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Tropical cyclone effects on rapid runoff responses: quantifying with new continuous-time transfer function models

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Abstract The South Creek Experimental Catchment (Queensland, Australia) was the first forest hydrological study established within cyclone-affected areas of the humid tropics to address runoff processes or surface-groundwater interactions. From the outset it was believed that the very flashy nature of the responses within this area of Queensland was at least partly attributed to rainfall characteristics associated with tropical cyclones. This study quantifies the impact on the dynamic response characteristics of very flashy streamflow responses to rainfall from a sequence of tropical cyclones relative to those associated with local convective events. To achieve this we have applied state-of-the-art time-series modelling methods to South Creek data and to that from a basin not directly affected by tropical cyclones but where the soils and slopes are comparable. For both datasets our analyses best captured the rainfall-runoff responses with second-order continuous-time transfer functions where 60% of the streamflow was associated with a fast pathway. While the recession time constant (*TC*) of this fast pathway was 75 minutes for the basin with rainstorms produced by local convective events (namely the Baru Experimental Catchment in Malaysian Borneo), the *TC* was only 21 minutes at South Creek. With an identical model structure and an identical value describing the rainfall-runoff nonlinearity, this shows quantitatively that for a unit rainfall input (sampled on a sub-hourly basis), the basin affected by tropical cyclones produced flashier stream responses in comparison to that only affected by localised tropical thunderstorms.

Key words continuous-time model; data-based mechanistic model; experimental catchment; surface-groundwater interactions; tropical cyclone

INTRODUCTION

Experimental catchment studies have shown that rainfall-runoff systems within the humid tropics can be some of the most responsive of any global region (Gilmour et al., 1980; Elsenbeer & Lack 1996; Bonell, 2004; Chappell et al., 2006). The very flashy nature of these catchment systems heightens the risk of downstream flooding, accelerates soil erosion, and gives a greater sensitivity to soil disturbances during forestry, agriculture or civil engineering operations. Improving our quantitative knowledge of how to simulate these hydrological systems and attribute the causes of the flashy nature is, therefore, fundamental to progress in forecasting floods in headwaters, quantifying the dynamic behaviour of erosion and linking land-use change to environmental impacts within dynamic simulation models.

The first research basins or ‘experimental catchments’ to be established in a *cyclone-prone* part of the humid tropics were the South Creek and North Creek basins near Babinda in northeast Queensland, Australia (Bonell and Gilmour, 1978; Queensland Government, 2008). Earlier rainfall-runoff studies in the humid tropics (Dagg & Pratt, 1962; Pereira et al., 1962) were undertaken within areas not directly affected by tropical cyclones. Tropical cyclones are synoptic-scale low pressure systems with no fronts, occurring over tropical and subtropical waters with organised thunderstorm activity (McGregor & Nieuwolt, 1998). Parts of Australia, the Philippines and islands in the Caribbean and western Indian Ocean, including Madagascar are regularly affected by these systems. Other land areas of the humid tropics, e.g., Borneo Island, equatorial Africa and Brazil are normally free from cyclone tracks. In these areas the short-term behaviour of rainfall is usually dominated by the effects of individual convection cells, i.e., local thunderstorms (McGregor & Nieuwolt, 1998). The very flashy nature of the catchments in northeast Queensland has been attributed, often qualitatively, to the presence of tropical cyclones (Bonell and Gilmour, 1978; Gilmour et al., 1980; Bonell, 2004; Howard et al., 2010). Over 40 years since these experimental catchments were established, objective methods for analysing rainfall-runoff time-series have improved dramatically (Young et al., 1997; Box et al. 2008; Young, 2008, 2011). Consequently there is an incentive to *re-examine time-series data* collected by these studies to see if new modelling methods are able to *quantify* the role played by tropical cyclones in the generation of faster streamflow responses in comparison to those produced by localised tropical thunderstorms.

The publication of findings from earlier East African and these Queensland studies were partly responsible for stimulating the establishment of many more experimental basins throughout the humid tropics (see the review of Bonell, 2004). We would suggest that if basins exist elsewhere in the humid tropics differing from northeast Queensland only in respect of an absence of tropical cyclones, then new insights into the hydrological impact of these climatic disturbances might be gained by *comparative analysis* similar to the approach taken by traditional *'paired catchment'* studies.

This study has two key objectives: 1) to derive objective numerical characteristics of the rainfall-runoff system in the humid tropics in a period affected by tropical cyclones and another system similar in all respects, except for the absence of tropical cyclone activity, and 2) to use models with the least number of model parameters, to constrain simulation uncertainty and thereby allow more robust hydrological and hydro-climatic interpretations of the observed differences between the rainfall-runoff characteristics of the two micro-basins.

