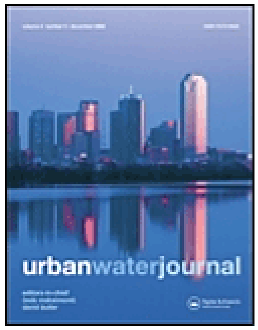

Modelling Accuracy for Urban Design Flood Estimation

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Modelling Accuracy for Urban Design Flood Estimation

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Modelling Accuracy for Urban Design Flood Estimation

Management of flood risk remains a major problem in many urban environments. To generate the data needed for estimation of the flood risk, catchment models have been used with the reliability of the predicted catchment response for design flood estimation dependent upon the model calibration. . However, the level of calibration required to achieve reliable design flood estimation remains unspecified. The purpose of this paper is to assess the event modelling accuracy needed if data from the calibrated model are to be used for continuous simulation of data for flood frequency analysis. For this purpose, a SWMM based catchment model was investigated using 25 monitored events while assessment of the calibration was based on a normalised peak flow error. Alternative sets of parameter values were used to obtain estimates of the peak flow for each of the selected events. The best performing sets of These sets of parameter values 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

Introduction

An increasing portion of the world's population now lives in urban environments; UN Department of Economic and Social Affairs (2018) estimated that 55% of the world's population currently reside 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 problems that require design flood estimation; for examples of different problems requiring estimation of design flood characteristics, see Andimuthu et al. (2019), Audisio and Turconi (2011), and Hettiarachchi et al. (2018).

Ball et al. (2011) categorised design flood estimation problems in terms of the desired flood characteristic (i.e., in terms of flow, level, volume, and system problems). For each of these problems, the design problem is the estimation of the magnitude and likelihood of the desired flood characteristic. To obtain this relationship, a fundamental need is data.

Data for estimating flood quantiles (i.e., the magnitude and likelihood of the flood characteristic) can be obtained from statistical analysis of data about the catchment response. This data can be obtained either from catchment monitoring or from catchment modelling; note that these alternative sources of data are complementary rather than competitive. In general, monitoring programs aim at collecting as much data as possible about the response of a catchment to one or more storm events. On the other hand, the aim of catchment modelling is to generate data that would have been recorded if catchment monitoring had been in place for the event, or sequence of events, at the locations being considered. Hence, the aim of both catchment monitoring and catchment modelling is the generation of data about the catchment response to storm events thereby enabling estimation of the magnitude and likelihood of the desired design flood characteristic.

There are numerous alternative approaches for estimation of the design flood characteristic; examples of these approaches are presented in the design flood guidelines for the UK (Centre for Ecology & Hydrology, 1999) and Australia (Ball *et al*., 2016). Smithers (2012) discusses these approaches and categorises the approaches as being either "analysis of streamflow data" or "rainfall based". Similar categories will be used herein although they are referred to as "catchment monitoring approaches" and "catchment modelling approaches"; these categories are consistent with the sources of data.

The absence of monitored data in many urban environments has resulted in the necessary data being obtained predominantly from the use of catchment modelling approaches. Ball (2020) presents two alternative approaches for the use of catchment models to generate the desired data; these approaches are shown in Figure 1.

The philosophical basis of the "Deterministic Approach" is the reproduction of data that would have been recorded if monitoring were undertaken for the climatic and catchment conditions modelled. When this approach is used, the likelihood of the resultant peak flows (or other flood characteristic) is unknown; statistical analysis of the predicted flows is required to predict the flood risk (i.e., the magnitude and likelihood of a flood characteristic). On the other hand, the "Probabilistic Approach" is premised on an Annual Exceedance Probability (AEP) Neutral philosophy; the probability of the rainfall is transferred to the probability of the desired flood characteristic, usually the peak flow or peak level; for application of this approach, it is necessary to assume that the statistical nature of other influential parameters do not influence the translation of frequencies from rainfall to flow.

Insert Figure 1 here - Alternative Conceptual Usage of Catchment Models for Flood Risk Assessment (after Ball, 2020)

While Teng *et al*. (2017) did not consider the alternative interpretations outlined above, they presented a comprehensive overview of how catchment models have been used and the types of catchment models used to define flood characteristics. It is apparent from this overview that catchment modelling can be subdivided further into event simulation and continuous simulation. From analysis of the literature cited by Smithers (2012) and Teng *et al.* (2017), it is apparent that e~~E~~vent simulations are the more common form of catchment modelling used to define flood characteristics. Nonetheless both styles of simulation have been used to define flood characteristics; ~~(???? Lit needed~~see, for example, Cameron *et al.*, 1999 for an example of continuous modelling for design flow estimation and Paquier *et al.*, 2019 for an example of event modelling for design flood level estimation~~)~~.

From the perspective of estimating design flood characteristics, there is a need for an unbiased estimate of the magnitude and likelihood of the desired characteristic. Thomson *et al*. (2015) investigated the use of event catchment models with an AEP Neutral interpretation for prediction of design flood characteristics for urban catchments in Australia. Comparing the model predicted magnitudes with those obtained from a frequency analysis of monitored data for the same catchments, Thomson *et al*. (2015) alternative modellers using similar techniques provided differing predictions. Furthermore, significant variation between the design flood characteristics estimated using catchment monitoring approaches and those estimated using single-event catchment modelling approaches were found. In general, using accepted catchment modelling approaches, they found that the estimations of flood characteristics were 100% greater than those obtained using catchment monitoring approaches; almost all scenarios undertaken the modelled result established a peak flow rate which was higher than the estimated peak flows from the recording stations.

The alternative approach is using a continuous simulation model to generate data analogous to the data that would have been obtained using a catchment monitoring approach. Using this approach, Ball (2020) showed that design flood flow estimates obtained from a frequency analysis of a model generated flow sequence can resemble those obtained from a frequency analysis of monitored data recorded at the same location within an urban catchment. However, Ball (2020) does not address the important practical question of what replication of recorded data is necessary for reliable prediction of design flood characteristics.

When a catchment model is used to generate data that could have been recorded, there is a need to calibrate and validate the model. Many different techniques have been proposed for calibration and validation of catchment models; these techniques include Bayesian (e.g., Bates and Townley (1988); Kuczera *et al*., (2006), Direct Search (e.g., Hendrickson *et al*., 1988), Genetic Algorithms (e.g., Wang, 1991; Fang and Ball, 2007), Shuffled Complex Evolution (e.g., Duan *et al*., 1992), and Particle Swarm Optimisation (e.g., Parsopoulos, 2007).

