# Impact of Natural Variability on Design Flood Flows and Levels

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#### Abstract

Hydrologic variability has traditionally been accounted for by choosing "average" values of the inputs (the so-called "simple design event" method), though "Australian Rainfall and Runoff" now recommends the use of more robust approaches based on ensemble sampling and Monte Carlo simulation where possible. The studies that have been undertaken using these more sophisticated techniques have generally focussed on the hydrologic rather than hydraulic aspects of the problem; that is, on estimates of the flood peak, not on the magnitude of the resulting flood depth. While the explicit treatment of hydrologic variability represents only a modest increase in computational burden for hydrologic models, it is not easily accommodated in hydraulic models. There is little information available on the manner in which hydrologic variability influences the different steps involved in the estimation of design levels, and improved understanding of this will help identify where efforts are best prioritised. This paper illustrates the manner in which natural variability influences hydrologic estimates of flood peak, and quantifies how this propagates through to estimates of flood depths using hydraulic modelling.

#### 1. INTRODUCTION

Design flood estimation is a focus for many engineering hydrologists. Estimates of frequent flood risks are most commonly required to size culverts and urban drainage systems, and estimates of rarer floods are required for the design of bridges for roads and railways, levees, detention basins and dam spillways. The flood characteristic of most importance depends on the nature of the problem under consideration, but it is often necessary to estimate peak flow and peak level, and depending on the nature of the system being studied these in turn may be dependent on the volume and rate of rise of the flood. The analysis might be focused on a single location – such as a bridge waterway or levee protecting a township– or it may be necessary to consider the performance of the whole catchment as a system, as required in urban drainage design.

The methods available for estimating flood risk can be divided into two broad classes of procedures, namely (i) the direct analysis of observed flood and related data and (ii) the use of simulation models to transform rainfall into flood maxima. The first class of procedures include flood frequency methods and various forms of regional equations for the direct prediction of flood quantiles (eg Kuczera and Franks, 2016; Rahman et al, 2016). These approaches are particularly attractive as they avoid the need to consider the complex processes and joint probabilities involved in the transformation of rainfall into flood. However, the utility of these methods is heavily dependent on both the length of available records and their representativeness to the catchment and climatic conditions of interest. The second class of procedure involve the use of either event-based or continuous simulation models to convert rainfalls into floods. These approaches are widely used as they provide information on hydrograph shape as well as peak, and are readily able to simulate the mitigating influence of artificial storages and structures on flood behaviour. Importantly, such methods are also able to take advantage of rainfall data which is much more extensively available and more easily extrapolated (in both space and time) than streamflow data. Continuous simulation approaches utilise model structures which generally differ markedly from those used in event-based models. While these models are particularly suited to certain classes of design problems, event-based models are more widely used as they are applicable to a greater variety of design problems and more easily applied (Nathan and Ball, 2016).



Figure 1. Study catchment area.

Regardless of which rainfall-runoff modelling approach is used, the key problem to solve is how best to assign an exceedance probability to the derived flood magnitudes. That is, rather than merely focus on the *magnitude* of the flood that results from the input design rainfall, special effort is made to minimise bias in the resulting exceedance probability in the transformation of rainfall into flood. This objective of "probabilityneutrality" is given considerable attention in the recently released Australian guidelines on flood estimation (ARR 2016, Ball et al, 2016), which is a key difference between the current document and its three earlier versions. In natural catchments the sources of hydrologic variability which contribute most to flood magnitude (and hence the need for probability-neutral treatment) are antecedent soil moisture conditions and event losses, and the temporal and spatial patterns of rainfall. In engineered systems, this would most commonly include initial water level in artificial storages. In estuarine systems, flood depths may also be heavily dependent on tide levels and storm surge. The influences that need most attention varies with the system being

analysed, but without taking steps to explicitly cater for the joint probabilities involved, there is a considerable margin for error (Weinmann et al, 2002; Rahman et al, 2002; Nathan et al, 2003; Sih et al, 2008; Kuczera et al., 2006).