METHODS OF MODEL AND PARAMETER IDENTIFICATION

Within this study we identify the structure of rainfall-runoff models by following a three-stage DBM approach or philosophy, where DBM means data-based mechanistic. The first stage of this approach is to apply a large range of mathematical relationships to attempt to capture to the dynamics of the output variable of streamflow from the input variable of rainfall. Thus the model structures identified are based on those that can describe the dynamics between the observed input data and observed output data; hence the models can be defined as *data-based*. This first stage is undertaken without making any *a priori* assumptions about the functioning of the hydrological system. Thus there are no assumptions about the quantities of overland flow relative to subsurface flow, which can never be defined precisely even with direct observations from localised runoff plots (Chappell et al., 2006). Similarly, there is no assumption that subsurface flows can be described by the Richards Equation, as many hillslope hydrologists this to be inadequate given the acknowledged role of flow within soil macropores (Kirkby, 1988). The second stage of the DBM approach involves the rejection of as many of the identified models as possible based upon purely mathematical-statistical criteria. This involves model rejection based upon: a) an unacceptable degree of correspondence between the observed and simulated streamflow (i.e., poor simulation efficiency), b) an unacceptable degree of *over-parameterisation* (i.e., rejection of models that are more complex than can be warranted by the information contained in the observations), and c) the failure of various mathematical diagnostic checks, e.g., models exhibiting unstable behaviour. Indeed many physics-based catchment models should be rejected on the basis of tests of over-parameterisation, but such tests are rarely undertaken and consequently underlying mathematical-statistical problems can remain uncorrected. The third and final stage of the process is then the rejection of mathematically acceptable DBM models that do not have a feasible *hydrological interpretation*. For example, a DBM model of streamflow that is a combination of one rainfall-runoff pathway that adds water to stream and one that removes it, may be valid statistically, but is not considered consistent with perceptual models of runoff generation systems. DBM models accepted as having a hydrological interpretation can then be defined as *mechanistic* and therefore, described as data-based mechanistic models. This approach of building hydrological understanding by *falsification* of models is consistent with the scientific method developed by Popper (1959), and thereby differs from the approach used within most physics-based catchment modelling studies that start with the identification of pertinent scientific laws.

Modelling methods based on *transfer functions* (Box et al., 2008) have proved to be very efficient at capturing the dynamic relationships between rainfall and runoff (i.e., streamflow per unit catchment area) over a range of climate, geology and scale (Jakeman et al., 1993; Young & Beven, 1994; Chappell et al., 2006; McIntyre et al., 2011; Ockenden & Chappell, 2011). As a result, the central mathematical method used in the first stage of our modelling is transfer function identification. The key procedure leading to the efficient identification of a transfer function is the parameter identification routine. Here we use the latest version of the Refined Instrumental Variable (RIV) method (Young, 2008), where: a) the observed data are initially pre-filtered to remove high-order noise (i.e., dynamics much shorter than shortest *time constant* of the system: Young, 2011) that effects the identification of the true model structure, and b) the *covariance matrix* (Box et al., 2008) is used explicitly to find the most robust model with least uncertainty. The software to identify transfer function parameters using the RIV method forms part of the CAPTAIN Toolbox (Taylor et al., 2007).

Most rainfall-runoff models based on transfer functions historically have been *discrete-time dynamic models*. Discrete-time dynamic models describe a system using *difference equations* e.g., $y_t = ax_{t-1}$ (Box et al., 2008) and are very fast and easy to solve. *Continuous-time dynamic models* by contrast describe a system using *differential equations* (Box et al., 2008). These models are generally more difficult to estimate, however, they produce more reliable model parameter estimates where the system dynamics are very fast, i.e., where the dynamics are nearly as fast as the sampling interval (or time-step) of the data. More recent developments with the CAPTAIN Toolbox have led to significant improvements in the continuous-time versions of the RIV identification routines, e.g. the RIVCBJID algorithm (or *R*efined *I*nstrumental *V*ariable *C*ontinuous-time *B*ox-*J*enkins *ID*entification algorithm). As the sampling interval for the South Creek streamflow data is 15 minutes this may be relatively close to the recession time constant of the fastest component of the rainfall-runoff response in this tropical cyclone region, and thus makes use of continuous-time models preferable for this study.

