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ARR2016: Uncertain about uncertainty short course

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Outline

1. What's changed in ARR2016?
2. Probability distributions – fitting and assessing
3. What is uncertainty and how does it arise?
4. Estimating parameter distributions and confidence limits
5. Assessing your model to reduce uncertainties
6. What do we do when data is limited?

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What's changed in ARR2016?

- Flood frequency analysis
- Regional Flood Frequency Estimation
- Ensembles of temporal pattern

(IFDs, climate change, rational method, joint probability, blockage….)

Statistics and uncertainty are much more integral

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Flood frequency analysis and RFFE

Both based on fitting a **probability distribution** to estimate peak flow(s)

ARR2016 assumes you know (quite) a lot about probability distributions and their uncertainty

Probability distribution

A mathematical function that provides information on the probability of occurrence of different outcomes

Water quality data

Rainfall extremes (IFDs)

Streamflows

Wind speed

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Some terminology

Random variable – this is the particular data that we are interested in e.g. flood peaks in River X

Sample – this is the data that is observed e.g. the annual maximum flood from each year from 1932 to 2014 in River X

Population – this is the overall set of all data values that we believe our sample represents e.g. the annual maximum floods from every year from when the river first started flowing until the end of the earth

Discrete random variable – the outcomes are finite or countable e.g. rolling dice

Continuous random variable – outcomes take any value in continuous range e.g. heights or temperatures or streamflow

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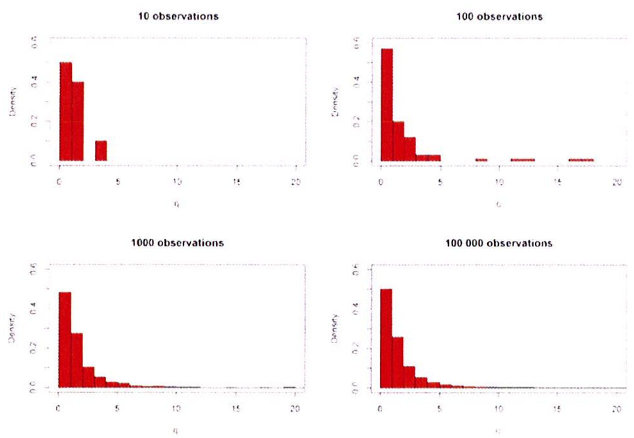
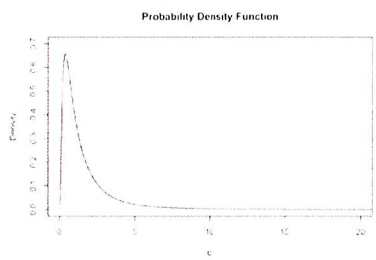
Some maths (but not too much...)





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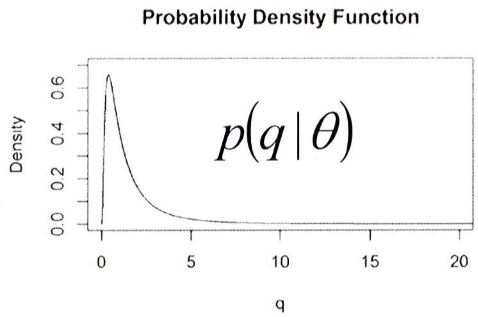
Using the Probability Density Function



$$P(Q \le q^*) = \int_0^{q^*} p(q \mid \theta)\,dq$$

ARR2016 EQUATION 3.2.1

Q is the random variable of flood peaks

q* is a particular recorded flow

p(q|θ) is the probability density function

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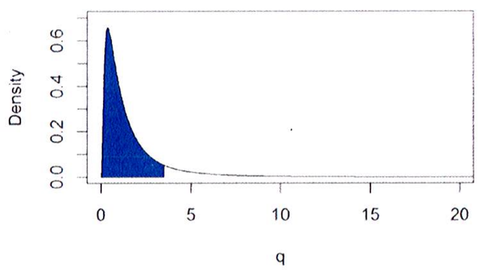
Using the Probability Density Function



$$P(Q \le 3.5) = \int_0^{3.5} p(q \mid \theta)\,dq$$

Probability of the flow being less than or equal to 3.5 m3/s is 0.89

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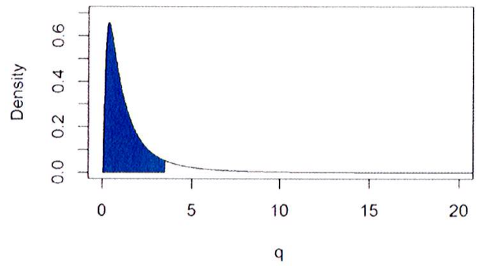
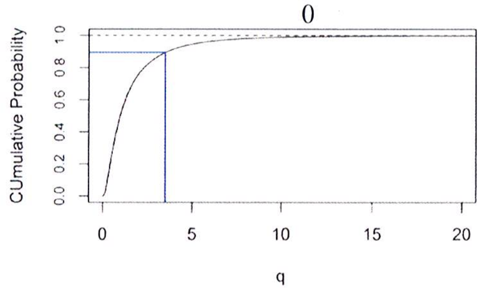
(Cumulative) Distribution Function

$$p(q \mid \theta)$$

$$P(Q \leq q^*) = \int_0^{q^*} p(q \mid \theta)\, dq$$





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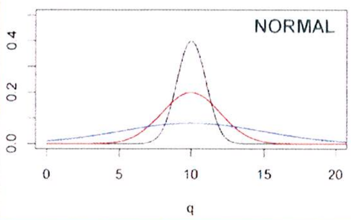
Common probability distributions

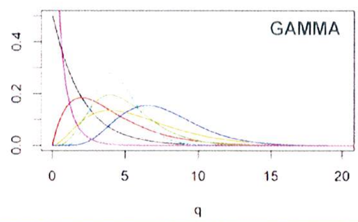
Normal distribution – good for many problems, large data samples often normal distribution

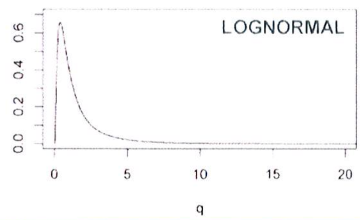
Flood and rainfall data is **not** normally distributed

Very skewed data – long tail of very large, rare events

Use **extreme value** probability distributions (e.g. LPIII, Generalised Extreme Value)







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Extreme value distributions

- Lognormal
- Log Pearson Type III
- Generalised Extreme Value Distribution
- Generalised Pareto Distribution

Where is all this heading?

