Uncertainty in Design Rainfall Estimation: A Review

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Abstract: *Design rainfall is an essential input to a hydrologic model, which is used to estimate design discharge that is needed in the planning and design of many engineering infrastructure projects. Design rainfall estimation is made using recorded rainfall data over many stations in a given region. Uncertainties in design rainfall estimates arise from various sources such as data error, sampling error, regionalization error, model error and error due to climate change. This paper reviews various sources of uncertainties in design rainfall estimation. It has been found that uncertainty in design rainfall estimates are hardly considered in design applications. Uncertainty in design rainfall estimation can be assessed using Monte Carlo simulation and bootstrapping techniques. These techniques require significant computer power, which however is not a problem now a days. The biggest challenge in uncertainty estimation lies in the assessment of the impacts of non-stationarity in the rainfall data on design rainfall estimates. The findings of this paper would be useful to future studies on design rainfall estimation.*

Keywords: *Design rainfalls, IDF, uncertainty, climate change, Monte Carlo simulation, Bootstrapping.*

1. Introduction

Design rainfall is a probabilistic representation of rainfall intensity (depth of rainfall over a time period) at a given location for a given duration and average recurrence interval (ARI). Design rainfall is an essential input to a hydrologic model, which is used to estimate design discharge that is needed in the planning and design of many engineering infrastructure projects such as street drainage systems, culverts, bridges and regulators. In design rainfall estimation, recorded rainfall data at many stations are used to develop intensity-duration-frequency (IDF) curves by adopting statistical techniques such as regional frequency analysis.

Many countries in the world have carried out research on the derivation of IDF curves such as Australia (I. E. Aust., 1987; Haddad et al., 2011; Johnson et al., 2012), U. K. (NERC, 1975), USA (Hershfield, 1961; Bonnin et al., 2006; Trefry et al., 2005), Hong Kong (Yu and Cheng, 1998), Italy (Baldassarre et al., 2006), Israel (Ben-Zvi, 2009), Denmark (Madsen et al., 2002, 2009), Malaysia (Zakarai et al., 2012), Iran (Avolverdi and Khalili, 2010), Norway (Hailegeorgis et al., 2013) and Qatar (Mamoon et al., 2013, Mamoon et al., 2014). In many cases, the quantity and quality of recorded rainfall data (in particular the continuous rainfall data) are inadequate, which results in a significant uncertainty in the derived IDF curves. Also, climate change brings another dimension of uncertainty in the IDF derivation as in many cases the past rainfall data may not satisfy the stationarity assumption (Ishak et al., 2013; Seidou et al., 2012; Leclerc and Ouarda, 2007).

As compared to humid region, design rainfall estimation in the arid region is more challenging mainly due to significant spatial and temporal variability in rainfall and the limited availability of recorded rainfall data (Kwarteng et al., 2009; Zhang et al., 2005; Nasrallah and Balling, 1993). There can be long dry periods with little or no rainfall in the arid regions. Rainfall data time series must cover longer time periods to capture the long term variability in rainfall to derive valid IDF curves that can be applied in the design with confidence. For example, shorter rainfall data covering either dry or wet climatic regime would provide under- and over-estimation, respectively i.e. biased IDF curves.

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There have been many studies on design rainfall estimation; however, the uncertainty in design rainfall estimation has not been incorporated in the final IDF curves in most of the previous applications. This paper focuses on the uncertainty in design rainfall estimation by identifying various sources of uncertainty, reviewing various methods to account for the uncertainty and making recommendations on how uncertainty can be incorporated in the final IDF curves.

2. Sources of uncertainties in design rainfall estimation

Zadeh (2005) defined uncertainty as an attribute of information. This definition can be applied to hydrology, where uncertainty has traditionally been estimated using probability theory (Montanari, 2007). Uncertainty may be defined as a measure of the lack of accuracy concerning observed data and modelling outcome.

Many attempts have been made to study different types of uncertainties in design rainfall estimation and rainfall runoff modelling (Yen and Ang, 1971; Kavetski et al., 2006; Yu and Cheng, 1998; Ewen et al., 2006; Renard et al., 2010; Wu et al., 2011; Hailegeorgis et al., 2013 and Tung and Wong, 2014). In general, the uncertainty in hydrological modelling can be divided into two main categories: (i) data and sampling errors and (ii) modelling or structural errors (Haddad and Rahman, 2014). The data uncertainty is originated from measurements errors resulting from instrumental and human errors and also due to inadequate representativeness of a data sample due to temporal and spatial variability of the data.

The use of a limited quantity of rainfall data (such as data of short record length) in the frequency analysis introduces sampling uncertainty. Due to sampling uncertainty, the estimates of higher order moments (such as skewness) become unstable, in particular due to the presence of extremes/outliers data points. The sampling uncertainty is transmitted to the establishment of rainfall IDF model, model coefficients and, eventually, to the design rainfall amount and adopted hyetograph (Tung and Wong, 2014). Uncertainty features of design rainfall via rainfall IDF model coefficients in the risk-based design of urban drainage systems was addressed in an earlier study by Yen and Tang (1976). Wu et al. (2011) addressed the cascade transmission of uncertainties starting from sampling errors to the analysis and design of drainage infrastructures as illustrated in Figure 1.

The assumptions made during modelling may result in errors in the conceptual structure of the model. The choice of a model also introduces errors in predicting quantile of interest. The uncertainty in the model parameters is attributed to inability in accurately quantifying the input parameters for a model. The parameters obtained from the calibration process are also not free from uncertainty for various reasons including data uncertainty (data used to calibrate the model contains errors), insufficient amount of data from which the parameters in an assumed model are estimated, model uncertainty (the model structure used to calibrate the model is not adequate), and lack of sufficient data.

