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**STATISTICAL DOWNSCALING AND
DISAGGREGATION FOR SUPPORTING REGIONAL
CLIMATE CHANGE IMPACT STUDIES**

LU YAN

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

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DISAGGREGATION FOR SUPPORTING REGIONAL
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SUMMARY

A warmer climate may affect the frequency and severity of weather extremes, such as heavy rainfalls, hurricanes and heat-waves. Based on the records around the world, the numbers of observed extreme events have presented increasing tendencies over the past decades. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report points out that the temperature would be continuously increasing in this century. This implies that some disasters (e.g. flood and drought) which are caused by weather extremes could become more frequent. The Southeast Asia is vulnerable to the impact of climate change. Especially in the urban areas, the flash flood has become one of major disasters caused by heavy rainfall. It is thus critical to develop flexible and applicable approaches to investigate the climate change impact on local regions. The General Circulation Models (GCMs) are the powerful tools to simulate either current or future climate conditions. But the bias and resolution problems have limited their applications for some specific regions like Southeast Asia. The dynamical and statistical downscaling are the two basic approaches to help bridge the gaps between GCMs and local weather information. Compared with dynamical approaches, the statistical ones are computationally cheap and easily applicable to many different regions. The objective of this PhD study is to develop and apply statistical downscaling and disaggregation methods for supporting hydrological and climate change impact studies. It covers three major components including development of novel statistical downscaling tools, applications of combined statistical downscaling and disaggregation methods, and assessment of climate change impact on hydrological processes.

Firstly, two novel methods of statistical downscaling approaches were developed. One was a regression-based method which included the K nearest neighbor (KNN) and Bayesian neural network (BNN) models. In this method, KNN was used for classifying the dry/wet day and rainfall typing based on rainfall intensity. BNN was

applied for prediction of rainfall amount. The other one was a semi-empirical stochastic weather generator which was mainly based on the Markov chain, semi-empirical random generator, and KNN. In detail, a four-state first-order Markov chain was employed to estimate day status which includes dry-day, wet-day with low-intensity rain, wet-day with moderate-intensity rain and wet-day with high-intensity rain based on the mean areal rainfall; then, three semi-empirical distributions were used to fit the three wet categories of rainfalls; finally, the KNN method was used in spatial disaggregation to generate daily rainfalls at multiple stations. A common idea of the two models was to use classification technique to describe different rainfall magnitudes based on rainfall intensity. The study results demonstrated that classification was helpful to enhance characterization of the convective rainfalls in the tropical region in the downscaling processes.

Secondly, a number of combined downscaling and disaggregation methods were applied, from different angles, to assess the climate change impact on local weather variables in Singapore. Three studies were conducted. (i) Four different statistical models were used to investigate the rainfall variation under climate change conditions at Singapore. They include Generalized linear model – Quantile regression – K nearest neighbor (GQK) model, Bias Correction with Spatial and Temporal Disaggregation (BCSTD) model, Automated Statistical Downscaling (ASD) model and Modified K nearest neighbor – Bayesian neural network (Modified KNN-BNN) model. (ii) A systematic downscaling-disaggregation study was conducted over Singapore Island with an aim to generate high-resolution spatial and temporal (i.e. hourly) rainfall data under future climate-change conditions. Through inter-comparison of various alternatives of downscaling and disaggregation methods, GLM, KNN and MuDRain (Multivariate Rainfall Disaggregation tool) were considered as the best combination of methods for future projections. (iii) A novel combined statistical downscaling-disaggregation framework (CSDD) based on Long Ashton Research Station - Weather Generator (LARS-WG) and K-nearest neighbor

(KNN) was proposed to examine the climate change impact on regional extreme rainfalls in Singapore. The approach could generate high-resolution rainfall sequences both spatially (e.g. station level) and temporally (e.g. 5-min) based on 12 emission scenarios under 4 general circulation models (GCMs). This study further examined the impacts of climate change on rainfall intensity-duration-frequency (IDF) curves. The different approaches reproduced the local weather data (mainly for rainfall) at different timescales (i.e. daily, hourly and 5-minutes), with reasonable spatial correlations being kept. For the simulation of sub-daily data, two different schemes were proved effective: master station-based approach and regional spatial disaggregation approach.

Finally, a statistical and data-driven framework was proposed to evaluate the flood risk in the Duhe river basin, China. In this study, a hybrid model based on ASD and KNN was used for downscaling rainfall and CDEN (Conditional Density Estimate Network) was applied for downscaling minimum temperature and relative humidity from GCMs to local weather stations. Then, BNN was used for simulating monthly river flows based on projected weather information. KNN was applied for converting monthly flow to daily time series and adopted for flood frequency analysis. The proposed framework took full advantages of statistical methods and offered a parsimonious way of projecting flood risks under climate change conditions.

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LIST OF SYMBOLS

<i>ANN</i>	Artificial Neural Network
<i>AAFC-WG</i>	Agriculture and Agri-Food Canada – Weather Generator
<i>APHRODITE</i>	Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources
<i>ASD</i>	Automated Statistical Downscaling tool
<i>BCSD</i>	Bias Correction Spatial Disaggregation
<i>BNN</i>	Bayesian Neural Network
<i>BPNN</i>	Back-Propagation Neural Network
<i>CART</i>	Classification And Regression Tree
<i>CC</i>	Correlation Coefficient
<i>CCSM3</i>	Community Climate System Model version 3
<i>CDEN</i>	Conditional Density Estimation Network
<i>CFSR</i>	Climate Forecast System Reanalysis
<i>CGCM3</i>	Canadian Coupled Global Climate Model
<i>ECHAM5</i>	5th Generation of the ECHAM General Circulation Model
<i>GAM</i>	Generalized Additive Model
<i>GCM</i>	General Circulation Model
<i>GEV</i>	Generalized Extreme Value distribution
<i>GLM</i>	Generalized Linear Model
<i>HadCM3</i>	Hadley Centre for Climate Model version 3
<i>IPCC</i>	Intergovernmental Panel on Climate Change
<i>KNN</i>	K nearest neighbor

<i>LARS-WG</i>	Long Ashton Research Station - Weather Generator
<i>MAPE</i>	Mean Absolute Percentage Error
<i>NCEP</i>	National Centers for Environmental Prediction
<i>QRNN</i>	Quantile Regression Neural Networks
<i>RCM</i>	Regional Climate Model
<i>RH</i>	Relative Humidity
<i>RMSE</i>	Root Mean Square Error
<i>SDSM</i>	Statistical Downscaling Model
<i>SVM</i>	Support Vector Machine
<i>Tmax</i>	Maximum Temperature
<i>Tmin</i>	Minimum Temperature

CHAPTER 1 INTRODUCTION

1.1 Purpose

This thesis is a write up on the research works conducted by the PhD candidate in the past 3 years. The PhD topic mainly focused on development of statistical downscaling and disaggregation techniques and their applications in regional hydrological and climate change impact studies. The thesis firstly gives a comprehensive review on the statistical downscaling and disaggregation models and their applications in hydrological processes. Afterwards, three major research components (covered by 6 chapters), including methodology advancement, model applications, and climate change impact assessment, form the main body of the thesis.

1.2 Background

The report of Intergovernmental Panel on Climate Change (IPCC) pointed out that an increasing trend (at a rate of 0.7°C) of the average air and ocean temperatures has been observed over the world (IPCC, 2007). The climate variation is more likely one of the major causes leading to the increasing frequency and severity of extreme weather events like heavy precipitation and heat waves (Seneviratne et al., 2012; Benestad et al., 2012; Coumou and Rahmstorf, 2012; Dai, 2013; Kendon et al., 2014). The weather extremes could lead to many types of disasters, and consequently, bring huge losses for human society and ecosystems (Min et al., 2011; Benestad et al., 2012). The study of Coumou and Rahmstorf (2012) presented a series of disaster due to the weather extremes. It is also a serious problem for Southeast Asia which has plentiful rainfall all year around. For example, the flood in Jakarta during 15-23 January 2013 caused 47 deaths and more than 20, 000 affected. The rainfall flooding is major triggering factor of this flood. In another tropical country, Singapore, the

average annual rainfall exceeds 2,300 mm, and the city has been seriously affected by heavy rainfalls. The statistics from PUB (Public Utilities Board) pointed out that the annual maximum hourly rainfall has shown an increasing rate at 10 mm/decade (PUB, 2012). It is for such a reason that the flash flood problem could become more alarming in the future, and this has necessitated the study of investigating climate-change impact on rainfall patterns in this region.

The General Circulation Models (GCMs) are important tools to simulate either current or future climate conditions (Chen et al., 2011). In the past decades, many GCMs were developed and applied around the world, such as the HadCM3 (UK Hadley Centre for Climate Model version 3) (Pope et al., 2000), CCSM3 (The Community Climate System Model, version 3) (Kiehl and Gent, 2004 and Collins et al., 2004), and ECHAM5 (5th generation of the ECHAM general circulation model, Roeckner et al., 2003 and 2004). Due to bias and resolution problems (Kharin et al., 2005; Fowler et al., 2007; Coumou and Rahmstorf, 2012), the output from GCMs is generally difficult to be directly used for hydrological studies in small regions like urban areas. To bridge such a gap, two fundamental approaches are proposed to generate high-resolution climate data from GCMs, including dynamical downscaling and statistical downscaling (Fowler et al., 2007). The dynamical one relies on physically-based numerical models, such as WRF (Weather Research and Forecasting) and MM5 (the Fifth Generation Pennsylvania State University/National Center for Atmospheric Research mesoscale model), to generate local climate information with high spatial and temporal resolutions based on the GCM/Reanalysis data boundary conditions. The main limitation of a dynamical approach is its highly intensive computational requirement. It is also difficult to transfer the model parameters to different regions (Wilby and Wigley, 1997; Fowler et al., 2007). The statistical one is to use statistical methods for downscaling and disaggregating climate data from GCMs output. Comparing with dynamical approaches, the statistical ones do not consider any physical processes and their performances are

highly dependent on selection of predictors. Therefore, the statistical downscaling relies on the empirical relationship between historical local weather information and output of large scale predictors. If the climate change show non-stationarities, the prediction performance of statistical downscaling tool would be affected. However, the statistical approaches are computationally cheap and easily applicable to different regions. Over the past decades, many successful applications of statistical downscaling and disaggregation were reported. From literature review (in Chapter 2), it is found that (i) the performance of the current statistical downscaling approaches, especially in the context of tropical regions, needs further enhancement; and (ii) more applications of statistical downscaling/disaggregation approaches in rainfall analyses, climate-change projections, and flood-risk predictions are desired.

1.3 Objective and Scope of Study

The objective of this PhD study is to develop and apply statistical downscaling and disaggregation methods for supporting hydrological and climate change impact studies. The overall structure of the thesis is shown in Figure 1.1, which covers three major components including development of novel statistical downscaling tools, applications of combined statistical downscaling and disaggregation methods, and assessment of climate change impact on hydrological processes. The specific scopes include:

(1) To review the statistical downscaling and disaggregation methods. It includes the statistical downscaling methods, statistical disaggregation methods, application of combined downscaling and disaggregation approaches, and studies of climate change impact on hydrological processes (Chapter 2).

(2) To develop novel methods for different types of statistical downscaling approach, including (i) the regression-based method which is consisted by K nearest neighbor (KNN) and Bayesian neural network (BNN); (ii) a semi-empirical stochastic weather

generator which is based on first-order four-state Markov chain and semi-empirical random generator (Chapter 3 and Chapter 4).

(3) To investigate the future variation of rainfall using four different statistical downscaling methods, including (i) Generalized Linear Model – Quantile regression – K nearest neighbor (GQK) model, (ii) Bias Correction with Spatial and Temporal Disaggregation (BCSTD) model, (iii) Automated Statistical Downscaling (ASD) tool and (iv) Modified K nearest neighbor – Bayesian neural network model (Chapter 5).

(4) To generate hourly rainfall at multiple stations using a master-station-based approach through the combination of statistical spatial downscaling and temporal disaggregation methods. The study consisted of two major components. The first part was to perform an inter-comparison of various alternatives of downscaling and disaggregation methods. In the second part, the proposed downscaling - disaggregation system was employed to generate hourly rainfall data at multiple stations based on HadCM3 predictors (Chapter 6)

(4) To investigate Intensity-Duration-Frequency curves based on the coupled weather generator and statistical disaggregation method under climate change condition. This study developed a novel combined statistical downscaling-disaggregation framework (CSDD) based on Long Ashton Research Station - Weather Generator (LARS-WG) and KNN was proposed to examine the climate change impact on regional extreme rainfalls in Singapore (Chapter 7).

(5) To evaluate the flood risk using an integrated climate and hydrologic models based on statistical and data-driven framework. In this study, an integrated statistical and data-driven (ISD) framework was proposed for analyzing river flows and flood frequencies under climate change in the Duhe River Basin, China. The methods include (i) a hybrid model based on ASD and KNN was used for downscaling rainfall and CDEN (Conditional Density Estimate Network) was applied for downscaling

minimum temperature and relative humidity from global circulation models (GCMs) to local weather stations; (ii) Bayesian neural network (BNN) was used for simulating monthly river flows based on projected weather information; (iii) KNN was applied for converting monthly flow to daily time series and adopted for flood frequency analysis (Chapter 8).

1.4 Organization of the Thesis

Figure 1.1 Structure of the thesis.

This thesis consists of nine chapters. In Chapter 2, a comprehensive review about statistical downscaling, disaggregation and climate change impact on hydrological processes is provided. In Chapter 3, a coupled K-nearest-neighbor and Bayesian neural network method is developed for daily rainfall downscaling. In Chapter 4, a

multisite multivariate semi-parametric weather generator is developed. In Chapter 5, the future rainfall trend of Singapore is analyzed by using three different statistical methods. In Chapter 6, a combined statistical downscaling and disaggregation method is applied for generating hourly rainfall at multiple stations. In Chapter 7, the regional extreme rainfall is examined by using a combined weather generator and K-nearest-neighbor approach. In Chapter 8, an integrated statistical and data-driven framework is proposed for supporting flood risk analysis under climate change condition. In Chapter 9, conclusions are drawn and potential future research topics are discussed.

CHAPTER 2 LITERATURE REVIEW

General Circulation Models (GCMs) are powerful tool to help assess climate changes caused by the increasing emission rate of greenhouse gases. However, the outputs from GCMs are in low resolutions at both spatial and temporal scales. Generally, the spatial resolution of a GCM ranges from 250 to 350 km, and the temporal resolution is at daily or sub-daily (e.g. 6-hourly) timescale. The coarse resolution of GCM means it has limited values in revealing climate change impact on hydrological systems for a smaller region, as many hydrological models require weather data at station-level or regional scales. Downscaling and disaggregation approaches could effectively help bridge such a gap and have received wide attentions over the past decades. Downscaling is meant to generate finer-resolution data spatially. Disaggregation is mainly used to produce finer temporal data, like from monthly to daily or from daily to hourly timescale.

Using GCMs to study hydrological processes involves two major steps. Firstly, the GCM outputs need to be downscaled and/or disaggregated to local weather variables with finer spatial and temporal resolutions. Secondly, the downscaled variables are plugged into the hydrological models to project future variations of hydrological system components (Chen et al., 2011). Hence, the downscaling and disaggregation approaches could facilitate climate change impact studies, especially for small regions like urban areas. As mentioned in Chapter 1, both dynamical and statistical approaches could be used for downscaling. This study only focuses on the statistical ones, aiming to build empirical statistical relationships between large-scale predictors and small-scale predicands (Fowler, *et al.*, 2007). The literature review is split into four parts, including (i) statistical downscaling methods, (ii) statistical disaggregation methods, (iii) application of combined downscaling and disaggregation approaches, and (iv) studies of assessing climate change impact on

hydrological processes.

2.1 Spatial Downscaling Methods

In this section, four different types of statistical downscaling methods are reviewed, including: regression-based models (Wilby *et al.*, 2002; Chandler and Wheeler, 2002; Hessami *et al.*, 2008; Zorita and von Storch, 1999; Tripathi *et al.*, 2006), stochastic weather generators (Racsko *et al.*, 1991; Wilks, 1992; Hayhoe, 2000), weather typing schemes (Fowler *et al.*, 2000), and bias-correction methods (Tryhorn and DeGaetano, 2011).

2.1.1 Regression-based models

The regression-based models rely on regression techniques to build the relationship between large-scale predictors (i.e. GCM output or reanalysis data) and local weather information. The model could be either linear or non-linear, and applied individually or coupled with other types of models (e.g. stochastic weather generator) for more flexible simulation.

(1) Neural network models

Cavazos (1999) employed two neural networks to downscale large-scale atmospheric predictors to assess extreme events at Mexico and southeastern Texas, USA. In this study, a neural network model was used for the pre-classification of winter circulation and humidity patterns to make a self-organizing map. Then, the output was used as the input to another feed-forward neural network to downscale daily rainfall. The results showed that downscaled result could match 60% of the observed daily rainfall record. Olsson *et al.* (2001) proposed a two-stage neural network method to downscale short-term extreme rainfall at Southern Japan. In this study, the neural network was firstly used to classify rainfall into four levels: zero, low, high and

extreme. Then, another neural network was applied to determine the rainfall amount. The results showed that the new method had a better performance than direct neural network method. Tatli *et al.* (2004) applied a recurrent neural network (RNN) model to downscale monthly precipitation from GCM predictors over Turkey. The RNN model showed a good performance, especially at the regions less affected by monsoons. Haylock *et al.* (2006) compared six statistical downscaling methods including Canonical correlation analysis (CCA), four neural network methods (i.e. MLPK, MLPS, MLPR and Radial basis function), SDSM, and two dynamical downscaling methods (i.e. HadRM3 and CHRM) for heavy rainfall downscaling at the northwest and southeast England. The results indicated that the neural network based models performed better for modelling inter-annual variability, but underestimated the extreme rainfall.

Cannon (2008) applied an Expanded Bernoulli-gamma Density Network (EBDN) to downscale multisite precipitation at British Columbia, Canada. It uses the output of artificial neural network to estimate the parameters of Bernoulli-gamma distribution. The model could be seen as a regression model with a stochastic weather generator. The results indicated that the model could reproduce the rainfall well while keep the spatial correlations. Cannon (2011) developed a quantile regression neural network (QRNN) model to downscale precipitation at Canada. The QRNN model is the artificial neural network extension of linear quantile regression. The results showed a good performance on quantile verification skill score (QVSS). Therefore, it was more suitable for prediction of the extreme events due to its non-stationarity characterization. Cannon (2012) developed another tool based on the conditional density estimation network, named Conditional Density Estimation Network Creation and Evaluation (CaDENCE), and applied it for the probabilistic environmental prediction.

(2) SDSM models

Wilby *et al.* (2002) developed a regression-based downscaling tool, named the Statistical Down-Scaling Model (SDSM). SDSM consists of two sub-models, including occurrence model and amount model. In SDSM, the NCEP reanalysis data is normally used for predictor selection, model calibration and verification; GCM outputs under various emission scenarios are applied for generation of the time series of climate data for future conditions. A stochastic method is added into the model to reflect inflation of variance of the downscaled data. Figure 2.1 shows the overall modeling process of SDSM. In recent years, SDSM has gained the most popularity around the world, compared with other alternatives. Coulibaly *et al.* (2005) compared the time-lagged feed-forward neural network with SDSM in downscaling daily precipitation and temperature at northern Quebec (Canada). The neural network method performed better than SDSM for both precipitation and temperature. The study result also indicated that the mean annual flow and early spring peak flow both would have increasing tendencies under future conditions.

Wetterhall *et al.*, (2006) applied four different methods, including principal components analysis (PCA), Teweles-Wobus scores (TWS), SDSM and fuzzy – rule - based weather – pattern - classification method (MOFRBC), for downscaling daily rainfall at three different regions (i.e. southern, eastern, and central) of China. The results showed that rainfall was the most successfully downscaled variable at the locations that were close to the coastal areas, and the performance of SDSM model was overall better than the analogue methods. Scibek and Allen (2006) used SDSM to assess the effect of climate change for underground water resources. In this study, SDSM was applied to downscale future climate scenarios from Canadian Global Coupled Model 1 (CGCM1) model. The output of SDSM under future climate conditions was coupled with a stochastic weather generator, a hydrological model, and a ground water model for evaluating future changes of groundwater resources.

The study revealed that the SDSM could be successfully used for downscaling precipitation, which presented an increasing trend in the spring and summer. Dibike and Coulibaly (2007) used SDSM to downscale daily precipitation and temperature from CGCM1 predictors, and projected the hydrological responses under future climate at Quebec, Canada. The downscaled results were used as input to two hydrological models, WatFlood and HBV-96. However, it was found that the performance of the hydrologic models was poor in fitting observed data, if the downscaling data was used as input.

Figure 2.1 The operation process of SDSM (after Wilby *et al.*, 2002)

Tryhorn and DeGaetano (2011) compared the performance of extreme rainfall simulation for two downscaling methods, including statistical downscaling (SDSM) and dynamic downscaling (regional climate model, HadRM3), over the Northeastern USA. The results showed that SDSM could provide the best simulation for extreme precipitation, but HadRM3 presented an overestimated tendency. This study also simulated the daily precipitation for future conditions, which showed a barely increasing trend as most of the downscaled data was within the 95 percentile of the

confidence interval of the 1961-1980 observed record. Keshta *et al.* (2012) studied the impact of climate change on soil moisture and evapotranspiration at northern Alberta, Canada. In this study, SDSM was used to downscale daily precipitation and temperature from CGCM3 A2 and B1 emission scenarios in the twenty-first century. The downscaled results showed an increasing tendency of mean annual temperature for the study region. It was also found that the precipitation would increase significantly under A2 scenarios and slightly under B1 scenarios.

Liu *et al.* (2013a) applied three different downscaling models, including CR-SDSM, GLIMCLIM and non-homogeneous hidden Markov model (NHMM), to model the multisite daily rainfall in the North China Plain. The results indicated that CR-SDSM could better capture the annual and monthly statistical properties and extreme characteristics; GLIMCLIM performed better in terms of rainfall frequency simulation but overestimated the daily rainfall amount; NHMM presented better result for daily rainfall and annual dry/wet days, but poorer for dry/wet spell and extreme events.

(3) ASD models

Hessami *et al.* (2008) proposed another linear-regression-based model, named Automated Statistical Downscaling (ASD) tool. The model improves upon SDSM by incorporating the backward stepwise regression and partial correlation coefficients to help identify suitable predictors, and using the ridge regression to reduce the non-orthogonality effect (Wilby *et al.*, 2002). A comparison study of ASD and SDSM by Hessami *et al.* (2008) showed that neither ASD nor SDSM consistently outperformed the other in rainfall downscaling, but ASD was more straightforward to use. ASD models daily rainfall through two steps, including occurrence and amount simulations. The related equations are given by Wilby *et al.* (1999):

$$O_i = a_0 + \sum_{j=1}^n a_j p_{ij} \quad (2-1)$$

$$R_i^{0.25} = \beta_0 + \sum_{j=1}^n \beta_j p_{ij} + e_i \quad (2-2)$$

where O_i is the daily rainfall occurrence, R_i is the daily rainfall amount, p_{ij} is the predictors, α and β are the model parameters, and e_i is the residual (error) (Hessami *et al.*, 2008). For error analysis, the method assumes that the residual e_i fits a Gaussian distribution as follows (Hessami *et al.*, 2008):

$$e_i = \sqrt{\frac{VIF}{12}} z_i S_e + b \quad (2-3)$$

where z_i is a random number fitted by normally distribution, S_e is the standard deviation of estimate, b is the model bias, and VIF is the variance inflation factor. When the GCM variables (predictors) are used for generation of daily data, the b and VIF could be given by the following equations (Hessami *et al.*, 2008):

$$b = M_{obs} - M_d \quad (2-4)$$

$$VIF = \frac{12(V_{obs} - V_d)}{S_e^2} \quad (2-5)$$

where M_{obs} is the observed mean of calibration period, M_d is the mean of deterministic part of model in the calibration period, and V_{obs} and V_d are the variances of the observed and deterministic part at calibration period. In this method, the variables (predictors) selection is based on the backward stepwise regression and partial correlation. Two regression methods are provided in the ASD tool: multiple linear regression and ridge regression. Ridge regression method could reduce the instability caused by the non-orthogonality of the predictors (Hoerl and Kenard, 1970; Hessami *et al.*, 2008).

Burger *et al.*, (2012) compared five statistical models in downscaling climate

extremes (i.e. precipitation and temperature) at British Columbia, Canada. These models include ASD, bias correction spatial disaggregation (BCSD), quantile regression neural networks (QRNN), TreeGen (TG), and expanded downscaling (XDS). The results showed that the performance of each model in downscaling the extremes could be ranked from good to poor as follows: XDS, BCSD, QRNN, ASD and TG. Guo *et al.* (2012) used ASD to downscale daily precipitation from HadCM3 at 138 meteorological stations and interpolated over the Yangtze River basin, China. It was suggested that the annual rainfall amount would decrease at 2020s and increase at 2050s and 2080s under A2 scenario. There would also be increased tendencies for rainfall intensity and maximum amount at sub-basins.

(4) GLM models

Generalized linear model (GLM) is another popular method to build statistical relationship between predictors and local observed rainfall data. Chandler and Wheeler (2002) developed a GLM, named GLIMCLIM, to downscale atmospheric predictors based on logistic regression for occurrence model and gamma distribution for amount model. The occurrence model depends on logistic regression which can be given by (Coe and Stern, 1982; Stern and Coe, 1984; Chandler and Wheeler, 2002):

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i' \beta \quad (2-6)$$

where p_i is the probability of rain for the i^{th} day, x_i is the vector of input variables for the i^{th} day, β is the coefficient, and T means the transpose of matrices. The rainfall amount of a wet day is assumed in gamma distribution with mean μ_i , given by (Chandler and Wheeler, 2002):

$$\ln \mu_i = \varepsilon_i' \gamma \quad (2-7)$$

where ε_i is the vector of input variables and γ is the coefficient. Another added parameter for rainfall amount model is dispersion coefficient ν for all gamma distributions in a common shape (Yang *et al.*, 2005; Segond *et al.*, 2006). The atmospheric predictors affecting rainfall process may not be independent, and generally interact with each other. Therefore, the interaction parameters could be added into the model framework. The responses of occurrence and amount models are both linked to the non-linearly transformed predictors. Normally, the covariate selection and coefficient calculation are both estimated by the likelihood methods (Chandler and Wheeler, 2002).

Yang *et al.* (2005) applied GLM to generate daily rainfall at southern England which covered an area over 2,000 km². The results showed that GLM model could effectively produce the daily rainfall sequences at a site network. In this model, the beta-binomial scheme was used to calculate the occurrence of rainfall dependently at the smaller region which was not significantly related to the predictors. Segond *et al.* (2007) used GLM in a spatial-temporal disaggregation system to generate hourly rainfall at multisite to assess the climate change impact on urban drainage and urban flood. In this system, GLM was used to simulate the daily rainfall from GCM variables. Then, a single-site disaggregation model, i.e. HYETOS, was applied to disaggregate the output of GLM model to generate hourly rainfall. Next, the modeled hourly rainfall profile was extended to all sites to disaggregate daily rainfall to hourly timescale. The regional rainfall profile could be obtained by the interpolation method based on inverse distance weighting scheme. It showed that the results matched the observed record at an accepted level.

Mezghani and Hingray (2009) developed a GLM to downscale regional precipitation and temperature and applied it at the Upper Rhone River basin, Switzerland. The GLM model also consists of two sub-models similar to the study of Chandler and Wheeler (2002), which were based on the logistic regression and distribution to

estimate the regional precipitation. For the regional temperature, the simulation model was based on the classical linear regression. The model was coupled with a K nearest neighbor (KNN) method to generate the weather variables at sub-region and sub-daily timescale. The results indicated that the combined statistical downscaling and disaggregation weather generator could reproduce the hourly weather variables over complex terrain. Kenabatho *et al.* (2012) applied GLM to generate daily rainfall over 13 gauges at the semi-arid Limpopo basin, Botswana. It was found that the factors of autocorrelation, seasonality, elevation and location posed significant influences on spatial-temporal variability of rainfall. Three variables including pressure, humidity and temperature could help enhance the capability of GLM for daily rainfall reproduction.

(5) SVM models

Tripathi *et al.* (2006) applied a least square support vector machine (LS-SVM) approach to downscale precipitation at India. Compared with the traditional ANN method, LS-SVM could provide more emphasis on generalization performance. The results also showed that the LS-SVM had a better performance than multi-layer back-propagation neural network (BPNN). Gohosh (2010) proposed a SVM and probabilistic global search algorithm (SVM-PGSL) method to downscale rainfall from GCM output. The PGSL method was used to calculate the optimal parameters of SVM. The new model showed a notable improvement compared with the original SVM method. Chen *et al.* (2010b) applied SVM and multivariate analysis to simulate daily precipitation at Taiwan. The study used the support vector classification method to estimate the dry/wet day and support vector regression method to calculate the precipitation amount at a wet day. The SDSM was used for comparison. The results showed that the SVM model had better performances in terms of many properties, such as the monthly precipitation day and extreme data. Tisseuil *et al.* (2010) built the relationship between large-scale GCM predictors and local hydrological data (e.g.

runoffs at station levels) using four statistical downscaling models, including GLM, generalized additive model (GAM), aggregated boosted trees (ABT) and multi-layer perceptron neural networks (ANN). The results showed that three non-linear models performed better than GLM in terms of fortnightly flow simulation.

Ghosh and Katkar (2012) used three different statistical downscaling methods to simulate monthly rainfall at Assam and Meghalaya, India. In this study, the rainfall was classified into three states (e.g. low, medium and high) based on Classification and Regression Tree (CART) method. Then, three downscaling methods including linear regression, ANN and SVM, were compared and used for downscaling rainfall at different states. Based on performances, SVM was used for downscaling high-level rainfall and ANN was used for low and medium levels. By projection under future conditions (i.e. 2010-2039, 2040-2069 and 2070-2099), the rainfall at this region was suggested to increase.

2.1.2 Stochastic weather generator

The stochastic weather generator is used to reproduce synthetic time series of weather variables which has similar statistical properties as those based on the observed data. The generated synthetic data is not restricted by time period. Therefore, it could be used for many fields, like water resources management, agricultural irrigation planning, and flood risk assessment (Semenov et al., 1998; Kevin et al., 2005; Chen et al., 2010a). It could also be used for generating daily weather data at ungauged areas using spatial interpolation algorithms based on data from surrounding stations (Chen et al., 2010a; Fodor et al., 2010). Generally, a weather generator simulates precipitation first; afterwards, other weather variables are simulated upon the condition of precipitation. Based on algorithms, weather generator could be classified into different types, such as Richardson-type, serial-type, and parametric or nonparametric model.

(1) Richardson-type models

Richardson and Wright (1984) advanced a weather generator named WGEN, based on the study of Richardson (1981), to simulate the precipitation, maximum temperature, minimum temperature, and solar radiation. The model was based on the first-order Markov chain to estimate occurrence of precipitation. The gamma distribution was used for generating precipitation amount. The mean and coefficient of variation for temperature and solar radiation were fitted by cosine curves which consider the Fourier series of order. The model assumes constant auto- and cross-correlations for temperature and radiation. Some improved versions were developed in the follow-up works, e.g. second-order Markov chain (Marson, 2004) and third-order Markov chain (Dubrovsky *et al.*, 2004). Wilks (1992) adapted a stochastic weather generator to generate the future climate scenarios based on GCM output. The weather generator is also based on the first-order two-state Markov chain and gamma distribution to simulate daily precipitation. The projection assumed that the climates are specified in terms of commonly available monthly mean and variances, including time-dependent climate change. The method could not only change the mean value of historical data, but also present the viability of simulated time series.

Hayhoe (2000) developed another stochastic weather generator, i.e. Agriculture and Agri-Food Canada – Weather Generator (AAFC-WG), to downscale the rainfall at three Canadian stations. The method of AAFC-WG has the advantage of Richardson-types weather generator which also could model the variety of probability distribution using empirical distributions. The results showed that the model could well reproduce the statistical properties such as the means, standard deviations, correlations, probability distributions and extreme values. Qian *et al.* (2005) did a comparison between LARS-WG and AAFC-WG, and the results showed that AAFC-WG was better in reproducing dry and wet spells and simulating the

temperature-related properties, especially daily maximum and minimum temperatures. Overall, AAFC-WG performed better than LARS-WG. But it was also found that the stochastic weather generators have an over-dispersion problem for annual variability.

McKague et al. (2003) proposed a ‘Richardson-type’ weather generator, named ClimGen. It was based on the first-order two-state Markov chain to estimate daily precipitation occurrence, which was similar to WGEN. For daily precipitation amount, the model assumes the precipitation amount following a Weibull distribution. The model also could be used for generating the precipitation data at sub-hourly timescale based on the method of Arnold and Williams (1989).

Baigorria and Jones (2010) developed a weather generator named GiST which could consider spatial and temporal correlations. GiST relied on a two-state orthogonal Markov chain to judge rainfall occurrence at multiple sites. The orthogonal transition probabilities in Markov chain could consider the rainfall events at other stations and previous days. To generate rainfall amount, two steps were applied: (i) generation of the spatially correlated random number; (ii) transformation of the generated random number to a gamma distribution based on cumulative probability function. Compared with WGEN, the results showed that GiST performed better for dry and wet spells, total number of wet days, rainfall amount, and cross correlations. Chen et al. (2010a) proposed a daily weather generator to enhance the simulation of low-frequency weather variables, named WeaGETS. The model was also based on two-state Markov chain and gamma distribution to calculate precipitation. The low frequency variability is modelled by the power spectra of the observed data at monthly and annual scales. The model was applied for generating precipitation to drive a hydrological model. The results showed that the simulated monthly and annual discharges were both improved compared with the simulated data by standard weather generators (i.e. spectral correction; Wang and Nathan’s method, 2007).

(2) Serial-type models

Semenov and Barrow (1997) advanced a stochastic weather generator based on the works of Racsko *et al.* (1991), called LARS-WG. It is a serial-type weather generator based on the sequence of dry and wet series of days. The generator uses semi-empirical distributions to calculate the precipitation occurrence and amount, and solar radiation. The normal distribution is applied to simulate temperature which is conditioned upon precipitation occurrence. Semenov *et al.* (1998) compared LARS-WG and WGEN, and indicated that LARS-WG performed better than WGEN in reproducing the average monthly precipitation and temperature. However, the two models performed both poorly in reflecting inter-annual variability of monthly precipitation, frost and hot spell.

Iizumi *et al.* (2012) proposed a LARS-WG-based bootstrap approach to assess the daily precipitation changes at Japan. The future climate conditions were projected from dynamical and statistical models. Firstly, three RCMs (NHRCM, NRAMS and TWRF) and statistical downscaling method (CDFDM) were used to generate the daily precipitation over 20 years. Based on the 20 years record, LARS-WG was applied to simulate a long period (i.e. 2000 years) precipitation series. The proposed approach could provide probabilities of multiple types of precipitation extremes. Xu *et al.* (2012) applied LARS-WG to investigate daily rainfall variations under climate-change conditions in Qiantang River Basin, China. Three GCMs with various emission scenarios were applied. The results showed that the daily rainfall would increase at most of the stations. However, a wide range of uncertainty interval was also presented. For example, the 100-year rainfall at one station showed a variation range from -16% to 113%.

(3) Other type's models

Apipattanavis *et al.* (2007) developed a semi-parametric multisite weather generator

based on Markov chain and KNN method. The first-order three-state Markov chain was applied for simulating rainfall status, including dry, wet and extreme day. The KNN bootstrap resampling method was used for generating rainfall amount and other variables. The method could keep the distribution and lag-dependence statistics well. Kisby et al. (2007) developed a daily weather generator consisting of two submodels. The first one was used for modelling rainfall based on the stochastic point process model, Neyman-Scott rectangular pulses model. Then, the second sub-model was applied for generating other variables conditioned upon rainfall occurrence. The generator could well reproduce multiple weather variables, including rainfall, temperature, humidity, wind and sunshine. This study also applied the generator to consider future climate-change impact based on a change-factor approach. Burton et al. (2008) proposed a spatial-temporal stochastic rainfall generator based on the study of Kisby et al. (2007), named RainSim. This model could simulate single- or multi-site rainfall based on Neyman-Scott rectangular pulses model. The model could simulate rainfall at different timescales (e.g. daily, hourly or etc.). The study result showed that RainSim could well capture the basic statistical properties and extreme events.

More recently, Jeong *et al.* (2012) applied a hybrid statistical model to downscale the daily rainfall at southern Quebec, Canada. This model combined regression approach and stochastic weather generator for multisite downscaling of daily precipitation. The results showed that the model performed well for the temporal reproduction of the number of wet days, cross-site correlation, probability of consecutive wet days, and maximum 3-days precipitation amount. But the reproduction of daily rainfall variance was poor.

2.1.3 Weather typing scheme and bias correction method

Weather typing scheme method is to build the relationship between the occurrence of

different weather class and the local weather information. Based on the summary of Wilby et al. (2004), the weather typing scheme could provide possible physical mechanisms in the statistical downscaling approach. Boé et al. (2006) developed a multivariate statistical downscaling method based on weather typing scheme to simulate precipitation and temperature. It used regional climate properties to build the discriminating weather types. The distance of a given day to weather types was applied to capture the intra-type variations. The results showed that the proposed weather typing method had a good performance in simulating precipitation and temperature. Willems and Vrac (2011) applied two sets of methodologies to investigate the short-duration precipitation extremes. The first method set was to use the output of climate model directly based on quantile perturbations method; the second one was based on weather typing. The two methods presented similar results where about a 30% increasing tendency of extreme rainfall was suggested at the end of this century.

The bias correction is generally used for adjusting output of GCM or RCM due to existing biasness (Benestad et al., 2012; Eisner et al., 2012). There are different ways to do the adjustment based on observed or reanalysis data, such as standardization and quantile based mapping method (Wilby et al., 2004; Li et al., 2010; Salvi et al., 2011). For applications in specific regions, the methods should be compared in order to determine which one was the most suitable. The application of bias correction method for statistical downscaling is generally coupled with the spatial disaggregation method to generate high resolution data both spatially and temporally.

Sharma et al. (2007) proposed a spatial disaggregation and bias correction method to downscale precipitation from GCM output at Ping River basin, Thailand. The bias correction method was based on gamma-gamma transformation and spatial disaggregation method was based on multiplicative random cascade theory. The method was coupled with hydrological model HEC-HMS, and could well reproduce

runoffs. Terink et al. (2010) applied the bias correction method to adjust the precipitation and temperature from ERA15 at Rhine basin, Western Europe. The bias correction method for precipitation was based on the mean and coefficient of variation; the method for temperature was based on mean and standard deviation. The results showed that the fitting of temperature was satisfactory, but that of precipitation was relatively poor. Eisner et al. (2012) compared two methods of bias correction to assess the climate change impact on flood discharge at Europe. One method was the delta change approach and another one was based on quantile mapping method. The results showed that the obtained flood discharges were distinctively different from the two methods. Ahmed et al. (2013) applied the statistical downscaling and bias correction (SDBC) method to downscale precipitation and temperature from the outputs of six GCMs and four RCMs to assess climate change impact at Northeast US. The bias correction method was based on the cumulative distribution functions (CDF) of the observed and GCM data. The results demonstrated that bias correction method was important for both RCM and GCM.