Consistent among these calibration 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 Lettenmaier and Wood (1993), Gupta *et al*. (2009), and Jackson *et al*. (2019). These discussions have focussed on the scientific foundation underpinning the use of alternative calibration metrics. Nonetheless, the basis of the calibration metric is the definition of a measure of the similarity in catchment responses obtained from modelling and monitoring the catchment. As shown by Sefe and Boughton (1982), the optimal set of parameter values varies with the selection of the calibration metric. There is a need, therefore, to ensure not only the scientific foundation of the calibration metric but also to ensure that the calibration metric is consistent with the desired flood characteristic.

In addition, many studies into catchment model calibration have focussed on determining the optimal (best-performing) set of parameter values for a given calibration metric; for example, while Ball (2020) showed that design flood flow estimates obtained from a frequency analysis of model generated flow sequences can resemble those obtained from a frequency analysis of recorded data, the approach used was to select the set of parameter values that resulted in the best calibration metric over the events considered. Similar approaches were adopted by Brath et al. (2004) and Barco (2008).

While use of the optimal set of parameter values is a rational approach, it does not address the question outlined earlier of what replication of recorded data is necessary for reliable prediction of design flood characteristics. This can be restated as what value of calibration metric is required for estimation of reliable flood characteristics from the model generated data. This question is addressed herein. In other words, the accuracy in prediction of historical events necessary for reliable At-Site Flood Frequency Analysis in an urban environment the subsequent use of those parameter values for through the use of continuous flow sequences generated using the selected set of parameter values is considered.

Powells Creek Catchment

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, as shown in Figure 2 lies within the Sydney suburbs of Homebush West, North Strathfield, Rookwood and Strathfield. The stormwater drainage network consists of a system of pipes and lined channels that discharge north into the Parramatta River. The main open channel was established in 1890's while the pipe system was established in the 1920's (Meutia, 2002).

Insert Figure 2 Here - Powells Creek Catchment

Insert Table 1 here - Land Use in the Powells Creek Catchment (after Meutia, 2002)

Shown in Table 1 are the alternative land uses within the catchment as outlined by Meutia (2002) with, as indicated in Table 1, the major land use within the catchment being residential. Soils in the catchment are fine textured with slow infiltration rates (equivalent to Hortonian type 3). In general, the catchment is classified as low-lying, with gentle slopes between 4% and 5.5%. The maximum elevation is 40m AHD (Australian Height Datum) while the minimum elevation is governed by the Parramatta River to the north.

Available Data

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 consisted of 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. Shown in Figure 2 are the locations of the gauging station and the pluviometers.

From the collected data, 25 events were extracted for calibration of the catchment model; these events were extracted from the period 1980 to 1997. Selection of events only post 1980 was related to the availability of reliable precipitation data. Details of these events are presented in Table 2 while the events are plotted in Figure 3 on a flood frequency diagram; the Cunnane Plotting Position is used to define the estimated likelihoods. As shown in Figure 3, the largest recorded events occurred prior to 1980. The lack of these larger events will be reflected in the estimated flood quantiles obtained from the At-Site Flood Frequency Analysis of both the recorded and the monitored data undertaken as part of this study.

Insert Table 2 here - List of Events

Insert Figure 3 here - FFA and Events for the Gauging Station in Powells Creek Catchment

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 (Rossman, 2015) was used herein for data generation. This model has received extensive application; see, for example, Leutnant *et al*. (2019) and Broekhuizen *et al*. (2020) for recent applications of SWMM in urban environments.

SWMM is a physically distributed catchment modelling system consistent with the conceptual components of a catchment modelling system proposed by Ball (1992); 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 assessment of 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 design flood flows, SWMM was operated in a continuous mode to predict the data to be used in an At-Site Flood Frequency Analysis. Use of a catchment model in a continuous mode has many advantages inclusive of the inherent capacity to include variability in factors influencing the joint probability of floods; these factors include antecedent conditions, precipitation, and the interdependence between factors.

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 Choi and Ball (2002). 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 while the inferred parameters are not measured and are estimated during the calibration process.

It is worth noting that, while SWMM was used herein as the basis for the catchment model, alternative software packages could be applied. However, to use the approach outlined, it is necessary that the software implemented to generate the catchment model be capable of operation in both event and continuous modes.

Model Use

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 this study. For the purposes of assessing the calibration of the Powells Creek SWMM model, the concept of Choi and Ball (2002) was used. Using this concept, only the inferred parameters were considered with the parameters considered shown in Table 3.

Insert Table 3 here - Parameters considered during model calibration

A previously calibrated model of Powells Creek was available from Meutia (2002). These parameter values were used as the median of the search space considered. Using a range of ±50% of the values obtained by Meutia (2002), 1000 alternative sets of parameter values were developed assuming parameter values were uniformly distributed within the search space; in other words, all parameter values considered were within ±50% of the calibrated values obtained by Meutia (2002). Each of the 25 events extracted from the monitored data were simulated with each of the 1000 sets of parameter values. Furthermore, calibration metrics were determined for each alternative set of parameter values for each of the 25 selected events.

As discussed earlier, t~~T~~here are many alternative calibration metrics that can be used to test the suitability of a set of parameter values. The suitability of a particular metric is related to the information content of the data being generated and the data available for calibration of the model. For example, the Nash-Sutcliffe efficiency (NSE) or the Kling-Gupta efficiency (KGE) are metrics commonly applied to assess data generated using continuous simulation but rarely for assessment of individual event simulation.

There are two points to note about the approach presented herein. Firstly, the calibration is for individual events with the aim being to develop a catchment model focussed on prediction of the hydrograph peaks, in other words, an event calibration. Secondly, for production of the desired data, the catchment model is used in a continuous mode to predict flow sequences over many years. These flow sequences are then analysed to prepare Annual Maxima Series suitable for Flood Frequency Analysis.

The critical information sought from the generated data, therefore, is the hydrograph peak. ~~As the purpose of the calibration is to use the model to predict flow sequences for use with an At-Site Flood Frequency~~Hence, the absolute value of the normalised peak flow error was used as the calibration metric; a normalised peak flow error was used to remove potential biases introduced by the magnitude of the peak flows considered. This metric 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 obtained from use of the 1000 alternative sets of parameter values with the 25 extracted events.