We have a set of data to analyse

Fit an appropriate probability distribution to the data

Check if it fits the data well

Use the probability distribution for design

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Describing a probability distribution

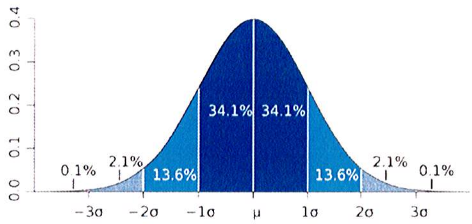
Mean, standard deviation – most important summary statistics of a set of data

Mean = $\frac{1}{N}\sum x$

Standard deviation = $\frac{1}{N-1}\sum(x-\mu)^2$

For a normal distribution:

- 68% of data is within ± 1 sd of the mean
- 90% of data is within ± 1.64 sd of the mean
- 95% of data is within ± 1.96 sd of the mean



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More terminology…

Parameters – the "coefficients" of the probability distribution that we want to estimate given a set of data

Quantiles – the estimates of the size of the flood based on the fitted probability distribution

Table 3.2.1. Selected Homogeneous Probability Models Families for use in Flood Frequency Analysis

Family	Distribution	Moments
Generalized Extreme Value (GEV)	$p(q\|\theta) = \frac{1}{\alpha} e^{\left\{-\left[1-\frac{\kappa(q-\tau)}{\alpha}\right]^{\frac{1}{\kappa}}\right\}} \left[1 - \frac{\kappa(q-\tau)}{\alpha}\right]^{\frac{1}{\kappa}-1}$ $P(Q \le q\|\theta) = e^{\left\{-\left[1-\frac{\kappa(q-\tau)}{\alpha}\right]^{\frac{1}{\kappa}}\right\}}$ $when\ \kappa > 0, q < \tau + \frac{\alpha}{\kappa};\ when\ \kappa < 0, q > \tau + \frac{\alpha}{\kappa}$	$Mean\,(q) = \tau + \frac{\alpha}{\kappa}[1 - \Gamma(1+\kappa)]$ $for\ \kappa > -1$ $Variance\,(q) = \frac{\alpha^2}{\kappa^2}\left[\Gamma(1+2\kappa) - [\Gamma(1+\kappa)]^2\right]$ $for\ \kappa > -\frac{1}{2}$ $where\ \Gamma(\ )$ is the gamma function

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Where is all this heading?

We have a set of data to analyse

Fit an appropriate probability distribution to the data by estimating the **parameters**

Check if it fits the data well

TUFLOW FLIKE

Use the probability distribution for design by estimating the **quantiles** of interest

Think about the uncertainty in quantiles… (Lucy)

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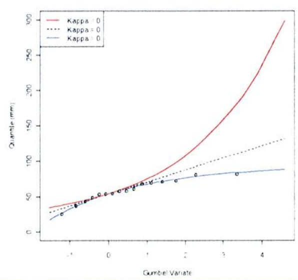
Picking the right distribution?

Generalised Extreme Value distribution Is the asymptotic distribution of extreme values from a number of underlying parent distributions



Log Pearson Type III

- Widely used in practice
- Performed best of those tested on Australian catchments
- When the skewness is 0, it simplifies to a log-normal distribution

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Fitting probability distribution parameters

Method of moments – simplest and problematic, standard in Australia until now

L-moments

Bayesian calibration

Method of Moments

Mean $M = \frac{1}{N}\sum_{i=1}^{N} X_i$

Standard deviation $S = \left[\frac{\sum (X_i - M)^2}{N-1}\right]^{0.5}$

Skewness $g = \frac{N\sum (X_i - M)^3}{(N-1)(N-2)S^3}$

L-moments and Bayesian Calibration

Both methods are more mathematically complicated than the method of moments

Specialised software is required (e.g. Matlab, R or commercial software TUFLOW FLIKE)

Introduction here to the basic theory.

ARR Book 2 Chapter 3 has very detailed information

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L-moments (Equations 3.2.64 to 3.2.67)

Linear combinations of moments

No squared terms so less sensitive to outliers than method of moments

Unbiased estimator

LH moments increase weight on highest flows

With the L-moments, you can then calculate the parameters of the distribution (ARR Table 3.2.3)

Then estimate quantiles from the fitted distribution

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Bayesian Calibration

Based on Bayes formula

$$\underbrace{p(\theta \mid D)}_{\text{Posterior}} = \frac{\overbrace{p(D \mid \theta)}^{\text{Likelihood}}\,\overbrace{p(\theta)}^{\text{Prior}}}{\underbrace{p(D)}_{\text{Normalizing Constant}}}$$

Prior – best guess on parameters before you see any data

Likelihood – describes the probability of seeing your data given a certain set of parameters

Posterior – the probability of θ being the correct set of parameters given the data

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Bayesian Calibration (section 2.6.3)

Main idea:

The data D comes from a probability model that has the pdf p(D|θ) where θ is a vector of the unknown parameters

The aim is to estimate θ

The general philosophy of Bayesian approaches is that θ is a random vector that has its own probability distribution. This probability distribution describes what is known about the true value of θ

Once we estimate the probability distribution of θ, we then estimate the quantiles

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Traditional vs Bayesian approaches

Rainfall → Flood Model e.g. WBNM
Parameter = Initial Loss → Flow

There is a **true** value for IL

We want to find this true value

We wish we had all the rainfall and flow events

We have a (small) sample of events and we estimate IL based on the sample

There is a **distribution** of ILs

We know something about this range of IL (**prior**) because we're expert modellers

We have recorded data. The **likelihood** tells us whether this data is consistent with the values of IL