In modelling hydrologic systems, there are two sources of random variation that may affect the estimated system outputs: (i) the natural temporal and spatial variability of climate and catchment factors being modelled; and (ii) the uncertainty in the definition of the model structure, the model inputs and in the estimated model parameters (Nathan and Weinmann, 2013).

In general, hydrologic modelling is affected by four main sources of uncertainty (Renard et al., 2010): (i) input uncertainty, e.g., sampling and measurement errors in catchment rainfall estimates; (ii) output uncertainty, e.g., rating curve errors affecting runoff estimates; (iii) structural uncertainty (sometimes referred to as "model uncertainty"), arising from lumped and simplified representation of hydrological processes in hydrologic models; and (iv) parametric uncertainty, reflecting the inability to specify exact values of model parameters due to finite length and uncertainties in the calibration data, imperfect process understanding and model approximations.

Hailegeorgis et al. (2013) suggested that the regional frequency analysis of extreme precipitation events and hence derivation of IDF curves is subject to the major uncertainties of different sources:

- Data series used: data quality, which is related to the questions like is the data series stationary and independent; and sampling of data, which are related to the time period and length of data series and the sampling type e.g. annual maximum series (AMS) and partial duration series (PDS);
- Selection of frequency distribution to describe the data;
- Parameter estimation; and
- Regionalization and quantile estimation.

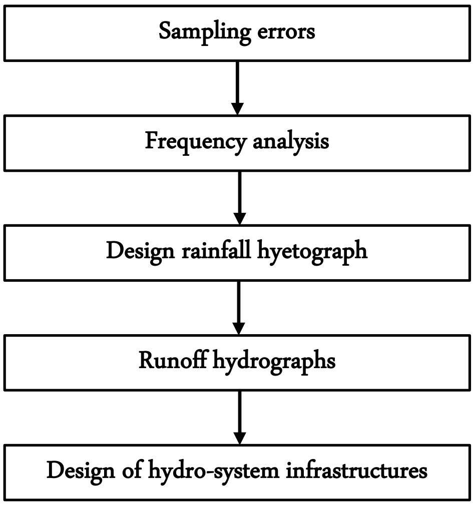

Figure 1 Propagation of uncertainties in hydrological modelling

3. Uncertainty associated with regional rainfall frequency analysis

For estimation of design rainfalls (i.e. IDF curves), regional rainfall frequency analysis (RRFA) methods are generally used. The RRFA is preferred over the at-site estimation to achieve consistency in estimation over the space. In RRFA, use of rain data from several sites and grouping the rain gauges in homogeneous regions allow to trade space for time (Stedinger et al., 1993). Moreover, a regional approach allows estimation of design rainfall at any arbitrary location within the region, in particular at ungauged locations. In RRFA approach, recorded rainfall data within a 'homogeneous region' is pooled to compensate the scarcity of temporal data with the spatial data i.e. recorded rainfall data from other stations in the region. In a homogeneous region, it is assumed that all the sites within the region have same regional growth curve/factors, but the at-site scaling factor (e.g. mean or median value) is unique for each site which reflects the variation of at-site characteristics governing rainfall generation. Principal steps of RRFA approach is illustrated in Figure 2. Types of uncertainties related to RRFA include the degree of homogeneity of the assumed region, number of sites in the region, record lengths of the individual sites and how the regional data is pooled.

4. Uncertainty due to climate change

Climate change can be defined as any change to atmospheric forcing resulting from human activities, including the emission of greenhouse gases as well as anthropogenic aerosols, whereas, climate variability is defined as changes resulting from 'natural' features of the climate (Ishak et al., 2013). Climate change has been affecting different aspects of hydrological cycle including rainfall and runoff (Wang et al., 2013). This can eventually lead to increased occurrence of extreme events such as rainfalls, floods, droughts, heat waves, summer and ice storms (Simonovic and Peck, 2009; De Paola et al., 2013; Laz et al., 2014; Mamoon and Rahman, 2014; Mamoon et al., 2014). Since there is a strong link between the global climate system and the hydrological cycle, a change in a component of the climate system will have a notable impact on the magnitude and frequency of hydrological extremes, including the potential for changes to rainfall. This challenges the assumption of stationary, which is fundamental in frequency analysis of hydrological data (Milly et al., 2008; Westra and Sisson, 2011). Failure to take such change into consideration can undermine the usefulness of the return period concept in hydrological frequency analysis (Khaliq et al., 2006).