Shown in Figures 4 and 5 **Error! Reference source not found.**are representative predicted and recorded hydrographs. The predicted hydrographs shown in these figures are those obtained using the best set of parameter values 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 5) where the recorded rainfall at the gauging station is not representative of the rainfall over the catchment; Umakhanthan and Ball (2005) and Zhang and Han (2017) discuss rainfall models in more detail and their importance in the simulation of fast responding urban catchments.

Insert Figure 4 here - Predicted and Recorded Flows for November 1984 Event

Insert Figure 5 here - Predicted and Recorded Flows for April 1989 Event

Since the aim of the catchment modelling was the prediction of the peak flow of the flood hydrograph for use in an At-Site Flood 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; this approach to improving the calibration of the catchment model is consistent with Umakhanthan and Ball (2005).

A search for the most generic set of parameter values is the philosophical basis for the approach used in this study; in other words, the desire is to find the parameter set that provides reliable predictions for the greatest number of events rather than the set of parameter values that results in the best replication of an individual event. Hence, for each event, the number of sets of parameter values resulting in the normalised peak flow error being less than the specified criterion were counted. Five alternative criterion for the normalised peak flow error were considered; these criterion represented errors of 5, 10, 15, 20, and 25% in the normalised predicted peak flow.

Shown in Table 4 are the results of this search for generic sets of parameter values. In column 1, the specified criterion, or acceptable error in the normalised peak flow, is shown. Other results shown along a row in this table relate to this criterion.

For each of the 25 events, the number of parameter sets meeting the specified criterion were counted with the average number, over the events considered being shown in column 2 of Table 4. As an example, if the specified criterion is a normalised peak flow error less than 5% then an average of 146 parameter sets per event would satisfy the criterion. Relaxation of the specified criterion results in an increased number of sets of parameter values satisfying the criterion. Relaxing the allowed error from 5% to 25% resulted in the proportion of parameter sets having a normalised peak flow error satisfying the criterion increasing from 15% to 72% of the 1000 available sets of parameter values.

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Insert Table 4 here - Peak Flow Prediction Accuracy

In addition, the set of parameter values that had the highest number of events satisfying the criterion was determined. These sets of parameter values and the proportion of events where the criterion was satisfied are shown in the third and fourth columns of Table 4, respectively. While five values of the criterion were considered, only four alternative sets of parameter values were identified as providing the highest number of events satisfying individual criteria. This arose due to the same set of parameter values resulting in the highest number of events meeting the criterion for both the 5% and 10% error criteria.

Shown in Figure 6 are the peak flows predicted using these sets of parameter values for each of the 25 events considered. No obvious trends in the predictions are apparent in Figure 6. As poor predictions for a particular event are replicated in all 4 sets of parameter values, it is suggested that these events have poor rainfall representation over the catchment; in other words, the monitored rainfall is not a good sample of the actual rainfall over the catchment.

Insert Figure 6 here Predicted Peak Flow vs Recorded Peak Flow for the Selected Sets of Parameter Values

Flood Frequency Analysis

The 4 selected sets of parameter values were used with precipitation records for the period 1981-1990 (i.e., a 10-year period) to generate continuous flow sequences throughout the stormwater drainage network. At the location of the gauging station, Annual Maxima Series were extracted from the generated data and At-Site Flood Frequency Analyses were undertaken using the approaches outlined in Kuczera and Franks (2016). 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 sets of parameter values.

Insert Figure 7 here - FFA using Selected Parameter Sets

While the predicted quantiles from all four parameter sets fit within the 90% confidence limits, it is apparent that design flood predictions using parameter set 308 more closely replicate those obtained from the recorded data than those from the other sets of parameter values. A comparison between the design flood quantiles estimated from the monitored data and the model data using the four selected sets of parameter values is shown in Table 5. Also shown in this table are the variations in design flood quantiles when compared with those obtained from analysis of the monitored data and the average error in the predicted quantile. Consistent with the trends shown in Table 5 the design flood quantiles obtained using parameter set 308 had the smallest relative error. As expected, relaxation of the calibration metric (i.e., an increase in the acceptable error) results in an increase in the relative error in the predicted quantiles obtained using the model generated data.

Insert Table 5 here - Design Flood Quantiles

Parameter set 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. Furthermore, the estimated flood quantiles obtained from analysis of the flow sequence predicted using parameter set 308 were within 2.2% of the estimates obtained from analysis of the monitored flow sequence. If the full period of monitored flow is considered, the estimated design quantiles differ from those shown in Table 5; for example, the 1 in 100 years AEP design flood quantiles are 53.8m^3/s and 30.6m^3/s when the monitored flow sequences are analysed for the full period of record and for the 10-year analysis period. This outcome highlights the need for consistent periods when monitored and predicted flow sequences are analysed for statistical characteristics.

While the alternative sets of parameter values (set 431 at 15%, set 20 at 20% and set 109 at 25%) had a greater number of peak flow predictions within the calibration metric, the estimated design flood quantiles had a greater variation. The average variation in the selected design flood quantiles were 8.6%, 10.4% and 12.5% for parameter sets 431, 20, and 109, respectively.

In this study, the aim of using the catchment model was the prediction of flow sequences that would have been recorded if monitoring were undertaken at that site. These flow sequences were then analysed to obtain estimates of flood quantiles. Hence, it can be concluded that reliable estimation of design flood quantiles using At-Site Flood Frequency Analyses requires the normalised peak flow prediction of individual events to be within 10% of that obtained from the monitored data for the same event.

Conclusions

Estimating floods in urban catchments is a complex task that usually is complicated by the lack of reliable data. To circumvent this data deficiency, a common approach is to use data generated by catchment models. Calibration of the catchment model will influence the reliability of this data. An analysis of the calibration accuracy has been presented herein. The calibration metric considered was a normalised peak flow error for individual events from the monitored flow sequences. Furthermore, the calibration approach used was a search for the set of parameter values that provided the most generic model performance, i.e., the set of parameter values that resulted in acceptable performance over the largest number of events. Hence, from the 1000 alternative sets of parameter values analysed, the set of parameter values with the greatest number of peak flow predictions within the acceptance criterion was determined. Alternative acceptance criteria, i.e., 5, 10, 15, 20 and 25% errors were considered.

The set of parameter values found to provide the best generic model performance for each acceptance criteria was used to generate a 10-year flow sequence suitable for an At-Site Flood Frequency Analysis. It was found that the set of parameter values selected using the 5% and 10% error criteria (the same set of parameter values was selected for both criteria) provided design flood quantiles with the lowest variation from those obtained using the historical data over the same 10-year period. It was concluded, therefore, that an acceptable error in the prediction of the calibration events was a 10% error in the normalised peak flow.

