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Calibration of a continuous hydrologic simulation model in the urban Gowrie Creek catchment in Toowoomba, Australia

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ABSTRACT

Study region: Toowoomba, Queensland, Australia
Study focus: In this study we derive loss model parameters suitable for use in the dynamic loss Australian Representative Basin Model (ARBM) through the calibration of a continuous simulation hydrologic model. We compare the derived parameters to those published in the literature, and our results highlight the need to develop a database of calibrated loss parameters for urban catchments.
New hydrological insights: The development of design storms for flood modelling commonly uses the initial loss/continuous loss model to estimate the conversion of rainfall to runoff. This loss model, when applied to pervious areas, uses parameters that have been calibrated for gauged rural catchments. These same parameters are often applied to the pervious component of ungauged urban catchments with minimal understanding of the resulting impact on runoff. This research uses a continuous simulation modelling approach to calibrate parameters suitable for use in the ARBM loss model built into the hydrological modelling software XPRAFTS. Through a two-stage calibration approach, the model offered a satisfactory fit (Nash Sutcliffe Efficiency > 0.5) for 9 of the 11 selected storm events, with seven events exceeding a Nash Sutcliffe Efficiency of 0.75. Events used in the calibration/validation included peak flows as low as 9 m^3/s and as high as 600 m^3/s. Developing these loss model parameters offers new insights into the suitability of a dynamic loss model approach in an urban catchment in regional Australia and provides an alternative to the parameters already available in the literature which were found to overestimate the peak flow in frequent events.

1. Introduction

Understanding the hydrologic response of urban catchments to extreme rainfall events is fundamental to making informed engineering and planning decisions around urban development, flood mitigation and disaster management (Pathiraja et al., 2012). The need for an accurate hydrologic model and an understanding of the uncertainty associated with the model's results cannot be overstated. In January 2011, Toowoomba, a regional town in the state of Queensland, Australia, experienced its worst flood on record with Gowrie Creek breaking its banks in multiple locations. In addition to inundation, the floodwaters proved hazardous, with high

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velocities resulting in dangerous conditions for pedestrians and motorists at major road crossings, resulting in the death of at least four people. Following this major flooding, a design event hydrologic model was developed as part of the Gowrie Creek Flood Risk Management Study undertaken for the Toowoomba Regional Council. A subsequent peer review panel highlighted the need to understand the uncertainty in flood hydrographs being produced by the hydrologic modelling.

A critical hydrologic parameter that leads to a high level of uncertainty in hydrologic modelling is rainfall loss (Ball et al., 2019). Rainfall loss can be defined as the amount of rainfall that does not appear as immediate runoff (Hill et al., 1998). Rainfall losses are often accounted for by separating the losses into two categories: the initial loss (interception and infiltration prior to saturation or antecedent moisture conditions) and the continuing loss (infiltration post saturation) (Phillips et al., 2014). Most initial loss/continuing loss models greatly simplify the condition of the catchment prior to the event (Cameron et al., 1999). Rainfall losses in the catchment can vary as a result of geography, antecedent moisture conditions, and the intensity of the rainfall event (Ball et al., 2019). The most commonly used approach for simulating a catchment's runoff response to rainfall in Australia is the design event method (Ball et al., 2019). This method uses the widely adopted initial loss/continuing loss model. While it is simple to implement in practice, it assumes that the transformation of rainfall to runoff is probability neutral, i.e. the annual exceedance probability of the design rainfall data will always result in a flood of the same annual exceedance probability (Kavetski et al., 2006). The literature offers minimal guidance on the adoption of appropriate loss values (Rahman et al., 2002; Tularam and Ilahee, 2007), therefore rural catchment based initial loss/continuing loss parameter assumptions continue to be used for urban pervious areas even though the suitability of the parameters for use in urban catchments is not well understood (Ball et al., 2019).

Dynamic loss models differ from initial loss/continuing loss models as they account for the interaction between periods of wetting and drying through direct simulation of the physical processes occurring in the catchment (Cameron et al., 1999; Kavetski et al., 2006; Muncaster et al., 1999). The impact each loss model has on the estimated rainfall excess is demonstrated in the hyetographs in Fig. 1.

Increased computational capacity and the availability of (or ability to generate) sub daily rainfall data has allowed for more complex modelling with improved representation of the complex physical processes within a catchment (Boughton and Droop, 2003). Continuous simulation models seek to overcome the issue of assumed antecedent moisture conditions by modelling a complete sequence of rainfall data over a much longer duration than that of a typical design temporal pattern (Blazkova and Beven, 2009; Boughton, 2005; Calver et al., 2009; Camici et al., 2011), thereby rejecting the concept of probability neutral conversion of rainfall to runoff. Continuous simulation modelling removes the need for assumptions of the antecedent moisture conditions of the catchment, and allows for a more accurate accounting of the hydrologic losses (Boughton and Droop, 2003; Muncaster et al., 1999). While continuous simulation modelling is no less complex than design event methods, it provides a more realistic 'design hydrograph' in terms of volume and duration that has a variety of applications (Grimaldi et al., 2021).

Linsley and Crawford (1974) were one of the early adopters of continuous simulation modelling in an urban catchment with their discussion on a computer based continuous simulation model (the Stanford Watershed Model) they developed in the 1960 s and later modified for other applications. More recently, Rangari et al. (2015) described a number of urban stormwater models available to undertake continuous simulation, however there still appears to be limited published applications or case studies in urban catchments. Ling et al. (2015) compared various design flood estimation methods for both urban and rural catchments, however excluded continuous simulation modelling from the urban catchment case study. Grimaldi et al. (2021) proposed a step forward and testing for the practical use of their continuous simulation approach in an ungauged catchment, however the catchment used in the assessment was less than 25% urban.

Several continuous simulation models of rural catchments have been documented in literature. The study of the Moore River catchment in Western Australia, completed by Newton and Walton (2000) using continuous simulation modelling, achieved good agreement with both a flood frequency analysis of the stream gauge and design event modelling. Boughton and Hill (1997) compared the results of a continuous simulation model for the Boggy Creek catchment in Victoria, Australia against the available stream gauge and found good agreement for rare and extreme events. Boughton et al. (2002) followed up this study with an assessment of the Avon

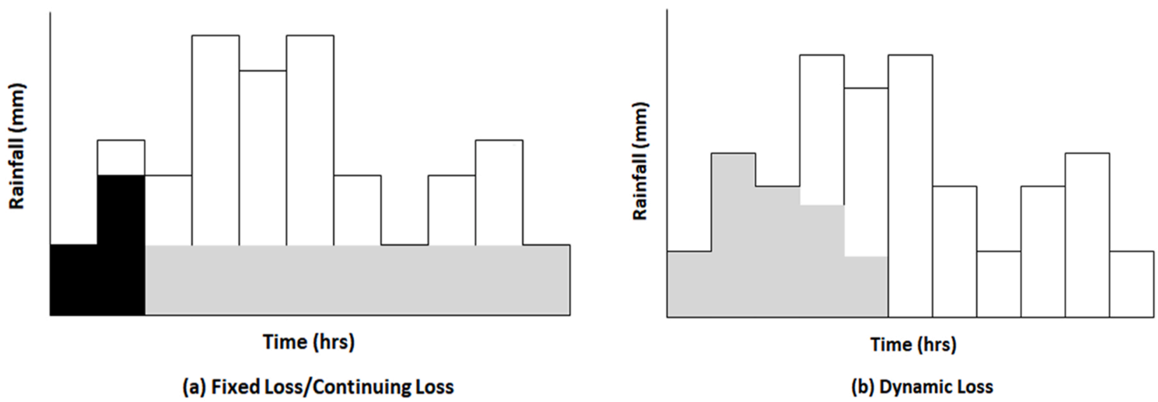


Fig. 1. (a) Rainfall excess (white area) from the commonly used fixed Initial Loss/Continuing Loss model, with the darker hatch representing initial loss and the lighter hatch representing the fixed continuing loss, and (b) Rainfall excess (white area) from a dynamic infiltration loss model with the lighter hatch representing the loss (drawn based on the concept of O'Loughlin et al. (1996).

River and Spring Creek catchments in Victoria, Australia and found that limited rainfall and stream gauge data offered minimal opportunity for calibration. The availability of a sufficient length of continuous rainfall data with a small enough time step to accurately model the catchment of interest is a key limitation of continuous simulation modelling (Viviroli et al., 2009). However, if data is available, continuous simulation modelling is seen as the most rigorous modelling approach for understanding the interaction between variables with joint probability as it directly simulates a long period of climatic conditions (Kavetski et al., 2006).

