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Real time adjustment of slow changing flow components in distributed urban runoff models

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ABSTRACT

In many urban runoff systems infiltrating water contributes with a substantial part of the total inflow and therefore most urban runoff modelling packages include hydrological models for simulating the infiltrating inflow. This paper presents a method for deterministic updating of the hydrological model states governing the infiltrating inflow based on downstream flow measurements. The fact that the infiltration processes follows a relative large time scale is used to estimate the part of the model residuals, at a gauged downstream location, that can be attributed to infiltration processes. This information is then used to update the states of the hydrological model. The method is demonstrated on the 20 km^2 Danish urban catchment of Ballerup, which has substantial amount of infiltration inflow after succeeding rain events, for a very rainy period of 17 days in August 2010. The results show big improvements for regular simulations as well as up to 10 hour forecasts. The updating method reduces the impact of non-representative precipitation estimates as well as model structural errors and leads to better overall modelling results.

KEYWORDS

Urban runoff; distributed model; infiltration; updating; data assimilation; RDII.

INTRODUCTION

A crucial point for any urban drainage model running real time is to be able to be updated to reality (measurements) in runtime. For linear models this can be done using mathematical tools such as the Kalman filter (Kalman, 1960) and for small models in general it can be done using ensemble based data assimilation methods, such as Ensemble KF (Evensen, 2003; Komma et al., 2008), Particle Filter (Gordon et al., 1993) etc. For these reasons, among others, urban drainage models used for real time applications are most often simple lumped models with nice mathematical characteristics, such as linearity, or small non-linear models that enable lots of model runs in a short time. These characteristics enable data assimilation and make it possible to produce forecasts from the right offset with associated meaningful prediction bounds. The modern physically based, distributed, hydrodynamic urban runoff models, such as DHI MOUSE/MIKE URBAN, SWMM, InfoWorks etc., are neither computationally fast nor linear which might explain why the use of these models in general has been limited to planning, design and analysis purposes. For real time applications these models are often regarded as being too slow and the non-linearity makes data assimilation troublesome. Nevertheless, this article is the first step in a work process running for the next couple of years, which aims at utilizing the power of the distributed models in real time applications.

The physically based models have some potential advantages compared to the lumped conceptual models. The distributed nature of the models give them the ability to fully utilize the information in the spatially distributed precipitation data from radars and to produce water level and flow estimates for all parts of the urban drainage system. Having states relating directly to most of the large number of online data sources available from the modern urban drainage system, such as flow and level measurements, settings of weirs and gates and pumping status etc., makes it possible to utilize this huge source of information in the modelling, and thereby reduce to dependence on any specific data source. Besides giving more accurate modelling results, this gives the ability to monitor the condition of the very same data sources as well as the condition of the drainage system. Another example where an online updated distributed model could be useful, even without forecasting, is tracking of pollutants for control purposes. Therefore the use of data assimilation is not reserved strictly for making better forecasts but to improve modelling results in general.

The only operational updating method for large detailed distributed urban runoff models known to the authors are the tool MOUSE UPDATE (Hansen et al., 2011) from DHI that is capable of controlling local water levels and flows in the system. Since this tool only has direct local impact on the system, the information about upstream states contained in the measurements is not utilised. Non-ensemble based data assimilation methods are widely used in hydrology for flood forecasting, also when the rivers are modelled using distributed models that, like the hydrodynamic urban runoff models, are based on solving full St. Venant equations (see for instance (Madsen and Skotner, 2005) that estimates a static Kalman gain based on historical observations). These methods are not directly transferrable to urban drainage systems due to their branched nature, fast response times and big local differences in gradients. This does not mean that non-ensemble based updating methods are an impossibility but a pragmatic approach has to be taken. In this article the work of creating updating methods for distributed urban runoff models is launched by focussing on the slow changing flow components from infiltrating water since these components change slowly enough to enable an updating scheme to make a difference. The infiltrating water will seldom be the sole cause of problems such as CSO or sewer surcharge, but in many systems the infiltrating water contributes with a substantial part of the total runoff volume and results in long tails after rain events which link together otherwise separate events. This means that if the infiltrating water is not included in the model the impact of consecutive events can be underestimated.

