., 2012;Del Giudice et al., 2013). In other applications (Schoups and Vrugt, 2010;Schaefli et al., 2007), AR models are applied directly to raw errors, but residual errors of the AR models may be explicitly specified as heteroscedastic and non-Gaussian.

There is no agreement on whether it is better to apply an AR model to normalised or raw errors. Recent work by Evin et al. (2013) found that an AR model applied to raw

errors may lead to poor performance with exaggerated uncertainty. They demonstrated that such instability can be mitigated by applying an AR model to standardised errors (raw errors divided by standard deviations). Here, standardisation has a similar effect to normalisation in that it homogenises the variance of the errors (but does not consider the non-Gaussian distribution of errors). Conversely, Schaefli et al. (2007) pointed out that when an AR model is jointly estimated with a hydrological model, there is a clear advantage in applying an AR model to raw errors rather than normalised (or standardised) errors. Schaefli et al. (2007) found that using raw errors leads to more reliable parameter inference and uncertainty estimation, because the mean error is close to zero and therefore the simulations are free of systematic bias. The same is not necessarily true when applying an AR model to normalised errors.

In this study, we evaluate AR models applied to both raw and normalised errors on four Australian catchments and three United States (US) catchments. We show that when estimated jointly with a hydrological model, the AR model applied to normalised errors sometimes degrades the stand-alone performance of the base hydrological model. We also identify that both of these conventional AR models can sometimes cause over-correction of forecasts. We introduce a restricted AR model applied to normalised errors and demonstrate its effectiveness in overcoming the adverse effects of the conventional AR models.

## 2. Autoregressive error models

### 2.1 Formulations

A hydrological model is a function of forcing variables (precipitation and potential evapotranspiration), initial catchment state, $S_0$, and a set of hydrological model parameters, $\theta_H$. We denote the observed streamflow and model simulated streamflow at time $t$ by $Q_t$ and $\tilde{Q}_t$, respectively. An error model is used to describe the difference between $Q_t$ and $\tilde{Q}_t$. The log-sinh transformation defined by Wang et al. (2012)

$$f(x) = b^{-1}\log\{\sinh(a+bx)\} \quad (1)$$

is applied to stabilise variance and normalise data.

In this study, we firstly examine two first-order AR error models:

(1) An AR error model applied to normalised errors (referred to as *AR-Norm*) defined by:

$$Z_t = \tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t \,, \tag{2}$$

where $Z_t$ and $\tilde{Z}_t$ are the log-sinh transformed variables of $Q_t$ and $\tilde{Q}_t$;

(2) An AR error model applied to raw errors (referred to as *AR-Raw*) defined by

$$Z_t = f\left\{\tilde{Q}_t + \rho\left(Q_{t-1} - \tilde{Q}_{t-1}\right)\right\} + \varepsilon_t \,. \tag{3}$$

For both models, $\rho$ is the lag-1 autoregression parameter, and $\varepsilon_t$ is an identically and independently distributed Gaussian deviate with a mean of zero and a constant standard deviation $\sigma$.

Both the AR-Norm and AR-Raw models represent the lag-one autocorrelation by an AR process and both employ the log-sinh transformation. However, the way the log-sinh transformation is applied differs between the two models. The AR-Norm model first applies the log-sinh transformation to the observed and model simulated streamflow, and then assumes that the error in the transformed space follows an AR(1) process. In contrast, the AR-Raw model essentially assumes that the error in the original space follows an AR(1) process and only applies the log-sinh transformation to fit the asymmetric and non-Gaussian error distribution.

The median of the updated streamflow forecast (referred to as *updated streamflow*) for the AR-Norm and AR-Raw models (see Appendix A for proof), denoted by $\tilde{Q}_t^*$, are respectively

$$\tilde{Q}_t^* = f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right)\right\}, \tag{4}$$

and

$$\tilde{Q}_t^* = \tilde{Q}_t + \rho\left(Q_{t-1} - \tilde{Q}_{t-1}\right), \tag{5}$$

where $f^{-1}(x)$ is the inverse of log-sinh transformation (or back-transformation). The magnitude of the error update by the AR-Raw model, $\tilde{Q}_t^* - \tilde{Q}_t$, is dependent only on the difference between $Q_{t-1}$ and $\tilde{Q}_{t-1}$. In contrast, the magnitude of the error update

by the AR-Norm model is dependent not only on the difference between $Q_{t-1}$ and $\tilde{Q}_{t-1}$, but also on $\tilde{Q}_t$ . Put differently, the AR-Norm model uses errors calculated in the transformed domain, and this means that the error in the original domain can be amplified (or reduced) by the back-transformation (Equation (4)). The AR-Raw model uses errors calculated in the original domain and no back-transformation is used in calculating $\tilde{Q}_t^*$ (Equation (5)), meaning that the error in the original domain cannot be amplified (or reduced). In Appendix B, we show that the AR-Norm model gives greater error updates for larger values of $\tilde{Q}_t$ .

We will demonstrate in Section 4 that the AR-Norm and AR-Raw models can sometimes cause over-correction of forecasts. Motivated to overcome the potential for over-correction, we introduce a modification of the AR-Norm model, called the restricted AR-Norm model (referred to as *RAR-Norm*). A condition $\left|\tilde{Q}_t^* - \tilde{Q}_t\right| \le \left|Q_{t-1} - \tilde{Q}_{t-1}\right|$ is used to limit the correction amount to not exceeding the error in the last time step in absolute value. The updated streamflow is given by

$$\tilde{Q}_t^* = \begin{cases} f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right)\right\} & \text{if } D_t \le \left|Q_{t-1} - \tilde{Q}_{t-1}\right| \\ \tilde{Q}_t + (Q_{t-1} - \tilde{Q}_{t-1}) & \text{otherwise.} \end{cases} \tag{6}$$

where

$$D_t = \left| f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right)\right\} - \tilde{Q}_t \right|. \tag{7}$$

The full RAR-Norm model in the transformed space is given by

$$Z_t = \begin{cases} \tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t & \text{if } D_t \le \left|Q_{t-1} - \tilde{Q}_{t-1}\right| \\ f\left(\tilde{Q}_t + Q_{t-1} - \tilde{Q}_{t-1}\right) + \varepsilon_t & \text{otherwise.} \end{cases} \tag{8}$$

## 2.2 Estimation

The AR-Norm, AR-Raw and RAR-Norm models are each calibrated jointly with the hydrological model. The method of maximum likelihood is used to estimate the error model parameters $\theta_E$ and the hydrological model parameters $\theta_H$ . Using a similar derivation as given by Li et al. (2013), the likelihood functions can be written as

(a) for AR-Norm

143 $$L(\theta_E,\theta_H)=\prod_t P(Q_t\mid\tilde{Q}_t,\tilde{Q}_{t-1};\theta_E,\theta_H)=\prod_t J_{Z_t\to Q_t}\phi\left(Z_t\mid\tilde{Z}_t+\rho\left(Z_{t-1}-\tilde{Z}_{t-1}\right),\sigma^2\right), \quad (9)$$

144 (b) for AR-Raw

145 $$L(\theta_E,\theta_H)=\prod_t P(Q_t\mid\tilde{Q}_t,\tilde{Q}_{t-1};\theta_E,\theta_H)=\prod_t J_{Z_t\to Q_t}\phi\left(Z_t\mid f\left\{\tilde{Q}_t+\rho\left(Q_{t-1}-\tilde{Q}_{t-1}\right)\right\},\sigma^2\right) \quad ,$$

146 (10)

147 (c) for RAR-Norm

148 $$L(\theta_E,\theta_H)=\prod_t P(Q_t\mid\tilde{Q}_t,\tilde{Q}_{t-1};\theta_E,\theta_H)=\prod_{t:D_t\le\left|Q_{t-1}-\tilde{Q}_{t-1}\right|} J_{Z_t\to Q_t}\phi\left(Z_t\mid\tilde{Z}_t+\rho\left(Z_{t-1}-\tilde{Z}_{t-1}\right),\sigma^2\right)$$
$$+\prod_{t:D_t>\left|Q_{t-1}-\tilde{Q}_{t-1}\right|} J_{Z_t\to Q_t}\phi\left(Z_t\mid f\left\{\tilde{Q}_t+\rho\left(Q_{t-1}-\tilde{Q}_{t-1}\right)\right\},\sigma^2\right),$$

149 (11)

150 where $J_{Z_t\to Q_t}=\left\{\tanh(a+bQ_t)\right\}^{-1}$ is the Jacobian determinant of the log-sinh
151 transformation and $\phi\left(x\mid\mu,\sigma^2\right)$ is the probability density function of a Gaussian
152 random variable $x$ with mean $\mu$ and standard deviation $\sigma$. The probability density
153 function is replaced by the cumulative probability function when evaluating events of
154 zero flow occurrences (Wang and Robertson, 2011;Li et al., 2013). The Shuffled
155 Complex Evolution (SCE) algorithm (Duan et al., 1994) is used to minimize the
156 negative log likelihood.