While there is agreement that continuous simulation models should be used where data permits, there is a disconnect between the modelling software used in the literature and the modelling used by practitioners. The abovementioned studies all adopted the rainfall excess model, the Australian Water Balance Model (Boughton, 2004), and routed the rainfall excess through the this model (Boyd et al., 1996). However, industry practitioners generally use software models that have a graphical user interface, including XPRAFTS

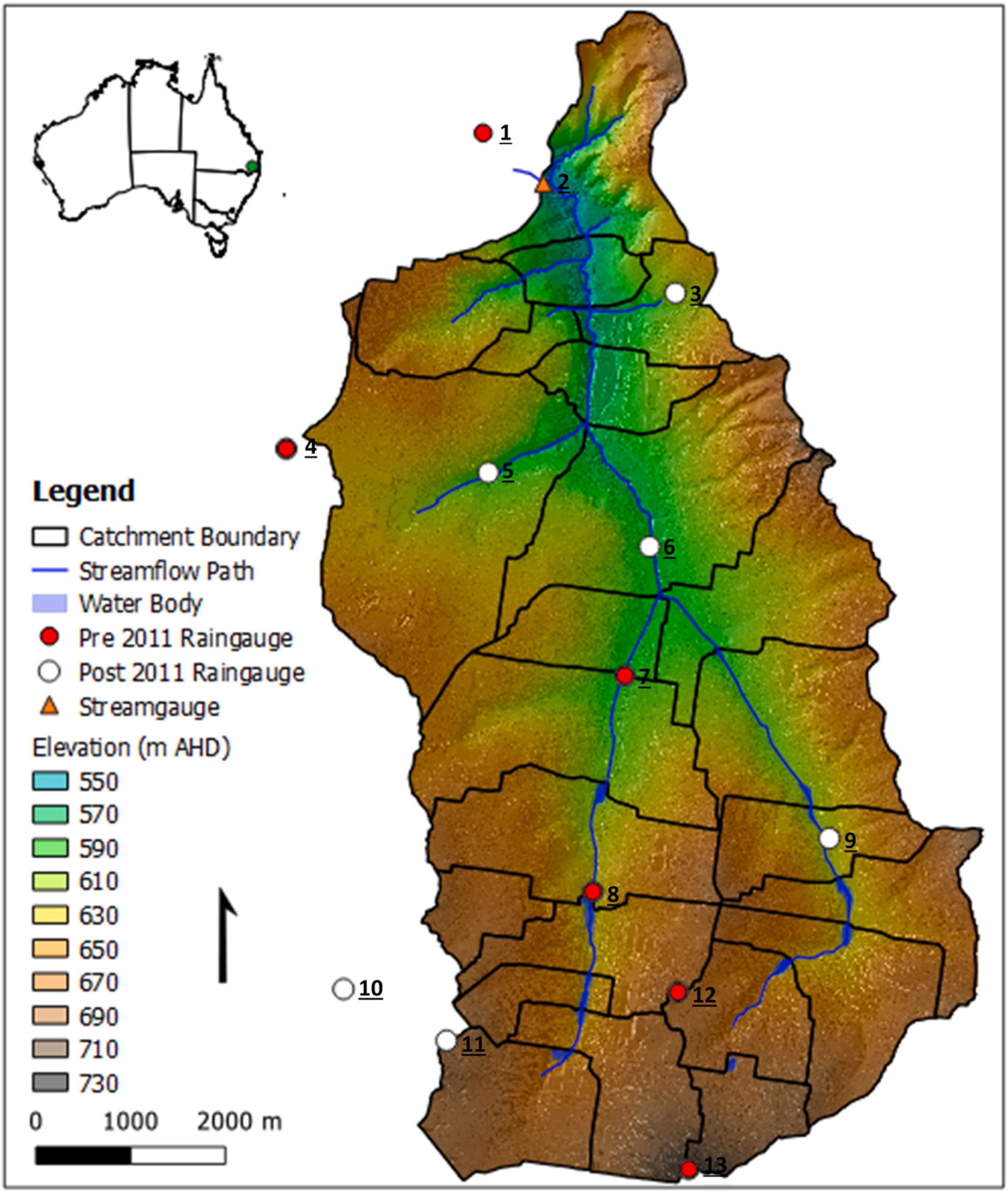


Fig. 2. Gowrie Creek catchment in Toowoomba with key catchment features shown.

(XPSolution, 2008), SWMM (EPA, 2015) or URBS (Carroll, 1994). XPRAFTS is a non-linear runoff routing model used extensively throughout Australia and the Asia Pacific region and is recommended by Australian modelling guidelines (i.e. Australian Rainfall and Runoff (Ball et al., 2019)) for use in catchment hydrologic modelling. Despite its widespread use, the documentation of suitable loss parameters for the ARBM dynamic loss model is limited to a set of parameters presented by Goyen (1981) and another documented in the Australian Capital Territory stormwater design guidelines (Department of Urban Services, 2021), herein referred to as the 'ACT guidelines'. This is a significant gap in research given Australia's tropical, temperate, arid and alpine habitats and climate regimes; all of which have high variability (Head et al., 2014). Limiting practitioners to either the initial loss/continuing loss model or the ARBM model, with parameters based on Goyen's research, leads to increased uncertainty, especially in ungauged catchments where calibration is not possible.

Using continuous simulation models in urban catchments presents several challenges in addition to the lack of documented input loss parameters. The spatial distribution of available rainfall data, as well as the connection of impervious area and hydraulic controls, all influence the timing and volume of runoff at the catchment outlet. For example, Dayaratne and Perera (2004) modelled the urban Giralang catchment in Canberra and found variations in time to peak with a lag of up to one hour between the modelled and observed event as a result of adopting a single representative rain gauge despite a catchment area of only 94 ha. While there is uncertainty in all hydrologic modelling approaches, the level of uncertainty declines with model calibration.

The development of a catalogue of suitable ARBM loss parameters would be a significant achievement for the hydrologic community and would be of particular importance to applied hydrologists working with similar simulation models. The new contribution being offer by this paper is the development of loss parameters for a regional urban catchment and highlight the need for a catalogue of parameters that can be used more broadly by applied hydrologists across other catchments. This research aims to: 1) develop a continuous simulation hydrologic model for an urban catchment, 2) calibrate the ARBM parameters for the Gowrie Creek catchment, and 3) compare these model results to existing documented model parameters to assess the need for further cataloguing of region-specific parameters both within Australia and internationally. Materials and methods used to develop the model are described in Section 2, Section 3 presents the calibration results which are then compared to other documented parameters in Section 4. Finally, our conclusions are presented in Section 5.

2. Materials and methods

2.1. Study area

The Gowrie Creek catchment is a heavily urbanised catchment in the city of Toowoomba, in the state of Queensland, Australia. Toowoomba is considered to be sub-tropical with an average annual rainfall of 700 mm, the majority of which falls over the wet season from November to March. The 51 km^2 catchment, shown in Fig. 2, is twice as long as it is wide, and has a well-defined, heavily modified creek line. Elevations within the catchment range from 750 m Australian Height Datum (AHD) at the southern and eastern extents, to 550 m AHD at the catchment outlet to the north. This significant height difference across the catchment results in sub-catchment areas varying in slope from 3% near the valley, to 9% at higher elevations.

The tributaries within the catchment contain a series of detention basins installed to help reduce flood risk. After the major flooding in 2011, additional flood mitigation measures and monitoring stations were installed. Fig. 2 shows the gauge locations, and Table 1 provides additional details for each gauge. Fifteen rain gauges and one stream gauge currently monitor the catchment, however only six of these were in operation during the 2011 flood event. Since 2016, 11 gauges have been found to provide reliable measurements.