In this article the urban drainage system is modelled using the MOUSE Hydro Dynamic (HD) model that is a part of DHI’s MIKE Urban software. The infiltrating water is modelled using the RDII model (DHI, 2009). The aim is that the update method is applicable for big online distributed models where there is no time for ensemble model runs. The proposed technique takes advantage of the fact that the infiltration process follows a time scale bigger than the response time of the hydraulic system, thus making it possible to measure/estimate the states of the upstream hydrological model by downstream flow comparisons. By correcting the states upstream of the HD model the modelling results for the entire drainage system can be improved to the extent that the description of the relative distribution of infiltrating water in the hydrological model is correct. The goal of the update procedure presented in this article is not solely to produce better downstream forecasts, but better modelling results in general. Better forecasts are, however, an indication of the upstream model states being closer to the optimum and therefore the forecast quality is used as indicator of the quality of the update. The update procedure is tested in a case study covering data from a period of 17 days in august 2010 for the Danish catchment of Ballerup.

THE RDII MODEL

In many urban sewer systems part of the inflow is runoff from perimeter drains or soil water entering the sewer network through damaged pipes sections and leaky joints. Most sewer network modelling packages include physically inspired conceptual models for simulating this delayed rainfall dependent infiltrating inflow. Wallingford's InfoWorks and USEPA's SWMM both use a similar Ground Water Infiltration (GWI) model for infiltration while DHI's MIKE URBAN (MU) includes the Rainfall Dependent Infiltration and Inflow (RDII) model. Both the GWI and RDII models are intended for long term simulations (years) and provide the runoff model with a hydrological memory due to slow-changing state variables, so that the runoff is dependent on previous events.

The RDII model is the most complex of the above mentioned infiltration models. Figure 1 shows a simplified schematic of the RDII model and how it is linked into the full MU model. The RDII model consists of three interacting non-linear reservoirs: Surface Storage, Lower Zone Storage and Ground Water Storage (GWS). Rain enters the surface storage from where the water is either evaporated, infiltrated further down or gives cause to an Immediate Response (IR) to the sewer system. The IR is routed through two linear reservoirs, S1 and S2, before entering the hydrodynamic model. The states of the Surface and Lower Zone Storage determine how much of the rain that runs off as IR and how much infiltrates, and thus represents the hydrological memory of the model. GWS mainly governs the slowly changing Base Flow (BF). Each sub-catchment in the model can have its own RDII model setup.

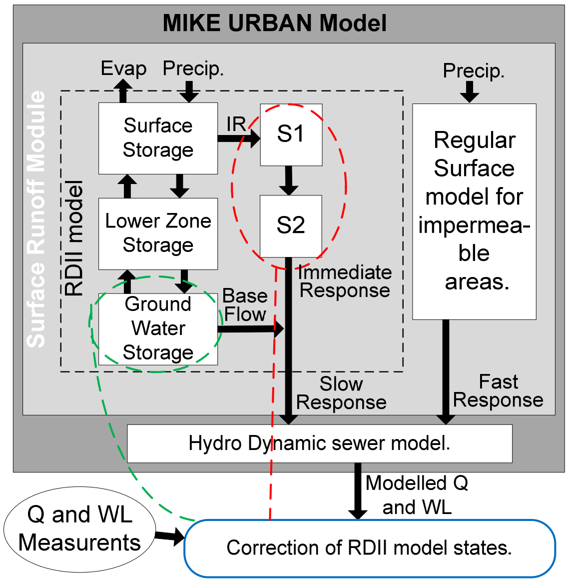

Figure 1. Simplified schematic of MIKE URBAN (gray shaded parts) when using RDII. Dashed parts indicate how the updating scheme interacts with the RDII model.

Instead of using the build in RDII module of MIKE URBAN to simulate the infiltrating water, a copy of DHI's RDII model has been made in Visual Basic using MIKE URBAN's COM interface to communicate with the hydro dynamic (HD) module of MIKE URBAN. This has been done to gain control over the states of the RDII module.

