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Regionalization of Storm Duration for Determining Derived Flood Frequency Curve: A Case Study for Victoria in Australia

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Abstract: A holistic approach of design flood estimation such as the Monte Carlo simulation technique involves the simulation of thousands of storm and runoff events to determine a derived flood frequency curve. The implementation of such a technique requires the specification of the distributions of various input variables to the rainfall runoff model such as storm duration, storm intensity and initial and continuing losses. This paper presents a case study which focuses on the regionalization of the distribution of storm duration in the state of Victoria, Australia. This in particular compares the one-parameter exponential and two-parameter Gamma distributions in approximating the distribution of storm duration from 91 pluviograph stations in Victoria. Based on the Kolmogorov–Smirnov and Anderson–Darling tests, it has been found that the two-parameter Gamma distribution provides a better fit to the storm duration data in Victoria than the one-parameter exponential distribution. The application of the fitted Gamma distribution in the Monte Carlo simulation technique for generating flood frequency curves shows that this approximates the observed flood frequency curves for the selected test catchments quite well. The methodology presented in this paper can be adapted to other states of Australia or other countries, in particular where a sufficient quantity of continuous rainfall and stream flow data are available. This would particularly be useful in hydrological study of the important/large water infrastructure projects.

Key words: Design flood estimation, Monte Carlo simulation, regionalization, flood modelling, rainfall runoff modelling, design rainfall.

Introduction

Flood modelling and forecasting provides useful information for many urban and rural development projects subject to flood risk (Becker et al., 2006; Chaudhury and Chattopadhyay, 2006; Alam et al., 2008; Weinmann et al., 2002). Design flood is one of the most useful hydrological input, which is a flood discharge associated with a given annual exceedance probability (AEP) and is used in sizing hydraulic structures and in various water resources management tasks. For design flood estimation, rainfall-based methods are often preferred over streamflow-based methods because rainfall data generally have longer records and have a greater spatial coverage than the stream flow data and also physical features of the catchments can easily be incorporated with the rainfall-based flood estimation methods.

In Australia, the national guide for design flood estimation known as Australian Rainfall and Runoff (ARR) recommends the Design Event Approach as the preferred method of rainfall-based design flood estimation (IEAust 2001). This method considers the probabilistic behaviour of rainfall depth in rainfall runoff modelling but ignores the probabilistic nature of other flood-producing variables such as rainfall duration,

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rainfall temporal pattern and initial loss. As a result of the arbitrary treatment of various flood-producing variables, the Design Event Approach is likely to introduce 'probability bias' in the final flood estimates (Yue, 2000; Kuczera et al., 2003; Rahman et al., 2002a). In Australia, the Design Event Approach is commonly used with a runoff routing model such as RORB (Laurenson and Mein, 1997), WBNM (Boyd et al., 2001) and URBS (Carroll, 2001). The use of this approach involves formulation of a hypothetical design rainfall event, characterised by a duration, average rainfall depth (intensity) and temporal pattern. A loss model such as 'initial loss and continuing loss' is then applied to produce net rainfall, which is then routed through the catchment storages using a runoff routing model.

In recent years, there has been notable research on the application of a holistic approach in hydrologic and environmental modelling (e.g., Uhlenbrook et al., 1999; Iacobellis and Fiorentino, 2000; Rahman et al., 2002a, 2002b; Prudhomme et al., 2003; Weinmann et al., 2002; Kuczera and Coombes, 2002; Muzik, 2002; Kuczera et al., 2003; Apel et al., 2004; Carrasco and Yuh Chang, 2005; Natale and Siva, 2007; Aronica and Candela, 2007; Blasone et al., 2008). The most commonly adopted holistic approach in flood modelling was introduced by Eagleson (1972) who analytically determined the derived flood frequency curves for an idealised V-shaped channel.

The application of a holistic approach to design flood estimation such as the Monte Carlo simulation technique (Muzik, 2002) for both gauged and ungauged catchments would require regionalization of the parameters of the distributions of the key flood-producing variables such as rainfall duration, intensity and temporal pattern and losses (Aronica and Candela, 2007). This paper examines the regionalization of the distribution of rainfall duration for the state of Victoria in Australia for application with the Monte Carlo simulation technique of flood modelling.