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Table Captions

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

Table 2. List of Events.

Table 3. Parameters considered during model calibration.

Table 4. Peak Flow Prediction Accuracy.

Table 5. Design Flood Quantiles.

Figure Captions

Figure 1. Alternative Conceptual Usage of Catchment Models for Flood Risk Assessment (after Ball, 2020)

Figure 2. Powells Creek Catchment

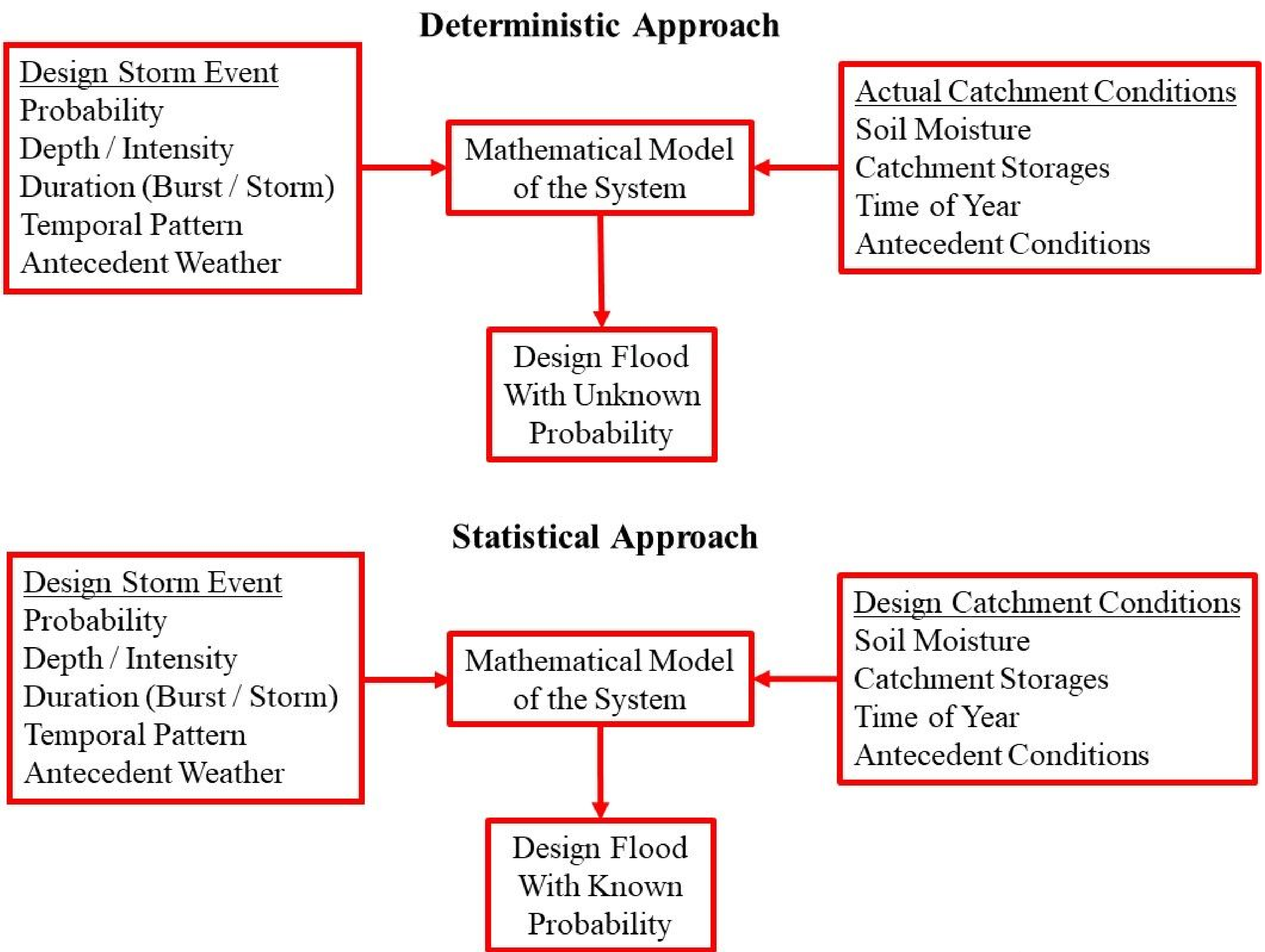
Figure 3. FFA and Events for the Gauging Station in Powells Creek Catchment