157 ## 3. Data

158 We use daily data from four Australian catchments and three catchments from the
159 United States (US; Figure 1, Table 1). Australian streamflow data are taken from the
160 Catchment Water Yield Estimation Tool (CWYET) dataset (Vaze et al., 2011).
161 Australian rainfall and potential evaporation data are derived from the Australian
162 Water Availability Project (AWAP) dataset (Jones et al., 2009). All data for the US
163 catchments come from the Model Intercomparison Experiment (MOPEX) dataset
164 (Duan et al., 2006). The selected US catchments are amongst the 12 catchments used
165 by Evin et al. (2014) to compare joint and postprocessor approaches to estimate
166 hydrological uncertainty, and allows us to compare results with that study (the other
167 catchments used by Evin et al. (2014) are influenced by snowmelt, which is not
168 considered in the hydrological model used in this study). The Abercrombie River and

the Guadalupe River intermittently experience periods of very low (to zero) flow, while the other rivers flow perennially (Table 1). Such dry catchments are challenging for hydrological simulations and error modelling. All catchments have high-quality streamflow records with very few missing data.

We forecast daily streamflow with the GR4J rainfall-runoff model (Perrin et al., 2003) . We apply updating procedures to correct these forecasts. All results presented in this paper are based on this cross-validation instead of calibration in order to ensure the results can be generalised to independent data. We use different cross-validation schemes for the Australian and US catchments, because of the shorter streamflow records available for the Australian catchments:

i. For the Australian catchments we use data from 1992 to 2005 (14 years) for these catchments. We then generate 14-fold cross-validated streamflow forecasts. The data from 1990-1991 are only used to warm up the GR4J model. For a given year, we leave out the data from that year and the following year when estimating the parameters of GR4J and error models. For example, if we wish to forecast streamflows at any point in 1999, we leave out data from 1999 and 2000 when we estimate parameters. The removal of data from the following year (2000) is designed to minimise the impact of hydrological memory on model parameter estimation. We then generate streamflow forecasts in that year (1999) with model parameters estimated from the remaining data.

ii. For the US catchments we follow the split-sampling validation scheme suggested by Evin et al. (2014) to make our results comparable to that study: (1) an 8-year calibration (09/09/1973- 26/11/1981) (i.e. 3000 days) with an 8-year warm-up period and (2) a 17-year validation (27/11/1981-01/05/1998) (i.e. 6000 days) with an 8-year warm-up period.

To demonstrate the problems of over-correction of errors in updating and poor stand-alone performance of the base hydrological model, we consider only streamflow forecasts for one time step ahead. We will consider longer lead times in future work. Forecasts are generated using observed rainfall (i.e., a ‘perfect’ rainfall forecast) as input. In streamflow forecasting, forecasts may be generated from rainfall information that comes from a different source (e.g., a numerical weather prediction model). Our study is aimed at streamflow forecasting applications, so we preserve the distinction

between observed and forecast forcings by referring to streamflows modelled with observed rainfall as *simulations* and those modelled with forecast rainfall as *forecasts*. As the forecast rainfall we use is observed rainfall, the terms *forecast* and *simulation* are interchangeable.

## 4. Results

### 4.1 Over-correction of forecasts as the hydrograph rises

The first adverse effect of the conventional AR models is over-correction of errors in updating as streamflows are rising. By over-correction, we mean that the AR model updates the hydrological model simulations too much. Over-correction is difficult to define precisely, however we will demonstrate the concept with two examples in the Mitta Mitta catchment: the first example illustrates over-correction by the AR-Norm model, and the second example illustrates over-correction by the AR-Raw model.

To illustrate the problem of over-correction caused by the AR-Norm model, Figure 2 presents a 1-week time series for the Mitta Mitta catchment, showing streamflow forecasts with GR4J before error updating (referred to as streamflows forecast with the *base hydrological model*) and after error updating. Figure 2 shows that the base hydrological models consistently under-estimate the streamflow from 23/09/2000 to 25/09/2000, and the corresponding updating procedures successfully identify the need to compensate for this under-estimation. For the AR-Norm model, however, the correction amount for 26/09/2000 is unreasonably large. Because the forecast streamflow on 26/09/2000 is much higher than that of the previous day, the correction is greatly amplified by the back-transformation, leading to the over-correction. In contrast, the AR-Raw model works better in this situation because the magnitude of the error update never exceeds the simulation error on the previous day regardless of whether the forecast streamflow is high or low. The RAR-Norm model behaves similarly to the AR-Raw model for correcting the peak on 26/09/2000 and avoids the over-correction made by the AR-Norm model.

Figure 3 shows instances of possible over-correction by the AR-Norm model, identified by the condition $D_t > \left|Q_{t-1} - \tilde{Q}_{t-1}\right|$. Figure 3 shows that about 10-25% of the AR-Norm updated forecasts have an error update that is larger than the forecast error on the previous day and therefore are susceptible to over-correction. The frequency of these instances varies somewhat from catchment to catchment. The RAR-Norm model

identifies 10-30% of the forecasts as possible instances of problematic updating, and the AR-Norm model identifies a similar number of instances (slightly fewer – they are not identical because the parameters for each model are inferred independently).

Figure 4 presents a time-series for the Orara catchment that shows the instances susceptible to over-correction for the AR-Norm model. These instances all occur when the streamflow rises. The RAR-Norm model effectively rectifies the problem of over-correction caused by the AR-Norm model. We note that there is nothing that forces the instances susceptible to over-correction identified by the AR-Norm model to be the same as those identified by the RAR-Norm models because the two models are calibrated independently (and therefore base hydrological model simulations may be different). However, the restriction defined in the RAR-Norm model is largely applied to the instances where the AR-Norm model is susceptible to over-correction.

## 4.2 Over-correction of forecasts as the hydrograph recedes

The second adverse effect of conventional AR models is over-correction of forecasts as streamflows reced. Anexample is presented in Figure 5 where the AR-Raw model causes over-correction. Here, the base hydrological model over-estimates the receding hydrograph on 05/10/1993. The magnitude of the error update given by the AR-Raw model cannot adjust according to the value of the forecast. As a result, the AR-Raw model updates the forecast on 06/10/1993 by a large amount, resulting in serious under-estimation (the forecast is for near zero streamflow), and an artificial distortion of the hydrograph. (We note that we have seen this problem become much worse in unpublished experiments of forecasts made for several time-steps into the future, sometimes resulting in forecasts of zero flows during large floods.) In contrast, the AR-Norm model performs better in this example, giving a smaller magnitude of error update by recognising that the hydrograph is moving downward. It is generally true that in applying the AR-Raw model, over-correction may occur when the streamflow is receding. The RAR-Norm model produces updated streamflow similar to the AR-Norm model when the hydrograph recedes rapidly and avoids the over-correction by the AR-Raw model on 06/10/1993.

Figure 6 provides more examples of the over-correction caused by the AR-Raw model from a longer time-series plot for the Abercrombie catchment. There are three clear instances of over-correction, all occurring on the time step immediately after large

peaks in observed streamflows. The RAR-Norm works better than the AR-Raw model to avoid the three instances of over-correction for the Abercrombie catchment. Overall, the RAR-Norm model takes a conservative position when streamflow changes rapidly, either rising or falling. When streamflow changes rapidly, it is difficult to anticipate the magnitude of forecast error. Accordingly the conventional AR models are prone to over-correction in such instances.

### 4.3 Poor stand-alone performance of the base hydrological model

The third adverse effect with conventional AR error models is the stand-alone performance of the base hydrological model (GR4J). As noted above, the parameters of the base hydrological model are estimated jointly with each error model. For streamflow forecasting, we expect to obtain a reasonably accurate forecast from the base hydrological model followed by an updating procedure as an auxiliary means to improve the forecast accuracy. At lead times of many time-steps (e.g., streamflow forecasts generated from medium-range rainfall forecasts) the magnitude of AR error updates becomes rapidly smaller (tending to zero), and thus the performance of the base hydrological model is crucial for realistic forecasts at longer lead times. While we investigate only forecasts at a lead time of one time step in this study, we aim to develop methods that can be applied to forecasts at longer lead times. Further, if the base hydrological model does not replicate important catchment processes realistically, the performance of the hydrological model outside the calibration period may be less robust.