Monte Carlo Simulation for Flood Modelling

In the Design Event Approach of flood estimation (IEAust 2001), for a selected average recurrence interval (ARI), a number of trial rainfall durations and their corresponding average rainfall intensities are used with fixed temporal patterns, initial loss and other input variables to obtain a flood hydrograph for each duration. The flood hydrograph corresponding to the 'critical rainfall duration', i.e., the one that produces the highest peak flow, is taken as the design flood for that ARI. In this approach, it is assumed that all other model input variables except the rainfall depth are 'probability-neutral'; however, in practice, model inputs such as rainfall temporal patterns and losses show wide variability and it is often difficult to select a representative value of these input variables from a wide range of the observed values. Due to the non-linearity of the rainfall-runoff process, the use of representative values (e.g. mean or median) of model inputs is unlikely to preserve the ARI of the input rainfall intensity through to the final design flood estimate.

Unlike the Design Event Approach, the Monte Carlo simulation technique considers the probabilistic behaviour of the main flood producing variables in a more explicit manner. The approach described by Rahman et al. (2002a) treats four input variables (rainfall duration, intensity, temporal pattern and initial loss) as random variables while continuing losses, runoff routing model parameters and base flow are treated as fixed input.

In the Monte Carlo Simulation technique to provide the basis for a rigorous assessment of flood probabilities, a storm event definition is required that produces rainfall events of random durations. Two different storm event definitions were considered: a 'complete storm' and a 'storm-core' within each complete storm (the most intense part of the storm). A complete storm is defined as a period of significant rain preceded and followed by a minimum period of dry hours (e.g. 6 hours). The corresponding storm-core is selected as the period within a complete storm that has the highest rainfall intensity ratio compared to the 2-year ARI design rainfall at the location of interest. The selected storm-core events are then analysed to identify probability distributions of rainfall duration, intensity and temporal pattern.

The Monte Carlo Simulation technique presented in this paper involved the following major steps. (a) Selection of pluviograph stations on/near the study catchment and abstraction of the continuous pluviograph data at hourly time intervals (b) Identification of the storm-core rainfall events having potential to produce significant runoff. This was achieved by comparing the rainfall intensity over the entire storm-core period or part thereof with the threshold rainfall intensity. This generally allowed the selection of 4-7 partial series storm-core rainfall events on average per year. (c) Identification of the probability distribution of the storm-core duration (d_c). (d) Representation of the distribution of rainfall intensity (I_c) in the form of intensity-frequency-duration (IFD) table. (e) Representation of the temporal patterns (TP_c) in the form of dimensionless mass curves and storing in a database for random selection during simulation. (f) Analysis of the concurrent rainfall and stream flow events to estimate initial losses. A four-parameter Beta distribution was then used to approximate the initial loss distribution (Rahman et al., 2002b). (g) Calibration of the runoff routing model parameters using the selected rainfall and streamflow events. (h) Identification of the representative values of runoff routing model parameters, continuing loss and design base flow. (i) Generation of N rainfall events and routing through the calibrated runoff routing model to obtain N stream flow hydrographs. In this paper, N was taken to be 15,000.

Study Area and Data

This study uses data from the state of Victoria in Australia. For the purpose of this study, Victoria was divided into four hydrometeorological zones: Zone 1 (South-eastern Victoria), Zone 2 (North-eastern Victoria), Zone 3 (North-western Victoria) and Zone 4 (South-western Victoria), roughly cutting the state into quadrants along the Great Dividing Range and North from Melbourne, as shown in Figure 1. These hydro meteorological zones are characterised by some distinct hydrometeorology; Zone 2 and Zone 3, located on the north of the Great Dividing Range, are relatively dry with smaller mean annual rainfall (250 mm to 550 mm where Zone 3 is the driest among the four zones with mean annual rainfall below 300 mm). Zone 4 has the highest mean number of rain days in a year (as high as 210 days) as opposed to Zone 3 which has as low as 45 mean number of rain days in a year. Zone 1 and Zone 4 have smaller mean annual Class A pan evaporation (about 1000 mm) than Zones 2 and 3, with the highest value of 1600 mm for Zone 3.

A total of 91 pluviograph stations were selected (27, 22, 16 and 26 stations from Zones 1, 2, 3 and 4, respectively) which are listed in Table 1. These stations have an average of 30 years of continuous pluviograph data. To examine the impacts of the distribution of d_c on the derived flood frequency curves, three catchments were selected from Victoria (from Zones 1, 2 and 3 as listed in Table 2).