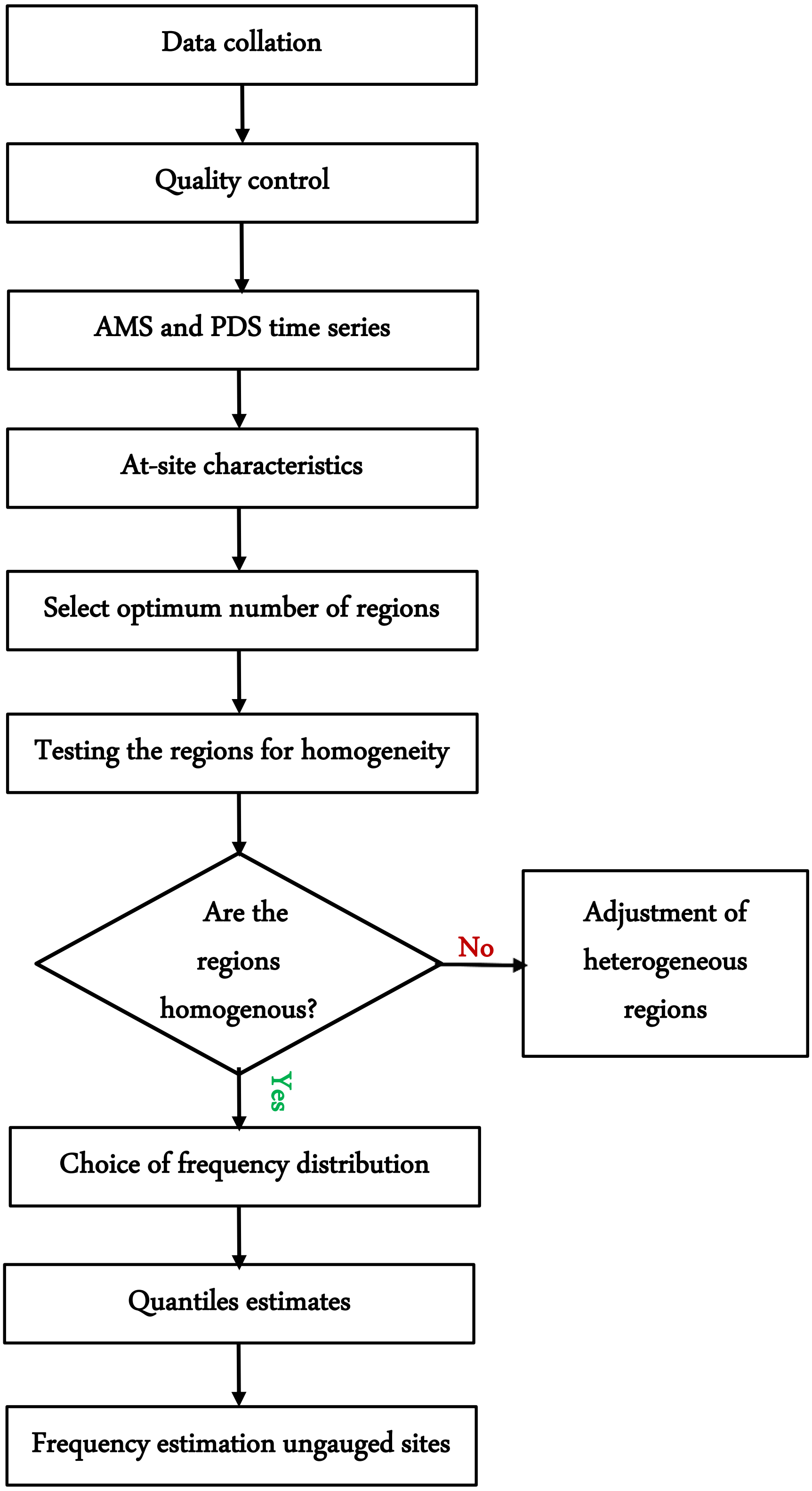

Figure 2 Principal steps in regional rainfall frequency analysis (RRFA)

The Intergovernmental Panel on Climate Change (IPCC) in its fourth Assessment Report AR4 predicts more extreme climate towards the end of the century, which will impact the design of engineering infrastructure projects with a long design life. Since extreme rainfall data is used in the derivation of design rainfalls, which is used to design future drainage infrastructure, it has become an important research question whether the extreme rainfall at a given region would change in future due to climate change and how this change will happen. As temperature increases, the evaporation will increase, which will result in an increase in intensity of heavy precipitation events in many regions globally, including some regions where average precipitation may even show a decrease (Meehl et al., 2007).

The regional design rainfall estimates are made using the recorded rainfall data. It is however expected that the climate change will modify the at-site and regional rainfall characteristics, which will undermine the use of the past data to make realistic long-term projections. For example, the rainfall data statistics such as the mean or median may change due to climate change and hence the statistical distributional parameters or the parent distribution itself would change. Due to the non-stationarity of rainfall under changing climate conditions, the change of intensity for design storm under given duration and frequency has been observed in many regions (Willems and Vrac, 2011; Olsson et al., 2012).

Attempts have been made by researchers in various parts of the world to update IDF relationship under changing climate conditions. For example, Simonovic and Peck (2009) applied two climate scenarios obtained as simulations outputs of global climate model (GCM) to assess the impact of climate change on extreme rainfall events for the city of London in Western Ontario, Canada. Comparison of updated IDF curves for climate change indicated that the rainfall intensity would most certainly increase under climate change scenario.

Wang et al. (2013) assessed the impact of climate change on IDF data at Apalachicola River basin using seven regional climate models under emission scenario A2. Even though some models projected decreased rainfall intensity, the extreme rainfall intensity and frequency were projected to increase by most models at the study area.

Mirhosseini et al. (2013) evaluated impacts on IDF curves for Alabama using high-resolution projections (for 2038–2070) derived from dynamical downscaling of GCMs by regional climate models. Future IDF curves were constructed using 3-hourly precipitation data simulated by six combinations of global and regional climate models being temporally downscaled using a stochastic method. The results of all six climate models suggested that the future precipitation patterns for Alabama were expected to veer toward less intense rainfalls for short duration events. However, for long duration events (e.g. 4 hours), the results were not consistent across the models.