The techniques required to minimise bias in the resulting exceedance probabilities are more computationally intensive than traditional techniques. The hydrologic modelling techniques required to derive probability-neutral floods have been gaining in popularity over the past 10 or so years, and – with the right investment in modelling tools – the majority of practising flood hydrologists should make the transition to the new procedures with little difficulty. However, the effort required to adapt these procedures to hydraulic modelling represent a more onerous burden. The simulation times of hydraulic models are many thousands times longer than those of most hydrologic models, and thus it is worthwhile thinking carefully about which aspects of the simulation need focus, and which can be simplified.

This paper illustrates the manner in which natural variability influences hydrologic estimates of flood peaks and quantifies how this propagates through to estimates of flood depths using hydraulic modelling. The concepts are illustrated using simulation models of a large "natural" catchment in south-east Queensland, which is briefly described in the following section.

# 2. STUDY CATCHMENT

The Brisbane River catchment lies upstream of the city of Brisbane, in Queensland Australia. It has a catchment area over 13,600 km<sup>2</sup> (Figure 1). The western border of the catchment is formed by the Great Dividing Range, and there are a number of smaller coastal ranges to the north and east. The

upper reaches of the catchment are covered by natural and plantation forests, and it supports grazing. The lower reaches of the catchment support a mix of light forest cover, dryland and irrigated agriculture. The rainfall gradient across the catchment is highly variable, from the wetter coastal hinterland ranges to the drier areas in the west of the catchment. Seven major tributaries drain into Brisbane River. The flood response of the catchment is very complex, and the potential for flooding from individual or multiple tributaries depends heavily on the speed and direction of the storm, and the spatial distribution of rainfall depths.

Two major dams are located approximately in the centre of the Brisbane River catchment: Somerset Dam was built in stages between 1935 and 1959, and Wivenhoe Dam was built in 1984. Both dams are gated, and they have a large mitigating influence on flood flows in the lower half of the catchment. Since the objective of this paper is to assess the impact of hydrologic variability on flood peaks and flow depths, these dams were excluded from all simulations. That is, the catchment was modelled under "pre-development" conditions, and the results have no bearing on current levels of flood risk.

## 3. SIMULATION FRAMEWORK

#### 3.1. Modelling Flood Magnitude

The model used to simulate the hydrologic flood response of the catchment is the RORB event-based storage-routing model (Laurenson et al, 2007). The adopted model was calibrated by the Department of Natural Resources (1992) to ten large historic floods. It is a complex model comprised of 216 subareas, and catchment response is divided into 18 homogeneous regions, each with its own set of loss values and routing parameter values. The catchment is densely gauged, with around 25 long-term streamflow stations and over 75 rainfall gauges, and there was a good standard of data available for calibration purposes.

The last storm used to calibrate the adopted model occurred in 1989, though it is worth noting that this data set included simulation of the 1974 flood, which is of similar magnitude to the devastating event which occurred in January 2011. This provides an ideal validation event, and the fit obtained to the derived inflows to Wivenhoe Dam (which impounds about half the Brisbane River catchment) is shown in Figure 2(a).

A branched 1-D hydraulic model using the TUFLOW software (Ryan et al, 2013) was used to simulate flood levels associated with the derived flows. The model solves the 2nd order solution of the full 1D St Venant equations using an explicit numerical solution. A 1D solution was adopted in lieu of a 2D approach to ensure that the run times were sufficiently fast to allow the processing of many thousands of Monte Carlo simulations, as discussed in the following section. The model comprises more than 2,500 channels covering the Brisbane River and major tributaries along the lower reaches of the Brisbane River. Loss parameters associated with bends and channel formations were finalised by calibration, and an example comparison with observed data is shown in Figure 2(b).