Goodness-of-fit Tests

Previous studies on a smaller number of pluviograph stations (e.g. Rahman et al., 2002a) indicated that the probability distribution of the 'storm-core' durations in Victoria can be approximated by an exponential distribution. In this study, it was found that for many of the selected pluviograph stations, the mean and standard deviation values of 'storm-core' durations were quite different, suggesting a distribution other than the exponential. Thus, two candidate distributions are considered in this study: one-parameter exponential distribution and the two-parameter gamma distribution. To test the statistical hypothesis that the storm-core duration data in a particular pluviograph station follow either exponential or gamma distribution, two different goodness-of-fit tests were applied: Kolmogorov–

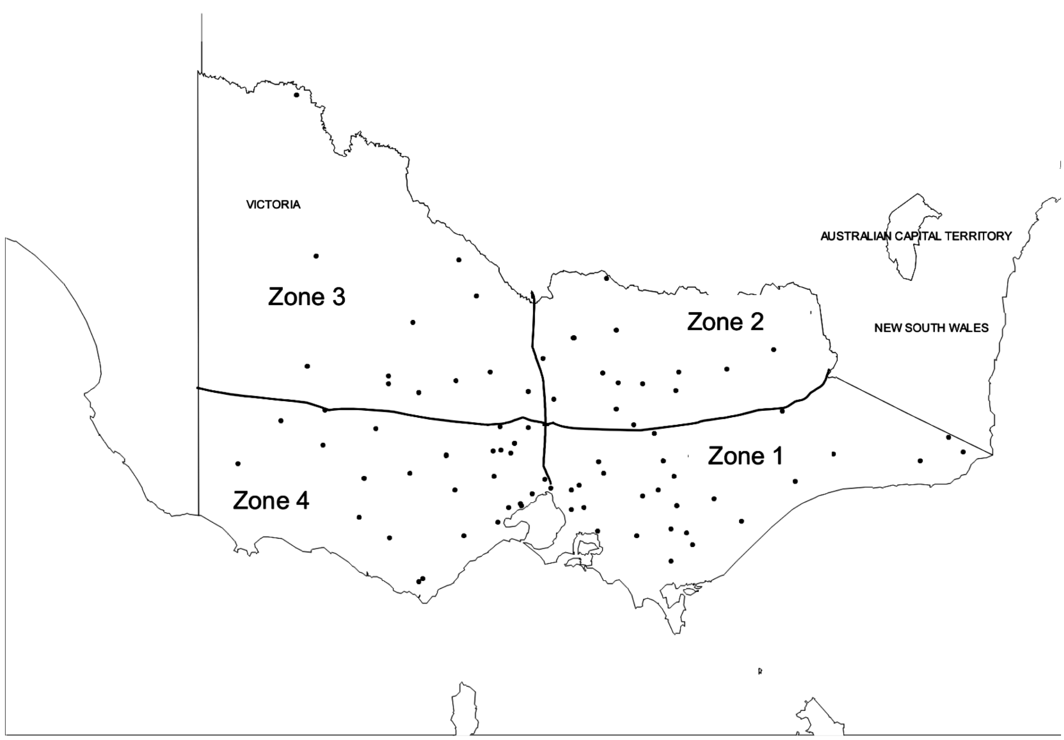

Figure 1: Locations of study pluviograph stations in Victoria.

Table 1: Selected pluviograph stations and observed mean and standard deviation values of $\bar{d}_c$ values