2.2 Temporal Disaggregation Models

Acting as the input to hydrological models, weather data in a finer timescale is essential for accurate and reliable hydrologic simulation and forecasting. In many regions of the world, weather data is generally available at daily (or coarser) timescale due to the cost and technological limitations. Statistical disaggregation of rainfall from daily to sub-daily is a cost-effective approach to generate high resolution temporal data. A number of statistical models have been developed for disaggregating rainfall in single sites, such as stochastic point processes model (Cox and Isham, 1980; Rodriguez-Iturbe *et al.*, 1987a; Rodriguez-Iturbe *et al.*, 1987b; Debele *et al.*, 2007), correlation dimension method (Gaume *et al.*, 2006), modified version of Eagleson (1972) exponential model (MEEM) and random multiplicative cascade processes approach (Gunter *et al.*, 2001) and nonparametric model (Prairie et

al., 2007; Nowak et al., 2010).

2.2.1 Rectangular pulses point processes model

The rectangular pulses point process model could be used for analyzing rainfall data (Rodriguez-Iturbe *et al.*, 1987a and 1988), including rectangular pulses Poisson model, Neyman-Scott rectangular pulses (NSRP) model, Bartlett-Lewis rectangular pulses (BLRP) model and other improved versions. Generally, the stochastic point process models have advantages of representing statistical properties and structures of rainfall by a limited number of parameters, and are widely used in many areas (Hanaish *et al.*, 2011a). There are also a number of studies focusing on stochastic models. Some earlier works can be found in Rodriguez-Iturbe et al. (1988), Cowperwait (1994), Velghe *et al.* (1994), Onof and Wheeler (1993, 1994), Cowperwait (1995), Khaliq and Cunnane (1996), and Cowperwait and O'Connell (1997), Camron et al. (2000), Cowpertwait *et al.* (2002), Cowpertwait (2004), Evin and Favre (2008).

HYETOS, developed by Koutsoyiannis and Onof (2001), is used for disaggregation of single-site rainfall data based on two versions of Bartlett-Lewis rectangular pulse (BLRP) model, the original one and the modified version (i.e. MBLRP). There are several assumptions in such a model: (i) the rainfall event occurrence follows a Poisson process; (ii) the rain-cell arrival also follows a Poisson process; (iii) the duration of rainfall event and rain-cell are both following exponential distributions; (iv) the rain-cell intensity (depth of rectangular pulse) follows an exponential or gamma distribution. The method of moments (MOM) is used to fit the MBLRP model parameters. An adjustment procedure is added into the framework of HYETOS model based on the concept of tolerance distance (d), which can be defined by the following equation (Koutsoyiannis and Onof, 2001):

$$d = \left[\sum_{i=1}^L \ln^2 \left(\frac{Y_{Mi} + c}{\tilde{Y}_{Mi} + c} \right) \right]^{\frac{1}{2}} \quad (2-8)$$

where Y_{Mi} and $\tilde{Y}_{Mi}$ are the original and modeled daily rainfall data, respectively, L is the number of wet day in sequence, c is the constant of threshold (normally 0.1 mm). The model would run continuously until the simulated daily depths match the sum of the whole sequence daily data within d . Four levels of repetition procedures were included in HYETOS to minimize error.

Debele *et al.* (2007) developed a disaggregation method to generate weather variables such as wind speed, precipitation and temperature at a finer timescale. In this study, HYETOS was used to reproduce hourly rainfall. The results showed that HYETOS could well reflect the average hourly rainfall characteristic due to the added adjustment procedure. Another study proposed by Hanaish *et al.* (2011b) illustrated similar results, where the HYETOS model was applied to disaggregate daily rainfall based on the historical record from 1970 to 2008 in Petaling Jaya, Malaysia. The results showed that the average hourly rainfall value could be fitted very well, but the properties such as autocorrelation and standard deviation showed a notable bias. The extreme events were also significantly underestimated. Montesarchio *et al.* (2012) applied two stochastic rainfall disaggregation models to analyze the rainfall characterizations such as intermittency, seasonality and scaling behavior at a finer timescale at Italy. The results showed that HYETOS performed better and its output could be used as input for hydrologic models.

Gyasi-Agyei and Willgoose (1997) developed a hybrid model based on the nonrandomized Bartlett-Lewis rectangular pulse and an autoregressive model to disaggregate daily rainfall in Central Queensland, Australia, to a finer timescale. Gyasi-Agyei (2005) proposed an improved hybrid disaggregation model that

combined repetition techniques and a proportional adjusting procedure in an Australian site. Later on, Gyasi-Agyei and Bin Mahbub (2007) proposed another extended version which focused on the disaggregation of rainfall at any finer timescales.

2.2.2 Nonparametric method

KNN is a nonparametric method which could provide some local functional fitting and could also capture non-normality data (Prais *et al.* 2007). The KNN-based disaggregation framework was firstly proposed by Tarboton *et al.* (1998). It is capable of directly simulating hourly data at multiple stations based on historical hourly records (Nowak, *et al.*, 2010). The observed hourly data are converted to a proportion of the daily amount, and given a matrix $\mathbf{P}$ with dimensions $n \times 24$, where n is the number of observed wet days. The daily rainfall amount $\mathbf{Z}$ needs to be disaggregated to hourly timescale. The nearest neighbor of $\mathbf{Z}$ should be computed from the observed daily record matrix $\mathbf{W}$ with $l \times n$ dimensions. According to the previous studies, Lall and Sharma (1996) provided a method based on heuristics to define the K value and weight scheme of neighbors (Nowak, *et al.*, 2010):

$$K = \sqrt{n} \quad (2-9)$$

$$W_i = \left(\frac{1}{i} \right) / \left(\sum_{i=1}^K \frac{1}{i} \right) \quad (2-10)$$

where K is the number of the nearest neighbors, i is the ‘index of neighbor’, W_i is the weight scheme of the i^{th} index of neighbor (when $i = 1$, the index refers to the closest of the nearest neighbors). Once the nearest neighbor (observed daily data) is selected, the disaggregated hourly data from the given $\mathbf{Z}$ could be obtained by multiplying $\mathbf{Z}$ with the corresponding proportion vectors. If the method is to be used for multi-site transformation, the observed hourly data profile at the master station could be

extended to the satellite stations.

Prairie *et al.* (2007) used KNN for spatial-temporal disaggregation of stream flows. Through comparison with a parametric model, the results illustrated that the KNN method could ensure performance of the simulation of statistical properties in original space. Nowak *et al.* (2010) applied KNN for multi-site streamflow disaggregation, and showed a good performance of reproducing statistical properties of mean, variance, skew, maximum and minimum data. Kalra and Ahmad (2011) applied the KNN method to evaluate the changes of seasonal precipitation by disaggregation of annual precipitation for the Colorado River Basin, US. The results showed that the nonparametric method could generate a higher quality precipitation series at spring and winter than the rest two seasons. The study also compared this model with a parametric disaggregation method, i.e. first-order periodic autoregressive parametric approach, and indicated that KNN performed better in terms of both correlation and error analysis.

2.2.3 Other disaggregation methods

Some other types of disaggregation methods were also reported. Koutsoyiannis and Manetas (1996) discussed a disaggregation model based on the type of periodic autoregression (PAR1) with adjusting procedure, and it showed an overestimation of variance and extreme data. Hidayah *et al.* (2011) applied the Bayesian PAR1 model combined with adjusting and filtering procedure to generate hourly rainfall data. Beuchat *et al.* (2011) discussed a robust model to generate sub-daily rainfall statistics based on multivariate adaptive regression splines and applied it at three regions including UK, US and Swiss. This model was trained by the sub-daily statistical properties, large-scale atmosphere variables and aptitude information. The results showed that the model could correctly reproduce all key rainfall statistical properties (e.g. average, standard deviation, and lag-1 autocorrelation) and the extreme events

in the study area for all months.

Multiplicative random cascade model is another useful tool to describe rainfall patterns (Schertzer and Lovejoy, 1987). Güntner et al. (2001) applied cascade-based disaggregation model to generate hourly rainfall from daily timescale in Brazil and UK. The model performed better for semi-acid tropical rainfall, especially for reproduction of extreme rainfall in Brazil. Pui et al. (2009) compared three different disaggregation models, including multiplicative random cascade model, randomized Bartlett Lewis model (RBLM) coupled with proportional adjusting procedure and method of fragments. The results showed that three model could reproduce the general statistics, such as mean, variance, lag-1 autocorrelation and dry proportion. But only the method of fragments could fit the Intensity-Frequency-Density (IDF) curve well. Licznar et al. (2011) applied six multiplicative random cascade models to generate 5-minute rainfall data. The result showed that the proposed beta-normal generator for a microcanonical cascade could reproduce the intermittency and variability of 5-min rainfall well.

2.3 Combined downscaling and disaggregation for hydrological impact study

The output of GCM is generally too coarse to be applied with hydrological models. Downscaling and disaggregation methods could help generate finer-resolution weather data on spatial and temporal scales to bridge such a gap. The hydrological model could be generally classified into two major types: (i) physical-based hydrological model, such as Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) and Semi-distributed Land Use-based Runoff Processes (SLURP) (Kite et al., 1994); (ii) statistical-based hydrological model (also named ‘black-box’ model), such as artificial neural network (ANN) (Gao et al., 2010) and support vector machine (SVM) (Okkan and Serbes, 2012). For the climate change impact study, the

approaches are generally based on the combination of downscaling and/or disaggregation models and different types of hydrological models (Mwale and Gan, 2010).

Kuo et al. (2010) developed a climate-hydrologic system to investigate the seasonal streamflow variation. There are three components: (i) seasonal rainfall prediction model based on ANN–GA model (Artificial Neural Network calibrated by Genetic Algorithm); (ii) rainfall disaggregation model to generate 3-day rainfall from seasonal timescale; (iii) hydrologic model based on modified HBV model. The results showed that the proposed system presents the better performance for NDJ season than JFM season.

Bar et al. (2011) applied a stochastic weather generator (WXGEN) and three physical-based hydrological models to investigate the hydrologic uncertainty under climate change conditions in Chungju Dam basin, Korea. The study used 13 GCMs with three emission scenarios to provide future climate variation. Three hydrological models and seven potential evapotranspiration (PET) computation methods are applied to compare different responses of climate. The results indicated that there was a larger uncertainty for dry season and drought risk for future period.

Jun *et al.* (2011) developed a novel system to assess spatial vulnerability of water resources under climate-change conditions. Two sub-models, SDSM and HSPF (Hydrological Simulation Program - Fortran) were combined to assess the impact of climate change on flood/drought damage and water quality. Four indices, including potential flood damage (PFDC), potential drought damage (PDDC), potential water quality deterioration (PWQDC), and watershed evaluation index (WEIC) were used for performance evaluation. SDSM was used to downscale the predictors of CGCM3 to generate daily precipitation. HSPF was applied for simulation of varying hydrologic information for future period. The results showed that the system

succeeded in demonstrating the factors that would increase the vulnerability of water resources under changing climatic conditions.

Liu et al. (2011a) used two statistical downscaling methods, SDSM and 'bilinear-interpolation and delta' method to downscale temperature and precipitation from HadCM3. Then, the output was applied as the input to SWAT to predict the stream runoff for the future conditions. The results showed that the annual flow would generally increase under A2 and B2 scenarios in Yellow River Basin, China. Zarghami et al. (2011) applied two statistical models, i.e. LARS-WG and ANN, to project the runoff variations for future period in East Azerbaijan, Iran. The LARS-WG was used for generating climate data for future period under HadCM3 A1B, A2 and B1 scenarios. ANN model was employed for simulating runoff. The results showed a significant decrease of runoff in future conditions.

More recently, Eum et al. (2012) proposed an integrated reservoir management system which combined KNN weather generator, HEC-HMS hydrological model and Differential Evolution (DE) optimization model. The results presented that the proposed system could help optimize the reservoir management options under climate change. Meenu et al. (2012) applied SDSM and HEC-HMS hydrological model to assess the climate change impact on hydrological processes in Tunga-Bhadra river basin, India. SDSM was used for downscaling maximum and minimum temperatures, and precipitation at daily timescale from HadCM3 (GCM) A2 and B2 scenarios. Then, the output from SDSM was applied into HEC-HMS for hydrological modelling. The results showed that the precipitation and runoff would increase and the actual evapotranspiration losses would decrease under future conditions. Wang et al. (2012) used two physical-based models, including Providing Climates for Impacts Studies (PRECIS) regional climate model and SWAT, to investigate the climate change impact on steamflow in northwest China. The RPECIS RCM offered A2 and B2 emission scenarios. The results showed that monthly

maximum streamflow would increase continuously, and the maximum monthly flow would decrease in the period of 2050s and 2080s. Ficklin et al. (2013) applied the bias-correction and statistical disaggregation method and SWAT model to project the climate change impact on hydrological systems in Mono Lake Basin, USA. In total, 16 GCMs with A2 and B1 scenarios were considered to project future climate conditions. The results indicated that there would be a significant decrease for annual streamflow, a decrease of frequency of ‘wet’ hydrology year, and an increase of drought condition.

2.4 Summary of Literature Review

The previous studies made great efforts in exploring statistical tools for downscaling and disaggregating weather data in different regions around the world. However, there are still a number of areas that need improvement.

Firstly, the related studies in Southeast Asia are relatively limited, merely none for Singapore. In fact, the tropical area generally has abundant and complex rainfall, primarily in convective type (Rosenzweig and Liverman 1992). The statistical downscaling/disaggregation methods may be sensitive to the local features like regional climatic types (like monsoons) and topographical conditions. For example, it is found that the rainfall in Singapore shows a high spatial variation, with e-folding correlation distances being about 10 km at hourly scales and 33 km at daily scales (Mandapaka and Qin, 2013); this highlights the necessity to keep the spatial correlation in the statistical downscaling and disaggregation procedures. Also, the quantity and quality of large-scale atmospheric variables in this region are not satisfactory due to high degree of sensitivity of GCM predictions over tropical areas (Holland et al., 2005); this somewhat affect the climate projection results. Therefore, exploration of specific statistical downscaling/disaggregation methods for such a region is desired.

Secondly, one of the major applications for statistical downscaling is to investigate the climate change impact on hydrological processes by bridging GCM models with physically-based hydrological models. There are relatively limited studies in using combined statistical downscaling and blackbox models (like ANN and SVM) for hydrological impact studies. Moreover, many of the previous studies focused on prediction of monthly or yearly flows for long-term periods using data-driven methods. The results are difficult to be used by studies that need flow data at higher temporal resolutions, such as flood frequency analysis under climate change.

CHAPTER 3 A COUPLED K-NEAREST NEIGHBOR AND BAYESIAN NEURAL NETWORK MODEL FOR DAILY RAINFALL DOWNSCALING

3.1 Introduction

General circulation model (GCM) is an effective tool to assess the future climate change impact caused by greenhouse gas emissions. However, the large-scale GCM data has limited applicability on local hydrological studies due to its coarse spatial resolution. With an increasing frequency of flash flooding events in recent years, the need to accurately predict the response of hydrological systems under changing climate has grown rapidly. Many studies have been devoted to downscale the large-scale weather variables from GCM to a finer hydrologically meaningful resolution. Currently, there are two major types of downscaling methods, including dynamic downscaling and statistical downscaling. Dynamic downscaling could produce weather information based on physical processes, but its applicability is restricted by intense computational efforts (Wilby and Wigley, 1997). Statistical downscaling method is a more economical way to build a direct linkage between large-scale GCM outputs and local weather data, and has been widely used in climate-change impact studies for hydrological systems.

The statistical downscaling methods generally consist of three groups: stochastic weather generators, regression models and weather typing schemes (Richardson, 1981; Racsco *et al.*, 1991; Wilks, 1992; Hayhoe, 2000; Fowler *et al.*, 2007). Additionally, there are also a number of hybrid models coupling different types of techniques for more effective applications. Wilby *et al.* (2002) developed a statistical downscaling model based on stochastic random error generator and multiple regressions called Statistical DownScaling Model (SDSM). In this model, the stochastic method is mainly used for inflating the variance of the downscaled data

(Fowler *et al.*, 2007). The SDSM is the one of the most popular downscaling tools and applied in many regions successfully (Crawford *et al.*, 2007; Dibike and Coulibaly, 2007; Koukidis and Berg, 2009; Sharma *et al.*, 2011; Souvignet and Heinrich, 2011; Tryhorn and DeGaetano, 2011; Chung *et al.*, 2011; King *et al.*, 2012). However, SDSM is relatively weak in predictors' selection, easily affecting the model performance (Wilby *et al.*, 2002). Against this point, the automated statistical downscaling tool (ASD) was proposed by Hessami *et al.* (2008). ASD uses a backward stepwise regression and partial correlation coefficient for selecting predictors. From comparison studies by Hessami *et al.* (2008) in Canada, ASD showed an equally good performance compared with SDSM. Burger *et al.* (2012) compared the downscaling capability of climate extremes using ASD and other four statistical methods (i.e. bias correction spatial disaggregation, quantile regression neural networks, TreeGen, and expanded downscaling method), and illustrated that the performance of ASD was not good enough to downscale extreme events.

The climate generalized linear model (GLM) was proposed by Chandler and Wheeler (2002), and the developed program is called GLIMCLIM (Generalized Linear Model of Daily Climate Sequences). It has been used for downscaling large-scale weather predictors to daily rainfall sequence. It is based on two basic models, a rainfall occurrence model based on logistic distribution and a rainfall amount model based on gamma distribution. GLM has been widely used for downscaling rainfall in many cases (Abaurrea and Asin, 2005; Yang *et al.*, 2005; Kenabatho, *et al.*, 2012). Segond *et al.* (2007) used GLM in a combined spatial-temporal downscaling and disaggregation system to downscale rainfall, and demonstrated that the produced daily rainfall by GLM could preserve the statistical properties compared with the observed data. Frost *et al.* (2011) compared three dynamic downscaling methods and three statistical downscaling methods. The results showed that the GLM method was good at simulating rainfall occurrence, and the coupled GLM-KDE (kernel probability density) model demonstrated the best performance.

Artificial neural network (ANN) has been developed more than half a century (McCulloch and Pitts, 1943) and gained popularity in many fields. Cavazos and Hewitson (2005) applied ANN for downscaling daily rainfall at fifteen sites based on NCEP reanalysis data. Ramirez *et al.* (2006) compared ANN with multiple linear regression (MLR) method for rainfall forecasting over southeastern Brazil. The results showed that ANN was superior to MLR in most seasons, especially for prediction of moderate and high rainfall during the austral summer. Tolika *et al.* (2007) also applied ANN to simulate seasonal precipitations and the number of wet days in Greece, and proved its high efficiency in prediction at winter and spring seasons. However, ANN also showed poor performance when it was compared with other statistical downscaling methods. Harpham and Wilby (2005) applied three statistical downscaling models, ANN with radial basis function (RBF), multi-layer perceptron (MLP) ANN and SDSM to downscale daily rainfall in northwest and southeast England. The results showed that the SDSM method outperformed the two types of ANN models. Khan *et al.* (2006) used three statistical methods (including ANN, SDSM and LARS-WG) to downscale daily precipitation at Quebec, Canada. The study showed that both SDSM and LARS-WG were better than the ANN model. Karamouz *et al.* (2009) also compared SDSM with ANN and concluded that SDSM performed better than ANN for modeling a long lead rainfall. Cannon (2008) applied the expanded Bernoulli-gamma density network (EBDN) to reproduce the precipitation density at multisite in British Columbia, Canada. In this study, ANN was used for generating the parameters of the Bernoulli-gamma distribution. The results showed that the EBDN model could represent the rainfall occurrence and amount and keep the spatial correlations.

From the previous studies, it is found that the classical models, such as SDSM, ASD, and GLM, use residual analysis to compensate for the errors in regression. The models could easily lead to over- or under-estimation of extreme rainfalls, as the regression process is normally based on a full range of rainfall magnitudes and the

error for adjustment is based on independent stochastic distributions. A possible way to mitigate such a limitation is to divide the rainfall into various groups and apply downscaling methods individually. Over the past years, a number of researchers have attempted to incorporate classification of rainfall amount and neural network for downscaling. Olsson *et al.* (2001) tried a two-stage neural network to downscale the short-term extreme rainfall at Southern Japan. In this study, a neural network was firstly used to classify rainfall into four levels (i.e. zero, low, high and extreme), and then, another neural network was applied to determine the rainfall amount. The study showed that the neural network was less capable of differentiating zero (i.e. dry day) and low intensity rainfall, but it exhibited a satisfactory accuracy in classifying higher intensity rains. Ghosh and Katkar (2012) applied multiple downscaling methods to assess climate change impact for hydrological systems in north-east India. The method used the Classification and Regression Tree (CART) method to divide the rainfall into three groups (i.e. low, medium and high) based on monthly amount, and then applied three regression-based methods, including linear regression (LR), ANN and support vector machine (SVM), to downscale monthly rainfalls for different groups. The results demonstrated that ANN performed better in predicting the low and medium monthly rainfall groups and SVM showed better results for the high rainfall group.

The above-mentioned studies made viable attempts in using classification of rainfalls to enhance downscaling. However, Olsson *et al.* (2001) attempted to deal with daily rainfall, but encountered difficulty with ANN in addressing classification of non-occurrence (i.e. zero value) and low-intensity rains. It is more desirable that the determination of dry/wet days be separated from regressions (similar to the way adopted by ASD and GLM). Ghosh and Katkar (2012) only tested the CART method for classification for monthly rainfall downscaling; its validity for daily scale was not investigated. Thus, in this study, a coupled K-nearest neighbor and Bayesian neural network (KNN-BNN) model is proposed for daily rainfall downscaling. K-nearest

neighbor (KNN) method is specifically used for determination of dry/wet day, and for classification of rainfall types. Bayesian neural network (BNN) with error analysis will be used for estimation of rainfall amount based on classification results. A case study based on the gauge record of rainfall in Singapore and the climate forecast system reanalysis (CFSR) data will be used for demonstration. A comparison of the developed model to two conventional statistical downscaling methods (i.e. ASD and GLM) will be provided.

3.2 Model Description

Similar to ASD and GLM, KNN-BNN involves two steps in downscaling: occurrence modeling and amount modeling. Both steps are based on non-linear models (KNN and BNN), while ASD and GLM are based on linear ones. The detailed descriptions of ASD and GLM can be referred to Hessami *et al.* (2008) and Chandler and Wheeler (2002), respectively. The KNN-BNN method includes the classification of rainfall types and statistical downscaling model. From the study of Olsson *et al.* (2001), it is found that the neural network method is relatively weak to classify zero and low intensity rainfall event. Thus, the K-nearest neighbor (KNN) method is applied first for determination of dry/wet days and then for classification of rainfall groups based on intensity. Bayesian neural network (BNN) is used for regression of 'base rainfall amount' for the wet days in each rainfall group. Afterwards, a random residual will be added to the regression results to obtain the total rainfall time series. The threshold of wet day is set as 0.1 mm. If the estimated rainfall amount is below 0.1 mm (including negative values), the day will be considered as a dry day. Figure 3.1 shows the overall framework of the KNN-BNN downscaling method.

Figure 3.1 Framework of KNN-BNN

To illustrate the reason why KNN and BNN are preferred to be combined with each other, we give a comparison between different classification and regression methods (the result is shown in Table 3.1). From the table, KNN is compared with artificial neural network (ANN) with feedforward propagation (Mustafa *et al.*, 2012) and linear classification (LC) (Huang and Yang, 2013) in terms of accuracy of rainfall-occurrence determinations and dry-day proportion. The determination is based on December data and the regression is based on all-year daily rains with intensities above 53.5 mm/day. Calibration data is from 1980 to 2004 and verification data is from 2005 to 2010. It shows that the two nonlinear methods (i.e. KNN and

ANN) both perform better than the LC method. The KNN method offers a slightly higher accuracy (0.672) of occurrence prediction than ANN (0.651) in the verification stage. But the dry-day proportions (i.e. zero value) from both ANN (0.226) and LC (0.172) are considerably underestimated (0.226) compared with the observed data (0.36). The result is consistent with that from Olsson *et al.* (2001). For rainfall classification, KNN is also deemed a preferable option, as it is relatively straightforward to implement and does not require complex operation structure. For regression of wet-day rains, BNN is compared with two traditional regression methods, including ANN and multiple linear regression (MLR). BNN shows an obvious lower mean-square-error (MSE) in reproducing the tested rainfall data (i.e. high-intensity rains). For lower-intensity rainfalls, all three methods show similar performances and have no notable difference. The detailed procedures of KNN-BNN are described in the following sections.

Table 3.1 Comparison of different dry/wet day determination and regression methods

Performance	Determination of dry/wet days			
	KNN	ANN	LC	OBS
Accuracy of occurrence in calibration	n/a	0.717	0.701	n/a
Dry-day proportion in calibration	n/a	0.292	0.240	0.339
Accuracy of occurrence in verification	0.672	0.651	0.639	n/a
Dry-day proportion in verification	0.323	0.226	0.172	0.360
	Regression			
	BNN	ANN	MLR	
MSE (mm ² /day) in calibration	22.016	41.230	88.830	
MSE (mm ² /day) in verification	49.279	61.299	99.386	

Note: Determination of wet/dry days is based on December and regression is based on all daily rains with intensities above 53.5 mm/day; calibration is from 1980 to 2004 and verification is from 2005 to 2010. Accuracy of occurrence means the rate of

successful determination of dry/wet days, based on equation (3-16).

3.2.1 KNN for determination of rainfall occurrence and classification

KNN is a non-parametric method for classification through majority vote of its neighbors based on a similarity distance. There are three general distance functions used for estimation of nearest neighbors: Euclidean, Manhattan and Minkowski (Celisse and Mary-Huard, 2011). In this study, Euclidean distance function is used:

$$D_{EUC} = \sqrt{\sum_{i=1}^K (A_i - B_i)^2} \quad (3-1)$$

where A_i and B_i is the two points (i.e. i^{th} neighbor) in Euclidean space and K is the input number of neighbors. KNN is used for both determination of dry/wet days and classification of rainfall groups (i.e. rainfall class). The estimation of a proper K value is important in order to obtain reliable results (Celisse and Mary-Huard, 2011). In this study, two major steps are used to verify the K value, including estimation of an expected proportion and identification of a suitable K value based on the trial-and-error method. The detailed cross validation procedures consist of: (i) using the ‘simple moving average (SMA)’ (Bali et al., 2008) method to generate an expected proportion interval (EPI) and an expected average proportion of rainfall number (EPRN) for each rainfall class based on observed rainfall data during calibration; (ii) identifying the calculated proportion of rainfall number (CPRN) which is the ratio of calculated rainfall number in a class to the total number of rainfall events over a time period of concern; it can be determined from the KNN classification results using multiple K values (e.g. 1 to 20); (iii) determining a best K value or a group of suitable K values based on trial-and-error within the range of EPI. The related equations are given as follows:

$$SMA(f_t) = \frac{\sum_{i=1}^n p_{t-i+1}}{n} \quad (3-2)$$

$$EPI = \{ \min(f_{t+1}, f_{t+2}, \dots, f_{t+n}), \max(f_{t+1}, f_{t+2}, \dots, f_{t+n}) \} \quad (3-3)$$

$$EPRN = \frac{\sum_{i=1}^n f_{t+i}}{n} \quad (3-4)$$

$$CPRN = \frac{\sum_{i=1}^n q_{t+i}}{n} \quad (3-5)$$

where n is the number of years during verification period; t is the index of a year; p_t is the observed proportion of wet day at the t^{th} year; q is the proportion of wet day which is classified by KNN method; f_t is the expected proportion of wet day (calculated by SMA method) at the t^{th} year; f_{t+i} denotes the expected proportion at the $(t+i)^{\text{th}}$ year ($i = 1, 2, \dots, n$). Two alternative methods could also be used to replace SMA. They include: (i) ‘weighted moving average’ (WMA) method with a decreasing kernel function for weight assignment (Zhuang, *et al.*, 2007); (ii) ARIMA (Autoregressive Integrated Moving Average) model from Mills (1990) with the exogenous variables. In this study, SMA method is adopted.

Based on our test, a suitable range of K is from 1 to 20 (Nieminen *et al.*, 2012). There are two options to select K values (in both wet/dry day determination and rain-group classification). The first one is to choose any K values that make CPRN fall within EPI (i.e. the multiple- K scheme). The other one is to choose a single K value that will lead to the closest distance between CPRN and EPRN (i.e. the single- K scheme). Generally, multiple K values would lead to wider fluctuations of the downscaled outputs; a single K would result in minimal level of uncertainty. In this study, the downscaling results based on a single K scheme will be presented first; and a comparison to the results from multiple K scheme will be given later.

Figure 3.2 Comparison of KNN-BNN downscaled results using (a) 1 class, (b) 6 classes, (c) 8 classes, and (d) 12 classes, respectively. The quantile-quantile plot is based on the daily rainfall amounts in wet days.

For wet-day rainfall classification by KNN, it is also an important issue that the number of rainfall classes is properly identified. This is due to the fact: (i) if the class number is small, the advantage of rainfall classification will not be significant; (ii) if the class number is large, the number of training data will be insufficient, leading to a poor fitting. It is suggested that, for a particular application, a trial-and-error approach is used to seek the optimal number of classes. Figure 3.2 shows the quantile-quantile (Q-Q) plots with different class numbers (i.e. 1, 6, 8, and 12) for the downscaled and observed rainfalls. The data is based on daily rainfall amount on wet days. It is indicated that, the class numbers of 6 and 8 lead to a better performance compared with others as the points are more close to the center lines compared with others; while, the result from 6 rainfall classes shows a slight overestimation for rainfalls from 30 mm/day to 50 mm/day and considerable overestimation for rainfall above 100 mm/day. Therefore, 8 is considered as the most suitable number of classes in this study.

3.2.2 Bayesian neural network for regression

Generally, a neural network model consists of input, output and hidden layers with hidden neurons. The basic function of a conventional ANN model can be written as (Zarghami *et al.*, 2011):

$$y_k = f_o \left[\sum_{j=1}^m w_{kj} \cdot f_h \left(\sum_{i=1}^n w_{ji} x_i + b_{jo} \right) + b_{ko} \right] \quad (3-6)$$

where y_k is the k^{th} output; f_o is the activation function for the output neuron; f_h is the activation function for hidden neurons; i, j , and k represent the i^{th} , j^{th} , and k^{th} input neurons, respectively; m is the number of hidden neurons; n is the number of input neurons; w_{kj} means the weight between the j^{th} hidden neuron and the k^{th} output neuron; w_{ij} means the weight between the i^{th} input neuron and the j^{th} hidden neuron; b_{jo} is the bias for the j^{th} hidden neuron; b_{ko} is the bias for the k^{th} output neuron.

The Bayesian statistical method proposed by Mackay (1992) is used for inferring the weights. For the neural network operation, the Bayesian method could provide a principled framework to solve the structure complexity of the model and prevent overfitting problems. In Bayesian theory, suitable prior distribution information of weight and bias is used for deriving uncertain relationship between input and output. If the data is observed, the prior distribution is updated and becomes the posterior distribution based on a likelihood function (Khan and Coulibaly, 2006). The posterior distribution of weights based on the Bayes' theorem could be obtained by (Mackay, 1992):

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} \quad (3-7)$$

where w is the weight, $p(D|w)$ is the likelihood function, $p(w)$ is the prior distribution,

and $p(D)$ is the normalization factor. The Bayesian learning in the neural network consists of the following major procedures (Khan and Coulibaly, 2006; Pedersen and Larsen, 2009):

- (i) Select suitable prior distributions for weights and biases; define the noise model and the likelihood function; in this study, the Gaussian prior distribution and Gaussian noise model are applied (Khan and Coulibaly, 2006);
- (ii) Develop the posterior distributions of weights, which is approximated to Gaussian distribution for prediction;
- (iii) Train the network to maximize the objective function based on an optimization scheme and identify the most probable weight vector; in this study, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization scheme is used (Nielsen, 2000; Sigurdsson *et al.*, 2004);
- (iv) Evaluate the noise model using the most probable weight vector and obtain the output distribution through integrating noise model and posterior distribution of weights.

More details about BNN could be found at Svarer *et al.* (1993), Khan and Coulibaly (2006) and Pedersen and Larsen (2009). In addition, similar to standard ANN model, the number of the hidden neurons in the hidden layer of a BNN model should be determined. Based on our test, when the BNN regression is applied for the full-year record, 20 neurons could lead to a reliable result. If the seasonal effect is considered, the best number of neurons is found to be 10.

3.2.3 Residual analysis

Similar to ASD and GLM, a “residue analysis” can also be used for each rainfall class in KNN-BNN method, in order to have a reasonable simulation of extreme values.

Once a rain amount is estimated by regression, an error item shall be added to obtain a total rainfall amount. The error item is normally generated from a specific stochastic distribution that is fitted using ‘real’ residues during the calibration stage. The procedures of residue estimation include: (i) estimation of the regression residuals based on the observed data and BNN regression results; (ii) fit of the residuals using a suitable distribution; in this study, it is found that a Generalized Extreme Value (GEV) distribution has the best fit for rainfall in a tropic region like Singapore. During prediction stage, multiple ensembles are necessary to have a more comprehensive evaluation on possible fluctuations of the downscaled results (Gosling *et al.* 2010). Based on the fitted distribution of residuals, random errors can be generated and added to the regression results from BNN. Such an operation will add randomness to the downscaled results; each run will be considered a stochastic ensemble.

3.2.4 Descriptions of ASD and GLM models

Automated statistical downscaling tool (ASD)

ASD is based on multi-linear regression. It adds two procedures to enhance downscaling performance: (i) backward stepwise regression and partial correlation coefficients to select predictors; (ii) ridge regression to alleviate the effect of non-orthogonality (Hessami *et al.*, 2008). The two sub-models of ASD for downscaling rainfall, occurrence model and amount model could be written as follows (Hessami *et al.*, 2008):

$$O_i = a_0 + \sum_{j=1}^n a_j p_{ij} \quad (3-8)$$

$$R_i^{0.25} = \beta_0 + \sum_{j=1}^n \beta_j p_{ij} + e_i \quad (3-9)$$

where i means i^{th} of day; j means j^{th} of predictors; n is the number of predictors; a and β are the model parameters; e_i is the error; O_i is the occurrence of daily rainfall; R_i is the amount of daily rainfall. Other details could be found in Hessami *et al.* (2008).

Generalized linear model (GLM)

GLM was proposed by Chandler and Wheeler (2002) and applied at western Ireland. It also needs two sub-models, occurrence model and amount model, to estimate daily rainfall. Beside the large-scale predictors, GLM also considers other covariates used in models to filter noise and predict the daily rainfall, such as seasonal effect, station correlation, autocorrelation, and interaction among covariates. Therefore, GLM has advantages to address many effects that are difficult to be tackled by other methods. Generally, two sub-models based on logistic regression and gamma distribution are used for occurrence and amount modeling, respectively (Chandler and Wheeler , 2002; Yang *et al.*, 2005; Segond *et al.*, 2006):

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i^T \beta \quad (3-10)$$

$$\ln \mu_i = \varepsilon_i^T \gamma \quad (3-11)$$

where p_i is the probability of rain for the i^{th} day, x_i is the predictors for the i^{th} day in occurrence determination, β is the coefficient vector, and T means the transpose of matrices; ε_i is the predictors for the i^{th} day in amount model, γ is the coefficient vector. Another parameter for rainfall amount model is the dispersion coefficient v for all gamma distribution, which is assumed a common shape (Yang *et al.*, 2005; Segond *et al.*, 2006). Predictor selection is based on MSE values on each regression step. For detailed description of GLM, readers are referred to Chandler and Wheeler (2002), Yang *et al.* (2005) and Segond *et al.* (2006).

In this study, we choose 50 as the number of ensembles for generating the envelopes

of monthly indicators of rainfall. The selection of 50 for running ensembles is based on both references and our own test. Many previous studies used multiple ensembles for generating the envelopes of downscaled indicators. For example, Segond *et al.* (2006) used 40, Mezghani and Hingray (2009) used 50 ensembles and Yimer *et al.* (2009) used 20 ensembles. Based on our test, no significant improvement of results (less than 1%) is found when the number of ensembles exceeds 50 for KNN-BNN, ASD and GLM.

3.3 Study Area and Data

Singapore is located in Southeast Asia, the southern tip of the Malay Peninsula and classified as the tropical rainforest climate with no distinct seasonal variations. The average temperature over the entire year is within the interval from 29 to 31°C. There is plentiful rainfall around the year, with an average annual rainfall being around 2,300 mm. According to historical record, the wettest month is December with an average rainfall about 280 mm; the driest month is February with an average rainfall being 160 mm. The two months are both in the Northeast Monsoon period, which occurs from December to early March. Another is the Southwest Monsoon season which occurs from June to September (NEA, 2009). There is a general decreasing trend of rainfall from west to east of the island, but no distinct difference from north to south (NEA, 2009). Therefore, two stations, which are located in the eastern (S24) and western (S44) parts, respectively, are selected for model testing. Both stations have good quality data for the study period from 1980 to 2010. S24 has a complete rainfall dataset and S44 has a slightly missing record (i.e. 0.09%). Due to more complex rainfall in western region, the results of S44 station is fully presented; the results of S24 station are partially given for the purpose of comparison. The whole record is divided into calibration period (1980-2004) to train downscaling models and verification period (2005-2010) to evaluate the predicted results.

Due to complexity of tropical climate, the Climate Forecast System Reanalysis (CFSR) data (from 1980 to 2010) with a $0.5^\circ \times 0.5^\circ$ spatial resolution are used as the candidate predictors for statistical downscaling (Saha, 2010). CFSR has been considered as both spatially ($0.5^\circ \times 0.5^\circ$ vs. $2.5^\circ \times 2.5^\circ$) and temporally (1-hour instantaneous vs. 6-hour instantaneous) superior product to NCEP reanalysis (Liléo and Petrik, 2011; Wang *et al.*, 2011). Figure 3.3 shows the study area and boundary of CFSR grids, in comparison with the NCEP/NCAR (National Center for Atmospheric Research) Gaussian grid (DAI, 2008). There are two CFSR grids (i.e. CFSR-East and CFSR-West) to cover Singapore; the coordinate of central points for two grids are (1.5°N , 103.5°E) and (1.5°N , 104°E), respectively. The large-scale predictors which used for S24 station downscaling are obtained from the grid of CFSR-East; predictors for S44 downscaling are obtained from the grid of CFSR-West.

Figure 3.3 The grid boundary of CFSR data for Singapore region.

Regarding predictor selection, two different methods are used in the KNN-BNN model for determination of rainfall occurrence and calculation of wet-day rainfall

amount. Firstly, the Two-Sample Kolmogorov-Smirnov Test is used for estimating the status of the day (i.e. wet or dry day and rainfall classes in wet day). For example, if the predictor leads to a significant distinction between a dry day and a wet day, it will be considered (Chen, *et al.*, 2010a). It also considers the cross-validation results of KNN method. Secondly, the backward stepwise regression (Hocking, 1976) is used for choosing predictors for the rainfall amount in a wet day. The method is similar to the one used in the ASD method and its detailed description could refer to the study of Hessami *et al.* (2008). The major difference of predictor selection in KNN-BNN is that the selection has to be conducted for each group of rainfall. GLM uses the likelihood ratio tests (or deviance comparisons) for determining the input variables (covariates) of the model (Chandler, 2012). We have tested all the three methods for this study and found that they would lead to similar results. This may partially because the area has a highly complex rainfall pattern, and there are only a limited number of potential predictors to be selected from CFSR database (see Table 3.2). It is also good for a fair comparison of the three methods.

