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Fundamental issues

Scope and Philosophy, 2019 / Ball, J., Babister, M., Nathan, R., Weeks, W., Weinmann, E., Retallick, M., Testoni, I. (ed./s), Ch.2, pp.6-30

Series/Report no.: Australian Rainfall and Runoff - A Guide to Flood Estimation; Book 1

Chapter 2. Fundamental Issues

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Chapter Status	Final
Date last updated	14/5/2019

2.1. Introduction

This chapter introduces important concepts of probability and statistics with respect to flood estimation, and defines the recommended terminology for these probability concepts. The chapter also discusses the difference between design and actual events, conversion of rainfall of a given probability to a flood of the same probability, risk-based design and dealing with uncertainty in flood estimates. Much of the text from the 1987 edition of Australian Rainfall and Runoff is still relevant and has formed the basis for the information provided in some of following sections.

2.2. Terminology

2.2.1. Background

Probability concepts are fundamental to design flood estimation and appropriate terminology is important for effective communication of design flood estimates. Terms commonly used in the past have included "*recurrence interval*", "*return period*", and various terms involving "*probability*". It is common for these terms to be used in a loose manner, and sometimes quite incorrectly. This has resulted in misinterpretation by the profession, the general community impacted by floods, and other stakeholders.

In considering the terminology that should be used in this edition of Australian Rainfall and Runoff, the National Committee on Water Engineering's three major concerns were:

- Clarity of meaning;
- Technical correctness; and
- Practicality and acceptability.

2.2.2. Clarity of Meaning

Use of the terms "*recurrence interval*" and "*return period*" has been criticised as leading to confusion in the minds of some decision-makers and members of the public. Although the terms are simple superficially, they are misinterpreted regularly as implying that the associated event magnitude is only exceeded at regular intervals, and that they are referring to the expected elapsed time till the next exceedance. This misinterpretation of the terms used for expressing probabilities of flood magnitudes can be misleading and result in poor decisions.

It is believed that irrespective of the terms used, it is critical that all stakeholders have a common interpretation of the terms. Furthermore, it is important that stakeholders understand that the terms refer to long term averages. This means, for a given climatic environment, that the probability of an event of a given magnitude being equalled or exceeded in a given period of time (for example, one year) is unchanged throughout the life of the structure or the drainage network. Furthermore, it is not uncommon for an event to occur more than once in a single year.

Additionally, given the wet and dry phases that occur in many regions of Australia, these events are likely to be clustered in time. The occurrence of these wet and dry climatic phases highlight the misleading and inappropriate interpretation that flood events occur at regular intervals as implied by "*recurrence interval*" and "*return period*".

Flood events generally are random occurrences, and the period between exceedances of a given event magnitude usually is a random variate, the properties of which are assumed to be constant in time for a given location and climatic environment. The adopted terminology reflects this fundamental concept and is intended to convey a clear and precise interpretation.

2.2.3. Technical Correctness

In view of the loose and frequently incorrect manner in which probability terms are often used, it was considered that Australian Rainfall and Runoff should adopt terminology that is technically correct, as far as this is possible and in harmony with other objectives. Additionally, even if this is not entirely popular with all practitioners, Engineers Australia has a responsibility to encourage and educate engineers regarding correct terminology.

The two approaches used when describing probabilities of flood events in previous editions of Australian Rainfall and Runoff were:

- *Annual Exceedance Probability (AEP)* - the probability of an event being equalled or exceeded within a year. Typically the AEP is estimated by extracting the annual maximum in each year to produce an Annual Maxima Series (AMS); and
- *Average Recurrence Interval (ARI)* - the average time period between occurrences equalling or exceeding a given value. Usually the ARI is derived from a Peak over Threshold series (PoTS) where every value over a chosen threshold is extracted from the period of record.

Details of AMS and PoTs and the background to these alternative techniques for extracting flood series from recorded data are presented in Book 3, Chapter 2. Included in this discussion are the assumptions necessary for conversion of one probability terminology to the other using the Langbein formula (Langbein, 1949).

Using the Langbein formula, in probability terms, there is little practical difference for events rarer than 10% AEP. Historically, however, there has been a reluctance to convert from the approach used for derivation of the design flood estimate. Furthermore, terminology was attached to particular design flood estimation techniques; for example, when AMS were used to derive design flood estimates, the resultant probability was expressed as an AEP while when a PoTS was used for the same purpose, the resultant probability was expressed as an ARI.

In many situations, this distinction between an ARI and an AEP was imprecise as the design flood prediction methodology adopted did not explicitly note the use of either an AMS or a PoTS in the methodology. As a result, use of ARI and AEP was considered to be interchangeable. This interchangeable use often resulted in confusion.

The National Committee on Water Engineering believes that within Australian Rainfall and Runoff a terminology should be used which, while being technically correct, is consistent with other uses. Furthermore, the terminology adopted should be easily understood both by the profession and by other stakeholders within the community.

2.2.4. Practicality and Acceptability

The National Committee on Water Engineering is aware that while the terminology adopted must be technically correct it must also be relatively simple and suitable for use in practice. Terminology that meets this criterion will be accepted by the profession and by other stakeholders.

The interaction of the profession with the community and the increased public participation in decision making means that terminology needs to be clear not only to the profession but also to the community and other stakeholders, other professions involved in flood management, and to the managers of flood-prone land. This need has resulted in a move away from the terminology adopted in the 1987 Edition of Australian Rainfall and Runoff towards a clear and unambiguous terminology supported by the National Committee on Water Engineering of Engineers Australia and the National Flood Risk Advisory Group (NFRAG, a reference group under the Australian and New Zealand Emergency Management Committee). All parties believe that terminology involving annual percentage probability best conveys the likelihood of flooding and is less open to misinterpretation by the public.

2.2.5. Adopted Terminology

To achieve the desired clarity of meaning, technical correctness, practicality and acceptability, the National Committee on Water Engineering has decided to adopt the terms shown in Figure 1.2.1 and the suggested frequency indicators.

Frequency Descriptor	EY	AEP (%)	AEP (1 in x)	ARI
Very Frequent	12			
	6	99.75	1.002	0.17
	4	98.17	1.02	0.25
	3	95.02	1.05	0.33
	2	86.47	1.16	0.5
	1	63.21	1.58	1
Frequent	0.69	50	2	1.44
	0.5	39.35	2.54	2
	0.22	20	5	4.48
	0.2	18.13	5.52	5
	0.11	10	10	9.49
Rare	0.05	5	20	19.5
	0.02	2	50	49.5
	0.01	1	100	99.5
Very Rare	0.005	0.5	200	199.5
	0.002	0.2	500	499.5
	0.001	0.1	1000	999.5
	0.0005	0.05	2000	1999.5
Extreme	0.0002	0.02	5000	4999.5
			↓	
			PMP/ PMP Flood	

Figure 1.2.1. Australian Rainfall and Runoff Preferred Terminology

Navy outline indicates preferred terminology. Shading indicates acceptable terminology which is depends on the typical use. For example in floodplain management 0.5% AEP might be used while in dam design this event would be described as a 1 in 200 AEP.

As shown in the third column of Figure 1.2.1, the term Annual Exceedance Probability (AEP) expresses the probability of an event being equalled or exceeded in any year in percentage terms, for example, the 1% AEP design flood discharge. There will be situations where the use of percentage probability is not practicable; extreme flood probabilities associated with dam spillways are one example of a situation where percentage probability is not appropriate. In these cases, it is recommended that the probability be expressed as 1 in X AEP where 100/X would be the equivalent percentage probability.

