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Article

An Investigation of Modelling Accuracy Needs for Urban Design Flood Estimation

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Abstract: Flood Management remains a major problem in many urban environments. Commonly, catchment models are used to generate the data needed for estimation of flood risk; event-based and continuous-based models have been used for this purpose. Use of catchment models requires calibration and validation with a calibration metric used to assess the predicted catchment response against the recorded catchment response. In this study, a continuous model based on SWMM using the Powells Creek catchment as a case study is investigated. Calibration of the model was obtained using 25 selected events from the monitored data for the catchment. Assessment of the calibration used a normalised peak flow error. Using alternative sets of parameter values to obtain estimates of the peak flow for each of the selected events and different accuracy criteria, the best datasets for each of the accuracy criteria were identified. These datasets were used with SWMM in a continuous simulation mode to predict flow sequences for extraction of Annual Maxima Series for an At-Site Flood Frequency Analysis. From analysis of these At-Site Flood Frequency Analyses, it was concluded that the normalised peak flow error needed to be less than 10% if reliable design flood quantile estimates were to be obtained.

Keywords: urban; flood; calibration; model; SWMM; continuous

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1 Introduction

An increasing portion of the world's population now lives in urban environments; [1] estimated that 55% of the world's population currently live in urban areas and that, by 2050, that portion will have grown to 68%. Management of water in these environments to satisfy the needs of this increasing urban population is a problem that many managers are encountering. Of the many water management issues in urban catchments, estimation of the magnitude and likelihood of flood events is a common issue. There are many different issues requiring design flood estimation; see, for example, [2], [3], and [4] who present different aspects of the need to estimate design floods in urban environments. Nonetheless, the fundamental need for all issues is data enabling estimation of the magnitude and likelihood of flood events.

Data for estimating flood quantiles (i.e. the flood magnitude and its likelihood) can be obtained from catchment monitoring or catchment modelling with these data sources being complementary rather than competitive. Numerous alternative approaches have been developed for determination of the flood risk; [5] discusses these approaches and categorises the approaches considered as being either "analysis of streamflow data" or "rainfall based"; herein, similar categories are used although they are referred to as "catchment monitoring approaches" and "catchment modelling approaches".

The absence of monitored data in many urban environments has resulted in the necessary data being obtained predominantly from the use of catchment modelling. Two alternative approaches for catchment modelling have been developed (see, for example, [6]). Irrespective of the approach used, the application of catchment modelling requires the calibration and validation of the catchment model. Many different techniques have been proposed for calibration and validation of catchment models; these techniques include Bayesian (e.g. [7], [8]), Direct Search (e.g. [9]), Genetic Algorithms (e.g. [10], [11]), Shuffled Complex Evolution (e.g. [12]), and Particle Swarm Optimisation (e.g. [13]).

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Consistent among these techniques is the need to define a calibration metric suitable for defining accuracy of the predicted catchment response. Discussion of calibration metrics can be found in [14], [15], and [16]). These discussions have focussed on the calibration metrics and have rarely addressed the related question of what value of calibration metric needs to be achieved for prediction of reliable catchment response data. This question is addressed herein through consideration of the required accuracy in prediction of single event hydrograph peak flows and the subsequent use of the parameter values for prediction of reliable flow sequences suitable for an At-Site Flood Frequency Analysis in an urban environment.

2 Powells Creek Catchment

2.1 Catchment Description

The Powells Creek catchment, sometimes referred to as the Strathfield catchment, is an 841ha catchment situated 10km west of Sydney's central business district. The location of this catchment is shown in **Figure 1**. The catchment lies within the Sydney suburbs of Homebush West, North Strathfield, Rookwood and Strathfield, and is administered by the local government areas of Strathfield, Canada Bay and Auburn. The drainage network comprises a closed piped system that opens out to a lined channel and then into the Parramatta River. The main open channel was established in 1892 ([17]) while the closed pipe system was established in the 1920's.