Figure 2. Simulation of the January 2011 event showing a) validation of RORB model parameters, and b) an example calibration achieved by the hydraulic model.

# 3.2. Modelling Hydrologic Probability-Neutrality

Event-based approaches are based on the transformation of a discrete rainfall event into a flood hydrograph using a simplified model of the physical processes involved. It requires the application of two modelling steps, namely: a runoff production model to convert the storm rainfall input at any point in the catchment into rainfall excess or runoff at that location, and a hydrograph formation model to simulate the conversion of these local runoffs into a flood hydrograph at the point of interest. The rainfall event is described by a given depth of rainfall occurring over a selected duration, where it is necessary to specify the manner in which the rainfall varies in both time and space. The input rainfall may represent a particular observed event, or else it may represent the depth of rainfall with a specific annual exceedance probability (AEP), ie a "design rainfall". The former approach is most commonly used for model calibration and flood forecasting, the latter approach is used to estimate flood risk for design and planning purposes. The defining feature of such models is that they are focused on the simulation of an individual flood event, and that antecedent (and baseflow) conditions need to be specified in some explicit fashion.



Event-based approaches represent traditional current practice in Australia and most overseas countries for derivation of design floods from design rainfalls. Traditionally, event-based models have been applied "simple event" using a approach, whereby probability-neutrality is assumed to be satisfied by careful selection of fixed values of parameter values and inputs. The recent recommends ARR two additional approaches, namely "ensemble event" "Monte Carlo and simulation", to better ensure that probability neutrality is preserved (Nathan and Ling, 2016).

The typical steps involved in the Simple Event method are shown by blue shading in Figure 3. The first step (point A) is to estimate the average intensity or depth of rainfall corresponding to a given AEP for a selected duration. The next step is to select representative

Figure 3. Different simulation frameworks for achieving probabilityneutrality: simple event (blue shading), ensemble event (grey dashed), Monte Carlo treatment of aleatory uncertainty (green shading) and epistemic uncertainty (orange shading).

values of other factors that influence the transformation of rainfall to flood hydrograph. At a minimum, this involves selecting representative temporal and spatial patterns of rainfall, and selecting appropriate loss parameters. Direct runoff (also known as "rainfall excess") is simulated using a loss model, and this is then routed through the catchment to generate the design flood hydrograph. The hydrograph corresponding to the rainfall burst duration that results in the highest peak (the "critical rainfall duration") is taken as the design flood hydrograph, and it is *assumed* to have the same annual exceedance probability as its causative rainfall. It needs to be stressed that probability-neutrality is an untested assumption with the simple event approach, and without reconciliation with flood frequency estimates using at-site or transposed gauged maxima, there is clear potential for this approach to produce biased results (Kuczera et al, 2006; Green et al, 2005; Sih et al, 2008; Ling et al, 2015).

With the ensemble approach (grey dashed lines, point B of Figure 3), a fixed factor with large influence on flood magnitude is replaced by a sample of values (an "ensemble"); each of these values is then input to the flood event model to derive a set of flood hydrographs. The magnitude of the design flood is then estimated from the weighted average of the hydrographs, where the weighting applied to each result reflects the relative likelihood of the selected input occurring. If a sample of observed temporal patterns is used instead of a single pattern of average variability, then studies have shown (Sih et al, 2008; Ling et al, 2015) that a simple arithmetic average based on a sample of 10 to 20 patterns provides a reasonably unbiased estimate of the design flood. The rationale for this approach is that each of the patterns selected for the ensemble is equally likely.