The data and prior give us a final estimate (**posterior**) of the distribution of IL

Traditional vs Bayesian approaches

Rainfall → Flood Model e.g. WBNM
Parameter = Initial Loss → Flow

Intensity = X mm/hr → Traditional
IL = 3 mm → Q = Y m^3/s

Intensity = X mm/hr → Bayesian
IL = → Q =

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Bayesian Calibration – pros and cons

Flexible

Can explicitly use information from different sources e.g. other locations

If we don't have a lot of data, the prior is useful. When we have a lot of data, the data dominates the fitting

Uncertainty in the parameters is explicitly assumed and modelled

Despite simplicity of Bayes' theorem, there are often no analytical solutions

Computationally challenging

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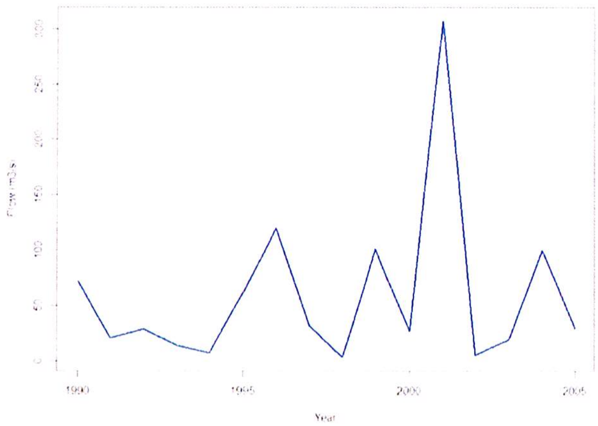
Example

YEAR	Q
1990	72.64
1991	21.13
1992	28.9
1993	14.41
1994	7.44
1995	61.59
1996	119.89
1997	32.24
1998	3.83
1999	101.4
2000	27.05
2001	307.26
2002	5.41
2003	19.98
2004	99.89
2005	29.51



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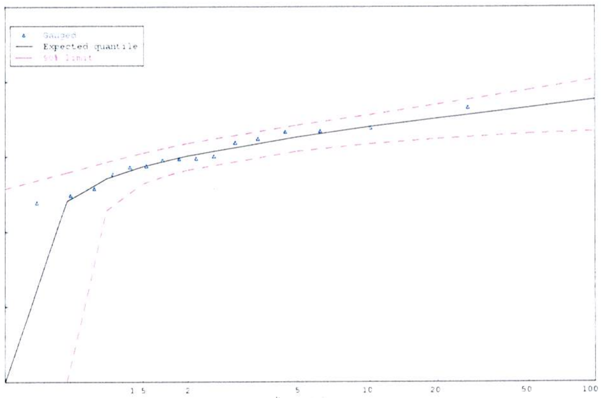
FLIKE output – L moments GEV

L moment	Value
1	59.536
2	35.124
3	17.781
4	11.632

Parameter	LH
tau	22.829
a	25.862
k	-0.465



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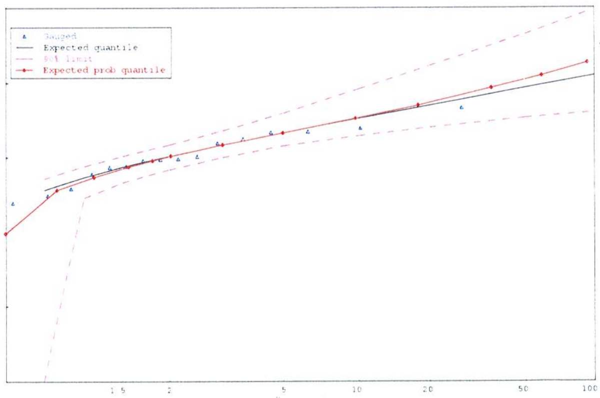
FLIKE output – Bayesian GEV

Parameter Name	Mean	Std dev
1 Location u	22.62401	6.16524
2 loge (Scale a)	3.22387	0.38210
3 Shape k	-0.83705	0.41433

Parameter	LH
tau	22.829
a	25.862
k	-0.465



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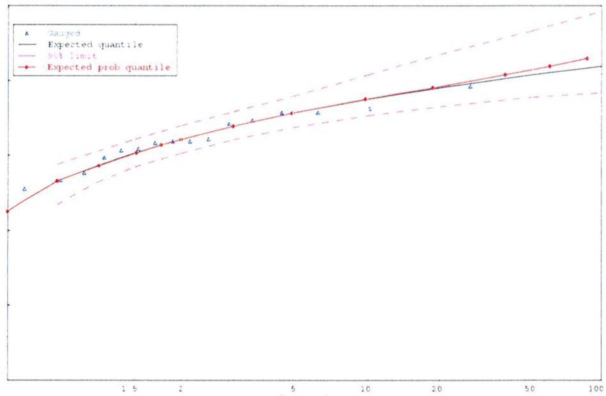
FLIKE output – Bayesian LPIII

Parameter	Mean	Std dev
Mean	3.46690	0.34512
Loge SD	0.29504	0.21697
Skew	0.01147	0.65215



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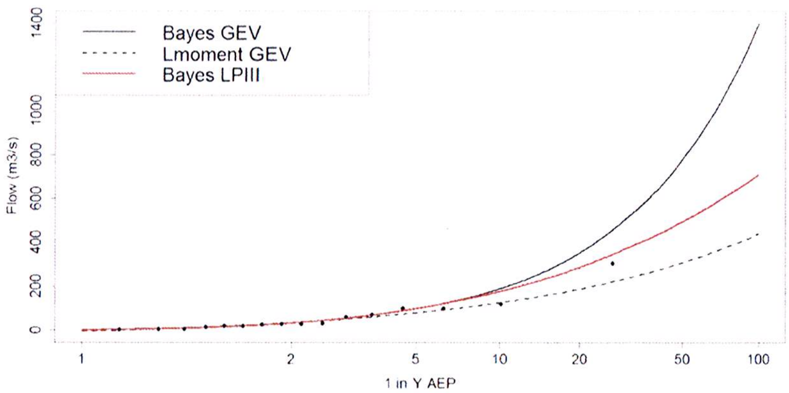
Comparison of quantiles