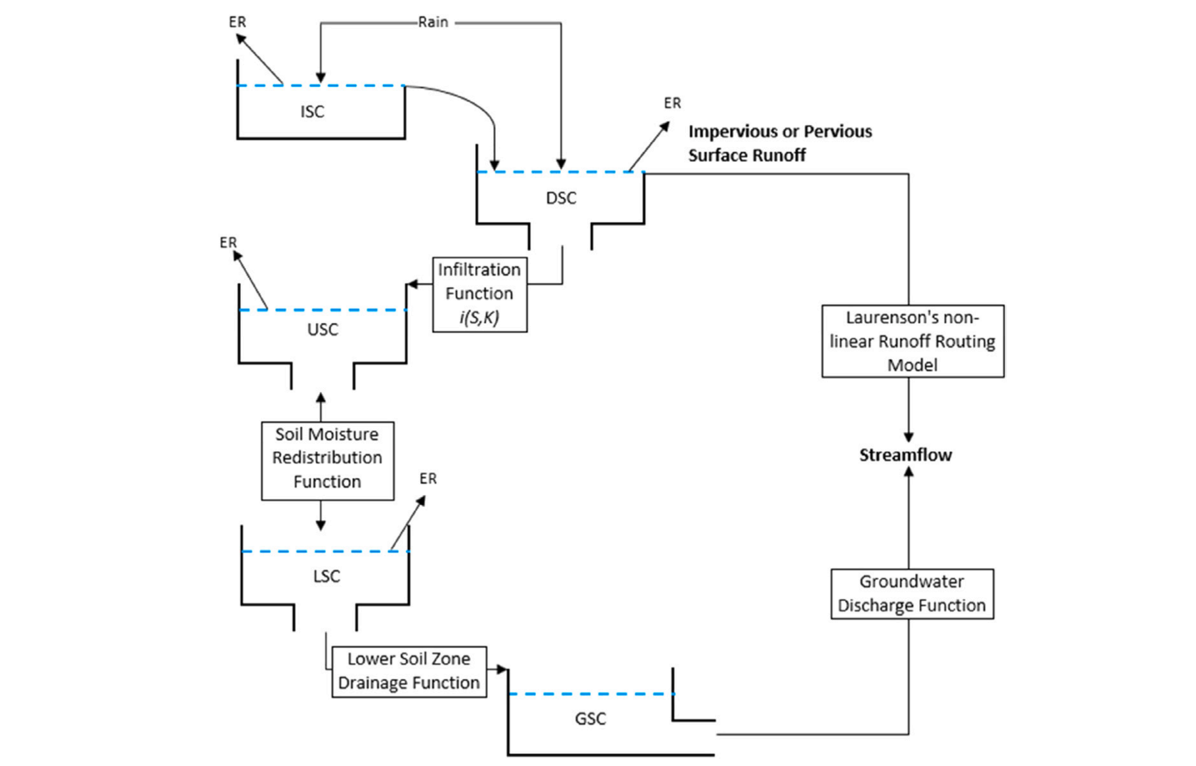
Table 1
Details of the gauges located within the Gowrie Creek catchment and used in this research.

Gauge Details						
Number	Name	Type	Owner	Location		Wet Season with Reliable Rainfall Data
				Easting (m)	Northing (m)	
1	Wetalla	Rain	Toowoomba Regional Council	394414	6957064	2010/11, 2016–2019
2	Cranley	Level	Queensland Government	395431	6955810	1969 - present
3	Dwyer	Rain	Toowoomba Regional Council	396805	6954647	2016–2019
4	Toowoomba Airport	Rain	Toowoomba Regional Council	392716	6952996	2010–2019
5	Black Gully	Rain	Toowoomba Regional Council	394846	6952747	2016–2019
6	Gowrie Creek	Rain	Toowoomba Regional Council	396532	6951986	2016–2019
7	Prescott and Goggs	Rain	Toowoomba Regional Council	396151	6950321	2010/11, 2016–2019
8	Alderley	Rain	Toowoomba Regional Council	395935	6948336	2010/11, 2016–2019
9	Eastern Valley	Rain	Toowoomba Regional Council	398433	6948899	2016–2019
10	Drayton	Rain	Toowoomba Regional Council	393314	6947305	2016–2019
11	Platz	Rain	Toowoomba Regional Council	394404	6946760	2016–2019
12	Middle Ridge	Rain	Toowoomba Regional Council	396868	6947225	2010/11, 2016–2019
13	Gabbinbar	Rain	Toowoomba Regional Council	396983	6945342	2010/11, 2016–2019

2.2. *XPRAFTS model description*

An XPRAFTS semi-distributed hydrological model was used to represent the Gowrie Creek system. The software outputs runoff hydrographs at defined points throughout a catchment based on a user-defined set of catchment characteristics and rainfall data. Key user defined catchment characteristics include sub-catchment area, impervious area and loss.

The pervious area loss within this software is represented by the ARBM dynamic loss approach adapted from the research of Chapman (1968, 1970), and is summarised in Fig. 3. This loss approach can be visualised as a series of interconnected buckets of varying sizes. Rainfall that isn't intercepted by trees or plants (Interception Storage Capacity (ISC)) may be captured in minor surface depressions (Depression Storage Capacity (DSC)). If the rainfall is intense enough, runoff may result from the DSC, otherwise infiltration to the Upper Soil Capacity (USC) occurs. Water is redistributed between the USC and the Lower Storage Capacity (LSC) depending on the capacity available within the bucket. Water from the LSC can then be drained into the Groundwater Storage Capacity (GSC) which contributes to baseflow. The ARBM allows for the simulation of soil moisture depletion through evaporation between rainfall events (Fleming, 1974) with evapotranspiration depleting the ISC, DSC, USC and LSC. Any excess rainfall is routed to the catchment outlet based on the non-linear runoff-routing method developed by Laurenson (1964).



Model Parameters		Model Functions	
Impervious Interception Capacity	ISCIMP	Laurenson's non-linear Runoff Routing Model	Refer Eq. 7 (XPSolution, 2008)
Pervious Interception Capacity	ISCPER	Infiltration Function	Refer Eq. 14 (XPSolution, 2008)
Depression Storage Capacity	DSC	Soil Moisture Redistribution Function	Refer Eq. 17 (XPSolution, 2008)
Upper Soil Storage Capacity	USC	Groundwater Discharge Function	Refer Eq. 23 (XPSolution, 2008)
Lower Soil Storage Capacity	LSC		
Groundwater Storage Capacity	GSC		
Constant Groundwater Recession Rate	KG		
Variable Groundwater Recession Rate	GN		
Evapotranspiration Rate	ER		

Fig. 3. Graphical representation of the ARBM loss model, which forms the basis of runoff generation in the XPRAFTS model, with supporting equations for key components of the runoff generation process (drawn based on the concept of XPSolution (2008).

The ARBM has 15 input parameters. Goyen (1981) found that nine of these are consistent across all land use types, four have a negligible impact on runoff during extreme rainfall events, and two parameters within the infiltration function are highly sensitive: sorptivity (S_0) and hydraulic conductivity (K_0). As sorptivity is a component of hydraulic conductivity, the two parameters are degenerate, meaning they cannot be solved in isolation and, therefore, one of the two parameters has to be fixed to allow the infiltration function to be optimised. For this reason, we fixed sorptivity at 10 mm/min$^{0.5}$, in line with the results of Goyen (1981). In addition to the infiltration function's sensitivity, it is logical that the DSC would be sensitive given that it directly controls the initial conversion of rainfall to runoff. An increasing DSC allows more rainfall to transfer to the USC. Direct measurement of the ARBM parameters is difficult, uncertain, costly and impractical (Mein and McMahon, 1982) and, as a result, was not attempted as part of this research.

2.3. Sub-catchment delineation

The total Gowrie Creek catchment was delineated into 23 sub-catchments (as shown in Fig. 2) based on a 1 m digital elevation model derived from an aerial survey captured in 2010. This data, drainage infrastructure data and overland flow mapping completed in 2018, were supplied by the Toowoomba Regional Council. The urban nature of the catchment required manual catchment delineation as automatic methods could not accommodate the hydraulic impact of roads and underground drainage infrastructure.

While further delineation to increase the number of sub-catchments could have been undertaken, Boyd (1985) showed that for natural catchments of this size, the number of sub-catchments should be at the lower end of the 9–45 range. As the catchment being assessed is urban, a number closer to the middle of the range was targeted. In addition, Rezaei-Sadr (2020) showed that delineating sub-catchments to a size less than 3% of overall catchment offered no improvement in modelling accuracy. The area of the Gowrie Creek sub-catchments is approximately 5% of the overall catchment size.

2.4. Rainfall data and spatial distribution

The hydrologic model requires rainfall data to be applied to each of the delineated sub-catchments. The rainfall data for all 11 rain gauges shown in Fig. 2 was supplied by the Toowoomba Regional Council as a cumulative rainfall total in five-minute increments with the accumulation resetting at the end of each day. There were some clear errors in the rainfall data, including increments of rainfall significantly higher than would be expected, such as rainfall intensities greater than 500 mm/hr with no corresponding stream gauge record. In addition, one of the gauges showed an annual period of no rainfall, suggesting that it had malfunctioned. Periods of erroneous data were removed from the datasets to allow the data to be used.

The rain gauge data needs to be spatially distributed via interpolation to the sub-catchment centroid. Many schemes with varying degrees of complexity have been proposed for the spatial interpolation of rainfall (Thiessen, 1911; Shepard, 1968; Delhomme, 1978). Statistical approaches, such as Kriging, have been found to perform better than interpolation methods such as Thiessen or Inverse Distance Weighted (IDW) to estimate monthly and annual totals (Tabios III and Salas, 1985; Bussières and Hogg, 1989; Creutin and Obled, 1982). However, these previous studies or reviews have focussed on sites with an order of magnitude lower spatial density of rain gauges (0.01–0.001 per km^2) than the Gowrie Creek catchment (0.12–0.22 per km^2). Dirks et al. (1998) conducted a comparison study of three interpolation methods (Thiessen, IDW and Areal-mean) and a statistical method (Kriging) for Norfolk Island, a small catchment with high gauging density similar to the Gowrie Creek catchment. All methods were performed in a comparable manner, and Dirks et al. (1998) concluded that the IDW method was the most appropriate choice for practical use due to its minimal computational effort.