Zone 1			*Zone 2*			*Zone 3*			*Zone 4*		
Station ID	$\bar{d}_c$ *(h)*	*SD of* d_c *(h)*	*Station ID*	$\bar{d}_c$ *(h)*	*SD of* d_c *(h)*	*Station ID*	$\bar{d}_c$ *(h)*	*SD of* d_c *(h)*	*Station ID*	$\bar{d}_c$ *(h)*	*SD of* d_c *(h)*
83033	18.5	19.4	80109	8.6	9.4	76031	9.8	8.5	79052	10.8	12.6
84005	13.6	16.4	81013	11.8	11.3	77087	8.7	8.2	86038	10.1	10.2
84015	10.6	15.4	81049	9.8	9.2	79046	11.0	12.1	86071	9.4	10.8
84078	11.8	13.4	81114	11.5	11.8	79079	10.7	10.8	87017	14.9	16.7
84112	23.3	29.1	81115	11.9	12.3	79082	9.6	8.4	87029	13.4	14.5
84122	17.8	20.1	82011	14.2	13.1	79086	10.9	10.2	87031	9.2	9.1
84123	10.4	10.6	82016	11.8	10.9	80006	8.6	5.6	87033	9.2	9.2
84125	16.7	20.6	82039	10.5	10.5	80102	8.9	9.6	87036	14.8	17.0
85000	11.0	14.9	84042	15.1	15.9	80110	9.5	8.6	87075	12.7	14.6
85026	14.3	15.3	82076	18.8	17.1	81003	11.9	11.8	87097	10.9	12.7
85034	11.7	14.0	82107	13.7	14.8	81026	11.0	10.2	87104	10.3	9.7
85072	12.9	13.2	82121	11.5	10.6	81038	12.1	12.1	87105	9.3	8.5
85103	20.3	21.2	83017	16.6	20.1	87036	14.6	17.0	87133	9.6	11.2
85106	19.9	20.2	83025	13.1	14.2	87153	8.1	9.4	89002	11.1	14.9
85170	12.3	14.0	83031	16.5	17.8	88029	11.5	10.2	89016	9.8	10.4
85176	25.3	25.2	83033	18.5	19.4	88037	11.7	12.5	89019	9.6	12.0
85236	10.7	13.3	83067	14.1	14.4	*Average*	*10.5*	*10.3*	89025	14.5	15.8
85237	20.7	20.1	83074	20.9	20.9				89082	11.3	13.2
85240	12.8	15.4	88023	9.7	12.1				89085	10.2	10.5
85256	15.6	19.2	88029	10.9	9.4				89094	12.9	14.8
86074	10.9	13.5	88049	9.7	8.4				90058	12.9	15.7
86085	9.4	11.2	88153	9.1	10.1				90083	28.7	29.5
86142	11.6	14.4	*Average*	*13.1*	*13.3*				90087	22.3	31.8
86219	18.5	22.6							90135	12.4	16.4
86224	7.6	9.5							90153	15.4	15.6
86234	10.2	12.6							90166	14.3	16.6
86314	13.3	16.4							*Average*	*12.7*	*14.4*
Average	*14.5*	*16.7*									

Table 2: Selected catchments for flood frequency analysis

Catchment name and ID	*Latitude*	*Longitude*	*Area (km^2)*	*Zone*
Boggy Creek at Angleside (403226)	36.72	146.33	108	2
Tarwin River East Branch at Dumbalk (227226)	38.51	146.16	127	1
Avoca River at Amphitheatre (408202)	37.18	143.41	78	3

Smirnov (K–S) test and the Anderson–Darling (A–D) test, at the 5% level of significance.

The K–S test is based on the maximum difference (D_{max}) between the observed cumulative distribution function $F_n(x)$ and expected cumulative distribution function $F_o(x)$. This test can be applied in two ways. The first method uses the absolute D_{max} value which can be worked out by the following equation (Kottegoda and Rosso, 1997):

$$D_{\max} = [F_n(x) - F_o(x)] \qquad (1)$$

Hence the maximum difference between the two sets of data, the critical D_{max} value is compared to the rejection region. In this study, since most stations have over 35 events *(n)*, the following equation is used to compute the rejection region (based on 5% level of significance).

$$D_{n,\ 0.05} = 1.36/\sqrt{n} \qquad (2)$$

In the second approach, the D_{max} value is incorporated into the equation that uses the number of storm events n. This equation is shown below (Stephens, 1974):

$$D = D_{\max}\left(\sqrt{n} + 0.12 + 0.11/\sqrt{n}\right) \qquad (3)$$

To accept the null hypothesis, the value of D should be less than the rejection region, which is 1.358 for the 5% significance level (Stephens, 1974). In this study, both the approaches are adopted, i.e., if a station satisfies both the criteria (Equations 1 and 3), it passes the test. Here, the parameters of the distributions are obtained from the same sample that is used for the test.