Table 3.2 Available predictors from CFSR and screened predictors for downscaling

Symbol	Content	
prmsl	Mean Sea Level Pressure	√
q500	Specific Humidity at 500 hPa	√
q850	Specific Humidity at 850 hPa	√
q925	Specific Humidity at 925 hPa	√
z500	Geopotential at 500 hPa	√
z850	Geopotential at 850 hPa	
z1000	Geopotential at 1000 hPa	
u-w 500	Zonal Wind at 500 hPa	
v-w 500	Meridional Wind at 500 hPa	√
u-w 850	Zonal Wind at 850 hPa	
v-w 850	Meridional Wind at 850 hPa	

The selection of predictors is critical for building a reliable downscaling model and predicting future rainfall conditions (Wilby, 1998; Fowler *et al.*, 2007). The physical

meaning of predictors should be judged to be somewhat related to rainfall generation mechanisms (Fowler *et al.*, 2007). Thompson and Green (2004) found that the relationship between sea-level pressure and precipitation was consistent for different timescales, such as seasonal, monthly and daily using trajectory analysis. Wilby and Wigley (1997) indicated that the humidity was more useful for downscaling precipitation. Xoplaki *et al.* (2002) found that the large-scale 500 hPa geopotential height is strongly correlated to precipitation. Similar conclusion was also presented by Cavazos and Hewitson (2005). In the downscaling study field, Cannon (2008) tried to use mean sea level pressure, 850 hPa relative humidity, 850 hPa temperature, 700 hPa relative vorticity and 500 hPa geopotential height as predictors for downscaling precipitation in Canada; Chen *et al.* (2009) used 850 hPa vorticity, 850 hPa geopotential height, 500 hPa and 850 hPa relative humidity and near surface specific humidity for downscaling rainfall at Taiwan. More study cases could be found in King *et al.* (2012), Tavakol-Davani *et al.* (2013), and Nasser *et al.* (2013). In this study, the selection of predictors is mainly based on the findings from the previous works and also considerations of available candidates from CFSR datasets for the Singapore region.

3.4 Results and Discussion

3.4.1 Model configurations

Five statistical indicators of rainfall characteristics are used for evaluating model performances: average daily rainfall (Mean), standard deviation of daily rainfall (STD), probability of wet days (Pwet), 90th percentile of daily rainfall (PERC90) and maximum daily rainfall (Max) (Hessami *et al.*, 2008). The accuracy of the simulated indicators will be assessed by correlation coefficient (CC) (Myers and Well, 2003), mean-square-error (MSE) (Armstrong and Collopy, 1992) and absolute percentage error (APE) (Ghosh and Kathar, 2012). The equations are given by:

$$CC = \frac{\sum_i (R_i^{obs} - \bar{R}^{obs})(R_i^{sim} - \bar{R}^{sim})}{\sqrt{\sum_i (R_i^{obs} - \bar{R}^{obs})^2 \sum_i (R_i^{sim} - \bar{R}^{sim})^2}} \quad (3-12)$$

$$MSE = \frac{1}{n} \left[\sum (X_{j,obs} - X_{j,sim})^2 \right] \quad (3-13)$$

$$APE = \frac{|X_{j,obs} - X_{j,sim}|}{X_{j,obs}} \quad (3-14)$$

where i is the index for day and j is the index for month; R_i^{obs} is the rank of the i^{th} observed daily data; $\bar{R}^{obs}$ is the average of the observed daily data positions; R_i^{sim} is the rank of the i^{th} simulated daily data; $\bar{R}^{sim}$ is the average of simulated daily data positions; $X_{j,obs}$ is the j^{th} observed monthly rainfall data, $X_{j,sim}$ is the j^{th} simulated monthly rainfall data, and n is the number of month. To assess the uncertainty range of the modeled results, a mean absolute percentage boundary error (MAPBE) is proposed and defined as:

$$MAPBE = \frac{1}{n} \sum (APE_{L,j} + APE_{U,j}) \quad (3-15)$$

where n is the number of month, $APE_{L,j}$ is the lower-boundary APE for the j^{th} month, and $APE_{U,j}$ is the upper-boundary APE for the j^{th} month.

3.4.2 Results of S44 station

Classification results

The determination of dry/wet day could be assessed by accuracy of occurrence determination (AO):

$$AO = \frac{N(D_{sim}/D) + N(R_{sim}/R)}{N(D) + N(R)} \quad (3-16)$$

where $N(D_{sim}/D)$ means the number of days that a dry day is correctly classified as a dry day; $N(R_{sim}/R)$ means the number of days that a wet (Rainfall) day is correctly classified as a wet day; $N(D)$ is the number of dry days; $N(R)$ is the number of wet days (Chen *et al.*, 2010a). The AO values of downscaled results using the three methods are listed in Table 3.3. Those of ASD, GLM and KNN-BNN methods are determined based on 50 ensembles. For the single-K scheme of KNN-BNN approach, the uncertainty is mainly caused by residual analysis. If a regression result added by a residual leads to a negative value, the day will be considered as a dry day. Generally, the accuracies of the three methods in determining rainfall occurrence are comparable. ASD shows a higher maximum AO than other two methods; KNN-BNN performs better in terms of minimum and average AO values.

Table 3.3 Accuracy of occurrence determination (AO) for dry/wet days at S44

	Min.	Max.	Average
ASD	0.560	0.605	0.582
GLM	0.550	0.591	0.566
KNN-BNN	0.582	0.597	0.591

Note: The AO values are calculated based on 50 ensembles.

Table 3.4 Classification of rainfall types during verification period at S44

Class number	Rainfall Intensity range (mm/day)	Expected proportion ^a			Average predicted proportion ^b	Observed proportion ^c
		Min	Max	Ave.		
Class 0	Dry day	0.441	0.496	0.466	0.437	0.461
Class 1	0-3.1 ^d	0.186	0.235	0.215	0.232	0.196
Class 2	3.1-8.7	0.087	0.097	0.096	0.094	0.105
Class 3	8.7-13.5	0.044	0.060	0.051	0.061	0.058
Class 4	13.5-27.9	0.074	0.089	0.080	0.090	0.093
Class 5	27.9-36.8	0.022	0.033	0.027	0.033	0.031
Class 6	36.8-53.3	0.022	0.033	0.026	0.028	0.036
Class 7	53.3-73.5	0.011	0.020	0.015	0.014	0.011
Class 8	Above73.5	0.007	0.012	0.010	0.010	0.010

^aExpected proportion is estimated by ‘simple moving average’ method (Bali et al., 2008). ^bAverage value for calculated proportions by KNN–BNN model for verification period. ^cObserved proportions for verification period. ^d0–3.1 means the value greater than 0 and lesser or equal to 3.1.

Table 3.4 shows the classification results for rainfall classes based on rainfall intensity. The expected proportion is calculated by the ‘simple moving average’ method based on calibration data; the average predicted proportion (i.e. calculated values during verification period) is the mean value of the entire 50 ensembles generated by KNN-BNN. From the table, except for an overestimation for Class 4, the observed proportions in the verification period fall within the range of the expected proportions. The predicted proportion illustrates a close representation for medium-intensity (i.e. Class 3, Class 4 and Class 5) and extreme rainfalls (i.e. Class 8). Somewhat underestimations by KNN are observed for Class 0 and Class 6, and overestimation for Class 1. Overall, the average predicted proportions are close to the observed ones. It gives a reasonable classification of rainfall amount before regression, which is especially useful for reproduction of the extreme events.

Downscaled results

Totally, 50 ensembles of downscaled rainfall series for the verification period are generated, and the related Q-Q plots are presented in Figure 3.4. ASD and GLM methods show a wide varying range when the rainfall amounts are above 100 mm/day. Several peak values generated by ASD and GLM are over 250 mm/day, while the observed one is only about 150 mm/day. KNN-BNN shows a notable improvement over extreme data simulation. The varying range is significantly narrower than ASD and GLM. However, the results of KNN-BNN are slightly overestimated when the rainfall amount ranges from 80 mm/day to 100 mm/day. This may be because there is only one class when the rainfall is above 73.5 mm/day, and the error of regression for this range is seriously biased by extreme rainfalls (e.g. above 100 mm/day).

Moreover, the ASD method shows an underestimation when the rainfall intensity is below 35 mm/day. Overall, the classification by KNN-BNN could effectively control the superposition error that would occur in ASD and GLM, and lead to downscaled results with reduced uncertainties.

Figure 3.4 Quantile-quantile plot for wet-day rainfall amounts using (a) ASD, (b) GLM, and (c) KNN-BNN

Figure 3.5 shows a comparison between the observed and predicted monthly indicators. There are two predicted intervals used in the assessment of uncertainty range: Envelop Range (ER) and 5th/95th percentiles range (P95R). ER means the lower and upper boundary of prediction and P95R represents the 5th and 95th percentiles (i.e. the grey area). The average value of multiple ensembles is a common practice to assess the model performance (Ghosh and Katkar, 2012). In terms of the average simulated indicators vs. observed ones, all five indicators from the downscaled results by KNN-BNN show lower MSE levels compared with those generated by ASD and GLM. Particularly, the MSE values of the monthly Mean, Pwet, PERC90, and Max from KNN-BNN are about 40.7%, 100%, 37% and 38.7% lower than the average MSEs from ASD and GLM.

From Figure 3.5, the KNN-BNN method shows notable narrower ranges of uncertainty for the five indicators, in comparison to those from ASD and GLM. However, it is also indicated that a number of observed data (particularly for August data) for KNN-BNN are beyond the range of the envelope generated by multiple ensembles, although they are still fairly close. The insufficient range of interval shows the limitation of a single-K scheme in addressing modeling uncertainties. Pwet shows the worst performance as there is an obvious underestimation in January. But this occurs as well for other two models, as quite a number of observed values going beyond the uncertain ranges. Furthermore, ASD and GLM both show a larger distance between ER and P95R for all indicators than KNN-BNN, especially for the upper boundaries. This implies that KNN-BNN has less abnormal fluctuations of the predicted indicators. Another fact from the figure is that, the KNN-BNN has a relatively lower prediction uncertainty for the Southwest monsoon season (from June to September) than Northeast one (from November to February). This is perhaps due to the fact that the rainfall patterns in the Northeast Monsoon are more consistent (e.g. strong rainfalls in December or low rainfalls in February).

Table 3.5 shows the MAPBE values of the simulated results using the three methods. MAPBE is a quantitative indicator showing the level of uncertainty of the downscaled results. It could be calculated based on either ER or P95R. From Table 3.5, KNN-BNN generates the lowest MAPBE values for all five indicators based on both ER and P95R. It shows that the reduced uncertainty level by KNN-BNN for these four predictors is more than 53%. GLM has a similar level of performance compared with ASD. It is also indicated that ASD has a relatively lower uncertainty in Pwet prediction among other indicators, but it is still inferior to that of KNN-BNN. The results of Table 3.5 are consistent with those from Figure 3.5. Overall, the KNN-BNN method has demonstrated a fairly reasonable prediction of rainfalls from GCM, and an impressive capability in generating narrower uncertain ranges of the downscaled results caused by multiple ensembles, in comparison to both ASD and GLM.

Figure 3.6 shows the simulated daily rainfall distributions by the three models. Only one random sequence is presented and compared with the observed daily rainfall for the wettest month in Singapore, i.e. December. The threshold of extreme event is set as 50 mm/day, and the observed number of extreme events (NEE) is 12 for December during the verification period. The observed peak rainfall is 141.2 mm/day. ASD underestimates the frequency of extreme events, where only 7 predicted rainfall events have amounts exceeding the threshold. GLM performs better than ASD but it also slightly underestimates the frequency of extreme events (NEE equals to 10), and overestimates the peak rainfall amount (160.3 mm/day). KNN-BNN method generates closer results to observations regarding both NEE (equals to 11) and the peak rainfall amount (131 mm/day). Based on 50 ensemble results, it is found that the average NEE values for ASD, GLM, and KNN-BNN are 7.3, 7.9, and 10.2 respectively, and the average peak amounts are 124.68, 123.61, and 140.76 mm, respectively. KNN-BNN demonstrates a better performance in extreme-rainfall descriptions.

Figure 3.5 Comparison of observed and simulated monthly indicators at S44 station. Subscripts 1, 2, 3 in the subfigures represent the indicators from ASD, GLM and KNN-BNN, respectively. The grey range is the simulated 5th and 95th percentiles of the predicted range (P95R) and the dash lines are the envelopes generated by all 50 ensembles (ER); Ave. means the averaged indicators from 50 ensembles.

Table 3.5 MAPBE values of the simulated results using three methods at S44

MAPBE	ASD	GLM			KNN-BNN	
	ER	P95R	ER	P95R	ER	P95R
Mean	0.66	0.52	0.67	0.52	0.22	0.21
STD	0.94	0.70	0.83	0.60	0.30	0.28
Pwet	0.28	0.25	0.67	0.32	0.13	0.13
PERC90	0.80	0.60	0.74	0.58	0.29	0.24
Max	1.83	1.26	1.58	1.21	0.61	0.52

Note: ER means the full range of data (using envelope of ensemble results) is used to calculate MAPBE; P95R means the 5th and 95th percentiles of the predicted range of data (i.e. lower is 5th percentile amount, upper is the 95th percentile amount) are used to calculate MAPBE.

Comparison between single-K and multiple-K schemes

As mentioned in the methodology section, a multiple-K scheme can offer more K values, leading to wider uncertain ranges of downscaling results. Multiple K values could be used in either the determination of dry/wet days, or classification of rainfall types. However, based on our test, a multiple-K scheme is better used only in the determination process of dry/wet days. The classification process has a number of rainfall classes, which will lead to a large number of ensembles and wide uncertainty ranges of the final downscaled results. Figure 3.7 shows a comparison between the single-K and multiple-K schemes (used in occurrence determination only) based on Mean, Pwet, PERC90 and Max. It is demonstrated that, the multiple-K scheme could provide a sufficiently wide prediction interval to cover the observed data. Interestingly, the envelope is still narrower than those of ASD and GLM models as shown in Figure 3.5. In addition, the MSE levels of statistical indicators from the multiple-K scheme are lower than those of ASD and GLM. The results imply that the uncertainty intervals of downscaled results from multiple ensembles are affected by the selection of K schemes. A tradeoff between reliability and accuracy of the downscaled results is useful before a proper scheme is selected. In this study, both schemes lead to better performance in downscaling than the conventional methods

Figure 3.6 Downscaled December daily rainfalls for the verification period using (a) ASD, (b) GLM, and (c) KNN-BNN at S44 station.

(i.e. ASD and GLM). A single-K scheme is recommended when more accurate results with narrower uncertain ranges are desired, although a slight risk of deviating from observation may occur; multiple-K scheme is better used in conditions that the decision makers want a more reliable result with a full range of ensembles being reflected.

Figure 3.7 Comparison between the single-K and multiple-K schemes at S44 station, in terms of (a) Mean, (b) Pwet, (c) PERC90, and (d) Max. The grey ranges mean envelop of the downscaled indicators using the single-K scheme; the dash line means envelop from the multiple-K scheme. MSE value is calculated by multiple-K scheme average and observed data.

KNN-BNN downscaling based on monthly data

The seasonal effect may affect the performance of downscaling models. Generally speaking, each month has specific feature of rainfall pattern (e.g. the properties of mean, standard deviation and 90th percentile amount for June and August in Figure 3.5). To examine if an individual monthly fit will enhance the downscaling performance, ASD, GLM and KNN-BNN are applied based on the December data only; they are denoted as ASD-D, GLM-D and KNN-BNN-D, respectively. The

results are compared with those obtained based on rainfall data over all months (denoted as ‘model name’-F). Through comparison, the best class number is 6 (mainly based on the training data) for the KNN-BNN method. Table 3.6 lists the ensemble envelopes and the average values of five statistical properties for the three models. Compared with those based on full year record, the December-data results demonstrate a notable improvement in terms of both ensemble envelopes and average values. The reduced percentages of MAPBE (reflecting uncertainty level) for ASD-D, GLM-D and KNN-BNN-D are 25.8%, 20.2% and 43.6%, respectively. KNN-BNN-D offers the narrowest envelopes and the closest average values for Mean, STD, Pwet and Max. However, when only single month data is used, the data may be insufficient to fit well the downscaling models, particularly for the extreme events. For example, PERC90 values for ASD-D, GLM-D and KNN-BNN-D are somewhat underestimated, as shown in Table 3.6. The downscaled results based on individual month data for June and August are presented in Figure 8.

Table 3.6 Comparison of performances among ASD, GLM and KNN-BNN for December rainfall downscaling at S44

	ASD-F	GLM-F	KNN-BNN-F	OBS
Mean	(7.83, 10.19, 12.79)	(7.05, 10.23, 13.55)	(10.40, 11.15, 12.11)	10.39
STD	(12.89, 17.97, 32.23)	(12.23, 18.09, 32.70)	(20.31, 22.34, 26.12)	21.31
Pwet	(0.65, 0.69, 0.75)	(0.58, 0.66, 0.77)	(0.60, 0.61, 0.61)	0.64
PERC90	(27.00, 38.24, 52.00)	(29.03, 41.19, 60.53)	(41.92, 48.44, 56.37)	50.40
Max	(67.78, 124.68, 366.81)	(74.44, 123.61, 329.09)	(113.54, 140.76, 176.31)	141.40
	ASD-D	GLM-D	KNN-BNN-D	OBS
Mean	(6.28, 9.25, 11.65)	(6.29, 9.96, 12.12)	(9.85, 10.19, 10.49)	10.39
STD	(10.39, 16.06, 25.34)	(12.46, 17.34, 24.89)	(19.80, 20.74, 22.12)	21.31
Pwet	(0.66, 0.71, 0.76)	(0.55, 0.65, 0.73)	(0.63, 0.66, 0.68)	0.64
PERC90	(27.54, 33.69, 48.77)	(26.11, 38.42, 48.61)	(41.74, 44.84, 48.52)	50.40
Max	(58.84, 109.45, 224.68)	(68.66, 115.54, 282.27)	(121.03, 139.39, 158.76)	141.40

Note: The three numbers in the bracket denote the minimum, average and maximum values; -F and -D mean that the downscaled results are based on a full year and December rainfall data, respectively.

Figure 3.8 Comparison of performances among KNN-BNN model for June and August rainfall downscaling at S44 based on both full-year and individual-month data. 1 and 2 denote the June and August, respectively; a, b and c denote the Mean, Standard Deviation (STD) and 90th percentile rainfall amount (PERC90), respectively; APE – I and APE – F denote the absolute percentage error (APE) for individual month and full year, respectively. The APE values are calculated based on mean value and observed value.

In Figure 3.5, there is a reproduction of rainfall for June and August, in terms of the properties of Mean, STD and PERC90. The corresponding downscaled results could not well cover the observed data. The individual monthly data of June and August are applied for KNN-BNN model, aiming to mitigate such a problem. The number of KNN classes is 6, which are classified according to the 10th, 25th, 50th, 75th and 90th percentile values for rainfall amount. Figure 3.8 illustrates the comparison of performances of KNN-BNN model for June and August rainfall downscaling based on full-year and individual-month data, respectively. Compared with the absolute percentage error (APE), the downscaled results based on monthly data show some improvement regarding various monthly indicators except for the Mean of June. It is worth mentioning that the PERC90 shows the most notable enhancement but with a slightly increase of the uncertainty range. The results indicate that the downscaled results based on the full-year data could not well reflect the rainfall patterns in these two months, although it has a narrower uncertainty range. In terms of the maximum values, the results from individual-month downscaling for June and August are 104.6 mm/day and 97.6 mm/day, respectively, which are slightly closer to observed data (i.e. 131.2mm/day and 85.7 mm/day) than those based on full-year data (i.e. 101.1 mm/day and 62.8 mm/day). Overall, the above analysis demonstrates that the separation of yearly data into monthly could considerably enhance the model performance.

3.4.3 Results of S24 station

To verify the robustness of the proposed model, the downscaled result for the S24 station is also presented. Figure 8 shows the comparison of downscaled monthly indicators using three models including ASD, GLM and KNN-BNN. Since there is a weather disparity from western to eastern Singapore Island, S24 shows a slightly drier weather pattern than S44 (the probabilities of rainfall occurrence are 49.6% and 51.2% during the study period for stations S24 and S44, respectively). To evaluate the

new model comprehensively, two options of KNN-BNN application for S24 station will be considered: (i) downscale rainfall on a full year basis, and (ii) downscale based on different seasons, namely wet (from October to January) and dry (from February to September) seasons in Singapore. Based on our test, the number of groups for rain classification is determined to be 7 for the first option and 6 for the second one.

Table 3.7 MAPBE values of the simulated results using three methods at S24

MAPBE	ASD		GLM		KNN-BNN	
	ER	P95R	ER	P95R	ER	P95R
Mean	0.736	0.613	0.825	0.672	0.313	0.308
STD	0.786	0.566	0.914	0.736	0.369	0.361
Pwet	0.430	0.392	0.391	0.307	0.116	0.114
PERC90	0.855	0.744	0.946	0.789	0.456	0.416
Max	1.414	1.046	1.777	1.315	0.654	0.598

Note: ER means the full range of data (using envelope of ensemble results) is used to calculate MAPBE; P95R means the 5th and 95th percentiles of the predicted range of data (i.e. lower is 5th percentile amount, upper is the 95th percentile amount) are used to calculate MAPBE.

Table 3.7 illustrates the MAPBE values of the downscaled results based on full-year records using three methods at S24. Similar performance is observed for the downscaled results compared with that of S44. KNN-BNN shows a narrower uncertainty range for the monthly indicators, especially for the indicators of extreme data (PERC90 and Max). Figure 3.9 shows the comparison of observed and downscaled monthly indicators considering seasonal effect at S24 station. It is found that the simulated rainfall frequency (Pwet) of KNN-BNN method is notably improved, especially for the wet season. While, due to unavoidable reduction of sampling size of extreme data in different seasons, the mean of the downscaled maximum rainfall amount shows some deviations from the observed mean (Figure 3.8d), although most of the envelopes of monthly indicators could well cover the

observed ones.

Figure 3.9 Comparison of observed and downscaled monthly indicators considering seasonal effects at S24 station. Subscripts a, b, c, d in the subfigures represent the indicators of Mean, standard deviation (SD), Probability of wet day (Pwet) and Maximum daily rainfall (Max), respectively.

3.4.4 Further discussions on model comparison

Based on the results of the case study, the proposed KNN-BNN model could be deemed a hybrid model, as it takes full advantages of the regression-based method, weather typing and stochastic generator. In detail, (i) it could build the ‘transfer function’ (Giorgi and Hewitson, 2001) between local weather information and large-scale predictors like what regression model does; (ii) it performs a residual

analysis and randomly generates an error term with a suitable distribution during the prediction process, which is, in some sense, behaves like a weather generator; (iii) it groups rainfall into different classes so that the local rainfall distribution could be better reflected; this is similar to the concept of weather typing which is based on classification of the occurrence of local climate (Fowler *et al.*, 2007).

From the comparison of the developed model with two conventional statistical downscaling methods of ASD and GLM (GLIMCLIM, Chandler and Wheeler, 2002), it is indicated that the similarity of the two models lies in that ASD (including SDSM) and GLM are both hybrid of the linear regression and stochastic generator. The major differences between them are: (i) GLM could not only consider the predictor variables (GCM predictors), but also address possible effects related to autocorrelation, seasonal variation, and location difference etc.; (ii) GLM could provide both independent and dependent spatial structures. The proposed KNN-BNN method has a similar framework as those of SDSM/ASD or GLM, in the sense of two major procedures: (1) estimation of dry/wet day and calculation of rainfall amount in the wet day, and (2) inclusion of a stochastic generator based on residual analysis. The major difference of KNN-BNN is that it judges rainfall occurrence and estimates its wet-day amount for a specific 'rainfall/weather class' (Fowler *et al.*, 2007); this is somewhat similar to weather typing method. In addition, the two fundamental modules (i.e. KNN and BNN) have their own advantages. KNN is a non-parametric supervised classification method, which is straightforward and flexible to apply (He and Wang, 2007). KNN model could also combine with other methods to accomplish cross-validation or optimize K value (Celisse and Mary-Huard, 2011). BNN is considered superior than linear regression models in approximating wet-day rainfall amount; it could mitigate overfitting or underfitting problems based on Bayesian learning algorithm (Khan and Coulibaly, 2006), and better reflect extreme data.

3.5 Summary

A coupled K-nearest neighbor and Bayesian neural network (KNN-BNN) model was developed for downscaling single-site daily rainfall in Singapore. The high resolution reanalysis data, CFSR with a $0.5^{\circ} \times 0.5^{\circ}$ spatial resolution, was used as the large-scale predictors. In this model, K-nearest neighbor (KNN) was used for determination of dry/wet day occurrence and classification of rainfall types. Bayesian neural network (BNN) was applied for nonlinear regression of the rainfall amount during wet days. The random errors were found following a generalized extreme value (GEV) distribution. The downscaled results of KNN-BNN method were compared with those from two traditional approaches, including automated statistical downscaling tool (ASD) and generalized linear model (GLM). The result showed that the KNN-BNN method was superior to these two in generating obviously narrower uncertain ranges in terms of monthly indicators including mean, standard deviation, probability of wet day, 90th percentile rainfall amount and maximum daily rainfall amount. The results demonstrated that the precision of KNN-based classification played an essential role at the downscaling process. A properly identified number of rainfall classes and consideration of seasonal effect in KNN-BNN could notably improve the performance of determination of rainfall occurrence; but this could also lead to reduced number of sampling size for extreme events and affect model performance.

Generally, the proposed new downscaling model, i.e. KNN-BNN, could effectively reduce the uncertain ranges of the downscaled results and prevent overestimation of extreme rainfalls, in comparison to traditional ways. Further study could consider more local meteorological factors into the model, such as the monsoon influence and inter-annual effect. Another room for improvement is to enhance the model to address multi-site spatial downscaling, with cross-correlations be reflected. Furthermore, the prediction for future period was not included in this study as we

intended to focus on methodology demonstration and verification using historical record. The application of the proposed method in hydrological impact studies could be attempted by using global circulation model (GCM) predictors under future climate scenarios.

CHAPTER 4 A MULTISITE MULTIVARIATE SEMI - PARAMETRIC WEATHER GENERATOR

4.1 Introduction

A stochastic weather generator is a framework consisting of a series of statistical algorithms to produce synthetic weather data over a long-term period. The synthetic data are normally in a continuous time series with similar statistical characteristics with the observed record, and useful for many studies, such as water resources management, agricultural irrigation planning, and flood risk assessment (Semenov et al., 1998; Kevin et al., 2005; Chen et al., 2010a). It could also be used for generating daily weather data at ungauged area using spatial interpolation algorithms based on data from surrounding stations (Chen et al., 2010a; Fodor et al., 2010). In the field of climate change studies, the weather generator could be coupled with General Circulation Models (GCMs) or Regional Climate Models (RCMs) to generate weather scenarios under future conditions (Semenov and Stratonovitch, 2010). Such a procedure is also called statistical downscaling (Fowler et al., 2007). In the past years, many studies were devoted to the development and application of hybrid models (i.e. coupled weather generator and statistical approaches) for downscaling future climate-change scenarios such as Statistical DownScaling Model (SDSM), (Wilby et al., 2002) and Generalized Linear Model (GLIMCLIM) (Chandler and Wheeler, 2002).

A stochastic weather generator normally involves two basic procedures. The first one is to model the precipitation occurrence and the second one is to calculate the precipitation amount and other variables (such as minimum/maximum temperature, solar radiation and wind speed) which are conditioned upon the occurrence of precipitation. There are different methods in simulating precipitation occurrence.

One of the well-known methods is the weather generator (WGEN) developed by Richardson (Richardson, 1981; Richardson and Wright, 1984). The model relies on the first-order two-state Markov chain to estimate the wet/dry day status and the two-parameter gamma distribution to calculate the precipitation amount in the wet days. Later on, several improved versions based on the second-order (Mason, 2004) or the third-order (Dubrovesky et al., 2004) Markov chain models were developed to simulate the wet/dry day status (Fowler et al., 2007). Such a type of weather generator is called ‘Richardson type’ (Wilks and Wilby, 1999). A number of well-known weather generators in this category have been developed, such as SIMMETEO (Geng et al., 1988), Cligen (Nicks and Gander, 1994), ClimGen (Stockle et al., 1999), MARKSIM (Jones and Thornton, 2000), AAFC-WG (Qian et al., 2005), and CLIMA (Donatelli et al., 2009). Apipattanavis et al., (2007) developed a semi-parametric multivariate and multisite weather generator and applied it into pampas region, Pergamino, Argentina. It used a first-order three-state Markov chain to estimate the day status of precipitation, and the modified K-nearest neighbor (KNN) bootstrap resampler with weight function to resample the amount of weather variables from historical records. Based on the used methodologies, it was also called ‘KNN weather generator’. The results showed that the weather generator could well keep the basic statistical properties (i.e. spell statistics, distributional and lag-dependence statistics), the inter-variable correlation, and the inter-site correlation. Baigorria and Jones (2010) developed another ‘Richardson Type’ model named Geospatial-temporal (GiST) weather generator and applied in north-central Florida and North Carolina, USA. This model could generate the precipitation at multiple stations considering the spatial correlation based on an orthogonal Markov chain for discrete distribution. The precipitation amount was generated and rescaled by gamma distribution for each station and the spatial correlation was kept by using a factorized correlation matrix. The results showed that the generator could produce the pairwise correlation coefficients (CC) of precipitation occurrence and amount with a low

root-mean-square-error (RMSE). However, the model also presented an over-dispersion for the generated rainfall amount. To prevent the underestimation of low-frequency precipitation data (e.g. extreme events) of weather generator (Wilks, 1999), Chen et al. (2010a) proposed a stochastic weather generator called WeaGETS and applied it to southwest Quebec, Canada. This model was also based on the first-order two-state Markov chain to simulate the precipitation occurrence and exponential or gamma distribution to calculate the precipitation amount. The observed power spectra of monthly and annual time series were used for modelling the lower-frequency variability. The results showed that the corrected data was significantly improved than the directly generated data in reproducing the low-frequency data.

In addition to the ‘Richardson-type’ model, there are also other types of stochastic weather generators, such as the ‘serial type’ (Wilks and Wilby, 1999) and ‘stochastic point process model’ (Kilsby et al., 2007). Long Ashton Research Station Weather Generator (LARS-WG) belongs to the ‘serial type’ model and was developed by Racsco et al. (1991), Semenov and Barrow (1997), and Semenov and Stratonovitch (2010). It is based on a semi-empirical distribution to estimate the length of dry/wet spell and rainfall amount. LARS-WG is also widely used in many regions with different climate conditions around the world (Zarghami et al., 2011; Xu et al., 2012; Kim et al., 2013). Fodor et al. (2010) developed a multi-variable weather generator (MV-WG) and applied it in 109 meteorological stations across the USA. The three-parameter Weibull functions were applied for simulating the length of dry/wet spell and precipitation amount in this model. The ‘stochastic point process model’ includes the Bartlett-Lewis Rectangular Pulses (BLRP) model, Neyman-Scott Rectangular Pulses (NSRP) model and some modified versions. Burton et al. (2008) developed a stochastic weather generator based on NSRP model called RainSim. The generator could simulate rainfall for multiple timescales (e.g. hourly and daily) at multiple sites. Based on seven parameters of Spatial-Temporal version of NSRP

model (STNSRP), RainSim could generate the synthetic rainfall data through fitting observed statistical properties (e.g. mean, standard deviation, and probability of wet-dry day or hour) while capturing the spatial correlations.

Since there are various types of weather generators, comparison among different alternatives have aroused much interest. Semenov et al. (1998) compared the LARS-WG and WGEN in 18 stations around the world, and demonstrated that the LARS-WG generator could reproduce more accurate synthetic data than WGEN due to its more thorough distributions for weather variables. The two generators were both poor in modelling the inter-annual variance in monthly mean and frost/hot spells. Qian et al. (2005) compared the AAFC-WG and LARS-WG using the data in Canada and indicated that the AAFC-WG model presented a better performance in simulation of dry and wet spells. Fodor et al. (2010) compared the MV-WG and LARS-WG based on the data from 109 meteorological stations across the USA. The results illustrated that the MV-WG presented a better performance in simulating precipitation amount and the distribution of dry and wet spell lengths. Hartkamp et al. (2003) compared three 'Richardson types' weather generators (including MARKSIM, SIMMETEO and WGEN) for crop modeling in northwest Mexico,. The results showed that SIMMETEO performed robustly at single locations, but MARKSIM presented a poor performance in capturing inter-annual variability and the length of wet spell. Chen et al. (2012a) compared three 'Richardson types' weather generators, including WeaGETS, CLIGEN and WGEN, and indicated that all generators underestimated the extreme dry spells, but performed well for reproducing precipitation occurrence. Overall, WeaGETS was found consistently better than the other two (WGEN and CLIGEN) in terms of reproducing precipitation, maximum temperature and minimum temperature. More recently, some studies focused on the comparison between stochastic weather generator and other types of statistical downscaling models, such as regression-based models or hybrid models. Sunyer et al. (2012) compared five different models, including Statistical Correction Method with

Change in Mean, Statistical Correction Method with Change in Mean and Variance, Markov Chain Weather Generator (MC-WG), LARS-WG and RainSim to investigate extreme rainfalls under future climate scenarios. These models relied on the ‘change factor’ method for projecting future changes of weather conditions in comparison to the current condition.

From the previous research works, it is found that very few generators are specifically designed for tropical regions like Singapore. This region is classified as tropical rainforest climate with no distinct seasons, and characterized by high humidity and complex rainfall. The maximum daily rainfall could reach up to 500 mm and the annual average rainfall is about 2,340 mm (NEA, 2014). Many previous generators use “dry/wet” judgment to separate rainfall into two groups and focus on wet group to fit the statistics of rainfall amount. This may not be sufficient in reflecting tropical rainfalls, as the wet group of rainfall exhibit a wide spectrum of rainfall magnitudes and might need further classification. Inspiring from the work of Apipattanavis et al. (2007), a separate treatment for extreme rainfall could improve the simulation of large rainfall amount, and keep lag-dependence statistics to ensure a more realistic result. It is also found that the rainfall in Singapore shows a high spatial variation, with e-folding correlation distances being about 10 km at hourly scales and 33 km at daily scales (Mandapaka and Qin, 2013). The existing generators are relatively weak in reflecting such highly-varied spatial correlations of rainfall over multiple sites due to their inadequacy in grouping rainfall magnitudes. Another reason for this is that many generators are linked with hydrological models or crop models for large-scale applications which may not highlight spatial correlations. In addition, there is a lack of comprehensive comparison study over different types of generators, especially for tropical regions.

Thus, this study aims to develop a novel weather generator, named Multisite Multivariate Semi-parametric Weather Generator (MMS-WG), for rainfall and

temperature simulations in the tropical region of Singapore. The proposed weather generator is based on four-state Markov Chain to estimate the status of daily rainfall; this is for the purpose of better reflecting the spectrum of magnitude for rainfall in such a region. Then, a semi-empirical distribution is employed to reproduce the rainfall amount for each rainfall type except for the dry day. For temperature simulation, two semi-empirical distributions are applied upon dry and wet day, respectively. The performance of the proposed generator will be compared with other well-known generators including WeaGETS (Chen et al., 2010a), LARS-WG version 5.5 (Semenov and Barrow, 1997; Semenov et al., 2010) and RainSim version 3.1.1 (Burton et al., 2008), which are representative of ‘Richardson types’, ‘serial types’, and ‘stochastic point-process model’, respectively. Section 2 gives a detailed introduction of MMS-WG and Section 3 introduces a configuration of other generators for comparison. Section 4 presents the study case and the related data and Section 5 shows the study result. A conclusion is drawn in Section 6.

4.2 MMS-WG Description

The proposed generator (i.e. MMS-WG) could be classified as ‘Richardson type’ as it is mainly based on the first-order four-state Markov chain. Figure 4.1 shows the schematic diagram of MMS-WG. To simulate multiple weather variables, the MMS-WG adopts a similar idea as LARS-WG (Semenov et al., 2010). The rainfall simulation is the basic module in the generator; simulation of other variables is conditioned upon the results of rainfall. Firstly, the Mean Areal Precipitation (MAP) (Mezghani and Hingray, 2007) is used as the input to MMS-WG. The occurrence of MAP event is determined using a first-order four-state Markov chain. Gregory et al. (1993) and Apipattanavis et al. (2007) indicated that the first-order multiple-state Markov model could better capture the seasonal variation of rainfall. The four states represent the classifications of rainfall intensity. Then, a semi-empirical distribution is used for fitting rainfall amount in each class (i.e. a specific state) of MAP. Finally,

Figure 4.1 Schematic diagram of MMS-WG

the K-nearest neighbor (KNN) method is used to spatially disaggregate MAP to rainfalls at multiple sites. For temperature simulation (e.g. including either maximum or minimum temperature), it is conditioned upon the regional dry/wet status. The temperatures in a dry-day and a wet-day are reproduced by two semi-empirical distributions separately. For simulation of multisite temperatures, the KNN method can also be used for spatial disaggregation similar to rainfall; but it is normally necessary when there is a significant spatial variation of temperature. In this study, KNN is not used for temperature disaggregation due to relatively a smaller fluctuation of temperature profile over Singapore Island. It should be noted that the

proposed MMS-WG could also be extended for modeling other variables (e.g. wind, radiation, and humidity) in a similar way as temperature, but this is not covered in this study. The details of MMS-WG are described in the followed sections.

4.2.1 Occurrence of rainfall

Based on the definition of ‘Richardson-type’ weather generator, the rainfall occurrence in this study is also estimated by the Markov chain. The basic form of Markov chain could be written as follows (Cogill, 2011):

$$P\langle X_{t+1} = x_{t+1} | X_t = x_t, \dots, X_0 = x_0 \rangle = P\langle X_{t+1} = x_{t+1} | X_t = x_t \rangle, \text{ and} \\ \begin{cases} x_0, \dots, x_{t+1} \geq 0 \\ t \geq 0 \end{cases} \quad (4-1)$$

where $X_0, X_1 \dots$ are random variables, and the possible value of X_t is called the state space. $P(X_{t+1}=x_{t+1}|X_t=x_t)$ is the transition probability. In this study, a first-order four-state Markov chain is used for simulation of wet/dry day status for the entire region based on daily rainfall (for single site) or MAP value (for multiple sites). It is fitted for each month individually. Based on Singapore’s rainfall characteristics, the four states are classified manually into dry day (daily rainfall or MAP < 0.014 mm), low intensity rainfall (0.014 mm ≤ daily rainfall or MAP < 3 mm), moderate intensity rainfall (3 mm ≤ daily rainfall or MAP < 50 mm) and high intensity rainfall (daily rainfall or MAP ≥ 50 mm). Hence, there are three states for the wet day. Table 4.1 shows the proportions of different rain states at each station based on the local observed rainfall characteristics. From the table, the proportions of low, moderate and high intensity rainfall are around 20%, 30% and 3%, respectively. The idea of classification of rainfall intensity is referred to the study of Apipattanavis et al. (2007), where it was found that the separation of extreme rainfall could improve the representation of heavy rainfall spells (Gregory et al., 1993; Apipattanavis et al.,

2007). The detailed procedures of simulating day status using Markov chain is described as follows:

STEP 1: Provide an initial value for the Markov chain. In this study, the initial value is estimated from the largest percentage of status, namely dry day. Therefore, the initial value is set to 1.