The IDW interpolation method proposed by Shepard (1968), and represented in Eq. 1, assumes that the rainfall observations closer to a position at which rainfall is to be estimated will have a greater influence on the value.

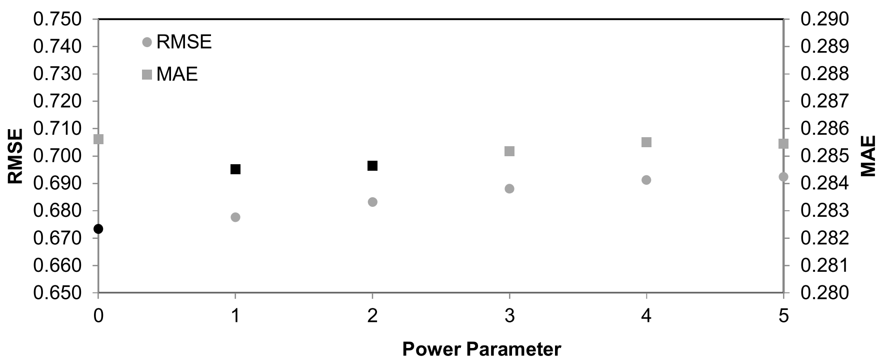


Fig. 4. Error associated with the adoption of a different power parameter in the IDW function, with the best performing variable highlighted in black.

$$Z_p = \frac{\sum_{i=1}^{n} \left(\frac{Z_i}{d_i^{\,p}} \right)}{\sum_{i=1}^{n} \left(\frac{1}{d_i^{\,p}} \right)}. \tag{1}$$

where, Z_p = interpolated rainfall value at location of interest (mm), Z_i = known rainfall value at *i* rainfall station, d_i = distance to *i* rainfall station from location of interest, p = power parameter.

The adopted power parameter compounds the influence of the nearest observation and, as the power parameter approaches infinity, the IDW interpolation approaches that proposed by Thiessen (or nearest neighbour) interpolation. The optimum power parameter was determined using the leave one out or fictitious point method, where a known observation point (we used gauge number 11, Drayton) is left out and the surrounding gauges are used to estimate its rainfall series. The interpolated and observed rainfall series for Drayton were evaluated for their Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE), with a lower error identifying a better fit. Fig. 4 shows that the error decreases with a reduction in the power parameter. The magnitude of the error, however, is not significant enough to suggest that the estimated series is sensitive to the power parameter adopted, and the difference in annual rainfall between a power parameter of one and a power parameter of six is only 60 mm. Dirks et al. (1998) reached a similar conclusion, and suggested that the default power parameter of two would be suitable. Due to the high density of rainfall gauges and the known rainfall variability in the catchment, only the nearest three gauges were used for the interpolation in this research.

2.5. Impervious area

Runoff in a hydrologic model is highly sensitive to the impervious fraction of the catchment (Alley and Veenhuis, 1983) as a greater impervious fraction results in a higher conversion of rainfall to runoff. The Total Impervious Area (TIA) is generally determined using land use mapping and the use of impervious fractions to convert the total area of different land uses to impervious areas only. The fraction of the TIA that is directly connected to stormwater infrastructure, including urban roads and rooves, is known as the Effective Impervious Area (EIA) (Hartcher and Chowdhury, 2017), and it is well established that the EIA is of greater importance than the TIA (Cherkaver, 1975; Beard and Chang, 1979). In this research, the EIA was determined using both a regression analysis and land use mapping.

2.5.1. Determining EIA via regression analysis

The EIA of the Gowrie Creek catchment was estimated through the analysis of rainfall and streamflow records using the method described by Miller (1978). This estimation method has been used extensively in research (Boyd et al., 1993; Chiew and McMahon, 1999). The assessment involves calculating the gradient of the regression between runoff and rainfall, excluding events with runoff from pervious areas as rainfall is linearly proportional to impervious runoff. Rainfall events suitable for the regression analysis were chosen by adopting an inter-event time (as proposed by Lloyd, 1990, Aryal et al., 2007 and Rodríguez-Blanco et al., 2012) of two hours to separate individual storms, and were then further filtered to consider a minimum rainfall depth of 2 mm and a maximum rainfall duration of 10 h. A regression analysis of the remaining events is shown in Fig. 5. The gradient of the line indicates an EIA fraction of 0.18 or 18%.

2.5.2. Determining EIA via land use mapping

Catchment planning mapping was used to estimate the Total Area (TA) of different land uses, including Urban Areas (UA), commercial, roads, other development types and open space. With the TA of each land use known, ratios of TA to TIA and TIA to EIA for each land use, as detailed in the Queensland Urban Drainage Manual (IPWEAQ, 2016) and presented in Table 2, were used to determine the overall catchment EIA of 41%. This is significantly higher than the regression-based EIA (18%) and is likely due to the relatively unknown EIA to TIA ratio of differing road types as well as a likely overestimation of the EIA to TIA ratio of UAs due to the age of catchment development. The land use mapping method also found the EIA to be 87% of the UA, which doesn't reflect the

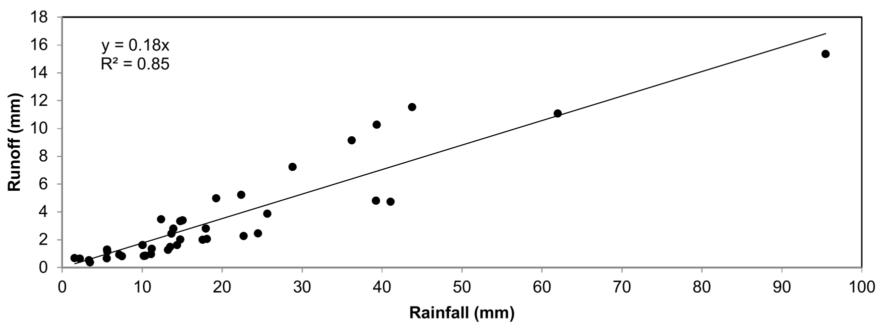


Fig. 5. Runoff vs Rainfall for over 40 storms selected (represented by the dots) using the method of Miller (1978) to determine the effective impervious area as indicated by the gradient of the line (0.18). The regression line indicates a good level of fit.

Table 2
Ratios of Total Area to Total Impervious Area, and Total Impervious Area to Effective Impervious Area for each land use within the Gowrie Creek catchment, used to determine the Effective Impervious Area via land use mapping.

Land use	TA (ha)	TIA/TA (%)	TIA (ha)	EIA (ha)	EIA/TIA (%)
Urban Area (UA)	2417	65	1571	864	36
Commercial	369	90	333	283	77
Road Reserve	979	70	685	685	70
Other Development	523	50	262	262	50
Open Space	811	0	0	0	0
Total	**5099**		**2850**	**2093**	**41**

findings of Phillips et al. (2014) who found that across eight catchments it was consistently around 35% of the UA. This compares well to the regression-based method which was 38% of the UA. The land use mapping method is therefore overestimating the EIA for the catchment and the regression analysis best represents the effective impervious area of the catchment.

While the land use mapping method overestimated the EIA, it did allow disaggregation to a sub-catchment level. We, therefore, adopted the impervious area ratios for each sub-catchment from the land use mapping method while achieving an overall EIA equivalent to the regression analysis (18%). The results of this analysis for each sub-catchment was used as the impervious component of the hydrologic model and is shown in Fig. 6.

2.6. Calibration and validation

2.6.1. Principles

A two-stage calibration approach, as performed by Dayaratne (2000) and Broekhuizen et al. (2020), was utilised. Stage 1 calibrated small historic storm events resulting in runoff from impervious areas only. This was followed by Stage 2, in which larger historic storm events that included pervious area runoff were calibrated.