UPDATING THE RDII STATES

The updating of the RDII states is done by looking at the downstream difference between modelled and measured flow. It is assumed that these model residuals can be divided into three components arising from the surface models governing the slow and fast runoff, respectively, and the HD model:

$$\varepsilon = Q_{measured} - Q_{modelled} = \varepsilon_{fast} + \varepsilon_{slow} + \varepsilon_{HD}$$

The part of the model residuals that is estimated to arise from errors in the slow runoff, ε_{slow}, is fed back into the hydrological model by adjusting the RDII states to generate the necessary change in the inflow to the HD model. The corrections to the IR are bound to be of a much larger scale than the corrections to the slowly changing BF. Therefore the correction to the IR can be done without considering the correction to the BF. The IR enters the HD model through the linear reservoir S2, which has the depth S2h as state value, the ground area A, and empties according to the time constant *Ck*. Hence, ε_{slow} can be written as:

$$\varepsilon_{slow} = \sum_i IR_i = \sum_i \frac{\Delta S2h_i \cdot A_i}{Ck_i}$$

where *i* refers to the individual RDII catchments. In this article it is assumed that change $\Delta S2h$ is the same for all RDII catchments, which leads to:

$$\Delta S2h = \varepsilon_{slow} \cdot \sum_i \frac{Ck_i}{A_i}$$

Estimating the correction

The timescale of the infiltrating flows to the drainage system is usually much larger than the response time of the hydraulic system and the runoff from impervious areas. Therefore the development in the part of the model residual that arises from the RDII model is expected to follow a rather steady trend compared to the more fluctuating errors from the fast runoff components. To suppress the impact of fast fluctuations from measuring errors and flow from nearby impervious catchments, ε is divided into one hour averages before estimating the slow flow error component $\hat{\varepsilon}_{slow}$ as the prediction of the latest ε using an ordinary least squares linear regression over the latest model residuals ε from a predefined preceding period of time. This period of time should be chosen big enough to suppress the fluctuating flows from the impervious areas but not bigger than necessary since this would make the update process slower reacting.

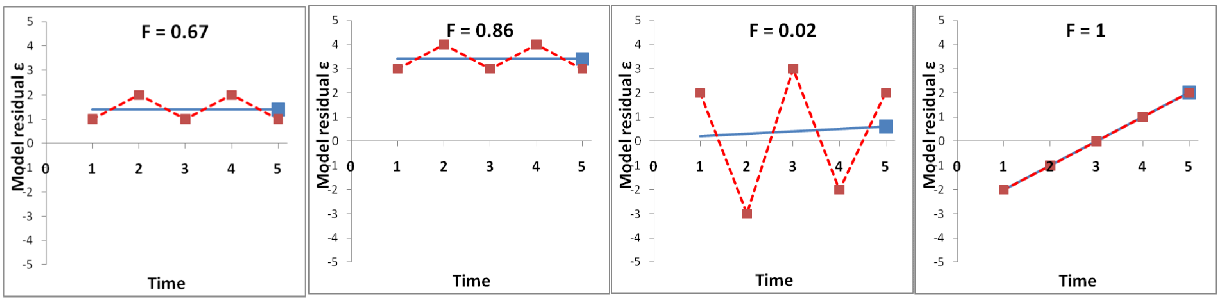

Figure 2. The red dots are the one hour averages of $\boldsymbol{\varepsilon}$. The blue line is the regression used to estimate $\hat{\varepsilon}_{slow}$ (the blue square at the end of regression line). F is the value of the belief in the estimated $\hat{\varepsilon}_{slow}$.

The certainty in which the estimated $\hat{\varepsilon}_{slow}$ is believed to equal the true ε_{slow} is depending on the size of the regression residuals *e* relative to the size of the model residuals ε. By quantifying this certainty it becomes possible to put weight to the individual updates depending on the belief in the estimated $\hat{\varepsilon}_{slow}$. The certainty is quantified as the belief *F* defined as one minus the quadratic mean of the regression error *e* scaled by the quadratic mean of the model residuals used as basis for the regression:

$$F = 1 - \frac{RMS(e)}{RMS(\varepsilon)} = 1 - \sqrt{\frac{\sum e^2}{\sum \varepsilon^2}}$$

This measure has the desired property of being close to unity only when the regression error is small compared to the absolute size of the data, and it can handle data sets with mixed signs in a meaningful way. Visual representations of the regression used for estimating $\hat{\varepsilon}_{Slow}$ with the associated beliefs F are shown in Figure 2.