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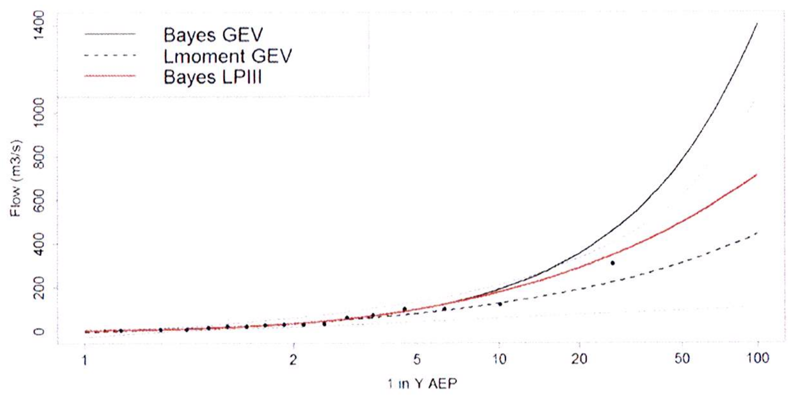
Comparison of quantiles with uncertainty



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Regional Flood Frequency Estimation

Applied example of parameters and quantiles....

The RFFE uses a regression model to estimate the parameters of the LPIII distribution at gauged locations

The modelled parameters are used to estimate the flood quantiles at the gauged sites

At (the ungauged) study site, the quantiles are estimated by averaging the quantiles from the gauged sites

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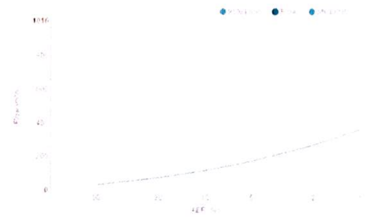
RFFE



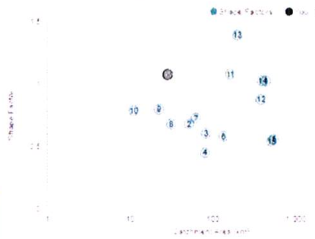
AEP (%)	Discharge (m³/s)	Lower Confidence Limit (5%) (m³/s)	Upper Confidence Limit (95%) (m³/s)
[illegible]	[illegible]	[illegible]	[illegible]

Statistics

Variable	Value	Standard Dev	Correlation		
Mean	[illegible]	[illegible]	1.000		
Standard Dev	1.010	0.233	0.330	1.000	
Skew	0.105	0.026	0.170	0.280	1.000

$$Mean = b_o + b_1 \ln A + b_2 \ln\left(I_{6,50}\right) + b_3 \ln(shape)$$

Shape Factor vs Catchment Area



Uncertainty in probability distributions

Outline

1. What is uncertainty and how does it arise?
2. Estimating parameter distributions and confidence limits
3. Assessing your model to reduce uncertainties
4. What do we do when data is limited?

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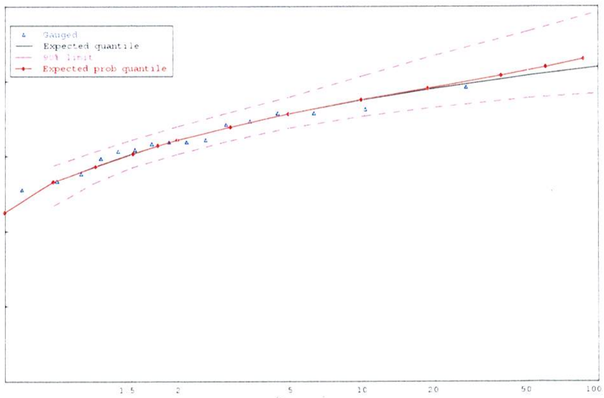
What is uncertainty?

Parameter	Mean	Std dev
Mean	3.46690	0.34512
Loge SD	0.29504	0.21697
Skew	0.01147	0.65215



FLIKE output – Bayesian LPII

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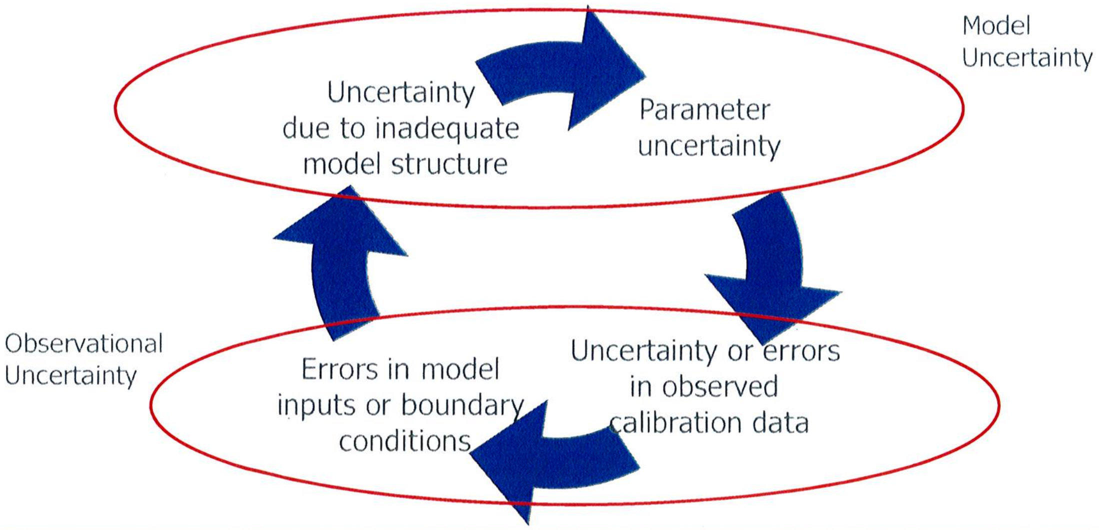
Sources of model uncertainty