Monte Carlo methods provide a framework for simulating the natural variability in the key processes that influence flood runoff: all important flood producing factors are treated as stochastic variables, and the less important ones are fixed. The primary advantage of the method is that it allows the exceedance probability of the flood characteristic to be determined without bias (subject to the representativeness of the selected inputs). In the most general Monte Carlo simulation approach for design flood estimation, rainfall events of different duration are sampled stochastically from their distribution. This avoids any positive bias of estimated flood probabilities which may be associated with the application of the critical rainfall duration concept (Weinmann et al., 2000, 2002; Rahman et al, 2002). However, the Monte Carlo approach can be applied with selected rainfall durations (Nathan et al, 2003), where the resulting peak flows are then enveloped to select the critical event duration. Whilst adherence to the 'critical duration' concept could possibly introduce systematic bias into the results, it has the advantage of ensuring consistency with existing design approaches and allows much of the currently available design data to be readily used.

The overall steps involved in a simple Monte Carlo simulation are shown by the green and blueshading in Figure 3. Details of the approach are provided in ARR (Nathan and Ling, 2016), but in essence the approach involves running the event model many hundreds or thousands of times, where the inputs that most impact on flood magnitude are sampled in accordance with the variation observed in nature (using either statistical distributions or ensemble samples). Once the synthetic maxima have been generated, the required design floods are obtained (point C, Figure 3) by traditional frequency analysis (eg Kuczera and Franks, 2016) or some more efficient approach, such as the Total Probability Theorem (Nathan et al, 2003) or importance sampling (Diernense et al, 2014). It should be noted that the steps involved between points A and C in Figure 3 represents the scheme required to consider the joint probabilities associated with the variability of selected inputs. It represents the characterisation of *aleatory* uncertainty, which is the (irreducible) uncertainty associated with variability inherent in the selected inputs (eq, in the variability of rainfall patterns and catchment wetness). However, Monte Carlo schemes can also be used to consider epistemic uncertainty, and the additional steps involved in this are shown by the first and last steps in Figure 3 (orange shading). Epistemic (or reducible) uncertainty is due to lack of knowledge, and is associated with errors in the data or the simplifications involved in representing the real world by a conceptual model. In essence, the consideration of aleatory uncertainty allows the derivation of a single (probability-neutral) "best estimate" of flood risk, and consideration of epistemic uncertainty allows the characterisation of "confidence limits" about this best estimate.

# 3.3. Modelling Hydraulic Probability-Neutrality

All the schemes in the preceding section relate to the hydrologic modelling required to derive probability-neutral floods. Similar concepts apply to the hydraulic modelling required to convert these flows into depths, but the sources of aleatory and epistemic uncertainty are different. Typical major sources of aleatory uncertainty include variation in flows (at upstream or tributary locations) and tide levels in estuarine systems, though debris may also be an important factor, particularly where it may block control structures and reduce waterway area. Typical sources of epistemic uncertainty include the parameterisation of roughness and loss values, and any limitations on survey data that relate to channel and floodplain morphometry. The conceptual framework illustrated in Figure 3 is directly applicable to hydraulic modelling, the only differences being in the selection of the model and sources of uncertainty.

# 4. IMPACT OF NATURAL VARIABILITY

## 4.1. Scenarios considered

The manner in which natural variability (aleatory uncertainty) impacts on design flood peaks and flow depths is assessed by selectively relaxing the assumptions of probability-neutrality discussed in the previous section. A number of scenarios are considered, as summarised in Table 1. In this table the first two rows represent results for the traditional "simple event" method, in which fixed losses are used and a single temporal pattern based on the average variability method (AVM, Pilgrim and Cordery, 1975); the only difference between the first two rows is that in the first, the AVM pattern is based on the sample of regional storms derived for the South-East Queensland region for ARR (Babister et al, 2016), and in the second, the AVM pattern is based on a sample of 15 large storms prepared by Sequater (2013). The third row of the table represents ensemble sampling of temporal patterns with all other inputs fixed. The final four rows provide the results for Monte Carlo sampling in which different sources of variability are progressively introduced. The first of these only considers the variation of losses throughout the year, the second then considers their seasonal variation, the third introduces variability in the temporal patterns, and the final - the most comprehensive simulation - considers variation in the spatio-temporal characteristics of rainfall over the catchment in combination with seasonally varying losses. This last scenario is considered to provide the most accurate set of flood estimates. Information on the annual and seasonal variation of losses was obtained from Hill et al (2015), and the median loss estimate is derived from the regional ARR design estimates derived by Hill et al (2016). The Monte Carlo scheme adopted uses the Total Probability Theorem to derived expected probability quantiles, as described in Nathan and Ling (2016). A total of 5000 simulations were undertaken to derive the flood quantiles (using the rainfall-runoff event model), and a stratified sub-set of 1250 simulations were then used to derive Monte Carlo estimates of flood levels (using the hvdraulic model).