For events more frequent than 50% AEP, expressing frequency in terms of annual exceedance probability is not meaningful and misleading , as probability is constrained to a maximum value of 1.0 or 100%. Furthermore, where strong seasonality is experienced, a recurrence interval approach would also be misleading. An example of strong seasonality is where the rainfall occurs predominately during the Summer or Winter period and as a consequence flood flows are more likely to occur during that period. Accordingly, when strong seasonality exists, calculating a design flood flow with a 3 month recurrence interval is of limited value as the expectation of the time period between occurrences will not be consistent throughout the year. For example, a flow with the magnitude of a 3 month recurrence interval would be expected to occur or be exceeded 4 times a year; however, in situations where there is strong seasonality in the rainfall, all of the occurrences are likely to occur in the dominant season.

Consequently, events more frequent than 50% AEP should be expressed as X Exceedances per Year (EY). For example, 2 EY is equivalent to a design event with a 6 month recurrence interval when there is no seasonality in flood occurrence.

Different users of Australian Rainfall and Runoff, in general, will use different segments of the relationship between flood magnitude and exceedance probability. To reduce confusion, that may arise from switching between different terminologies, it is recommended that consistent terminology in accordance with one of the columns of Figure 1.2.1 be used within an industry segment.

These expressions of estimated frequencies relate directly to the particular time period for which data have been analysed and frequencies determined with no consideration given to the long term effects of climatic change. Nonetheless, the adopted terminology is considered to be equally applicable to both stationary and non-stationary climatic environments, as there is no requirement for the annual exceedance probabilities to be constant over time. Consequently, where flood characteristics are changing as result of long term climatic change, the AEP of a flood characteristic for a future time period may be different or, conversely, a flood characteristic magnitude corresponding to a given AEP may change.

2.3. Difference Between Design Events and Actual Events

Much confusion has resulted from lack of recognition of the fundamental differences between these two types events and associated of flood estimation problems. Although the same mathematical procedures may be involved in both cases, the implications and assumptions involved, and the validity of application, are quite different. The emphasis in this document is largely on design floods.

A design flood is a probabilistic or statistical estimate, being generally based on some form of probability analysis of flood or rainfall data. An Annual Exceedance Probability is attributed to the estimate. This applies not only to normal routine design, but also to probable maximum estimates, where no specific probability can be assigned but the intention is to obtain a design value with an extremely low probability of exceedance. In the flood estimation methods based on design rainfalls, the probability relationship between design rainfall events and design flood events is not a direct one. Occurrence of a rainfall eventwhen the catchment is wet might result in a very large flood, while occurrence of the same rainfall event when the catchment was dry might result in relatively little, or even no runoff. For the design situation, the combinations of different factors combining to produce a flood event are not known and must be assumed, often implicitly in the design values that are adopted.

The approach to estimating an actual (or historic) flood from a particular rainfall event is quite different in concept and is of a deterministic nature. All causes and effects are directly related to the specific event under consideration. The actual antecedent conditions prevailing at the time of occurrence of the rain are directly reflected in the resulting flood and must be allowed for in its estimation. No real information on the probability of the on flood probability can be gained from consideration of a single actual flood event.

Although the differences in these two types of events are often not recognised, they have three important practical consequences. The first is that a particular procedure might be might be appropriate for analysing actual flood events but quite unsuitable for probabilistic design flood events.

The second concerns the manner in which values of parameters are derived from recorded data, and the manner in which designers regard these values and apply them. If actual floods are to be estimated, values for use in the calculations should be derived from calibration on individual observed events. If design floods are to be estimated, the values should be derived from statistical analyses of data from many observed floods.

The third practical consequence concerns the manner in which parameters are viewed by designers and analysts. For example, design initial losses for bursts can be very different from event initial losses derived from actual events, yet practitioners still often compare them without understanding the differences.

2.4. Probability Concepts

2.4.1. Probability Relationship Between Design Rainfall and Design Flood Characteristics

In the flood frequency based design flood estimation approaches covered in Book 3, the probabilities of a specific event magnitude being equalled or exceeded are estimated directly for the flood characteristic of interest (e.g. peak flow or flood volume). However, for the catchment simulation and hydrograph estimation procedures covered in Book 4, Book 5 and Book 7, the exceedance probability associated with design rainfall, as the primary probabilistic input to the design flood estimation procedure, needs to preserved in its transformation to a design flood. This concept is often referred to as AEP neutrality.

However, each of the processes represented in a model that converts rainfall to runoff and forms a flood hydrograph at the point of interest introduces some joint probability, resulting in the fundamental problem that the true probability of the derived flood characteristic may be obscure, and its magnitude may be biased with respect to the true flood magnitude with the same probability as the design rainfall, especially at the low probabilities of interest in design.

Since publication of ARR 1987 (Pilgrim, 1987) there has been a steady shift towards methods that better account for the stochastic nature of how floods of different magnitude and exceedance probabilities are generated. Procedures of different complexity to deal with this fundamental issue are discussed in Book 1, Chapter 3.

2.4.2. Choosing a Quantile Estimator

The 1 in Y AEP quantile corresponds to the flood magnitude with annual probability of exceedance equal to 1/Y. Because the parameters of the flood frequency distribution have to be estimated from limited data, the true quantile is not known. Different quantile estimates are available depending on the application. These are described in Book 3, Chapter 2.

In cases where the interest is principally on the accurate estimation of the AEP that corresponds to a specified flood magnitude (e.g. the flood level at which a particular flood protection structure is expected to fail), an expected AEP (or expected probability) quantile should be used. The use of such a quantile ensures that, on average, its AEP equals the true value. In cases where the mean-squared-error in the flood magnitude is to be minimized for a given AEP, expected parameter quantiles should be used.

The difference between these quantile estimates is typically not of significance when there is little or no extrapolation of the observed range of data, and especially if the skew is small. However, if extrapolation is required and high skews are involved, the difference can be appreciable. The methods in Book 3, Chapter 2 describes how to estimates these quantiles.

2.4.3. Avoiding Inconsistencies in Procedures and Resolution

The important step often overlooked by practitioners is mistakenly using an input or parameter that was derived a particular way and at a particular resolution in a manner that is different to how it was derived. This is particularly difficult to avoid with digital data sets compiled from different sources and resolutions. Historically problems have arisen when a method was derived from one scale map and used at a different scale.

2.5. Risk-Based Design

Floods can cause significant impacts where they interact with the community and the supporting natural and built environment. However, flooding also has the potential to be the most manageable natural disaster as the likelihood and consequences of the full range of flood events can be understood, enabling risks to be assessed and where necessary managed. There is strong move from managing floods by a by simple standards approach, where a certain frequency of flooding is deemed acceptable, to risk-based approaches, where the consequence and probability of design capacity being exceeded are assessed explicitly. Risk and design flood estimation concepts are discussed in detail in Book 1, Chapter 5.

2.5.1. Route Serviceability

A particular aspect of risk based approaches is where total system risk is of main interest. With a railway or major road, flooding of any one of many stream crossings will cause closure of the route. The item of real interest is the probability of this closure, and not of failure at any particular site. This probability of closure will be much greater than that at an individual site. Closure of the route at any site may cause major disruption and economic losses. Upgrade works can be targeted at reducing the probability of closure.