Sources of model uncertainty: ARR2016

- The 'true' probability distribution family is unknown in FFA
- Limited data or short records can affect parameter estimates
- Errors in gauging equipment can occur
- It can be difficult to deal with scenarios where the catchment conditions have changed

Despite this, methods have been developed to quantify these uncertainties

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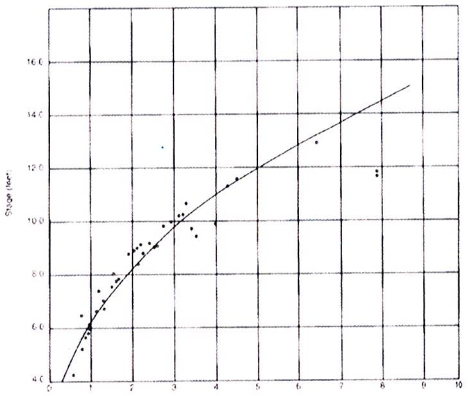
Example: rating curve error



- Usually we are interested in peak flow values, where the curve has been developed with only a few points.
- Extrapolating the curve to higher values leads to more potential error.

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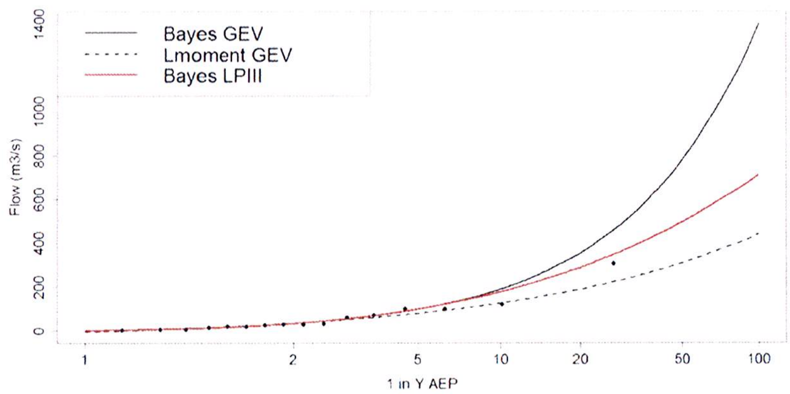
Example: model uncertainty



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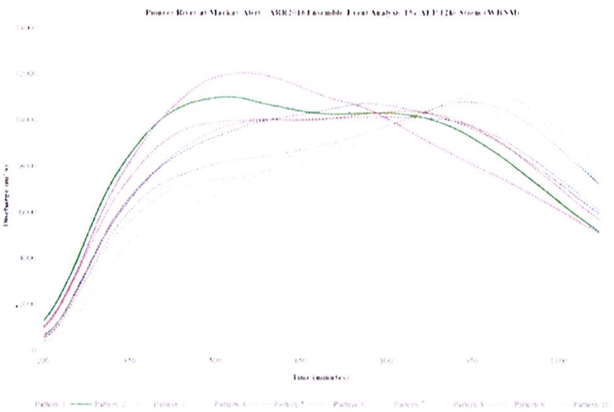
Example: hydrologic modeling ensembles



- Multiple rainfall patterns lead to hydrologic model ensembles
- Which ensemble or value do we select for design? Median? Mean? Which peak value?

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Recall: where is all this heading?

We have a set of data to analyse

Fit an appropriate probability distribution to the data by estimating the **parameters**

Check if it fits the data well

Use the probability distribution for design by estimating the **quantiles** of interest

Think about the uncertainty in quantiles…

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Uncertainty analyses

- Provide confidence intervals rather than a single best fit to the data
- Estimate distributions of model parameters
- Most common ways to do so are:
  - Bayesian approaches - develop theoretical probabilities of parameters
  - L-moments - use numerical sampling to approximate uncertainty

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Confidence limits

Confidence limits describe how much uncertainty there is in the fitted probability distribution

The confidence limits describe the set of all probability distributions (i.e. distribution of parameter sets, θ) that are consistent with the observed data

Generally specified as percentage widths e.g. 5^{th} and 95^{th} percentile confidence limits

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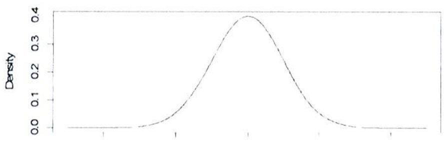
Estimating flood quantiles

Given the data D, what is the best estimate of the 1 in Y AEP flow, including uncertainty?

- If we knew the true probability distribution then we could calculate $q_Y(\theta)$ directly from the pdf $p(q|\theta)$
- But in reality we don't know $p(q|\theta)$ we can only estimate $p(\theta|D)$ and thus we only estimate the pdf $p(q_Y|D)$



The distribution $p(\theta|D)$ is the posterior distribution (Bayesian) or the sampling distribution (bootstrap).

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Bayesian parameter uncertainty

Recall:

Posterior Likelihood Prior

$$p(\theta | D) \propto p(D | \theta) p(\theta)$$

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Bayesian likelihood

- Relates the probability of observing the data given the model parameters
- Is the joint pdf of the data, assuming some probability distribution

$$p(q_1,\ldots q_n \mid \theta) = \prod_{i=1}^{n} p(q_i \mid \theta)$$

Bayesian prior

- Represents any existing knowledge about the model parameters (e.g. regional analysis, real catchment properties)
- Frequently assumed to be non-informative, i.e. there is no prior information
- Is one way to perform FFA in regions with few records, using an informative prior with regionalised data (i.e. using the RFFE estimates as a prior)

Bayesian calibration (section 2.6.3)

Main idea:

The data D comes from a probability model that has the pdf p(D|θ) where θ is a vector of the unknown parameters

The aim is to estimate θ ← a vector.