Table 4.1 Proportions of different states of daily rainfall in seven stations over Singapore

Station/Location	Dry	Low	Moderate	High
S24 (Northeast)	0.533	0.184	0.262	0.021
S40 (North)	0.434	0.229	0.310	0.027
S44 (Southwest)	0.466	0.208	0.296	0.030
S46 (Central)	0.454	0.213	0.307	0.026
S50 (Central)	0.461	0.214	0.297	0.028
S60 (South)	0.511	0.198	0.267	0.024
S66 (Northwest)	0.468	0.193	0.312	0.027

STEP 2: Estimate the followed day status. The initial probability P_i is randomly generated from a uniform distribution between $[0, 1]$, where i means the index of the days among a particular month ($i = 2, 3, 4, \dots, I$) and the total number of days is $(I - 1)$ (Apipattanavis et al., 2007). The simulation of Markov chain starts from the second day. Hence, the status of the second day is conditioned upon the status of the previous day, i.e. P_2 and transition probability. The transition probability is defined as the probability from the status of the previous day to the status of the current day (Apipattanavis et al., 2007). If the status of the first day is dry, the transition probabilities are used as thresholds. For example, the state of second day (D2) could be defined by the following equation:

$$\begin{cases} D2 = dry & \text{if } P_2 < P_{dd} \\ D2 = L & \text{if } P_{dd} \leq P_2 < (P_{dd} + P_{dl}) \\ D2 = M & \text{if } (P_{dd} + P_{dl}) \leq P_2 < (P_{dd} + P_{dl} + P_{dm}) \\ D2 = H & \text{if } (P_{dd} + P_{dl} + P_{dm}) \leq P_2 < 1 \end{cases} \quad (4-2)$$

where P_{dd} , P_{dl} , P_{dm} and P_{de} ($P_{de} = 1 - P_{dd} - P_{dl} - P_{dm}$) are defined as the transition probabilities of four states when the previous day belongs to a dry day; L , M and H represent the low, moderate and high intensity rainfall, respectively.

STEP 3: Repeat the previous step to generate the status sequence of rainfall for the whole month (Apipattanavis et al., 2007).

4.2.2 Semi-empirical distributions for rainfall amount and temperature

Once the day-status is identified, the semi-empirical distributions are used to describe rainfall amount and temperature. The semi-empirical distribution is calculated using the probability distribution function (PDF). The method is also based on the observed (empirical) distribution and defined histograms to re-produce simulated data which has the same PDF distribution with the observed one (Sopasakis, 2013). The idea is similar to that adopted in LARS-WG (Semenov and Stratonovitch, 2010). For the model input based on the observed data, define a histogram of empirical distribution with a number of disjoint categories, named bins or intervals; for each bin, find out the frequency of events, which will be used as the selection probability (Semenov and Stratonovitch, 2010). Then, in the generation process, the random values are reproduced in different bins based on the uniform distributions. The selection of the number of bins is vital for fitting empirical distribution. In the model of LARS-WG (version 5.5), 23 bins in histogram are used to fit the observed rainfall distributions; in our study, we use 50 bins based on direct trial-and-error test. In the past decades, many methods are developed to help seek a suitable number of bins, such as Struges' formula (Struges, 1926), Scott's normal reference rule (Scott, 1979) and

Freedman–Diaconis' rule (Freedman and Diaconis, 1981). The first two methods are generally used for normal distributions which is not suitable for this study. To verify if the number we have selected is suitable, we have tried to use Freedman-Diaconis (FD) rule for comparison. The results show that the number of bins selected by FD method performs worse in the most of statistical properties. In particular, the skewness and maximum data from direct trail-and-error test show a notably higher accuracy. The details are presented in Section 4.7. However, our selected bins (i.e. 50) may cause some empty-bins in extreme rainfall fitting; but this would not pose considerable effects on the final output based on our test. Technical details of the related procedures could be referred to the works of Semenov and Stratonovitch (2010) and Sopasakis (2013).

4.2.3 KNN for resampling temperature and spatial disaggregation of MAP (multisite option)

The KNN method is employed for spatially disaggregating MAP to multisite rainfall sequences. The conventional weather generators based on KNN normally adopt a stochastic selection scheme with a weighting function to generate multiple ensembles for the output (Sharif et al., 2007; Apipattanavis et al., 2007; Raje and Mujumdar, 2011). In this study, a cross-validation procedure is applied to select the K value. KNN method is followed the study of Nowak et al. (2010). The detailed steps of spatial disaggregation using KNN is given as follows:

STEP 1: According to the previous procedures, the synthetic MAP series is obtained based on Markov chain and semi-empirical distribution method. If the value of synthetic MAP equals to zero, the rainfall records at multiple stations are zero in that day. Otherwise, the non-zero (i.e. wet-day amount) synthetic MAP (**S**) value with a dimension of $L \times I$ (L is the number of wet days) would be used for spatial disaggregation.

STEP 2: The historical daily rainfall records at multiple stations are converted into the ratios of individual rainfall to the MAP value, represented by a matrix $\mathbf{H}$ with a dimension $N \times M$ where N is the number of non-zero MAP values in historical record and M is the number of rainfall stations. Let $\mathbf{O}$ be a vector of historical MAP (with a dimension $N \times 1$) which only represents the observed (historical) daily rainfall. Therefore, each row of $\mathbf{O}$ corresponds to the same row in $\mathbf{H}$. Then, the nearest neighbors of $\mathbf{S}$ are found from $\mathbf{O}$ based on the Euclidean distances between the elements in $\mathbf{S}$ and $\mathbf{O}$, respectively (Raje and Mujumdar, 2011). The number of the nearest neighbors (i.e. K value) should be carefully selected, as a smaller value of K means that the results would be affected by noise and a larger value of K would destroy the locality of the estimation and original distribution properties (Apipattanavis et al., 2007). Many studies have discussed the selection of appropriate K values (Lall and Sharma, 1996; Buishand and Brandsma, 2001; Mezghami and Hingray, 2009; Nowak et al, 2010). Based on our test for the study case, the K value is set to 10.

STEP 3: Use cross-validation to select the best K value. Firstly, the K nearest neighbors of each synthetic MAP in $\mathbf{S}$ are found from $\mathbf{O}$. For each neighbor, the corresponding ratios (denoted as a vector $\mathbf{R}_l, l = 1, 2, \dots, L$) could be identified in $\mathbf{H}$ at the same row, where l means the index of wet-day for the synthetic MAP data. The nearest neighbor's series could form a matrix $\mathbf{Z}$ with a dimension of $L \times K$, where K means the number of the nearest neighbors (i.e. 10 in this study). Let k ($k = 1, 2, \dots, K$) represent the index of column in $\mathbf{Z}$. Then, $k = 1$ means the nearest neighbor (e.g. the first column vector $\mathbf{Z}_1$), $k = 2$ means the second nearest neighbor (e.g. the second column vector $\mathbf{Z}_2$) and so on. Traditionally, the candidate neighbor in KNN is randomly selected from K potential neighbors using a decreasing kernel function (Mezghami and Hingray, 2009), which gives the highest weight to the nearest neighbor. In this study, we use cross-validation to search the best K value from matrix $\mathbf{Z}$. The procedures are: (i) form K groups of neighbors ($\mathbf{Z}_k, k = 1, 2, \dots, K$) based on

the columns of $\mathbf{Z}$ (i.e. each column of $\mathbf{Z}$ is one group, denoted as a vector $\mathbf{Z}_k$ with a dimension $L \times 1$); (ii) for each group $\mathbf{Z}_k$, find out the corresponding ratio matrix $\mathbf{RM}_k$ (the l^{th} row of $\mathbf{RM}_k = \mathbf{R}_l$) with a dimension of $L \times M$ from $\mathbf{H}$; (iii) obtain potential disaggregation results $\mathbf{DR}_k$ (with a dimension $L \times M$) by multiplying each element of $\mathbf{RM}_k$ with the corresponding row element of $\mathbf{S}$ (Nowak et al, 2010). After the above procedures, K groups of $\mathbf{DR}_k$ can be obtained. For each group, the mean absolute percentage error (MAPE) or root mean square error (RMSE) for seven statistical properties (i.e. mean, standard deviation, skewness, probability of wet day, maximum 5-day rainfall, 90th percentile of rainfall and percentage of extreme event) are calculated for each month at each station (Hessami et al., 2008; Fodar et al., 2010). The group with the smallest MAPE or RMSE value is selected as the final output of KNN spatial disaggregation. More details about the cross-validation procedures could be referred to study of Lu and Qin. (2014a).

4.3 Configuration of LARS-WG, RainSim and WeaGETS

This section shows the settings of LARS-WG, RainSim and WeaGETS for comparing with MMS-WG. The basic features of the three models are illustrated in Table 4.2. For other details, readers are referred to the works of Burton et al. (2008), Semenov and Stratonovitch (2010) and Chen et al. (2010a). For LARS-WG (version 5.5), QTEST is applied for searching the best random seed to guarantee the simulation reliability. The RainSim model (v3.1.1 in this study) could treat both single-site and multisite data (Burton et al., 2008). This model is based on the Neyman-Scott rectangular pulses to simulate the rainfall processes. For WeaGETS, different options of model setting are tested to choose the best one in our preliminary test. A third-order Markov chain is used for simulating precipitation occurrence; Gamma distribution is applied for generating precipitation amount. Both the low-frequency variability of precipitation and temperature data would be corrected at the monthly and yearly scales using power spectra of observed records (Chen et al., 2010a). In this

Table 4.2 Comparison of the procedures of weather variables simulation in LARS-WG, RainSim and WeaGETS

Weather Variable	LARS-WG ¹	RainSim ²	WeaGETS ³
Rainfall Status	Rainfall amount > 0 mm	Threshold to be set	Threshold to be set
Determination of rainfall status	(i) Lengths of alternate wet and dry sequences chosen from a semi-empirical distribution fitted to the observed series. (ii) To calculate the parameters for each month	(i) Based on the Neyman-Scott rectangular pulses (NSRP) model (ii) Storm (e.g. rainfall event) occurrence follows a uniform Poisson process. It also generates rain-cells with a Poisson random number, the time interval between rain-cells is independent and follows an exponential distribution	WeaGETS offers three options (i.e. first, second and third-order Markov models) to generate precipitation occurrence based on the previous day's status
Rainfall amount	Semi-empirical distribution based on observed data	(i) The duration and intensity of rain-cell are also independent and exponentially distributed. (ii) The rainfall intensity is equal to the sum of intensities of all rain-cells	One-parameter exponential distribution or two-parameter gamma distribution
Temperature	Normal distribution. The parameters are obtained by fitting Fourier series to the mean and standard deviation. Separate treatment for dry and wet day	Not Applicable.	First-order autoregressive model
Schemes for extreme-event simulation	In the new version (5.5), the number of intervals in semi-empirical distribution is changed from 10 to 23, which offer a higher accuracy for extreme data	Increase the intervals compared with the previous version for dealing with the extreme data	Correction of low-frequency variability using a Fast Fourier Transform (FFT) based on the power spectra of rainfall series
Others	Future climate scenarios based on relative change factor	Consider the spatial correlation of multisite rainfall; treatment of different timescales	Include the parameter-smooth scheme for rainfall.

Note: 1 = Long Ashton Research Station Weather Generator (LARS-WG, Semenov and Barrow, 1997); 2 = RainSim (Burton et al., 2007); 3 = Weather Generator École de Technologie Supérieure (WeaGETS, Chen et al., 2010a).

study, the three generators, including LARS-WG, WeaGETS and MMS-WG, are used for reproducing three local weather variables, including rainfall, maximum temperature, and minimum temperature. RainSim is only applied for reproducing rainfall. For all generators, 300 years synthetic data for each variable at each station is generated.

4.4 Study Case and Data

In this study, four weather generators are applied into the tropical urban area, Singapore. Singapore is a highly urbanized region with nearly constant temperature and pressure. The variation of monthly temperature for the whole year is concentrated within the range between 30.2 °C and 32.3 °C (NEA, 2009). Therefore, there is no true distinct of seasons. The 12 months are divided into dry and wet seasons based on rainfall amount. The dry season is from February to September and the wet season is from October to January of next year. Two monsoons exist: Northeast Monsoon from December to March and Southwest Monsoon from June to September (NEA, 2009). The wet season is mainly contributed by the first monsoon season. Rainfall in the western side of the island is more than that in the eastern side due to the ‘rainfall shadow’ phenomenon. Therefore, selection of weather stations should consider this problem and reflect the characteristic of spatial distribution. In this study, seven stations (spreading over the island) are chosen based on the locations, including S07, S24, S40, S46, S50, S60 and S66 (see Table 4.1). The rainfall historical record lasts for 30 years (from 1981 to 2010). The data quality for most of the stations is high, where the missing rates are below 1%. The historical daily temperature (including maximum and minimum temperatures) is extracted from National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) dataset for the period 1981-2010 (Saha et al., 2010). There are two grids to cover the entire Singapore region, including east grid and west grid. According to our preliminary test, the temperature data in the two grids are roughly

identical. The eastern grid contains 5 stations. Based on the correlation of mean regional precipitation (MAP) values, the east grid is selected and applied in this study. The CFSR temperature data is validated by comparing with the official data during the same period (NEA, 2014). The errors of daily maximum and minimum temperature are about 1.5% and 0.9% respectively.

4.5 Result Analyses

4.5.1 Model evaluation

The evaluation of the model performance includes both rainfall and temperature (Tmax and Tmin). Four basic properties of rainfall, including average daily rainfall (MEAN), standard deviation (STD), skewness (SKEW) and probability of wet day (PWET), and three extreme indicators including maximum 5-day rainfall (M5D), 90th percentile of rainfall amount (PERC90) and percentage of extreme rainfall (PEXT) are calculated. Based on the station-year method (Buishan, 1991), the regional extreme rainfall amount are also reviewed. The spatial distribution of rainfall is evaluated by using the inter-site correlation. For temperature (including Tmax and Tmin), the mean and standard deviation for each month are examined. The closeness of the simulated and observed statistical properties is evaluated by RMSE (Liu et al., 2011a), MAPE (Ghosh and Kathar, 2012) and CC (Liu et al., 2011b) using the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_{obs,i} - x_{sim,i})^2}{N}} \quad (4-3)$$

$$MAPE = \frac{\sum_{i=1}^N abs(x_{obs,i} - x_{sim,i})}{N} \quad (4-4)$$

$$CC = \frac{\sum_{i=1}^N (x_{obs,i} - \bar{x}_{obs,i})(x_{sim,i} - \bar{x}_{sim,i})}{\sqrt{\sum_{i=1}^N (x_{obs,i} - \bar{x}_{obs,i})^2 \sum_{i=1}^n (x_{sim,i} - \bar{x}_{sim,i})^2}} \quad (4-5)$$

where x_{obs} represents the observed data; x_{sim} represents the simulated data; $\bar{x}_{obs}$ means the average value of observed data; $\bar{x}_{sim}$ means the average value of simulated data; N means the number of data.

4.5.2 Rainfall simulation

The proposed MMS-WG model could generate synthetic weather data for either single site or multiple sites. For the single-site option, the weather data at a single site should be used instead of the MAP data, and there is no need to use the KNN method for spatial disaggregation. In this section, the comparison of various generators is divided into two parts: rainfall simulations at (i) each site separately (single-site option), and (ii) multiple sites all together (multisite option). Firstly, the single-site option is adopted by both MMS-WG and RainSim to generate rainfall data at S24 and S44 stations. Secondly, the two generators use the multisite option to generate rainfall data for all seven stations. LARS-WG and WeaGETS will run at single sites in both parts.

Performance of single-site rainfall reproduction

Figure 4.2 shows the comparison between observed and simulated four statistical properties of rainfall at site S24 and S44. The single-site option is adopted by MMS-WG and RainSim. MMS-WG presents an overall superior performance, with RMSE values being the lowest for most of the properties (except for MEAN which ranks the second). From Figure 4.2a, all models perform satisfactory in reproducing MEAN. WeaGETS has the best performance in terms of MEAN, but shows much

poorer fitting for reproduction of STD (Figure 4.2b) and SKEW (Figure 4.2c). WeaGETS illustrates a significant overestimation for SKEW in February at both stations. For PWET (Figure 4.2d), RainSim, LARS-WG and WeaGETS show somewhat underestimations for almost all months at the two stations; while MMS-WG presents the lowest error. Figure 4.3 shows the performances of the four generators in terms of three extreme indicators at stations S24 and S44. In terms of M5D, all four models show overestimations at two stations, especially for RainSim (i.e. RMSE = 152.1 mm for S24 and RMSE = 101 mm for S44); however, MMS-WG shows the lowest RMSE value. For PERC90 (Figure 4.3b1 and 4.3b2), MMS-WG also presents an outstanding performance with a much lower RMSE value than others. For PEXT, the result of MMS-WG is also the best. In addition, the lag-1 autocorrelation is also an important property to reflect the rainfall characteristics.

Figure 4.2 Comparison between the observed and simulated statistical properties of rainfall using four weather generators at sites S24 and S44. Note: 1 represents station S24; 2 represents station S44; a, b, c, and d represent MEAN, Standard Deviation (STD), Skewness (SKEW), and Probability of wet day (PWET), respectively; O, L, R, W and M represent observation, LARS-WG, RainSim, WeaGETS and MMS-WG, respectively; Single-site option is adopted by both MMS-WG and RainSim.

Figure 4.3 Comparison between the observed and simulated extreme indicators using four weather generators at sites S24 and S44. Note: 1 represents station S24; 2 represents station S44; a, b, and c represent maximum 5-day rainfall (M5D), 90th percentile of rainfall (PERC90) and percentage of extreme rainfall (PEXT), respectively; L, R, W and M represent LARS-WG, RainSim, WeaGETS and MMS-WG, respectively. Single-site option is applied into MMS-WG and RainSim.

It is examined based on the simulated result of S24 (i.e. which is not shown in the figure). MMS-WG also shows a better fit with the smallest RMSE (i.e. 0.037); the RMSE values for LARS-WG, RainSim and WeaGETS are 0.093, 0.052 and 0.082, respectively. This is because the four-state Markov chain could provide more details about the state of the previous day than traditional way like two-state processes.

Overall, for single-site rainfall simulation, MMS-WG outperforms other generators in terms of most of the statistical properties, especially for SKEW, PWET, PERC90

and PEXT. LARS-WG presents a relatively better capability in reproducing SKEW, M5D and PEXT, but shows weakness in simulating PWET and PERC90; RainSim has a relatively better performance for most of the properties, but is poor for M5D; WeaGETS provide the best results for MEAN, but shows much poorer performance in terms of STD and SKEW.

Performance for multisite rainfall reproduction

This section shows the performances of the four models in reproducing rainfall at seven stations. Multisite option is adopted by MMS-WG and RainSim. Table 4.3 lists the RMSE values of statistical properties using four weather generators. From the table, WeaGETS has the best performance for MEAN; but worst performance for STD and SKEW. LARS-WG presents the best results for reproduction of STD,

SKEW, M5D and PEXT, but relatively poorer performance for MEAN and PWET. MMS-WG provides the best fit for PWET, but a relatively worse fit for MEAN; for other indicators, the performance of MMS-WG generally ranks in the second position. Compared with the results from single-site simulation at S24 and S44, the RMSE values of MMS-WG become higher due to adoption of multisite option. This implies that the non-parametric KNN method for spatial disaggregation could affect the simulation performance, possibly due to the reasons of: (i) the trade-off procedure of K value selection; (ii) the significant spatial variation of rainfall in this region. Overall, LARS-WG shows the best result followed by MMS-WG, where the average MAPE values for LARS-WG, RainSim, WeaGETS and MMS-WG are 0.096, 0.161, 0.150 and 0.130, respectively.

Table 4.3 Comparison of RMSE values of observed and simulated statistical indicators among four weather generators.

RMSE	Model	S24	S40	S44	S46	S50	S60	S66	AVE
Mean	L	0.371	0.336	0.279	0.251	0.207	0.308	0.512	0.323
	R	0.298	0.472	0.428	0.460	0.441	0.375	0.453	0.418
	W	0.163	0.084	0.062	0.082	0.053	0.043	0.100	0.084
	M	1.054	0.394	0.552	0.259	0.551	0.415	0.437	0.523
STD	L	0.767	0.650	0.530	0.662	0.601	0.847	0.760	0.688
	R	1.710	0.925	0.907	0.786	0.554	1.419	1.168	1.067
	W	2.150	1.460	1.242	1.211	1.087	0.862	1.695	1.387
	M	0.621	1.217	1.590	0.744	1.370	0.897	0.717	1.022
SKEW	L	0.217	0.287	0.337	0.198	0.210	0.214	0.395	0.265
	R	1.119	0.900	0.773	0.739	0.715	0.737	0.896	0.840
	W	1.442	1.104	0.871	0.893	0.790	1.046	1.325	1.067
	M	1.186	0.766	0.347	0.499	0.429	0.885	0.562	0.668
PWET	L	0.067	0.070	0.080	0.059	0.051	0.063	0.052	0.063
	R	0.053	0.096	0.070	0.078	0.072	0.059	0.066	0.071
	W	0.041	0.049	0.043	0.043	0.045	0.041	0.036	0.043
	M	0.051	0.030	0.033	0.028	0.021	0.049	0.017	0.033
M5D	L	100.84	67.31	44.67	100.96	74.87	93.53	73.10	79.33
	R	130.71	141.20	189.92	194.28	196.19	159.31	107.55	159.88
	W	121.52	114.14	100.57	93.03	99.36	90.78	161.40	111.54
	M	129.57	83.87	79.64	67.94	105.14	117.93	70.01	93.44
PERC 90	L	3.848	3.431	4.068	3.047	2.968	3.350	2.970	3.383
	R	4.285	5.405	4.384	3.229	3.180	4.599	4.553	4.234
	W	4.094	3.022	2.639	2.459	2.345	3.018	2.580	2.880
	M	3.840	2.435	3.445	2.556	3.387	3.027	3.753	3.206
PEXT	L	0.003	0.002	0.002	0.003	0.003	0.002	0.003	0.003
	R	0.004	0.003	0.003	0.003	0.004	0.007	0.003	0.004
	W	0.005	0.004	0.004	0.003	0.004	0.005	0.004	0.004
	M	0.009	0.005	0.006	0.004	0.006	0.004	0.004	0.005

Note: L = LARS-WG; R = RainSim; W = WeaGETS; M = MMS-WG; AVE = the average value; MEAN = average daily rainfall; STD = standard deviation; SKEW = skewness; Pwet = probability of wet day; M5D = maximum 5-day rainfall; PERC90 = 90th percentile of rainfall; PEXT = percentage of extreme rainfall (i.e. above 50 mm/day); multisite option is adopted by RainSim and MMS-WG models.

Figure 4.4 shows the comparison of dry- and wet- spell between observed and simulated data at S46. In Figure 4.4a, the two ‘Richardson type’ weather generator, WeaGETS and MMS-WG both present poor performances for dry spell. Dobi et al. (2000) have mentioned that Markov chain method has the weakness in generating long dry spells (Dodi et al., 2000; Fodor et al., 2010). And the MMS-WG is also affected by the KNN disaggregation procedure. For the wet-spell (i.e. Figure 4.4b), all of four models present somewhat underestimations. The results demonstrates that MMS-WG is good at reproduction of rainfall frequency (i.e. PWET), but not superior in simulating dry- and wet- spells.

Figure 4.4 Comparison of dry- (a) and wet- (b) spell between the observed and simulated data at s46 station

Figure 4.5 presents the quantile-quantile plot of daily MAP values. This indicator is important in reflecting the spatial-temporal variability of rainfall for the entire region, and is useful for hydrological modeling studies (Moulin et al., 2009). The two single-site weather generators, LARS-WG and WeaGETS, show significant underestimation in simulating MAP. This is because the mean areal rainfall is easily attenuated by a lack of spatial correlation, even if some individual sites may exhibit high rainfall amounts. RainSim and MMS-WG show much better results of MAP simulations, especially when the daily rainfall depth is lower than 120 mm. Figure 4.6 illustrates the comparison of observed and simulated inter-site correlation coefficients from the four generators. MMS-WG notably outperforms other generators with the CC value being 0.989. RainSim shows somewhat fluctuations in simulating spatial correlations at different inter-gauge distances. This demonstrates that the KNN method could more reliably capture the spatial characteristic of rainfall than the parametric method adopted in RainSim. LARS-WG and WeaGETS are totally incapable of keeping spatial correlations of multisite rainfalls.

Figure 4.5 Quantile-quantile plot of the mean areal precipitation (MAP) data

Figure 4.6 Comparison of observed and simulated inter-site correlation coefficients

Frequency Analysis of regional extreme rainfalls

The station-year method is applied to assess the model performance in capturing regional rainfall extremes. In Singapore, the Public Utilities Board (PUB) also used the station-year method to develop the Intensity-Duration-Frequency (IDF) curve as a guideline for surface water drainage system design (PUB, 2011). In this study, the 30-years rainfall record at seven stations is combined into one station-year data. Gumbel distribution is found suitable to fit the annual maximum data for this region according to the study of Chang and Hiong (2013). The simulated data from MMS-WG and RainSim are both based on multisite option. Figure 4.7 presents the intensity-frequency curves based on the rainfall data fitted by the four generators. RMSE values are calculated by the rainfall amount for 12 return periods (including 2-, 3-, 5-, 10-, 15-, 25-, 50-, 100-, 200-, 500- and 1000-year). It appears that all models perform well in capturing rainfall extremes, with RMSE values being generally lower than 7 mm/day. MMS-WG shows the highest RMSE value (i.e. 6.653), and WeaGETS slightly outperforms others.

Figure 4.7 Analysis of regional rainfall frequency based on Gumbel distribution; the number in brackets is the root-mean-square-error (RMSE)

4.5.3 Reproduction of temperature

In this section, three weather generators, LARS-WG, WeaGETS and MMS-WG are applied for simulation of maximum and minimum temperatures (e.g. T_{max} and T_{min}). As mentioned before, the temperature record is only obtained from one station due to nearly uniform spatial distribution of temperature. For all models, temperature is simulated upon the condition of mean regional rainfall (MAP). Figure 4.8 shows the comparison of observed and simulated values of T_{max} and T_{min} for each month. The results show that all of three generators could well reproduce T_{max} and T_{min} , in terms of monthly mean temperature (Figure 4.8a1 and 4.8a2). The MMS-WG shows a superior performance with much lower RMSE values for both T_{max} and T_{min} (i.e. 0.024 and 0.006, respectively). Regarding standard deviation (Figure 4.8b1 and 4.8b2), WeaGETS has a somewhat overestimation for all months, while LARS-WG shows a notable underestimation. Again, MMS-WG shows an outstanding fit (i.e. RMSE values are 0.011 and 0.008 for T_{max} and T_{min} , respectively). For the MAX and MIN values of each month, WeaGETS performs quite poor both for T_{max} and

Tmin, with the RMSE values being generally above 1; LARS-WG also shows inferior performance than MMS-WG. This may be because the normal distribution

Figure 4.8 Comparison of observed and simulated maximum temperature (Tmax) and minimum temperature (Tmin). Note: a, b, c and d represent MEAN, Standard deviation (STD), Maximum (MAX) and Minimum (MIN) respectively; 1 and 2 represent Tmax and Tmin, respectively.

adopted in LARS-WG and the first-order linear autoregressive model in WeaGETS both could not well reflect temperature profile in this region. However, it is found that LARS-WG provides excellent reproduction of cross-correlation between T_{min} and T_{max} (i.e. 0.17), which is the closest to observed one (being 0.19). WeaGETS and MMS-WG show serious overestimation (0.59) and underestimation (0.06) for this property, respectively.

4.5.4 Further discussions

Based on the study results, MMS-WG shows a superior performance in reproducing both rainfall and temperature than other conventional methods for the tropical region of Singapore. The first-order four-state Markov chain seems to better reflect the rainfall patterns in terms of basic statistics and autocorrelation. KNN method shows good capability in keeping spatial correlation at this region which is characterized by significant spatial variations. For single-site simulation, MMS-WG showed outstanding performances in terms of many statistical indicators, especially the monthly standard deviation, rainfall frequency, and extreme properties. For multisite simulation, the proposed model presented a notable advantage in capturing spatial distributions of rainfalls while keeping a reasonable fit of basic statistics.

There are some limitations of the proposed weather generator which could be enhanced in further investigations. Firstly, the performance of MMS-WG is relatively poor in fitting dry/wet spell and cross correlation between maximum and minimum temperatures. The former one may be improved by better settings of Markov chain. For example, the initial value could be estimated by the initial probability P and the observed unconditional probability of rainfall. The probability of the connection days between two months could be obtained by a special transition probability (Apipattanavis et al., 2007). The cross-correlation problem could be improved by generating one variable first and seek another based on KNN. Secondly, MMS-WG is

found good at simulating weather data at the tropical climate conditions. For other regions, its advantage and suitability should be further verified. Thirdly, MMS-WG is meant for simulating historical rainfall patterns and incapable of projecting future climate scenarios. One potential solution is to use a change-factor approach, similar to that adopted in LARS-WG (Semenov and Stratonovitch, 2010). The above-mentioned limitations and possible improvements will be left to our future works. It should also be noted that the selection of four states for Markov chain in this study is based on the rainfall characteristics of Singapore and the major purpose is to demonstrate the advantage of introducing classification for better performance. It is also possible to select more than four states, which may further improve the property of autocorrelation. However, adjustment of the number of intervals in rainfall amount simulation using empirical distributions is necessary. Also, attention should be paid on the linkage of different months.

4.6 Summary

This study proposed a ‘Richardson type’ semi-parametric weather generator, named MMS-WG, for both rainfall and temperature simulations. For rainfall simulation, MMS-WG used a first-order four-state Markov chain to estimate the day status based on the intensity of mean areal precipitation (MAP), which included dry day, low-intensity rainfall, moderate-intensity rainfall and high-intensity rainfall. Then, three semi-empirical distributions, corresponding to three wet-day rainfall magnitudes, were used for simulating rainfall amount of MAP. Finally, the KNN spatial disaggregation method with cross-validation was employed to generate the rainfall sequence for each station. The temperature (including Tmax and Tmin) simulation was also conditioned upon the MAP data. By judging the status of dry or wet day, two semi-empirical distributions were applied. For a single-site rainfall simulation, MMS-WG could be used without KNN spatial disaggregation.

Using rainfall data at seven local stations in Singapore island, MMS-WG was compared with three well-known weather generators (including LARS-WG, WeaGETS and RainSim). The results demonstrated that MMS-WG generally outperformed other generators in terms of not only basic statistical indicators (like rainfall mean, standard deviation, and extremes), but also spatial correlations. However, similar to other ‘Richardson type’ models (such as WeaGETS), MMS-WG showed a relatively poor performance in reproducing long dry- and wet-spells. For temperature simulation (using single-grid data from CFSR), MMS-WG was compared with others, and demonstrated superior performances in terms of simulating the maximum and minimum temperatures. Overall, the proposed new generator is novel in the sense of (i) employing combined Markov chain and semi-empirical distributions in simulating rainfall and other weather variables; (ii) using four-state Markov chain to classify rainfall intensity for improvement of rainfall reproduction at tropical regions; (iii) applying KNN for spatial disaggregation which could well keep spatial correlation among multiple sites. The generators are limited mainly in its relatively poor performance in simulating dry/wet spell and incapability of projecting future climate-change conditions. The model’s applicability and advantage for other regions are also worthy of further investigations.

4.7 Supporting Information

Table 4.4 The comparison of simulation result based on Freedman-Diaconis rule and 50 bins.

RMSE	FD-RE	50 Bins
MEAN	0.251	0.234
STD	0.534	0.621
SKEW	0.227	0.126
PERC90	1.328	1.551
MAX	1.161	0.307

To verify if the number we have selected is suitable, we have tried to use Freedman-Diaconis (FD) rule for comparison. The comparison is based on the data of S24, and five properties of rainfall including mean, standard deviation, skewness, 90th percentile and maximum data. From this table, the results show that the number of bins selected by FD method leads to slightly better simulation of standard deviation and 90th percentile, but worse in terms of others.

CHAPTER 5 EVALUATION OF FUTURE RAINFALL TRENDS FOR SINGAPORE: COMPARISON OF FOUR DOWNSCALING OPTIONS

5.1 Introduction

In the past decades, the number of extreme weather events, such as heavy rainfalls and heat waves, presented an apparently increasing trend (Coumou and Rahmstorf, 2012). The Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) from Intergovernmental Panel on Climate Change (IPCC) has also indicated that the frequency of heavy rainfall could increase in many regions over the world in the 21st century (Benestad et al., 2012; Seneviratne et al., 2012). Southeast Asia is considered particularly vulnerable to climate change as many countries are exposed with many climate-related hazards, like cyclones, rainfall extremes, floods and droughts (Sharma et al., 2007; Yuen and Kong 2009). For tropical urban areas, like Singapore, the increasing heavy rainfall also resulted in serious urban flash flood problems in the past years (PUB, 2014).

Prediction of future climate is an important task for adaptation study in reducing the impact of disaster losses. General Circulation Models (GCMs) have been widely used for investigating the climate information under different emission conditions but their coarse spatial resolution and bias problem hinder direct applications in impact studies (Sharma et al., 2007; Coumou and Rahmstorf, 2012). The downscaling approaches have been successfully used to mitigate the resolution issues (Wilby and Wigley, 1997; Fowler et al., 2007; Orskaug et al., 2011; Benestad et al., 2012; Ahmed et al., 2013). Dynamical downscaling is one of the major types and its applications have been reported in many countries like Canada (Caya and Laprise, 1999), US (Caldwell et al., 2009), Europe (Soares et al., 2011), Africa (Ratnam et al., 2013), and Asia

(Mannig et al., 2013). The statistical downscaling is another major type, with some well-known methods including LARS-WG (Long Ashton Research Station – Weather Generator, Semenov and Barrow, 1997), SDSM (Statistical DownScaling Model, Wilby et al., 2002), GLIMCLIM (Generalized Linear Modelling of daily CLIMate sequences, Chandler and Wheater, 2002), Bias Correction and Spatial Disaggregation SVM (Support Vector Machine, Tripathi et al., 2006) and ASD (Automated Statistical Downscaling tool, Hessami et al., 2008).

Generally, the main idea of using statistical approaches is to build a direct relationship between large-scale predictors and local weather data (Fowler et al., 2007). Over the past years, the reanalysis data (e.g. National Centers for Environmental Prediction) is generally used as the observed large-scale predictors and the observed local weather variables (e.g. precipitation, temperature, solar radiation and etc.) are considered as predicands. After establishment of the statistical relationship, the output from GCMs is applied to project climate scenarios under either current or future periods (Wilby et al., 2002). Another idea is to establish the relationship between GCM outputs (e.g. temperature, precipitation) and local weather data based on bias correction and spatial disaggregation method (Sharma et al., 2007, Salvi et al., 2011). Wood et al. (2002) used bias correction and spatial disaggregation to generate high resolution weather information based on the precipitation from GCMs output. Sharma et al. (2007) applied the spatial disaggregation of bias corrected GCM precipitation for studying the climate change impact on runoff using HEC-HMS at Thailand. Ahmed et al. (2013) developed a modified method of Bias Correction and Spatial Disaggregation (BCSD), named Statistical Downscaling and Bias Correction (SDBC), to generate finer resolution data for maximum/minimum temperatures and rainfall sequences from six GCMs and four RCMs at U.S. northeast. The results indicated that the bias correction could enhance the output for both GCM and RCM outputs.

To evaluate the variability of weather variables under climate change, different statistical downscaling methods could be applied. Mearns (2009) pointed out that the GCM boundary is the main source of uncertainty for downscaling techniques, and different downscaling methods (based on even the same GCM output) could lead to notably varied future conditions. Raje and Mujumdar (2011) applied three different downscaling methods, including conditional random field (CRF), K-nearest neighbor (KNN) and support vector machine (SVM) to project future precipitation in Punjab region, India. The results demonstrated that the three downscaling methods provided different projections. Eisner et al. (2012) applied two methods for adjusting GCM bias, and used the outputs for large scale modeling of flood flows. The results presented significant different trends for future period. For the study area, the quality and quantity of large scale predictors (i.e. GCM output) are not well-content. However, the predictor is critical for statistical downscaling (Fowler et al., 2007), and would affect the prediction of future scenarios.

Due to the existence of bias and resolution problems, GCM outputs are generally difficult to be used directly for climate change impact studies (Sharma et al., 2007; Rashied et al., 2013). This is especially true for tropical regions in Southeast Asia, where there is a high degree of sensitivity and uncertainty of GCM predictions (Holland et al., 2005; Buytaert et al., 2009). For example, the convective rainfall in our study region, Singapore Island, presents unstable characteristics and has rapidly changing intensity. It may affect establishing empirical relationship based on statistical method. In addition, there are a limited number of studies that have provided evaluation of uncertainty using different downscaling methods in such a region. Thus, the objective of this study is to compare four different downscaling models in projecting future rainfall variations in the tropical region of Singapore. The predictors from CGCM3 A2 scenario during period of 1980-2099 will be used to project both current and future conditions. For future projections, the areal annual rainfall and regional frequency analysis at different periods will be examined.

5.2 Methodology

Figure 5.1 The methodology frameworks of (a) GQK, (b) BCSTD, (c) ASD and (d) Modified KNN-BNN

Four different models are applied in this study to project the future rainfall variations under climate change. The first one is named GQK (Generalized linear model – Quantile regression – K nearest neighbor) model, based on the idea of Mezghani and Hingray (2009). It consists of three sub-models, including generalized linear model (GLM), quantile regression neural network and K nearest neighbor (KNN) method. The second model is the Bias Correction with Spatial and Temporal Disaggregation (BCSTD) model, which is an enhanced method based on the study of Sharma et al. (2007). The third model is based on the traditional method, i.e. Automated Statistical Downscaling (ASD), which has been successfully applied in many regions with different climatic conditions. The fourth one is the Modified KNN-BNN model, based on the work of Lu and Qin (2014b) by adding the capacities of projecting future conditions and multisite downscaling. Figure 5.1 shows the methodology frameworks for the four methods. Except for ASD (as it has its own adjustment module), the other three models all need bias correction, in order to make sure the data from GCMs are consistent with the reanalysis (or observed) data (Rashid et al., 2013). In addition, the application of BCSTD method is under the assumption that there are only three stations in the grid of GCM. In this study, the bias correction for rainfall and large scale predictors is based on the empirical quantile mapping method (Boe et al., 2007; Gudmundsson et al., 2012).

5.2.1 Generalized linear model-Quantile regression-K nearest neighbor (GQK) model

The GQK model consists of three sub-models for daily rainfall downscaling: areal occurrence model, areal amount model and spatial disaggregation model. The areal occurrence model is based on GLM in the form of logistic regression (Beckmann and Buishand, 2002; Mezghani and Hingray 2009) to generate the probability of wet day (π_t). And then, an independent uniform random variable (μ_t) would be generated by a random generator. There are twofold procedures to estimate if a day is wet or dry.

Firstly, the initial state could be estimated by the following equation (Mezghani and Hingray, 2009):

$$\begin{cases} y_t = 1 & \mu_t > \pi_t \\ y_t = 0 & \mu_t \leq \pi_t \end{cases} \quad (5-1)$$

where y_t means the initial state of the t^{th} day, 1 means a wet day, and 0 means a dry day. In this study, 30 ensembles would be generated by the random generator. Therefore, there are 30 groups of the initial status. And then, the dry-day probability (p_t) of 30 ensembles for each day is calculated. A cross-validation procedure is applied for determining the optimum threshold o_t of dry-day probability based on the calibration data. The final states for prediction data is estimated by the following equation:

$$\begin{cases} f_t = 1 & p_t < o_t \\ f_t = 0 & p_t \geq o_t \end{cases} \quad (5-2)$$

where f_t is the final state for the t^{th} day of areal rainfall occurrence, 1 means a wet day, and 0 means a dry day.

The mean areal rainfall amount in a wet day is calculated by quantile regression neural network (QRNN) with pseudo-random generator (Cannon, 2011). QRNN, an artificial neural network extension of quantile regression, is developed by Cannon (2011) and applied for downscaling precipitation at Vancouver, Canada. A cross validation procedure is included to estimate the hidden nodes. The technical details of the model could be referred to Cannon (2011). In this study, the QRNN method is used for calculating different quantiles. Then, the GCM data could be divided into three periods: 1980-2010, 2011-2050 and 2050-2099. The calculated quantiles for each period could generate an empirical probability distribution function (EPDF). Based on the EPDF, the pseudo-random generator is used to generate the areal rainfall amount. The generator is similar to the method adopted in LARS-WG

(Semenov and Stratonovitch, 2010) and the technical details could refer to the studies of Sopasakis (2013) and Semenov and Stratonovitch (2010). In this study, 30 ensembles would be generated for the mean areal amount in each period.