This problem is receiving increasing attention from transport managers and is discussed in detail in Book 1, Chapter 5.

2.6. The Importance of Data

Data is fundamental to flood estimation. Data is needed to understand the processes involved in the formation of floods and to ensure that models are accurate and reflect the real world issues being analysed. Flood estimation primarily uses data that describes the rainfall, streamflow and water levels. The procedures and guidelines presented in ARR could not have been developed without historical data, and often the reliability of the methods presented depends on the extent of data that has been used in development.

For the first time, ARR has been based completely on Australian data to better reflect Australia’s variable landscape, including a national database of extreme flood hazards. A major task of the current ARR update was assembling a national databases of rainfall and streamflow data for developing inputs and methodologies. ARR 1987 (Pilgrim, 1987) used 600 pluviographs rainfall gauge (measures the amount of rainfall which fell) with greater than 6 years data and 7500 daily rainfall gauges with over 30 years record. ARR 2016 uses almost 30 years of extra rainfall and streamflow data, including data from over 2200 pluviographs and over 8000 daily rainfall gauges. Over 900 streamflow gauges were analysed. Over 100, 000 storm events were analysed. This data provides a valuable resource for the development of future methodologies.

Major improvements have been made to design flood estimation methods but national databases will allow the use and parameterisation of more complex methods. Major advances will continue that will allow us to leverage the limited data we can afford to collect on the continent nation. Many projects have opened the eyes of researchers and practitioners on what could be done with more time, money and the still limited data available. The data sets developed as part of this update should be enhanced and applied to for future improvements.

Book 1, Chapter 4 provides a summary of the types of data used for flood estimation.

2.7. Climate Change

ARR 1987 (Pilgrim, 1987) while acknowledging climate change did not address climate change or non-stationarity or provide guidance on the inclusion of climate change impacts in flood estimation. One key aim of this edition was the incorporation of the best available information of climate change impacts on flooding.

This edition of ARR funded research projects which investigated the following aspects:

- How climate change will affect flooding and the factors influencing flooding;
- How to incorporate climate change into the investigation methodologies used by the engineering profession to estimate design floods;
- Updating of the methodology in Australian Rainfall and Runoff so that the outcomes from climate change research (e.g. regional dynamic downscaling) can be incorporated easily into the investigation methodology as the science and results become available.

The impacts of climate change on design flood estimation are discussed in detail in Book 1, Chapter 5, Section 10. More detail can be found in the ARR Climate Change Research Plan and ARR Project 1: Climate Change Synthesis report (Bates and Westra, 2013; Bates et al., 2015).

2.7.1. Climate Change Impacts on Flooding

Global warming has been observed over several decades, and has been linked to changes in the large-scale hydrological cycle including increasing atmospheric water vapour content; changing precipitation patterns, intensity and extremes; changes in soil moisture and runoff; and increasing melting of snow and ice (Bates et al., 2008).There is increasing evidence that human-induced climate change is changing precipitation extremes, and that extreme flooding globally has increased over the 20th century (Trenberth, 2011). There is confidence that these changes in the hydrological cycle will lead to increased variability in precipitation and increased frequency of flood events over many areas (IPCC, 2007; Bates et al., 2008). Changes in climate will result in changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events, and may lead to unprecedented extreme weather and climate events (IPCC, 2012).

The major areas where climate change will impact flooding are:

- Design rainfall intensity-frequency-duration;
- Storm type, frequency, and depth;
- Rainfall spatial and temporal patterns;
- Antecedent conditions;
- Changes in sea level; and
- The joint probability of storm surge and flood producing rainfall.

2.7.1.1. Climate Change Impacts on Rainfall

Changes in extremes events, such as floods, can be linked to changes in the mean, variance, or shape of probability distributions, or all of these (IPCC, 2012). For example, climate change projections have shown that a relatively small shift in the distribution of precipitation may result in a large change in the frequency and magnitude of extreme precipitation events (Nicholls and Alexander, 2007). Studies have shown that a change in the shape of the distribution of precipitation is likely to have a greater effect on the frequency of extremes than a shift in the mean precipitation (White et al, 2010; Groisman et al., 1999), and that climate change is most likely to increase climate variability, particularly affecting the extremes (Jones et al., 2012; Fowler and Ekstrom, 2009).

A warming climate leads to an increase in the water holding capacity of the air, which causes an increase in the atmospheric water vapour that supplies storms, resulting in more intense precipitation. This effect is observed, even in areas where total precipitation is decreasing (Trenberth, 2011). Indeed, some of the largest impacts of climate change are likely to result from a shift in the frequency and strength of climatic extremes, including precipitation (White et al, 2010). It is likely that the frequency of heavy precipitation will increase by the end of the 21st century, particularly in the high latitudes and tropical regions and there is likely to be an increase in heavy rainfalls associated with tropical cyclones (IPCC, 2012).

There have been many studies globally that have found increases in the intensity or frequency of extreme precipitation events (Bates et al., 2008; Westra et al., 2013). It is likely that since the 1970s the frequency of heavy precipitation events has increased over most areas (Bates et al., 2008). From 1950 to 2005, extreme daily rainfall intensity and frequency has increased in north-western and central Australia and over the western tablelands of New

South Wales, but decreased in the south-east and south-west and along the central east coast (CSIRO and Australian Bureau of Meteorology, 2007). Projections analysed by CSIRO and Australian Bureau of Meteorology (2007) showed that an increase in daily precipitation intensity is likely under climate change. The study found that the highest 1% of daily rainfalls tends to increase in the north of Australia and decrease in the south, with widespread increases in summer and autumn, but not in the south in winter and spring when there is a strong decrease in mean precipitation (CSIRO and Australian Bureau of Meteorology, 2007).

The increases in precipitation are more evident in sub-daily rainfalls and major changes in the intensity and temporal patterns of sub-daily rainfalls can be expected by the end of the 21st century (Westra et al., 2013). In a study of downscaled outputs from climate models, Abbs and Rafter (2008) found that by 2070 the models projected an increase of an average of 40% in intensity for 24 and 72 hour events around the Queensland-New South Wales border, and an increase of more than 70% in the two hour rainfall events in the high terrain inland from the Gold Coast.

2.7.1.2. Antecedent Conditions

Changes in the patterns of precipitation and in evaporation will lead to changes in antecedent conditions prior to flood events, affecting soil moisture and thus loss rates in the catchment (Bates et al., 2008). Potential evaporation is projected to increase almost everywhere on a global scale due to an increase in the water-holding capacity of the atmosphere with higher temperatures combined with little projected change in relative humidity (Bates et al., 2008).

Projections of potential evapotranspiration over Australia show increases by 2030 and 2070. The largest projected increases are in the north and east, where the change by 2030 ranges from little change to a 6% increase, with the best estimate being a 2% increase. By 2070, the A1FI scenario gives increases of 2% to 10% in the south and west with a best estimate of around 6%, and a range of 6% to 16% in the north and east with a best estimate around 10% (CSIRO and Australian Bureau of Meteorology, 2007).

Projected decreases in rainfall over much of Australia combined with increases in evaporation may result in disproportionate decreases in runoff due to a disconnection between surface and groundwater, as was experienced in parts of Australia during the Millennium drought (CSIRO, 2012).