Previous rainfall-runoff modelling using transfer functions has demonstrated the value of capturing the *nonlinear* aspects of the rainfall-runoff response in addition to that component captured by the transfer function. Within this study we capture the nonlinearity using power term p within the store-surrogate sub-model, SSSM (Young & Beven, 1994; Chappell et al., 1999a), where the normalised effective rainfall (that incorporates the nonlinearity effects) is defined as:

$$r_{en} = r_{eff}\left(\frac{\sum r}{\sum r_{eff}}\right) \;\; ; \;\; r_{eff} = r{q_{t-1}}^{p} \tag{1}$$

and r is the observed rainfall at each time-step, q_{t-1} is the observed discharge at the previous time-step to that for the observed rainfall (which is a measure of the relative catchment wetness that causes the nonlinearity in response) and r_{eff} is the calculated effective rainfall.

To ensure that the rainfall-runoff dynamics through several storms are analysed, the methods are applied to a wet period with a continuous sequence of 8640 data points. The South Creek rainfall-runoff data are available at 15 minute intervals throughout a period of regular cyclonic activity over the three months of December 1990 to February 1991; where the 8640 data points equate to 90 days of contiguous data. Data were available at a higher sampling resolution of 5 minute intervals for the comparison basin in a tropical region not affected by cyclones. Here the 8640 data points equate to 30 days of contiguous data including more than ten storm-events. Data sampled at a high frequency are necessary for the identification of the most reliable models of rainfall-runoff response where hydrograph recessions were expected to be very rapid.

CHARACTERISTICS OF THE EXPERIMENTAL CATCHMENTS, HYDRO-CLIMATE AND MONITORING SYSTEMS

The South Creek Experimental Catchment is 0.257 km^2 in area, was instrumented in 1967 and lies on steep slopes covered by natural forest (i.e., lowland tropical rainforest) on Wyvuri Holding close to Babinda town, Queensland (Fig. 1a; Queensland Government, 2008). The discharge was derived from measurements of water-level made using a capacitance probe installed at a compound V-notch weir at 17^o 20’ S 145^o 59’ E. The lower section of the weir incorporated a 90^o thin-plate V-notch, while the upper section a 120^o V-notch (Fig. 1b). The rainfall was measured in a forest clearing adjacent to the micro-basin using a tipping-bucket raingauge. In addition to the rainstorm characteristics, the key catchment factors that may regulate fast runoff pathways are likely to be the slope angle and subsoil hydraulic conductivity (Bonell, 2004). The South Creek basin (Fig. 2) has steep slopes of around 19^o (Bonell et al., 1998) and a subsoil with a relatively high saturated hydraulic conductivity (Table 1).

The soil type dominating within the South Creek basin is a *Kandosol* (Bonell, 2004). By definition a Kandosol is a soil that is not a Hydrosol but has all of the following characteristics: a) a B2 soil horizon in which the major part is massive or has only a weak grade of structure, b) a maximum clay content in some part of the B2 soil horizon which exceeds 15 %, c) no tenic B horizon, d) no clear or abrupt textural B horizons, and e) is not calcareous throughout the solum or below the A1 or Ap horizons or to a depth of 0.2 m if the A1 horizon is only weakly developed (Isbell, 2002).

The Baru basin was chosen for comparison with the South Creek basin as it is also covered by a Kandosol, when re-classified according to the Australian system using data from Chappell et al. (1999b). Furthermore, the subsoil horizons in both basins have similar values of field-saturated hydraulic conductivity (Table 1). The mean slope angle of approximately 20^o is also comparable to that of the South Creek basin, and it is also covered by natural forest, namely lowland tropical rainforest (Chappell et al., 2006). The basin area is 0.440 km^2 and therefore the same magnitude as the South Creek basin.

a) 

b) 

Fig. 1 The South Creek Experimental Catchment at 17^o 20’ S 145^o 59’ E, a) shown with a white cross in the foreground and located near to Babinda town visible in the background, and b) gauged with a compound V-notch weir.