Figure 7 presents the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) calculated from the base hydrological model and the error models. When the AR-Norm model is used, the forecasts from the base hydrological model are very poor for the Orara catchment (NSE<0). The scatter plot in Figure 8 shows a serious over-estimation of the streamflow simulation for the Orara. When the AR-Norm model is used, the base hydrological model greatly over-estimates discharge and the AR-Norm model then attempts to correct this systematic over-estimation. This is also shown in Figure 4 where the base hydrological model has a strong tendency to over-estimate streamflows for a range of streamflow magnitudes. The base hydrological model with the AR-Norm model also performs poorly for the Abercrombie catchment (Figure 7). In this case, the base hydrological model tends to under-estimate streamflows (results

not shown). For the other three catchments, however, the base hydrological model with the AR-Norm model performs reasonably well.

In general, the AR-Raw base hydrological model performs as well or better than the AR-Norm base hydrological model. The AR-Raw base hydrological model is notably better than the AR-Norm base hydrological model in the Abercrombie and Orara catchments (Figure 7). This suggests that more robust performance can be expected of base hydrological models when AR models are applied to raw errors.

The RAR-Norm model generally improves the performance of the AR-Norm base hydrological model to a similar performance level of the AR-Raw base hydrological model (Figure 7). The improvement over the AR-Norm base hydrological model is especially evident for the Orara (Figures 4 and 7) and Abercrombie catchments (Figures 7).

We note that for the AR-Norm models, the updated forecasts are not always better than forecasts generated by the base hydrological models. For the Tarwin and Guadalupe catchments, AR-Norm forecasts are not as good as the forecasts generated by the AR-Norm base hydrological model. This points to a tendency to overfit the parameters to the calibration period, resulting in the error model undermining the performance of the base hydrological model under cross-validation. Such a lack of robustness is highly undesirable in forecasting applications, where the hydrological models should be able to operate in conditions that differ from those experienced during calibration. Note that this problem also occurs in the RAR-Norm model (Guadalupe) and in the AR-Raw model (Abercrombie, Guadalupe) but to a much smaller degree.

In general, the updated forecasts from the RAR-Norm model show similar or better forecast accuracy, as measured by NSE, than both the AR-Raw model and the AR-Norm model (Figure 7). We note that the Orara catchment is an exception: here the AR-Raw model shows slightly better performance than RAR-Norm model. Conversely, the RAR-Norm model shows notably better performance than both the AR-Norm and AR-Raw models in the Abercrombie and Guadalupe catchments. This suggests the RAR-Norm model may work better in intermittently flowing catchments, although further testing is required to establish that this is true for a greater range of catchments.

## 4.4 Further analyses

We further evaluate the NSE of the three different error models calibrated when streamflows are receding (i.e. $\tilde{Q}_t \le \tilde{Q}_{t-1}$) and rising (i.e. $\tilde{Q}_t > \tilde{Q}_{t-1}$) (Table 2). For the receding streamflows (constituting 70-85% of streamflows), the AR-Raw model leads to the overall worst forecast accuracy because of the over-correction explained in Section 4.1. This is especially evident for the Abercrombie catchment (and, to a lesser degree, the Guadalupe catchment). The RAR-Norm model significantly outperforms the other two models for the Abercrombie catchment and shares similar forecast accuracy to the (strongly performing) AR-Norm model for the other catchments. When streamflows are rising (which also includes streamflow peaks), the AR-Norm model can cause over-correction and leads to the least accurate forecasts (in terms of NSE), and the RAR-Norm model behaves similarly to the AR-Raw model, which consistently provides the most accurate forecasts. (The only exception is the Guadalupe River, where the AR-Raw model clearly outperforms the RAR-Norm model when streamflows are rising. This is somewhat compensated for by the markedly better performance the RAR-Norm model offers over the AR-Raw model when streamflows are receding for this catchment, leading to better forecasts overall (Figure 7).) We conclude that the AR-Norm model generally tends to perform least well when streamflows recede, and that the AR-Raw model tends to perform least well when streamflows rise. We also conclude that the RAR-Norm model tends to combine the best elements of the AR-Norm and AR-Raw models, leading to the best overall performance.

We have shown that over-corrections can lead to inaccurate deterministic forecasts, and we now discuss the consequences for the probabilistic predictions given by each of the error models. We assess probabilistic forecast skill with skill scores derived from two probabilistic verification measures: the Continuous Rank Probability Score (CRPS) and the Root Mean Square Error in Probability (RMSEP) (denoted by CRPS_SS and RMSEP_SS, respectively) (Wang and Robertson, 2011). Both skill scores are calculated with respect to a reference forecast. The reference forecast is generated by resampling historical streamflows: for a forecast issued for a given month/year (e.g. February 1999), we randomly draw a sample of 1000 daily streamflows that occurred in that month (e.g. February) from other years with replacement (e.g. years other than 1999). Table 3 compares these two skill scores

363 calculated for the all catchments. The RAR-Norm model performs best across the
364 range of skill scores and catchments, attaining the highest CRPS_SS in 4 of the 7
365 catchments and the highest RMSEP_SS in 4 of 7 catchments. Even where RAR-Norm
366 was not the best performed model, it performs very similarly to the best performing
367 model in all cases. Interestingly, the AR-Raw model tends to outperform the AR-
368 Norm model in CRPS_SS while the reverse is true for RMSEP_SS. The CRPS tests
369 how appropriate the spread of uncertainty is for each probabilistic forecast, while
370 RMSEP puts little weight on this. The results suggest that while the median forecasts
371 of AR-Norm tends to be slightly more accurate than those of the AR-Raw model, the
372 forecast uncertainty is represented slightly better by the AR-Raw model.

373 To better understand how reliably the forecast uncertainty is quantified by each model,
374 we produce Probability Integral Transform (PIT) uniform probability plots (Wang and
375 Robertson, 2011) in Figure 9. There are two main points to draw from these plots.
376 First, the curves are very similar for all error models (a partial exception is the San
377 Marcos catchment, where the AR-Raw model is slightly closer to the one-to-one line
378 than the other models). This demonstrates that in general the models produce similarly
379 reliable uncertainty distributions. Second, all models show an inverted S-shaped curve,
380 which is characteristic of the forecasts with uncertainty ranges that are too wide. This
381 underconfidence is a result of using a Gaussian distribution to characterise the error.
382 The Gaussian distribution is not flexible enough to represent the high degree of
383 kurtosis in the distribution of the residuals after error updating (partly because the
384 errors become very small after updating). We are presently experimenting with other
385 distributions in order to address this issue, and will seek to publish this work in future.
386 For the purposes of the present study, we conclude that the three error models are
387 similarly reliable.

## 388 5. Discussion and conclusions

389 For streamflow forecasting, rainfall-runoff models are often augmented with an
390 updating procedure that corrects the forecast using information from recent simulation
391 errors. The most popular updating approach uses autoregressive (AR) models that
392 exploit the “memory” in model errors. AR models may be applied to raw errors
393 directly or to normalised errors.

We demonstrate three adverse effects of AR error updating procedures on seven catchments. The first adverse effect is possible over-correction on the rising limb of the hydrograph. The AR-Norm model can exhibit the tendency to over-correct the peaks or on the rise of a hydrograph, because error updating can be (overly) amplified by the back-transformation. The second adverse effect is the tendency to over-correct receding hydrographs. This tendency is most prevalent in the AR-Raw model, which can fail to recognise that a large error update may not be appropriate for small streamflows.

The third adverse effect is that the stand-alone performance of base hydrological models can be poor when the parameters of rainfall-runoff and error models are jointly estimated with the AR parameters. We show that poor base hydrological model performance is particularly prevalent in the AR-Norm model. The poor performance appears to occur in catchments with highly skewed streamflow observations (the intermittent Abercrombie River, and the Orara River, a catchment in a subtropical climate). For example, in the Orara River, the base hydrological model tends to greatly over-estimate streamflows, and then relies on the error updating to correct the over-estimates. This is not desirable in real-time forecasting applications for two major reasons. First, modern streamflow forecasting systems often extend forecast lead-times with rainfall forecast information (Bennett et al., 2014). The magnitude of AR updating decays with lead times, and forecasts at longer lead times rely heavily on the performance of the base hydrological model. Second, hydrological models are designed to simulate various components of natural systems, such as baseflow processes or overland flow. In theory, simulating these processes correctly will allow the model to perform well for climate conditions that may substantially differ from those experienced during the parameter estimation period. If the hydrological model parameters do not reflect the natural processes for a given catchment, the hydrological model may be much less robust outside the parameter estimation period.