Label	Catchment	Seasonality	Rainfall temporal pattern	Rainfall spatial
	wetness			pattern
Simple ARR	Fixed	Annual	Fixed AVM pattern based	Fixed
			on regional storms	
Simple Local	Fixed	Annual	Fixed AVM pattern based	Fixed
			on local storms	
Ensemble Local	Fixed	Annual	Sample of 15 spatially	Fixed
			averaged temporal patterns	
			based on local storms	
Monte Carlo	Single distribution	Annual	Fixed AVM pattern based	Fixed
Annual Losses	over whole year		on local storms	
Monte Carlo	Four distributions	Four	Fixed AVM pattern based	Fixed
Seasonal Losses	(one for each	seasons	on local storms	
	season)			
Monte Carlo	Four distributions	Four	Sample of 15 spatially	Fixed
Lumped Temporal	(one for each	seasons	averaged temporal patterns	
patterns	season)		based on local storms	
Monte Carlo	Four distributions	Four	Sample of 15 spatially	Variable, based
space-time	(one for each	seasons	variable temporal patterns	on 15 local
patterns	season)		based on local storms	storms

Table 1. Adopted modelling scenarios used to assess aleatory uncertainty

# 4.2. Impacts on flood magnitude

Selected results from the different flood simulations are summarised in Figure 4. Results were derived for three sites, namely Savages Crossing, Mt Crosby, and the Brisbane Port Office (see Figure 1). The results shown in Figure 4 are for Savages Crossing, though a similar pattern of behaviour was found at the other two sites. The stochastic maxima shown in these plots represent the derived flood peak for a particular combination of inputs, where the result is plotted against the AEP of the causative rainfall. The derived frequency curves represent the relationship between the magnitude of the design flood and its AEP. The results obtained using the simple and ensemble event methods are repeated

on all four panels to facilitate comparison.

The dependence of flood magnitude on the variability of different inputs is seen by the relative spread of results between the Monte Carlo simulations in the four panels of Figure 4. It is seen that the range of stochastic maxima associated with an annual distribution of losses (Figure 4a) is much narrower than is obtained when seasonal losses are considered as there is a lower variety of combinations possible. (It should be noted that the seasonality of storm arrivals has not been specifically derived for this illustrative application. Over 80% of simulated events occur in summer/autumn season, which is not particularly evident from the plot as the more numerous events plot over one-another; also, in reality the seasonality of losses varies gradually throughout the year, and not in four distinctive bands as approximated here). A greater spread of values is associated with the inclusion of temporal pattern variability (Figure 4c), and this increases slightly once spatial variability is included (Figure 4d). While the degree of scatter in the stochastic flood maxima differ markedly between the different Monte Carlo scenarios, the difference in their derived frequency curves is relatively modest as the derivation of expected flood quantiles takes the conditional probability of each maxima into account. The difference in the 1% AEP flood quantile across all three sites is generally less than 5% to 10% for the four scenarios considered.



Figure 4. Stochastic maxima and derived flood peak quantiles for four Monte Carlo scenarios at Savages Crossing, where the results obtained using "simple event" and "ensemble event" methods are shown on all four panels.