2.7.1.3. Sea Level

The relatively small rise in sea level that is seen in observed data over the past century has already caused a significant change in the frequency of extreme sea-level events, and associated flooding (Hunter, 2007). Studies of observed sea level data worldwide have shown that sea level rise is the predominant cause of increases in the frequency of extreme sea level events (IPCC, 2007; Hunter, 2007). There is high confidence that there has been an increase in the frequency of high coastal sea level events of a given magnitude, and that extreme flooding events due to sea level rise will increase significantly, dependent on location (Church et al., 2012). The likely range of global-mean sea level rise between the 1980 – 1999 and 2090 – 2099 periods is given by (IPCC, 2007) as 0.18 – 0.59 m. There is high confidence that the global rate of sea level rise has increased between the mid-19th and the mid-20th centuries. The average rate was 1.7 ± 0.5 mm/yr for the 20th century and 3.1 ± 0.7 mm/yr for 1993–2003 (Bates et al., 2008). The observed rate of sea level rise in the Australian region from 1993 - 2011 has high spatial variability, with a maximum in the north and north-west coasts of Australia of 9mm/yr, and a rate of 2 to 4 mm/yr on the south-eastern and eastern Australian coastline (Church et al., 2012).

2.8. Dealing with Uncertainty

2.8.1. Introduction

This section provides an overview of the uncertainties in the design flood estimation. The specific aims are to:

- Identify the types of uncertainty in design flood estimation;
- Motivate practitioners on the value of undertaking uncertainty analysis; and
- Raise awareness of the various sources of uncertainty in common techniques for design flood estimates.

2.8.2. Types of Uncertainty in Design Flood Estimation

It is typical in current practise for design flood estimation to ignore the uncertainty in the estimates of the design flood. This is despite the considerable uncertainties that are introduced when undertaking a Flood Frequency Analysis using short data records and extrapolating the fitted flood frequency distribution to estimate the 1% or 0.5% Annual Exceedance Probability flood. Similarly, when using a catchment modelling approach to obtain estimates of the design flood, the typical situation is that the catchment modelling system is calibrated to data from a few selected flood events, and the calibrated model is then extrapolated using design rainfall estimates (which itself is an extrapolation of observed rainfall data, Book 2, Chapter 3) to provide estimates of the 1% or 0.5% Annual Exceedance Probability flood. Both these type of approaches introduce significant uncertainties in estimates of the design flood.

The causes of these uncertainties are that practitioners are required to: (1) Use mathematical algorithms to represent the complexity of catchment processes that transform rare rainfall into rare flood events. (2) Calibrate and validate these algorithms using measurements of the catchment process that are highly uncertain. It is widely acknowledged that there is significant spatial variation in catchments and temporal and spatial variation in the antecedent catchment wetness and rainfall events that drive significant flood events. Practitioners use hydrologic models, which are simplified mathematical conceptualisations to represent these complex spatially and temporally distributed hydrological processes. These hydrologic models are calibrated to measurements of data on variables such as rainfall, evaporation and flow. It is widely acknowledged that these data can have significant measurement errors (refer to Book 1, Chapter 4). Rainfall is spatially heterogeneous, however, typically there are only a small number rainfall gauges in a given catchment. Streamflow is based on river height (stage) measurements and a rating curve, which can be difficult to reliability estimate for large flood events. Typically these uncertainties are ignored in the design flood estimation process.

Uncertainty analysis provides the tools with which to handle this uncertainty and incorporate it into the design flood estimates. To enable the use of uncertainty analysis tools, it is first important to distinguish two broad types of uncertainty:

- *Aleatory (or inherent) Uncertainty* - refers to uncertainty that arises through natural randomness or natural variability that we observe in nature; and

- *Epistemic (or knowledge-based) Uncertainty* - refers to uncertainty that is associated with the state of knowledge of a physical system (our estimation of reality), our ability to measure it and the inaccuracies in our predictions of the physical system.

These definitions are consistent with the broad definitions provided by Ang and Tang (2007) in wider context of general engineering and the specific context of flood risk by Pappenberger and Beven (2006). The major differences between the two types of uncertainty is that epistemic uncertainty can be reduced, through advances in process understanding or improvement in measurement techniques, while aleatory uncertainty cannot be reduced, and therefore needs to be characterised. Both types of uncertainty can be characterised using tools of uncertainty analysis. Ang and Tang (2007) provide a wealth of examples of the two types of uncertainty in a general engineering context.

In the context of design flood estimation, a simple example to understand the differences between these two types of uncertainty is to consider an example of a flood frequency distribution, as shown in Figure 1.2.2, with probability limits on the design flood estimates over the range of Annual Exceedance Proabilities.

An illustration of aleatory uncertainty is the natural variability in annual maximum floods which is due to the climate variability in extreme rainfall and antecedent soil moisture condition from year to year. This aleatory uncertainty influences the shape of the flood frequency distribution, and influences the values of 1% Annual Exceedance Probability design flood estimates. The aleatory uncertainty is why practitioners undertake a risk-based design approach to estimate the likelihood of flooding. At different catchments, the flood frequency distribution changes due to the natural variability in the climate and catchment processes, hence this is also of type aleatory uncertainty.

An illustration of epistemic uncertainty is the uncertainty in the estimate of the design flood for a given Annual Exceedance Probability, e.g. Figure 1.2.2, the design flood for a 1% Annual Exceedance Probability has an expected flow of 100 m^3/s and the 95% probability limits are 65 and 155 m^3/s. This uncertainty in the design flood estimate for a given Annual Exceedance Probability is primarily of type epistemic (or knowledge based) uncertainty. There is an opportunity to reduce this uncertainty, if there were longer flow records which would reduce the uncertainty in the parameters of the flood frequency distribution fitted to the annual maximum floods. Similarly, for catchment modelling, or if there was a better understanding on the catchment processes obtained through better data to calibrate and verify the catchment modelling system, this would reduce the uncertainty in the flood estimates of the catchment model.

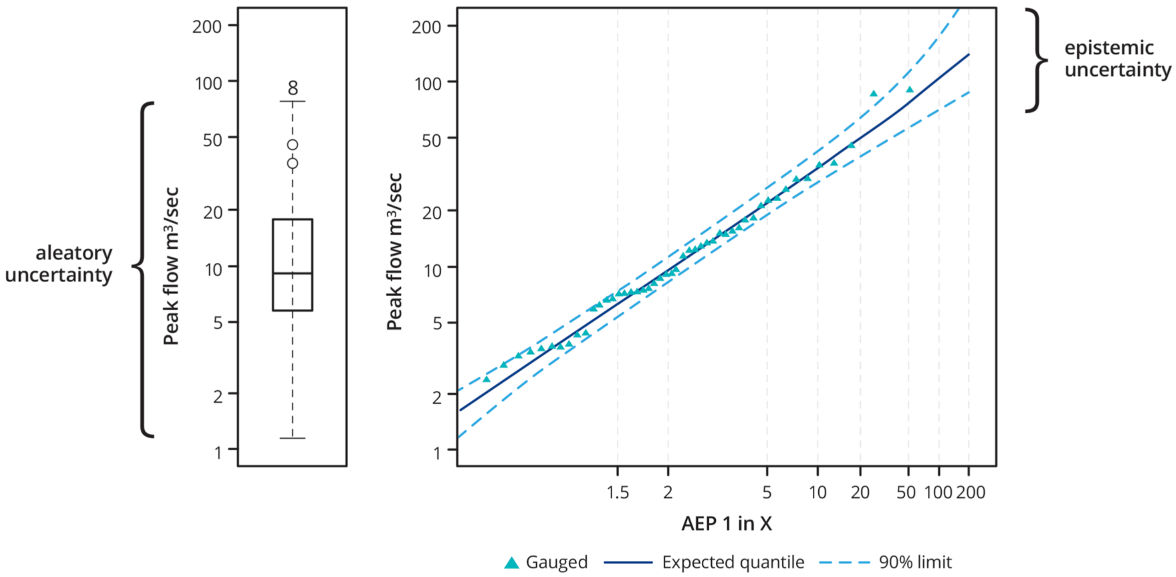

Figure 1.2.2. Different Types of Uncertainty, Aleatory and Epistemic, in the Context of Design Flood Estimation