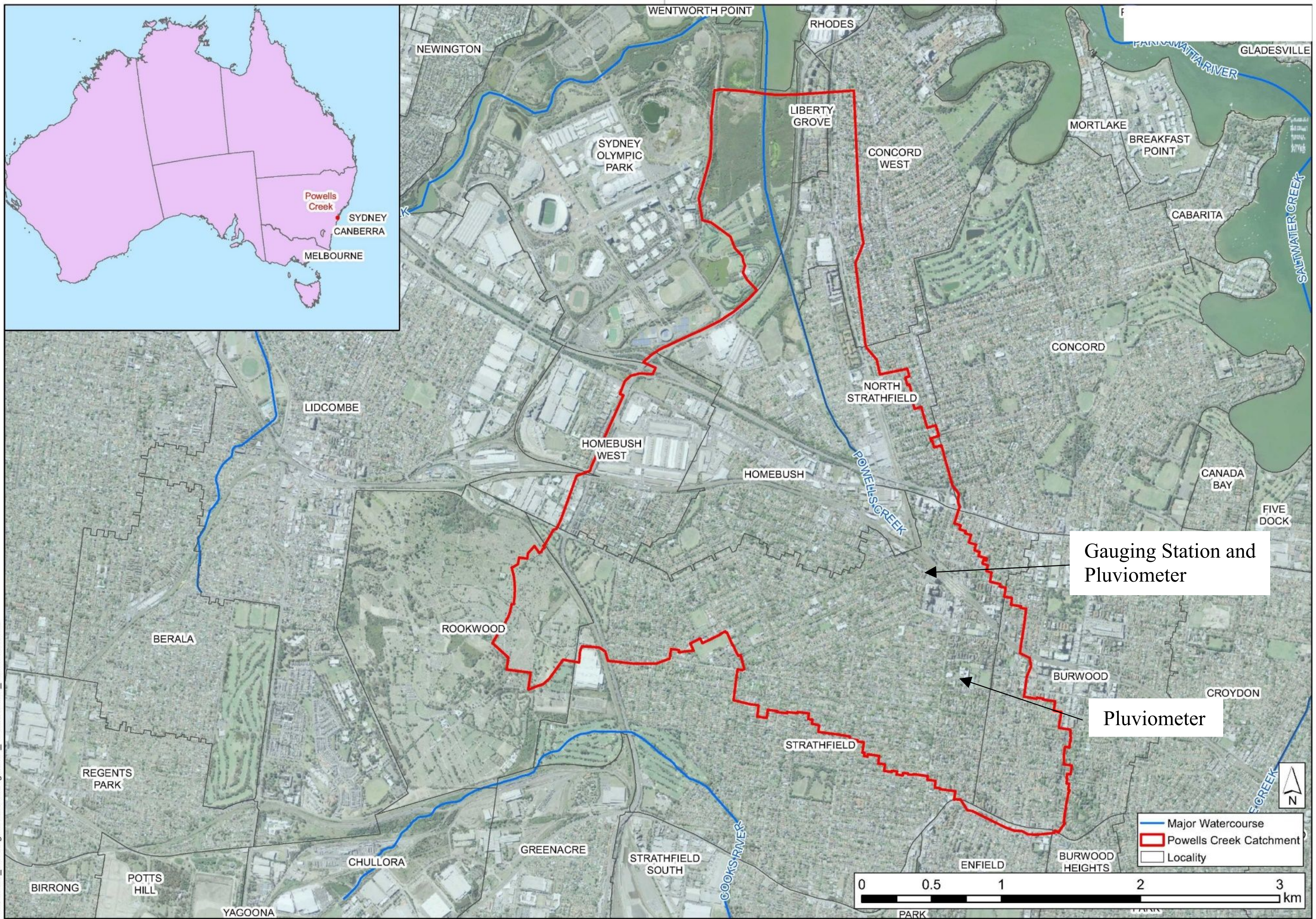
Figure 4. Predicted and Recorded Flows for November 1984 Event

Figure 5. Predicted and Recorded Flows for April 1989 Event

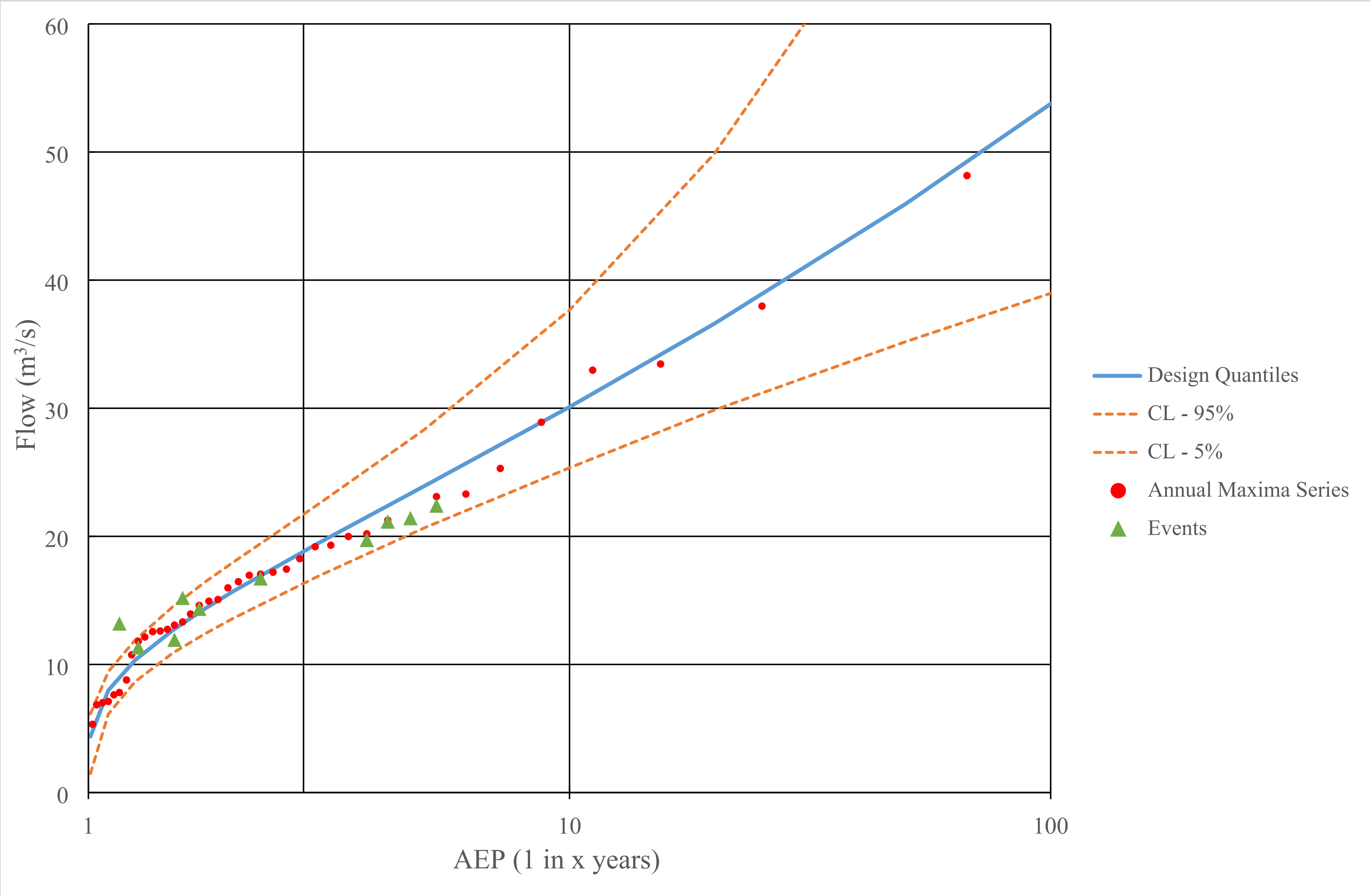
Figure 6. Predicted Peak Flow vs Recorded Peak Flow for the Selected Sets of Parameter Values