It should be noted that significant uncertainty is associated with rainfalls generated by climate models (Wang et al., 2013). This could be introduced by failure in improving long-term climate projection accuracy beyond what could be achieved by interpolating global model predictions onto a finer-scale landscape (Pielke and Wilby, 2012). The rainfall observation is generally obtained from weather stations which are point-based rainfall depth, but the rainfall depth from climate models is the average value at a very large spatial scale varying from 50 to over 300 km. Due to large grid size, climate models provide coarse rainfall data, not easily comparable with point rainfall data.

5. Uncertainty analysis methods

Many studies in recent years suggest a range of methods for quantifying uncertainties (Hill et al., 2012; Renard et al., 2010; Pappenberger and Beven, 2006; Aster et al., 2012; Gupta et al., 2005; Montanari, 2007). A few of the numerous approaches for understanding and quantifying uncertainty are listed below:

- Analytical methods (Tung, 1996);
- Approximation methods e.g., first-order second moment method (Melching, 1992);
- Simulation and sampling-based Monte Carlo methods (Kuczera and Parent, 1998; Burgman, 2005; Nathan and Weinmann, 2013);
- Bayesian methods (Renard et al., 2010; Ye et al., 2008);
- Methods based on the analysis of model errors (Montanari and Brath, 2004);
- First-order variance estimation method (Tung and Yen, 2005) based on the Taylor series expansion;
- Bootstrapping (Efron and Tibshirani, 1993);
- Cross-validation approaches (Haddad et al., 2013); and
- Methods based on fuzzy set theory (Maskey et al., 2004; Zadeh, 1978).

Uncertainty analysis methods in all of the above cases involve: (i) identification and quantification of the sources of uncertainty; (ii) reduction of uncertainty; (iii) propagation of uncertainty through the selected model; (iv) quantification of uncertainty in the model outputs; and (vi) application of the uncertain information in decision making process. However, Pappenberger and Beven (2006) noted that the practice of uncertainty analysis and use of the results of such analysis in decision making is not widespread.

The Monte Carlo simulation technique is widely used in hydrology to assess uncertainty in the modeling (Abolverdi and Khalili, 2010; Zakaria et al., 2012). It allows the quantification of the model output uncertainty resulting from uncertain model parameters. The Monte Carlo simulation technique is based on the principle that model input variables are random instead of fixed values. The advantages of the

Monte Carlo simulation technique are that this allows examining the impacts of many possible combinations of the input variables and model parameters in rainfall estimation.

Zakaria et al. (2012) used Monte Carlo simulation technique to evaluate the performance between the simulated and calculated rainfall quantiles of specific recurrence intervals in Malaysia. Hailegeorgis et al. (2013) used non-parametric bootstrap resampling approach to quantify the sampling uncertainty in terms of interval estimates of quantiles (i.e. 95% confidence bounds). The interval estimate showed that there is a huge uncertainty in quantile estimation due to sampling of data which needs to be incorporated in any frequency analysis from historical data. The updated estimated quantiles and IDF curves with uncertainty bounds obtained from this study were found to be more reliable as compared to the existing IDF curves for the city of Trondheim, Norway.

Various sources of uncertainties and their methods of analyses are illustrated in Figure 3.

5.1 Monte Carlo simulation

Monte Carlo simulation is a technique for iteratively evaluating a deterministic model using sets of random samples as inputs. The term Monte Carlo was coined by S. Ulam and Nicholas Metropolis to capture the random properties of the roulette wheel played at Casinos in Monte Carlo, Monaco. This method is often used when the model is complex, nonlinear, or involves more than just a couple of uncertain parameters and simulation involving numerous evaluations of the model (Wittwer, 2004).

Monte Carlo simulation has been widely used to determine the impacts of model and parameter uncertainty on simulation results; these are generally expressed in the form of confidence limits on hydrologic estimates (Rahman et al., 2002; Nathan and Weinmann, 2013). In Monte Carlo simulation, the inputs are randomly generated from probability distributions to simulate the process of sampling from an actual population. The data generated from the simulation can be represented as probability distributions (or histograms) or converted to error bars, reliability predictions, tolerance zones, and confidence intervals. The basic principle behind Monte Carlo simulation is schematically shown in Figure 4.

The steps involved in undertaking a Monte Carlo simulation for analysing parameter uncertainty are outlined below:

- Identify the probability distributions of the input variables and model parameters;
- Generate random values of each of the variables from their respective probability distributions;
- Run the model with each set of the generated input variables and generate a model output for the given set of model parameters;
- Store the model outputs;
- Repeat the steps until the convergence criterion is satisfied or total number of simulation is reached; and
- Analyze the distribution of model outputs to derive cumulative distribution function and other statistical properties (e.g., mean and standard deviation).