The general philosophy of Bayesian approaches is that θ is a random vector that has its own probability distribution. This probability distribution describes what is known about the true value of θ

Once we estimate the probability distribution of θ, we can then estimate the quantiles with uncertainty

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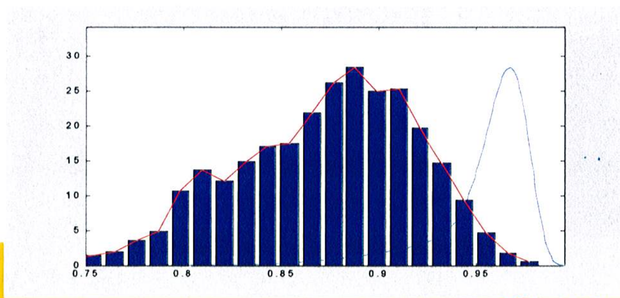
The Prior Distribution

Posterior Distribution ← Information from prior ← less observations

Posterior Distribution ← Information from data ← more objective observations



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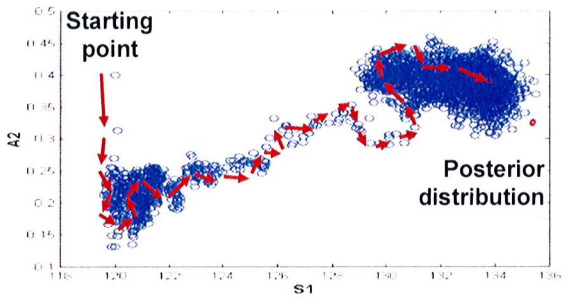
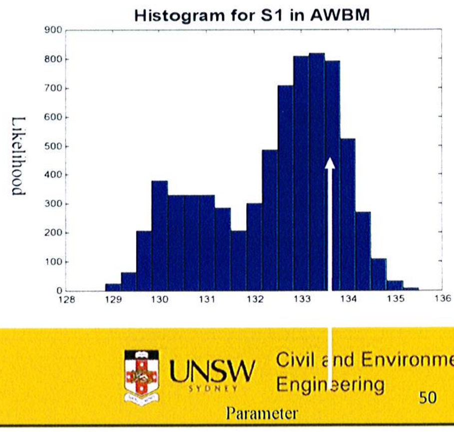
Bayesian parameter estimates

- We estimate θ via numerical sampling approaches, like Markov chain Monte Carlo or Importance Sampling





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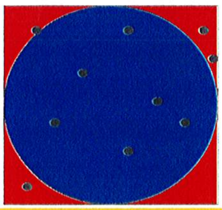
Monte Carlo Analysis

- MC methods are stochastic techniques, based on using random numbers and probability distributions to represent uncertainty or lack of knowledge about a process or parameter
- It is a formalized way of taking into account risk in any modeling application, by generating data from known or unknown probability distributions to analyze the risk of the system being characterized behaving an any manner.



Example: estimating π

Calculate the number of darts that hit inside the circle vs outside

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The MC approach

1. Set up a model to describe the system of interest
2. Define probability distributions for the input variables (and/or parameters)
3. Define the outputs of interest
4. Generate random values from the input distributions and simulate the resulting outputs
5. Summarize the resulting distribution of output values, including sensitivities in the model, ranges of model simulations, probabilities of exceeding some threshold value.

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Monte Carlo methods for estimating $p(\theta|D)$

ARR2016 describes importance sampling for the Bayesian approach: ~~algorithms.~~

Step 1: Find most probable parameters of the target distribution, θ^*

Step 2: Estimate a multi-normal approximation to the target distribution (the 'importance distribution):

$$\theta|D \sim N(\theta^*, \Sigma)$$

Step 3: Undertake Monte Carlo importance sampling of this distribution:

- Sample N particles (i.e. parameter samples) from Step 2
- Calculate weights for the samples based on the likelihood
- Scale the particle weights so they sum to 1.

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Estimating Bayesian confidence limits

- Using our posterior distribution, we can sample uncertainty in the flow quantiles.
- Confidence limits describe this uncertainty based on the distribution of θ_i:
  1. Draw N samples from the posterior distribution $\{\theta_i, w_i, i=1,...,N\}$
  2. Rank in ascending order the N quantiles $\{q_Y(\theta_i), i=1,...,N\}$
  3. For each ranked quantile evaluate the non-exceedance probability $\sum w_j$ for $j=1:I$, where w_j is the weight for the j^{th} ranked quantile $q_Y(\theta_j)$
  4. The lower and upper confidence limits are approximated by the quantiles whose non-exceedance probabilities are nearest to $\alpha/2$ and $1-\alpha/2$ respectively.

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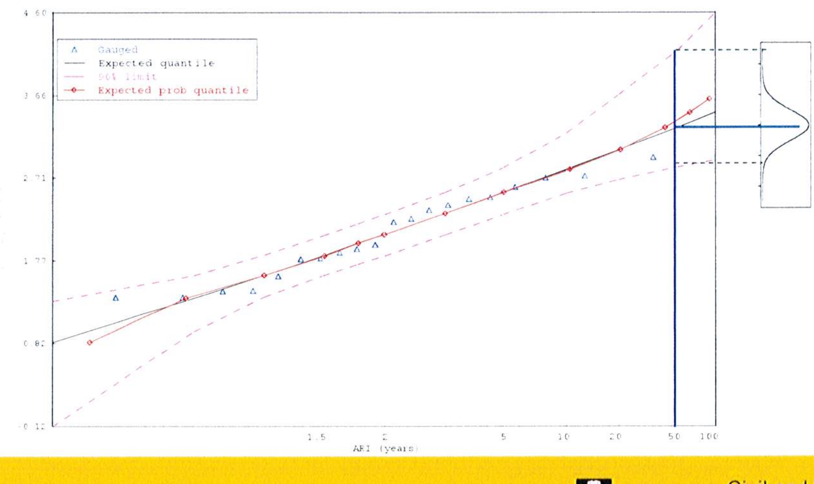
Expected Bayesian quantiles



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L-moments and parameter uncertainty

- Estimating uncertainty in parameters for L-moments is done by a method known as parametric bootstrapping
- Bootstrapping relies on random samples from a model to estimate the distribution of almost any statistic
- We use it when we can't sample a whole population (e.g. we only have limited flow data), so we have to resample the existing data to try to estimate what the uncertainty is. The data is 'pulling itself up by its own bootstraps.'