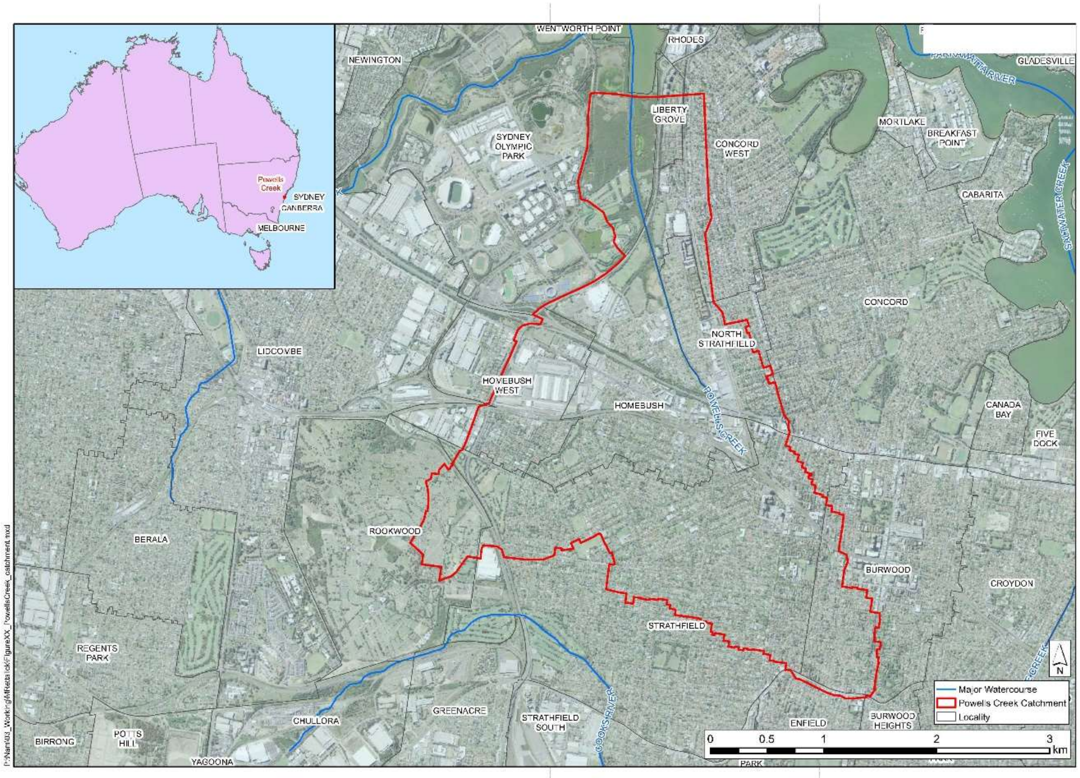

Figure 1. Powells Creek Catchment

Shown in **Table 1**are the types and proportions of alternative land uses within the catchment as outlined by [17]. In general, the catchment is classified as low-lying, with gentle slopes between 4% and 5.5%. The maximum elevation is 40m AHD while the minimum elevation is governed by the tidal regime of the Parramatta River.

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Table 1. Land Use in the Powells Creek Catchment (after Meutia, 2002)

LAND USE	AREA (ha)	PROPORTION (%)
Residential	504.7	60.0
Industrial	40.5	4.8
Commercial	27.1	3.2
Open Space	61.1	7.3
Special Use	208.1	24.7

2.2 *Available Data*

The School of Civil and Environmental Engineering at The University of New South Wales operated a gauging station on the main Powells Creek Stormwater Channel during the period 1958 to 2005. The catchment area draining to this gauging station consists of only 2.3km^2 of the total catchment area. In addition, rainfall was monitored at the centroid of the monitored catchment and, for a short period, at the gauging station itself.

