

A framework for quantifying and incorporating climate data uncertainty into water resources assessment

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# A framework for quantifying and incorporating climate data uncertainty into water resources assessment

Fitsum Markos Woldemeskel

A thesis submitted in fulfilment of the requirements of the degree of Doctor of Philosophy



School of Civil and Environmental Engineering Faculty of Engineering

June 2014

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### **Summary**

Rainfall and temperature (the main driver of evaporation) are key inputs for hydrologic models in studying catchment responses to climate scenarios. Both rainfall and temperature, however, are uncertain, with rainfall having a larger degree of uncertainty. Using uncertain inputs in hydrologic models, without due consideration of their associated uncertainties, results in biased outcomes. The purpose of this thesis is to develop methods for quantifying uncertainties in climate data (with emphasis on rainfall) towards proposing strategies to incorporate these uncertainties into water resource assessment.

Rain gauge and satellite rainfall data are initially compared and merged to produce an improved gridded rainfall dataset with its associated standard error. This is implemented for Australian rainfall. The standard error estimation logic is then extended to develop a novel uncertainty metric, the square root error variance (SREV), for quantifying uncertainties in global climate model (GCM) data. The method is applied to estimate GCM-projected rainfall and temperature uncertainty across the world. It is found that GCM uncertainty arises mainly from model structural errors. Subsequently, two case studies that implement the SREV metric into hydrologic systems are carried out.

First, future drought, across the world, is estimated with due consideration to the uncertainties involved in GCM rainfall projections. Simulation extrapolation, which reduces parameter bias when input errors are known, is used to mitigate biases in drought estimates. It is found that consideration of GCM rainfall uncertainties is vital, as drought values with and without considering the uncertainties are significantly different. Second, a comprehensive analysis is carried out to evaluate water availability at the Warragamba

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Catchment in Sydney, Australia. An additive error model is proposed to generate rainfall and temperature realizations that are used to simulate streamflow. Future storage requirement with its associated uncertainty is then evaluated using reservoir behavior analysis. It is found that the existing storage capacity suffices the future requirements, although large uncertainty exists in storage estimates.

In conclusion, the thesis presents methods to quantify and account for uncertainties in key hydrologic variables. Provision of these uncertainties offers an effective platform for riskbased assessments of any integrative or adaptive water management plans that may be formulated using measured or simulated climate data.

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# List of publications

### Journal papers

- Woldemeskel, F.M., B. Sivakumar, and A. Sharma (2013), Merging gauge and satellite rainfall with specification of associated uncertainty across Australia, *Journal of Hydrology*, 499 (0), 167-176, <u>http://dx.doi.org/10.1016/j.jhydrol.2013.06.039</u>.
- Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2012), An error estimation method for precipitation and temperature projections for future climates, *Journal of Geophysical Research-Atmospheres*, 117 (D22), D22104, doi:10.1029/2012JD018062.
- Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), A framework to quantify GCM uncertainties for use in impact assessment studies, *Journal of hydrology, submitted*.
- Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), A new framework for incorporating GCM uncertainty for reservoir storage estimation for future (warmer) climates, *Journal of Hydrology, submitted*.

### **Conference papers and abstracts**

- Woldemeskel, F.M., A. Sharma, and B. Sivakumar (2011), Estimation of monthly gridded rainfall by merging rain gauge and satellite rainfall data. *Proceedings of the 34th IAHR World Congress*, 26 June–1 July 2011, Brisbane, Australia.
- Woldemeskel, F.M., A. Sharma, and B. Sivakumar (2011), Estimation of monthly rainfall in Australia using rain gauges and satellite rainfall data. *Asia-Oceania Geosciences Society*, 8-12 August 2011, Taipei, Taiwan.
- Sharma, A., F.M. Woldemeskel, R. Mehrotra, and B. Sivakumar (2012), An error model for GCM precipitation and temperature simulations. *European Geosciences Union*, 22-27 April 2012, Vienna, Austria.