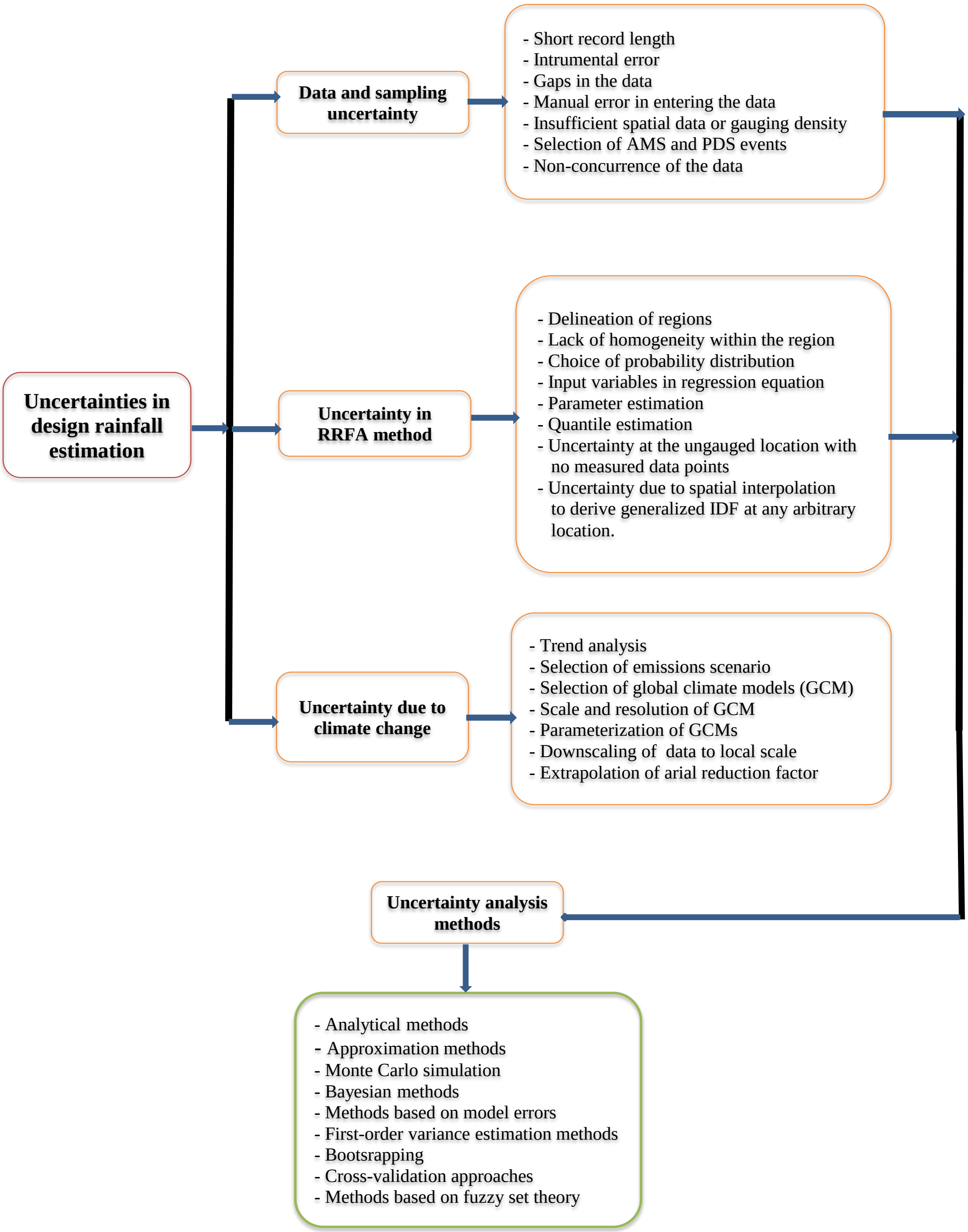

Figure 3 Classification and analysis of uncertainties in hydrological modelling

Some advantages of the Monte Carlo simulation technique are provided below:

- Probabilistic results: Results show not only what could happen, but how likely each outcome is;
- Graphical results: Because of the data a Monte Carlo simulation generates, it is easy to create graphs of different outcomes and their chances of occurrence;
- Sensitivity analysis: In Monte Carlo simulation, it is easy to see which inputs had the biggest effect on bottom-line results;
- Scenario analysis: Using Monte Carlo simulation, analysts can see exactly which inputs had been combined to generate certain outcome. This is invaluable for pursuing further analysis.
- Correlation of inputs: In Monte Carlo simulation, it is possible to model interdependent relationships between input variables. It is important for accuracy to represent how, in reality, when some factors go up or down.

Although flexible, robust and conceptually simple, Monte Carlo simulation methods tend to be among the most computationally demanding (Hill et al., 2012) as they require a large number of model runs, time and resources to produce a reliable and meaningful uncertainty estimation.