Based on first two sub-models, the mean areal rainfall sequence would be obtained. Then, the KNN method is applied for spatial disaggregation to generate single site data from areal rainfall sequence. The Euclidean distance is used for searching the K nearest neighbors. The potential neighbor is selected randomly based on the decreasing kernel function with given weights (Lall and Sharma, 1996; Mezghami and Hingray, 2009; Nowak et al., 2010). The details of KNN method could be found in the studies of Mezghami and Hingray (2009) and Nowak et al. (2010).

5.2.2 Bias Correction with Spatial and Temporal Disaggregation (BCSTD) model

In this model, the input data include the observed monthly rainfall of observed areal data and GCM grid data. The bias correction is based on the empirical quantile-based mapping method (Boe et al., 2007; Gudmundsson et al., 2012; Lafon et al., 2013), which makes adjustment of the GCM data by comparing the cumulative distribution functions (CDFs) between the observed and GCM variables (Ahmed et al., 2013). The technical details of applying such a bias correction could be referred to the studies of Salvi et al. (2011) and Gudmundsson et al. (2012). After bias correction, the KNN method (i.e. refer to the *step c* of GQK model) is used to spatially and temporally disaggregate the adjusted GCM monthly rainfall to daily rainfalls at multiple sites (Mezghani and Hingray, 2009). To keep the spatial correlations among multiple stations, the temporal disaggregation is carried out first to generate daily areal rainfall amount; then, the spatial disaggregation is employed to produce single-site rainfall at daily timescale.

5.2.3 Automated Statistical Downscaling (ASD) tool

The ASD model is a regression-based model which is similar to SDSM. It chooses the large-scale predictors automatically based on the backward stepwise regression and partial correlation coefficients (Hessami et al., 2008). It provides two regression methods including the multiple linear regression and ridge regression. The ASD model includes two sub-models, the occurrence model and the amount model for rainfall simulation. For more details of the ASD model, readers are referred to the Chapter 3 and the study of Hessami et al. (2008).

5.2.4 Modified K-nearest neighbor – Bayesian neural network (KNN-BNN) model

Modified KNN-BNN is modified from the KNN-BNN model reported in the study of Lu and Qin (2014b). There are two major improvements: (i) the model could address multi-site downscaling by introducing KNN for spatial disaggregation; (ii) the error analysis in the original model has been replaced with method of Mezghani and Hingray (2009) based on Gamma distribution to better address accuracy and uncertainty. In this model, the predictor selection in the classification procedures (i.e. dry/wet day and rainfall amount group) is based on consideration of both two-sample Kolmogorov–Smirnov test and cross-validation results; the predictor selection for amount calculation is based on Spearman correlation coefficients.

There are three procedures of in applying Modified KNN-BNN model. Firstly, the KNN method is used to estimate the regional dry/wet day status based on NCEP reanalysis data and the observed mean areal rainfall. If the day is a wet day, KNN method is further applied for classification of rainfall groups based on rainfall intensity. In this study, six groups are adopted based on the try-and-error method. The cross-validation of K value selection is based on the observed proportions of each

group during the calibration period (i.e. 1980-2000) and a single K is selected. Secondly, the mean areal rainfall amount is calculated. For the lower intensity rainfall group (i.e. the rainfall amount below 3 mm/day), a stochastic random generator, based on the observed distribution, is used (Semenov and Stratonovitch, 2010; Sopasakis (2013). For other groups of rainfall, BNN is employed for calculating the mean areal rainfall amount. Different from the original version, the modified model uses the equations proposed by Mezghani and Hingray (2009) to generate ensembles:

$$P = \bar{P} \times u_t \quad (5-5)$$

$$u_t = k^{-1} \times \text{Gam}(k, 1) \quad (5-6)$$

where P is the calculated mean areal rainfall amount; $\bar{P}$ is the output from BNN model; u_t is a random variable with a mean of 1; $\text{Gam}(k, 1)$ is the standard gamma variable with shape parameter k and scale parameter 1; the k could be calculated by equation $k = 1/CV^2$, where CV is the coefficient of variation of observed mean areal rainfall amount for each group. Finally, the KNN method is used for spatial disaggregation to model single site rainfall sequence similar to GQK model.

5.3 Study Area and Data

The study area is Singapore Island, which is located in the tropical area with no distinct season. The average annual rainfall amount is around 2,300 mm, and the rainfall in October to January is generally higher than that in other months (Mandapaka and Qin, 2013). From the year of 1980, the maximum hourly rainfall presented an increasing tendency at a rate about 10 mm/decade and many serious urban flash flood problems were observed during the past years (PUB, 2010). Considering climate-change may further exacerbate the risk of extreme events, it is desired that the rainfall variations in the future period in such a region be examined for the benefit of anticipating potential risks and guiding adaptation planning.

The observed rainfall data is collected from three rainfall gauges, including S50, S60 and S66, which are situated in the Central, South and North-West of the island, respectively. The data period is from 1980 to 2010 with very few missing record. For the large-scale predictors, the NCEP/NCAR reanalysis data (Kalnay et al., 1996 and 2001; DAI, 2008) is considered as the observed atmospheric variables and used for training the downscaling models and adjusting the GCM output. The CGCM3 A2 (DAI, 2008) is used for generating future scenarios in this study. The NCEP/NCAR reanalysis data have been interpolated into the CGCM3 grids (DAI, 2008). The simulated rainfall data of CGCM3 A2 output is extracted on a monthly timescale. Considering the different periods for three datasets (i.e. rain gauge 1980-2010, NCEP reanalysis data 1961-2000; CGCM3 A2 data 1961-2099), the baseline periods for predictor correction and monthly rainfall correction are defined as 1980-2000 and 1980-2010, respectively. The verification period for three methods is from 1980 to 2010.

5.4 Results Analysis

5.4.1 Bias-corrected GCM output

Figure 5.2 The cumulative distribution functions (CDFs) for (a) SHUM and (b) S500 based on reanalysis, CGCM3 A2, and bias-corrected CGCM3 A2 data. Note: C3A2

means CGCM3 A2 emission scenario; SHUM represents near surface specific humidity and S500 represents specific humidity at 500 hPa height.

Figure 5.3 Empirical CDFs of observed monthly mean areal rainfall (OBS), original GCM monthly rainfall (C3A2), and corrected GCM monthly rainfall (Corrected C3A2)

Bias-corrections are implemented for the methods of Wood et al. (2002), Sharma et al. (2007), Salvi et al. (2011), Ahmed et al. (2013) and etc. based on (i) the reanalysis data from 1980 to 2000 for GCM predictors, and (ii) observed monthly rainfall data from 1980 to 2010 for GCM rainfall output. The GCM is based on CGCM3 A2 scenario. Figure 5.2 shows the comparison among reanalysis data, original GCM output, and corrected GCM output for near surface specific humidity (SHUM) and specific humidity at 500 hPa height (S500). From Figure 5.2(a), the original SHUM presents an underestimation when the cumulative probability is below 0.25 and a

slight overestimation when the cumulative probability is above 0.25. For S500 in Figure 5.2(b), the original GCM data shows an overestimation when the cumulative probability is below 0.2 and an underestimation when it is above 0.2. Through bias correction, the adjusted data of SHUM and S500 are both consistent with the observed one. Other predictors also show acceptable results after bias correction (i.e. the results is not shown). Figure 5.3 shows a comparison among the observed monthly mean areal rainfall, the original GCM monthly rainfall, and the corrected GCM monthly rainfall. Overall, the corrected data shows a good fit with the observed one; only a slight overestimation is observed when the cumulative probability is below 0.1.

5.4.2 Model validation based on CGCM3 A2 scenario

Figure 5.4 Comparison of observed and simulated statistical properties using GQK, BCSTD, ASD, and Modified KNN-BNN at S50 station. The labels 1, 2, 3 and 4

represent the GQK, BCSTD, ASD and Modified KNN-BNN, respectively; the labels a, b, c and d represent the properties of Mean, Standard Deviation (STD), Probability of wet day (PWET) and maximum data (MAX).

Table 5.1 Comparison of observed and simulated spatial correlation coefficients among three stations

Inter-site	Model	Min	Ave	Max	OBS
S50-S60	GQK	0.531	0.568	0.596	0.577
	BCSTD	0.545	0.580	0.606	
	ASD	0.014	0.037	0.052	
	Modified KNN-BNN	0.518	0.549	0.572	
S50-S66	GQK	0.477	0.505	0.540	0.509
	BCSTD	0.475	0.510	0.537	
	ASD	0.024	0.047	0.069	
	Modified KNN-BNN	0.451	0.473	0.503	
S60-S66	GQK	0.356	0.389	0.418	0.410
	BCSTD	0.382	0.404	0.436	
	ASD	0.022	0.040	0.063	
	Modified KNN-BNN	0.310	0.340	0.366	

Table 5.1 shows a comparison of spatial correlation coefficients using the four models. It seems that, the GQK, BCSTD and Modified KNN-BNN models could well capture the spatial property of rainfalls in this region due to adoption of the KNN spatial disaggregation procedure. ASD is incapable of keeping such a property.

In this section, the simulated statistical properties using GQK, BCSTD, ASD and Modified KNN-BNN at S50 are validated under CGCM3 A2 scenarios for the period of 1980-2010. For statistical properties are used for evaluating the model performance, including MEAN (mean value), STD (standard deviation), PWET (probability of wet day) and MAX (maximum value). From Figure 5.4, BCSTD model (i.e. a2, b2, c2 and d2) presents the lowest RMSE values for the properties of MEAN, STD and MAX. Modified KNN-BNN shows the best performance for PWET. ASD performs slightly better than GQK in terms of MEAN, STD and MAX, but poorer for PWET. However, ASD model shows the widest uncertainty interval among the four

alternative models, in particular for MAX. The BCSTD and Modified KNN-BNN models present similar levels of uncertainty intervals for MEAN and STD; but they are both better than those from the GQK model. The reasons are that the uncertainty interval of BCSTD model is generated by the KNN method only, and the rainfall classification procedure in Modified KNN-BNN method could help to reduce the uncertainty range. Regarding PWET, the four models present similar uncertainty levels, and all of models underestimate the value of December, particularly for ASD. Overall, the four models show acceptable performances in reproducing the rainfall statistics for the current period under CGCM3 A2 scenario, and they could be used for projecting the future rainfall patterns. For the rest two stations, i.e. S60 and S66, the performances of the four models are similar.

5.4.3 Simulation of annual rainfall for current and future periods

Figure 5.5 The simulated average annual rainfalls at three stations from (a) GQK, (b) BCSTD, (c) ASD and (d) Modified KNN-BNN

After validation, the four models are used for reproducing the current condition and projecting future variations. Figure 5.5 shows the average values of annual rainfall at

the three stations using four models. It is found that, the four models would lead to distinctively different trends of rainfall variations under future conditions: (i) GQK and BCSTD (Figure 5.5a and 5.5b) present similar variations with no pronounced trend; compared with BCSTD, the GQK projections presents more smooth changes for the future period; (ii) the results of ASD model (Figure 5.5c) presents completely different varying tendencies for the three stations, i.e. an increasing trend for S50, a decreasing trend for S60 and a nearly constant trend for S66. This may because the ASD model could not consider the spatial correlation and is sensitive to large-scale predictors due to its linear regression method; (iii) The MODIFIED KNN-BNN model suggests a notably decreasing tendency. By comparing the observed with simulated average value (based on 30 ensembles) of annual areal rainfall for the baseline period (i.e. 1980-2010), the relative errors for GQK, BCSTD, ASD and MODIFIED KNN-BNN are 1.4%, -0.8%, -10.3% and 1.23%, respectively.

Figure 5.6 Comparison of the average annual areal rainfalls per decade between the original CGCM3 A2 output and the simulated results using GQK, BCSTD, ASD and Modified KNN-BNN

Figure 5.6 shows a comparison of the average value of annual areal rainfall per decade between the original CGCM2 A2 scenarios and the simulate data. All data have been normalized into an interval of [0, 1] for easier comparison. It is seen that, GQK and BCSTD better capture the variation tendencies of the CGCM A2 data (which has shown an increasing trend followed by a decreasing one); MODIFIED KNN-BNN shows a generally decreasing trend, and only the results during 2066-2099 follow the variation tendency of CGCM A2; while the ASD model shows a continuously increasing tendency. Compared with the baseline period (1980-2010), the rates of change in the period of 2011-2050 for the average areal rainfall (over 30 ensembles) from CGCM3 A2, GQK, BCSTD, ASD and Modified KNN-BNN would be 1.9%, 1.4%, 3.8%, 4.4% and -17.4%, respectively; in the period of 2051-2099, the rates of change would be 1.2%, 2.0%, 6.4%, 18.6% and -50.2%, respectively. Generally, the GQK results are the closest to CGCM3 A2 rainfall data, and the BCSTD shows the highest correlation (i.e. correlation coefficient = 0.864).

5.4.4 Regional rainfall frequency analysis

In this section, the regional rainfall frequency analysis is carried out based on the simulated rainfalls at the three stations using the station-year method (Buishand, 1991). The results are presented in Figure 5.7. The extreme rainfall amount at 10 return periods (i.e. 2-, 3-, 5-, 10-, 15-, 20-, 25-, 50-, 100- and 200-year) are examined and compared with the observed data of baseline period (1980-2010). The results in the Figure 5.5(a1) to 5.5(a4) are for the baseline period and can be used for verification. BCSTD model shows the best performance by comparing the observed data and the average values. The GQK, ASD and Modified KNN-BNN models show somewhat underestimations for the current condition. For the period 2011-2050, GQK, BCSTD and ASD present a generally increasing trend compared with the simulated average value of baseline period. The average relative percentage of changes (over ten return periods) for the results from the three methods are 4.4%,

11.5% and 8.0%, respectively. The Modified KNN-BNN illustrates a decreasing tendency at a percentage of 16.8%. The extreme data is from BCSTD, where the upper boundary of the 200-years rainfall exceeds 500 mm/day.

In the period 2050-2099, both BCSTD and Modified KNN-BNN suggest a decrease trend. Taking the 200-years rainfall as an example, the average relative percentages of change for those two methods are 16.1% and 42.5%, respectively. BCSTD and Modified KNN-BNN both show narrower uncertainty intervals than other methods. GQK and ASD show an increasing tendency, where the average values of the extreme increase rates (i.e. based on the values of upper boundary) for those two models are 45.2% and 41.1%, respectively. Considering the results from all downscaling models, the variation interval of extreme rainfall are between -24.9% and 31.6% (i.e. this values are calculated by the lower/upper boundaries for future periods and average simulated data for baseline period) for the first 40 years of this century; for the later 50 years, the change rates of extreme rainfalls are between -37.3% and 45.2%.

5.5 Summary

This study compared four different statistical models in investigating the rainfall variations under climate change conditions in the tropical urban area, Singapore. Based on the input of four models, the statistical models could be classified into two major types: (i) all of GQK, ASD and Modified KNN-BNN model are based on reanalysis data to build the statistical relationship between large-scale predictors and local weather information and GCM data to project future condition; (ii) BCSTD model could utilize the GCM output directly. The GQK, BCSTD and Modified KNN-BNN could keep the spatial correlation between rain gauges; ASD model was only a single site downscaling tool. The result demonstrated that the four models could all reproduce the statistical properties (i.e. mean, standard deviation, probability of wet day and maximum data) well for the baseline period. For

projection of future period, the results showed that different downscaling methods would lead to different projections. This conclusion was consistent with the studies of Mearns (2009) and Raje and Mujumdar (2011). Synthesizing all of downscaling results, the variation intervals of regional extreme rainfall are between -24.9% and 31.6% for the first 40 years of this century and between -37.3% and 45.2% for the last 50 years. The results also demonstrated that the effect of spatial correlation should be considered for climate projection in the region with less predictors and multiple stations.

Figure 5.7 Regional rainfall frequency analysis based on observed and simulated

data over three periods. Note: the labels 1, 2, 3 and 4 represent the GQK, BCSTD, ASD and Modified KNN-BNN, respectively; the labels a, b, and c represent the baseline periods of 1980-2010, 2011-2050 and 2051-2099.

This study provides an assessment of downscaling uncertainty due to the applications of different models. Previously, few studies were found in conducting such an assessment in the tropical area which was characterized by a high degree of sensitivity and uncertainty of GCM predictions. However, some limitations also need further consideration. Firstly, only one scenario of GCM was considered in this study. From Mailhot et al. (2007), multiple GCMs and multiple emission scenarios are necessary for a more comprehensive analysis of uncertainty in future projections. Kerkhoven and Gan (2011) also pointed that the climate projection is expected to apply multiple GCMs. Secondly, the application of BCSTD method is under the assumption that there are only three station in the grid of GCM. If the study area is large enough while have the evenly distributed weather stations, the research is more reasonable. Thirdly, the bias correction is, in nature, a statistical method, and subject to incapability of addressing stationarity issue.

CHAPTER 6 MULTISITE RAINFALL DOWNSCALING AND DISAGGREGATION IN A TROPICAL URBAN AREA

6.1 Introduction

High-resolution spatial and temporal rainfall data is essential for studies of water resources management, hydrological modeling, and flood risk assessment. This is especially true for tropical urban areas where highly complex rainfall patterns exist (Abustan et al., 2008). The previous studies on climate variables and their implications to runoffs have highlighted the necessity to have input data at short timescales for many hydrological models (Mezghani and Hingray, 2009). However, high-resolution data is limited at many regions due to restrictions of cost, technical capability and physical geographic condition. It is also challenging to conduct high-resolution impact studies for hydrological systems under climate change, due to the coarse resolution of general circulation models (GCMs). Using statistical methods (such as spatial downscaling and temporal disaggregation methods) to generate high-resolution rainfall data has demonstrated a viable alternative and the number of the related studies has increased dramatically in the past years.

The fundamental concept of statistical downscaling is to build a linkage between the variables of GCMs at a large scale (predictors) and local observed weather information (predictands) (Fowler et al., 2007). The widespread used downscaling models could be classified into three types: (i) linear regression models, such as statistical downscaling model (SDSM) (Wilby et al., 2002), generalized linear model (GLM) (Chandler and Wheeler, 2002), and automated statistical downscaling tool (ASD) (Hessami et al., 2008); (ii) non-linear regression models, such as artificial neural network (ANN) (Zorita and von Storch, 1999) and support vector machine (SVM) (Tripathi et al., 2006); (iii) weather generators, such as Long Ashton research station-weather generator (LARS-WG) (Racsko et al., 1991), 'Richardson' type

weather generator (WGEN) (Wilks, 1992), and agriculture and agri-food Canada-weather generator (AAFC-WG) (Hayhoe, 2000). Among many alternatives, GLM is an effective stochastic rainfall model based on linear regression, and has proved to be advantageous in addressing issues of spatial correlation, site effect, and seasonal variations etc. Chandler and Wheeler (2002) applied GLM to downscale atmospheric predictors at western Ireland, where logistic regression and gamma distribution were used for occurrence and amount modeling, respectively. Yang et al. (2005) employed GLM to generate daily rainfall at southern England, and showed that the model could reproduce properties at a scale ranging over 2,000 km². Tisseuil et al. (2011) used GLM, generalized additive model (GAM), aggregated boosted trees (ABT), and multi-layer perceptron neural networks (ANN) to downscale precipitation and evaporation at southwest France. The results showed that the three non-linear models had a better performance than GLM for modeling fortnightly flow percentiles. Beuchat et al. (2012) applied GLM with weighting schemes for downscaling rainfall at 27 sites covering Switzerland. The results showed that the downscaled rainfall exhibited a spatially coherent pattern at seasonal timescale, although spatial independence was assumed by the GLM method.

Many studies also focused on generation of rainfall at a finer timescale using different disaggregation methods. The major types include stochastic point process models (Rodriguez-Iturbe et al., 1987a; Rodriguez-Iturbe et al., 1988; Khaliq and Cunnane, 1996; Heneker et al., 2001; Debele et al., 2007; Engida and Esteves, 2011), non-parametric resampling models (Prairie et al., 2007; Nowak et al., 2010; Kalra and Ahmad, 2011) and others (Gyasi-Agyei, 2005; Gyasi-Agyei 2011; Beuchat et al., 2011). Among these models, HYETOS and K-nearest neighbors (KNN) were widely used. Koutsoyiannis and Onof (2001) developed a hybrid model based on the Bartlett-Lewis rectangular pulses model, called HYETOS. It added an adjustment procedure to assure the sum of disaggregated hourly data be consistent with the given daily data. Debele et al. (2007) applied HYETOS to disaggregate daily rainfall to

hourly ones at Cedar Creek watershed in US. Prairie et al. (2007) explored a stochastic nonparametric method, KNN, for spatial-temporal disaggregation of stream flows, and indicated that the KNN method could guarantee the simulation of statistical properties in the original space (historical record). Kalra and Ahmad (2011) applied KNN nonparametric method to generate seasonal precipitation by disaggregating annual precipitation, and the study results indicated that the KNN method performed better than the first-order periodic autoregressive parametric approach, and the seasonal precipitation reproduced on winter and spring seasons was more satisfactory. These studies focused on single-site disaggregation. For multiple sites, the cross-correlation becomes an important factor to be considered. Some studies attempted development of stochastic weather generators for multi-site rainfall generations (Wilks, 1998; Burton et al. 2008; Jennings et al., 2010), but most of them were not able to deal with disaggregation at the same time. As a viable attempt, Koutsoyiannis et al. (2003) developed a method, called MuDRain, by combining a simplified multivariate rainfall model and transformation model to disaggregate daily rainfall to hourly ones at multiple sites. In the study of Debele et al. (2007), MuDRain model was applied and showed an outperformed result for reproduction of expected statistical properties (e.g. average hourly rainfall, standard deviation, probability of wet hour and skewness) with small RMSE values, especially for the reproduction of peak value and temporal distribution; more importantly, the inter-site cross-correlation could be captured very well.

Based on the above review, it is recognized that many hydrological applications require a full spatial distribution of rainfall at finer timescale. This is especially true for climate change impact studies, where the global circulation models could only offer projections at coarse spatial and temporal resolutions. Hence, integrated downscaling and disaggregation effort is necessary as it provides rainfall data with both high spatial and temporal resolutions to meet the requirement of hydrological modeling. There are relatively few studies in such an area. Second et al. (2006)

proposed a combined spatial-temporal downscaling and disaggregation approach using GLM, HYETOS and an artificial profile multisite transformation method. In this approach, the daily data was generated by GLM for multiple sites; HYETOS was used for disaggregating daily data to hourly ones at the master station which contained a historical hourly record; then, the disaggregated hourly data pattern was projected to other sites (i.e. satellite stations) using the artificial profile method. Through compared the observed values, simulated rainfall preserved the desired statistical properties (e.g. mean, standard deviation, autocorrelation, probability of dry day/hour, skewness and cross-correlations) with a lower error values (e.g. between 0.3% and 18%), and generated envelope could cover the observed data. Mezghani and Hingray (2009) developed another combined downscaling - disaggregation approach for both temperature and rainfall over the Upper Rhone River basin in the Swiss Alps. GLM was used for downscaling mean areal weather variables (including total precipitation, rainfall and temperature) from GCM model, and KNN was used for disaggregating them to sub-daily and sub-regional scales. The study results showed a good performance of the proposed method in generating statistical relationship, including spatial cross-correlations.

Generally, the integration of spatial downscaling and temporal disaggregation could offer high-resolution rainfall data projected from GCM scenarios, and has great potential to help examine the impact of climate change on rainfall patterns and hydrological systems. From reviewing the recent research works, it turns out that such studies are relatively limited. Essentially, there is a lack of an inter-comparison study that could show the advantages or limitations of various options of single-site or multisite rainfall downscaling and disaggregation techniques that could keep the key statistics at different time scales, particularly in connection with the output from a downscaling model. In addition, most of the previous studies focused on a relatively larger scale watershed or basins. There are limited efforts on integrated downscaling and temporal disaggregation for the urban areas at Southeast Asia, which is

characterized by tropical climate with rainfalls showing high temporal-spatial variations.

Therefore, the objective of this research work is to conduct a systematic rainfall downscaling-disaggregation study at a tropical urban area (i.e. Singapore Island). An inter-comparison study will be performed first to evaluate various options in implementing single and multiple site downscaling and disaggregation, based on statistical indicators (at daily and hourly scales) and observed data. Downscaling will essentially be based on GLM model as it has already been proved as an advantageous tool in keeping many key daily statistics of rainfall (Yang et al., 2005). Options of KNN, HYETOS, and MuDRain will be tested for temporal disaggregation. Based on the comparison result, the deemed best option of downscaling-disaggregation framework will be used for projecting high-resolution rainfall patterns under future climate conditions for the Singapore Island.

6.2 Methodology

There are four methods to be used in this study: GLM (Chandler and Wheeler, 2002), HYETOS (Koutsoyiannis and Onof, 2001), KNN (Prairie et al., 2007) and MuDRain (Koutsoyiannis et al., 2003). Two types of downscaling strategies are employed: (i) single-site GLM downscaling plus KNN for spatial disaggregation (denoted as S-G-K) and (ii) multisite GLM downscaling (denoted as M-G). S-G-K means, a single-site GLM is implemented to downscale the summation of daily rainfalls from eight stations; then KNN method is used to downscale spatially from daily rainfall summation to individual stations. Such an idea is similar to the one proposed by Mezghani and Hingray (2009). M-G means the rainfall will be downscaled for multiple sites at the same time, with inter-site correlation being taken into consideration. The inter-comparison study include: (i) S-G-K vs. M-G for multisite daily rainfall downscaling, (ii) HYETOS vs. KNN for single-site hourly rainfall

disaggregation, and (iii) KNN vs. MuDRain for multisite hourly rainfall disaggregation. Based on the comparison results, a relatively better framework of performing an integrated downscaling and disaggregation for the study region will be identified. Then, it will be used to project future sub-daily rainfall patterns. In the entire framework, a number of basic statistical indicators (including mean, standard deviation etc.) and spatial cross-correlation at both daily and hourly timescales will be evaluated. Figure 6.1 shows the structure of the study methodologies. Detailed introduction on individual components will be given in the following sections.

Figure 6.1 The flowchart of study framework

6.2.1 Generalized linear model (GLM)

GLM is a popular method to build flexible and veracious relationship between predictors and local observed rainfall data. It simulates the daily rainfall based on two sub-models. The occurrence model depending on logistic regression and the rainfall-amount distribution of wet day is assumed in gamma distribution. For the single site version, the details could refer to the Chapter 5 and the study of Mezghani and Hingray (2009). For multisite version, another added parameter for rainfall amount model is dispersion coefficient ν for all gamma distribution, which assumed having a common shape (Yang et al., 2005; Segond et al., 2006). The atmospheric predictors affecting rainfall process may not be independent, and generally interact with each other. Therefore, the interaction parameters are added into the model framework. The response of occurrence and amount model are both linked with non-linearly transformed predictors. A joint distribution for the rainfall of the next day at all stations is built by the spatial dependence of model construction. Normally, the covariate selection and coefficient calculation are both estimated by likelihood methods. Otherwise, the effect of monsoon season specifically for this region also is considered into model. More detailed descriptions of multisite version of GLM can be found in Chandler and Wheeler (2002), Yang et al. (2005), and Segond et al. (2006).

6.2.2 HYETOS

HYETOS is used for disaggregation of single-site based on two versions of Bartlett-Lewis rectangular pulse (BLRP) model. The original version was developed by Rodriguez-Iturbe et al. (1987a and 1987b, 1988); the modified BLRP (MBLRP) model was proposed by Onof and Wheeler (1993). This study is mainly based on MBLRP. There are several assumptions in such a model: (i) the rainfall occurrence

and rain-cell arrival both follow Poisson processes; (ii) the duration of rainfall event and rain-cell both follow exponential distributions; (iii) the rain-cell intensity (depth of rectangular pulse) follows an exponential or gamma distribution. The method of moments (MOM) is used to fit MBLRP model parameters. An adjustment procedure is added into the framework of HYETOS model. The HYETOS model would be applied within the maximum tolerance distance in the adjusting procedure, where the tolerance distance d was defined as (Koutsoyiannis and Onof, 2001):

$$d = \left[\sum_{i=1}^L \ln^2 \left(\frac{Y_{Mi} + c}{\tilde{Y}_{Mi} + c} \right) \right]^{1/2} \quad (6-1)$$

where Y_{Mi} and $\tilde{Y}_{Mi}$ are the original and modeled daily rainfall data respectively, L is the number of wet day in sequence, c is a constant (threshold, 0.1 mm here). The model would run continuously until the simulated daily depths match the sum of whole sequence of daily data within d . There are four levels of repetition procedure in HYETOS model to minimize error. For details, readers are referred to Koutsoyiannis and Onof (2001) and Second et al. (2006).

6.2.3 MuDRain

The MuDRain model is a simplified multivariate autoregressive model of rainfall and the major equation can be written as (Koutsoyiannis et al., 2003):

$$X_t = aX_{t-1} + bV_t \quad (6-2)$$

where X_t is the hourly rainfall at time t and n location, and could be written as $X_t = [X_t^1, X_t^2, \dots, X_t^n]$; a and b are parameters as $[n \times n]$ matrixes; V_t is an independent identically distributed sequence of size n vectors of innovation random variables (Debele et al., 2007). A transformation procedure is adopted to adjust the output from

multivariate rainfall model to reduce error of stochastic properties. Koutsoyiannis et al. (2003) provided the following method to calculate the cross-correlation for satellite stations:

$$r_{ij,h} = (r_{ij,d})^m \quad (6-3)$$

where $r_{ij,h}$ is the hourly cross-correlation coefficient, $r_{ij,d}$ is the daily cross-correlation coefficient, and m is a constant need to be estimated. If the hourly data for multiple stations is available, the actual correlation coefficients can be applied into the model; if the hourly data is not available, m value could be assumed in the range from 2 to 3 (Koutsoyiannis et al., 2003; Debele et al., 2007). In this study, the actual correlation coefficients based on hourly data of the studied stations are used.

6.2.4 K-Nearest Neighbors

KNN, as a nonparametric method, is used for both spatial and temporal disaggregation in this study. The spatial disaggregation is to project from the daily rainfall summation from eight stations (whole region) to each single station (sub-region). The temporal disaggregation is to generate hourly rainfall from daily record, for single site or multiple sites (Nowak et al., 2010). The nearest neighbor of Z should be computed from the observed daily record matrix W with $I \times n$ dimensions. The ‘neighbors’ are selected among the potential candidates using Euclidean distance, given by (Deza and Deza, 2013):

$$E[(x,y),(a,b)] = \sqrt{(x-a)^2 + (y-b)^2} \quad (6-4)$$

where (x, y) and (a, b) are the coordinates of two points. Lall and Sharma (1996) provided a method based on heuristics to define the weight scheme of neighbors:

$$W_i = \left(\frac{1}{i}\right) / \left(\sum_{i=1}^K \frac{1}{i}\right) \quad (6-5)$$

where the K is the number of the nearest neighbors, i is the ‘index of neighbor’, W_i is the weight scheme of i^{th} index of neighbor; when $i = 1$, the index refers to the closest of the nearest neighbors. The candidates of daily or region data could be selected as the ‘nearest neighbor’ based on the arranged weight scheme based on a decreasing kernel function. Then, the sub-daily or sub-region data from the candidates are converted to a proportion of the candidate. Let T be the target daily or region data which need to be disaggregated. P is the selected candidate daily or region data with m number of sub-daily or sub-region records. Then, P could be converted to a sub-record proportion vector matrix Z with dimension $1 \times m$. Finally, the disaggregated sub-daily or sub-region data of T could be calculated by T multiplying matrix Z .

Instead of using a stochastic selection scheme for generating multiple ensembles, an optimization scheme to choose the best ensemble is adopted in this study (Mezghani and Hingray, 2009). This is for the benefit of reducing uncertainty and easiness of comparing with other methods (Khan et al., 2006). The optimization steps are given by (i) selecting 10 nearest neighbors based on Euclidean distance; (ii) arranging equivalent weight to each neighbor (potential disaggregated candidate), and dividing them into ten ensembles based on distance; (iii) using minimization of the objective function to estimate the optimal candidate from the ten ensembles. The objective function (OF) is given by:

$$OF = \frac{\sum_{i=1}^N MAPE_i}{N} \quad (6-6)$$

where $MAPE$ means the mean absolute percentage error (Ghosh and Katkar, 2012), i means the statistical properties, including mean, standard deviation, lag-1

autocorrelation, lag-2 autocorrelation, probability of wet hour and skewness for single-site disaggregation; another property, cross-correlation is added for multisite disaggregation; N is the number of properties (six for single-site disaggregation, and seven for multisite disaggregation in this study). Figure 6.2 shows the test result of the objective function value vs. the number of K for single-site disaggregation at station S24. It is found that, when K equals to 5, the objective function would reach its minimum. Similar results were found for other stations.

Figure 6.2 MAPE values of objective function at various K values for single-site disaggregation at S24

6.3 Study Area and Data

Singapore, with an area of about 723 km², locates at the equator pluvial region. Most of the surface elevation over the island is below 15 m, and the highest point is Bukit Timah hill which has a height of 165 m at the central region. The small hill leads to a ‘rain shadow’ phenomenon (Whiteman, 2000) that induces slight disparities of

weather distribution on the western and eastern sides of the island (e.g. the western side of Singapore is wetter than the eastern one). Singapore has a rich precipitation, with an average annual rainfall amount being more than 2,300 mm. The highest record of daily rainfall was near 520 mm which happened at the wettest month, December. There are two monsoons occurring each year: the Northeast Monsoon from December to early March, and the Southwest one from June to September (NEA, 2009). Other months range in period between the two monsoons and have relatively less rainfall. Figure 6.3 shows the map of the study region and locations of eight rainfall stations that will be used in this study.

Seven variables from National Centre for Environmental Prediction (NCEP) reanalysis data (Kistler et al., 2001), re-gridded on Hadley Centre Coupled Model, version 3 (HadCM3) grids (Collins et al., 2001) are used as the predictors to build the statistical relationship to local station data. They include: mean sea level pressure (*mslp*), 500 hPa geopotential (*p500*), 850 hPa geopotential (*p850*), near surface relative humidity (*rhum*), relative humidity at 500 hPa height (*r500*), relative humidity at 850 hPa height (*r850*), and near surface specific humidity (*shum*). The data has been pre-processed through standard normalization and are obtained from CCCSN (Canadian Climate Change Scenarios Network) project of Environment Canada (Dibike et al., 2008). The bias correction should be applied for GCM data before application. In terms of predicands, 31-years continuous daily and hourly rainfall record from 1980-2010 at eight stations over the island are available.

For the downscaling study, the NCEP reanalysis data from 1980 to 2000 is used for training (or building) the GLM model. Then, the HadCM3 modeled data from 1980 to 2010 based on the established GLM model will be used to evaluate the validity of HadCM3 in simulating the historical rainfall patterns. The future HadCM3 projected data (from 2011 to 2099) is applied to predict the rainfall amounts under changing climatic conditions. For disaggregation study, 21-years hourly data (from 1980 to

2000) is used for calibrating the disaggregation models, and the rest (from 2001 to 2010) is used for verification. For future predictions, all available data (from 1980 to 2010) is used for building the disaggregation model.

Figure 6.3 Study area and location of rain gauges

6.4 Results and Discussions

6.4.1 Model configurations

Six statistical indicators (reflecting rainfall characteristics) are used for evaluating model performances: rainfall mean ($\text{Mean}_h/\text{Mean}_d$), standard deviation of rainfall ($\text{STD}_h/\text{STD}_d$), lag-1 autocorrelation of hourly rainfall (AC1_h), probability of wet hour/day ($\text{Pwet}_h/\text{Pwet}_d$), skewness of hourly rainfall (Skewness_h), maximum daily rainfall (Max_d) and cross-correlation coefficients (r_d/r_h), where the subscripts of d and h represent daily and hourly, respectively. The simulated statistical indicators will be evaluated by standard deviation (S_e), relative bias (R_b), change in standard deviation (ΔS), significant test (Test) (Debele et al., 2007), root-mean-square-error

(*RMSE*) (Armstrong and Collopy, 1992), mean absolute percentage error (*MAPE*) (Ghosh and Kathar, 2012) and cross correlation coefficient (Liu et al., 2011b). The equations are given by:

$$S_e = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_{sim,i} - x_{obs,i})^2} \quad (6-7)$$

$$R_b = \frac{e}{x_{obs}} \quad (6-8)$$

$$\Delta S = \frac{S_{sim} - S_{obs}}{S_{obs}} \quad (6-9)$$

$$Test = \frac{abs(\overline{x_{obs}} - \overline{x_{sim}})}{2S_e} \quad (6-10)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_{obs,i} - x_{sim,i})^2}{N}} \quad (6-11)$$

$$MAPE = \frac{\sum_{i=1}^n abs(x_{obs,i} - x_{sim,i})}{N} \quad (6-12)$$

$$CC = \frac{\sum_{i=1}^n (x_{obs,i} - \overline{x_{obs,i}})(x_{sim,i} - \overline{x_{sim,i}})}{\sqrt{\sum_{i=1}^n (x_{obs,i} - \overline{x_{obs,i}})^2 \sum_{i=1}^n (x_{sim,i} - \overline{x_{sim,i}})^2}} \quad (6-13)$$

where $x_{obs,i}$ is the observed rainfall data, $x_{sim,i}$ is the simulated rainfall data, $\overline{x_{obs}}$ is the mean of observed data, $\overline{x_{sim}}$ is the mean of simulated data, S_{obs} is the standard deviation of observed data, S_{sim} is standard deviation of simulated data, and N is the number of record.

6.4.2 Multisite downscaling based on GLM

Two strategies of multisite downscaling based on GLM, namely S-G-K and M-G, are

compared in this section. The large-scale predictors are from NCEP reanalysis data ranging from 1980 to 2000. Twenty ensembles are generated by each method to form

Figure 6.4 Comparison of downscaled results at site S46 from (a1-d1) single-site GLM combined with KNN (S-G-K), and (a2-d2) multisite GLM. MAPE is based on the observed and average downscaled data. The solid line with squares (OBS)

represents the observed data; the pure solid line (SIM average) shows the average values of downscaled data from 20 ensembles; two dash lines (SIM envelope) represent the upper and lower boundaries of the envelope of downscaled data.

envelops of the downscaled results. Figure 6.4 shows the downscaled results vs. the observed data for four statistical properties ($Mean_d$, STD_d , $Pwet_d$ and Max_d) at station S46. The results indicate that the S-G-K and M-G methods perform fairly close for standard deviation (Figure 6.4a1). S-G-K shows a slightly better result in terms of daily maximum data (Figure 6.4d1) but is inferior to M-G with reference to other two indicators. However, both methods show somewhat underestimation of rainfall frequency, especially at the northeast monsoon season (as shown in Figures 6.4c1 and 6.4c2). Table 6.1 shows the average cross-correlation coefficients which are calculated from twenty ensembles. It is indicated that the two methods could both capture the spatial structure well. Overall, the multisite GLM method performs slightly better than single-site GLM plus KNN.