Despite the simplicity of the two illustrations of aleatory and epistemic uncertainty, given in the flood frequency distribution in Figure 1.2.2, there are occasions where the distinction between the two different types of uncertainty is not always clear. For example, the illustration of Figure 1.2.2 implies that as level of information increases and the epistemic uncertainty is reduced then “true” flood frequency distribution for a given catchment will emerge. There is practical limit on the level of information (data and/or process understanding) available on a given catchment hence the concept of a single “true” flood frequency distribution for a given catchment is likely to unobtainable. Hence the epistemic uncertainty given in Figure 1.2.2, will have a component of aleatory uncertainty.

The concepts of aleatory and epistemic uncertainty are similar to concepts of flood likelihood and uncertainty from risk-based decision-making (Book 1, Chapter 5).

2.8.3. Motivation for Incorporating Uncertainty Into Design Flood Estimates

There are a range of approaches for dealing with uncertainty, the simplest of which is to ignore it, to qualitative descriptions (highly uncertain) or relative rankings, (option 1 is more uncertainty than option 2) ie. to rigourous quantitative approaches which use uncertainty analysis techniques to characterise the individual sources of uncertainty, and use advanced techniques to estimate their impacts on the uncertainty in the design flood estimations (refer to Book 4, Chapter 3 for an overview of the various approaches). The greater the rigour in uncertainty analysis approach the more effort and resources is required. The reward for this greater effort is more informed decision making.

An example of the potential benefits of incorporating uncertainty for more informed decision making is provided in Figure 1.2.3. Consider two different designs; Design A and Design B. The practitioner needs to choose the design that reduces the flood magnitude for given catchment location. Design A has a higher value for the most likely estimate of the design flood, but has a lower uncertainty than Design B. The differences in the uncertainty estimates could arise because Design B is a more complicated design option than design A and requires the use of more complex catchment modelling approach (e.g. fully distributed model (Book 5)) and there was a lack of spatial data in the catchment to calibrate the distributed model and hence parameter estimates had to be based on regional information. In contrast Design A was based on catchment modelling approach that was well-calibrated using high quality data that was readily available in the catchment. If the uncertainty is ignored then Design B would be the preferred choice of the practitioner, because the most likely estimate of the flood magnitude is lower than Design A. If the uncertainty in the flood magnitude incorporated than a practitioner who is risk-averse may prefer to choose Design A, because it the probability of a large magnitude flood with major/catastrophic consequence is lower than Design B. This example illustrates how the uncertainty in the design flood estimates, when combined with risk attitude (risk-averse, risk-neutral, or risk-seeking) of the practitioner provides a more information on which to base the design choice.

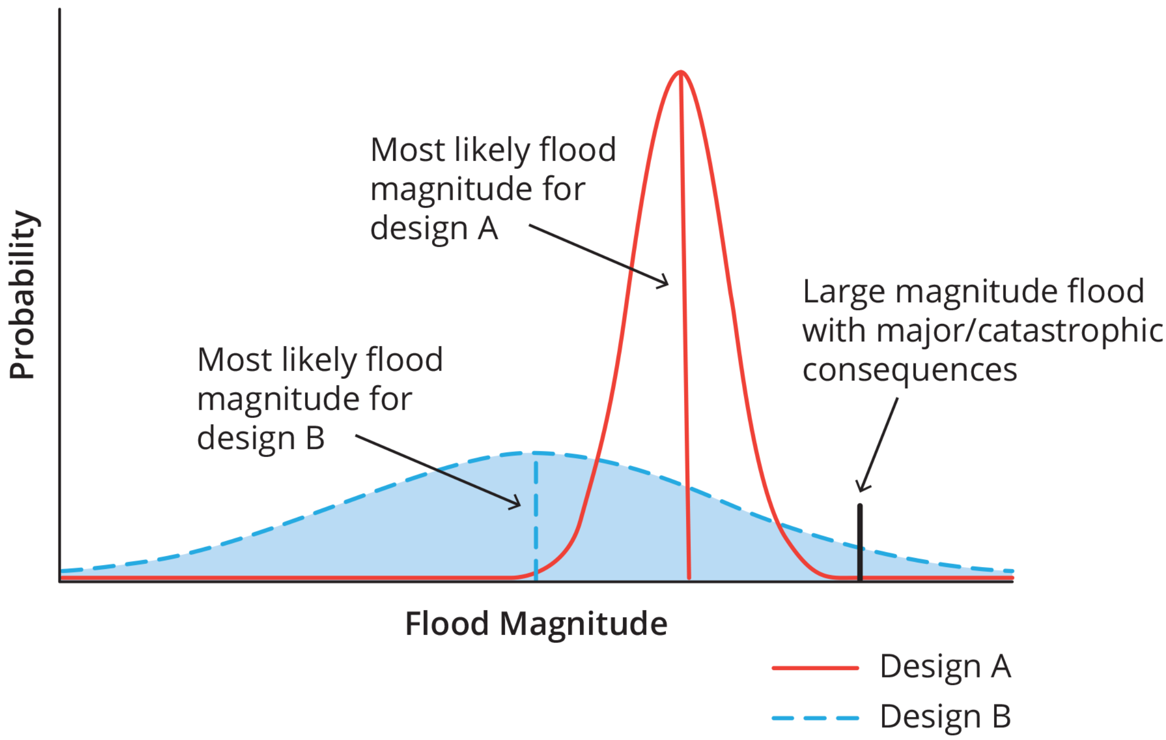

Figure 1.2.3. Impact of Uncertainty on a Design Flood Estimate for Two Design Cases

From a practical and scientific perspective Pappenberger and Beven (2006) provide an overview of the common reasons for not undertaking uncertainty analysis for hydrologic and hydraulic models and argue that these arguments are not tenable. A summary of the reasons provided by Pappenberger and Beven (2006) and their counter arguments are summarized as follows:

1. *Uncertainty Analysis is Not Necessary Given Physically Realistic Models*

   Pappenberger and Beven (2006) states there are a group of practitioners who believe that their models are (or at least will be in the future) physically correct and thus parameter calibration or uncertainty analysis should not be necessary (or only minimal) if predictions are based on a true understanding of the physics of the system simulated. This position is difficult to justify considering published discussions of the modelling process in respect of the sources and impacts of uncertainties (Beven, 1989; Beven, 2006; Oreskes et al., 1994). It is argued that this group of practitioners have too much faith in the model representation of physical laws or empirical equations. An alternative is a group of practitioners who inherently accept uncertainties in the modelling process, at least as a result of errors and natural variability in time and space.