The results for the simple and ensemble simulations are also shown in Figure 4. It is seen that the "simple event" approach using single AVM patterns based on the 15 largest local storms (solid black diamond symbols) yield results that are close to the "best estimate", which is indicated by the orange solid line in Figure 4(d). The same approach, but using patterns derived from regional storms over a wider region (black hollow diamond symbols), provide estimates that are around 25% to 30% lower. On the one hand it could be argued that the results based on local storms should give the better results because the data is sourced directly from the catchment of interest. However, it could also be argued that those based on a regional sample of storms reflect the variability in a larger more comprehensive set of storms, and these should provide more accurate results, at least for the rarer events considered. In reality, the degree to which simple event approaches are probability neutral are

very catchment-specific (Green et al, 2005; Sih et al, 2008), and it is not possible to determine (without the Monte Carlo results, or a frequency analysis based on a long reliable streamflow record) which set of results are more defensible.

It is also seen that the average ensemble results (large red diamonds) also lie reasonably close to the "best estimate" based on the Monte Carlo simulation of seasonal losses and space-time patterns of rainfall (Figure 4d). The individual maxima used to derive the average ensemble estimate (small red diamonds) span the range of results obtained using the simple event models; indeed, they span the majority of the variability exhibited when both losses and temporal patterns are varied (Figure 4c), which indicates that the floods are more sensitive to temporal patterns than they are to losses.



Figure 5. Stochastic maxima and derived flood peak quantiles for both flood peaks and flood volumes at Savages Crossing (based on consideration of variability in seasonal losses and space-time patterns of rainfall), showing the range of rainfalls contributing to a 5% AEP event.

These simulations also demonstrate the difficulty of achieving probability-neutrality in the transformation of rainfall into floods. Figure 5 shows the stochastic flood maxima derived using seasonally varying losses and variable space-time patterns of rainfalls for Savages Crossing. The left hand panel of this figure shows variation in the derived flood peaks, and the right hand panel shows the corresponding plot for maximum 3-day flood volumes. The horizontal red arrow shows the range of AEPs of rainfalls that contribute to a 5% (ie, 1 in 20) AEP flood. With respect to flood peaks, it is seen that rainfalls as frequent as 20% to 50% AEP (falling on a wet catchment) and some rainfalls rarer than 1% (ie 1 in 100) AEP (falling on a very dry catchment) yield flood peaks that have an exceedance probability of 5% AEP. The range of rainfalls relevant to flood volumes is slightly narrower, but the range is still considerable.

# 4.3. Impacts on flood depth

The flow hydrographs generated for the results shown in the previous section were input to the hydraulic model to derive probability-neutral estimates of design flood levels. One practical problem with this kind of analysis is that running a hydraulic model is many thousands of times more computationally intensive than an event model. For example, 5000 runs of the flood event model take less than 30 seconds on a standard windows computer, whereas – without parallelisation – this number of simulations of the hydraulic model on a workstation computer would take around 20 days to complete. To undertake these runs, a sub-set of 1250 runs were extracted in a stratified manner from the sample of 5000 hydrographs, and the hydraulic model was configured to run in parallel across around 20 computer cores. This approach enabled each 1250 set of simulations to be undertaken in an elapsed time of about 8 hours.

The results obtained from the hydraulic modelling is similar in behaviour but with a reduced range, compared to the flow results. Two Monte Carlo scenarios for flow depths (above channel invert) at Savages Crossing are shown in Figure 6, and again, similar behaviour was evident at the other two sites. The median difference between the three Monte Carlo scenarios over all AEPs and across all three sites is only 2% of the best estimate based on seasonal losses and space-time patterns of rainfall. The corresponding median difference between the "simple event" and "ensemble average" estimates is 5% of the best estimate. Overall, while the estimates of flood depth displayed a similar pattern of response as the flood peak estimates, the range of the variation is reduced.



Figure 6. Stochastic maxima and derived flood level quantiles for two Monte Carlo scenarios at Savages Crossing, where the results obtained using "simple event" and "ensemble event" methods are shown on both panels.