Table 2. List of Events

Date	Rainfall (mm)	Flow (m^3/s)	Duration (hrs)	Flow AEP[1] (1 in years)
May 1981	87.0	9.025	63	0.40
October 1981	61.5	14.31	21	1.70
January 1982	19.5	8.908	4	0.40
March 1982	44.0	18.79	4	1.95
March 1983	113.3	21.12	78	4.19
November 1984	179.5	21.16	5	4.67
October 1985	16.2	11.89	3	1.51
February 1986	57.5	19.68	4	3.79
December 1987	34.8	11.30	16	1.27
12 April 1988	53.4	8.656	18	0.37
28 April 1988	328.9	22.36	59	5.29
July 1988	120.3	22.90	38	6.09
April 1989	17.5	7.742	4	0.30
6 March 1990	23.1	10.14	5	0.47
18 March 1990	55.2	22.94	5	7.18
July 1990	152.3	10.30	74	0.48
February 1992	321.6	16.68	50	2.28
January 1993	16.0	9.516	3	0.44
April 1994	95.6	15.16	40	1.57
2 March 1995	31.4	12.24	14	0.70
15 March 1995	57.2	5.282	25	0.17
September 1995	153.2	13.16	22	1.16
January 1997	52.2	6.871	32	0.24
June 1997	18.0	6.588	4	0.21
October 1997	46.0	5.706	9	0.18

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From this data, 25 events in the documented period post 1980 were extracted for calibration of the catchment model. Details of these events are presented in **Table 2** and in **Figure 2** where the extracted events are plotted on a flood frequency diagram. As shown in that figure, the largest recorded events occurred prior to 1980. Selection of events only post 1980 was related to the availability of reliable precipitation data over the catchment. The lack of these larger events will be reflected in the estimated flood quantiles obtained from the At-Site Flood Frequency Analyses undertaken as part of this study.

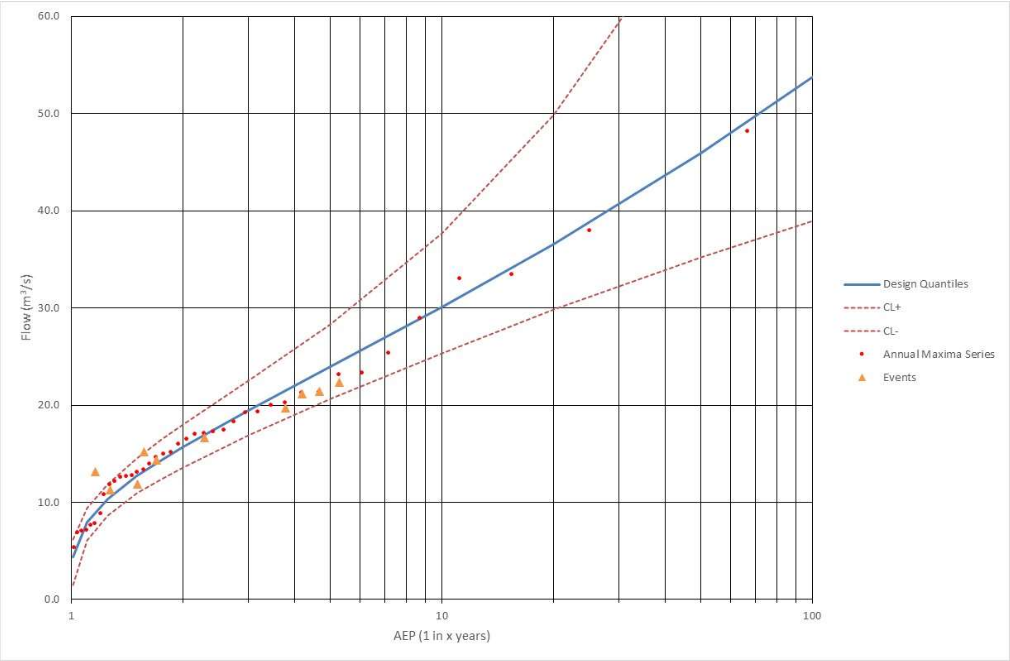

Figure 2. Events shown on the FFA for the Gauging Station

2.3 Catchment Model

There are numerous alternative software systems suitable for process-based modelling of existing and potential urban catchments. After considering these alternatives, the SWMM system ([18]) was used herein for data generation. This model has received extensive application; see, for example, [19] and [20] for recent applications.