- Woldemeskel, F.M., A. Sharma, B. Sivakumar, and R. Mehrotra (2012), An uncertainty metric for precipitation and temperature projections from global climate models. *Asia-Oceania Geosciences Society*, 13-17 August 2012, Singapore.
- Sivakumar, B., F.M. Woldemeskel, A. Sharma, and R. Mehrotra (2012), An error model for precipitation and temperature projections for future climates. *American Geophysical Union*, 3-7 December 2012, San Francisco, USA.
- Woldemeskel, F.M., A. Sharma, B. Sivakumar, and R. Mehrotra (2012), Factoring uncertainty into climate change impact assessment of hydrologic systems. *American Geophysical Union*, 3-7 December 2012, San Francisco, USA.
- Woldemeskel, F.M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), A new method for estimating uncertainty in climate change impacts on hydrologic systems. *Asia-Oceania Geosciences Society*, 24-28 June 2013, Brisbane, Australia.
- Woldemeskel, F.M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), GCM uncertainty and reservoir storage estimation: A case study of the Warragamba catchment in Australia. *International Congress on Modelling and Simulation* (MODSIM 2013), 1-6 December 2013, Adelaide, Australia.

### Collaboration

**Note**: The following papers and conference abstracts have been published/submitted in collaboration with others during the PhD study period; however, they are not included in this thesis, as they are unrelated to the objectives of the thesis.

### **Journal papers**

Sivakumar, B., F.M. Woldemeskel, and C.E. Puente (2013), Nonlinear analysis of rainfall variability in Australia. *Stochastic Environmental Research and Risk Assessment*, doi:10.1007/s00477-013-0689-y. Sivakumar, B., and F.M. Woldemeskel (2013), Spatial rainfall correlations and their implications: A correlation-scale-threshold method, *Journal of Hydrology*, *submitted*.

### **Conference papers and abstracts**

- Sivakumar, B., F.M. Woldemeskel, V.P. Singh, and A.A. Tsonis (2013), A correlationscale-threshold method for analysis of spatial rainfall correlations. *Asia-Oceania Geosciences Society*, 24-28 June 2013, Brisbane, Australia.
- Sivakumar, B., and F.M. Woldemeskel (2013), A new method for study of spatial variability. Proceedings of the 2<sup>nd</sup> EIT International Conference on Water Resources Engineering, 5-6 September 2013, Chiang Rai, Thailand.
- Sivakumar, B., F.M. Woldemeskel, and V.P. Singh (2013), Spatial rainfall correlations and their implications for raingage network and rainfall interpolation. *Proceedings of the 35<sup>th</sup> IAHR World Congress*, 8-13 September 2013, Chengdu, China.

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### **Chapter One**

### 1. Introduction and Literature review

This chapter begins by introducing the important research questions and, thus, motivation for the research addressed in the thesis. It then reviews the relevant literature, and highlights the gaps in the existing body of knowledge. The main objectives and outline of the thesis are presented towards the end. The terms 'uncertainty' and 'standard error' in regards to a given variable are used synonymously throughout the thesis.

#### 1.1. Research motivation

Global warming, caused by anthropogenic changes, likely alters the global climate system. According to the Intergovernmental Panel on Climate Change [*IPCC*, 2007], global average surface temperature has increased by 0.74°C during the last century (1906 to 2005) and an increase of up to 4°C (based on high greenhouse gas emission scenario) is also projected for the end of the 21st century. Although it is hard to make exact predictions of these impacts on water resources, a majority of studies suggest occurrences of more-frequent extreme climate events, such as floods and droughts [*IPCC*, 2007; *Kundzewicz et al.*, 2008; *Milly et al.*, 2002]. Climate projections simulated from global climate models (also known as, general circulation models (GCMs)) are typically used to assess the impacts of climate change on water resources. The GCMs are state-of-the-art tools, developed by different climate modelling groups around the world, that exhibit the physical processes in the atmosphere, ocean, cryosphere and land surface [*IPCC*, 2007].