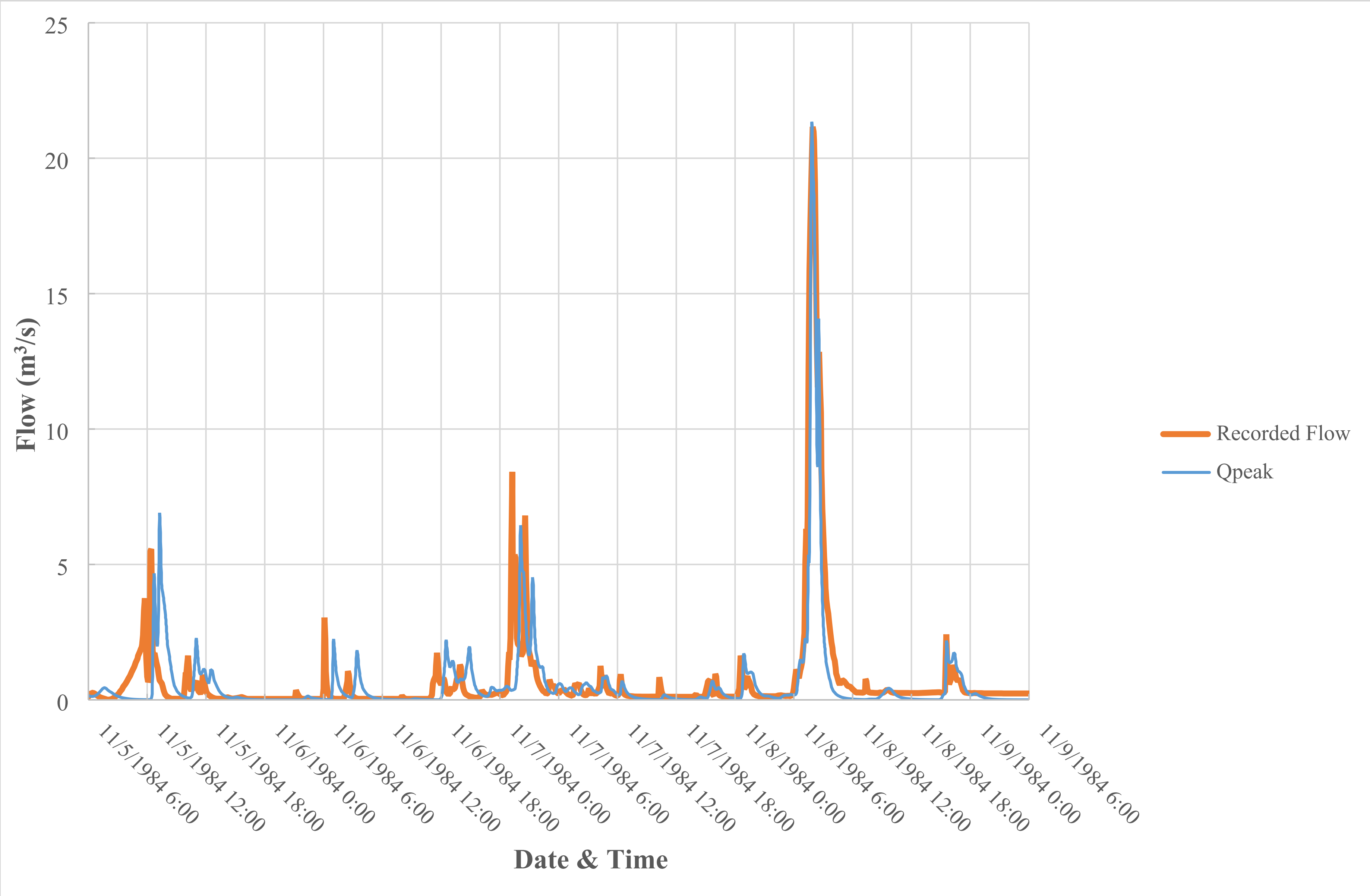
Figure 7. FFA using Selected Parameter Sets