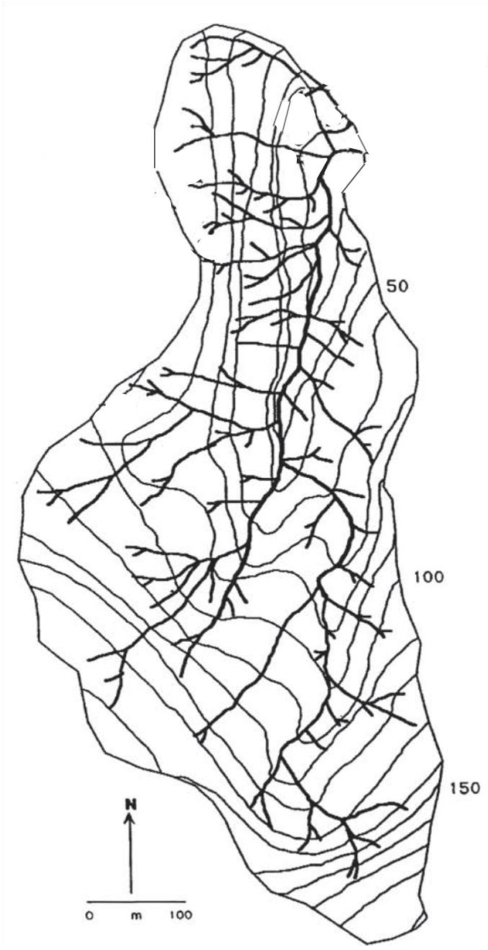

Fig. 2 The topography and drainage network of the 0.257 km^2 South Creek Experimental Catchment. Contours are drawn for every 10 m increments of elevation.

Table. 1 The geometric mean of field-saturated hydraulic conductivity (cm hr^{-1}) within the subsoil, i.e., B soil horizon of: a) the South Creek Experimental Catchment (from Bonell et al., 1979), and b) from 70 measurements taken within a 10 km^2 region containing the Baru basin (Malaysian Borneo).

Strata	South Creek Basin	Baru basin
Upper subsoil	6.25 cm hr^{-1} (10-20 cm depth)[1]	5.7 cm hr^{-1} (15-30 cm depth)[1]
Lower subsoil	1.25 cm hr^{-1} (20-100 cm depth)[2]	3.4 cm hr^{-1} (30-60 cm depth)[1]

[1]From ring permeametry (Talsma, 1969; Bonell et al., 1983; Chappell & Ternan, 1997); [2]From well permeametry (Talsma & Hallam, 1980)

The Baru basin was gauged with a 120^o thin-plate V-notch weir (Fig. 3; 4^o 58’ N 117^o 49’ E) where water-level was monitored with a PDCR1830 pressure transducer (General Electric Company, Fairfield, USA). The catchment rainfall was derived from a Thiessen polygon averaging (Shaw et al., 2010) of data from five tipping-bucket raingauges (model: 103755D-04, Casella CEL Ltd, Kempston, UK).

Fig. 3 The 120° thin-plate V-notch weir used for gauging the 0.440 km^2 Baru Experimental Catchment in Malaysian Borneo (4° 58' N 117° 49' E).

The key differences between the South Creek and Baru basins relate to the *types of tropical disturbance* (McGregor & Nieuwolt, 1998) that dominate in each region. The South Creek catchment is regularly impacted by tropical cyclones, indeed severe Category 4 Tropical Cyclone Joy of 22nd – 25th December 1990 lies within the sequence of cyclone events analysed for this stud over the period 1st December 1990 to 29th February 1991 (Bannister & Smith, 1993; Bonell & Callaghan, 2008). By contrast, the Baru basin is located within an area of Borneo Island that is not directly affected by the tracks of tropical cyclones. The resultant lower rainfall intensities of the Baru compared to South Creek basin are observable over time scales from minutes for days (see Fig. 5 in Bidin & Chappell, 2006). The average annual rainfall at South Creek is around 4000 mm/yr (Barnes & Bonell, 1996) and is, therefore, much larger than the average of 2862 mm/yr (± 442 mm standard deviation: 1986-2009) recorded in the vicinity of the Baru catchment.

RESULTS OF THE MODEL IDENTIFICATION

Using the RIVCBJID algorithm we attempted to identify models of the South Creek rainfall-runoff system ranging from first-order structures with a single runoff pathway to sixth-order structures with six dominant runoff pathways generating the observed streamflow. For each model structure a range in pure time delay between individual rainfall events and a hydrograph response of between zero and four time-steps was investigated. This range of scenarios gave a total of 130 possible DBM models. The best twenty models according to a measure of the simulation efficiency (R_t^2: see e.g., Chappell et al., 2006; Young, 2011) are shown in Table 2.