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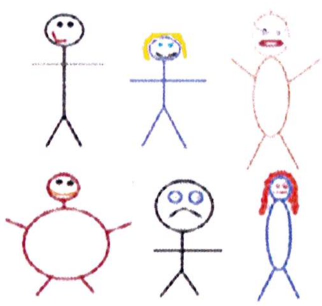
Bootstrap concepts

Suppose we have a random sample of 6 people:



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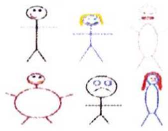
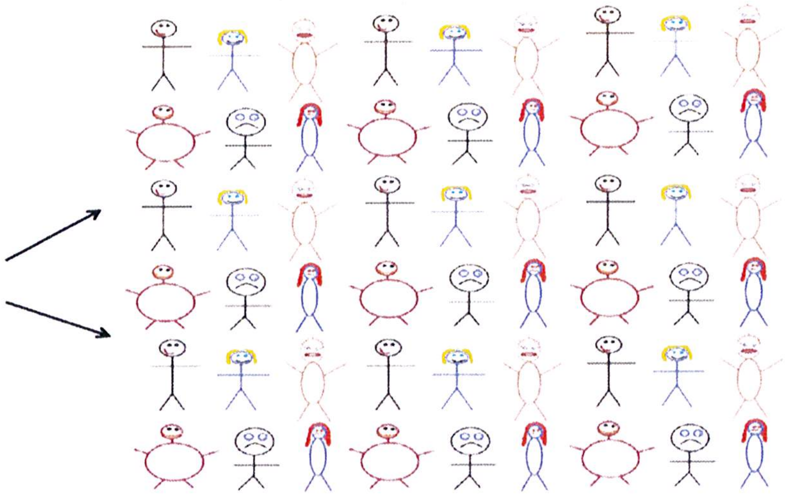
Original Sample





A simulated "population"

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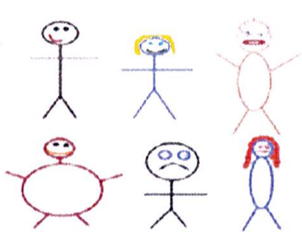
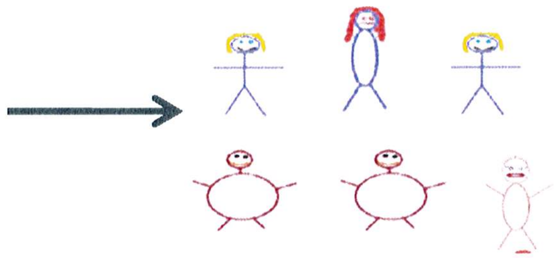
Bootstrap Sample: Sample with replacement from the original sample, using the same sample size.



Original Sample



Bootstrap Sample

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'resampling' – eliminating 1 data point and doubling up on one other sample to make up the total of original sample.

L-moments and parameter uncertainty

- General bootstrap algorithm:
  1. Fit a probability model to the available data (e.g. using L moments) to determine θ
  2. Set i=1
  3. Randomly sample n data points from the fitted distribution;
  4. Fit the probability model to the sampled data to yield a new parameter estimate θ_i
  5. Increment i. Repeat steps 3-4 until i = N.
  6. Use the resulting θ_i to represent uncertainty about the model

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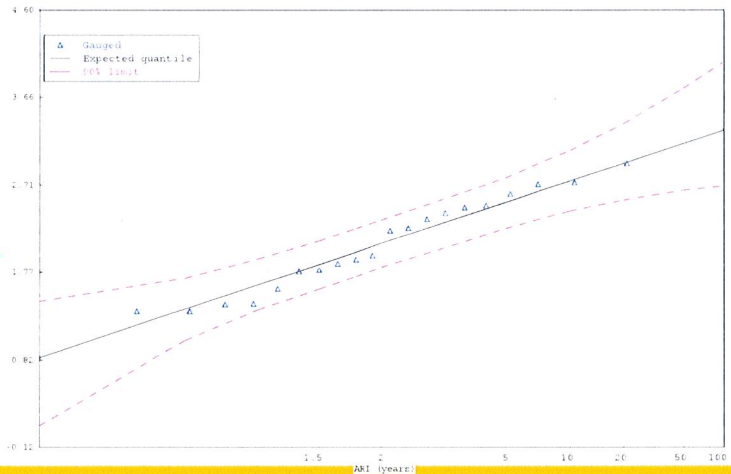
Confidence limits – L moments



This tends to underestimate uncertainty: assumes the best estimate parameter is the 'truth'.

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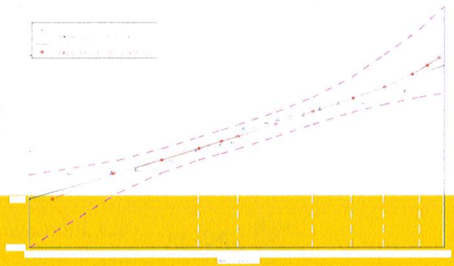
Why are uncertainty estimates useful?

- They help evaluate the potential upper and lower limits of your prediction: can help in cost/benefit or risk analysis
- They help evaluate whether the model is appropriate, and if the observations are well distributed within the confidence limits

Estimating the posterior pdf with loss functions

- Most of the time the expected value of the pdf $p(q_x|D)$ will be appropriate
- However it depends on the loss function or likelihood used to estimate the parameters
- What is the consequence if we're wrong? Would an under design have greater loss than an overdesign?



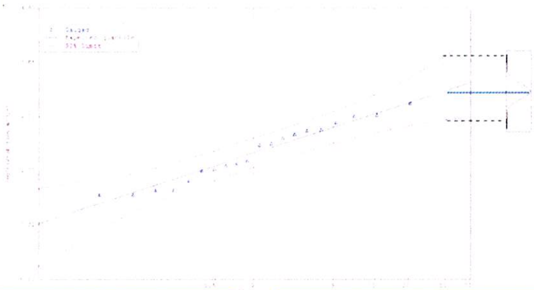
What are appropriate loss functions?