6.4.3 KNN vs. HYETOS for single-site disaggregation

In this section, the observed hourly rainfall from 1980 to 2000 is used to build the disaggregation model; the observed record from 2001 to 2010 is used for model verification. Figure 6.5 shows the statistical properties of disaggregated hourly data using KNN and HYETOS during the verification period at two stations. It shows that, KNN and HYETOS could both keep the standard deviation of the disaggregated results. From Figures 6.5b1 and 6.5b2 and Figures 6.5c1 and 6.5c2, HYETOS illustrates a notable underestimation for the $AC1_h$ and $Pwet_h$ at the two stations; KNN shows a better performance in fitting the observed data, especially for the reproduction of rainfall frequency. Hanaish et al. (2011b) applied HYETOS to disaggregate daily rainfall in Southeast Asia (Malaysia) and the results also showed that the HYETOS had a lower accuracy in reproducing of $Pwet$. However, there are also a slight underestimation by KNN at the two wettest months, i.e. January and

December. The reason is that KNN does not consider the seasonal effects due to limited number of samples for individual months. Reproduction of skewness is useful for assessing the extreme-event representation for the disaggregation models. From

Table 6.1 Comparison of average cross-correlation coefficients between single-site GLM plus KNN and multisite GLM method based on NCEP reanalysis data in the period of 1980-2000.

Distance	Station	OBS	S-G-K	M-G
3.3	S46-S69	0.74	0.72	0.73
4.65	S40-S69	0.67	0.70	0.68
6.3	S40-S66	0.64	0.70	0.66
7.85	S46-S40	0.63	0.62	0.60
9.13	S55-S69	0.51	0.53	0.55
9.55	S46-S55	0.54	0.55	0.58
10.2	S46-S60	0.52	0.51	0.54
10.71	S66-S69	0.50	0.54	0.53
10.9	S24-S55	0.56	0.58	0.60
11.7	S40-S55	0.50	0.54	0.52
11.8	S44-S66	0.46	0.50	0.46
13.3	S40-S44	0.49	0.51	0.49
13.52	S60-S69	0.44	0.42	0.46
13.6	S46-S66	0.50	0.52	0.48
13.73	S44-S69	0.46	0.47	0.46
14.2	S46-S44	0.51	0.51	0.52
16.1	S55-S60	0.42	0.43	0.45
17.8	S55-S66	0.41	0.45	0.42
17.9	S40-S60	0.43	0.42	0.41
19.2	S46-S24	0.48	0.51	0.50
19.2	S44-S60	0.46	0.44	0.46
19.8	S24-S69	0.41	0.44	0.43
21.6	S24-S60	0.44	0.46	0.47
22.6	S24-S40	0.44	0.45	0.43
22.9	S44-S55	0.38	0.40	0.39
23.14	S60-S66	0.36	0.40	0.36
28.5	S24-S66	0.38	0.40	0.38
33.4	S24-S44	0.38	0.38	0.38

Note: Average cross-correlation correlations are calculated from twenty ensembles.

Figure 6.5 Statistical properties of disaggregated hourly rainfall data using KNN and HYETOS during the verification period at the stations S24 (denoted as 1) and S46 (denoted as 2). $MAPE_K$ = MAPE value based on KNN; $MAPE_H$ = MAPE level based on HYETOS. The solid line with squares (OBS) represents the observed data; the dash line with circles (KNN) represents the disaggregated data by KNN; the dash line with triangles (HYETOS) represents the disaggregated data by HYETOS

Figures 6.5d1 and 6.5d2, KNN method performs better in terms of skewness at S24 than that at S46; HYETOS shows an opposite result. In Figure 6.5d1, KNN and HYETOS both underestimate the skewness in February, and HYETOS performs better than KNN. The underestimation of KNN is also caused by not considering seasonal effects, which is similar to KNN's underestimation of P_{wet} in January and December (i.e. Figures 6.5c1 and 6.5c2). HYETOS is a parametric approach and calculate the parameters for each month separately, and could better represent seasonal effects. The observed skewness of February in S24 is notably higher than those from other months; this somewhat affects the performance of both KNN and HYETOS.

Figure 6.6 presents the quantile-quantile plot for the extreme data at two stations for quantitative examination. The threshold of a large rainfall event is defined as the rainfall intensity being greater than 30 mm/hour. At S24 station (Figure 6.6a), HYETOS illustrates an overestimation for almost the entire range of rainfall data, and the error would increase with the increase of rainfall intensity; while, KNN shows a closer trend to the observed data. For S46 station, KNN provides a better fit than .

HYETOS when the rainfall is below around 70 mm/hour. However, a significant overestimation for peak value is seen by KNN (Figure 6.6b). This may because the KNN method resamples the historical extreme record for calibration period, but the twenty-four hours rainfall distribution of peak daily rainfall in the verification period does not follow the same distribution in the found 'nearest neighbors' in the calibration period.

Figure 6.6 Quantile-quantile plot between the observed and disaggregated data

Table 6.2 illustrates the summary of goodness of fit for each month at S24 station. It shows that the bias and the value of significant test for two models are both small. The absolute average values of RMSE, Rs and ΔS for KNN are 2.699, 1.274 and 0.097, respectively; those for HYETOS are 2.964, 1.415 and 0.131, respectively. Similar results are also observed for S46 station (not shown). Generally, the closer the values of RMSE, Rs and ΔS to zero, the better the models are (Debele et al., 2007). Overall, by comparing the MAPE values and other indicators in Table 6.2, KNN is

considered to perform generally better than HYETOS for single-site disaggregation.

Table 6.2 Goodness-of-fit statistics of disaggregated hourly rainfall at S24 station based on KNN and HYETOS

S24	Method	RMSE	R_s	ΔS	Test
Jan	KNN	3.566	1.316	0.099	0.001
	HYETOS	3.994	1.474	0.181	<0.001
Feb	KNN	2.219	0.88	-0.12	<0.001
	HYETOS	1.971	0.949	-0.051	<0.001
Mar	KNN	2.575	1.372	0.116	<0.001
	HYETOS	2.625	1.398	0.071	<0.001
Apr	KNN	2.674	1.344	-0.078	<0.001
	HYETOS	2.717	1.365	0.041	<0.001
May	KNN	2.582	1.206	-0.162	<0.001
	HYETOS	2.826	1.32	-0.113	0.002
Jun	KNN	2.11	1.391	0.065	<0.001
	HYETOS	2.327	1.534	0.195	<0.001
Jul	KNN	2.276	1.322	0.006	<0.001
	HYETOS	2.494	1.448	0.07	0.002
Aug	KNN	2.422	1.195	-0.149	<0.001
	HYETOS	3.145	1.552	0.195	<0.001
Sep	KNN	2.315	1.317	-0.024	<0.001
	HYETOS	2.773	1.578	0.219	<0.001
Oct	KNN	2.665	1.304	-0.075	<0.001
	HYETOS	2.88	1.41	0.107	<0.001
Nov	KNN	3.365	1.241	-0.085	<0.001
	HYETOS	3.757	1.386	-0.008	<0.001
Dec	KNN	3.626	1.404	0.184	0.003
	HYETOS	4.055	1.571	0.325	0.002

6.4.4 KNN vs. MuDRain for multisite disaggregation

KNN and MuDRain both need a master station that has historical hourly rainfall record to disaggregate hourly data to satellite stations. In this section, S46 station is used as the master station due to its central location. The performance assessment of multisite disaggregation should also consider the interstation cross-correlation. Figure 6.7 shows a comparison between KNN and MuDRain in terms of STD_h , $AC1_h$,

Pweth and Skewness_h at one of the satellite stations (S24) for the verification period.

Table 6.3 Goodness-of-fit statistics of rainfall from KNN and MuDRain at S24 station.

S24	Method	RMSE	Rs	ΔS	Test
Jan	KNN	4.11	1.52	0.33	<0.001
	MuDRain	3	1.11	-0.08	<0.001
Feb	KNN	2.2	0.9	-0.1	<0.001
	MuDRain	2.19	0.86	-0.14	<0.001
Mar	KNN	2.78	1.48	0.21	<0.001
	MuDRain	2.27	1.21	-0.15	<0.001
Apr	KNN	2.49	1.25	0.05	<0.001
	MuDRain	2.53	1.27	-0.15	<0.001
May	KNN	2.69	1.26	-0.05	<0.001
	MuDRain	2.61	1.22	-0.14	<0.001
Jun	KNN	2.15	1.42	0.08	<0.001
	MuDRain	1.64	1.08	-0.13	<0.001
Jul	KNN	2.33	1.35	-0.04	<0.001
	MuDRain	1.95	1.13	-0.1	<0.001
Aug	KNN	2.73	1.35	-0.04	<0.001
	MuDRain	2.3	1.13	-0.26	<0.001
Sep	KNN	2.36	1.34	-0.04	<0.001
	MuDRain	1.88	1.07	-0.23	<0.001
Oct	KNN	2.85	1.39	0	<0.001
	MuDRain	2.27	1.11	-0.24	<0.001
Nov	KNN	3.1	1.14	-0.08	<0.001
	MuDRain	3.39	1.25	-0.13	<0.001
Dec	KNN	3.47	1.34	0.1	<0.001
	MuDRain	3.15	1.22	0.03	<0.001

From Figure 6.6a, the standard deviation of the disaggregated rainfall by MuDRain is somewhat underestimated from January to November. KNN generally performs better than MuDRain except for January. For AC1_h, different from the result of single-site disaggregation, KNN shows a poorer performance (with MAPE level at 0.22) compared with MuDRain (0.08). From Figure 6.7c, both methods well capture the rainfall frequency. However, similar to those in single-site disaggregation, January and December are also underestimated (perhaps due to extreme rainfall

patterns in this two month). For skewness, MuDRain shows a much better fitting at the first six months from January to June; but for the rest four months, KNN outperforms MuDRain (Figure 6.7d). For other stations, the MuDRain generally shows a better result for Pwet, Skewness and AC1; but KNN performed generally better in terms of standard deviation. Table 6.3 shows the summary of goodness-of-fit of downscaled results at station S24 using other measurement criteria. The absolute average values of RMSE, Rs and ΔS for KNN are 2.772, 1.312 and 0.093, respectively; those for MuDRain are 2.432, 1.139 and 0.148, respectively. It shows that KNN could better reflect rainfall variation, but MuDRain has a smaller error in overall fitting of the rainfall time series.

Table 6.4 Comparison of spatial correlation coefficients between station S46 and station S24

	OBS	KNN	MuDRain
Jan	0.43	0.12	0.47
Feb	0.10	0.04	0.10
Mar	0.27	0.05	0.32
Apr	0.16	0.04	0.07
May	0.29	0.06	0.16
Jun	0.36	0.01	0.54
Jul	0.31	0.01	0.38
Aug	0.28	0.01	0.38
Sep	0.30	0.01	0.41
Oct	0.39	0.03	0.27
Nov	0.25	0.09	0.14
Dec	0.29	0.10	0.34
Average	0.29	0.05	0.30

Interstation correlation is another important factor that should be considered for model assessment in multisite disaggregation. Table 6.4 illustrates the correlation coefficients against master station (S46) for the observed and disaggregated hourly

Figure 6.7 Statistical properties of disaggregated rainfall at satellite station S24 from KNN and MuDRain. MAPE_K = MAPE value based on KNN; MAPE_M = MAPE level based on MuDRain. The solid line with squares (OBS) represents the observed data; the dash line with circles (KNN) represents the disaggregated data by KNN; the dash line with triangles (MuDRain) represents the disaggregated data by MuDRain.

rainfall data in each month. MuDRain seems to generate fairly close correlation coefficients in comparison to observed ones; whereas, KNN shows a notable underestimation. The reason is that KNN is incapable of addressing spatial correlation as the satellite stations rely heavily on the historical record from the master station. MuDRain has the capability to keep the correlation by the optimization procedure based on the input cross-correlations matrix. Overall, MuDRain model could reproduce most of the statistical properties reasonable well, especially for the extreme data and interstation correlation. It is selected for multisite disaggregation in further studies.

6.4.5 Integrated downscaling-disaggregation

Figure 6.8 Statistical properties of downscaled rainfall at S46 from GLM based on HadCM3 A2 scenario during 1980-2010. Solid line with square represents the observed data; two dash lines are present the upper and lower boundary for envelope of downscaled data. The solid line with squares (OBS) represents the observed data; two dash lines (Downscaled envelope) represent the upper and lower boundaries of the envelope of downscaled data.

From inter-comparison study, the multisite GLM, KNN and MuDRain are selected to be included in an integrated downscaling-disaggregation framework. GLM is established by using NCEP reanalysis data for multisite spatial downscaling and future projections are based on HadCM3 predictors.

(1) Spatial downscaling

GLM model is used for spatial downscaling at eight stations. The observed daily data and NCEP reanalysis data during the period from 1980 to 2000 have been used for establishing the GLM model. Then, HadCM3 modeled predictors with a period from 1980 to 2010 are linked with the GLM model for verifying the quality of the modeled data. Figure 6.8 shows the observed and simulated monthly statistical properties (i.e. $Mean_d$, STD_d , $Pwet_d$, and Max_d) for station S46 during the verification period 1980-2010. From Figure 6.8, all observed indexes are generally fall between the envelop curves generated by GLM (with 20 ensembles), especially for the simulation of standard deviation (Figure 6.8b). Figure 6.8(c) shows a slight underestimation for the rainfall frequency in two months of wet season, November and December. For the extreme data, except an underestimation for March, the observed data is well covered by the simulated envelopes (as shown in Figure 6.8d). Overall, it is indicated that the GLM model and HadCM3 predictors could generally offer acceptable reproduction and prediction of rainfall patterns for the historical condition. Figure 6.9 shows the spatial cross-correlation coefficients vs. inter-gauge distances for both observed and simulated rainfalls. GLM shows a good performance for keeping the spatial correlation, and the average values of 20 ensembles are much close to observed ones (CC equal to 0.99).

(2) KNN single-site disaggregation at master station

Figure 6.9 Cross-correlation coefficients vs. distance for observed and downscaled rainfall. OBS = observed data; SIM = downscaled data; CC = correlation coefficient between observed data and average value of downscaled data.

KNN is selected for single-site disaggregation based on the output of GLM model. As the error of mean is mainly from input data in the disaggregation procedure, Figure 6.10 only presents standard deviation, lag-1 autocorrelation, probability of wet hour and the skewness at the hourly scale. From the figure, most of the observed properties fall within envelop of the simulated series. The simulation of rainfall frequency (probability of wet hour) is slightly underestimated. This may be caused by errors of the downscaled results and KNN does not consider the seasonal effect. Regarding the prediction of extreme data (i.e. skewness), the simulated envelopes mostly cover the observed data.

Figure 6.10 Statistical properties of disaggregated rainfall at master station S46 using

KNN. The plot shows a comparison of the observed time series with envelope curves generated by 20 ensembles from GLM downscaled daily data. The solid line with squares (OBS) represents the observed data; two dash lines (Disaggregated envelope) represent the upper and lower boundaries of the envelope of disaggregated data.

(3) MuDRain multisite disaggregation at satellite stations

MuDRain is used for multisite disaggregation at seven satellite stations. The input data include the downscaled daily data for all stations and disaggregated hourly data for the master station. Figure 6.11 compares the disaggregated and observed statistical properties (STD_h , $AC1_h$, $Pweth$ and $Skewness_h$) at station S24. The standard deviation from disaggregated data shows a tendency of underestimation. There are slight overestimations for the probability of wet hour in April to June and the underestimations for January and December. Overall, the range of disaggregated data also presents good performance to cover most of the observed statistics. Other stations show similar trends. Figure 6.12 shows the cross-correlation coefficients for four selected months (February, June, September and December), which distribute in dry/wet seasons and two monsoon seasons, respectively. From the figure, the correlation coefficients from disaggregated data could well cover the observed data for the four months. Based on the average value of 20 ensembles, the correlation coefficients to the observed data are generally over 0.98, which demonstrates an acceptable performance of multisite disaggregation.

Figure 6.11 Statistical properties of disaggregated rainfall from multi-site disaggregation using MuDRain at satellite station S24. The solid line with squares (OBS) represents the observed data; two dash lines (Disaggregated envelope) represent the upper and lower boundaries of the envelope of disaggregated data.

Based on the above-mentioned results, the integrated downscaling-disaggregation framework based on GLM, KNN and MuDRain could offer reasonable simulations of hourly rainfall at multiple sites for the Singapore, using HadCM3 as the predictors. The approach shows the framework's high capability in capturing the average rainfall amount and extreme data, and maintaining spatial correlations at both daily and hourly timescales. The reason of a relatively poorer performance for $Pwet$ is mainly affected by the downscaled results. The limited number of samples in different seasons for this study also affects KNN's performance in simulation of rainfall frequency.

Figure 6.12 Cross-correlation coefficients of observed and disaggregated hourly data against distance in (a) February, (b) June, (c) September, and (d) December. OBS = observed data; SIM = disaggregated data; CC = correlation coefficient between observed data and average value of disaggregated data.

(4) Projected hourly rainfall to the future condition

Through the validation of GLM model and HadCM3 predictors, this section presents the projected rainfall for next century for the study region under the climate change conditions. The SRES A2 and B2 scenarios are used for downscaling model to assess rainfall variation during period of 2011-2099. Figure 6.13 illustrates the mean and maximum hourly rainfall for Singapore island during the baseline period (1980-2010) and three future periods including 2030s (2011-2040), 2050s (2041-2070) and 2080s

(2071-2099). It is indicated that, the annual average rainfall would increase (about 2%) in the first period (2030s) slightly, but drop in 2050s and 2080s. The annual rainfall amount would be expected to drop about 5% at the end of this century. For each month, the rainfall in the Northeast Monsoon season would generally increase (December, January and February); in the Southwest Monsoon season, the rainfall tend to reduce and the highest decreasing rate (more than 40%) would be occurring at September. This result is somewhat consistent with the findings in IPCC Fourth Assessment Report (2007), which points out a decreasing trend in precipitation over Southeast Asia, and HadCM3 projections presented in LARS-WG (Semenov and Barrow, 1997). Regarding the extreme rainfall amount, the results (Figure 6.13a2, b2 and c2) show a generally increasing tendency. Under A2 emission scenario, only August and September would have a decreasing trend of rainfall at the end of this century; other months, on the contrary, demonstrate notable increases. The maximum rainfall would reach up to 181 mm/hr in December, which is about 60% higher than the baseline level. Under B2 emission scenario, the increasing trend of maximum rainfall is generally milder than that in A2 scenario. At the end of this century, the maximum increase rate is about 47% in June, but the peak value (139 mm/hr) is still expected to occur in December. Overall, the projected results imply that the annual rainfall amount would have a slight reduction, but the extreme rainfall events and the rainfall in the wet season could increase notably.

It should be noted that, the projection results are largely determined by the type of GCMs selected. A multiple run of the integrated framework under various models and emission scenarios is essential for reaching a more reliable conclusion. This is especially important when the related results are to be used in adaptation planning. This study aims to demonstrate the validity of the proposed methodology, only one GCM with two emission scenarios is used. Furthermore, the integrated spatial downscaling and temporal disaggregation model is established based on the historical observed data. It is a common difficulty to exam the stationarity of the statistical

Figure 6.13 The mean and maximum hourly rainfall for the study region during baseline period (1980-2010) and future periods, including (a1 & a2) 2030s (2011-2040), (b1 & b2) 2050s (2041-2070) and (c1 & c2) 2080s (2071-2099). Two solid lines (H3A2 envelope) represent the upper and lower boundaries for simulated envelope of HadCM3 A2 Scenario; two dash lines (H3B2 envelope) represent the upper and lower boundaries for simulated envelope of HadCM3 B2 Scenario.

relationship between local data and large scale predictors under the future climate-change conditions. Two potential ways might be helpful to mitigate such a problem. Firstly, the high-resolution regional climate model (e.g. WRF) could consider to be coupled with the statistical method to predict future rainfall. This method could both consider the physical process and statistical adjustment. Secondly, if the observed dataset is sufficient, the rainfall data at different periods could be selected to examine the changing trend of the statistical relationship and the related information could potentially be used to update or improve the statistical models. Nevertheless, the integrated multisite downscaling and disaggregation framework investigated in this study is a viable way to investigate future rainfall patterns and uncertainties. Most importantly, the hourly rainfall data, with essential statistical properties being kept, will be particularly useful for urban hydrological impact studies. It is also noted that if the method is to be applied in other regions with a large area, the cross-correlation may not be of a serious concern and the framework could be largely simplified by assuming gauge independence.

6.5 Summary

With an aim of generating high spatial and temporal resolution rainfall data at multiple sites over Singapore Island under future climate-change conditions, a systematic downscaling-disaggregation study was conducted. The framework was based on multisite spatial downscaling, master-station-based disaggregation and multisite disaggregation models. The study was divided into two major components. The first one was to evaluate various alternatives of spatial downscaling and temporal disaggregation methods based on observed data, including the multisite GLM method versus single-site GLM combined with KNN spatial disaggregation, single-site KNN disaggregation versus HYETOS, multisite KNN disaggregation versus MuDRain. In the second component of study, an integrated downscaling-disaggregation framework based on three methods, including GLM,

KNN, and MuDRain, was used to predict rainfall patterns under future climate-change conditions under HadCM3 SRES A2 and B2 scenarios. It was indicated that the variation of annual rainfall amount would not be significant for future periods, but the rainfall in wet season and extreme events would notably increase.

The major contributions of this study include: (i) it made an inter-comparison on the performance of multiple downscaling and disaggregation tools; (ii) it proposed an integrated downscaling-disaggregation framework that could offer a cost-effective alternative for generating high-resolution rainfall data in tropical areas. The study outputs could help decision makers evaluate future rainfall patterns in tropical urban areas and examine the impacts of climate change on urban hydrological systems. The methodology can also be used for other regions where spatial correlations among multiple stations are high. Due to the limited number of predictors or accuracy of the general circulation models in the tropical region, the performance of statistical models is subjected to a certain level of uncertainties. It is necessary to use multiple GCMs or regional climate models (RCM) to improve the performance of the related downscaling and disaggregation models in future studies.

CHAPTER 7 A COMBINED WEATHER GENERATOR AND K-NEAREST-NEIGHBOR APPROACH FOR ASSESSING CLIMATE CHANGE IMPACT ON REGIONAL RAINFALL EXTREMES

7.1 INTRODUCTION

Study of extreme rainfall is important for hydrological design, flood control, and water resources management (Dourte *et al.*, 2013). This is especially true for heavily urbanized cities like Singapore which is characterized by complex tropical weather patterns and heavy storms. A warmer climate may lead to increase of extreme rainfall in many regions of the world (Gorman, 2012). Exploring the potential variation of regional extreme rainfall under climate change is necessary to help evaluate potential risks of rain extremes on urban infrastructure in the future and guide adaptation planning. Previously, many studies were conducted to investigate the changing tendency of extreme rainfall events in different regions of the world, such as North America (Karl *et al.*, 1995; Mailhot *et al.*, 2007), Europe (Willems and Vrac, 2011), Africa (Chen *et al.*, 2012), China (Zhai *et al.*, 2005), and India (Dourte *et al.*, 2013). For Southeast Asia (in particular for Singapore), studies quantifying the impact of climate change on extreme rainfall are limited. In fact, based on the analysis of annual rainfall using historical record, there is an increasing trend over the past thirty years, and the annual maximum hourly rainfall also rises at a rate of 10 mm per decade for the period from 1980 to 2008 (PUB, 2012). It is thus imperative to examine the potential impact of climate change on extreme rainfall events in this region for the purpose of aiding adaptation planning.

General circulation models (GCMs) can be used to simulate the future climate conditions (Xu *et al.*, 2012). However, the output of GCMs is too coarse, both

spatially (e.g. typical resolution of 100 – 200 km) and temporally (e.g. typically daily or 6-hour), for urban hydrological or water resource studies, and certainly difficult to be used in development of fine-resolution extreme rainfall or intensity-duration-frequency (IDF) curves (e.g. 5-minutes level). Downscaling tools can help bridge the gap between GCM and local weather information and have been widely used over the past decades. Downscaling methods can be broadly classified into two classes: dynamic and statistical (Fowler et al., 2007). Several studies in the past employed dynamic downscaling tools to obtain high-resolution extreme rainfall or IDF curves (Murphy et al., 2004, Greene et al., 2006, Grum et al., 2006, Mailhot et al., 2007, Kao and Ganguly, 2011, Zhu et al., 2013, Wang et al., 2013, Kuo et al., 2014). From these works, it is found that the dynamic approach based on regional climate models (RCMs) is a viable option for obtaining extreme rainfall but it sometimes requires bias correction and is also computationally expensive (Fowler et al., 2007; van Roosmalen et al., 2010; Teutschbein and Seibert, 2012; Bordoy and Burlando, 2013).

As another alternative of downscaling, statistical methods have been found cheaper in computation, and also could achieve reasonable results with high spatial and temporal resolutions (Fowler et al., 2007; Ghosh and Mujumdar, 2008; Fang et al., 2013). The statistical methods consist of either spatial downscaling or temporal disaggregation or both. Many earlier research works were devoted to the simulation of extreme rainfall or IDF curves using statistical downscaling or disaggregation methods (Hundecha and Bardossy, 2008; Benestad, 2010; Friederichs, 2010). Willems and Vrac (2011) used two statistical downscaling methods (including quantile perturbation and weather typing) to generate short-duration (i.e. 10-minute) rainfall extremes at Belgium. The results showed that the quantile perturbation method could directly use daily rainfall results from GCMs to generate 10-minute rainfall data. However, the changes in weather typing frequencies could not reflect the variation of rainfall intensity. Peck *et al.* (2012) employed a stochastic weather

generator based on K-nearest neighbor (KNN) method to downscale the daily maximum rainfall with nine durations (5-, 10-, 15-, 30-min and 1-, 2-, 6-, 12-, and 24-hour). In this method, the shuffling mechanism was used for generating synthetic rainfall sequence, and the perturbation method was employed to simulate extreme rainfall values for future period. The output from downscaling was used for producing the IDF curves for current and future periods, and the study indicated an increasing tendency of maximum rainfall for all nine durations.

Over the past years, studies have combined temporal disaggregation tools such as stochastic point processes models (Rodriguez-Iturbe et al., 1987), multiplicative random cascade models (Rupp et al. 2009), and nonparametric models (Nowak et al., 2010) with statistical downscaling methods to generate data with high temporal resolutions. Segond et al. (2006) proposed a master-station-based approach based on the statistical downscaling model (i.e. GLIMCLIM, Chandler and Wheater, 2002) and stochastic point processes disaggregation method (i.e. HYETOS, Koutsoyiannis and Onof, 2001) to generate hourly rainfall data at multiple sites in Thames region, UK. Mezghani and Hingray (2009) developed another novel downscaling-disaggregation framework based on generalized linear model and KNN nonparametric method to generate multisite hourly rainfall data in Switzerland. Licznar et al. (2011) compared six statistical temporal disaggregation methods based on multiplicative random cascade method in generating 5-minute rainfall data. These studies indicated that the temporal disaggregation methods could be applied individually or combined with statistical downscaling methods. For regional rainfall analysis, the rainfall data are normally collected from multiple weather stations in order to increase the sample size and the robustness of results (Zhu et al., 2013). In addition, the methods adopted in the studies of Segond et al. (2006) and Mezghani and Hingray (2009) could capture spatial distribution of rainfall. Representation of spatial structure of rainfall events is important for the

climate change impact studies (e.g. urban hydrological modeling) in regions with high spatial variability of rainfall.

The previous studies made viable attempt in deriving high-resolution rainfall data from coarse ones and laid a solid foundation for examining climate-change impact on extreme rainfall data or IDF curves. It is now well accepted that the projections of future climate-change conditions are sensitive to the type of GCMs and emission scenarios (Randall *et al.*, 2007; Santos *et al.*, 2008). It is therefore important to use multiple ensembles from multi-GCMs to reflect the potential uncertainties of future conditions (Mailhot *et al.*, 2007). The LARS-WG (Long Ashton Research Station - Weather Generator) is a popular tool for climate change impact studies and has been successfully applied around the world with different climate types (Semenov *et al.* 1998; Qian *et al.*, 2005; Hashmi *et al.*, 2011; Chen *et al.*, 2012; Xu *et al.*, 2012; Sunyer *et al.*, 2012; Luo *et al.*, 2013; Roshan *et al.*, 2013; Semenov *et al.*, 2013, Taye and Willems, 2013). From many previous studies, LARS-WG model has demonstrated a good capability in simulating the extreme rainfall events. Particularly, it has embedded the outputs from 15 GCMs (in version 5.5) and offers a parsimonious way of examining uncertainties associated with multiple climate-change scenarios (Semenov and Stratonovitch 2010). However, the previous studies based on LARS-WG mainly focused on daily time scale. Limited studies are found in applying LARS-WG for finer-scale (e.g. hourly or sub-hourly) rainfall analysis under climate change conditions.

Based on the review of previous research works, two main research gaps can be noted: Firstly, there are limited studies concerning analysis of regional extreme rainfall under climate change condition in Southeast Asia. One such study (Liew, 2012) attempted to use a dynamical downscaling method based on Weather Research and Forecasting (WRF) model to investigate the climate change impact on IDF curves in Southeast Asia (including Singapore, Kuala Lumpur, Jakarta and

Darmaga) with spatial resolution at about 30 km. However, the temporal resolution was limited at 6-hourly which was too coarse to be useful for urban drainage design. Recently, Chang and Hiong (2013) introduced a simple scaling method to estimate the IDF curves (temporal resolution is 15-min) for Singapore based on historical record. However, climate change impact was not taken into consideration in this work. Secondly, in tropical regions, in addition to the features such as frequency and quantity, characterization of the spatial correlation of rainfall is critical at both daily and sub-daily timescales (Manabe and Jozaki, 2011; Mandapaka and Qin, 2013). The spatial correlation among multiple sites is an important criterion in evaluating the results from statistical downscaling and disaggregation; there are limited studies that attempted to address this in regional extreme studies in tropical areas (Buishand, 1991; Mailhot et al., 2007).

To address aforementioned research gaps, this study proposed a combined statistical downscaling and disaggregation (CSDD) framework to investigate climate change impact on regional extreme rainfall using Singapore as illustration. Three different routes for simulating the high-resolution rainfall data are tested and compared. Route 1 uses single long-term rainfall record obtained by combining records from multiple sites, Route 2 treats each station individually (e.g. assume spatial independence), and Route 3 considers the inter-gauge correlation at both daily and sub-daily timescales. All three routes could generate continuous rainfall sequences which are useful for rainfall-runoff simulation. The objective behind the application of three routes is to evaluate the effects of different treatments of downscaling/disaggregation methods for modelling regional extreme events. These three routes could be adopted at different situations. For example, if the focus is on the station-level rainfall extremes or on a small sub-region, then one may employ the first two routes without explicitly accounting for spatial variability of rainfall. However, to analyze the cumulative effects of multiple storm events over a large

region or a river basin, the third route would be more appropriate to be used, as spatial correlation plays a critical role in such a scenario.

The LARS-WG method is used for generating synthetic rainfall at daily timescale for both current and future periods under 12 GCM outputs (from 4 GCMs). Following the idea of Mezghani and Hingray (2009), the KNN disaggregation framework (including three individual procedures) are applied for spatial and temporal disaggregation to generate rainfall data up to 5-minute levels at multiple stations in Singapore. The advantages and disadvantages of the proposed three routes will be compared and discussed. The regional extremes are produced for current condition benchmarked by local record, and those for future conditions are also projected. To summarize, we address the first research gap in detail by obtaining high resolution rainfall series via different routes, and address the second research gap partially by evaluating the effect of accounting spatial correlation of rainfall in statistical downscaling. It should be noted that the Route 1 is used in this study for future projections (further discussions are provided in Section 4.4).

7.2 Methodology

7.2.1 Combined Statistical Downscaling and Disaggregation (CSDD)

method

The proposed CSDD is developed for simulating high-resolution rainfall and studying regional extreme events' change under climate change. The proposed framework consists of three routes, and as discussed in the Introduction, only one route is used in this study for estimating future rainfall projections. Figure 7.1 illustrates the flowchart of three simulation routes of CSDD based on LARS-WG and KNN disaggregation. Route 1 is based on the single long-period record which is obtained by combining multiple station rainfall data. This means the approach

treats all stations as one ‘single site’ (e.g. n years of records from m stations were combined as $n \times m$ ‘years’ of one station) (Huff and Neil, 1959; Chang and Hiong, 2013). The idea is adopted from the ‘station-year’ method (Buishand, 1991) and generally used for extreme rainfall estimation (PUB, 2011; Chang and Hiong, 2013). Route 2 treats each station individually. It assumes that all stations are independent of each other. Route 3 is based on the total areal rainfall at multiple timescales (i.e. daily and hourly). For example, the total areal rainfall at one day (DTAP) or one hour (HTAP) equals to the summation of single-site rainfalls at three stations at the same day or hour. The flow path of applying Route 3 is: (i) disaggregate daily total areal precipitation (DTAP) to hourly total areal precipitation (HTAP) (i.e. the DTAP/HTAP could also be replaced by daily/hourly mean areal precipitation); (ii) generate hourly rainfall for individual station through spatial disaggregation; (iii) generate 5-minute (5-min) rainfall through a second-round temporal disaggregation. The reason for adopting the proposed flow path is that it could keep the spatial correlation at both daily and hourly timescales.

All routes are based on both LARS-WG and K-nearest neighbor disaggregation methods. The daily level rainfall data (including ‘real’ daily rainfall in Routes 1 and 2, and ‘pseudo’ daily rainfall - daily total areal precipitation in Route 3) is generated by LARS-WG model for current and future periods. The KNN disaggregation method is used for temporal disaggregation in all routes and for spatial disaggregation in Route 3. The temporal disaggregation procedure is divided into two steps: the first one is disaggregation from daily to hourly, and the second one is from hourly to 5-min. Theoretically, it is possible to disaggregate rainfall from daily to 5-min levels directly but several studies show that the scaling behavior of precipitation changes around 45 min to 2 h, which makes the two-step disaggregation approach more appropriate (Fraedrich and Larnder, 1993; Nguyen et al., 2007; Rysman et al. 2013; Mascaro et al., 2014; Mandapaka and Qin, in press). Also, due to the record limitation of 5-min data, it is difficult to apply the

cross-validation in disaggregation (see KNN methodology description) to keep the statistical properties for the results at the aggregated timescale (i.e. hourly). Some previous studies have also suggested similar multiple-step procedures to obtain sub-hourly data from daily scales (Santos and Salas, 1992; Nguyen et al., 2007; Nowak *et al.*, 2010). Finally, based on the generated rainfall sequences at daily, hourly and 5-min timescales, the regional extreme events are reproduced and updated. Following the official guidelines described in the sixth edition Code of Practice of PUB (Public Utilities Board) and the study of Chang and Hiong (2013), the station-year method and Gumbel distribution are applied for analyzing regional rainfall frequency. The details of LARS-WG and KNN are given as follows.

Figure 7.1 The roadmap of the three routes within a combined statistical downscaling and disaggregation (CSDD) framework

7.2.2 K-nearest neighbor (KNN)

The K-nearest neighbor is a nonparametric resampling method, where the weather scenarios are simulated from the historical record using conditional simulation (Prairie et al., 2007; Mezghani and Hingray, 2009; Nowak et al., 2010). The long-period historical record is not the essential condition of KNN model, although it is widely recognized that the more the better. In traditional method, the nearest neighbors are identified from the historical rainfall record and resampled by stochastic method with a weight scheme. KNN method presents a capability to capture nonlinear or non-normal feature (Nowak *et al.*, 2010). KNN method is straightforward to apply and has been suggested to couple with a cross-validation procedure (Sharif and Burn, 2006). The purpose of this study is to examine the regional extreme rainfall. Hence, the cross-validation procedure of KNN method is based on the extreme rainfall indices (please refer to the ***cross-validation*** part of this section). Table 7.1 shows the variables of input and output in KNN disaggregation procedures of three routes, which are divided into two groups based on the resolutions. The coarse scale variables represent the input; fine scale variables represent the output. The cross-validation procedure is used for choosing single ensemble of output for single-site daily and hourly durations (i.e. temporal disaggregation-1 and spatial disaggregation in Table 7.1). For simulation of 5-min data (i.e. temporal disaggregation-2 in Table 7.1), the multiple ensembles of output (i.e. based on the different distances of neighbors in KNN application) is adopted to obtain the possible uncertainty range of the results, which should cover the observed extreme data (i.e. official IDF curves) during the verification period. This operation could bring extra uncertainty to the results, but is necessary to ensure the data quality issue caused by the limited rainfall data at 5-min level would not

seriously affect the reliability of the projected results for future conditions. In this study, the KNN method follows the method suggested by Nowak et al. (2010). The implementation procedures are explained as follows.

Table 7.1 The input-output pairs of variables in KNN disaggregation procedures

Procedure	Coarse Scale			Fine Scale		
	Route 1	Route 2	Route 3	Route 1	Route 2	Route 3
Temporal disaggregation-1 ^a	Daily	Daily	DTAP	Hourly	Hourly	HTAP
Spatial disaggregation ^b	N.A.	N.A.	HTAP	N.A.	N.A.	Single-site hourly
Temporal disaggregation-2 ^c	Hourly	Hourly	Hourly	5-min	5-min	5-min

Note: DTAP = the daily total areal precipitation; HTAP = the hourly total areal precipitation. ^a Temporal disaggregation-1 represents the disaggregation from daily timescale to hourly timescale; ^b spatial disaggregation represents the simulation from areal data (i.e. HTAP) to single rain gauge data, and it is only applied in Route 3; ^c Temporal disaggregation-2 represents the disaggregation from hourly timescale to 5-minute timescale.

STEP 1: Let F be the matrix containing observed fine scale data, and C be the corresponding observed coarse scale data:

$$F = \begin{bmatrix} f_{1,1} & \cdots & f_{1,j} & f_{1,J} \\ \cdots & & & \cdots \\ f_{i,1} & & f_{i,j} & f_{i,J} \\ \cdots & & & \cdots \\ f_{I,1} & \cdots & f_{I,j} & f_{I,J} \end{bmatrix} \quad C = \begin{bmatrix} c_1 \\ \vdots \\ c_i \\ \vdots \\ c_I \end{bmatrix}$$

where f and c are elements of fine-scale and coarse-scale data matrices; i represents the index of coarse scale data ($i = 1, 2, \dots, I$) and I is the total number of coarse scale data; j represents the index of fine scale data ($j = 1, 2, \dots, J$) and J is the total

number of fine scale data for each i . Therefore, $f_{i,j}$ means the j^{th} fine scale data corresponding to the i^{th} coarse scale data. Construct a matrix $\mathbf{P}$ such that

$$\mathbf{P} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,j} & p_{1,J} \\ \cdots & & & \cdots \\ p_{i,1} & & p_{i,j} & p_{i,J} \\ \cdots & & & \cdots \\ p_{I,1} & \cdots & p_{I,j} & p_{I,J} \end{bmatrix}$$

where, p_{ij} is the percentage of the j^{th} fine-scale data over the corresponding coarse data, which can be defined as $p_{i,j} = f_{i,j} / c_i$.

STEP 2: Prepare vector E (which contains the new coarse scale data which is the data expected for disaggregation):

$$\mathbf{E} = [e_1 \quad \cdots \quad e_n \quad \cdots \quad e_N]^T$$

where n represents the index of coarse scale data which is expected to be disaggregated and N is the total number of coarse scale data which need to be disaggregated. The K nearest neighbors of E is found from the observed dataset C based on Euclidean distance (Danielsson, 1980). The number of neighbors, K , is chosen with caution. A smaller K means a higher noise effect; a bigger one means a more intensive computation. In the study of Lall and Sharma (1996), K is defined as $N^{1/2}$. However, it is found inappropriate for this study, as K would be higher than 108. Yeh and Gallagher (2005) pointed out that a too-large K is detrimental to locality of estimation. Based on other studies (Li *et al.*, 2003; Mezghani and Hingray, 2009), K is generally below 20. In this study, multiple K nearest neighbors from 1 to 10 are defined from the observed data. When K equals to 1, it denotes the nearest neighbor; K equaling to 2 means the 2nd nearest neighbor and so on. In total, 10 nearest neighbors (denoted as the potential

neighbors $k_1, k_2, \dots$, and k_{10}) are chosen for disaggregation. Therefore, each e_n in E has 10 corresponding nearest neighbors.