The structure of the DBM models identified are often shown in the form of a triad [*den num del*], where the number of denominators, *den* (i.e., number of *a* terms in the lower part of a transfer function, e.g., Equation 2), number of numerators, *num* (i.e., number of *b* terms in the upper part of a transfer function, e.g., Equation 2) and the number of time-steps of pure time delay, *del* (see Equation 2) are shown in square parentheses. The incorporation and magnitude of the nonlinearity term is then sometimes shown with a superscript outside the parentheses, e.g., [*den num del*]^p for the SSSM nonlinear model. The magnitude of the optimum value for this nonlinearity term (p) for the South Creek system was found to be 0.40. While the model with the highest simulation efficiency had an R_t^2 of 0.92605, i.e., 92.6% of the variance in the observed streamflow is explained by the model, this sixth order model (i.e., [6 6 0]$^{0.40}$) is *over-parameterised* in comparison to all other models shown in Table 2. Models are said to have become over-parameterised if the inclusion of additional model parameters has added considerably to the uncertainty around the best estimate of the simulated time-series or the values of each parameter, while only marginally improving the simulation efficiency. The degree of over-parameterisation is shown by the heuristic measure of the Young Information Criterion, *YIC*, where a low degree of over-parameterisation is shown by a large negative number (Ockenden & Chappell, 2011).

Table. 2 The best 20 models ranked according to the efficiency measure of R_t^2 (see e.g., Chappell et al., 2006; Young, 2011), where *den* is the number of transfer function denominators (i.e., recession or *a* parameters), *num* is the number of transfer function numerators (i.e., gain or *b* parameters), *del* is the number of time steps of pure time delay between rainfall and runoff response, *YIC* is the Young Information Criterion, R_t^2 is the efficiency measure, *BIC* is the Bayesian Information Criterion, while *S2* and *condP* are two further heuristic measures of model over-parameterisation.

den	*num*	*del*	*YIC*	R_t^2	*BIC*	*S2* ×100	*condP* ×10
6	6	0	-0.623	0.926	-36235	1.553	9.261
5	6	0	-0.851	0.926	-36243	1.553	9.260
6	5	0	-2.005	0.926	-36186	1.563	9.256
4	5	0	-2.858	0.925	-36164	1.570	9.252
6	4	0	-8.017	0.924	-35976	1.603	9.237
5	4	0	-2.497	0.923	-35952	1.609	9.234
3	4	0	-6.699	0.923	-35886	1.625	9.226
4	3	0	-4.572	0.921	-35646	1.670	9.205
3	3	0	-6.536	0.916	-35209	1.757	9.163
4	5	1	-1.519	0.916	-35161	1.760	9.162
4	4	1	-3.315	0.915	-35040	1.786	9.149
5	6	1	-5.173	0.915	-34993	1.790	9.147
3	4	1	-5.272	0.915	-35002	1.796	9.145
3	3	1	-5.603	0.912	-34719	1.857	9.116
2	3	1	-7.423	0.910	-34526	1.901	9.095
2	3	0	-7.597	0.905	-34130	1.991	9.052
2	**2**	**0**	**-8.732**	**0.903**	**-33904**	**2.045**	**9.026**
4	2	0	-11.16	0.891	-32894	2.292	8.909
2	2	1	-7.297	0.887	-32620	2.367	8.873
1	2	1	-9.214	0.879	-31981	2.549	8.786

Consequently, only those models shown in Table 2 that have a highly negative *YIC* (for this data a value more negative than -8.000) were examined in detail. The sixth-order $[6\ 4\ 0]^{0.40}$ and fourth-order $[4\ 2\ 0]^{0.40}$ models were subsequently rejected because oscillatory characteristics (i.e., complex roots of the transfer function denominator: Young, 2011) were present. This analysis left the second-order $[2\ 2\ 0]^{0.40}$ and first-order $[1\ 2\ 1]^{0.40}$ models as having the best *YIC* values without oscillatory behaviour and a top twenty R_t^2 value.

TOWARDS A HYDROLOGICAL AND HYDRO-CLIMATIC INTERPRETATION

In the last stage of the DBM modelling approach the first-order $[1\ 2\ 1]^{0.40}$ model was rejected because a model with two stores joined in series, that have the same denominator value (and hence same time constant), is difficult to explain *physically*. Consequently this DBM approach indicated that the second-order $[2\ 2\ 0]^{0.40}$ model (highlighted in bold in Table 2) provides the best descriptor of the rainfall-runoff response, even without recourse to the other available statistical measures of *BIC, S2,* or *condP*.