The A–D test is devised to give heavier weightings to the tails of a distribution where unexpectedly high or low values, called outliers are located (Kottegoda and Rosso, 1997). The rejection region for this test, with sample size greater than 5, at a 5% significance level is 2.492 (Stephens, 1974). This equation is shown below (Kottegoda and Rosso, 1997):

$$A^2 = -n\sum_{i=1}^{n} \frac{(2i-1)\{\ln F_o(x_{(i)}) + \ln[1 - F_o(x_{(n-1+1)})]\}}{n} \quad (4)$$

where $F_o(x)$ is the hypothetical cumulative distribution function and $x_{(1)}, x_{(2)}, \ldots, x_{(n)}$ are the observations ordered in increasing order.

These two tests were applied to each individual site and also to Zones 1, 2, 3 and 4 to assess the applicability of a regional exponential or gamma distribution.

The probability density function for the one-parameter exponential distribution is expressed by the following equation:

$$p(d_c) = \frac{1}{\sigma} e^{-d_c/\sigma} \quad (5)$$

where d_c is storm–core duration and σ is estimated from $\sigma = \bar{d}_c$, where $\bar{d}_c$ is the mean of the d_c values.

In the form of a cumulative density function this can be given by the following equation (Kottegoda and Rosso, 1997):

$$F(d_c) = 1 - e^{-d_c/\sigma} \quad (6)$$

The probability density function of the two-parameter gamma distribution can be given by the following equation (Kottegoda and Rosso, 1997):

$$p(d_c;\alpha;\beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} d_c^{\alpha-1} e^{-d_c/\beta} \quad d_c > 0 \quad (7)$$

where α and β are parameters of the gamma distribution, and can be obtained from using the method of moments:

$$\beta = \frac{SD^2}{\bar{d}_c} \quad (8)$$

$$\alpha = \frac{\bar{d}_c}{SD^2} \quad (9)$$

where $\bar{d}_c$ is the mean value of storm-core duration at a station or in a region and SD^2 is the variance of d_c values at a station or in a region.

Results

The mean values of storm-core duration ($\bar{d}_c$) and its standard deviations (SD) for the 91 stations are given in Table 1. The histograms of storm-core duration (d_c) values for each of the 91 stations were plotted at both the 5 and 10 hours class intervals (Figure 2). Plots of the cumulative frequency distributions of the observed and fitted exponential and gamma distributions were prepared for visual assessment of the goodness-of-fit of a

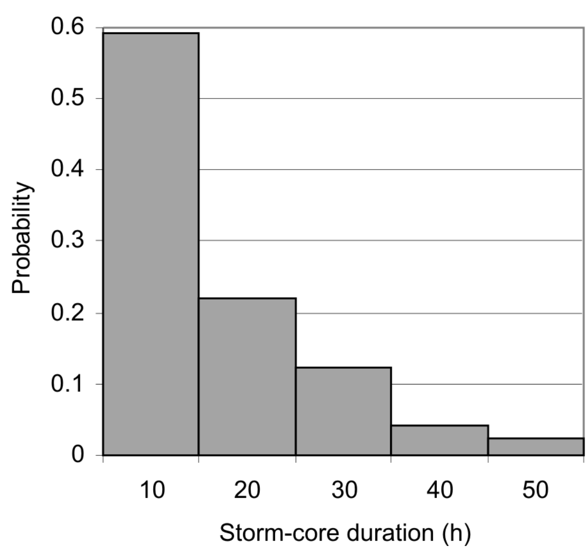

Figure 2: Histogram of storm-core duration (d_c) for Station 82121.

distribution (Figure 3). From the visual inspection, the fitting was rated on a criterion of 'poor', 'medium' and 'good'. The summarized results can be seen in Table 3, which shows that the gamma distribution apparently fits the at–site and regional observed frequency of d_c data better than the exponential distribution for all the four zones. Overall, the gamma distribution provides a 'good fit' visually for 65% of the stations in Victoria as compared to 46% of the stations for the exponential distribution.

Table 4 provides the results of hypothesis testing for at-site analysis. Based on the two tests (K–S and A–D) and considering all the four zones, 63% and 68% of the stations satisfy the at-site exponential and gamma distributions, respectively. For Zone 1 (south-eastern Victoria), 35% and 48% of the stations satisfy the exponential and gamma distributions respectively. For Zone 2 (north-eastern Victoria), 75% and 82% of the stations satisfy exponential and gamma distributions respectively. For Zone 3 (north-western Victoria), 81% and 88% of the stations satisfy the exponential and gamma distributions, respectively. For Zone 4 (south-western Victoria), 62% and 56% of the stations satisfy the exponential and gamma distributions, respectively. Thus, it is found that for three out of the four zones, the gamma distribution fits the at-site storm-core duration data relatively better than the exponential distribution.