STEP 3: Generate vector SE (with the same dimension as E) based on the selected candidate neighbors from E , and for each data from SE , formulate the corresponding proportions data series SP from P :

$$SE_k = \begin{bmatrix} se_1 \\ \vdots \\ se_n \\ \vdots \\ se_N \end{bmatrix}_k \quad SP_k = \begin{bmatrix} sp_{1,1} & \cdots & sp_{1,j} & sp_{1,J} \\ \cdots & & & \cdots \\ sp_{n,1} & & sp_{n,j} & sp_{n,J} \\ \cdots & & & \cdots \\ sp_{N,1} & \cdots & sp_{N,j} & sp_{N,J} \end{bmatrix}_k \quad \forall k = 1, 2, 3, \dots, K$$

where k means the k^{th} nearest neighbor of vector E (e.g. SE_k means the selected k^{th} nearest neighbor of vector E ; SP_k means the corresponding proportions of SE_k); $sp_{n,j}$ means the proportion of the j^{th} fine scale data corresponding to the n^{th} coarse scale data se_n . The final disaggregated results FD could be written as follows:

$$FD_k = \begin{bmatrix} fd_{1,1} & \cdots & fd_{1,j} & fd_{1,J} \\ \cdots & & & \cdots \\ fd_{n,1} & & fd_{n,j} & fd_{n,J} \\ \cdots & & & \cdots \\ fd_{N,1} & \cdots & fd_{N,j} & fd_{N,J} \end{bmatrix}_k$$

where FD_k means the final disaggregated results based on the k^{th} nearest neighbor; each element in FD is calculated by $fd_{n,j} = sp_{n,j} \times e_n$. As mentioned before, if the option of multiple ensembles is implemented, for each coarse data, 10 nearest neighbors (i.e. K equals to 10) are selected. Hence, there will be 10 groups of SE , SP , and FD .

Cross-validation: Based on Table 7.1, when the KNN method is used in the procedures of temporal disaggregation-1 and spatial disaggregation, the

cross-validation procedure is applied for selecting a single ensemble of output. Cross-validation is used to select the group of the nearest neighbors during verification of the model (Lu and Qin, 2014). The criteria of cross-validation are to obtain the minimum of root-mean-square-error (RMSE). In order to examine the regional extreme events, the objective function is defined by the RMSE of extreme events, which can be given as:

$$RMSE_{extreme} = \sqrt{\frac{(SIM_{extreme} - OBS_{extreme})^2}{N_{extreme}}} \quad (7-1)$$

where $RMSE_{extreme}$ means the RMSE values between observed and simulated rainfall amount for different return periods (in this study, the return periods include the 2-, 3-, 5-, 10-, 15-, 25-, 50- and 100-year). The return periods are estimated by using standard method, i.e. by analyzing frequencies (probabilities) of annual rainfall maxima (e.g., Brutsaert, 2005). $SIM_{extreme}$ and $OBS_{extreme}$ represent the simulated extreme data and observed extreme data, respectively, and $N_{extreme}$ is the number of return periods (equals to 8).

When the KNN method is used for disaggregation from hourly to 5-min duration (i.e. temporal disaggregation-2 in Table 7.1), the multiple ensembles of output (i.e. matrix **FD**) is used to reflect uncertainties. The conventional method is to use a random selection scheme based on a decreasing kernel function (Mezghani and Hingray, 2009; Nowak et al., 2010), which gives a higher weight to a closer/nearer neighbor. In this study, the output generated by stochastic method is found inappropriate. The reason is that the nearest neighbors (i.e. when the K below 4) assigned a large weight generally would underestimate the extreme data due to the limitation of historical data. In this study, the multiple ensembles of output are chosen by different groups (i.e. matrix **FD**) of nearest neighbors which are classified by distance (See **Step 2**). Based on our test, five groups of nearest

neighbors could effectively cover the observed data, while at the same time, keeping the uncertainty range as narrow as possible. For Routes 1 and 2, the five groups with K values from 1 to 5 are selected; for Route 3, the five groups with K values from 2 to 6 are selected. In this study, the group (consisting of five members) is selected using trial-and-error method based on the criteria of covering observed data and having relatively narrower uncertainty range. Another alternative is based on the minimum error between observed data and average value of multiple groups, which is not shown here.

7.2.3 LARS-WG downscaling

The semi-empirical stochastic weather generator, LARS-WG, was developed by Semenov and Barrow (1997). The model analyzes the statistical properties (e.g., wet/dry spell lengths, mean and standard deviation of rainfall) from observed daily data and produces the synthetic time series based on these properties. In this study, we employed version 5.5 of LARS-WG software, which has twenty-three intervals for the semi-empirical distribution to enhance the accuracy (i.e. it has narrower interval for histogram compared with the previous versions to construct the semi-empirical distribution). The semi-empirical distributions are used for fitting the wet/dry sequences and rainfall amount. LARS-WG model incorporates the seasonal effect by estimating parameters separately for each month. To simulate the rainfall using LARS-WG, the day status is determined first. Once the status is identified, the rainfall amount is simulated from semi-empirical distribution independently of the length of wet series or rainfall amount of previous days (Semenov *et al.*, 1998). To generate the climate scenarios for certain future periods, the model depends on the change factor ($rainfall-amount_{future}/rainfall-amount_{baseline}$) to adjust the rainfall amount of baseline (Semenov and Barrow, 2002). For each climate model and future period, the LARS-WG model calculates change factors based on the monthly variations

of rainfall amount (Semenov and Barrow, 2002; Semenov and Stratonovitch, 2010; Chen *et al.*, 2012), which are in turn projected to daily rainfall sequence. Therefore, in this study, we have to assume stationarity of the statistics of the hourly and 5-min level rainfall. One possible way to address this issue is to look at the variation of specific duration rainfall using a long-term historical record, and reflect such non-stationarity effect in the statistical model. Unfortunately, due to data limitation, we are unable to do such a work for the current study. Also, it should be noted that in the LARS-WG version used in this study, change factors for dry or wet spell sequences are not computed (therefore set to 1.0) for future conditions. We believe that this is not a significant limitation as the focus of the study is on reproducing rainfall probability distributions, and since the monthly variations in rainfall amount are accounted by the LARS-WG model in terms of change factors.

For implementation of LARS-WG in this study, QTEST is applied for searching the best random seed to ensure a reliable simulation. Kolmogorov-Smirnov Test, t-test, and F-test should pass each time. Once the random seed is chosen, the LARS-WG could generate synthetic data for the current and future period under specific emission scenarios. More details about LARS-WG are provided in the studies of Semenov and Barrow (2002), Semenov and Stratonovitch (2010) and Chen *et al.* (2012).

7.3 Study Area and Data

Singapore is located in Southeast Asia and its climate is characterized by heavy rainfall, nearly constant temperature and pressure, and no distinct seasonality. The island is highly urbanized with a high population density. The highest point is the Bukit Timah hill in the central part of the island. The rainfall variability in the island is more significant in the east-west direction compared to the north-south

direction (Chia and Foong, 1991; Fong, 2012). There are two monsoons over the island each year, including northeast monsoon from December to early March and southwest monsoon from June to September. The wettest month is December and driest month is February, which both occur in the northeast monsoon (Fong, 2012; Mandapaka and Qin, 2013).

Table 7.2 Selected GCM models and emission scenarios in LARS-WG

Model	Distribution Institute	Emission Scenarios
CCSM3 ^a	National Center for Atmospheric Research, USA	A1B, A2, B1
HadCM3 ^b	Hadley Centre for Climate Prediction and Research, UK	A1B, A2, B1
IPCM4 ^c	Institute Pierre Simon Laplace, France	A1B, A2, B1
ECHAM5 ^d	Max Planck Institute for Meteorology, Germany	A1B, A2, B1

Source: ^aKiehl and Gent (2004) and Collins et al. (2004); ^bGordon et al. (2000); ^cHourdin et al. (2006); ^dRoeckner et al. (1996).

Based on the characteristics of spatial distribution of rainfall in Singapore, three weather stations, including MacRitchie Reservoir (S07), Changi Airport (S24) and NTU (S44), are selected for analyzing climate-change effects on regional extreme rainfall. Figure 7.2 shows the location of these stations, where they are at eastern, western and central regions of Singapore Island, respectively. In terms of rainfall data, there are 33 years of records from 1980 to 2012 at daily and hourly timescales for three stations with few missing data (i.e. the missing hourly data is about 0.47%). The 5-min rainfall spans for 2.5 years (i.e. July 2010 to December 2012) with about 0.25% of missing data. The data from neighboring rain gauge (with high correlation) is used to fill the missing daily and hourly time steps. For the 5-min data, the missing data are assigned as zero based on the consideration that there is limited quantity of 5-min data and the missing data is mainly concentrated in only two days. Twelve GCM outputs are chosen to predict the climate variation for the future period. They are collected from four GCMs, namely CCSM3 (Kiehl and

Gent, 2004; Collins et al., 2004), HadCM3 (Gordon et al., 2000), IPCM4 (Hourdin et al., 2006), and ECHAM5 (Roeckner et al., 1996), which have been widely used around the world. For each GCM model, three emission scenarios (i.e. A1B, A2 and B1) over three future periods (i.e. 2011-2030, 2046-2065 and 2080-2099) are adopted (Table 7.2).

Figure 7.2 The study area and stations

7.4 Result Analysis

7.4.1 Reproduction of current condition

7. 4.1.1 Simulated results at daily level

LARS-WG is used for obtaining daily rainfall data (including station daily rainfall and DTAP) for current and future periods. For each period, 200-years synthetic rainfall data is generated. The selected scenarios are illustrated in Table 7.2. There

are 12 scenarios under 4 GCMs in this study. Figure 7.3 shows a comparison of the observed and simulated regional rainfall amount at three timescales (daily, hourly and 5-min). Regional rainfall data is obtained by combining all observed or simulated data record of three stations. This treatment is similar to ‘station-year method’ which was applied in this region by PUB (2011). Figure 7.3(a1) to (a3) present the simulated daily rainfall by three routes. In Figure 7.3(a1), the synthetic data of Route 1 from the LARS-WG shows a slight overestimation (for rainfall amount > 100 mm/day). The results may be caused by the combination of ‘single site’ input data, which could affect the monthly rainfall properties. In Figure 7.3(a2), the result of Route 2 also shows an overestimation when the rainfall amount is between 100 mm/day and 120 mm/day (e.g. when the observed data equals to 100 mm/day, the simulated data of Route 2 at same percentile is around 108 mm/day). The result of Route 3 shows a slight underestimation when rainfall is below 40 mm/day (e.g. when the observed data equals to 20 mm/day, the simulated data of Route 3 at same percentile is around 18.2 mm/day). This behavior is due to the criterion of group selection for daily timescale based on extreme events (refer to Equation 1 in Section 3.2). It may lead to slight deviations for other data except for extreme events, but the peak values of all three routes are reproduced well. The Figure 7.3(b1) to (b3) present the disaggregation results of hourly data using three routes, respectively; Figure 7.3(c1) to (c3) present disaggregation results of 5-min data using three routes, respectively. The description of those results would be provided in Sections 7. 4.1.2 and 7. 4.1.3, respectively.

Figure 7.4 shows a comparison of 33-years observed and 200-years LARS-WG generated DTAP data of Route 3 for the current period. The synthetic data from the LARS-WG shows somewhat overestimation when the DTAP amount is between 210 and 500 mm/day, but it reproduces the data above 500 mm/day quite well. This may be caused by the combination of the records from three stations (e.g. calculation of the areal total rainfall), which somewhat affect the statistical

properties. The maximum value in the synthetic DTAP series is close to the observed one. The histogram approach in LARS-WG can limit the maximum value that can be obtained during the simulation (Sunyer et al., 2012).

Figure 7.3 Quantile-quantile plot for observed and simulated regional rainfall amount at three timescales; the labels of 1, 2, and 3 represent the Route 1, Route 2, and Route 3 respectively, and the symbols of a, b, and c represent daily, hourly and 5-min timescales, respectively

Figure 7.5 shows a comparison between the observed and simulated probability distribution (with focus on cumulative probability above 0.9) by Route 2 and Route 3 at three stations. The results of Route 3 present slight underestimation at S24 station (e.g. the observed values at percentiles of 0.95 and 0.99 are 47.02 mm/day and 88.6 mm/day, respectively; the simulated values at the same percentiles are

42.4 mm/day and 77.4 mm/day, respectively). Route 2 shows a better performance and reproduces the daily results well. Through comparison of the Mean Absolute Percentage Error (MAPE) values (Swanson et al., 2011) for Mean, Standard Deviation and Probability of Wet Day, the average value of MAPEs of three properties from three stations for Route 2 is 0.057. Such a value is smaller than that of Route 3 which is 0.101. The reason is that the daily data of Route 3 is simulated by the aggregation of hourly data; since there are two additional procedures (e.g. disaggregation from DTAP to HTAP and HTAP to single-site hourly), the final aggregation result could be somewhat affected. Therefore, Route 3 shows a poorer performance at daily timescale than Route 2 which generates daily data directly from LARS-WG. In terms of inter-site correlations, the simulated results by Route 3 are 0.638, 0.625 and 0.551, respectively, which are slightly overestimated compared with the observed data (i.e. 0.539, 0.522 and 0.410).

Figure 7.4 Quantile-quantile plot for the observed Daily Total Areal Precipitation (DTAP) and simulated DTAP using LARS-WG in Route 3

Figure 7.5 The empirical cumulative distribution probability (above 0.9) for observed and simulated single-site daily rainfall at three stations from Route 2 and Route 3. The labels of 1 and 2 represent the Route 2 and Route 3, respectively; a, b and c represent the station S07, S24 and S44, respectively

Figure 7.6 Relative changes of calculated monthly rainfall under different GCM scenarios for future periods of (a) 2011-2030, (b) 2046-2065, and (c) 2080-2099

Figure 7.6 shows the relative change of monthly rainfall for three future periods under different climate emission scenarios which are obtained from LARS-WG. In this figure, the relative change factor for the baseline period (1980-2012) is taken as

1. Generally, the largest variation is found in the third period (2080-2099) where the change factor is from 0.75 to 1.3. There is no significant change in the recent future (2011-2030), and most of factors fall within the interval between 0.95 and 1.05 (Figure 7.6a). In the second future period (Figure 7.6b), a notable change is found for the months from January to July. The highest change factor (i.e. 1.36) would be occurring in March. For year 2080-2099, there is a general decreasing tendency for the first three months (January, February and March) as most of the factors are from 0.75 to 0.95. The change factors for the rest of the months are generally above 1, but focus more on the interval from 1.05 to 1.2. Overall, except for the two points, which correspond to March and April from IPCM4 A1B scenario during period 2046-2065, the rainfall projections at the end of this century (2080-2099) generally present a wider range than those in other two periods, especially for the months from May to December. This may because of the growing difference of greenhouse gas emissions under different scenarios.

7. 4.1.2 Simulated results at hourly level

Figures 7.3(b1), (b2) and (b3) show the comparison of observed and simulated regional hourly rainfall by three routes. Similar to the results of daily-level results, Route 1 and Route 2 both present a slight overestimation when rainfall amount is between 80 mm/hour and 100 mm/hour (e.g. when observed data equals to 80 mm/hour, the simulated data of Route 1 and Route 2 at the same percentile are about 84.7 mm/hour and 84.8 mm/hour, respectively). For the results of Route 3, there is an underestimation of around 90 mm/hour (e.g. when observed data equals to 90 mm/hour, the simulated data of Route 3 at the same percentile is about 88.1 mm/hour). For the extreme data (above 100 mm/hour), the results of Route 1 and Route 3 show slight overestimation and that of Route 2 is opposite. The maximum values of the three routes are 132 mm/hour, 119.2 mm/hour, and 132.6 mm/hour, which are close to the observed value (i.e. 123.7 mm/hour). The results also show

that the simulated hourly rainfall above 100 mm/hour could well fit the observed data. This demonstrates that the disaggregation procedures in three routes perform satisfactorily (i.e. the disaggregation procedure does not affect the reproduction of extreme events based on the output of LARS-WG). Figure 7.7 shows the quantile – quantile plot for the observed and synthetic disaggregated HTAP data, which is generated by disaggregation of synthetic DTAP data from LARS-WG. It shows a good performance for both low and high rainfall amounts. The extreme value also shows a reproduction (i.e. 225.5 mm/hour) compared with the observed data (i.e. 216.2 mm/hour).

Figure 7.7 Quantile-quantile plot for the observed and simulated Hourly Total Areal Precipitation (HTAP) from Route 3.

Figure 7.8 shows a comparison between the observed and simulated single-site hourly rainfall data by Route 2 and Route 3. For station S07 (Figure 7.8(a2)), the two routes both perform well. Route 3 shows an underestimation for peak values. From Figure 7.8(b1), Route 2 presents an overestimation when rainfall is above 70 mm/hour at S24, and a slight underestimation for the peak value. The result of Route 3 (i.e. Figure 7.8(b2)) shows a slight underestimation at S24, but performs well for extreme data. At S44, Route 2 shows a better performance than Route 3,

where there is a notable overestimation for heavy rainfall amount (above 90 mm/hour) under Route 3. For the spatial correlation of Route 3, the simulated values of cross correlations at the stations of S07, S24, and S44 are 0.298, 0.283 and 0.143 respectively, which are fairly close to the observed records (i.e. 0.283, 0.257 and 0.144).

Figure 7.8 The quantile-quantile plot for observed and simulated single-site

hourly rainfall at three stations from Route 2 and Route 3; a1, b1 and c1 represent the results for S07, S24 and S44 from Route 2, respectively; a2, b2 and c2 represent the results for S07, S24 and S44 from Route 3, respectively.

7.4.1.3 Simulated results at 5-mins level

In this section, the single-site hourly data (e.g. the coarse data matrix **E**) which is generated from *section 4.1.2* would be disaggregated to 5-minute timescale (the finer scale data in matrix **FD**). Figures 7.3(c1), (c2) and (c3) show the quantile-quantile plots for the observed and multiple ensembles of simulated 5-min rainfall amount for all stations under Routes 1, 2, and 3, respectively. Generally, all results demonstrate similar levels of performance. As mentioned before, the five ensembles of outputs could cover the observed data with relatively lower uncertainty range. In this study, the results tend to have a notable overestimation for peak values. This is due to the fact that the observed periods of 5-min rainfall record at the three stations are all from July 2010 to December 2012, and it is difficult to capture full statistical properties for this region with a relatively limited record.

7.4.2 Reproduction of current extreme events

In this section, the obtained rainfall data at daily, hourly and 5-min timescale for current and future period are used for reproducing regional extreme rainfall for this region. In regional frequency analysis, the extreme rainfall data should use the ‘pooled’ data which includes multisite datasets (Zhu *et al.*, 2013). The reason is that the multisite datasets could increase the sample size to generate more reliable results. The observed daily and hourly regional extreme data (annual maxima) are calculated based on 33-years historical record (1980-2012), and the 5-min data is extracted from the sixth edition Code of Practice of PUB. The station-year method (Buishand, 1991; PUB, 2011; Chang and Hiong, 2013) is applied to generate the

IDF curves at three timescales of concern. Station-year method requires the station data record be independent and have a long-term period. In this study, the period of daily, hourly and 5-min data is 200 years for each station. Based on the combined data, 600 station-year annual maximum daily, hourly and 5-min data are generated.

Figure 7.9 Comparison of the observed and generated regional extreme rainfall by three routes at 24-hour, 1-hour and 5-mins durations for the current period. The symbols of a, b and c represent the 24-hour, 1-hour and 5-min durations, respectively and the labels of 1, 2 and 3 represent the Route 1, Route 2 and Route 3, respectively

Figure 7.9 shows a comparison between the observed and generated regional extreme rainfall for the current period (1980-2012) at three durations (i.e. 24-hr, 1-hr and 5-min). From Figure 7.9(a1) to (a3), the results from Route 1 and Route 3

show slight overestimations for the 24-hr duration; the result of Route 2 shows an opposite trend. Route 2 and Route 3 present a similar level of performance by comparing the MAPE value (i.e. 0.019). Route 1 performs better when the return period is above 10 years, but worse in reproducing the extreme events at shorter return periods; this leads to a slightly higher MAPE value (i.e. 0.030) compared with those in Route 2 and Route 3. For the 1-hr duration in Figures 7.9(b1), (b2) and (b3), Route 1 also shows overestimations and Route 2 has the lowest MAPE value (i.e. 0.002). Since there are five ensembles for 5-min data, Figure 7.9(c1) to (c3) present the minimum, average and maximum values of 5-min rainfall extremes over different return periods. The MAPE values are the average values based on the results of multiple ensembles. It is indicated that there is somewhat underestimation of the rainfall extremes at different return periods in terms of average values; however, the observed record is well covered by ensemble envelope. If richer 5-min data are available, the ensemble range could be narrower and less uncertain.

7.4.3 Projection of future extreme events

For the three future periods, the extremes could be affected by a changing climate. This study only examines the variation of rainfall extremes. Therefore, the simplest one, Route 1 is selected to project future extreme events. Figure 7.9 has presented that the results of all of three routes could reproduce the regional extremes of current period (i.e. baseline). Figure 7.10 shows the projected regional extreme rainfall for three future periods under 12 GCM scenarios by Route 1. In the first period (2011-2030), there is no significant variation for 24-hr and 1-hr extreme rainfalls compared with the mean value of 12 scenarios. Due to the application of multiple ensembles of output, the predicted extreme events at 5-min duration show a larger uncertainty interval than other two durations. When the return period is above 15 years, the values of baseline period are higher than the average values of the predicted data. It may be caused by the underestimation of KNN method

Figure 7.10 Predicted regional extreme rainfall for three durations (1, 2, and 3 represent 24-hr, 1-hr, and 5-min durations, respectively) in three periods (a, b, and c represent 2011-2030, 2046-2065, and 2080-2099, respectively) based on Route 1. The upper line of whisker represents the 75 percentile; middle line of whisker represents the median value; lower line of whisker represents the 25 percentile; hollow-square represents the mean value; the line with solid-square represents the observed value.

(referring to Figures 7.9(c1), 7.9(c2) and 7.9(c3)). Comparing the average value of the simulated 5-min data with that in the current period, there seems to be not much significant variation (similar to the results of 24-hr and 1-hr durations). For the 100-year rainfall in the period of 2011-2030, the maximum increase rates at 24-hr, 1-hr and 5-min durations are 5.1%, 6.0% and 7.5% (reach up to 11.99 mm/hr,

125.79 mm/hr and 352.92 mm/hr), respectively. For the 5-min data, the maximum increase rate is calculated based on the upper boundary of simulated baseline and future periods; for 24-hr and 1-hr is calculated based on the observed value and upper boundary of simulated future period. In the middle of this century (2046-2065), the average maximum increase rates of rainfall extremes (based on the upper boundary values at eight return periods) for durations of 24-hr, 1-hr, and 5-min would be 15.1%, 11.7% and 11%, respectively. Towards the end of this century (2080-2099), maximum increase rates of 100-year extremes at durations of 24-hr, 1-hr, and 5-min would be 14.8%, 16.3% and 16.8%, respectively. Overall, for future extreme events, the results suggest a continued increasing tendency for various durations.

7.4.4 Further discussion

The study results demonstrate that the proposed CSDD framework could help generate high spatial and temporal resolution rainfall sequences under climate-change conditions and is useful for examining regional extreme rainfall. The proposed three routes of implementing CSDD framework have different pros and cons. Route 1 has the simplest simulation procedure, but it destroys the original monthly rainfall characteristics by combining multisite records and thus may affect the performance of LARS-WG. Compared to Route 1, Route 2 could not only simulate regional extreme events but also model extremes at each station individually; compared to Route 3, Route 2 is easier to apply. However, the use of this route depends on the focus of the study and the size of the region. Due to lack of spatial correlations, this route is not preferable for hydrologic modelling. Route 3 could generate rainfall time series with correct spatial correlations, and also reproduce the extreme events well. It is useful not only for regional rainfall frequency analysis but also for providing rainfall data for continuous hydrological modeling. The continuous simulation of rainfall-runoff process is especially

valuable in analyzing the cumulative effects of multiple storm events (Chu and Steinman et al., 2009). The weakness of such a route is that the statistical performance for daily rainfall sequence at an individual site may not be as good as that from direct simulation using Route 2 and its computation is more intensive; if spatial correlation of rainfall is of no concern, route 2 may be a better choice.

The relatively short historical record of 5-min rainfall in this study could lead to an underestimation of rainfall extremes. The ensemble approach (using multiple K values) is an attempt to mitigate the issue of limited sample size of 5-min data, as it gives an uncertainty range to the results. From a conservative point of view, the upper boundary of the related uncertainty range could be used for estimating the future increase of extreme rainfalls. Nevertheless, if the entire framework is applied in other regions with good quality data, a smaller number of ensembles or even a single KNN scheme could be used to reduce the uncertainty range of results and improve reliability of projections. In addition, this study chose three sites for demonstrating the proposed CSDD framework. These stations are located at different regions of the Singapore Island and could reflect some spatial variation of rainfall. Adding more sites may lead to more detailed description of spatial correlation or higher accuracy of results but this also brings largely increased computational burden. For the purpose of methodology demonstration, three sites are considered sufficient.

The study made a valid attempt in using a combined downscaling-disaggregation framework for studying regional rainfall extremes. The major innovations/contributions are: (i) CSDD takes the full advantages of both LARS-WG and KNN and could effectively help provide continuous high-resolution synthetic rainfall data (with consideration of spatial dependence/independence and uncertainty) under climate-change conditions for supporting hydrological impact study; and (ii) CSDD includes three different

routes to generate synthetic rainfall data and each one is suitable in a specific condition of application; thus it is flexible to be applied for many other regions with different rainfall patterns. However, a number of limitations also exist. Firstly, although the computational effort of statistical method is much lower than dynamical one, it still involves a large amount of data treatment for the KNN method, especially at 5-min time interval. To solve this problem, combining downscaling approach with the scaling methods (Menabde et al., 1999; Chang and Hiong, 2013) could be a potential way for improvement. Secondly, the proposed statistical downscaling and disaggregation framework assumes a stationary relationship of statistical properties for current and future periods; it could not reflect the dynamical variation of climate and lacks physical meaning in projection. If the period of short-duration (e.g. 5-min) rainfall data is combined with higher resolution dynamical downscaling models, the results could be more reliable.

7.5 Summary

A combined statistical downscaling and disaggregation (CSDD) framework based on LARS-WG and KNN disaggregation was proposed and applied to Singapore Island. Three different routes with the CSDD were proposed for generating high-resolution rainfalls and rainfall extremes. Route 1 used a single long period rainfall record which was obtained by combining records from multiple sites; Route 2 treated each station individually; Route 3 considered the inter-gauge correlation at both daily and sub-daily timescales. LARS-WG was employed to generate daily rainfall and KNN was employed for spatial and temporal disaggregation. The results showed that all the routes could reproduce the rainfall data well at daily, hourly and 5-min levels, and also capture the extreme events well. In addition, Route 3 has an advantage of reproducing spatial correlations for multisite record. This study also examined the variations of rainfall extremes under climate change condition, based on 12 GCM outputs and Route 1 of the

downscaling framework. The reason behind selecting Route 1 is that the study only focused on the rainfall projection (the output would not be applied for hydrologic modelling in this study) and Route 1 is the simplest one to use compared with other alternatives. The results showed a continued increase tendency of rainfall extremes for three periods in the future, namely 2011-2030, 2046-2065, and 2080-2099. At the end of this century, the average values (over return periods of 2-, 3-, 5-, 10-, 15-, 25-, 50- and 100-years) of maximum increase rates (i.e. upper boundary of uncertainty interval) for 24-hr, 1-hr, and 5-min durations would be 16%, 13.2% and 12.1%, respectively. For future studies, the proposed downscaling-disaggregation framework could be coupled with dynamical downscaling models (e.g. Weather Research and Forecasting Model) for better reflection of rainfall changes or urban hydrological models (e.g. Storm Water Management Model) for assessing the climate change impact on urban drainage flows.

CHAPTER 8 AN INTEGRATED STATISTICAL AND DATA-DRIVEN FRAMEWORK FOR SUPPORTING FLOOD RISK ANALYSIS UNDER CLIMATE CHANGE

8.1 Introduction

A warmer climate may lead to more frequent and intense floods for many areas around the world (IPCC, 2007; Schmocker-Fackela and Naef, 2010; Hirabayashi et al., 2013). This is especially alarming for central south part of China, where the region has already been suffering from continuous flood disasters over many decades. It is thus imperative to get an in-depth understanding of what the future risk of floods for this region would be, before effective adaptation planning efforts are to be made. The previous research efforts that looked into climate-change impact on hydrological systems are mainly based on integrated climate and hydrological modeling. The future climate change condition is mainly modeled by general circulation models (GCMs) considering various emission scenarios. Due to resolution problems, GCM model outputs are generally difficult to be used directly for hydrological impact studies, especially for those small to medium size watersheds (Tisseuil *et al.*, 2010). Many researchers have tried to develop either dynamic or statistical downscaling tools to help convert the coarse GCM data into higher-resolution local weather data (Wilby and Wigley, 1997; Wilby et al., 1999; Fowler et al., 2007). Hydrological model is an essential tool to help build the linkage between weather information and river runoff. Previously, a wide range of hydrological models have been developed, and most of them describe the rainfall-runoff transformation processes based on physical theory (Zhao and Liu, 1995; Refsgaard and Storm, 1995; Arnold et al., 1998; HEC, 2000; Huo et al., 2012; Fu et al., 2013).

From the previous studies, it is found that dynamic downscaling is normally computationally intensive and physically-based hydrological modeling has strict requirement on input data. This poses significant challenges for developing countries where there are relatively limited resources and data (Gao et al., 2010). The statistical and/or data-driven tools, which are computationally more efficient and easier to implement, have gained their popularity in the past decades in the fields of either downscaling or hydrological modeling (Fowler et al., 2007). For example, in terms of downscaling, the Statistical DownScaling Model (SDSM), Automated regression-based Statistical Downscaling tool (ASD) and Generalized Linear Model (GLM) are the most popularly used tools based on linear regression theory (Wilby et al., 2002; Chandler and Wheater, 2002; Yang et al., 2005; Khan et al., 2006; Dibike et al., 2008; Hessami et al., 2008; Hashmi et al., 2009; Chen, et al., 2012); data-driven approaches, like Artificial Neural Network (ANN) and support vector machine (SVM), are found to be effective in downscaling weather data, especially temperature (Wilby and Wigley, 1997; Schoof and Pryor, 2001; Coulibaly and Dibike, 2005; Khan et al., 2006; Moriondo and Bindi, 2006; Okkan and Serbes, 2012; Liu et al., 2013a and 2013b); other types of statistical downscaling tools, such as weather generator (Semenov and Barrow, 1997; Semenov et al., 1998) and weather typing scheme (Fowler et al., 2005 and 2007), are also widely used. In hydrological modeling field, applications of ANN can be found in Huang et al. (2004), Gao et al. (2010), Yilmaz et al. (2011), Song et al. (2012) and Piotrowski and Napiorkowski (2011 and 2013).

There are also a number of studies that rely only on statistical and/or data-driven approaches for hydrological impact study. Zarghami et al. (2011) applied the stochastic weather generator (LARS-WG) and ANN model to project monthly stream-flow response under three emission scenarios of HadCM3 in Iran. The results indicated a notable reduction of monthly runoff at the end of this century. Sachindra et al. (2011) employed the least square support vector machine (LS-SVM) method to

downscale GCM output to monthly stream flow directly, without using hydrologic models. The results showed that the proposed method was reasonable in reproducing stream flows in summer and winter, but its performance was poor for autumn. Hassan et al. (2012) applied SDSM and ANN to simulate daily stream flows under climate change conditions in Kurau River, Malaysia. The results demonstrated that the hydrological model based on ANN could effectively reflect the variation of monthly stream flow, and capture the mean and low flows well. However, the ANN model showed a notable underestimation for peak values. Liu et al. (2013a) applied GLM (GLIMCLIM) and non-homogeneous hidden Markov model (NHMM) methods to downscale the daily climate variables in North China Plain (NCP) under different emission scenarios, and assessed the annual runoff responses using Gardner's method (2009). The results showed that the two downscaling methods could generate consistent results, and the annual runoff would decrease in the period of 2081-2099.

Based on the above-mentioned studies, a number of research gaps are identified. Firstly, although there are some studies on using statistical and/or data-driven approaches for hydrological impact study, many of them focused on prediction of monthly or yearly flows. Daily flow prediction is rarely tackled. The major reason is that the forecasting performance of data-driven approaches (like ANN) for daily extreme data in a long-term time frame (e.g. more than thirty years) is relatively poor (Sulaiman et al., 2011; Hassan et al., 2012). Secondly, flood risk assessment is an important task for watersheds in central-south part of China as this region has suffered from serious flooding problems. Some previous studies of hydrological predictions under climate change in the Yangtze River Basin, China, were reported (Long et al., 2008; Xu et al., 2011; Liu et al., 2012); but few focused on tackling the variation of peak flows or flood frequencies under climate-change conditions. Moreover, many studies generally relied on single downscaling technique such as LARS-WG, ANN or SDSM to generate multiple weather data. In fact, it has been recognized that different downscaling methods could have different levels of

performances in allusion to different weather variables. For example, ANN model is found superior in temperature downscaling for certain regions, but poorer for precipitation (Schoof and Pryor, 2001; Coulibaly and Dibike, 2005); ASD is considered suitable for handling rainfall in large river basins like the Yangtze River Basin, China (Guo et al., 2012). It is thus desired to apply different statistical models for downscaling different weather variables in order to take the full advantages of individual methods considering the cross-correlations among multiple variables.

Therefore, this study aims to develop an integrated statistical and data-driven (ISD) framework to investigate the potential impact of climate change on flood frequencies. The Duhe watershed, Yangtze River Basin, China will be used as the study case for demonstration. The data-driven method is used to simulate the monthly runoff and statistical downscaling models are used for projection of rainfall, temperature and relatively humidity from GCM model predictors. Daily runoff is generated from monthly river runoff based on disaggregation technique and extreme flows are analyzed by flood frequency analysis. The study area is characterized by transitional climate from humid to sub-humid area and representative of watersheds in central-south part of China, where flooding risk is a major concern. The proposed framework mitigates the limitations of the previous studies mentioned above, and offers a computationally cheap alternative of studying flood risks under climate change.

8.2 Methodology

8.2.1 System framework

The ISD framework is proposed for analyzing river flows and flood frequencies under climate change. Figure 8.1 shows the overall system diagram. There are four major components in the integrated framework: downscaling, hydrologic simulation, disaggregation and flood frequency analysis. Before starting ISD framework, the

hydrological model (i.e. Bayesian Neural Network, BNN) should be trained by the observed meteorological/runoff data to identify suitable meteorological variables and input scheme. The interactions of different components are described as follows:

- (1) Firstly, the statistical downscaling models are applied to produce a number of meteorological variables (e.g. rainfall, temperature and relative humidity) from GCMs at daily scale. The hybrid model based on ASD and KNN, named ASD-KNN, is applied for multisite rainfall downscaling. In detail, ASD is used for downscaling the mean areal rainfall, and the monthly rainfall is calculated by the summation of daily data for each month (areal monthly rainfall). Next, KNN is applied for spatial disaggregation to generate monthly rainfall at multiple sites (to keep spatial correlation). Conditional Density Estimation Network (CDEN) is employed to generate the monthly temperature and relative humidity conditioned upon the downscaled rainfall.
- (2) Secondly, the generated monthly meteorological data is used as the input to the data-driven model (i.e. BNN) to predict the monthly runoff for both current and future periods. The BNN should be trained by the observed meteorological data first.
- (3) Thirdly, the KNN method is applied to disaggregate runoff from monthly timescale to daily one.
- (4) Finally, frequency analysis is carried out to analyze flood risks.

It should be noted that the main reason to convert the downscaled data to monthly scale first and then use disaggregation to get back to daily is to ensure the prediction accuracy of the data-driven model. As based on our own test (see *Section 8.6.1*), daily runoff prediction for long-term period for this study case is hardly reliable by using data-driven approaches. Similar findings are also reported by Sulaiman et al. (2011)

and Hassan et al. (2012). The detailed descriptions for each individual component are provided in the followed sections.

Figure 8.1 System diagram of the integrated statistical and data-driven (ISD) framework

8.2.2 Bayesian neural network

ANN is a popular data-driven method for building nonlinear relationships and has been widely used in hydrological predictions. It generally does not need to define the process for algorithmically converting the input to output (Sudheer et al., 2003). Khan and Coulibaly (2006) compared the Bayesian neural network and the standard artificial neural network. The results showed that the BNN model performed slightly

better than ANN in the simulation of mean and extreme flows. In this study, a two-layer feed-forward neural network with Bayesian learning algorithm is applied for modelling monthly runoffs. The Gaussian prior distribution is used as the initial values of the weights and biases. When the data is known, the posterior distribution could be obtained through the likelihood function from prior distribution (Khan and Coulibaly, 2006). For the mode of training, the posterior distribution is maximized based on optimization. Then, through the integration of noise model and posterior distribution of weights, the output distribution of network is obtained. Further details of the BNN method can be referred to Chapter 3, Nabney (2004) and Khan and Coulibaly (2006).

8.2.3 Automated regression-based statistical downscaling tool

The automated regression-based statistical downscaling tool (ASD) is developed by Hessami et al. (2008) and applied for downscaling daily rainfall at a single site. The implementation of ASD involves an automatic selection procedure of predictors, which includes the backward stepwise regression and partial correlation coefficients (Hessami et al., 2008). It has two options of regression, including multiple linear regression and ridge regression. Two basic sub-models, namely occurrence and amount models, are included in ASD and used for rainfall downscaling. For further technical details, readers are referred to Chapter 3 and the study of Hessami et al. (2008).

8.2.4 Conditional density estimation network

CDEN is developed based on the standard multilayer perceptron ANN. It could be seen as the probabilistic extension of an ANN model (Cannon, 2008). Different from the standard ANN, CDEN is used for estimating the parameters of a specified probability density function (PDF) conditioned upon the input predictors using ANN

architecture, and is a powerful tool for the point prediction (Cawley et al., 2007). Cannon (2012) developed a framework based on CDEN which included a variety of PDFs called Conditional Density Estimation Network Creation and Evaluation (CaDENCE) tool. In this study, the normal distribution is used for describing both temperature and relative humidity. The input predictors could include the large-scale GCM/NCEP variables and the generated rainfall data from ASD-KNN. More technical details could be found in Cannon (2008, 2012).

8.2.5 K-nearest neighbor

K-nearest neighbor (KNN) is a nonparametric method that resamples the current data from the historical dataset based on a defined weight scheme. The method is successfully applied for spatial and temporal disaggregation of rainfall and stream flow (Prairie *et al.*, 2007; Mezghani and Hingray, 2009; Nowak *et al.*, 2010; Kalar and Ahmad, 2011). In this study, KNN method will be applied for two purposes, including spatial disaggregation of monthly rainfall and temporal disaggregation of monthly runoff. The K nearest neighbors is found from the observed dataset based on Euclidean distance (*ED*) (Danielsson, 1980) which is given by:

$$ED[p, q] = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2} \quad (8-1)$$

where $p(p_x, p_y)$ and $q(q_x, q_y)$ are two points in the Cartesian coordinates. In the conventional approach, the potential neighbors are chosen using a decreasing kernel function (Lall and Sharma, 1996; Mezghani and Hingray, 2009). The K is estimated by $K = \sqrt{n}$ (Lall and Sharma, 1996), where n is the number of years of the observed record (i.e. K equals to 8 in this study). In order to reduce the uncertainty impacts caused by the stochastic selection of neighbors, a cross validation procedure is applied. In this study, K potential neighbors for each data (i.e. monthly rainfall and runoff) are chosen firstly. Based on the Euclidean distance, the potential neighbors

are classified into K groups (e.g. $K=1$ means the nearest neighbor and so on). Hence, there are K groups of disaggregation results from the K groups of neighbors. Then, the RMSE value of each group is calculated; the smallest one is considered as the final disaggregation results. The estimation of K value in the cross validation procedure is based on the observed data. The details of KNN method can be referred to Prairie *et al.* (2007), Mezghani and Hingray (2009) and Nowak *et al.* (2010).