SWMM is a physically distributed catchment modelling system consistent with the conceptual components of a catchment modelling system proposed by [21]; these components are:

- Generation – this component of the modelling system is concerned with spatial and temporal models necessary to convert point data into spatial-temporal data. An example is the conversion of point rainfall records into spatial rainfall models over the catchment at suitable resolution.
- Collection – the component of the model where those processes concerned with the generation of runoff are dominant. This is the hydrologic component of the modelling system.
- Transport – the component of the model where the processes concerned with the movement of water through the drainage system are dominant. This is the hydraulic component of the modelling system.
- Disposal – the component of the modelling system concerned with the discharge of water from the drainage system into receiving waters.

As a comprehensive catchment modelling system, SWMM can be operated in either an event mode, or a continuous mode. For model calibration, SWMM was operated in event mode; in other words, the model was calibrated to the 25 events presented in **Table 2**. However, for prediction of

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design flood flows, SWMM was operated in continuous mode to predict the data used in the At-Site Flood Frequency Analysis.

As a distributed catchment modelling system, application of SWMM requires users to deal with numerous spatially variable parameters. These spatially variable parameters were classified into two categories, namely measured parameters and inferred parameters, by [22]. The parameters that are measured (for example, the subcatchment areas, the length and slope of open channels and pipes) are assumed to be error free whereas the inferred parameters cannot be measured and are estimated during the calibration process.

3 Model Use

3.1 Model Calibration

For construction of the catchment model, the Powells Creek catchment was divided into 103 subcatchments and a similar number of channels. SWMM has the capacity for each subcatchment and channel to have unique parameter values. This capacity was utilised during calibration of the model. For the purposes of calibrating the SWMM model of Powells Creek used in this study, the parameters considered are shown in Table 3.

Table 3. Parameters considered during model calibration.

Subcatchment Parameter	Channel Parameter
Subcatchment Width Subcatchment Slope Imperviousness Surface roughness (impervious and pervious) Depression storage (impervious and pervious) Impervious area with no depression storage Infiltration parameters (maximum rate, minimum rate, infiltration decay, and infiltration recovery rate)	Conduit roughness

A previously calibrated model of Powells Creek was available from [17]. These parameter values were used as the median of the search space considered. Using a range of ±50% of the values obtained by [17], 1000 alternative sets of parameter values were developed assuming parameter values were uniformly distributed within the search space; in other words, all parameter values tested were within ±50% of the calibrated values obtained by [17]. Each of the 25 events extracted from the monitored data were simulated with these 1000 sets of parameter values.

There are many alternative calibration metrics that can be used to test the suitability of a set of parameter values. As the purpose of the calibration is to use the model to predict flow sequences for use with an At-Site Flood Frequency, the absolute value of the normalised peak flow error was used as the calibration metric. This can be expressed as:

$$\varepsilon = \left| \frac{(Q_p - Q_r)}{Q_r} \right| \tag{1}$$

where ε is the absolute value of the normalised peak flow error, and Q_p and Q_r are the peak flows of the predicted and recorded flow hydrographs. This calibration metric was determined for the predicted hydrographs resulting from use of the 1000 alternative datasets with the 25 extracted events.

Shown in **Figure 3** and **Figure 4** are representative predicted and recorded hydrographs; the predicted hydrographs shown are the best dataset for that event as defined by the normalised peak flow error. The importance of the rainfall model on the reliability of the predicted hydrographs can be seen in the April 1989 event hydrographs (**Figure 4**) where the recorded rainfall at the gauging station is not representative of the rainfall over the catchment; [23] and [24] discuss rainfall models in more detail and their importance in the simulation of fast responding urban catchments. Since the aim of the catchment modelling is the prediction of peak flows for use in an At-Site Flood

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Frequency Analysis, errors in the prediction of the occurrence time were not considered sufficient justification for deletion of the event from those considered; in most cases, a simple time-shift in the precipitation resulted in convergence of the predicted and recorded hydrographs.