For the regional analysis, the mean and standard deviation of the combined at-site d_c data for all the stations within the region were considered. The regional average mean $\bar{d}_c$ values are 14.5h, 13.1h, 10.5h and 12.7h respectively for Zones 1, 2, 3 and 4, respectively. The regional average standard deviation values of the d_c data are 16.7h, 13.3h, 10.3h and 14.4h for Zones 1, 2, 3 and 4 respectively. The regional average mean $\bar{d}_c$ value for a zone was used to fit the regional exponential distribution and hypothesis testing was conducted against the at-site d_c data to assess the viability of a regional exponential distribution. Similarly, the regional gamma distribution was fitted using the regional average mean $\bar{d}_c$ value and regional average standard deviation value of the d_c data for a zone. The results of the hypothesis tests for regional distributions are summarized in Table 5.

Considering the two tests and all the four zones, 41% and 49% of the stations satisfy a regional exponential and gamma distribution across the four zones. For Zone 1 (south-eastern Victoria), 19% and 41% of the stations satisfy regional exponential and gamma distributions respectively. For Zone 2 (north-eastern Victoria), 50% and 48% of the stations satisfy regional exponential and gamma distributions respectively. For Zone 3 (north-western Victoria), 69% of the stations satisfy regional exponential and gamma distributions. For Zone 4 (south-western Victoria), 25% and 40% of the stations satisfy

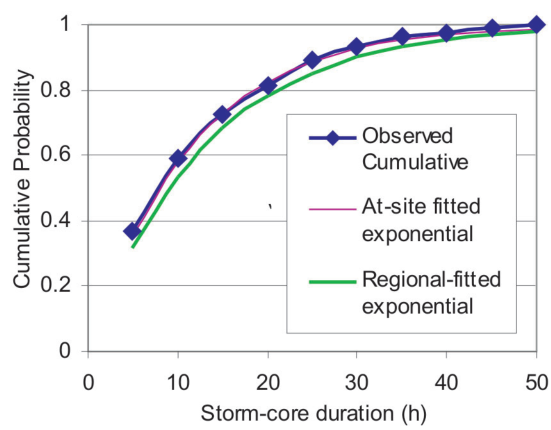

Figure 3: Observed distribution of storm-core duration (d_c) and the fitted Exponential distribution for Station 82121.

Table 3: Summary of goodness-of-fit results: visual assessment

Distribution	*Visual assessment*	*Zone 1*	*Zone 2*	*Zone 3*	*Zone 4*	*Average*
Exponential distribution	Good fit	15%	64%	69%	35%	46%
	Medium fit	44%	27%	13%	50%	33%
	Poor fit	41%	9%	18%	15%	21%
Gamma distribution	Good fit	41%	82%	69%	69%	65%
	Medium fit	44%	18%	25%	27%	28%
	Poor fit	15%	0	6%	4%	6%

Table 4: Summary of hypothesis test results for at–site distributions (stations that passed the test)

Distribution	*Zone 1 (27 stations)*	*Zone 2 (22 stations)*	*Zone 3 (16 stations)*	*Zone 4 (26 stations)*	*Average*
Exponential					
K–S test	7 (26%)	16 (73%)	14 (88%)	16 (62%)	
A–D test	12 (44%)	17 (77%)	12 (75%)	16 (62%)	
Average	35%	75%	81%	62%	**63%**
Gamma					
K–S test	11 (41%)	17 (77%)	13 (81%)	12 (46%)	
A–D test	15 (56%)	19 (86%)	15 (94%)	17 (65%)	
Average	48%	82%	88%	56%	**68%**

Table 5: Summary of hypothesis test results for regional distributions (stations that passed the test)

Distribution	*Zone 1 (27 stations)*	*Zone 2 (22 stations)*	*Zone 3 (16 stations)*	*Zone 4 (26 stations)*	*Average*
Exponential					
K–S test	5 (19%)	11 (50%)	12 (75%)	7 (27%)	
A–D test	5 (19%)	11 (50%)	10 (63%)	6 (23%)	
Average	19%	50%	69%	25%	**41%**
Gamma					
K**-** S test	6 (22%)	8 (36%)	11 (69%)	2 (8%)	
A–D test	16 (59%)	13 (59%)	11 (69%)	19 (73%)	
Average	41%	48%	69%	40%	**49%**

regional exponential and gamma distributions respectively. Thus, it is found that for three out of the four zones, a regional gamma distribution fits the at-site storm-core duration data equally well or better than the regional exponential distribution.