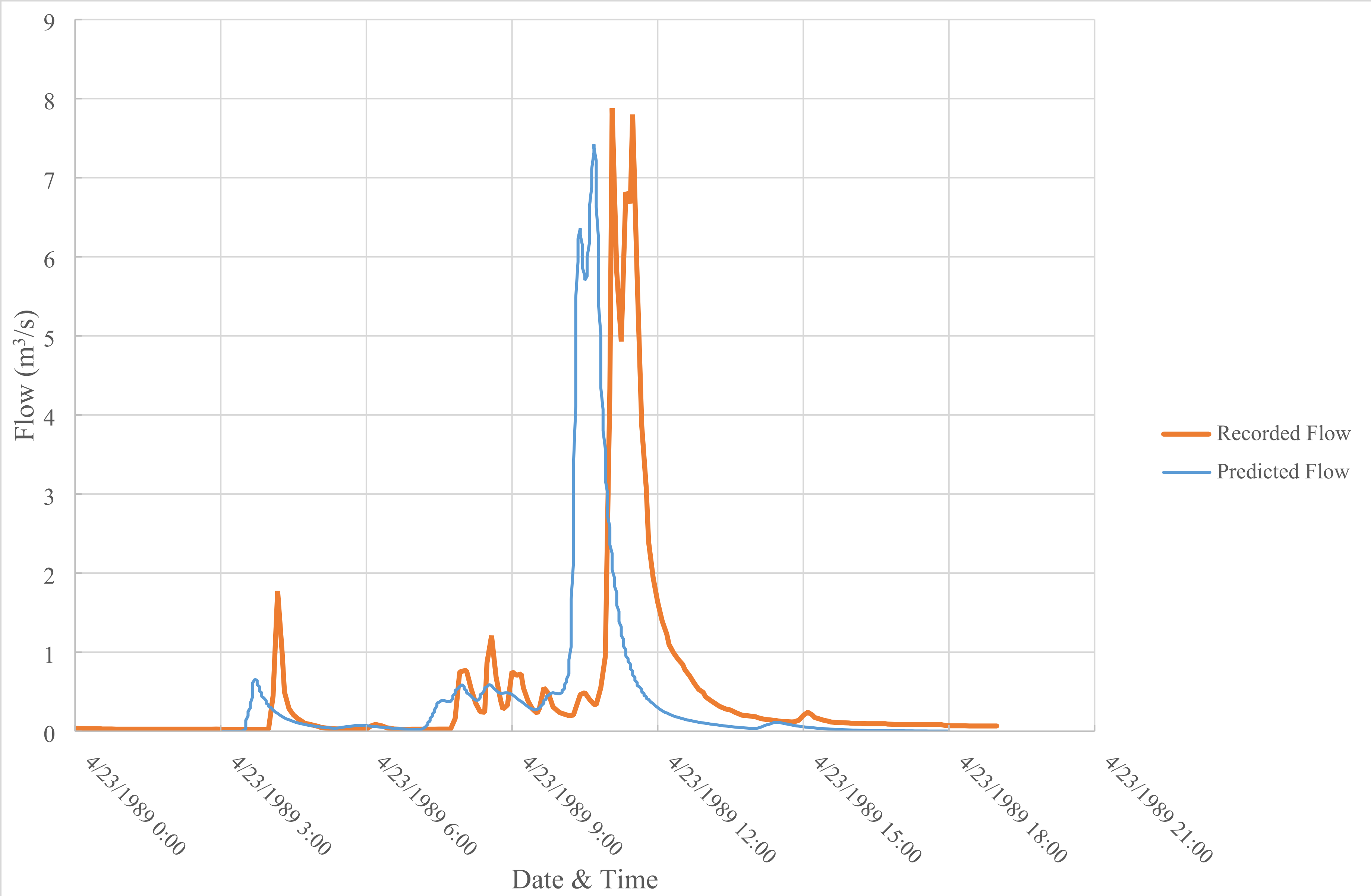

Deterministic Approach
Design Storm Event
Probability
Depth / Intensity
Duration (Burst / Storm)
Temporal Pattern
Antecedent Weather
Mathematical Model of the System
Actual Catchment Conditions
Soil Moisture
Catchment Storages
Time of Year
Antecedent Conditions
Design Flood With Unknown Probability
Statistical Approach
Design Storm Event
Probability
Depth / Intensity
Duration (Burst / Storm)
Temporal Pattern
Antecedent Weather
Mathematical Model of the System
Design Catchment Conditions
Soil Moisture
Catchment Storages
Time of Year
Antecedent Conditions
Design Flood With Known Probability

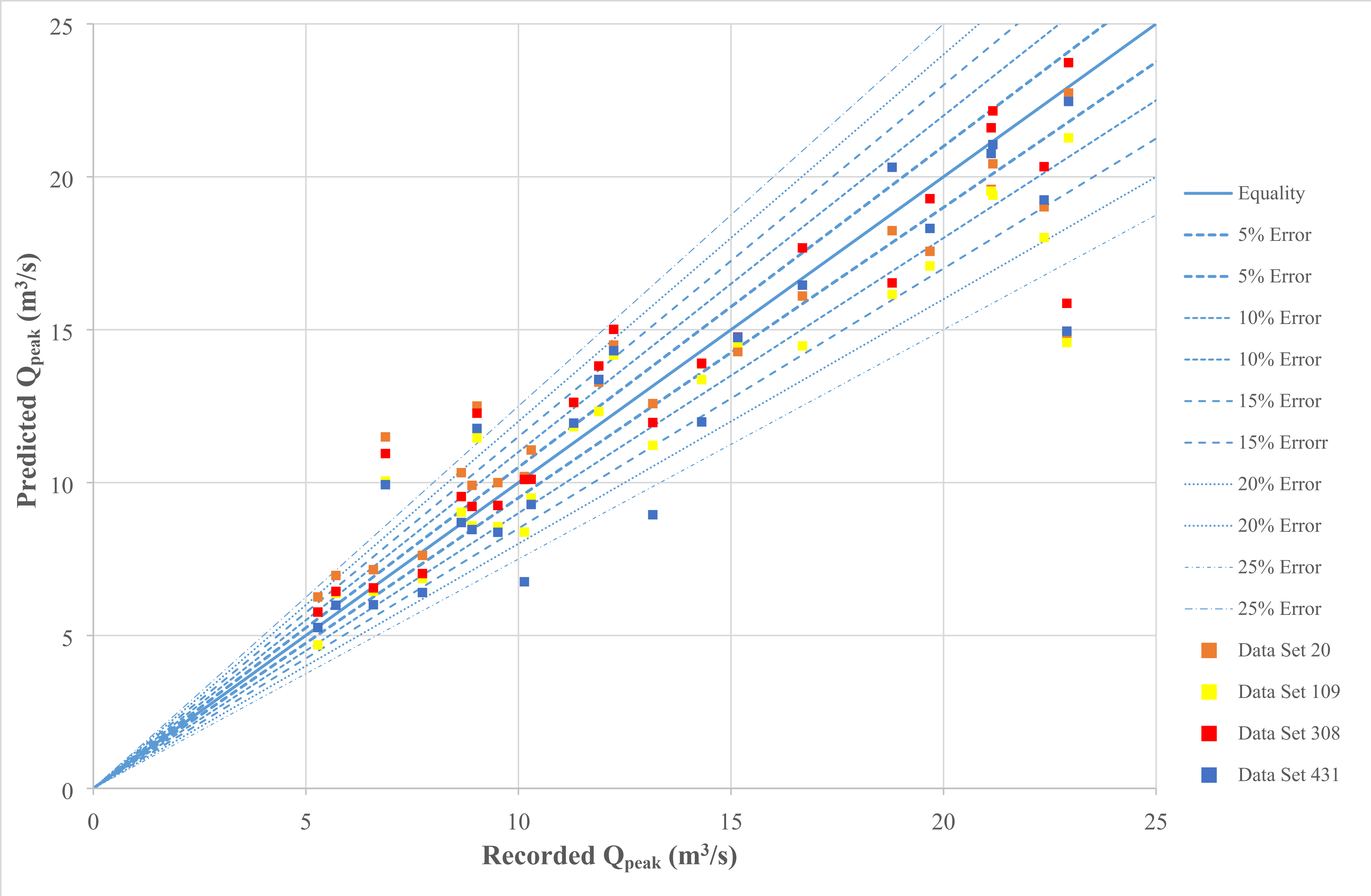


P:\Nam\03_Working\MRettalick\FigureXX_PowellsCreek_catchment.mxd


60
50
40
30
20
10
0
Flow (m³/s)
1
10
100
AEP (1 in x years)
Design Quantiles
CL - 95%
CL - 5%
Annual Maxima Series
Events