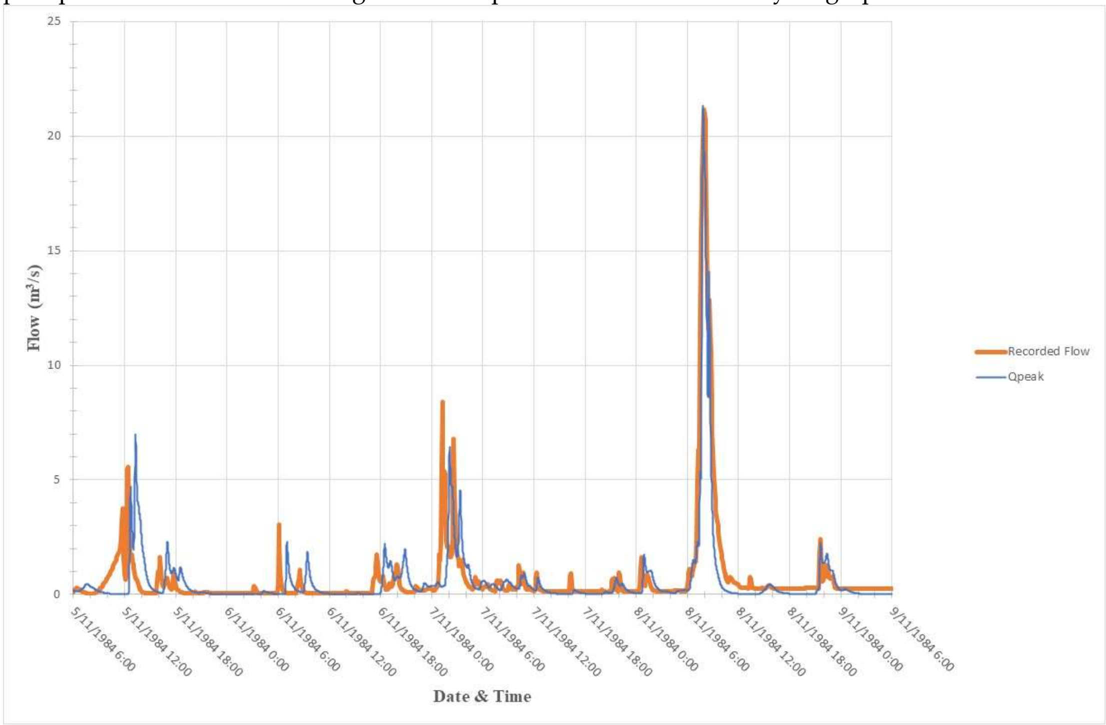

Figure 3. November 1984 Event

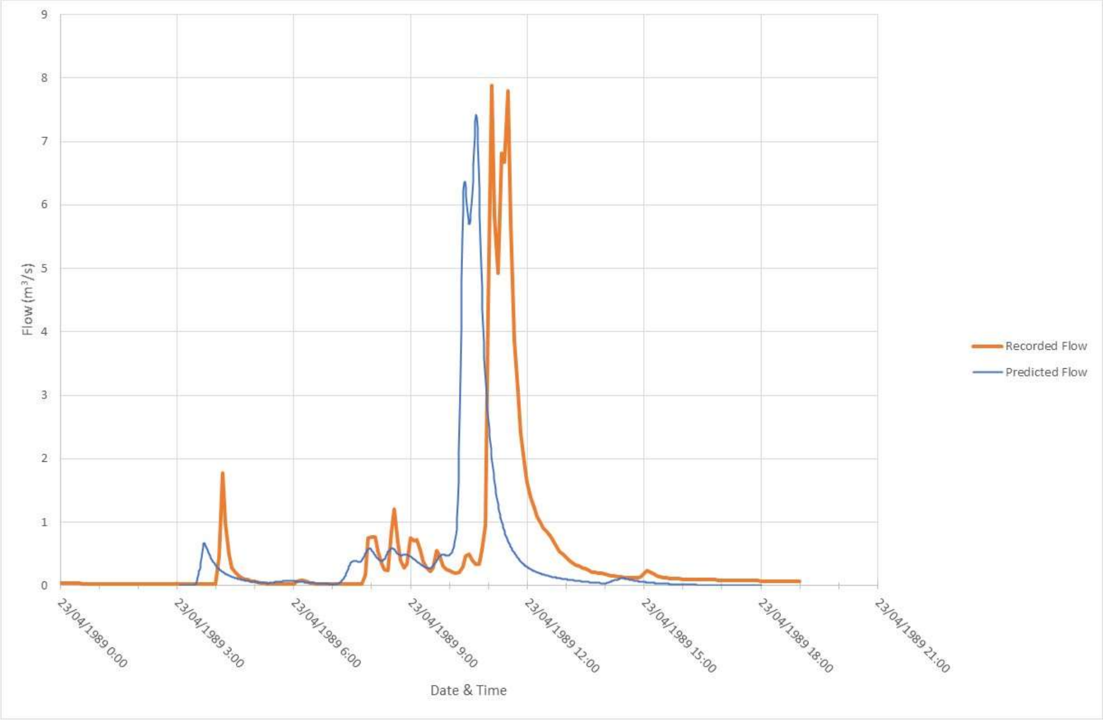

Figure 4. April 1989 Event

Five alternative values for the normalised peak flow error were considered; these were 5, 10, 15, 20, and 25% errors. For each event, the number of parameter sets resulting in the normalised peak

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flow error being less than the specified limit were counted. Shown in the second column of **Table 4** are the average number of datasets less than the specified limit when all extracted events are considered; in other words, for a normalised peak flow error of 5%, an average of 146 datasets per event resulted in satisfaction of the criterion. As expected, relaxation of the criterion results in an increased number of datasets satisfying the criterion. Relaxing the allowed error from 5% to 25% resulted in the proportion of datasets having a normalised peak flow error satisfying the criterion increasing from 15% to 72% of the 1000 available datasets.

Table 4. Peak Flow Prediction Accuracy

Normalised Peak Flow Error (%)	Average Number of Datasets	Best Dataset	Proportion of Events (%)
5	146	308	48
10	297	308	72
15	459	431	80
20	612	20	88
25	719	109	92

In addition to determining the number of datasets satisfying the criterion, the normalised peak flow error for each dataset and event were determined and the dataset with the highest number of events satisfying the criterion determined. For the criteria considered, these datasets and the proportion of events with satisfaction of the criterion are shown in the third and fourth columns of **Table 4** respectively. While 5 values of the criterion were considered, only 4 alternative datasets were identified as the same dataset provided the best performance for the 5% and 10% error criteria.

Shown in Figure 5 are the peak flows predicted using these datasets for the events considered. No obvious trends in the predictions are apparent in Figure 5. As poor predictions of a particular event are replicated in all 4 datasets, it is likely that these events have poor rainfall representation over the catchment.

3.2 *Flood Frequency Analysis*

The 4 selected datasets were used with precipitation records for the period 1981-1990 (i.e. a 10 year period) to generate flow data at the gauging station. Annual Maxima Series were extracted from these records and At-Site Flood Frequency Analyses (see **Figure 6**) were undertaken using the approaches outlined in [25]. In particular, the statistical model used was an LPIII with parameters estimated using Bayesian techniques. Shown in **Figure 6** are the resultant peak flow likelihoods arising from the monitored (recorded) data and the selected 4 datasets.