The second-order $[2\ 2\ 0]^{0.40}$ continuous-time transfer function between the normalised effective rainfall (see Equation 1) and streamflow per unit basin area (q) can be presented in the form:

$$q = \left(\frac{b_0 s + b_1}{s^2 + a_1 s + a_2}\right) e^{-s\tau} r_{en} \quad ; \quad s = \frac{d}{dt}$$

(2)

where b_n are the numerator terms, a_n are the denominator terms, τ is the pure time delay and s is the Laplace operator. When shown with the RIVCBJID-identified parameter estimates for the 90 days of South Creek data (using 8640 contiguous values of 15-minute data, with its simulation R_t^2 of 90.3% and *YIC* of -8.73: Table 2) this gives:

$$q = \frac{0.1567s+0.0014}{s^2+0.7025s+0.0025} r_{en} \tag{3}$$

Because $\tau = 0$ for this model (Table 1), the term $e^{-s\tau} = 1$ and therefore, is not shown. The preceding second-order transfer function can be expressed as two first-order continuous-time transfer functions in parallel:

$$q = \underbrace{\frac{0.1556}{s+0.6989} r_{en}}_{\textit{fast pathway}} + \underbrace{\frac{0.0012}{s+0.0036} r_{en}}_{\textit{slow pathway}} \tag{4}$$

The model is decomposed (Young, 2011) into two transfer functions in parallel because this has a hydrological interpretation, namely it describes water-flow along two separate pathways, with one allowing a response to propagate towards the stream much faster than the other. The key terms within the derived transfer functions are more commonly described by the three *dynamic response characteristics*, *DRCs* (Jakeman et al., 1993). These *DRC*s are: 1) the *time constant* or *TC*, 2) the *steady state gain* or *SSG*, and 3) the *pure time delay*, τ. Hydrologically, the time constant relates to the rate of propagation of the response from rainfall to the stream via a particular water pathway. These rates of response propagation relate to the speed of *pressure waves* or *kinematic waves* (see definitions in Rasmussen et al., 2000), not to velocities of water particles (or conservative tracers). For a first-order model, the steady state gain of a rainfall-runoff system is simply the *simulated runoff coefficient* (Chappell et al., 2006). Where the streamflow comprises of two separate components (from two separate water pathways), then the *SSG*s can be used to calculate the percentage of the total streamflow generated by each pathway (e.g., percentage of streamflow that travelled along the fast pathway, *Fast%*: Equation 5). Lastly, the pure time delay of a rainfall-runoff system is the delay between a rainfall event and the start of a response in the river hydrograph. This delay is typically short within micro-basins, but can be very long within macro-basins where it often relates to the time for water to travel from headwater channels to a downstream gauging station. The *DRC*s of *TC* and *Fast%* are derived directly from the *a* and *b* terms given in Equation 2, i.e.,

$$TC = \frac{\Delta t}{a} \quad ; \quad SSG = \frac{b}{a} \quad ; \quad Fast\% = 100\left(\frac{SSG_2}{SSG_1+SSG_2}\right) \tag{5}$$

where Δt is the time-step of the observations (i.e., 5 or 15 minutes for the Baru or South Creek data, respectively), SSG_1 is the steady state gain of the slow pathway and SSG_2 is the steady state gain of the fast pathway.

Within this study, we focus only on interpretations of the *DRC*s of the fast hydrological pathway. The principal means of this interpretation is a comparison of the *DRC*s for the South Creek rainfall-runoff system with those of a comparison basin. The comparison basin is the Baru Experimental Catchment in Malaysian Borneo, where the controls on the rapid runoff pathways are similar with respect of slope and soils, but different with respect of the *type of tropical disturbance* (McGregor & Nieuwolt, 1998), namely a hydro-climate dominated by the effects tropical cyclones versus one dominated by local thunderstorms.

An identical DBM modelling approach was applied to the rainfall and runoff data for the Baru Experimental Catchment. This analysis indicated that the optimal model structure was *identical* to that of the South Creek system, namely a second-order model (with an SSSM-nonlinearity). The simulation efficiency (R_t^2 of 87.6%; Fig. 4) was slightly lower that for the South Creek model. The magnitude of the optimal value of the nonlinearity term (p) was 0.40, *identical* to that identified for the South Creek system. Furthermore, the proportion of the streamflow associated with the faster of the two pathways (i.e., *Fast%*) was 59.5% and thus similar to the 61.1% for the South Creek basin.

If the model structure, the proportion of water following each pathway, or the magnitude of the nonlinearity term had been markedly different between the two catchments, then hydrological interpretation of the time constants (*TC*s) would have been difficult. This would have arisen because of the competing effects of nonlinearity, inertia and pathway proportion on the resultant fast response. In the case of the South Creek and Baru comparison of *DRC*s, only the time constants and the pure time delays differed. To show that the differences in the time constant were much larger than the modelling uncertainties (from errors in the observations or errors in the model identification), uncertainty information estimated by the RIVCBJID algorithm was used to select the range of values of a and b terms (Equation 2) within 1000 Monte Carlo realisations. Uncertainties on the resultant *DRC*s were found to be very small in comparison to the differences in each *DRC* between the two micro-basins. For example, Fig. 5 shows the uncertainties in the *TC*s for the optimal model of the South Creek rainfall-runoff system. Most of the 1000 realisations of the fast path varied by less than ± 0.15 minutes around the average of 21.46 minutes (Fig. 5); and comparable *TC* uncertainties were seen with the Baru data.