We note that the poor performance of the hydrological model may be specific to the GR4J model, and many not occur in other hydrological models. Evin et al. (2014) estimated hydrological model and error model parameters jointly using GR4J and another hydrological model, HBV, for the three US catchments tested here. While they did not assess the performance of the base hydrological models, they found that HBV tended to perform more robustly when combined with different error models. It

427 is possible that we may have achieved more stable base model performance had we
428 used HBV or another hydrological model. We note, however, that our conclusions can
429 probably be generalised to other hydrological models that do not offer robust base
430 model performance under joint parameter estimation (e.g. GR4J). Because the RAR-
431 Norm model essentially limits the range of updating that can be applied through the
432 AR-Norm model, it will tend to rely more heavily on the base hydrological model,
433 and therefore will tend to favour parameter sets that encourage good stand-alone
434 performance of the base model. For those hydrological models that already produce
435 robust base model performance under joint parameter estimation (perhaps HBV),
436 RAR-Norm is unlikely to undermine this performance for the same reasons. We see
437 some evidence of this in our experiments with GR4J: when the performance of the
438 base hydrological model is already strong relative to the updated forecasts for the AR-
439 Norm and AR-Raw models (e.g. the Tarwin, Mitta Mitta, or Guadalupe catchments),
440 the RAR-Norm model base hydrological model also performs strongly.

441 The tendency of the AR-Norm model to over-correct rising streamflows is probably
442 generic. In particular, transformations other than the log-sinh transformation may still
443 lead to over-correction at the peak of hydrograph. The proof in Appendix A shows
444 that if a transformation satisfies some conditions (first derivate is positive and second
445 derivate is negative), it will tend to correct more for higher forecast streamflows and
446 can cause the problem of over-correction. The conditions given by Appendix A are
447 generally true for many other transformations used for data normalisation and
448 variance stabilisation in hydrological applications, such as logarithm transformation
449 and Box-Cox transformation with the power parameter less than 1.

450 We use joint parameter inference to calibrate hydrological model and error model
451 parameters, in order to address the true nature of underlying model errors. Inferring
452 parameters of the error model and the base hydrological model independently – i.e.,
453 first inferring parameters of the base hydrological model, holding these constant and
454 then inferring the error model parameters - relies on simplified and often invalid error
455 assumptions (it assumes independent, homoscedastic and Gaussian errors), but
456 nonetheless could be a pragmatic alternative to the joint parameter inference to reduce
457 computational demands. The over-correction of conventional AR models is
458 independent of the parameter inference, whether the error and base hydrological
459 model parameters are inferred jointly or independently.

In order to mitigate the adverse effects of conventional AR updating procedures, we introduce a new updating procedure called the RAR-Norm model. The RAR-Norm model is a modification of the AR-Norm: in most instances it operates as the AR-Norm model, but in instances of possible over-correction it relies on the error in untransformed streamflows at the previous time step. That is, RAR-Norm is essentially a more conservative error model than AR-Norm: in situations where streamflows change rapidly, it opts to update with whichever error (transformed or untransformed) is smaller. This forces greater reliance on the base hydrological model to simulate streamflows accurately, leading to more robust performance in the base hydrological model. The RAR-Norm model clearly outperforms the AR-Norm model in both the updated and base model forecasts, as well as ameliorating the problem of over-correcting rising streamflows. The RAR-Norm model's advantage over the AR-Raw model is less clear: both the base hydrological model and the updated forecasts produced by the AR-Raw model perform similarly to (or sometimes slightly better than) the RAR-Norm model. However, the RAR-Norm model clearly addresses the problem of over-correcting receding streamflows that occurs in the AR-Raw model. As we show, this type of over-correction can seriously distort event hydrographs, and cause forecasts of near zero streamflows when reasonably substantial streamflows are observed. While these instances are not very common, the failure in the forecast is a serious one. As we note earlier, the over-correction of receding streamflows is likely to be exacerbated when producing forecasts at lead times of more than one time step. Accordingly, we contend that the RAR-Norm model is preferable to both AR-Norm and AR-Raw models for streamflow forecasting applications.

## Appendix A

For simplicity we only show the case of the AR-Norm model and analogues arguments can be used to prove the cases of the AR-Raw and RAR-Norm models. The streamflow ensemble forecast $Q_t$ given by the AR-Norm model defined by (1) can be written as

$$Q_t = \max\left[ f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t\right\}, 0\right]. \quad \text{(A1)}$$

where negative values after the back-transformation are assigned zero values. Because we assume that $\varepsilon_t$ is a standard normal random variable, In order to show $\tilde{Q}_t^*$ is the median of $Q_t$, we just need to show $P\left(Q_t \le \tilde{Q}_t^*\right) = 0.5$, which can be proved as follows:

$$\begin{aligned} P\left(Q_t \le \tilde{Q}_t^*\right) &= P\left(\max\left[ f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t\right\}, 0\right] \le \tilde{Q}_t^*\right) \\ &= P\left( f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t\right\} \le \tilde{Q}_t^* \text{ and } 0 \le \tilde{Q}_t^*\right) \end{aligned} \tag{A2}$$

Because $\tilde{Q}_t^*$ always has a non-negative value, we have

$$\begin{aligned} P\left(Q_t \le \tilde{Q}_t^*\right) &= P\left( f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right) + \varepsilon_t\right\} \le f^{-1}\left\{\tilde{Z}_t + \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right)\right\} \right). \\ &= P\left(\varepsilon_t \le 0\right) = 0.5 \end{aligned} \tag{A3}$$

## Appendix B

We will analytically show that the AR-Norm model gives a larger magnitude of the error update for a higher forecast streamflow.

Firstly, we will show that the first derivate of the log-sinh transform $f$ defined by (3) is positive and the second derivate is negative (i.e. $f'(x) > 0$ and $f''(x) < 0$) for any $b > 0$ and any $x$. Following some simple manipulation, we have

$$f'(x) = \frac{\cosh(a+bx)}{\sinh(a+bx)} > 0 \qquad \text{and} \qquad f''(x) = \frac{-b}{\sinh^2(a+bx)} < 0 \tag{B1}$$

Using the differentiation of inverse functions, we find the first and second derivates of the inverse transform $f^{-1}$

$$\left[ f^{-1}\right]'(x) = \frac{1}{f'\left\{ f^{-1}(x)\right\}} > 0 \quad \text{and} \qquad \left[ f^{-1}\right]''(x) = \frac{-f''\left\{ f^{-1}(x)\right\}}{\left[ f'\left\{ f^{-1}(x)\right\}\right]^3} > 0, \tag{B2}$$

for any $b > 0$ and any $x$.

Next, we will derive the difference of magnitudes of the error update between low and high forecast streamflows. For the sake of notation simplicity, we rewrite $q = \tilde{Z}_t$ and $u = \rho\left(Z_{t-1} - \tilde{Z}_{t-1}\right)$ and assume that $u > 0$. Using Equation (4), the updated streamflow can be written as $\tilde{Q}_t^* = f^{-1}(q+u)$. The magnitude of the error update can be written as

$$\left|\tilde{Q}_t^* - \tilde{Q}_t\right| = \left| f^{-1}(q+u) - f^{-1}(q)\right| = \begin{cases} \int_0^u \left[ f^{-1}\right]'(x+q)dx & \text{if} \quad u>0 \\ \int_u^0 \left[ f^{-1}\right]'(x+q)dx & \text{otherwise.} \end{cases} \tag{B3}$$

Suppose that we have two forecast streamflows $\tilde{Q}_{t,1} \le \tilde{Q}_{t,2}$ and denote the normalised forecast streamflow by $q_1 = \tilde{Z}_{t,1}$ and $q_2 = \tilde{Z}_{t,2}$ and the updated streamflow by $\tilde{Q}_{t,1}^*$ and $\tilde{Q}_{t,2}^*$. Because $f$ is an increasing function, we have $q_1 \le q_2$. The difference in the magnitude of the error update between $\tilde{Q}_{t,1}$ and $\tilde{Q}_{t,2}$ can be derived as

$$\left|\tilde{Q}_{t,1} - \tilde{Q}_{t,1}^*\right| - \left|\tilde{Q}_{t,2} - \tilde{Q}_{t,2}^*\right| = \begin{cases} \int_0^u \left\{ \left[ f^{-1}\right]'(x+q_1) - \left[ f^{-1}\right]'(x+q_2) \right\} dx & \text{if} \quad u>0 \\ \int_u^0 \left\{ \left[ f^{-1}\right]'(x+q_1) - \left[ f^{-1}\right]'(x+q_2) \right\} dx & \text{otherwise.} \end{cases} \tag{B4}$$

From (A2), we have shown that $\left[ f^{-1}\right]'$ is a positive increasing function and this ensures that $\left[ f^{-1}\right]'(x+q_1) - \left[ f^{-1}\right]'(x+q_2) \le 0$. Finally we have

$$\left|\tilde{Q}_{t,1} - \tilde{Q}_{t,1}^*\right| \le \left|\tilde{Q}_{t,2} - \tilde{Q}_{t,2}^*\right|. \tag{B5}$$

Therefore, the error update at larger forecast streamflows is always larger than error update at lower forecast streamflows.