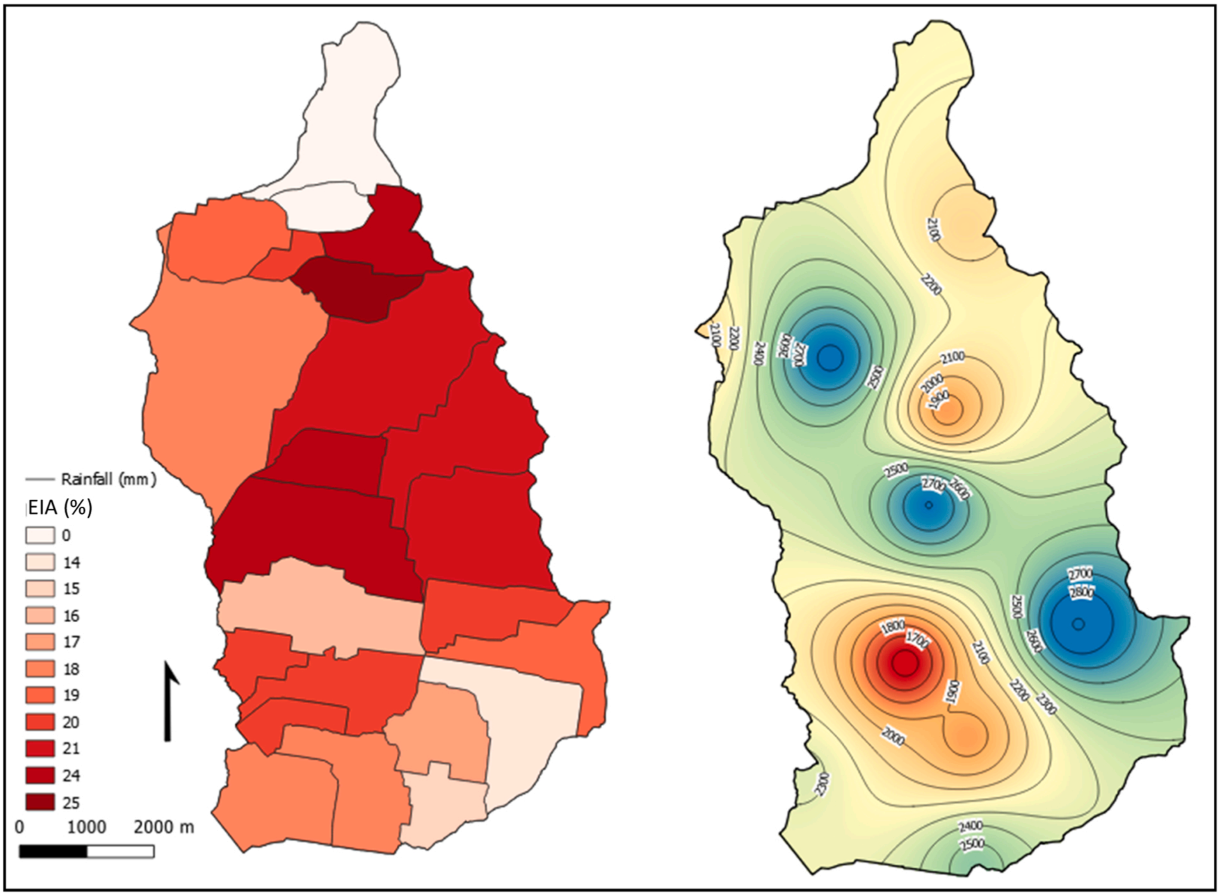


Fig. 6. Spatial variation of impervious area throughout the Gowrie Creek catchment (left) and total rainfall isohyets from 2016 to 2019 (right).

For the Stage 1 calibration, hydraulic conductivity (K_o) and storage capacities (DSC, USC and LSC) were adjusted until there was no runoff from the pervious area. This effectively set a lower limit for these parameters. For the Stage 2 calibration, K_o and DSC were adjusted with the aim of making the model's output hydrograph match the observed. The parameters determined via calibration were then used to run the model for several validation events to ensure that parameter performance was consistent across a range of observed events.

To determine calibration appropriateness, the performance statistics detailed by Moriasi et al. (2007) and summarised in Table 3 were used. The Nash-Sutcliffe Efficiency (NSE) is a coefficient commonly used to determine the predictive power of a hydrologic model (McCuen et al., 2006), with a coefficient of 1.0 representing a perfect fit. The RMSE-observation standard deviation Ratio (RSR) is a measure of the spread of model results relative to the observed results. RMSE values less than half the standard deviation are generally considered to indicate good model prediction (Singh et al., 2005), therefore the lower values of both RMSE and, in turn, RSR represented a good model fit. The percentage of bias (PBIAS) is a measure of the tendency of the modelled result to be above or below the observed result (Of et al., 1999), with a PBIAS of 0 representing a perfect fit. Peak flow and volume difference were also assessed. Peak flow is an important hydrologic criterion and a key input for hydraulic design.

2.6.2. *Historic storm events*

The continuous simulation model was run for the complete series of available and reliable historic rainfall data, and individual storm events were selected for calibration/validation. The selected storm events included 13 events during the 2010/11 wet season as well as the wet seasons between 2016 and 2019, as summarised in Table 4.

There was a distinct lack of large (Stage 2) calibration/validation flood events for the study catchment. Inspection of the stream gauge data at the outlet of the catchment highlighted that the 2010/11 wet season was the last significant wet season for the catchment. There were no subsequent wet seasons with events exceeding the peak flow of Event 13. No reliable rainfall data prior to the 2010/11 wet season was available for use.

3. Calibration/validation results and discussion

3.1. *Stage 1 calibration*

Eleven events were assessed as part of the Stage 1 calibration/validation process, ranging in observed peak flow from 9 m^3/s to 79 m^3/s. The calibration process confirmed that the DSC was a key calibration parameter as the volume of runoff was sensitive to this parameter. This is evident in Fig. 7, which shows the difference (%) between the volume of modelled runoff to the volume of observed runoff with an increasing DSC. The results also show that Events 3 and 4 were suitable for use in the calibration process due to the notable change with increasing DSC.

Comparing the performance statistics of NSE, PBIAS, peak flow difference and RSR for Events 3 and 4 (Fig. 8), a DSC of 7 mm clearly resulted in the best fit. Visual inspection of the model discharge against the observed discharge at the catchment outlet (Fig. 10) also suggests the model is representing the observed flows well. The DSC of 5 mm performed best for Event 4 in terms of PBIAS and RSR, but performed very poorly in NSE and peak flow difference for Event 3, suggesting that it is not suitable for other events. When calibrating the DSC, a K_o of 0.3 mm/min was adopted. The sensitivity of the model to K_o was also investigated, with the results (presented in Fig. 9) showing that 0.3 mm/min is optimum.

When adopting a DSC of 7 mm and K_o of 0.3 mm/min for the nine validation events, six performed satisfactorily, with NSE values ranging from 0.50 to 0.92 (NSE results for all events are presented in Fig. 13). While NSE is considered a key performance indicator, peak flow and volume were also critical to further justify the impervious fraction and spatial distribution of rainfall. Of the three Stage 1 events that performed unsatisfactorily, all produced peak flows within 20% of the observed, and two produced volumes within approximately 30% of the observed. These results suggest that the adopted impervious fraction is representative of the catchment, as a higher impervious fraction would result in a higher peak flow and increased volume. In addition, visual inspection of the Stage 1 calibration results showed that the shape of the modelled hydrograph matched the observed, suggesting the interpolated rainfall is representing the ungauged rainfall.

It was expected that, given the relatively small magnitude of observed flow used in the Stage 1 events, some results would be unsatisfactory. Smaller flow events often correspond to localised storms that may only fall over some sub-catchments but are intense enough to produce runoff from those sub-catchments. Distributing the recorded rainfall (if it did in fact fall over the rain gauge) over the entire sub-catchment may, therefore, not reflect the nature of the event. Despite this, the relatively small number of unsatisfactory

Table 3
Performance ratings for different model statistics, including the Nash-Sutcliffe Efficiency, the RMSE-observation standard deviation ratio, the Percentage of Bias, and the Peak flow/Volume difference as detailed in Moriasi et al. (2007).

Performance Rating	Model Statistic			
	NSE	RSR	PBIAS	Peak Flow/ Volume Difference
Very Good	0.75 – 1.0	0.0 – 0.5	< +− 10	
Good	0.65 – 0.75	0.5 – 0.6	+ −10 – + −15	
Satisfactory	0.50 – 0.65	0.6 – 0.7	+ −15 – + −25	+ −20
Unsatisfactory	< 0.5	> 0.7	> +− 25	> +− 20

Table 4
Chosen Calibration and Validation events.