25
20
15
10
5
0
Flow (m³/s)
11/5/1984 6:00
11/5/1984 12:00
11/5/1984 18:00
11/6/1984 0:00
11/6/1984 6:00
11/6/1984 12:00
11/6/1984 18:00
11/7/1984 0:00
11/7/1984 6:00
11/7/1984 12:00
11/7/1984 18:00
11/8/1984 0:00
11/8/1984 6:00
11/8/1984 12:00
11/8/1984 18:00
11/9/1984 0:00
11/9/1984 6:00
Date & Time
Recorded Flow
Qpeak


9
8
7
6
5
4
3
2
1
0
Flow (m³/s)
4/23/1989 0:00
4/23/1989 3:00
4/23/1989 6:00
4/23/1989 9:00
4/23/1989 12:00
4/23/1989 15:00
4/23/1989 18:00
4/23/1989 21:00
Date & Time
Recorded Flow
Predicted Flow



Predicted Q_{peak} (m^3/s)
Recorded Q_{peak} (m^3/s)
0
5
10
15
20
25
Equality
5% Error
5% Error
10% Error
10% Error
15% Error
15% Errorr
20% Error
20% Error
25% Error
25% Error
Data Set 20
Data Set 109
Data Set 308
Data Set 431

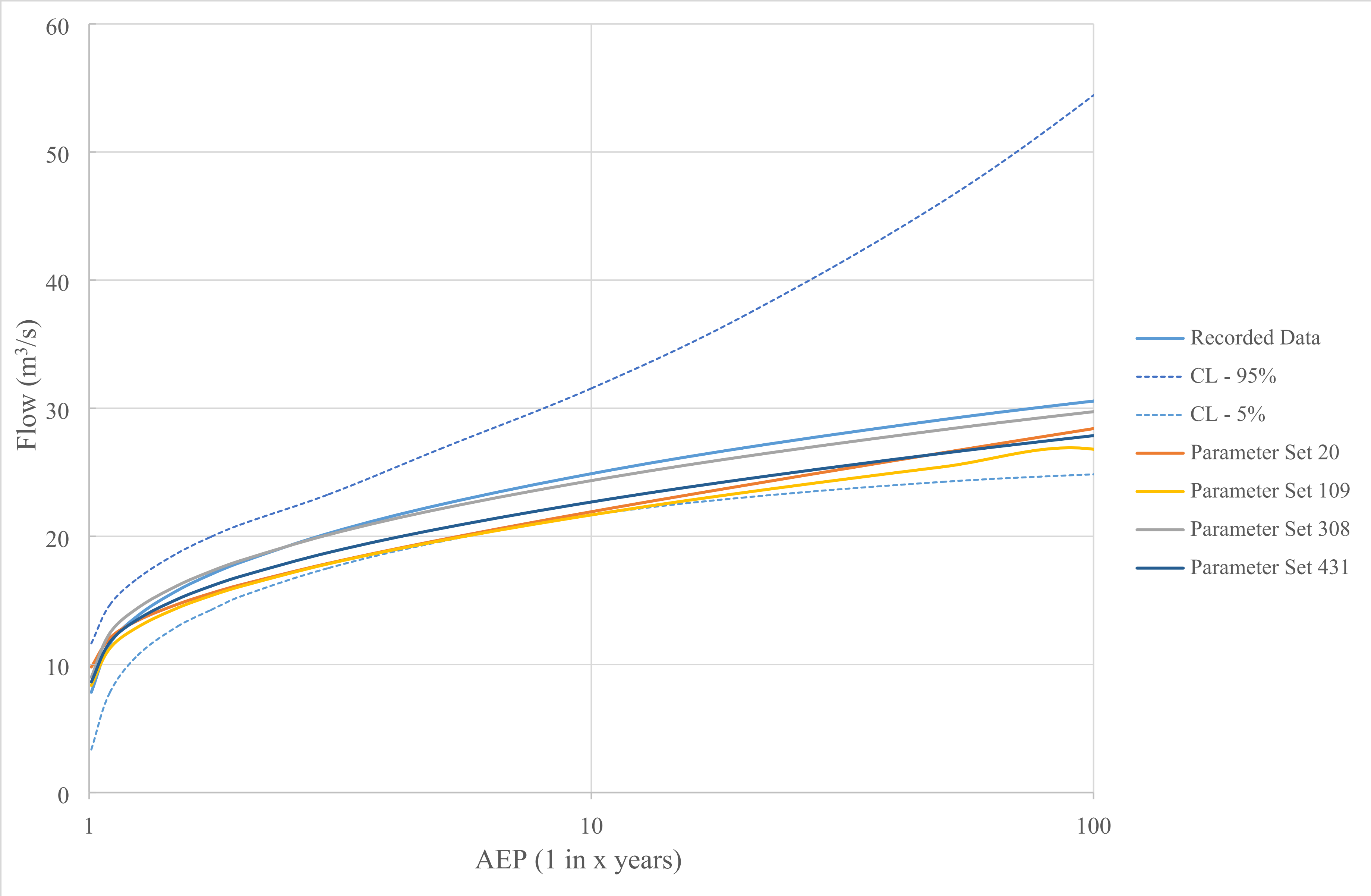

60
50
40
30
20
10
0
Flow (m³/s)
1
10
100
AEP (1 in x years)
Recorded Data
CL - 95%
CL - 5%
Parameter Set 20
Parameter Set 109
Parameter Set 308
Parameter Set 431

Table 1

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

Table 2

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
April 1988 (a)	53.4	8.656	18	0.37
April 1988 (b)	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
March 1990 (a)	23.1	10.14	5	0.47
March 1990 (b)	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
March 1995 (a)	31.4	12.24	14	0.70
March 1995 (b)	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

Notes:

1. Approx. AEP (Annual Exceedance Probability) determined from Cunnane Plotting Position

Table 3

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

Table 4

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

Table 5

AEP (1 in x years)	Monitored Data (m^3/s)	Predicted Quantile and Relative Error for Each Set of Parameter Values							
		308 (5%, 10%) (m^3/s)		431 (15%) (m^3/s)		20 (20%) (m^3/s)		109 (25%) (m^3/s)	
5	22.5	22.1	-1.8%	20.6	-8.4%	19.7	-12.4%	19.7	-12.4%
10	24.9	24.4	-2.0%	22.7	-8.8%	21.9	-12.0%	21.7	-12.9%
20	26.7	26.2	-1.9%	24.4	-8.6%	24.0	-10.1%	23.4	-12.4%
100	30.6	29.7	-2.9%	27.9	-8.8%	28.4	-7.2%	26.8	-12.4%
Ave. Error			-2.2%		-8.6%		-10.4%		-12.5%