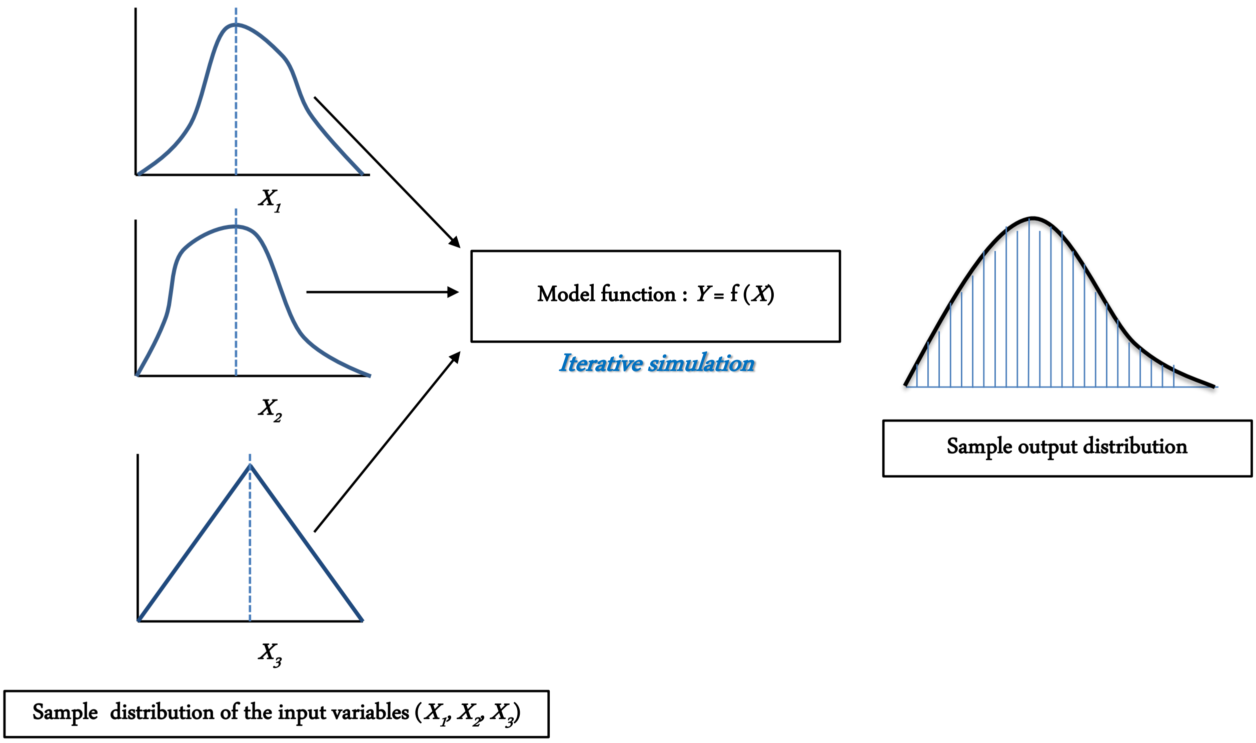

Figure 4 The principle of Monte Carlo simulation

5.2 Bootstrapping

Bootstrapping is a nonparametric statistical technique that allows computing estimated standard errors (bias variance), confidence intervals and hypothesis testing (Efron and Tibshirani, 1993). Generally, it falls in the broader heading of resampling methods. It involves a relatively simple procedure, but repeated many times and hence it is heavily dependent upon computer power.

This technique was introduced by Efron (1979a, 1979b) and further developed by Efron and Tibshirani (1993). The name "bootstrapping" originated from an old saying the phrase, "To lift himself up by his bootstraps." This refers to something that is unworkable and impossible. In bootstrapping, the samples are drawn randomly from the original sample with replacement.

Generally bootstrapping involves the following basic steps:

- Resample a given data set a specified number of times;
- Calculate a specific statistic from each sample; and
- Find the standard deviation of the distribution of that statistic.

Bootstrapping technique intends to be a more general and versatile procedure for sampling distribution problems without having to rely heavily on the normality condition on which most of the classical statistical inferences are based (Tung and Wong, 2014). It is not uncommon to observe non-normal data in hydro-system engineering problems. Although the bootstrapping technique is computationally intensive, such concern is diminishing as the computer power has been increasing with time.

6. Conclusion

Design rainfall is one of most commonly used inputs to hydrological models. Design rainfall estimation is made using recorded rainfall data over many stations in a given region. Uncertainties in design rainfall estimates arise from various sources such as data error, sampling error, regionalization error, model error and error due to climate change. This paper reviews various sources of uncertainties in design rainfall estimation. It has been found that uncertainty in design rainfall estimates are hardly considered in design application. Uncertainty in design rainfall estimation can be assessed using Monte Carlo simulation and bootstrapping techniques. These techniques require significant computer power, which however is not a problem now a days. The biggest challenge in uncertainty estimation lies in the assessment of the impacts of non-stationarity in the rainfall data on design rainfall estimates.

References

Abolverdi J, Khalili D (2010). Development of regional rainfall annual maxima for southeastern Iran by L-moments, Water Resources Management, 24, 2501-2526.

Aster RC, Borshers B, Thurber CH (2012). Parameter Estimation and Inverse Problems, Academic Press, Amsterdam.

Baldassarre DG, Brath A, Montanari A (2006). Reliability of different depth-duration-frequency equations for estimating short-duration storms, *Water Resources Research*, 42, W12501. doi:10.1029/2006WR004911.

Burgman MA (2005). Risks and decisions for conservation and environmental management. Cambridge University Press, Cambridge.

Ben-Zvi A (2009). Rainfall intensity-duration-frequency relationships derived from large partial duration series, *Journal of Hydrology*, 367, 104-114.

Bonnin GM, Martin D, Lin B, Parzybokt T, Yekta M, Riley D (2006). Precipitation-Frequency Atlas of the United States, vol. 1, NOAA Atlas 14, NOAA, USA.

De Paola F, Giugni M, Bucchignani AE (2013). Stationary Vs. Non-stationary of Extreme Rainfall in Dar Es Salaam (Tanzania), Proceedings of 2013 IAHR World Congress.

Ewen J, O'Donnell G, Burton A, O'Connell E (2006). Errors and uncertainty in physically-based rainfall-runoff modelling of catchment change effects, *Journal of Hydrology*, 330, 641– 650.

Efron B (1979a). Bootstrap methods: another look at the jackknife, *Annals of Statistics*, 3, 1189–1242.

Efron B (1979b). Computers and theory of statistics: thinking the unthinkable. SIAM Rev 21, 460–480.

Efron B, Tibshirani, R (1993). An Introduction to the Bootstrap. Boca Raton, FL: Chapman & Hall/CRC.ISBN 0-412-04231-2. software.

Gupta HV, Beven KJ, Wagener T (2005). Model calibration and uncertainty estimation. In: M. Andersen (ed.), Encyclopedia of Hydrological Sciences, John Wiley & Sons, New York, NY, USA, 2015-2031.