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Figure 7: NSE of streamflows forecast with the AR-Norm, AR-Raw and RAR-Norm models (colours). Performance of the corresponding base hydrological models is shown by hatched blocks.

Figure 8: Comparison of the observed streamflows ($Q_t$) and forecast streamflows ($\tilde{Q}_t$), as forecast: 1) with the base hydrological model (circles), and 2) with the base hydrological model and error updating models (dots) for the Orara catchment.

Figure 9: PIT-uniform probability plots. Curves on the diagonal indicate perfectly reliable forecasts.

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656

657 Table 1: Catchment characteristics.

| Name | Country | Gauge Site | Area ($km^2$) | Rainfall (mm/yr) | Streamflow (mm/yr) | Runoff coefficient | Zero flows |
|---|---|---|---|---|---|---|---|
| Abercrombie | Aus | Abercrombie River at Hadley no. 2 | 1447 | 783 | 63 | 0.08 | 14.4% |
| Mitta Mitta | Aus | Mitta Mitta River at Hinnomunjie | 1527 | 1283 | 261 | 0.20 | 0 |
| Orara | Aus | Orara River at Bawden Bridge | 1868 | 1176 | 243 | 0.21 | 0.6% |
| Tarwin | Aus | Tarwin River at Meeniyan | 1066 | 1042 | 202 | 0.19 | 0 |
| Amite | US | 07378500 | 3315 | 1575 | 554 | 0.35 | 0 |
| Guadalupe | US | 08167500 | 3406 | 772 | 104 | 0.13 | 1.7% |
| San Marcos | US | 08172000 | 2170 | 844 | 165 | 0.20 | 0% |

658

659

660 Table 2: Comparison of the NSE calculated at (a) the receding limb and (b) the rising
661 limb of the hydrograph for three different error models.
662

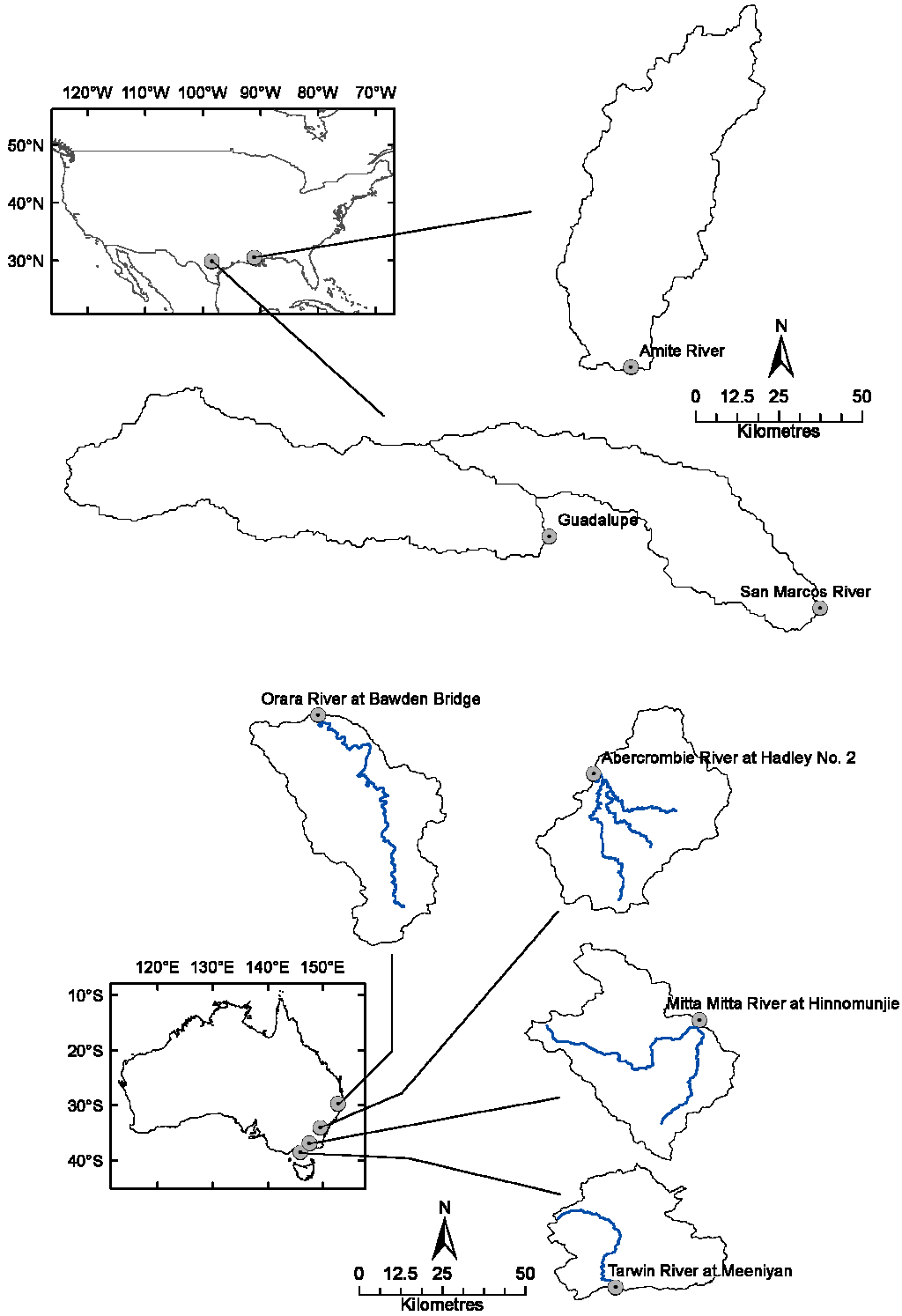
| | (a) $\tilde{Q}_t \leq \tilde{Q}_{t-1}$ | | | | (b) $\tilde{Q}_t > \tilde{Q}_{t-1}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Proportion of flows | AR-Norm | AR-Raw | RAR-Norm | Proportion of flows | AR-Norm | AR-Raw | RAR-Norm |
| Abercrombie | 82% | 0.11 | -0.41 | 0.52 | 19% | 0.58 | 0.66 | 0.65 |
| Mitta Mitta | 82% | 0.95 | 0.91 | 0.95 | 18% | 0.81 | 0.86 | 0.86 |
| Orara | 85% | 0.94 | 0.91 | 0.95 | 15% | 0.86 | 0.86 | 0.83 |
| Tarwin | 71% | 0.90 | 0.91 | 0.90 | 29% | 0.18 | 0.77 | 0.76 |
| Amite | 69% | 0.76 | 0.82 | 0.84 | 31% | 0.82 | 0.82 | 0.85 |
| Guadalupe | 83% | 0.75 | 0.35 | 0.77 | 15% | 0.24 | 0.55 | 0.45 |
| San Marcos | 82% | 0.80 | 0.66 | 0.80 | 17% | 0.63 | 0.64 | 0.64 |

663

664 Table 3: Comparison of the skill scores based on CRPS and RMSEP (denoted by
665 CRPS_SS and RMSEP_SS) for three different error models.
666

| | CRPS_SS (%) | | | RMSEP_SS (%) | | |
|---|---|---|---|---|---|---|
| | AR-Norm | AR-Raw | RAR-Norm | AR-Norm | AR-Raw | RAR-Norm |
| Abercrombie | 64.1 | 62.3 | 66.3 | 75.1 | 73.7 | 74.7 |
| Mitta Mitta | 80.3 | 79.7 | 80.7 | 84.1 | 83.2 | 84.0 |
| Orara | 74.0 | 75.7 | 75.5 | 81.7 | 80.7 | 81.4 |
| Tarwin | 74.9 | 79.3 | 78.8 | 86.1 | 85.1 | 86.1 |
| Amite | 67.5 | 68.3 | 69.5 | 71.0 | 70.9 | 71.2 |
| Guadalupe | 57.4 | 60.9 | 59.8 | 76.3 | 75.2 | 77.2 |
| San Marcos | 68.8 | 66.0 | 68.9 | 73.9 | 73.9 | 74.3 |