2. *Uncertainty Analysis is Not Useful in Understanding Hydrological and Hydraulic Processes*

   To be able to learn about how water flows through the landscape and the best model to represent this water flow requires the use of a hypothesis testing framework . In real applications, this hypothesis testing framework would evaluate different competing hypothesis (ie. models) against the observations, and should explicitly consider the potential sources of uncertainty in applications to real systems to enable the results to be stated in a probabilistic rather than a deterministic manner. This would enable evaluation of whether the differences in model performance, can be reliability identified given the uncertainty in the predictions and observations.

3. *Uncertainty (Probability) Distributions Cannot be Understood by Policy Makers and the Public*

   Pappenberger and Beven (2006) cite several scientific studies that suggest practitioners actually want to get a feeling for the range of uncertainty and the risk of possible outcomes. Furthermore, policy-makers derive decisions on a regular basis under severe uncertainties. If uncertainty is not communicated and there is a misunderstanding of the certainty of modeling results this can lead to a loss of credibility and trust in the model and the modelling process.

   However, it is acknowledge that there are a wide range of different perceptions of “risk” and “uncertainty” and that effort is required on the part of both pracitioners and policy-makers to work together to achieve a common understanding of uncertainty.

4. *Uncertainty Analysis Cannot be Incorporated into the Decision-Making Process*

   There are two supporting arguments to this reason (1) Decisions are binary; (2) Uncertainty bounds are too wide to be useful in decision making. Pappenberger and Beven (2006) conclude there is no question that, for many environmental systems, a rigorous estimate of uncertainty leads to wide ranges of predictions. There are certainly cases in which the predictive uncertainty for outcomes of different scenarios is significantly larger than the differences between the expected values of those scenarios. This leads to the perception that decisions are difficult to make. To counter these arguments, Pappenberger and Beven (2006) present numerous examples from the literature on decision support systems and decision analysis which provide a range of methods for decision making under uncertainty based on assessments of the risk and costs of possible outcomes. Examples of decisions under uncertainty for Flood Frequency Analysis are illustrated by Wood and Rodriuez-Iturbe (1975) and more recently by Botto et al. (2014). The key outcome from Botto et al. (2014) was that incorporating uncertainty in estimating the design floods (by minimising the total expected costs) leads to substantial higher estimates of the design flood compared to standard approaches when uncertainty is ignored. This suggests incorporating uncertainty leads to reduce expected costs and highlights the benefits of incorporating uncertainty.

5. *Uncertainty Analysis is Too Subjective*

   Pappenberger and Beven (2006) identify that in the application of uncertainty analysis methods, certain decisions must be made, some of which include an element of subjectivity, including the choice of probability distributions for data errors, prior distributions for parameter uncertainty or predictive errors. In principle, many of these assumptions can be checked as part of the analysis but it is common to find that not all assumptions can be fully justified or some assumptions cannot be checked, and hence this leads to the conclusion that predictions with uncertainty are too subjective. Pappenberger and Beven (2006) conclude that any analysis which does not considering uncertainties in the modeling can be objective. This view is based on a misplaced faith in deterministic modeling in the light of the inevitable uncertainty in the modeling process (refer to also argument 1 above). Even a fully deterministic model run requires necessarily subjective assumptions about model inputs and boundary conditions and performance evaluation. The important issue is that the nature of the assumptions should be made explicit so that they can be assessed and discussed. Uncertainty analysis provides a set of tools to make these assumptions transparent and subject them to explicit scrutiny.

6. *Uncertainty Analysis is Too Difficult to Perform*

   Pappenberger and Beven (2006) note this is a common attitude amongst practitioners and is consequence of the need to spend more time and money on assessing the different potential sources of uncertainty in any particular application, coupled with a lack of clear guidance about which methods might be useful in different circumstances. Pappenberger and Beven (2006) note that in general, uncertainty analysis is not too difficult to perform and provide list of relevant software that is available. Since, Pappenberger and Beven (2006) review, the research publications on uncertainty analysis in hydrologic modelling has increased substantially, with many new tools/techniques and reviews available (for example the recent review by Uusitalo et al. (2015)). These tools will be reviewed to provide guidance for practitioners on which is applicable for different situations in the context of design flood estimation. The continued increases in computational power have reduced the computational costs of uncertainty analysis, which reduces the difficulty in undertaking uncertainty analysis.

In summary, Pappenberger and Beven (2006) conclude that in the past many modelling and decision making processes have ignored uncertainty analysis and it could be argued that under many circumstances it simply would not have mattered to the eventual outcome. However, they note that the arguments for uncertainty analysis are compelling because:

1. It makes the practitioner think about the processes involved and the decisions made based on model results;

2. It makes predictions of different experts more comparable and leads to a transparent science;

3. It allows a more fundamental retrospective analysis and allows new or revised decisions to be based on the full understanding of the problem and not only a partial snapshot; and

4. Decision makers and the public have the right to know all limitations in order to make up their own minds and lobby for their individual causes.

2.8.4. Sources of Uncertainty in Context of Design Flood Estimation

Book 1, Chapter 2, Section 8 outlined the practical advantages of undertaking uncertainty analysis. The first step of undertaking uncertainty analysis is to identify the various sources of uncertainty in the modelling processes. To raise awareness of the various sources of uncertainty in the context of design flood estimation, this section will outline the various sources of uncertainty and identify how these sources of uncertainty manifest themselves in the two common techniques used for design flood estimation; the Flood Frequency Analysis and catchment modelling approaches to design flood estimation. The primary drivers of each of the sources of uncertainty will then also be discussed.

The various sources of uncertainty that are relevant to design flood estimation are outlined as follows:

- *Predictive Uncertainty*

Predictive uncertainty represents the total uncertainty in the predictions of interest, typically the estimates of the design flood. It is comprised of the various sources of uncertainty that are outlined below, including data uncertainty, parametric uncertainty, structural uncertainty, regionalisation uncertainty (if relevant) and deep uncertainty (if relevant). This total predictive uncertainty is what used as input to the decision making uncertainty framework, to provide reliable predictions. The magnitude of the total predictive uncertainty and the relative contribution of the various sources of uncertainty is of obvious interest. The magnitude provides an indication of the total uncertainty of the predictions, while the relative contribution highlights which sources of uncertainty are the key contributors and which can be reduced.

- *Data Uncertainty*

Data uncertainty is a key source of predictive uncertainty. The more uncertain the data used to inform the methods used to estimate the peak flows, the more uncertainty in the predictions of the peak flows. The definition of “data” is a challenging one in the context of design flood estimation since in each step of the modelling process, the data used an input maybe based on the output of a prior modelling process, rather than actual measurements. Data uncertainty is dependent on the quality and number of measurements undertaken to inform that data.

- *Parametric Uncertainty*

Design flood estimates relay on using mathematical models to predict design floods. These models are estimated using time series of uncertain data with finite length. These limitations induce uncertainty in the estimates of these parameters, called parametric uncertainty. This parametric uncertainty would occur even if the mathematical model were exact. The magnitude of this parametric uncertainty, decreases as the length of the time series of data increases and increases when the uncertainty of the data increases. When time series are short and/or uncertainty in the data are high then parametric uncertainty can contribute significantly to total predictive uncertainty.

- *Structural Uncertainty*

Structural uncertainty refers to the uncertainty in the mathematical model used to provide the predictions of the peak flows. It is a consequence of the simplifying assumptions made in approximating the actual environmental system with a mathematical hypothesis (Renard et al., 2010). The structural error of a hydrologic model depends the model formulation.