Haddad K, Rahman A (2014). Design rainfall estimation and changes, In Handbook of Engineering Hydrology: Modeling, Climate Change and Variability, Edited by Saeid Eslamian, CRC Press, 173-190

Haddad K, Rahman A, Green J (2011). Design rainfall estimation in Australia: a case study using L-moments and generalized least squares regression, *Stochastic Environmental Research and Risk Assessment*, 25, 6, 815-825.

Haddad K, Rahman A, Zaman A, Shrestha S (2013). Applicability of Monte Carlo Cross Validation Technique for Model Development and Validation in Hydrologic Regression Analysis Using Ordinary and Generalised Least Squares Regression, *Journal of Hydrology*, 482, 119-128.

Hailegeorgis TT, Thorolfsson ST, Alfredsen K (2013). Regional frequency analysis of extreme precipitation with consideration to uncertainties to update IDF curves for the city of Trondheim, *Journal of Hydrology*, 498, 305–318.

Hershfield DM (1961). Rainfall frequency atlas of the United States for durations from 30 minutes to 24 hours and return periods from 1 to 100 years,Weather Bureau Paper No.40. US Department of Commerce, Washington D.C.

Hill MC, Kavetski D, Clark M, Ye M, Lu D (2012). Uncertainty Quantification for Environmental Models, SIAM News, Volume 45.

Institution of Engineers Australia (I. E. Aust.) (1987). Australian Rainfall and Runoff: A Guide to Flood Estimation. Edited by D. H. Pilgrim, Vol. 1, I. E. Aust., Canberra.

Ishak EH, Rahman A, Westra S, Sharma A, Kuczera G (2013). Evaluating the non-stationarity of Australian annual maximum flood, *Journal of Hydrology*, 494, 134-145.

Johnson F, Haddad K, Rahman A, Green J (2012). Application of Bayesian GLSR to estimate sub-daily rainfall parameters for the IFD Revision Project. Hydrology and Water Resources Symposium, 19-22 Nov 2012, Sydney, Australia.

Khaliq MN, Ouarda TBMJ, Ondo JC, Gachon P, Bobée B (2006). Frequency analysis of a sequence of dependent and/or non-stationary hydro-meteorological observations: A review, *Journal of Hydrology*, 329 (3-4), 534-552.

Kwarteng AY, Dorvlob AS, Vijaya Kumar GT (2009). Analysis of a 27-year rainfall data (1977–2003) in the Sultanate of Oman, *International Journal of Climatology*, 29, 605–17.

Kavetski D, Kuczera G, Franks S (2006). Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory, *Water Resources Research*, 42, W03407.

Kuczera G, Parent E (1998). Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm, *Journal of Hydrology*, 211, 69-85.

Laz OU, Rahman A, Yilmaz A, Haddad K (2014). Trends in sub hourly, sub daily and daily extreme rainfall events in south-east Australia, Journal of Water and Climate Change, doi:10.2166/wcc.2014.035.

Leclerc M, Ouarda BMJT (2007). Non-stationary regional flood frequency analysis at un-gauged sites, *Journal of Hydrology*, 343, 254– 265.

Madsen H, Mikkelsen PS, Rosbjerg D, Harremoes P (2002). Regional estimation of rainfall intensity duration curves using generalised least squares regression of partial duration series statistics, *Water Resources Research*, 38, 11, 1-11.

Madsen H, Arnbjerg-Neilsen K, Mikkelsen PS (2009). Update of regional intensity-duration-frequency curves in Denmark: tendency towards increased storm intensities, *Atmospheric Research*, 92, 343-349.

Mamoon AA, Joergensen NE, Rahman A, Qasem H (2013). Estimation of Design Rainfall in Arid Region: A Case Study for Qatar Using L Moments. Proceedings of the 35th IAHR World Congress, September 8 to 13, 2013 Chengdu, China, 1-9.

Mamoon AA, Jeorgensen NE, Rahman A, Qasem H (2014). Derivation of new design rainfall in Qatar using L-moments based index frequency approach, *International Journal of Sustainable Built Environment*, 3, 111-118.

Mamoon AA, Rahman A (2014). Identification of Rainfall Trends in Qatar, International Conference on Environmental Systems Science and Engineering, 15 -16 Dec 2014, Sydney, Australia, 8, 12, Part VI, 735-739.

Mamoon AA, Jeorgensen NE, Rahman A, Qasem H (2014). An Exploratory Study on the Impact of Climate Change on Design Rainfalls in the State of Qatar, International Conference on Environmental Systems Science and Engineering, 15 -16 Dec 2014, Sydney, Australia, 8, 12, Part VI, 727-734.

Meehl G et al (2007). Global climate projections, in Climate Change. The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by S. Solomon et al., Cambridge Univ. Press, Cambridge, U. K, 747–845.

Mirhosseini G, Srivastava P, Stefanova L (2013). The impact of climate change on rainfall Intensity–Duration–Frequency (IDF) curves in Alabama, Regional Environ Change (Suppl 1): S25–S33

Milly PCD, Betancourt J, Falkenmark M, Hirsh RM, Zbigniew W, Kundzewicz ZW, Lettenmaier DP, Stouffer RJ. (2008). Stationarity is Dead: Whither Water Management? *Science*, 319, 573-574.

Melching CS (1992). An improved first-order reliability approach for assessing uncertainties in hydrological modelling, *Journal of Hydrology*, 132, 157-177.

Montanari A (2007). What do we mean by 'uncertainty'? The need for a consistent wording about uncertainty assessment in hydrology, *Hydrological Processes*, 21, 841–845.