Most critically, the optimal *TC* (or average *TC* from the Monte Carlo analysis) of the fast path within the South Creek basin was 21 minutes, while it was 75 minutes for the Baru basin. Thus the South Creek basin has a *quantified* flashier rainfall-runoff response in comparison to that of the Baru basin. This difference cannot be attributed to the effect of the greater sub-hourly rainfall totals in the South Creek micro-basin because of the effects of rainfall-runoff nonlinearity, as the models describing the nonlinearity (SSSM) and the magnitude of the nonlinearity term (p) were identical for both basins. Equally, the *TC* differences cannot be attributed to differences in the catchment controls, as both basins have similar subsoil permeability (Table 1) and similar hillslope angles.

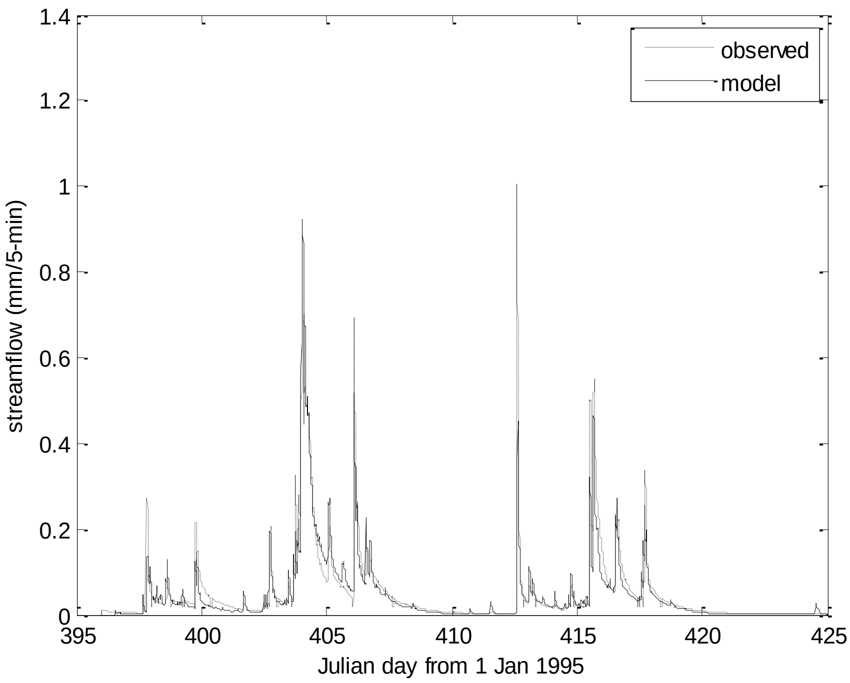

Fig. 4 Observed streamflow per unit basin area (i.e., runoff) from the Baru Experimental Catchment over February 1996 (8640 data points sampled every 5 minutes are shown) and that simulated by a $[2\ 2\ 2]^{0.40}$ DBM model.