It is found from the above results that neither the exponential nor gamma distribution fit the observed distributions of storm-core durations for all the stations in the region. As far as practical application of the Monte Carlo Simulation technique for design flood estimation is concerned, a reasonable fitting of the distribution to the observed data as found with the exponential or gamma distribution above should be acceptable provided that they can produce reasonably accurate flood frequency curve. This is investigated below.

The impact of having different distributions for the storm-core durations on flood frequency curves was assessed by adopting a simple conceptual runoff routing model with a single concentrated storage at the catchment outlet for which the storage-discharge relationship is expressed by:

$$S = kQ^m \tag{10}$$

where S is catchment storage in m^3, k is a storage delay parameter in hour, Q is the rate of outflow in (m^3/s) and m is a non-linearity parameter (taken as 0.8 here).

The derived flood frequency curves were obtained using at-site and regional exponential and gamma distributions for three test catchments as seen in Table 2. Here we present the results as shown in Figure 4 for the Boggy Creek catchment. The distributions of the other parameters were obtained from the at-site pluviograph and stream flow data analyses and were kept fixed between different runs for a given catchment. Figure 4 shows that the regional gamma distribution approximates the observed flood frequency curves reasonably well. The differences in derived flood frequency curves from at-site and regional distributions appear to be within the margin of expected sampling variability in flood frequency analysis.

To assess the impact of the variation in the parameters of the regional distributions on the derived flood frequency curves, the 95% confidence interval values of the distributional parameters of the gamma distribution were used in the Monte Carlo simulation, and the resulting flood frequency curves are compared in Figure 5. These show that the derived flood frequency curves obtained from the 95% confidence intervals of the distributional parameters compare very well with the derived flood frequency curves obtained based on regional average values of the distributional parameters.

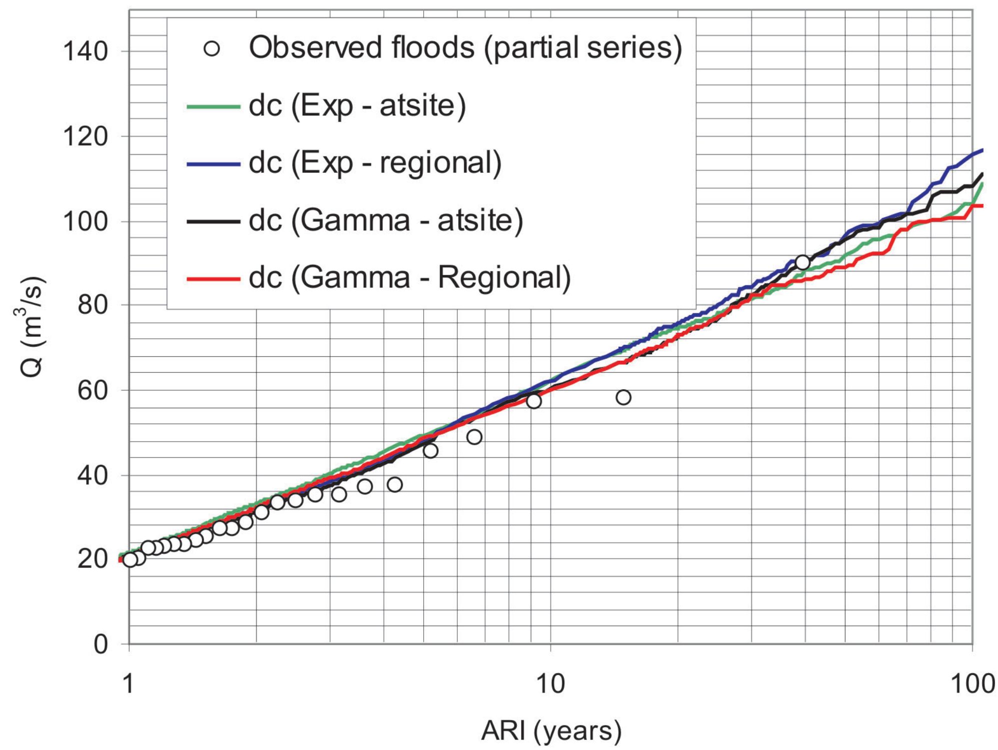

Figure 4: Comparison of the at-site and regional Exponential and Gamma distribution for the Boggy Creek catchment.