While the predicted quantiles from all 4 datasets fit within the 90% confidence limits, it is apparent that design flood predictions using dataset 308 more closely replicate those obtained from the recorded data than those from the other datasets. Shown in **Table 5** is a comparison between the design flood quantiles estimated from the monitored data and the 4 selected datasets. Also shown in this table are the variations in design flood quantiles when compared with those for the monitored data. Consistent with the trends shown in **Figure 6**, the design flood quantiles obtained using dataset 308 had the smallest variation.

Dataset 308 resulted in 48% of the peak flow predictions occurring within 5% of the recorded peak flow, and 72% of the peak flow predictions occurring within 10% of the recorded peak flow. An alternative dataset (i.e. dataset 431) had a greater number of peak flow predictions within 15% of the recorded peak flow. Hence, it can be concluded that reliable estimation of design flood quantiles using At-Site Flood Frequency Analyses requires the calibration metric of individual events to be within 10% of the recorded.

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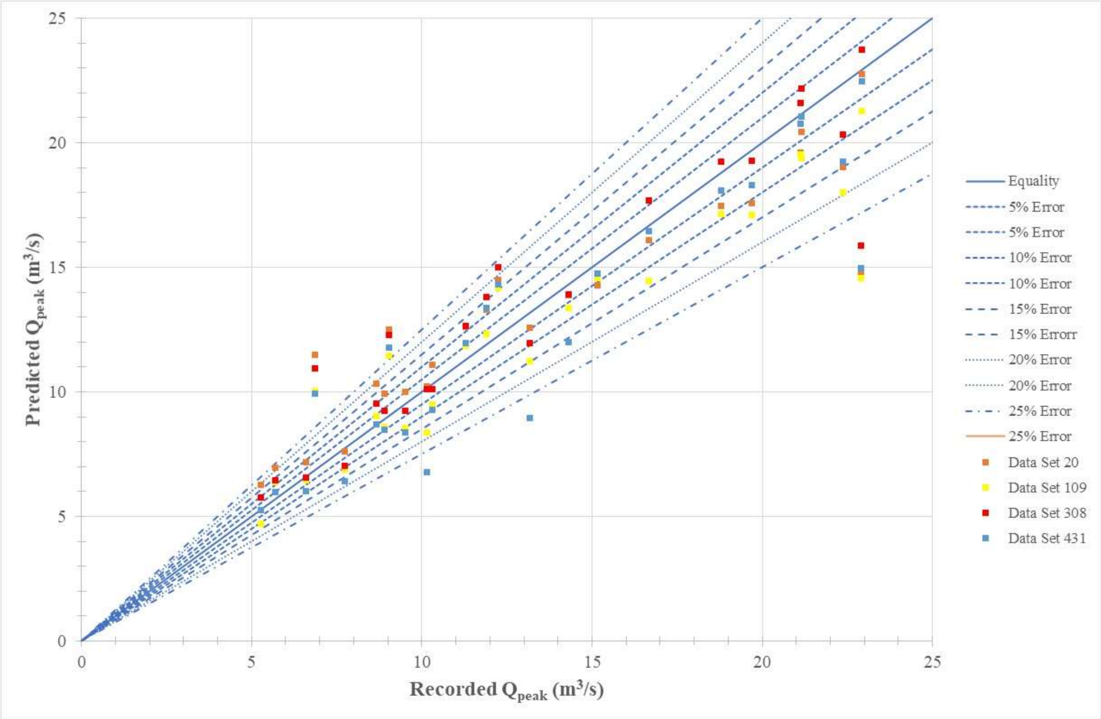