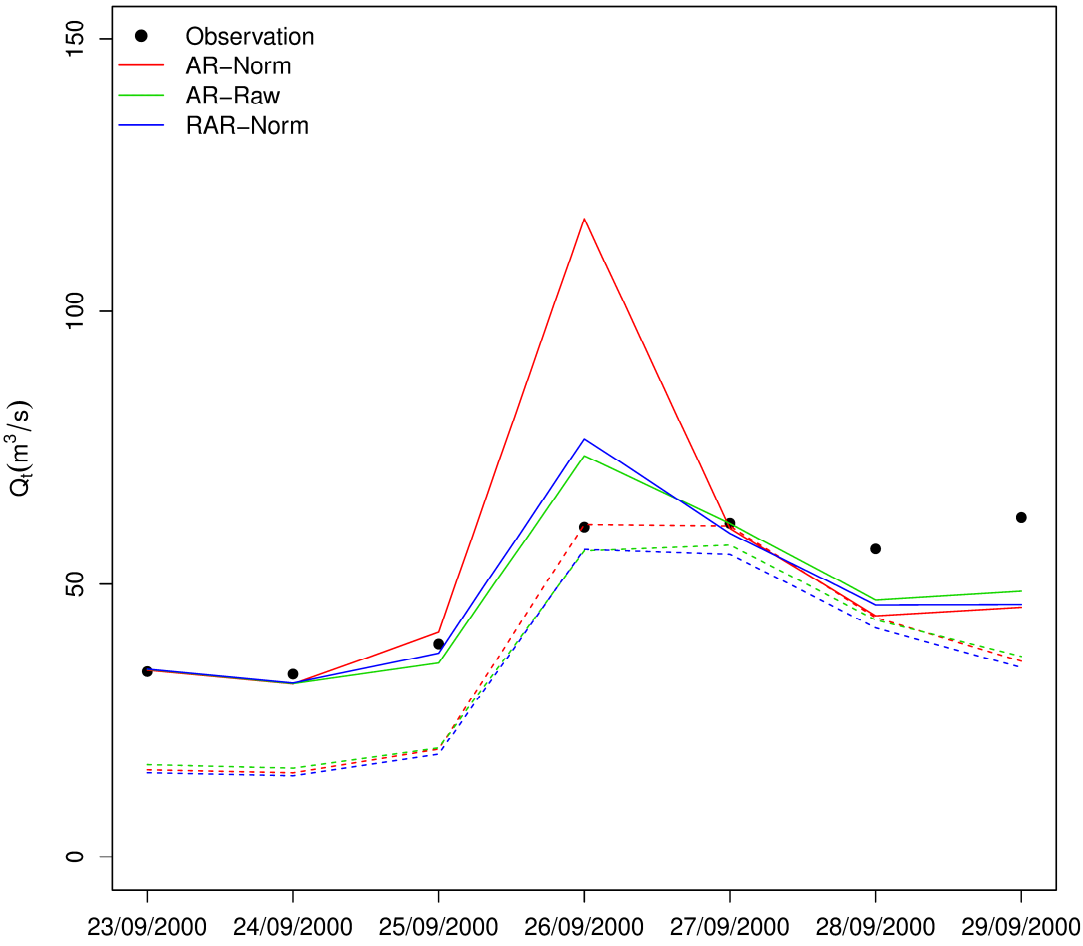
667




668

669 Figure 1: Map of US (top) and Australian (bottom) catchments.

670




671

672 Figure 2: An example of over-correction caused by the AR-Norm model in the Mitta
673 Mitta catchment. Dashed lines: forecasts from the base hydrological model (i.e.,
674 without error updating). Solid lines: forecasts with error updating.

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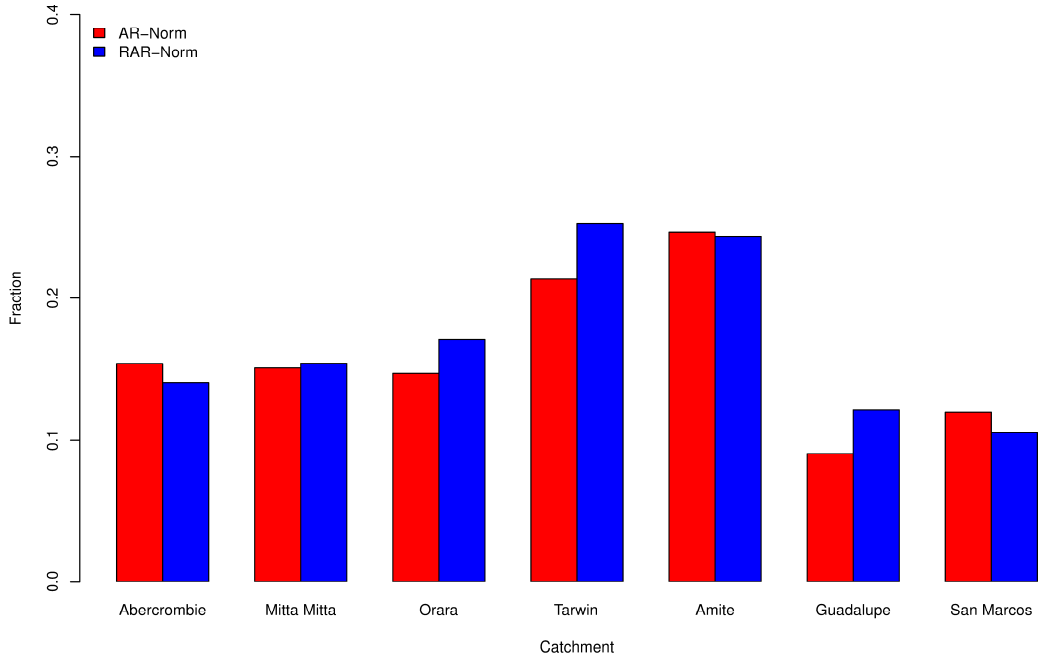
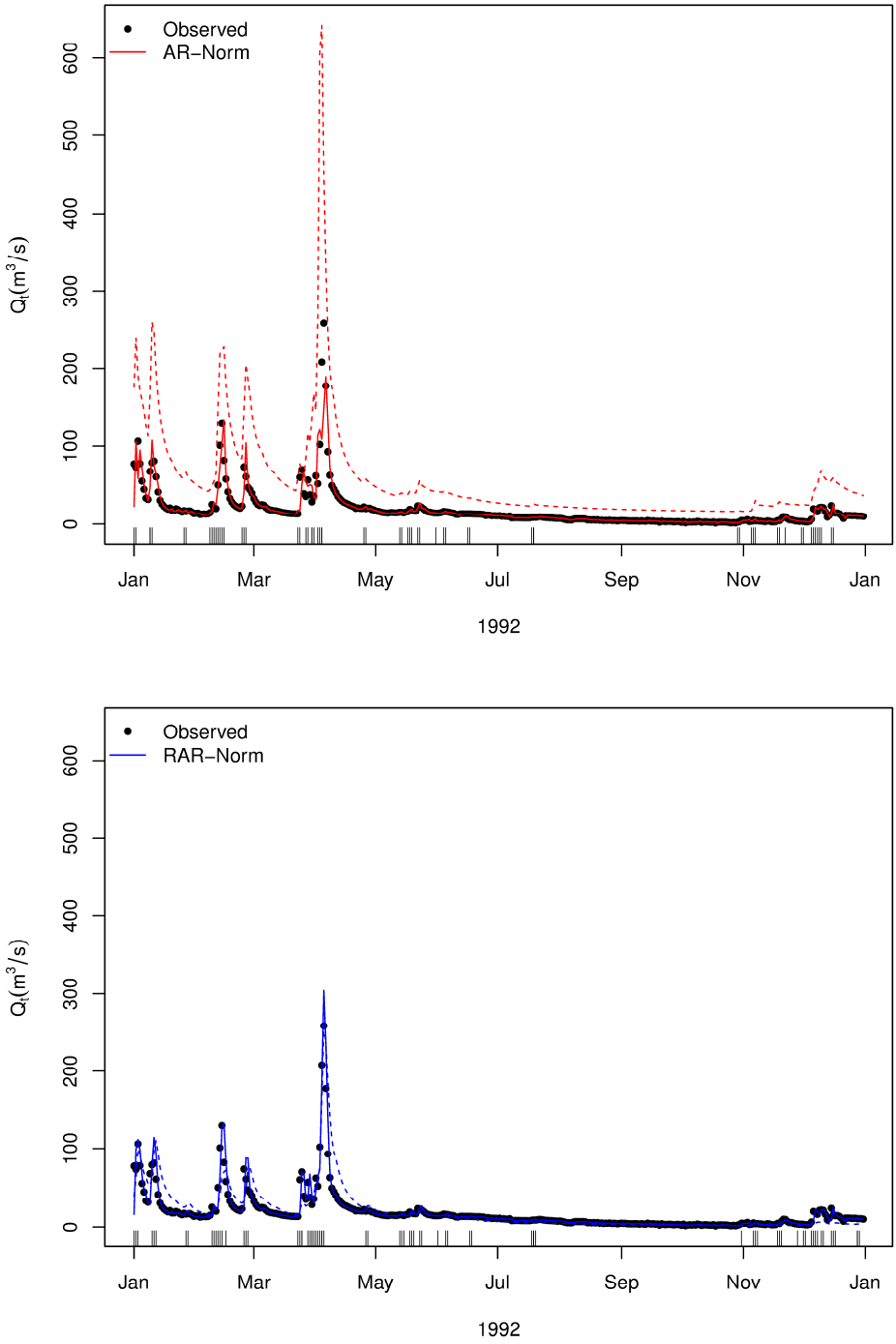