Montanari A, Brath A (2004). A stochastic approach for assessing the uncertainty of rainfall-runoff simulations, *Water Resources Research*, 40, W01106, doi: 10.1029/ 2003WR002540.

Maskey S, Guinot V, Price RK (2004). Treatment of precipitation uncertainty in rainfall runoff modelling: a fuzzy set approach, *Advances in Water Resources*, 27, 889-898.

Nasrallah HA, Balling Jr RC (1993). Analysis of recent climatic changes in the Arabian Gulf region, *Environmental Conservation*, 20(3), 223–226, doi:10.1017/S0376892900023006.

Nathan R, Weinmann PE (2013). Australian Rainfall and Runoff, Discussion Paper: Monte-Carlo Simulation Techniques, Engineers Australia.

Natural Environmental Research Council (NERC) (1975). Flood Studies Report, Vol. II Meteorological studies. NERC, London.

Olsson J, Willén U, Kawamura A (2012). Downscaling extreme short-term regional climate model precipitation for urban hydrological applications, *Hydrology Research*, 43 (4), 341–351. http://dx.doi.org/10.2166/nh.2012.135.

Pielke RAS, Wilby RL (2012). Regional climate downscaling: what's the point? Eos Trans. AGU 93, PAGE 52. doi:201210.1029/2012EO050008.

Pappenberge F, Beven KJ (2006). Ignorance is bliss: Or seven reasons not to use uncertainty analysis, *Water Resources Research*, 42, W05302, doi: 10.1029/2005WR004820.

Rahman A, Weinmann PE, Hoang TMT, Laurenson EM (2002). Monte Carlo Simulation of flood frequency curves from rainfall, *Journal of Hydrology*, 256, 196-210.

Renard B, Kavetski D, Kuczera G, Thyer M, Franks SW (2010). Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors, *Water Resources Research*, 46, W05521, doi:10.1029/2009WR008328.

Seidou O, Ramsay A, Nistor I (2012). Climate change impacts on extreme floods I: combining imperfect deterministic simulations and non-stationary frequency analysis, *Natural Hazards*, 61, 647–659.

Simonovic SP, Peck A (2009). Updated Rainfall Intensity Duration Frequency curves for the City of London under the changing climate, Report No. 065, The University of Western Ontario.

Stedinger JR, Vogel RM, Foufoula-Georgiou E (1993). Frequency analysis of extreme events. In: Maidment D. R. (ed) Handbook of Hydrology, McGraw-Hill, New York.

Trefry CM, Watkins Jr DW, Johnson D (2005). Regional Rainfall Frequency Analysis for the State of Michigan, *Journal of Hydrologic Engineering*, 10, 437-449.

Tung YK (1996). Uncertainty and reliability analysis. In: L.W. Mays (ed.), Water Resources Handbook, McGraw-Hill, New York, NY, USA, 7.1-7.65.

Tung YK, Yen BC (2005). Hydrosystems engineering uncertainty analysis. McGraw-Hill, New York.

Tung Y, Wong C (2014). Assessment of design rainfall uncertainty for hydrologic engineering applications in Hong Kong, *Stochastic Environmental Research and Risk Assessment*, 28,583–592.

Yen BC, Tang WH (1976). Risk–safety factor relation for storm sewer design, *Journal of Environmental Engineering*, ASCE, 102, 509–516.

Yen B, Ang A (1971). Risks analysis in design of hydraulic projects. In: C. Chiu (ed.), Stochastic Hydraulics, Proc. of First International Symposium, University of Pittsburgh, Pittburgh, PA, USA, 694-709.

Ye M, Meyer PD, Neuman SP (2008). On model selection criteria in multi-model analysis, *Water Resources Research*, 44, W03428, doi:10.1029/2008WR006803.

Yu P, Cheng C (1998). Incorporating uncertainty analysis into a regional IDF formula, *Hydrological Processes*, 12, 713-726.

Wang D, Hagen SC, Alizad K (2013). Climate change impact and uncertainty analysis of extreme rainfall events in the Apalachicola River basin, Florida, *Journal of Hydrology*, 480, 125–135.

Westra S, Sisson SA (2011). Detection of non-stationarity in precipitation extremes using a max-stable process model, *Journal of Hydrology*, 406, 1-2. doi:10.1016/j.jhydrol.2011.06.014. 2.

Willems P, Vrac M (2011). Statistical precipitation downscaling for small-scale hydrological impact investigations of climate change, *Journal of Hydrology*, 402 (3–4), 193–205. http://dx.doi.org/10.1016/j.jhydrol.2011.02.030.

Wittwer JW (2004). Monte Carlo Simulation Basics, Vertex42.com, http://www.vertex42.com/ExcelArticles/mc/MonteCarloSimulation.html

Wu SJ, Yang JC, Tung YK (2011). Risk analysis for flood control structure under consideration of uncertainties in design flood, *Natural Hazards*, 58(1), 117–140.

Zakaria ZA, Shabri A, Ahmad UN (2012). Regional frequency analysis of extreme rainfalls in the west coast of Peninsular Malaysia using partial L-moments, *Water Resources Management*, 26, 4417-4433.

Zadeh LA (1978). Fuzzy set as a basis for a theory of possibility, *Fuzzy Sets and Systems*, 1(1), 3–28.

Zadeh LA (2005). Toward a generalized theory of uncertainty (GTU)—an outline, *Information Sciences*, 172, 1–40.

Zhang X et al (2005). Trends in Middle East climate extreme indices from 1950 to 2003, *Journal of Geophysical Research*, 110