## 4.4. Propagation of aleatory uncertainty

The foregoing two sections illustrate how different approaches to modelling probability-neutrality impact on estimates of design flood peaks and flow depths. An understanding of the relative importance of this to the estimation of design peaks and flow depths helps determine how best to allocate effort to different aspects of the analyses. To this end, the results derived for the three locations shown in Figure 1 (Savages Crossing, Mt Crosby, and Port Office) were analysed, and the results of this are presented in Figure 7.

The top three panels of Figure 7 show the results for peak flow estimates at the three sites, and the lower three panels show the corresponding results for peak flow depths. The solid diamonds represent the best estimate derived from six of the design scenarios summarised in Table 1, and the bars represent the range in flood peaks and depths associated with the different sources of variability considered. To facilitate comparison, the results are expressed in non-dimensional terms (as proportions of the best estimate derived using Monte Carlo analysis of seasonal losses and space-time patterns of rainfall). The difference between the best estimates (ie the bias) and the variability of the corresponding peaks are calculated from the median results obtained for annual exceedance probabilities ranging between 10% and 1%. The range of the peaks contributing the simple event methods (based on local and ARR AVM patterns) is clearly zero as only one combination of inputs are considered. The range of peaks considered by the other methods increase as additional sources of aleatory uncertainty are considered, which reflects the patterns of results shown in Figures 4 and 6.

The most striking result evident from Figure 7 is that aleatory uncertainty has about two to three times more impact on peak flow rates than it does on flow depths at all three sites. That is, the uncertainty due to different natural combinations of losses, temporal and spatial patterns of rainfall has a bigger impact on flood flows than it does flood depths. This is perhaps not a surprising result, but it suggests that greater effort needs to be spent on modelling probability-neutrality in the transformation between rainfall and streamflows, than between streamflows and flood levels. The extent to which this conclusion might be applicable to other catchments needs to be investigated, but such a difference would suggest that more complex Monte Carlo schemes might only need to be developed for the less computationally intensive rainfall-runoff models, and that simpler schemes might be adequate for the more resource-intensive hydraulic models. That is, for those design problems requiring the estimation of inundation levels (and consequences) associated with a specified exceedance probability, there is strong evidence that aleatory uncertainty needs to be explicitly considered when transforming design rainfalls into flood hydrographs, but there may be a lesser need to accommodate such uncertainty when routing the probability-neutral design hydrographs through hydraulic models. The decision as to whether Monte Carlo modelling is required in the hydraulic analyses is likely to be very site-specific, and will depend on how sensitive the consequences of inundation are to small changes in level.



Figure 7. Bias and variability in design estimates of peak flow and depths associated with different approaches to modelling probability-neutrality, where the solid diamond symbols represent the best estimate from each approach, and the bars denote the range of flood peaks resulting from different combinations of losses, temporal and spatial patterns of rainfall.

# 5. CONCLUSIONS

The new Australian guidelines on flood estimation have introduced a range of procedures to accommodate the joint variability of major factors that influence the estimation of flood peaks and levels. The need for these new procedures is well established in the scientific literature, but it is only in the last decade that the necessary design information and procedures have been developed to allow their application to practical design problems. This paper illustrates that an estimate of design peak flow is influenced by rainfalls that span an order of magnitude around the exceedance probability of interest; similar results were found for design estimates of flood volume, and flood depths. These results are consistent with the findings of other published studies, and are likely to be of general relevance to flood estimation practice.

The analyses in this paper shows that for the catchment considered, natural variability in losses, temporal and spatial patterns of rainfall has about two to three times more impact on peak flood flows than it does flood depths at all three sites. Such results have implications for how effort is prioritised when modelling the probability-neutral transformation of rainfall into floods, and their subsequent transformation into levels. The extent to which this finding is relevant to other catchments needs further investigation.

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