Loss functions

Quadratic loss function – assumes that the consequences of over and under design are the same

This is the same as the Mean Squared Error and minimising this will give the optimal quantile estimate as the expected value of the pdf.

This is usually the default approach



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Loss functions

Linear asymmetric loss function – allows for different consequences for over and under design (equation 3.2.31)

$$P(Q_y \leq q_y(D)_{opt} \mid D) = \frac{\alpha}{\alpha + \beta}$$

If α and β are equal, this gives the optimal quantile estimator as the median of the distribution

If α is 4 times greater than β, then the optimal quantile estimator is the 80th percentile of the distribution, i.e. the consequences of under-design are four times more severe than over-design.

These functions can be incorporated into the Bayesian likelihood to estimate the posterior distribution of parameters.

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Expected flood quantiles vs expected AEP

- Depending on the exercise, we can derive uncertainty in the AEP rather than q
- Should we estimate flood quantiles to minimise uncertainty in θ or AEP? That depends on why the model is needed:
    - *Sizing a structure for a particular AEP flow – parameter estimator*
    - *Unbiased estimates of flood damages – parameter estimator*
    - *Probability of exceedance is the concern (floodplain management) – AEP estimator*

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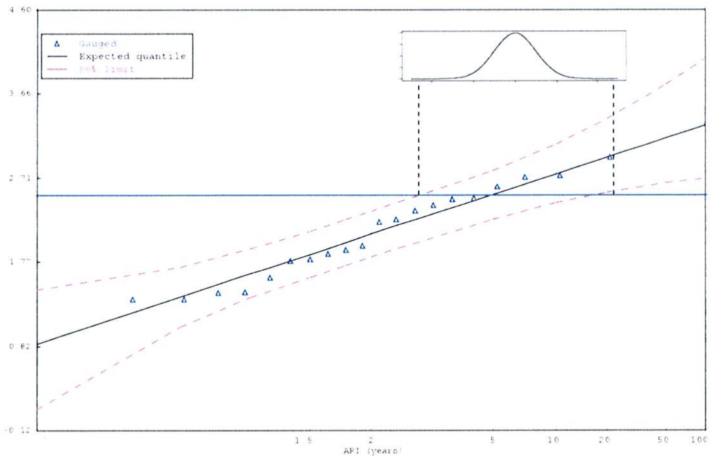
Expected AEP quantiles



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How good is the fit?

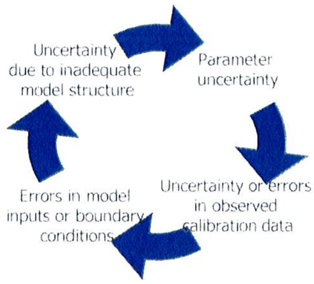
An important element of uncertainty analysis: need to check the observations and our model to see is they agree (or where they don't).

We can do this via:

1. Confidence limits
2. Probability plots

Any errors will be a function of uncertainty

in the data, model, parameters



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What do we do when the model is poor?

There are several sources of error that might lead to unacceptable uncertainty or bias in our model. We should check for:

1. Outliers in the upper or lower tail of the distribution. These might lie well outside the confidence limits, and be inconsistent with the rest of the data.
2. Systematic differences between observed and fitted distributions (e.g. overfit vs underfit).

Poor fits might be due to: sample data not representing true flood peaks (high or low) ; rating curve errors; selected probability model not representing complex flood dynamics; non-stationarity or non-homogeneity of data

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be unbiased, limit / recognise this when interrogating your results.

What do we do when model or data are limited?

To deal with unacceptable uncertainty we could:

1. Censor our observations (but data might be limited!)
2. Change our probability model
3. Give less weight to suspect data (change the loss function)
4. Develop meaningful priors, and use the Bayesian approach!

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What do we do when there is effectively no data?

RFFE is developed specifically for this scenario, however:

- Can be problematic in atypical catchments
- Can have large uncertainty in estimates
- Not applicable to urban catchments (>10% urban)

Hydrologic models might be more useful in this case, but will still have large uncertainties.

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Other ARR2016 Monte Carlo methods: some thoughts

- Spatial and temporal variation in rainfall can be characterised by Monte Carlo sampling (Book 2, Chapter 6).
- There are two general approaches:
  1. sampling from separate populations of spatial and temporal patterns
  2. sampling from a single set of "linked" space-time patterns
- Either way, the result is a set of rainfall ensembles representing variability/uncertainty in rainfall patterns

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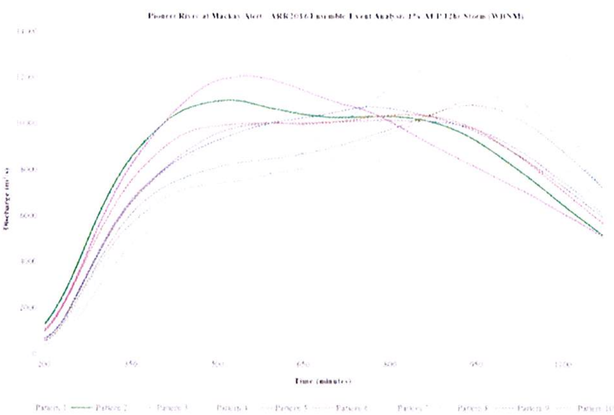
Other ARR2016 Monte Carlo methods: some thoughts



- Multiple rainfall patterns lead to hydrologic model ensembles
- Which ensemble or value do we select for design? Median? Mean? Which peak value?
- How do we select an ensemble when we are looking at results from a 2D model? Spatially adjacent ensembles may come from different rainfall events.

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Take home messages

- Explicitly quantifying uncertainty is the goal of many of the new parts of ARR2016
- Uncertainty estimates give more information about possible outcomes, which can be helpful but might also be more difficult to interpret
- Some more specific suggestions:
  - There is no theoretically correct probability distribution for FFA but the LPIII is generally pretty good
  - Bayesian calibration will always give you wider uncertainty bounds than L moments
  - The choice of using a mean, median or peak value in an ensemble will always depend on the ultimate design goal

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~~ARR87 – pragmatic assumptions~~, ~~different now in AR16~~