- *Regionalisation Uncertainty*

Regionalisation uncertainty refers to the uncertainty induced when there is a geographical migration of hydrological information from data rich location to a data poor location. This is an extension of the concepts of regionalisation of hydrologic model parameters, as outlined by Buytaert and Beven (2009). In the context of design flood estimation itt refers to any information that is transferred from one site to another, and could include the parameters of the flood frequency distribution, the parameters of the runoff-routing model, the loss model or the design rainfall used in the catchment modelling approach. It is a function of the predictive uncertainty of the original application of the model at the data rich location (which is a dependent on the structural, parametric and data uncertainty at that data rich site) and the regionalisation model used to transfer information from one site to another. Given there are large number of sources of uncertainty in regionalisation uncertainty, it can induce significant predictive uncertainty, when there is very limited at-site data.

• *Deep Uncertainty*

Deep uncertainty refers to the sources of uncertainty that impact on the robustness of design but are difficult to assign apriori probabilities measures to. It acknowledges that practitioners and decision makers may not be able to enumerate all sources of uncertainty in a system nor their associated probabilities (Herman et al., 2014). It is related to the emerging field of robust decision making, where it is assumed that future states of the world are deeply uncertainty and instead of assigning probabilities, it seeks to identify robust strategies which perform well across the range of plausible future states. In the context of design flood estimation, examples of deep uncertainty could include the effects of climate change, because the different scenarios used for future greenhouse gas emissions cannot be assigned probabilities, another example might be future land use changes within a catchment, because it depends on variety of political, social and economic factors, which can be difficult to reliably assign probabilities. This source of uncertainty requires a different approach to the other sources, where scenario analysis is used to test the system and identify thresholds where significant failures occur. This approach has seen recent application in analysing water resources systems for long-term drought planning, however the application in flood design is limited. Given this is still a burgeoning area with significant research required, the approaches to treat this source of uncertainty will not be further considered in the scope of this uncertainty in Australian Rainfall and Runoff.

2.8.5. Raising Awareness of the Sources of Uncertainty in Techniques Used for Design Flood Estimation

In this section, it will be illustrated how to identify the sources of uncertainty for the two common techniques used for design flood estimation; Flood Frequency Analysis and catchment modelling. The identification of the sources of uncertainty involves the following steps:

1. Identify the information required for each step of the methods; and

2. Identify the potential sources of uncertainty in the information required for each of the steps.

Uncertainty is related to the level of information (ie. available of at-site data, its length and quality). For the purposes of this illustration, two different scenarios of available information will be considered (a) Using at-site data (b) No at-site data available, using regional information only. In practise, the level of information will be commonly be somewhere in between these two scenario, nonetheless these two scenarios provide convenient “use” case, to illustrate the identification of the sources of uncertainty.

The relative contribution of each of these sources of uncertainty to the total predictive uncertainty is catchment specific, and depend on a range of factors (outlined below). Hence, to evaluate and determine the dominant source of uncertainty in a particular catchment requires a rigourous uncertainty analysis. Hence the following description will focus on describing the various source of uncertainty for each of the steps in both Flood Frequency Analysis and catchment modelling and identify the factors that will impact on the magnitude of that particular source. In any particular combination of information available means that one source could dominant the other. Hence in the following descriptions, each uncertainty source will not be described as low or high, rather the description will identify what increases or decreases the magnitude of the sources uncertainty.

2.8.5.1. Flood Frequency Analysis

1. *Estimate Flood Frequency Distribution Parameters*

   a. Using At-site Data

      Data Uncertainty

      When using at-site streamflow data to estimate the Flood Frequency Distribution, the data uncertainty in this streamflow data is a source of uncertainty. The factors that effect the magnitude of this source of uncertainty are primarily the quality of the rating curve used to estimate the streamflow, the number of gaugings (and their quality), the degree of extrapolation of the rating, the stability of the rating curve, among others (Le Coz et al., 2013).

      Parametric Uncertainty

      As parameters of the Flood Frequency Distribution are estimated based on limited time series of data, this induces uncertainty in the parameters. This parametric uncertainty is determined by the length of data (uncertainty increases as the length decreases) and the quality of the data (parametric uncertainty increases as data uncertainty increases).

      Structural Uncertainty

      The source of structural uncertainty is the assumed form of the food frequency distribution probability model, ie. log-Normal, Log Pearson III etc. When calibrating to at-site data, this source of uncertainty can be checked by comparing against the observed data, to determine if the quality of the fit to observed data.

   b. Using Regional Information without At-site Data

      Data, Parametric, and Structural Uncertainty

      When there is no at-site data, then regional information is used to inform the parameters and the choice of the probability model used for the flood frequency distribution. For this case, there data uncertainty is not a source of uncertainty, however the parametric uncertainty is higher than case (a), because no at-site data is available, and the structural uncertainty is also high than case (a) because no at-site data is available to evaluated if the chosen probability model for the flood frequency distribution is appropriate.

      Regionalisation Uncertainty

      When using regional information there is also regionalisation uncertainty because the parameters of the flood frequency has been transferred from another catchment. All the sources of uncertainty that contribute to the regionalisation uncertainty as described previously will be relevant to this source of uncertainty.

2. *Predicting Design Floods using Flood Frequency Analysis*

   In this Step 2 of predicting design floods using Flood Frequency Analysis, the data, parametric and structural uncertainty sources identified in Step 1 will be present. A additional contributor to the structural uncertainty when predicting design floods with Annual Exceedance Probability beyond the range of the streamdata (e.g. 1 in 100 Annual Exceedance Probability based on 30 years of streamflow data) is the assumption that the chosen probability model will provide a reliable estimate of design floods under extrapolation to the 1 in 100 or 1 in 200 Annual Exceedance Probability flood. This additional source of structural uncertainty will be present, irrespective of case (a) or case (b) levels of information. A longer time series of at-site streamflow data, and hence a lower degree of extrapolation will decrease, but not eliminate, the magnitude of this source of uncertainty.

2.8.5.2. Catchment Modelling Approach to Estimating Design Floods

The catchment modelling approach to design flood estimation relies on estimates of the design rainfall, which is converted into effective rainfall using a loss model and then used as input into runoff-routing model (calibrated to a limited number of flood events) to simulated flood events and therefore provide estimates of the design flood. The steps of this approach are at (1) Estimate runoff-routing model and loss model parameters (2) Estimating design rainfall and the temporal and spatial patterns (3) Predicting design floods using catchment modelling systems. These steps are outlined:

1. *Estimate Runoff-Routing Model and Loss Model Parameters*

   The parameters for the runoff-routing model and the loss model are usually calibrated jointly using flooding events in a given catchment. There are distinct components of the catchment modelling processes, however as their sources of uncertainty are similar, they will be discussed together.

   a. Using At-site Data

      Data Uncertainty

      Runoff-routing models (e.g. RORB) and loss models (e.g. required in the catchment modelling approach are typically calibrated to at-site flood event data. In this calibration step, the data uncertainty is the uncertainty in the streamflow data (discussed previously) and the additional uncertainty in the rainfall data, which as discussed previously, increases as the rainfall gauge density within the catchment decreases.