Event Number	Start Date	Start Time (hrs)	End Time (hrs)	Calibration	Validation
Stage 1					
1	December 16, 2010	1400	1800		x
2	December 11, 2010	1000	2100		x
3	December 19, 2010	0900	2030	x	
4	January 2, 2011	1800	2230	x	
5	October 2, 2017	1230	0500		x
6	October 15, 2017	1230	2100		x
7	October 21, 2017	0730	1830		x
8	October 26, 2017	1700	1930		x
9	October 12, 2018	1700	0400		x
10	October 21, 2018	1300	1800		x
11	October 24, 2018	1900	2200		x
Stage 2					
12	December 27, 2010	1000	1530	x	
13	January 10, 2011	1230	1700		x

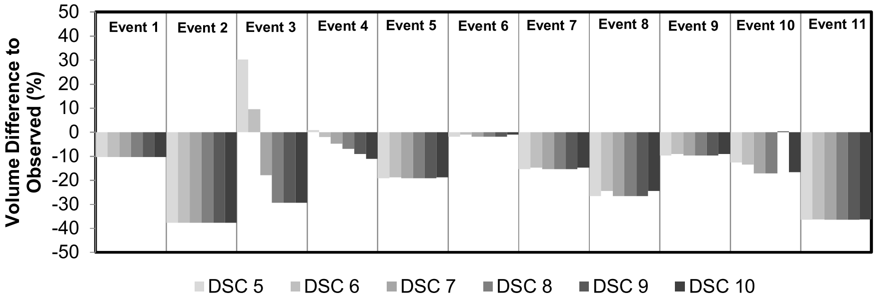


Fig. 7. Difference in volume between modelled and observed Stage 1 events with increasing DSC (in mm). The large variability in volume difference shown in Event 3 and Event 4 make them suitable for calibration.

validation results suggests that the model represents the hydrologic response of the catchment well.

3.2. Stage 2 calibration

As expected, the Stage 2 calibration was sensitive to both DSC and K_0. However, through the Stage 2 calibration, it was found that the impact of DSC and K_0 on the calibration process was similar; a decreasing DSC or K_0 value resulted in an increase in peak flow. The K_0 value of 0.3 mm/min adopted as part of the Stage 1 calibration to limit pervious area runoff, provided the lower limit for calibration as part of Stage 2.

The DSC parameters assessed as part of Stage 1 were also assessed in Stage 2. The results in Fig. 12 show that the NSE and peak flow generally increased with decreasing DSC, however, Event 12 appeared to reach a maximum NSE when DSC was near 7 mm, and the peak flow increase plateaued when DSC approached 5 mm. In addition, the Stage 1 calibration highlighted that a DSC less than 6 mm resulted in a very poor calibration for Event 3, suggesting that the relatively improved performance of Event 12 with decreasing DSC may be overstated.

Given that the results presented in Fig. 11 show that the model generally underestimated the recorded peak flow, increasing the K_0 value above 0.3 mm/min would only serve to reduce the peak flow further. Comparing the modelled hydrographs to the observed flows (Fig. 12) further highlights how both events, while visually achieving the hydrograph shape, underestimated both volume and peak flow. Event 13 seems to show an observed second smaller peak approximately one hour after the initial peak that wasn't apparent in the model. While the model did show a second peak, it was much closer to the first peak, resulting in a broadening out of the hydrograph. It is known that during this event, the stream gauge malfunctioned, and the results were interpolated from field observations after the event. It is likely that this interpolation overestimated the nature of the event and was the cause of the discrepancies shown.

3.3. Other ARBM parameter sensitivity

The ARBM parameters of DSC and K_o were identified by both the literature and this research as the most sensitive in estimating the pervious area loss. A sensitivity analysis of the other ARBM parameters, as defined in Fig. 3, was undertaken to ensure that they were also optimised as part of the two-stage calibration approach. The sensitivity analysis reduced the other ARBM parameters by 20%, while keeping the DSC and K_o at their calibrated values, with the results presented in Fig. 13 (Stage 1 calibration events) and Fig. 14

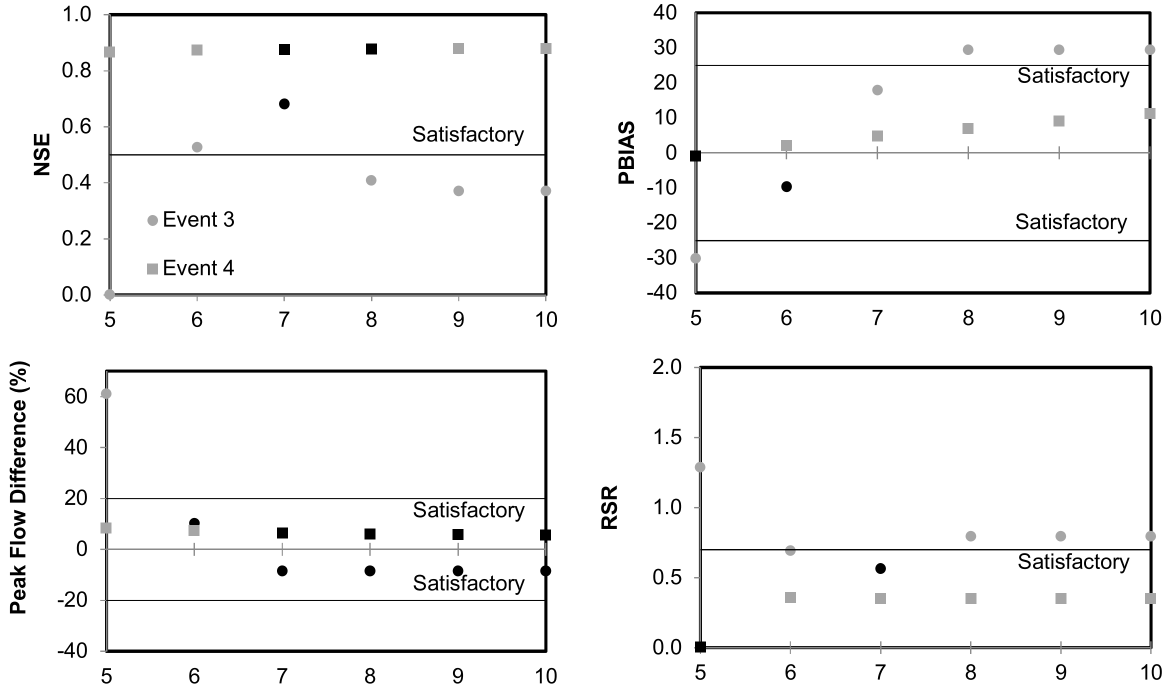


Fig. 8. Statistical performance of Events 3 and 4 with increasing DSC (in mm). The optimum DSC for each statistic is highlighted in black, and shows that a DSC of 7 mm performed best in terms of NSE and RSR, while still performing satisfactorily in both peak flow difference and PBIAS. The satisfactory text is located either above or below the line to show where the satisfactory limits are.

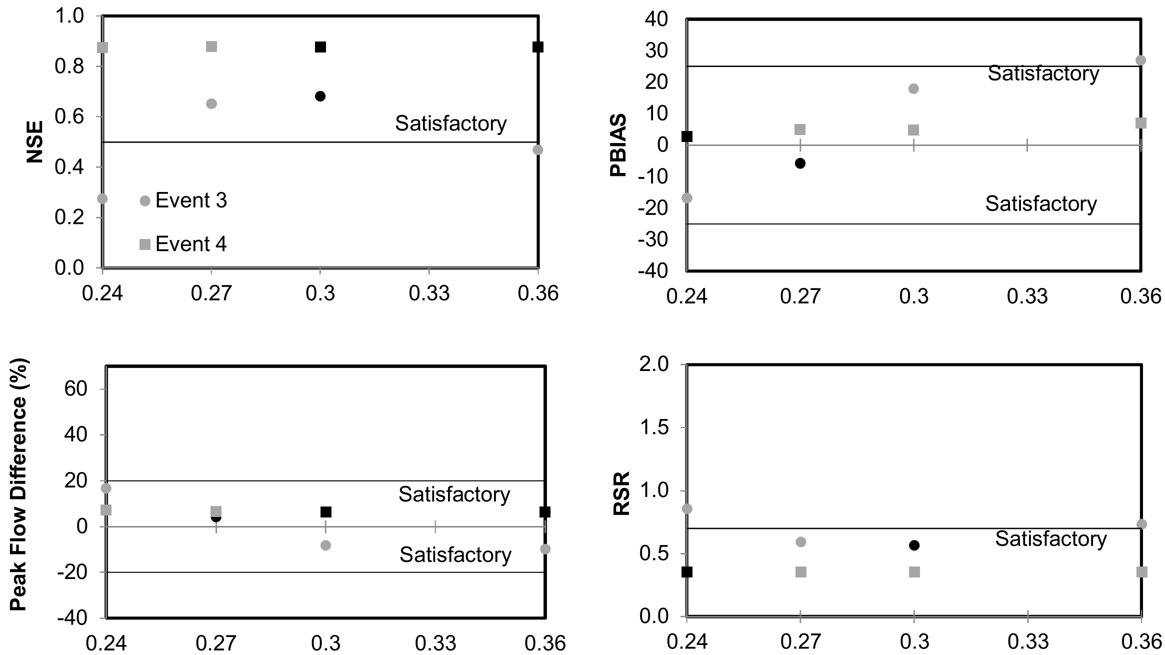


Fig. 9. Statistical performance of Events 3 and 4 with increasing K_o. The optimum K_o for each statistic is highlighted in black, and shows that a K_o of 0.3 mm/min performed best in terms of NSE and RSR, while still performing satisfactorily in both peak flow difference and PBIAS. The satisfactory text is located either above or below the line to show where the satisfactory limits are.