678

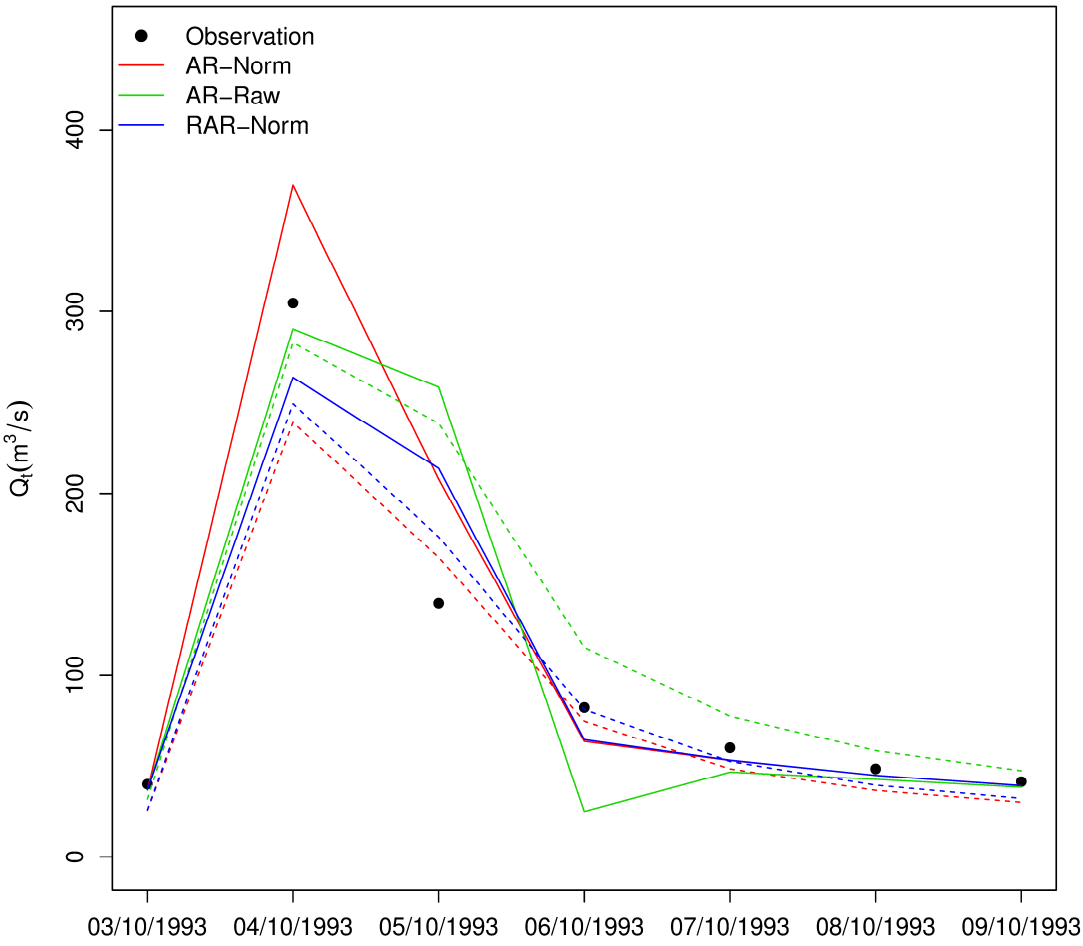
679 Figure 3: The fraction of instances where $D_t > \left|Q_{t-1} - \tilde{Q}_{t-1}\right|$ (i.e., instances where over-
680 correction may occur in the AR-Norm model and where error updating is restricted in
681 the RAR-Norm model) for the AR-Norm and RAR-Norm models for Australian
682 catchments.

683




684

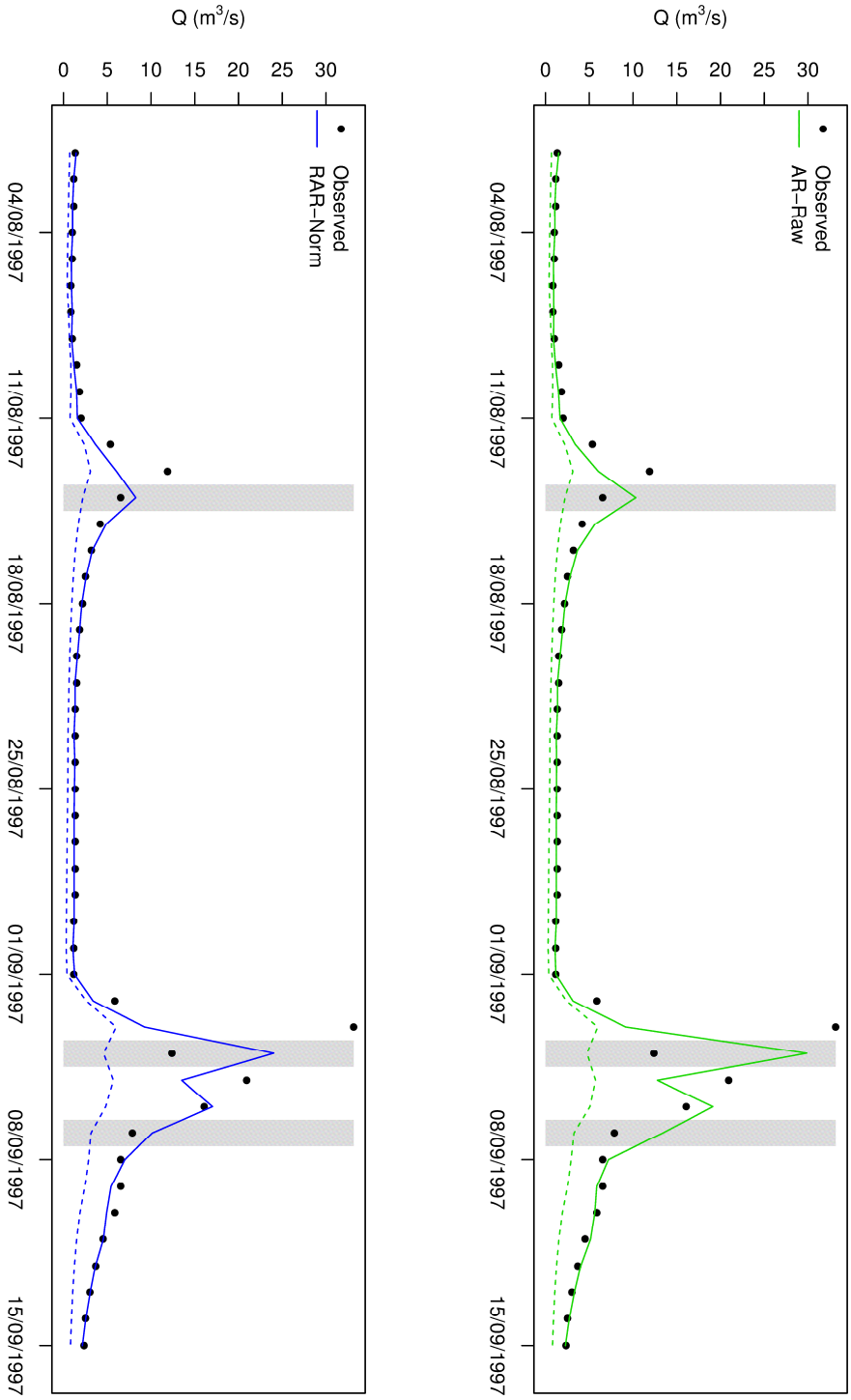
685 Figure 4: Forecast streamflows for the Orara catchment for an example 1-year period.
686 Top panel shows streamflows forecast with AR-Norm model, bottom panel shows
687 streamflows forecast with the RAR-Norm model. Dashed lines: forecasts from the
688 base hydrological model (i.e., without error updating). Solid lines: forecasts with error
689 updating. Tick marks in the x-axis denote the instance of updating where
690 $D_t > \left|Q_{t-1} - \tilde{Q}_{t-1}\right|$.