Stability

When feedback is introduced to a dynamic system there is always a danger of making the system instable or introducing unwanted harmonic oscillations. Part of the reason for this is due to the response time of the system as illustrated in Figure 3. The figure shows the development in the model residuals when updates occur relatively frequent compared to the response time of the system and each update is set to correct for the entire current residual. At the first update that occurs at time t=1 the model is corrected to compensate for the difference at t=1. At t=2 the impact of the first update has not propagated down through the model yet and therefore the second correction will overcompensate the model and result in an absolute difference that is just as big as the initial difference, but with a negative sign. More corrections would make this system oscillate with ever growing amplitude. Hence, stabilizing measures have to be taken if updates are to be performed more frequent than the response time of the system. In this work two different stabilizing methods are used.

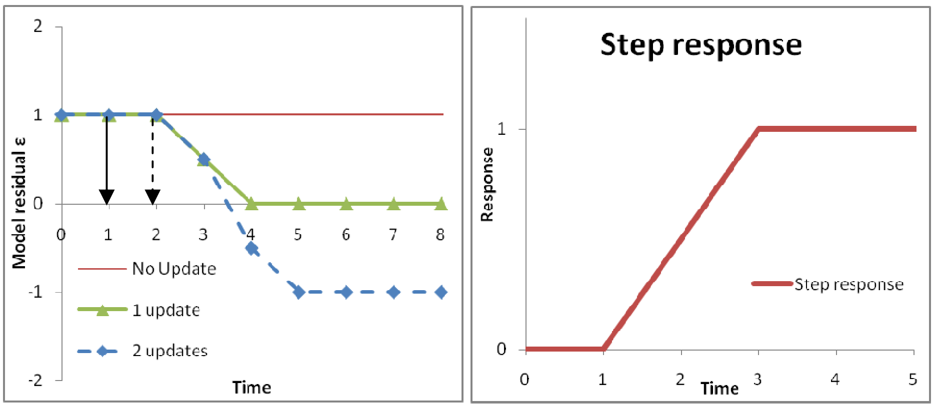

Figure 3. (Left) A theoretical example of the development in the model residuals for a dynamic system with the unit step response shown in the figure to the right when no update is performed (red line), an update is performed at time 1 (green line) and when an additional update is performed at time 2 (dashed blue line).

Dampening factor

A classical way of avoiding instability is to dampen the feedback by multiplying the feedback signal with a positive factor less than one. In the example in Figure 3 a dampening factor of 1/3 would be sufficient since it takes about 3 time units for majority of the impact to take place. This has the disadvantage that the correction becomes slower reacting.

Step response function

By using a model for the response of the dynamic system it is possible to estimate to which extent succeeding updates should be reduced due to the still missing impact of recent previous updates. In the case from Figure 3 the step response function could be used to recognize that the update at time 2 should be reduced with the full size of the update from time 1, since none of the impact from the first update has taken place yet. For hydraulic systems this technique would especially be useful when there is a delay before the first impact of the update has propagated down through the model, which is the case when there is a long transport time between the catchments and the flow gauge, or when there are outages in the measurement data. An appealing feature of the use of the step response function for stabilizing is that it is a property of the dynamic system itself and can therefore be estimated regardless of how the update values are calculated. For a non-linear hydraulic model, however, there is no time invariant step response function and a typical step response function has to be approximated. This approximation makes it necessary to include a dampening factor, but this factor can be larger than if no step response function was used in the feedback control which makes the update faster reacting. The full equation for the correction applied by the update procedure to levels in S1 and S2 becomes:

$$Correction_k = (\Delta S2h - MI(k)) \cdot F \cdot DF$$

Where $\Delta S2h$ is the calculated change to the levels in the S2 reservoirs based on the estimated $\hat{\varepsilon}_{slow}$, F is the belief in the estimated $\hat{\varepsilon}_{slow}$, DF is a dampening factor and MI() is the missing impact from previous corrections calculated as:

$$MI(k) = \sum_{i=1}^{k-1} (1 - USR\ (k-i)) \cdot Correction_i$$

Where k is the latest time index and USR is the Unit Step Response function.

Updating the Ground Water Storage

The slow variations in the BF make updating of the GWS rather simple. By assigning only a very small fraction of ε to the BF there is no risk of creating instability, and the slow rate of the adjustments due to the limited size of the feedback is not a problem as long as the adjustment rate is significantly faster than the first order kinetics governing the BF (The time constants for the base flow is typically in the range of thousands of hours). The required change in BF due to the update is calculated as:

$$\Delta BF = \varepsilon \cdot T_{update} / C_{update}$$

Where T_{update} is the time between updates (e.g. 5 minutes) and C_{update} is the time constant of the adjustment (e.g. 24*60 minutes). The updated state of the GWS is then calculated based on ΔBF.