(Stage 2 calibration event). The sensitivity analysis confirmed that the other ARBM parameters were optimised, as one of the Stage 1 calibration events (Event 4) produced pervious area runoff. In addition, there was an insignificant increase in the peak flow/volume in the Stage 2 calibration event. It is also worth noting that increasing the sensitivity of the other ARBM parameters was not needed as the

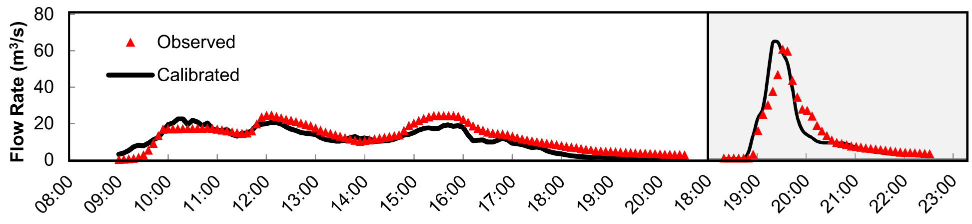


Fig. 10. Comparison of modelled hydrograph to observed values for Stage 1 calibration Event 3 (left) and Event 4 (right).

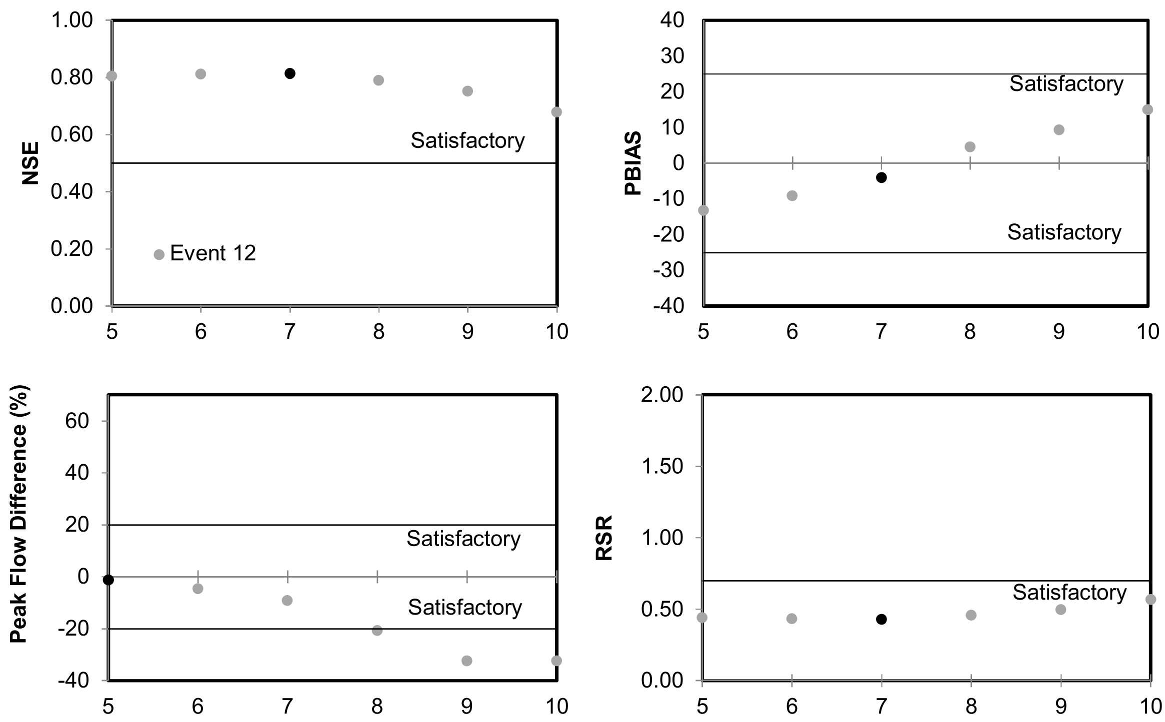


Fig. 11. Statistical performance of Event 12 with increasing DSC. The optimum DSC for each statistic is highlighted in black. The satisfactory text is located either above or below the line to show where the satisfactory limits are.

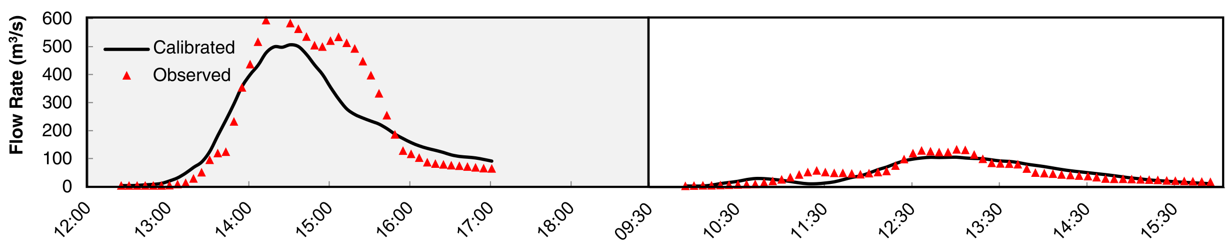


Fig. 12. Comparison of modelled hydrograph to observed values for Stage 2 calibration Event 13 (left) and validation Event 12 (right). The calibration performed well with the modelled peak flow within 10% of the observed.

parameters had already been reduced to ensure no pervious area runoff from the Stage 1 events. Increasing the other ARBM parameters by 20% would produce the same result as the calibrated parameters for the Stage 1 events, while potentially reducing the peak flow/volume in the Stage 2 events. (Fig. 15).

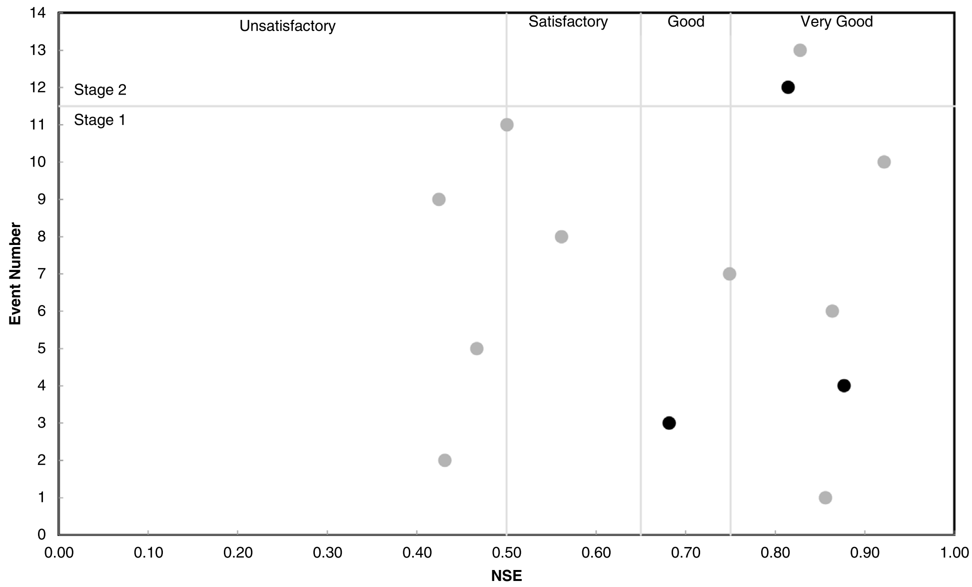


Fig. 13. NSE performance of all 13 storm events with calibration events highlighted in black.

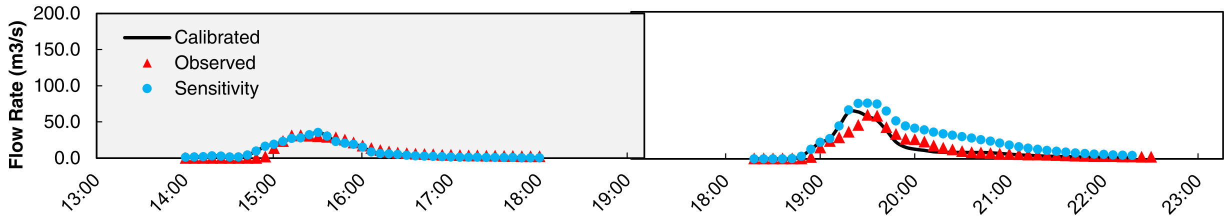


Fig. 14. Hydrographs comparing the calibrated and sensitivity ARBM parameters to the observed flow for Event 1 (left) and Event 4 (right). The results showed that while Event 1 was no sensitive to the change in ARBM parameters, Event 4 was highly sensitive, with a noticeable increase in both peak flow and volume. The volume increase is likely the result of pervious area runoff that wasn't evident in the observed hydrograph based on the steeper gradient of the falling limb.

