# Introduction

Natural disasters are inevitable, and they can bring devastating impacts on the global economy and human wellbeing. Two-third of global all-natural disasters are water-related, about 60% of which are identified as floods and droughts (Lee et al., 2020, Amarasinghe et al., 2020). Every year, floods and droughts cost billions of dollars in global economic losses and having great impacts on society (e.g. issues with mental health, chronic diseases) as well as on the environment (e.g. destruction of wildlife habitat) (Deloitte Access Economics, 2016, Kiem et al., 2016, Aon plc, 2021). For example, the catastrophic flood events in Yangtze River basin killed 280 people and costed China’s economy over $35 billion in the summer of 2020 (Wei et al., 2020, Aon plc, 2021); and the Queensland 2010-2011 floods caused a total of $14.1 billion (both tangible and intangible) in losses for Australia’s economy and accounted for 36 deaths (Deloitte Access Economics, 2016). Similarly, the Millennium Drought during 1997-2010 heavily impacted the Murray-Darling Basin, one of the largest agricultural area in Australia (Kiem et al., 2016), and many major cities within Australia were also affected by water restrictions which caused great environmental and socioeconomic impacts (van Dijk et al., 2013).

With applications in ecology, agriculture, and hydrology, the development of rainfall models has received considerable interest from researchers around the world in the past 50 years (Linsley and Crawford, 1974, Wilson et al., 1979, Richardson, 1981, Mhanna and Bauwens, 2012, Baxevani and Lennartsson, 2015). Specifically, stochastic rainfall modelling involves the generation of sequences of rainfall at a scale of interest (e.g. sub-daily, daily, monthly, annual, multi-annual) that is statistically similar to observed rainfall timeseries, typically measured at rain gauges. Rainfall models are typically calibrated and verified according to statistics of interest in the observed rainfall data (e.g. monthly average, 1-day extreme). However, rainfall possesses a strong variation in both space and time due to climate phenomena, which makes it challenging to mimic (Bacchi and Kottegoda, 1995). Developing rainfall models that are capable of accurately reproducing properties across the range of spatial and temporal scales remains a great challenge.

# Virtual hydrological calibration

## Overview

A typical calibration procedure for a stochastic rainfall model involves matching some rainfall statistics with the observed data by adjusting rainfall model’s parameters. Figure 4.2 illustrates the calibration procedure of stochastic rainfall models with observed rainfall data.



Calibrating with observed rainfall data allows stochastic rainfall models to preserve identified rainfall statistics. The simulated rainfall time series can be used as input for hydrological models to produce streamflow time series for hydrological assessment. However, it is not necessarily given that simulated rainfall time series will translate to streamflow time series that preserve the properties of observed streamflow data. Therefore, the first objective of this project is to assess the feasibility of calibrating stochastic rainfall models that are able to preserve streamflow statistics. Figure 4.3 illustrates a schematic of the hydrological calibration procedure for stochastic rainfall models.



## Step 1 – rainfall simulation

**Estimating stochastic rainfall model and rainfall model parameters**: To initiate the experiment, the stochastic rainfall model will be calibrated with at-site observed rainfall data; while the rainfall-runoff model will be calibrated with at-site observed runoff data. This procedure will allow the stochastic rainfall model to simulate rainfall data that are similar to the condition at the site which could avoid potential divergence to the hydrological calibration procedure at later stages. While the set of parameters for the rainfall-runoff model will be fixed throughout the process after they are calibrated and evaluated with the observed runoff.

## Step 2 – streamflow simulation

**Simulating streamflow with simulated rainfall input:** the sequences of simulated rainfall will be used as input to the (already calibrated) rainfall-runoff model to generate sequences of simulated streamflow. Note that a separate aim will investigate the influence of the hydrological model on the overall method.

**Simulating virtual-observed streamflow with observed rainfall input**: A sequence of observed rainfall data will be used as input to the same rainfall-runoff model to generate a sequence of virtual-observed streamflow. This approach removes the possibility of errors from observed streamflow influencing the comparison

# Step 3 – objective function

* Sum of square errors
* Relative errors

# Step 4 – optimization

**Comparing simulated streamflow and virtual-observed streamflow**: The flow duration curve (FDC) will be the subject of the comparison. The FDC is computed from the streamflow sequences produced in the previous stage. The simulated FDC and the virtual observed FDC will be compared against each other forming an objective function using the sum of squares error (SSE) metric. The value of the objective function will be used to inform the calibration of the stochastic rainfall model parameters (i.e. minimizing the SSE by changing stochastic rainfall model parameters).

**Evaluating stochastic rainfall model performance**: To ensure the performance of the stochastic rainfall model in simulating rainfall input that preserves streamflow characteristics, the model will be verified with a virtual-observed FDC at a different time period (split-sample validation)

# Case study

# Results

# Discussion

* Rainfall attributes

# Limitations and opportunities

* Rainfall runoff models
* Objective function
* Feasibility – runtime

# Conclusions

# Reference