CASE STUDY

A case study has been performed where the performance of the updating scheme is tested by comparing R^2 values for different forecast horizons for a MU model with and without the RDII module. To test whether the updating can compensate for the demanding setup, in terms of parameters and calibration, related to the Lower Zone Storage a model is included where the RDII module is reduced to being only S1, S2 and the GWS.

The catchment

The case is based on the runoff from the suburban Danish catchment of Ballerup that covers an area of approx. 20 km^2 and is a mix of combined and separate systems. The model contains a total of 167 sub catchments for all of which the runoff to the HD model are modelled by both an RDII setup for the pervious areas as well as a time-area curve model for the impervious areas. As it can be seen from Figure 4 there is a growing amount of slow runoff after succeeding events.

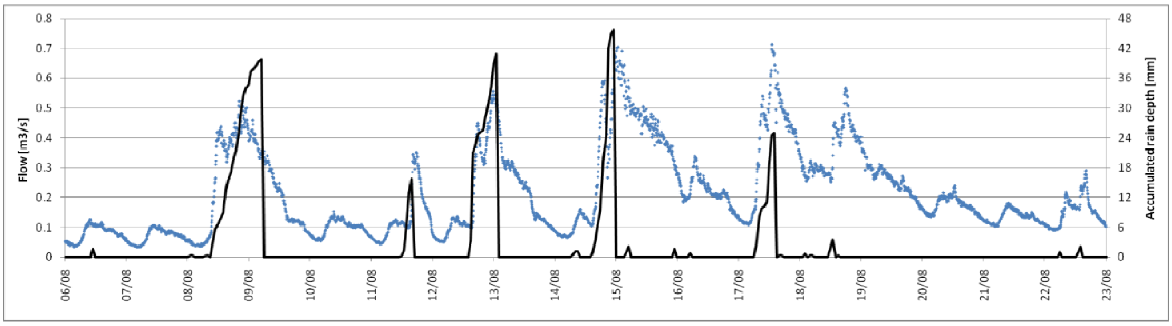

Figure 4. Measured runoff (blue dots) from the Ballerup catchment and event wise accumulated precipitation (black line) measured by a nearby rain gauge in august 2010.

Step response function and stability

To be able to use the proposed updating scheme the unit step response for the IR update needs to be estimated. This has been done by stepwise increasing S2h and then normalizing the downstream response to the increments, see Figure 5. Since there is no time delay before the actual response of this specific system the USR can be approximated fairly well with a simple exponential function. Alternatively, tabulated data could have been used instead of a function.

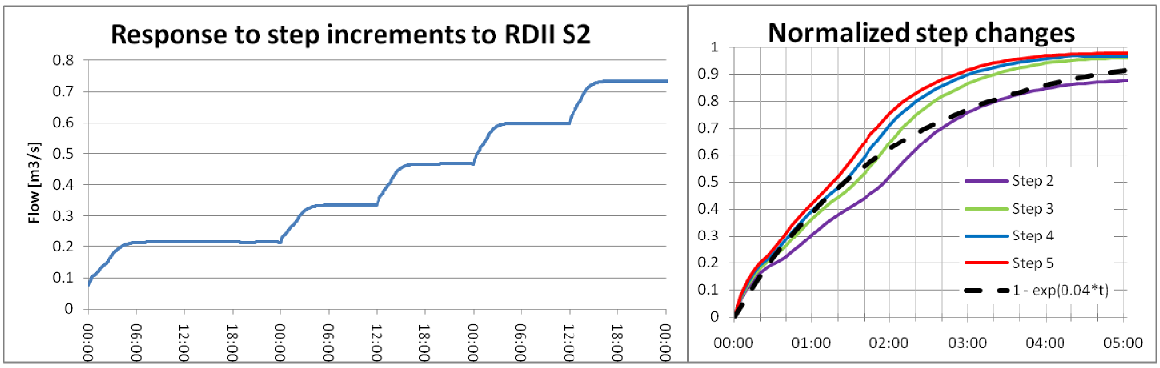

Figure 5. (Left) Downstream response to step increments to the water level in S2 and (Right) the normalize response used to estimate the Unit Step Response function.