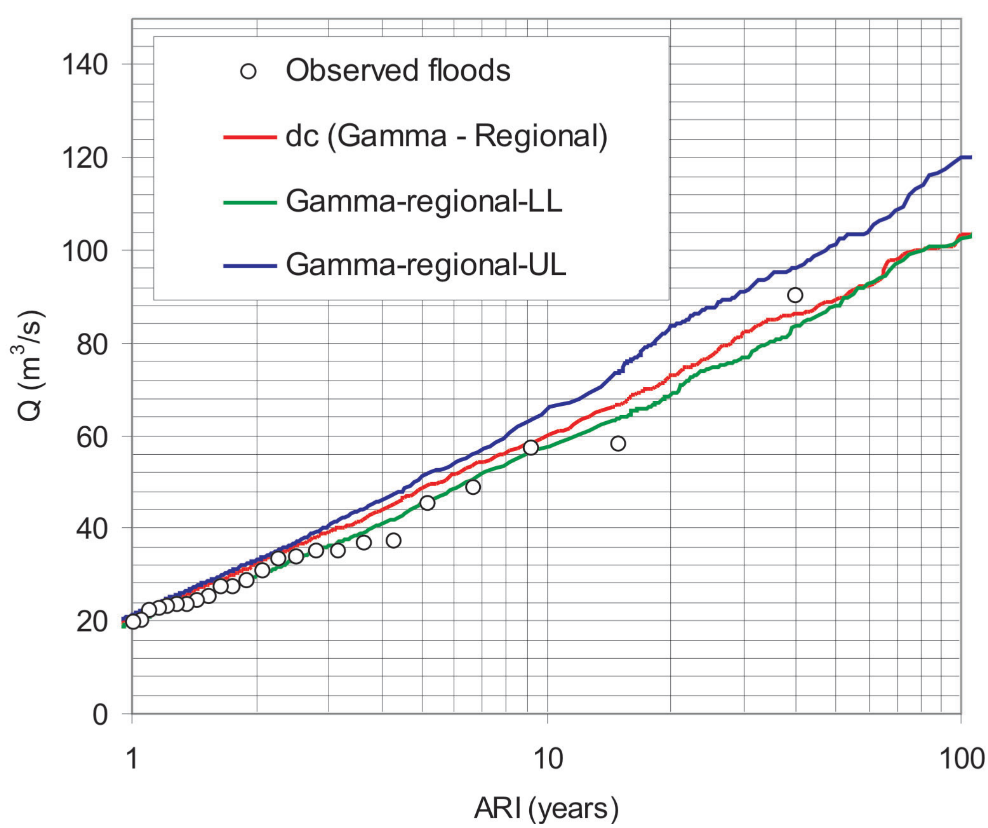

Figure 5: Derived flood frequency curves for the Boggy Creek using 95% confidence intervals of the parameters of the Gamma distribution.

Similar results were observed for both the Tarwin and Avoca river catchments.

The methodology presented in this paper can easily be adapted to other states of Australia or other countries, in particular where a sufficient quantity of continuous rainfall and streamflow data are available. This would particularly be useful in hydrological study of the important/large water infrastructure projects.

Conclusion

This paper compares the one-parameter exponential and two-parameter gamma distributions for describing the distribution of storm-core duration data in the state of Victoria Australia. Overall, the two-parameter gamma distribution provides a better fit to the storm-core duration data in Victoria than the one-parameter exponential distribution. Based on the Kolmogorov–Smirnov and Anderson–Darling tests, 63% and 68% of the stations satisfy the at-site exponential and gamma distributions, respectively. Considering these two tests, 41% and 49% of the stations satisfy a regional exponential and gamma distribution, respectively. The application of the fitted gamma distribution in the Monte Carlo Simulation technique for generating flood frequency curves shows that this approximates the observed flood frequency curves for the selected test catchments relatively better.

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