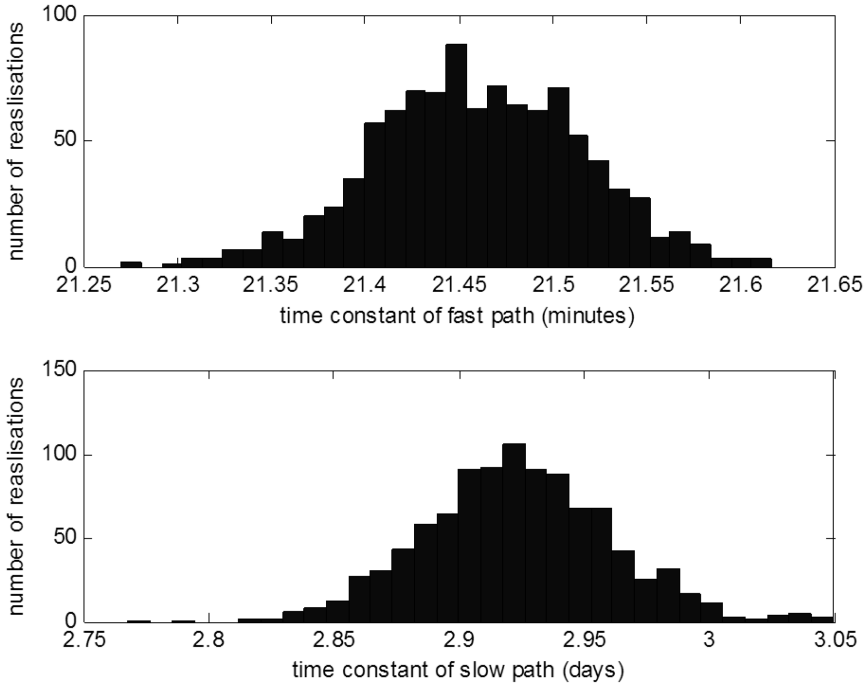

Fig. 5 Number of simulations (y-axis) for each value of time constant (x-axis) produced by 1000 Monte Carlo realisations of Equation 2. The upper figure shows the range of time constants for the fast pathway (in minutes) and the lower figure the range of time constants for the slower pathway (in days) of the decomposed second-order model.

Furthermore, the greater flashiness of the South Creek runoff system is not offset by a longer pure time delay, as the pure time delay is 0 minutes for the South Creek basin and 10 minutes (i.e., 2× 5-minute time-steps) for the Baru basin. Indeed, these two *DRC*s can be combined into a single term called the *mean travel time*, $\bar{t}$ (Wallis et al., 1989), where:

$$\bar{t} = TC + \tau \qquad (6)$$

By using this *DRC*, the difference between the two basins is even larger at 21 and 85 minutes for the South Creek and Baru basins, respectively.

For purely linear rainfall-runoff systems or where the effects of rainfall-runoff nonlinearity in each basin are identical (as here), any differences between the basins in the sub-hourly rainfall totals do not affect the flashiness of the rainfall-runoff system (i.e., *TC* or $\bar{t}$), therefore *differences in basin flashiness cannot be attributed to differences in sub-hourly rainfall totals*. As the only marked difference between the two basins relates to rainfall input from different types of tropical disturbance, the inference is that another characteristic of the short-term rainfall regime (other than sub-hourly totals) may be responsible for the observed differences in *TC* (or $\bar{t}$). The considerably greater magnitude of the b_0 term relative to b_1 term within the identified transfer functions (e.g., Equation 3) suggests that *filtered derivative effects* may be present within the rainfall-runoff data. We are now investigating novel DBM structures that incorporate the *filtered derivative of the rainfall rate* to explore these ideas, and thereby attempt to directly attributed differences in *DRC*s to characteristics of the short-term rainfall regime.

CONCLUSIONS

By using one of the most reliable model identification routines available, constraining model complexities, and by assessing parameter uncertainty, this study has derived a set of dynamic response characteristics (*DRC*s) of the rainfall-runoff system of two tropical micro-basins with minimised uncertainty. Fortuitously, the optimal DBM models for both micro-basins (based on the criteria of high simulation efficiency and a low degree of over-parameterisation) have: a) identical model structures (i.e., second-order transfer functions with SSSM nonlinearity), b) almost identical proportions of water travelling along each pathway (e.g., ca. 60% of streamflow derived from a fast pathway), and c) an identical value of the term describing the nonlinearity (i.e., p = 0.40). This leads to great confidence in the observation that the South Creek Experimental Catchment in Queensland, Australia is considerably flashier in its rainfall-runoff response ($TC_{fastpath}$ = 21 minutes) in comparison to the Baru Experimental Catchment on Borneo Island ($TC_{fastpath}$ = 75 minutes). This difference in flashiness is not due to differences in catchment characteristics, as the basins have similar hillslopes angles, soil types, subsoil permeability and basin areas. These basins are however, effected by different types of *tropical disturbance* (McGregor & Nieuwolt, 1998), namely the 90 day period investigated for the South Creek basin is influenced by a sequence of tropical cyclones, including the Category 4 Tropical Cyclone Joy (Bannister & Smith, 1993; Bonell & Callaghan, 2008), while cyclone tracks do not pass over the Baru basin with local thunderstorms dominating in this area (Bidin and Chappell, 2006). Because the DBM model structures and values of the nonlinearity term were identical, the difference in rainfall-runoff flashiness cannot be attributed to differences in the sub-hourly rainfall totals for these two types of tropical disturbance. In other words, this modelling shows quantitatively that for a unit rainfall input (sampled on a sub-hourly basis), the micro-basin affected by tropical cyclones produces flashier stream responses in comparison to the one affected by localised tropical thunderstorms. There are indications that the short-term rainfall characteristics other than sub-hourly totals may be responsible for the marked rainfall-runoff differences between these two hydro-climatic regimes and we will investigate these further.

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