Choice of updating parameters

The modelled response from the impervious areas happens within a couple of hours and therefore the period used for estimating $\hat{\varepsilon}_{Slow}$ has been chosen to 5 hours. The downstream flow measurements are available with an interval of 5 minutes, and therefore T_{update} is chosen to 5 minutes as well. The dampening factor was found iteratively by making some model runs with an instability provoking measurement data set (unnatural big sudden changes) and increasing the factor until the system was completely stable. This lead to an DF of 9, meaning that the same $\hat{\varepsilon}_{Slow}$ would have to be present for 9 consecutive updating time steps in a row (9*5 minutes = 45 minutes) for the update procedure to correct the model completely for the specific $\hat{\varepsilon}_{Slow}$ .The time constant for the base flow correction was chosen to 24 hours, since this seems to be sufficiently fast to be able to react on the changes observed in Figure 4.

Results

Figure 6 (left) shows the results when running the model with and without the RDII module and when running the model with an RDII module updated with the above described parameter values. It is impossible to tell whether the modelling errors for the ordinary model run with RDII is due to model structural errors or non-representative precipitation estimates, but non the less the updating improves the downstream simulation result greatly. Figure 6 (right) shows the R^2 when using the model for forecasting (future rain input assumed known).

The figure clearly shows that both the updated models perform much better than the model using RDII without update. This indicates that the difficult task of calibrating the many parameters of the RDII model to a large extent can be compensated for by a decent updating procedure. In fact, in lack of the long measurement time series required to perform a thorough RDII calibration the model can be reduced to a very simple three reservoirs model without any other input than the ones coming from the updating process with fairly good results.

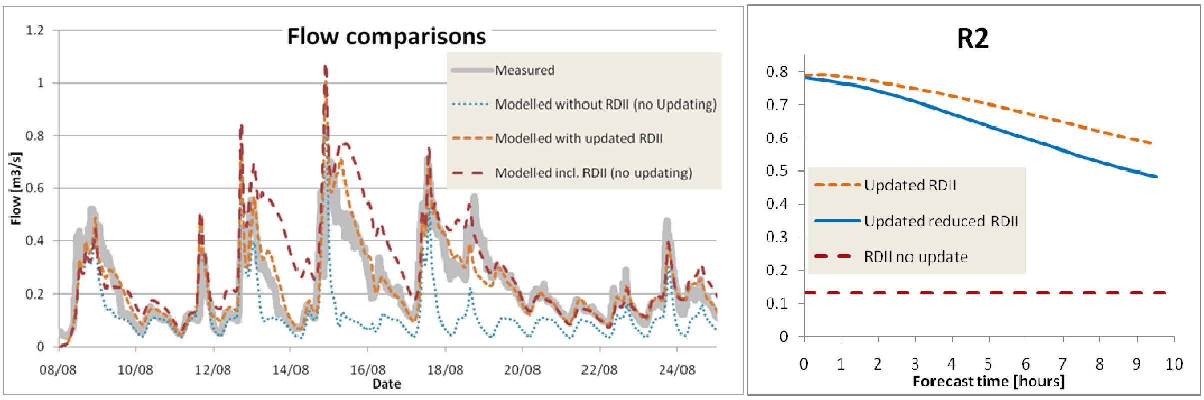

Figure 6. (Left) Measured and modelled runoff when using the model with and without the RDII module and when using updating on the RDII module states. (Right) R^2 (J. E. Nash and Sutcliffe,J.V., 1970) for up to 10 hour forecasts. The solid line is when the RDII module has been reduced to being only the Ground Water Storage and the S1 and S2 reservoirs.

CONCLUSION

The current work present an updating scheme that based on downstream flow comparisons deterministically updates the states of the hydrological RDII module that is responsible for modelling the infiltrating inflow to a Mike Urban runoff model. The result for a Danish case study showed big improvements using the updating scheme for both modelling and forecasting and since the correction was performed upstream of the hydrodynamic model it is likely that the update has improved model performance all over the drainage system. The potential benefits of using the update scheme are: Better overall modelling results and reduced dependence on optimal RDII model calibration and good precipitation estimates.

ACKNOWLEDGEMENTS

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