      Parametric Uncertainty

      The runoff-routing model loss model have parameters estimated through calibration to a limited number of flood events. This source of parametric uncertainty will decreases as the number of events decreases, and the consistency of the parameter estimates between events also increases. If the parameter estimates vary significantly between events, this will increase the parametric uncertainty.

      Structural Uncertainty

      As the runoff-routing model and the loss models represents a mathematical simplification of the actual catchment processes, will be a source of structural uncertainty. As the fit to the data used for calibration increases this source of uncertainty will decrease, but will not be eliminated. If the complexity of the runoff-routing model increases, e.g. move from lumped to a spatially distributed model, may potentially decreased the structural uncertainty, however, with a spatially distributed model the challenge becomes estimating the parameters over a spatial grid. Hence, if there is a lack of spatial streamflow and rainfall data to calibrate the model, than there is a potentially a shift from structural uncertainty to parametric uncertainty, which may results in no reduction the total predictive uncertainty.

b. Regional Information Only

Data, Parametric, and Structural Uncertainty

Similar to Flood Frequency Analysis, when there is no at-site data, the regional information is used to inform the parameter estimates, and choice of runoff-routing and loss model. For this case, there is data uncertainty is not a source of uncertainty, however the parametric uncertainty is higher than case (a), because no at-site data is available, and the structural uncertainty is also high than case (a) because no at-site data is available to evaluated if the runoff-routing model or loss model is appropriate.

Regionalisation Uncertainty

When using regional information there is also regionalisation uncertainty because the parameters of the runoff-routing model and loss model have been transferred from another catchment. All the sources of uncertainty that contribute to the regionalisation uncertainty as described previously will be relevant to this source of uncertainty, but they will apply both to the loss model and the runoff-routing model. In comparison to regionalisation of flood frequency distribution which is relatively well advanced , the regionalisation of runoff-routing models and loss models is still relatively unreliable and hence the regionalisation uncertainty of runoff-routing and loss models is likely to far larger than regionalisation of flood frequency distributions.

2. Estimating Design Rainfall and the Temporal and Spatial Patterns

In the majority of cases practitioners will use the design rainfall estimates provided by the Bureau of Meteorology, rather than undertake an Intensity Frequency Duration analysis of the observed rainfall data within a catchment, hence only the case when regional information is available will be considered in this description. There are many similarities to sources of uncertainty in the Flood Frequency Analysis, except the goal is to estimate extreme rainfall events rather than flow events.

Data, Parametric, Structural and Regionalisation Uncertainty

The source of data uncertainty is rainfall gauge density and the length of rainfall data across Australia, is highly variable in different parts of Australia and with far lower gauge density and shorter records for sub-daily rainfall data then daily. This can induce significant data uncertainty in the design rainfall estimates. Similar to Flood Frequency Analysis, a probability model is used to estimate the extreme rainfall events (e.g. 1 in 100 AEP) based on the limited rainfall data available. This probability model has parametric uncertainty, which increases as the length and quality of the rainfall data decreases. There is structural uncertainty in the choice of the probability model for extreme rainfall, and this is increased when the probability model is used to extrapolate to from shorter rainfall time series to extreme events. This is particular problematic for sub-daily rainfall, because records are typically shorter than daily rainfall data. There is regionalisation uncertainty because the design rainfall estimates are regionalised to areas with limited gauged data.

This design rainfall for an event is then disaggregated into a time series using temporal patterns, they have their own sources of data, parametric, structural and regionalisation uncertainty, because they are estimated based on rainfall data from outside the catchment of interest. If spatial patterns are used to distribute design rainfall spatially across a catchment, then they will similar sources of uncertainty.

Considering the high spatial and temporal variability of rainfall process these uncertainties in design rainfall are unlikely to be small.

3. Predicting Design Floods using Catchment Models

   When a catchment modelling approaches is used to predict design floods, the data, parametric, structural and regionalistion uncertainty identified in Steps 1 and 2 will be present. There are two sources of addition uncertainty, parameter uncertainty and structural uncertainty. These sources of uncertainty are because the runoff-routing and loss models in Step 1 are calibrated on runoff events are then extrapolated to larger design flow events, e.g. 1 in 100 AEP. The source of uncertainty is whether the parameters and model structural based on calibrations to (inevitable) smaller flood events can be applied to the larger design flow events.

2.8.5.3. Total Predictive Uncertainty

Table 1.2.1 provides a summary of the various sources of uncertainty for the two different techniques (Flood Frequency Analysis versus catchment modelling) for design flood estimation. It can be seen that due to the larger number of components in the catchment modelling, there are a greater number of sources of uncertainty in this process, compared with Flood Frequency Analysis. Typically when there are a larger number of sources of uncertainty the total predictive uncertainty is higher. Based on this analysis it can be concluded that catchment modelling is likely to have a higher total predictive uncertainty compared with Flood Frequency Analysis. However, the relative magnitude of the total predictive uncertainty for the two different techniques would vary on a catchment basis.

Table 1.2.1. Sources of Uncertainty in Design Flood Estimation

Steps	Information Available	Sources of Uncertainty			
		Data	Parametric	Regionalisation	Structural
Flood Frequency Analysis (FFA)					
1. Estimate Flood Frequency Distribution Parameters	a. At-site data	yes - streamflow	yes	No	yes
	b. Regional information only	No	yes – higher than case(a)	yes	yes – higher than case(a)
2. Predict Design Floods using Flood Frequency Analysis	Based on step 1	n/a - identified in step 1	n/a - identified in step 1	n/a - identified in step 1	yes - in addition to step 1

Steps	Information Available	Sources of Uncertainty			
		Data	Parametric	Regionalisation	Structural
Catchment Modelling					
1. Estimate Runoff-Routing Model and Loss Model Parameters	a. At-site data	yes – rainfall and streamflow	yes	No	yes
	b. Regional information only	No	yes – higher than case(a)	yes	yes – higher than case(a)
2. Estimate Design Rainfall and the Temporal/ Spatial Patterns	Based on Bureau of Meteorology IFD	yes – rainfall	yes	yes	yes
3. Predict Design Floods using Catchment Modelling Systems	Based on steps 1-2	n/a – identified in steps 1-2	yes – in addition to steps 1-2	n/a – identified in steps 1-2	yes – in addition to steps 1-2

2.8.6. Summary

This overview of the uncertainty in design flood frequency estimation has identified the two different types of uncertainty in the context of design flood estimation, aleatory uncertainty (due to natural variability) and epistemic uncertainty (due to knowledge uncertainty). It then outlined the motivation for undertaking uncertainty analysis, which is to provide more informed and transparent information on the uncertainty in the design flood estimates to enable practitioners and design makers to make better judgements on the appropriate design. The major sources of uncertainty in the context of design flood estimation were then outlined, and include data (uncertainty in measurements), parametric uncertainty of the models used, structural uncertainty in the models mathematical representation of the physical process, regionalisation uncertainty when information is moved from data rich to data poor catchments, and the total predictive uncertainty, which is composed of the elements of the individual sources of uncertainty. To raise awareness of the sources of uncertainty in the different techniques used for design flood estimation were identified. The conclusion, was that comparing Flood Frequency Analysis and catchment modelling, due to the larger number of components, the catchment modelling technique has a larger number of sources of uncertainty than Flood Frequency Analysis, and hence this will likely lead to a higher predictive uncertainty. However, the magnitude of the total predictive uncertainty is catchment specific, depending the availability of data and knowledge of the processes that driver design flood events.

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