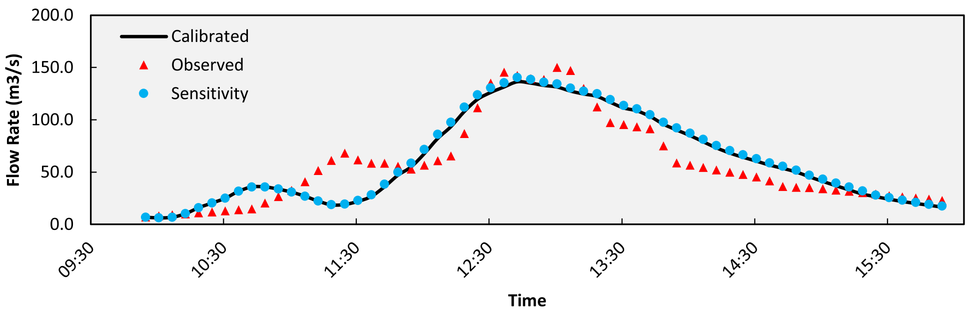


Fig. 15. Hydrograph comparing the calibrated and sensitivity ARBM parameters to the observed flow for Event 12. The results showed that Event 12 was not sensitive to the change in ARBM parameters.

4. Discussion on loss parameters and calibration challenges

4.1. Loss model parameter comparison to literature

The calibrated ARBM parameters determined from this study are presented in Table 5. The parameters recommended by Goyen (1981) for residential lawns, determined through calibration of a number of catchments in Canberra, along with parameters documented in the ACT guidelines (Department of Urban Services, 2021) are also shown. While the infiltration parameters (S_0 and K_0) are somewhat comparable, the storage capacities are significantly different, most notably the DSC. This result is surprising as Goyen's

Table 5
Calibrated ARBM parameters for the Gowrie Creek catchment and Comparative Values from Goyen (1981) and the ACT guidelines.

Parameter	Description	Gowrie Creek	Comparative Value		Unit
			Goyen (1981)	ACT guidelines	
Storage Capacities					
CAPIMP	Impervious	2	0.5	0.5	mm
ISC	Interception	3	1.0	1.0	mm
DSC	Depression	7	1.0	1.0	mm
USC	Upper Soil	40	12.5	25	mm
LSC	Lower Soil	70	25	50	mm
GSC	Groundwater	0	0	0	mm
Infiltration					
S_0	Dry Sorptivity	10	10	3	$mm/min^{0.5}$
K_0	Hydraulic Conductivity	0.3	0.84	0.33	mm/min
LDF	Lower Soil Drainage Factor	0.1	0.05	0.05	–
KG	Constant Groundwater Recession Rate	0.94	0.94	0.94	–
GN	Variable Groundwater Recession Rate	1.0	1.0	1.0	–
ER	Evapotranspiration	7.0	10	10	mm/hr

parameters are based solely on pervious area, whereas our study has some impervious areas included in the pervious area component of the model due to the impervious area component reflecting EIA only. This is a key contribution of this research and illustrates the need to develop a catalogue of ARBM parameters that can be used by applied hydrologists when investigating catchments with similar geographical or climatic conditions.

Adopting values in line with Goyen (1981) or the ACT guidelines resulted in runoff from the pervious areas in the Stage 1 events, and given the high proportion of pervious area within the catchment, the discharge flow rate and volume at the outlet of the catchment were significantly higher, as highlighted in Fig. 16.

4.2. Overcoming calibration challenges

Currently continuous simulation modelling in urban catchments is rarely undertaken in practice or reported in the literature. The challenges faced in the development of our continuous simulation model for the Gowrie Creek catchment demonstrate the reasons for its limited use.

Rainfall data provided for the catchment seemed reasonable on paper however, the rainfall isohyets provided in Fig. 4 show the significant spatial variation across what would be considered a relatively small catchment. The use of the IDW method of interpolation seemed to overcome this issue as the shape and magnitude of the hydrographs presented generally reflected the observed. However, to achieve the results presented, a lag of 30 min had to be applied to the modelled output. It is believed that this lag is not uncommon given the previously mentioned issues faced by Dayaratne and Perera (2004). Inspection of the input data highlighted that the lag is likely to be a combination of rainfall being recorded regularly (five minutes) while stream gauge records can have timesteps of up to 30 min. In addition, the hydrologic model's response to rainfall, on impervious areas in particular, may not represent real conditions, especially for small events.

The amount of impervious area, in particular EIA, is a vital input to an urban hydrological model. While it is difficult to directly source this data, the methods detailed in the study seem to have produced a value that represents the catchment well, given that 10 of the 11 Stage 1 calibration events produced peak flows within 20% of the observed. The lack of significant rainfall events in the catchment within the period of data available suggests that smaller, impervious runoff only events may form a critical part of a flood frequency analysis.

It is recognised that the lack of rainfall events does impact the validity of the Stage 2 calibration. Investigation of the stream gauge data shows that a peak flow above that of calibration Event 12 has only been recorded seven times, with all but two of these occurring prior to 2010, and one being validation Event 13. There was an event recorded early in January 2011, unfortunately the rain gauge

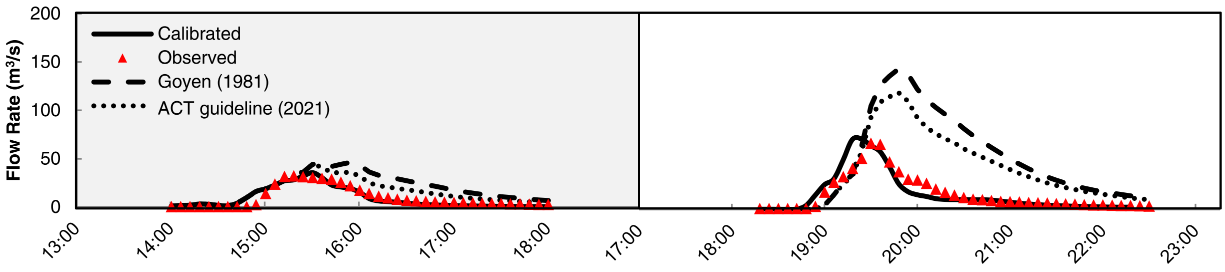


Fig. 16. Hydrographs comparing the calibrated, Goyen (1981) and the ACT guidelines ARBM parameters to the observed flow for Event 1 (left) and Event 4 (right).

data provided did not cover the full extent of the event and was, therefore, not used in the calibration. However, this does not detract however from the findings of this research and highlights the need for further cataloguing of ARBM parameters for wider adoption of continuous simulation modelling by applied hydrologists.

5. Conclusions

Predicting the hydrologic response of urban catchments to extreme rainfall events is fundamental to making informed engineering and planning decisions associated with urban development, flood mitigation and disaster management. Improving the uncertainty in all hydrologic modelling requires careful model calibration including the utilisation of appropriate model parameters for the specific catchment.

This paper focussed on determining catchment specific loss parameters for the Gowrie Creek catchment in Toowoomba, Australia as part of the model calibration. It developed and calibrated a continuous simulation hydrologic model for an urban catchment and then determined the ARBM parameters suitable for the Gowrie Creek catchment. These parameters have been documented within this paper and offer new values for the possible use by applied hydrologists dealing with similar catchment and climatic conditions. We then simulated other documented ARBM parameters to highlight the need for further cataloguing of suitable parameters both within Australia and internationally.

Despite the challenges discussed, this research effectively calibrated an urban continuous simulation model using modelling software widely used in industry. The performance of the model, in particular the NSE and peak flow, showed that the model could produce suitable design hydrographs for the catchment if a sufficient length of rainfall data was available. It also showed that loss model parameters available in the literature, in particular those provided by Goyen (1981), may significantly overestimate peak flows for small events. This research has provided industry with an additional set of loss parameters that may be applicable to other urban catchments whilst highlighting the gap that is preventing widespread industry adoption of continuous simulation models like XPRAFTS. By documenting a new set of parameters, this research may help improve confidence in the modelling of similar ungauged catchments, or at least highlight the variability likely to be experienced in urban catchments throughout Australia. This research also highlights that assumptions around impervious fractions and catchment losses may be overestimating urban catchment runoff.

CRediT authorship contribution statement

I.W. Brown – Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **K. McDougall** - Conceptualization, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Md. Jahangir Alam** – Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision. **R. Chowdhury** – Methodology, Validation, Writing – original draft, Supervision. **S. Chadalavada** – Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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