8.2.6 Data normalization and model performance evaluation

In the ANN model, most of the input data should be normalized to prevent the model being dominated by large values (Okkan and Serbes, 2012). In this study, all input data are normalized based on the following equation:

$$z_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (8-2)$$

where x_i is the i^{th} input variable; $x_{\min}$ and $x_{\max}$ are the minimum and maximum values for input variables, respectively.

To evaluate model performance, Nash-Sutcliffe efficiency coefficient (NS) and coefficient of determination (R^2) are applied (Liu *et al.*, 2011). Generally, NS and R^2 values above 0.5 are considered acceptable threshold of accuracy (Liu *et al.*, 2011). The root-mean-square-error (RMSE) can also be used for assessing the residual between simulated and observed data. The related equations are given as follows (Liu *et al.*, 2011; Okkan and Serbes, 2012):

$$NS = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \overline{Q_{obs}})^2} \quad (8-3)$$

$$R^2 = \left[\frac{\sum_{i=1}^n (Q_{obs,i} - \overline{Q_{obs}})(Q_{sim,i} - \overline{Q_{sim}})}{\sqrt{\sum_{i=1}^n (Q_{obs,i} - \overline{Q_{obs}})^2 \sum_{i=1}^n (Q_{sim,i} - \overline{Q_{sim}})^2}} \right]^2 \quad (8-4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2} \quad (8-5)$$

where $Q_{obs,i}$ means the i^{th} observed runoff; $Q_{sim,i}$ means the i^{th} simulated runoff; $\overline{Q_{obs}}$ means the average value of observed runoff; $\overline{Q_{sim}}$ means the average value of simulated runoff.

8.3 Study Area and Data

The study area is the Duhe watershed which is located at the upper Hanshui River basin (a tributary of Yangtze River Basin), China, with an area of 12,431 km². The annual runoff in the study area is about 6.2 billion m³, and half of the amount falls within the summer period from June to September. The region is a transition zone of humid to sub-humid areas; the average annual rainfall is about 990 mm and the average temperature is about 14.1°C. Rainfall is the major source of river runoff and the continuous storms could easily lead to flooding problems (Yao *et al.*, 2010). The average annual flow rate is about 196 m³/s and the maximum daily rainfall record was found at the year of 1867 which exceeded 12,400 m³/s (Wang *et al.*, 1997). This area is considered sensitive to climate change, as the rainfall patterns in the future may vary significantly, and potentially exacerbate flooding threats (Xu *et al.*, 2011).

In this study, meteorological data from one rainfall gauge and hydrometric data from one hydrological station are available, where the historical rainfall and flow records both range from 1958 to 2008. Other meteorological data, such as maximum and minimum temperature, wind speed and relative humidity are extracted from Climate Forecast System Reanalysis (CFSR) dataset, with a period from 1979 to 2010 (Saha

et al., 2010). Additional rainfall data is extracted from APHRODITE (Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources) dataset at multiple grids over the study watershed during the period from 1961 to 2007 (Yatagai et al., 2009). APHRODITE offers the state-of-the-art daily precipitation data with high-resolution grids (0.25 degree) for Asia (Yatagai et al., 2009). For the study area, more than 30 APHRODITE grids are available over the entire region. Based on our test, there is a high correlation ($R^2 > 0.9$) of rainfall between adjacent grids. For simplicity, three grids (based on center point) in different locations are selected and used as additional gauge data. For temperature and relative humidity, only one grid of CFSR data (which covers the main stream of the Duhe river) is selected due to the following reasons: (i) the spatial variations for temperature and relative humidity are not as sharp as rainfall, and (ii) the adjacent grids of CFSR also have a high correlation. Figure 8.2 shows the study area and the related data grids. The monthly data, such as monthly runoff and rainfall, are summated from the daily data for rainfall, and averaged from the daily data for temperature and relative humidity. The two GCM scenarios are CGCM3 A2 (McFarlane, 1992; Kim et al., 2002, 2003) and HadCM3 A2 (Gordon et al., 2000).

Figure 8.2 The study area and data grids

8.4 Result Analysis

8.4.1 Validation of BNN for hydrological modeling

From the previous studies, the meteorological data would notably affect the hydrological processes. The input variables for neural network models in hydrological application mainly include rainfall, temperature, humidity, evaporation and their different lag time series (Gao et al., 2010; Zarghami et al., 2011; Huo et al., 2012). Also, as the study area is over 12,000 km², the spatial variation of rainfall distribution should be taken into consideration. Hence, in this study, the potential candidates of BNN input variables include: (i) monthly rainfall (PCP) at four locations (including 3 APHRODITE grids' data and 1 observed rainfall gauge), and (ii) monthly solar radiation, maximum temperature (Tmax), minimum temperature (Tmin) and relative humidity (RH) in the previous and current months over the entire watershed (based on CFSR grid as shown in Figure 8.2). The concerned output of BNN is the monthly runoff. The correlation between monthly runoff and potential meteorological variables is analyzed in order to identify the main influencing factors. Table 8.1 shows the relevant correlation coefficients (CC). It indicates that there is no significant correlation (CC is lower than 0.2) between runoff and weather variables after a time lag of one month for most of the variables. However, the relative humidity shows a high correlation (CC is above 0.4) with flow lagging by both 1 and 2 months. Based on this preliminary examination, the variables with CC level above 0.2 are selected for further consideration (denoted as * in Table 8.1). Moreover, only Tmin is selected as one of the input variables due to two major reasons: (i) in terms of physical meaning, Tmax and Tmin both reflect the temperature variations, and inclusion of both Tmax and Tmin would not bring any significant improvement of the

final result based on our test; (ii) Tmin presents higher correlations with runoff than Tmax at lag-0, lag-1 and lag-2 month.

Table 8.1 Correlation coefficients between runoff and meteorological data.

	OBS	Grid1	Grid2	Grid3	RH	Tmax	Tmin	Solar
Lag-0	0.711*	0.712*	0.735*	0.739*	0.607*	0.392	0.534*	0.169
Lag-1	0.336*	0.320*	0.337*	0.357*	0.554*	0.274	0.303*	0.044
Lag-2	0.171	0.125	0.164	0.186	0.430*	0.028	0.149	-0.240

Note: OBS means observed rainfall; Grid1, Grid2, and Grid3 represent the rainfall data from three APHRODITE grids (shown in Figure 2); Tmax means maximum temperature; Tmin means minimum temperature; The grids with * denote the selected variables.

To avoid effect of spatial correlation of rainfall on model over-fitting, we have also examined the performance of runoff predictions from different locations of rainfall data. Table 8.2 shows 5 schemes of consideration. Scheme 1 contains the rainfall data from only the observation station; Scheme 2 includes that from Grid 3 (which shows the highest correlation coefficient); Scheme 3 involves those from all four rainfall points (3 APHRODITE Grids plus the observation station); Scheme 4 involves those from the observation station and Grid 3; Scheme 5 involves those from the observation station, Grid 2 and Grid 3. In this study, the runoff and rainfall data range from 1961 to 2007, and the data of RH and Tmin are from 1979 to 2010. Therefore, the period of 1979-2007 is used for validation of BNN model, where the data from 1979 to 2002 is used for calibration and the rest 5-years' data is for model verification. Table 8.2 shows the NS and R^2 between the observed and simulated results from each scheme. It is indicated that the NS (0.826) and R^2 (0.837) levels under Scheme 4 are both higher than 0.8 during the verification stage. In addition, by comparing with extreme data (i.e. extreme data is defined as the observed data above the average value $178 \text{ m}^3/\text{s}$), the RMSE for the five schemes are $95.88 \text{ m}^3/\text{s}$, $113.0 \text{ m}^3/\text{s}$, 91.37

m³/s, 83.30 m³/s and 99.10 m³/s, respectively. From a physical point of view, Grid 3 and the rain gauge are relatively closer to the main stream of the Duhe River, so that Scheme 4 may bring a better accuracy in terms of flood routing and hydrological prediction. Also, the rainfall records at Grid 2 and 3 are somewhat correlated which may cause over-fitting if both of them (or even more grid data) are taken into consideration. Therefore, Scheme 4 is considered relatively the best and selected for downscaling. Figure 8.3 shows the corresponding time series of simulated and observed monthly runoffs. Based on the above analysis, the following 9 variables are selected as BNN model inputs for further climate-change impact study: (i) lag-0 and Lag-1 PCPs at Grid 3, (ii) Lag-0 and Lag-1 PCPs at the observation station, (iii) lag-0 RH, lag-1 RH, lag-2 RH, lag-0 Tmin and lag-1 Tmin. To further justify the performance of BNN, the support vector machine (SVM) method is also used with the same input scheme (see *Section 8.6.2*). The results indicate that BNN is superior to SVM in monthly runoff prediction for our study case with reference to both NS and R².

Table 8.2 Performance of BNN model in runoff prediction during 1979-2007 using different schemes

BNN	Calibration		Verification	
	R ²	NS	R ²	NS
Scheme 1	0.675	0.675	0.818	0.783
Scheme 2	0.775	0.775	0.755	0.733
Scheme 3	0.684	0.684	0.806	0.805
Scheme 4	0.708	0.708	0.837	0.826
Scheme 5	0.760	0.760	0.786	0.772

Note: NS = Nash-Sutcliffe efficiency coefficient; R² = coefficient of determination

8.4.2 Establishment of downscaling models

In this section, rainfalls at the two locations (i.e. observation station and Grid 3) are downscaled by the hybrid model ASD-KNN at daily timescale, and monthly Tmin

and RH are downscaled by CDEN. The selected downscaling tools (i.e. ASD-KNN and CDEN) and timescales (daily for rainfall; monthly for Tmin and RH) are compared with other well-known alternatives (i.e. GLM, SVM, BNN, and SDSM) (details can be referred to the *Sections 8.6.3 and 8.6.4*). The results demonstrate that both ASD-KNN and CDEN could better capture the extreme values with uncertainty ranges generated from ensembles. In addition, the statistical correlations between different meteorological variables should also be considered by the downscaling tools (Semenov et al., 1998). For example, the daily generation of temperature may be conditional upon the precipitation status of the day (Semenov et al., 1998; Semenov and Stratonovitch, 2010). In this study, Tmin and RH are both conditional upon the downscaled output of rainfall from ASD-KNN.

Figure 8.3 Comparison of observed and simulated monthly runoff by BNN during 1979-2007

Firstly, ASD-KNN model is used for downscaling rainfall. The model calibration is based on predictors from NCEP reanalysis and the observed rainfall data (i.e. rain gauge data and APHRODITE data) is from 1961 to 2000; CGCM3 and HadCM3 predictors are used for model verification during 1961-2007. Monthly data is

calculated by the summation of daily rainfall. Twenty ensembles are generated by ASD-KNN for representing the uncertainty range of downscaled results. The main reasons of selecting twenty ensembles are: (i) the downscaled twenty ensembles of meteorological variables could well cover the observed data in the current period; (ii) the simulated hydrological results based on the downscaled data could cover the observed runoff, especially for the extreme events; (iii) selection of a larger number of ensembles could not significantly improve the results but leads to wider uncertainty ranges and higher computational needs.

Figure 8.4 Comparison of the observed and downscaled monthly rainfall at the rain gauge station during 1990-2007 under (a) CGCM3 A2 and (b) HadCM3 A2

scenarios.

Figure 8.4 shows a comparison between the simulated and observed monthly rainfalls (average value and boundary) at the observation gauge under the two scenarios during 1990-2007 (i.e. only part of the entire period 1961-2007). The results indicate that most of the observed data could be well covered by the boundaries from the downscaled twenty ensembles. However, there are overestimations for low intensity rainfalls based on the two scenarios (The quantile-quantile plots are provided in the *Section 8.6.5*). The extreme data are generally below the simulated upper boundary except for a couple of points in 2000 under CGCM3 and in 1996 under HadCM3. Similar performance is found for the downscaled result from APHRODITE data (Grid3). Furthermore, the simulated average spatial correlation coefficients (i.e. CGCM3 A2 is 0.878 and HadCM3 A2 is 0.876) between the observed and APHRODITE data are found fairly close to the observed value (i.e. 0.870) for the period 1961-2007. More details can be found in the *Section 8.6.5*.

Secondly, the CDEN method is used for downscaling Tmin. NCEP reanalysis and CFSR Tmin during 1979-2000 are used for training the model. When the model is established, the predictors from CGCM3 A2 and HadCM3 A2 from 1979 to 2007 are plugged into the model to generate monthly time series of Tmin data. The average value of daily data in each month is used to calculate monthly data. Figure 8.5 shows the downscaled monthly Tmin from CGCM3 A2 and HadCM3 A2 scenarios from 1979 to 2007. CGCM3 A2 (RMSE = 1.76) shows a slightly better performance than HadCM3 A2 (RMSE = 1.68). Compared with rainfall, the temperature has a more regular seasonal variation than rainfall. Therefore, the corresponding uncertainty range from twenty ensembles is significantly narrower than that of downscaled rainfall. The observed data could be well covered by the downscaled data. However, the downscaled Tmin from HadCM3 A2 is somewhat underestimated in terms of the

lower range of values (The quantile-quantile plots are provided in the *Section 8.6.6*). Overall, the downscaled results from both scenarios well represent the temperature trends.

Figure 8.5 Comparison of observed and downscaled monthly minimum temperature under (a) CGCM3 A2 and (b) HadCM3 A2 scenarios

Different from T_{min} , the seasonal variation of RH is more significant. Figure 8.6 shows the comparison of observed and downscaled RH levels using CDEN from CGCM3 A2 and HadCM3 A2, respectively. Both downscaled results show somewhat overestimation for the extreme data when RH is above 0.9. Regarding the

smaller range of values (e.g. RH is below 0.5), the results from HadCM3 A2 demonstrates a lower range of uncertainty than those from CGCM3 A2. In addition, a few downscaled data exceed 1, and it could be seen as the bias of the model. The bias rates for two results are 0.8% and 0.2%, respectively. Overall, the average RMSE value for CGCM3 A2 and HadCM3 A2 are 0.122 and 0.125, respectively.

Figure 8.6 Comparison of observed and downscaled relative humidity (RH) under (a) CGCM3 A2 and (b) HadCM3 A2 scenarios

8.4.3 Future climate projection (period 2011-2099)

From verification of downscaling results, the established models and GCMs' predictors are considered effective for current period. For future conditions, the projected climate data can be projected by these models. Figure 8.7 shows the downscaled annual average values of rainfall, Tmin, and RH for the period from 2011 to 2099, which can be used for analyzing the varying tendency of climate variables under climate change. From Figure 8.7a, the rainfalls from two GCM scenarios demonstrate similar increasing tendency, where the average annual rainfall amount for period 2011-2099 would rise up to above 1,082 mm, and is about 34.2% higher than the baseline level (the average annual rainfall of rainfall gauge data is 806 mm from 1961 to 2007). In light of Tmin (Figure 8.7b), both scenarios suggest a general increasing trend from 2011 to 2085 (i.e. from around 8 °C to around 12.5 °C).

However, after the middle of this century, the two trends are somewhat deviated and CGCM3 A2 scenario suggests a slightly higher increasing rate than HadCM3 A2. For RH, an increasing tendency of annual RH is observed from both scenarios (see Figure 8.7c), but CGCM3 suggests a more significant fluctuation. Overall, both GCM scenarios suggest a general increasing tendency for rainfall, Tmin and RH for the study region throughout this century.

Figure 8.7 Downscaled annual average values during 2011-2099 for (a) rainfall, (b)

minimum temperature, and (c) relative humidity

8.4.4 Simulation of monthly runoff based on downscaled climate data

In this section, the BNN model and downscaled climate data are used for simulating monthly runoff for both current and future periods. The model verification is based on the observed runoff data from 1961 - 2007. In total, there are 20 batches of monthly runoffs from BNN model due to multiple ensembles from downscaling. Figure 8.8 shows the comparison between the observed and simulated monthly runoffs during 1990-2007. It is indicated that the simulated results under the two GCM scenarios could cover most of the observed data, including extreme events. However, there is a slight overestimation for several points, especially at low flow conditions. Overall, the projected runoffs based on BNN and downscaled climate data could reasonably reflect historical condition considering possible uncertainties.

Figure 8.8 Comparison between observed and simulated monthly runoff using downscaled meteorological variables during 1990-2007 under (a) CGCM3 A2 and (b) HadCM3 A2 scenarios

Figure 8.9 Observed and simulated annual peak monthly record (APMR, i.e. the peak monthly record in a typical year) during 1961-2099 under (a) CGCM3 A2 and (b) HadCM3 A2 scenarios

Figure 8.9 shows the observed and simulated annual peak monthly record (APMR, i.e. the peak monthly record in a typical year) during 1961-2099 under the two GCM scenarios. The varying tendencies are similar to those of the average monthly runoffs, but with more intense fluctuations. Compared with the average baseline value for current period ($451 \text{ m}^3/\text{s}$), the average value of CGCM3 A2 scenario shows a slight

underestimation ($448 \text{ m}^3/\text{s}$) for the same period; the simulated data from HadCM3 A2 is overestimated ($507 \text{ m}^3/\text{s}$). Nevertheless, the boundaries of the two results could both cover the observed data. For future conditions, under the CGCM3 A2 scenario, the average value of maximum monthly runoff would gradually reach up to $592 \text{ m}^3/\text{s}$ at the end of this century (2056-2099). The maximum data of upper boundary for CGCM3 A2 would reach up to $1,100 \text{ m}^3/\text{s}$ in the years of 2057 and 2084. Under HadCM3 A2 scenario, the peak data occurs in the year 2086, and the value is $1,126 \text{ m}^3/\text{s}$. There is a decreasing tendency during a short period from 2027 to 2037, and the average value of APMR would reduce to $434 \text{ m}^3/\text{s}$. In addition, the maximum value of APMR for baseline 1961-2007 is around $1,037 \text{ m}^3/\text{s}$. However, the two scenarios both suggest that the upper boundary of APMR record could rise above $1,100 \text{ m}^3/\text{s}$, which is about a 19.7% increase compared with the baseline level. Overall, under CGCM3 A2 and HadCM3 A2 scenarios, the BNN model could reproduce the APMR values well for the baseline period in terms of both average values and the extreme values; the future projections demonstrate a general increasing tendency.

Figure 8.10 shows the simulated annual runoffs under CGCM3 and HadCM3 scenarios during 1961-2099. It is indicated that the baseline average data could be covered by the simulated boundaries under the two scenarios. For the current period (1961-2007), the average values from the two scenarios are both overestimated by 5.4% and 19.5%, respectively. For the future period (i.e. 2011-2099), CGCM3 and HadCM3 results both show a stable increasing trend, but HadCM3 still suggests a notable decreasing trend during 2027-2037 (Figure 8.10b). For future conditions, CGCM3 result suggests an average increasing rate of 8.8% during 2011-2055 and 21.7% in 2056-2099, in comparison to the average of simulated baseline level; those for HadCM3 are 2.5% during 2011-2055 and 12.5% during 2056-2099.

Figure 8.10 The observed and simulated annual runoff during 1961-2099 under (a) CGCM3 A2 and (b) HadCM3 A2 scenarios

8.4.5 Disaggregation of monthly runoff and flood frequency analysis

Generally, the results from Figures 8.8 to 8.10 demonstrate a notable increase of monthly and annual runoffs under climate change conditions. This may cause significant influence on daily runoff, and increase the flood risk. In this section, the KNN method is used for disaggregating simulated monthly runoffs into daily timescale (the disaggregated result of daily runoff based on CGCM3 A2 scenario is presented in the *Section 8.6.7*). In this section, we have tested a number of classic distributions (e.g. Generalized Extreme Value distribution, Log-Person Type-III distribution, Gumbel distribution, Weibull distribution, lognormal distribution, and

etc.) in fitting the observed annual maximum series for the study region. Base on the results, the Generalized Extreme Value (GEV) distribution shows the best performance and hence is selected for further analysis.

Figure 8.11 Boxplots of flood frequency under projected scenarios based on disaggregated daily flowrate. Subfigures a1-c1 denotes the results under CGCM3 A2 scenario for periods of 1961-2007, 2011-2055, and 2056-2099, respectively; Subfigures a2-c2 denotes the results under HadCM3 A2 scenario for periods of 1961-2007, 2011-2055, and 2056-2099, respectively; The lines with square marks

represent the baseline data; the lines in the middle of the boxes shows the median of the results; the square in the middle of the box denotes the mean value; the top and bottom lines of the box represent 75 and 25 percentile of the results, respectively; the bar at the top and bottom represent upper and lower whiskers, respectively

Figure 8.11 presents the observed vs. simulated flood frequencies in periods of 1961-2007, 2011-2055 and 2056-2099, respectively. The frequency information obtained from the observed runoff data during 1961-2007 is used as a benchmark for comparison. For the current period (Figure 8.11a1), the simulated frequencies at all return periods under both CGCM3 and HadCM3 scenarios fall within the 25th and 75th percentiles of the ensemble results. The results of CGCM3 A2 shows a better performance ($RMSE = 247 \text{ m}^3/\text{s}$) than those of HadCM3 A2 ($RMSE = 630 \text{ m}^3/\text{s}$), as the frequencies are closer to the mean of the observed values. Figure 8.11a1 shows that the simulated data under CGCM3 A2 is slightly overestimated (i.e. about 3.2%) compared with observed data. But under HadCM3 A2, the simulated data is considerably underestimated when the return period is above 10 years. The relative error for the 200-year flood magnitude is about 13.9%. For the period 2011-2055, the flood frequencies under both GCM scenarios show increasing trends and HadCM3 suggests a higher rate than CGCM3, in comparison to the average of the simulated baseline level. For example, the average values of the projected runoffs under CGCM3 during period 2011-2055 at return periods of 50, 100, and 200 are 10%, 8.9% and 7.9% higher than those baseline levels (1961-2007); whereas, for HadCM3, the projected results are about 18.4%, 21.1% and 23.8% higher, respectively.

Figure 8.11 also shows different levels of uncertainty under different scenarios and time frames. Firstly, the uncertainty range would increase along with the increase of return period. Secondly, the result from CGCM3 A2 presents a larger level of uncertainty range than HadCM3 A2 in the future period (2011-2099). For example, the maximum and minimum runoffs from CGCM3 A2 for the 200-years flood during

period 2056-2099 are 24,530 m³/s and 10,288 m³/s, respectively; while, those from HadCM3 A2 are 15,641 m³/s and 5,277 m³/s, respectively. Thirdly, the intervals of the 25th and 75th percentiles for the HadCM3 would both decrease from the baseline period to 2056-2099. It implies that the projected results are more concentrated and steady when time frame moves to a longer-term future under this scenario. Overall, despite the large uncertainty interval, the results imply a clear increasing tendency for flood risks under both HadCM3 and CGCM3 A2 scenarios in this region in the future period. The results from CGCM3 are quite alarming, as the return period of a 200-years flood for current period (baseline) would be shortened to 100 years during period 2011-2055 and 22 years during period 2056-2099 by comparing with the average values of two future periods; considering uncertainty, the situation for the most extreme conditions (i.e. upper boundary) would be worse.

8.4.6 Further discussions

This study uses integrated statistical and data-driven (ISD) framework to model flood frequencies under climate change conditions. It is found that the statistical properties, spatial distribution and inter-variables correlations could be well characterized by taking the advantage of different statistical methods in downscaling different weather variables. The hybrid method based on BNN model and KNN method is effective in long-term hydrological predictions at daily timescale. In addition, the proposed framework does not have extensive data requirement and mitigates the limitation of long-term forecasting of extreme daily data by using ‘black box’ hydrological models. The proposed framework is also advantageous in the possibility of switching/adding different methods for each individual component (i.e. downscaling or hydrological modeling); this facilitates comparison of different methodologies or attainment of more reliable results.

In the proposed ISD framework, ASD-KNN is selected to downscale rainfall at daily timescale first and summated to monthly level. This is based on the consideration that: (i) many well-known and validated downscaling tools (e.g. ASD, SDSM, GLM etc.) are specially designed for daily timescale; (ii) ASD-KNN presents a better performance in terms of both uncertainty reflection and extreme-value reproduction (see *Section 8.6.3*) for this region, compared with other commonly used methods (e.g. GLM, CDEN, SVM and BNN). A direct downscaling from monthly data is also applicable depending on the study region and data availability. The CDEN method is employed to simulate the T_{min} and RH directly at monthly timescale. The reason is that the downscaled rainfall data is one of the input predictors for T_{min} and RH, and it could help better capture the extreme values at monthly timescale by summation of daily data. Another reason is that the monthly T_{min} and RH are both more stationary than rainfall data and a direct monthly downscaling is considered accurate enough.

Some limitations of the proposed framework are also identified. Firstly, the proposed model only considers the meteorological factors involving rainfall, temperature and relative humidity. For other factors, such as snowmelt, topography, soil properties and human factors, they are generally difficult to be added in a statistical and data-driven framework due to a shortage of sufficient historical record. A physically-based distributed hydrological model may be more appropriate for addressing more influencing factors. Secondly, the statistical relationship is built based on the historical data; the stationarity problem for future projections, which has been a common concern, is not tackled. To mitigate such an issue, a coupled dynamical and statistical model may be a promising solution. Thirdly, in this study, the K value estimation in the cross validation procedure of the KNN method is based on the observed data which are split into calibration and verification periods. The K value could be affected by different sample sizes, although the calculated RMSE values for various groups have little difference in this study. The “trial-and-error” method and the conventional stochastic selection are both viable ways. Finally, only

two GCM scenarios are considered for the flood frequency analysis in this study. Mailhot et al. (2007) pointed out that the investigation based on multiple GCM ensembles is an essential component for climate change impact study. Additional emission scenarios would be useful in helping assess the uncertainty range of the climate change impact on flood risks. Since the main purpose of this study is to demonstrate the validity of the proposed ISD framework, we do not test more GCM scenarios and leave it to future works.

8.5 Summary

An integrated statistical and data-driven (ISD) framework was proposed for analyzing river flows and flood frequencies in the Duhe River Basin, China, under climate change. ISD entailed the following tasks: (i) ASD-KNN approach were used for downscaling rainfall, and CDEN method was employed to downscale minimum temperature and relative humidity based on the output of ASD-KNN method; (ii) the trained BNN model using observed meteorological data was applied for modelling monthly river flows based on projected weather information; (iii) KNN was applied for converting monthly flow to daily time series; (iv) the GEV distribution was used for analyzing regional flood frequency. The results indicated a generally increasing tendency for runoffs for both monthly and annual extremes under CGCM3 A2 and HadCM3 A2 emission scenarios. For the flood frequency analysis, it also presented an increasing trend of flood magnitude with a widening uncertainty range. Compared with the baseline period (1961-2007), it was suggested that there would be 11.5% and 61.3% average increase of runoffs (based on the results of 5-, 10-, 15-, 20-, 25-, 50-, 100-, and 200-year floods) in period 2011-2055 and period 2056-2099, respectively, under CGCM3 A2 scenario; for HadCM3 A2, the flood risks would increase by 11.6% and 28.6% for the two future periods, respectively. The proposed framework took full advantages of a series of statistical and data-driven methods and could offer

a computationally “cheap” and parsimonious way of projecting flood risks under climatic change conditions.

The combined BNN and KNN approach was employed to generate daily runoff in this study. The KNN model could lead to uncertainties due to K value estimation or stochastic selection of potential nearest neighbors (i.e. the uncertainty interval is narrower than downscaling results); while, such an uncertainty was considered not a dominant factor when compared with larger uncertainty sources from downscaling of meteorological variables. It is desired to develop a novel data-driven method that could directly simulate daily runoff (particularly the extreme values) with acceptable accuracy to avoid uncertainty from disaggregating from monthly to daily runoffs. Studies coupling ANN and wavelet approach (Nourani et al., 2012) while considering the external meteorological variables could be a viable solution. This is left to further studies. Moreover, the large-scale predictors of GCMs (based on CGCM3 and HadCM3 A2 emission scenario) in this study are not reflecting the most recent product from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012) due to the purpose of pure methodology demonstration. For further study, it is desired to test the proposed method under the new generation of scenarios for more robust analysis.

8.6 Supporting Information

8.6.1 Daily runoff simulation using BNN directly

As mentioned by the previous studies, the daily runoff prediction for a long-term period would notably underestimate the extreme data (Sulaiman et al., 2011; Hassan et al., 2012). To verify this for our own study, the result of simulating daily runoff directly using the BNN method is presented. The selected meteorological variables include observed daily rainfall, APHRODITE Grid 3 rainfall, minimum temperature and relative humidity, which are similar to those used in the monthly runoff

simulation. Their lag-1 daily time series are also selected as input data in the preliminary analysis. Ten years data (1981-1990) is used for model validation (calibration period is 1981-1986 and verification period is 1987-1990). Figure 8.12 shows the comparison of the observed and simulated daily runoff data for the verification period. BNN model illustrates a good performance for base flow. However, there is an obvious underestimation for extreme data. This is consistent with the results from the previous studies such as Hassan et al. (2012).

Figure 8.12 Comparison of the observed and simulated daily runoff using BNN method for the verification period of 1987-1990.

8.6.2 Comparison of hydrological simulation using BNN and SVM

This section presents the comparison of monthly runoff simulation using two non-linear ‘black box’ models, including Support Vector Machine (SVM) and Bayesian Neural Network (BNN). The two methods have the same input schemes based on the observed data. The details of the schemes are showed in the *Manuscript Section 4.1*. Table S1 shows the performance of SVM model in monthly runoff prediction during 1979-2007 under 5 Schemes. It is indicated that, BNN is superior to SVM for Schemes 1, 2, 4 and 5, but performs slightly poorer for Scheme 3. For both

models, the results of Scheme 3 are better in the calibration period and those of Scheme 4 show a good performance in the verification period.

Table 8.3 Performance of SVM model in monthly runoff prediction during 1979-2007 under 5 Schemes.

SVM	Calibration		Verification	
	R ²	NS	R ²	NS
Scheme 1	0.678	0.668	0.752	0.706
Scheme 2	0.749	0.748	0.749	0.747
Scheme 3	0.679	0.674	0.749	0.749
Scheme 4	0.708	0.705	0.768	0.765
Scheme 5	0.699	0.691	0.758	0.747

Note: NS = Nash-Sutcliffe efficiency coefficient; R² = coefficient of determination

Figure 8.13 Observed vs. simulated monthly runoffs by BNN and SVM during 1979-2007.

Figure 8.13 shows the observed and simulated monthly runoffs by BNN and SVM using Scheme 4. The two models both reproduce well the seasonal fluctuation of runoff. By comparing the NS and R² values of BNN and SVM for the full simulated time series (including calibration and verification periods), BNN model shows a

better result (i.e. NS and R^2 are 0.73 and 0.74 for BNN model respectively; those for SVM are 0.72 and 0.72, respectively). For the extreme events (which are more than 500 m³/s), BNN also shows a better prediction both in full period (RMSE = 168.53 m³/s) and verification period (RMSE = 71.31 m³/s) than SVM (full period RMSE = 187.3 m³/s and verification period RMSE = 89.64 m³/s). But for the peak event in the verification period, the simulated monthly runoff from SVM is 792 m³/s and is slightly closer to the observed data (827 m³/s) than that from BNN (763 m³/s). Overall, the BNN model is deemed performing relatively better for simulating monthly runoff than SVM.

8.6.3 Comparison of rainfall downscaling using ASD-KNN, GLM, CDEN, BNN and SVM

In this section, four well-known statistical tools, the proposed ASD (Automated regression based statistical downscaling tool) –KNN (K nearest neighbor), Generalized Linear Model (GLM), Conditional Density Estimation Network (CDEN), BNN and SVM are applied for downscaling monthly rainfall. The observed rain gauge record and National Centers for Environmental Prediction (NCEP) reanalysis data (Saha et al., 2010) are used for training the downscaling tools. For model verification, the Canadian Global Climate Model version 3 (CGCM3) A2 emission scenario (DAI, 2008) is applied during the period 1961-2007. ASD-KNN and GLM is used for downscaling rainfall at daily timescale and the results are summated to obtain the monthly data. The other three methods are used for downscaling from monthly timescale directly. Moreover, ASD-KNN, GLM and CDEN methods will generate 20 ensembles for output; BNN and SVM only have one ensemble.

Figure 8.14 Monthly rainfall downscaling using (a) ASD-KNN, (b) GLM, (c) CDEN, (d) BNN and (e) SVM.

Figure 8.14 shows the downscaled results based on the four tools. Only the results from 1971 to 1990 (20 years, different from the period 1991-2007 in *Manuscript - Figure 8.4*) are shown. ASD-KNN, GLM and CDEN could all capture the extreme data well based on twenty ensembles. Compared with the observed data and average values of 20 ensembles, GLM has slightly smaller RMSE (i.e. 52.93) than ASD-KNN (i.e. 55.1), CDEN (i.e. 58.93), BNN (i.e. 53.87) and SVM (i.e. 53.09). SVM performs as good as BNN, but both methods significantly underestimate the extreme data. Similar conclusions could be found in Gao et al. (2010) and Haylock et al. (2006). To compare the uncertainty range between ASD-KNN, GLM and CDEN,

the equations of Mean Absolute Percentage Error (MAPE) (Armstrong and Overton, 1977) is used:

$$MAPE = \left[\sum_{i=1}^n \frac{abs(SIM_{lower,i} - OBS_i) + abs(SIM_{upper,i} - OBS_i)}{2OBS} \right] / n \quad (8-6)$$

where i means the i^{th} data; $SIM_{lower,i}$ means the i^{th} simulated data of lower boundary; $SIM_{upper,i}$ means the i^{th} simulated data of upper boundary; OBS means the observed data; n is the number of data. The values of MAPE for ASD-KNN, GLM and CDEN are 2.04, 3.03 and 4.10, respectively. The lower MAPE value for ASD-KNN may be due to its better capability in capturing the lower intensity rainfalls (see Figure 8.14). It is indicated that downscaling result from ASD-KNN method has a notable smaller uncertainty range than that from GLM and CDEN methods, but with a slightly lower accuracy of fitting the mean value. In conclusion, the ASD-KNN method is deemed a better option and selected to downscale rainfall in this study.

8.6.4 Comparison of RH and Tmin downscaling using CDEN and SDSM

This section presents the comparison of downscaling relative humidity (RH) and minimum temperature (Tmin). Based on our test, the simulation of hydrological process using BNN model is sensitive to the extreme data of RH and Tmin. Similar results are also found in terms of rainfall downscaling for BNN and SVM, where the peak rainfalls are somewhat underestimated. In this section, two methods, namely SDSM (Wibly et al., 2002) and CDEN, are employed to downscale RH and Tmin at daily and monthly timescale, respectively. Two models are both trained by the NCEP reanalysis data, and the HadCM3 A2 scenario (Gordon et al., 2000) is used for validation of results based on monthly data. Figure 8.5 of the *Manuscript* shows the monthly Tmin data; Figure 8.15 shows the monthly RH data. The variation of Tmin is

found smoother than RH. Therefore, we highlight the downscaled results of RH during period 1990-2007 in Figure 8.15. Similar to downscaled rainfall, CDEN also shows a large uncertainty range compared with SDSM. However, for RH, the large interval could help the model to capture the extreme data (i.e. especially for lower data) better than SDSM which has a smaller uncertainty interval. However, CDEN illustrates a slightly larger RMSE (i.e. calculated based on the observed data and the average values of simulated data) value (i.e. 0.13) than SDSM (i.e. 0.11). Regarding Tmin, CDEN and SDSM both perform well, with RMSE values being 1.67 and 1.71, respectively. Based on the downscaling results, we have selected CDEN as the tool to downscaling RH and Tmin in this study.

Figure 8.15 Downscaling monthly relative humidity (RH) using CDEN and SDSM.

8.6.5 The comparison between observed and downscaled monthly rainfall and minimum temperature

Figure 8.16 shows the quantile-quantile plots of downscaled monthly rainfall. From this figure, the downscaled data based on CGCM3 A2 scenario (Figure 8.16a) presents a slight overestimation when the rainfall amount varies from 50 to 120 mm. The downscaled data based on HadCM3 A2 (Figure 8.16b) shows a notable overestimation when the rainfall amount is below 200 mm. This may be associated with the overestimation of the low-intensity rainfall time series, as shown in Figure 8.4 in the main *Manuscript*. However, the two datasets could reproduce the extreme rainfall well. Figure 8.17 shows the quantile-quantile plots of downscaled monthly Tmin. The downscaled result using CGCM3 A2 data seems to have somewhat overestimations for extreme data. For the HadCM3 A2, the result illustrates a slight underestimation when the data varies from 5 to 8 °C.

Figure 8.16 The quantile-quantile plot for downscaled monthly rainfall based on two GCM scenarios.

Figure 8.17 The quantile-quantile plot for downscaled monthly minimum temperature (Tmin) based on two GCM scenarios.

8.6.6 Spatial correlations for downscaled monthly rainfall

Table S2 shows the spatial correlation coefficients between the observed and APHRODITE data for downscaled monthly rainfall. From this table, the ASD-KNN approach seems well capturing the spatial characteristics of rainfall, where the ranges of simulated results are from 0.852 to 0.908. The average value of two scenarios is 0.877 which is fairly close to the observed one (0.870).

Table 8.4 The spatial correlation coefficients for downscaled monthly rainfall

	CGCM3 A2	HadCM3 A2
Ensemble 1	0.857*	0.882
Ensemble 2	0.900	0.852
Ensemble 3	0.900	0.873
Ensemble 4	0.908	0.854
Ensemble 5	0.893	0.887
Ensemble 6	0.866	0.896
Ensemble 7	0.883	0.889
Ensemble 8	0.884	0.871
Ensemble 9	0.870	0.872
Ensemble 10	0.856	0.896
Ensemble 11	0.867	0.873
Ensemble 12	0.903	0.873
Ensemble 13	0.877	0.867
Ensemble 14	0.876	0.880
Ensemble 15	0.876	0.884
Ensemble 16	0.877	0.879
Ensemble 17	0.880	0.871
Ensemble 18	0.867	0.890
Ensemble 19	0.865	0.869
Ensemble 20	0.864	0.865
Maximum	0.908	0.896
Minimum	0.856	0.852
Average	0.878	0.876

Note: * means the correlation coefficient.

8.6.7 Disaggregation result for daily runoff

Figure 8.18 shows the statistical properties (i.e. mean, standard deviation and maximum data) from the observed and simulated daily runoffs based on CGCM3 A2 scenario. For the mean value (Figure 8.18a), the simulated data presents somewhat underestimations for months with low flows, such as January, February, November and December. This may be caused by the overestimation of low intensity rainfalls. For the standard deviation (Figure 8.18b), there are underestimations for May and June. For the maximum data of each month (Figure 8.18c), most of the observed data are well covered by the simulated range, except for June. Regarding the

autocorrelation, the simulated values are between 0.638 and 0.713, which are slightly lower than the observed one (i.e. 0.727). Overall, the disaggregated daily runoff could reasonably reproduce the observed daily data.

Figure 8.18 The comparison of observed and simulated statistical properties for daily runoff based on CGCM3 A2

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