Figure 5. Predicted Peak Flow vs Recorded Peak Flow for the Selected Datasets

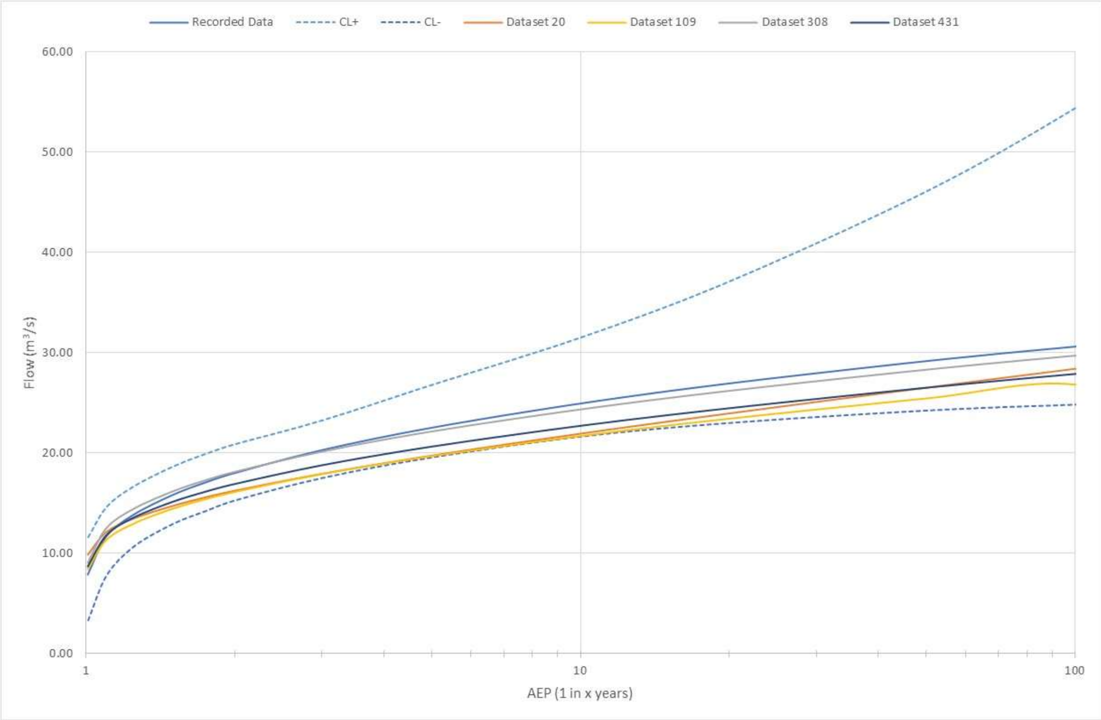

Figure 6. FFA using Selected Datasets

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Table 5. Design Flood Quantiles

AEP (1 in x years)	Monitored Data (m³/s)	Dataset 20 (m³/s)		109 (m³/s)		308 (m³/s)		431 (m³/s)	
5	22.5	19.7	-12.4%	19.7	-12.4%	22.1	-1.8%	20.6	-8.4%
10	24.9	21.9	-12.0%	21.7	-12.9%	24.4	-2.0%	22.7	-8.8%
20	26.7	24.0	-10.1%	23.4	-12.4%	26.2	-1.9%	24.4	-8.6%
100	30.6	28.4	-7.2%	26.8	-12.4%	29.7	-2.9%	27.9	-8.8%

4 Conclusions

Estimating floods in urban catchments is a complex task that is complicated by the lack of reliable data. To circumvent this data deficiency, data from catchment models commonly is used. Calibration of the catchment model will influence the reliability of this data. An analysis of the calibration accuracy has been presented. The calibration metric considered was a normalised peak flow error for individual events. From 1000 alternative sets of parameter values, the dataset with the greatest number of peak flow predictions less than the acceptance criterion was used to generate a 10-year flow sequence which was used for an At-Site Flood Frequency Analysis. Alternative acceptance criteria, i.e. 5, 10, 15, 20 and 25% errors were considered and it was found that the dataset selected for the 5% and 10% error criteria (the same dataset was selected for both criteria) provided design flood quantiles with the lowest variation from those obtained using the historical data. Therefore, it was concluded that the maximum acceptable calibration error was a 10% error in the normalised peak flow.

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