691

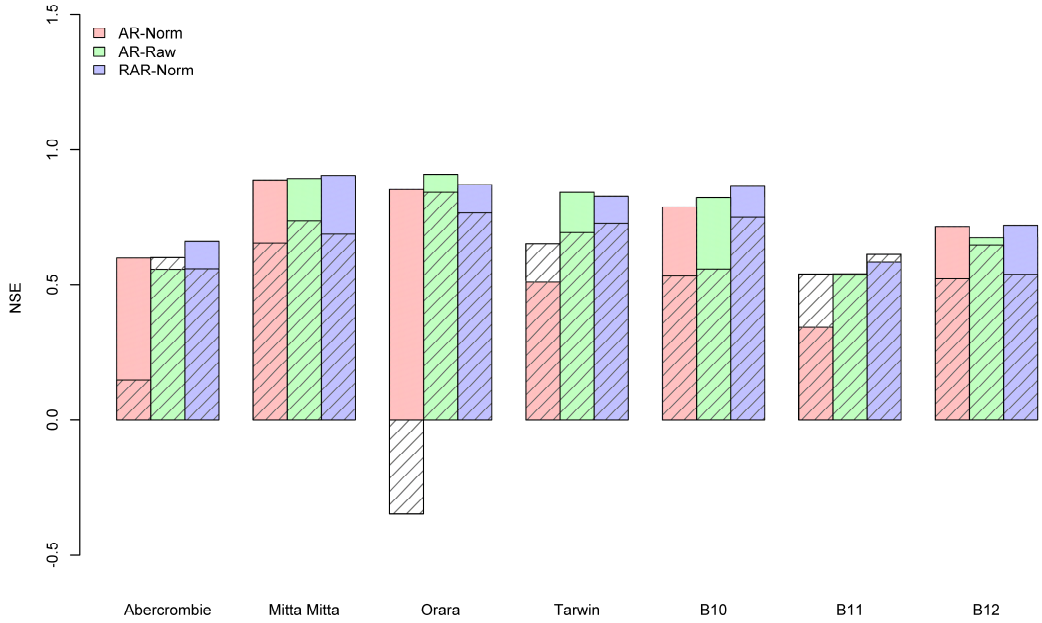
692 Figure 5: An example of over-correction caused by the AR-Raw model in the Mitta
693 Mitta catchment. Dashed lines: forecasts from the base hydrological model (i.e.,
694 without error updating). Solid lines: forecasts with error updating.

695




696

697 Figure 6: Forecast streamflows for the Abercrombie catchment for the period between
698 01/08/1997 and 15/09/1997. Top panel shows streamflows forecast with AR-Raw
699 model, bottom panel shows streamflows forecast with the RAR-Norm model. Dashed
700 lines: forecasts from the base hydrological model (i.e., without error updating). Solid
701 lines: forecasts with error updating. Gray shading denotes instances of over-correction
702 caused by the AR-Raw model.

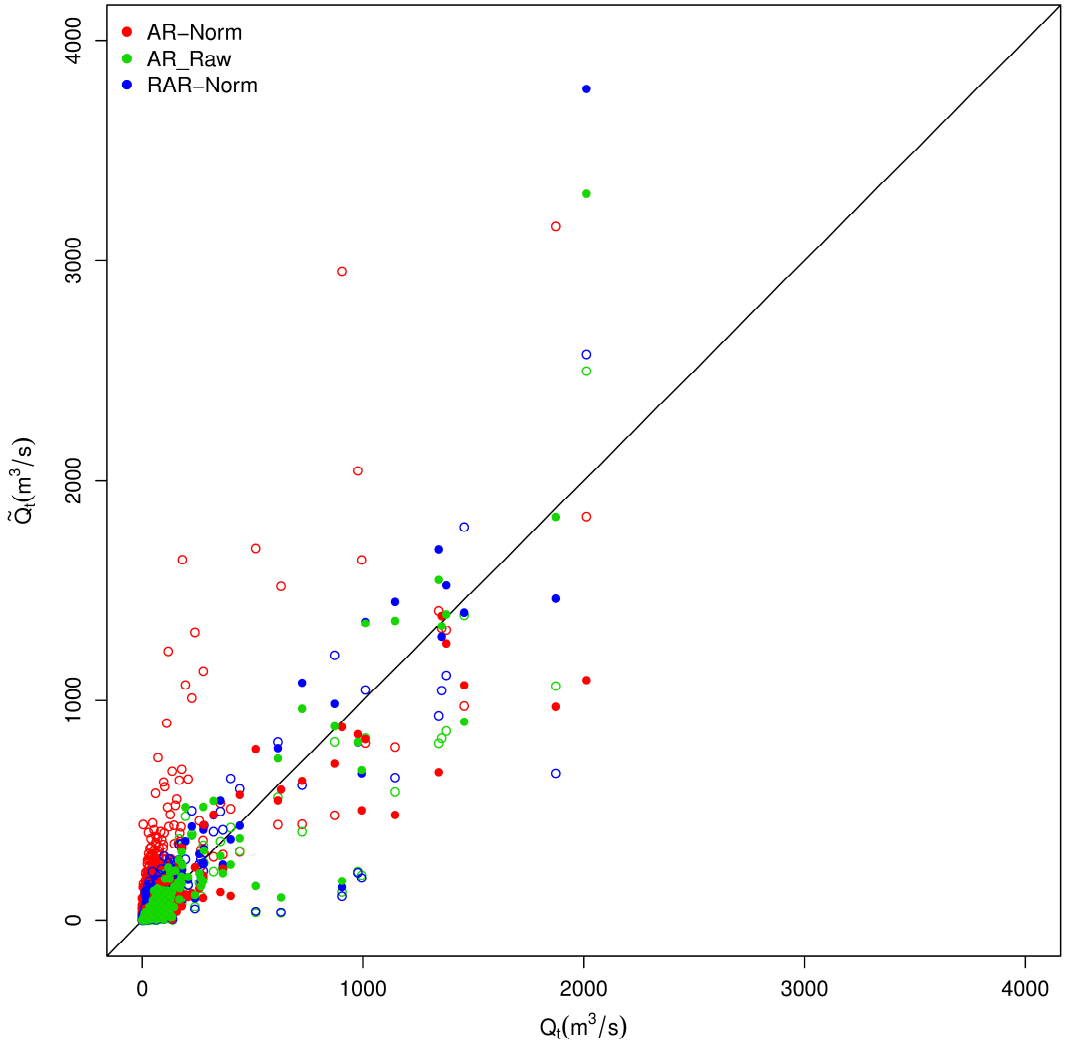



703

704 Figure 7: NSE of streamflows forecast with the AR-Norm, AR-Raw and RAR-Norm
705 models (colours). Performance of the corresponding base hydrological models is
706 shown by hatched blocks.

707

708




709

710 Figure 8: Comparison of the observed streamflows ($Q_t$) and forecast streamflows

711 ($\tilde{Q}_t$), as forecast: 1) with the base hydrological model (circles), and 2) with the base

712 hydrological model and error updating models (dots) for the Orara catchment.

713

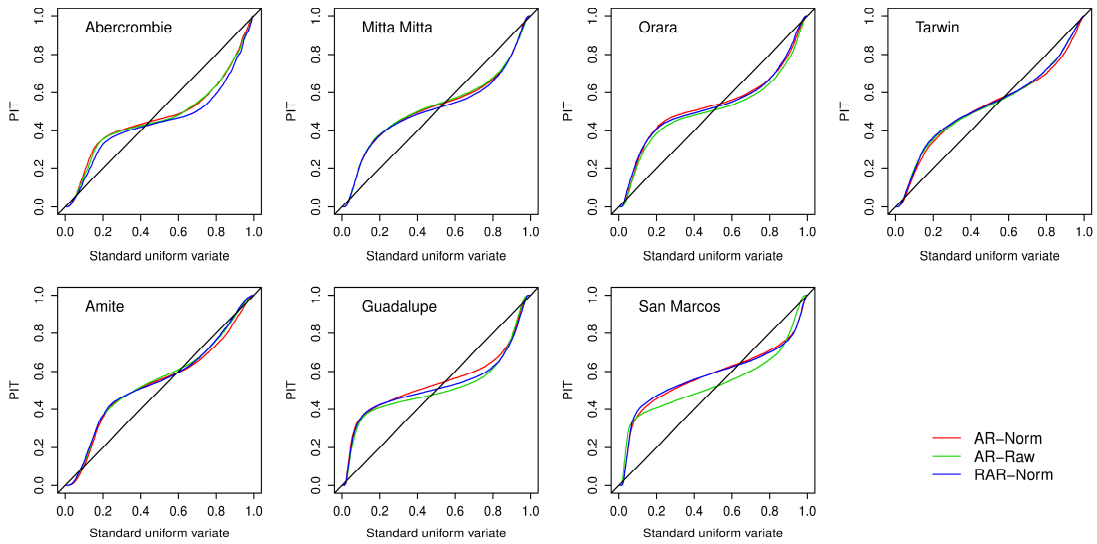



Figure 9: PIT-uniform probability plots. Curves on the diagonal indicate perfectly reliable forecasts.