Twenty four GCMs have been considered in the fourth assessment report (AR4) of the IPCC that commonly serves as the basis for climate change impact assessments. A number of studies have been carried out to evaluate the skills of these models through inter-comparison of the model outcomes with each other as well as with observations [e.g. Johnson and Sharma, 2009a; Johnson et al., 2011; Masson and Knutti, 2011; Perkins et al., 2007]. These studies have generally found that the GCMs show better accuracy at large scales (e.g., average across the world) than at small scales (e.g., at the GCM grid location), indicating that the uncertainty of GCM projections varies spatially. The uncertainty in GCM projections also vary temporally depending on the projection period (e.g., historical projections have better accuracy than future ones) as well as projection timestep (i.e., monthly projections have better accuracy than daily ones). Further, GCM projection uncertainty varies depending on the type of the variable under consideration. For example, rainfall, which is the main driver of hydrologic processes and the key input to hydrologic models, is poorly simulated when compared to temperature, which is also an important variable for estimating evaporation. Although both rainfall and temperature projections are uncertain, they are often used, without consideration of their uncertainties, as inputs to hydrologic models, in the assessment of the impacts of climate change on water resources.

Using uncertain rainfall and temperature as inputs to hydrologic models results in biased outcomes that will likely lead to erroneous science and policy plans and/or decisions. In view of this, it is of great practical interest to give due consideration to the uncertainties in GCM rainfall and temperature projections in water resources assessment. This provides the motivation for this thesis towards considering GCM uncertainties for climate change impact assessment as well as proposing strategies to incorporate GCM uncertainties for

planning and management of water resources. This is done in two steps: (i) quantification of spatio-temporal uncertainties in GCM projections; and (ii) consideration of these uncertainties in water resources assessment. An important research question that this thesis attempts to address with respect to the former step is:

• How to explicitly quantify the uncertainty in any GCM output that vary in space and time?

Although this thesis focuses mainly on rainfall and temperature projections, it is important to develop a generic method that allows its use for any other output from GCMs. After developing the GCM uncertainty estimation methods, this thesis investigates approaches to implement the uncertainties into water resources assessment. With regard to this, a research question of particular interest is:

• How can the uncertainty associated with GCM projections be taken into account in the assessment of climate change impacts on hydrologic systems?

#### **1.2.** Literature review

This section provides a review of literature relevant to the objectives of the thesis. An exhaustive literature review is also provided at the beginning of chapters 2 to 5.

Climate data (such as rainfall and temperature) form key inputs to hydrologic models. These data can be obtained through measurements or simulations using climate models (e.g. GCMs). In the context of climate change impact assessment, the former are often used to calibrate impact assessment models as well as to correct biases in GCM projections, whereas the latter are used to evaluate the potential impacts of climate change on water resources. Both data, however, are uncertain with varying degrees and sources

of uncertainty. Although this thesis mainly deals with uncertainties in GCM outputs, the methods proposed to quantify them will be initially developed using observed rainfall data. Therefore, a brief literature review of uncertainties involved in observed rainfall data will be discussed first in section 1.2.1, followed by a detailed review of uncertainties associated with GCM projections in section 1.2.2.

#### 1.2.1. Uncertainty in observed rainfall data

Rainfall is measured directly using rain gauges or indirectly using remote sensing methods (such as satellite-based techniques or weather radars). Rain gauge-based rainfall data, measured at sample locations, are uncertain due to systematic errors (such as errors due to wind, flaws in gauge installation and wetting losses), random errors [*Ren and Li*, 2007; *Sevruk*, 1996] as well as interpolation errors [*Tao et al.*, 2009]. Several interpolation methods have been developed and/or applied during the past century, such as Thiessen polygons [*Thiessen and Alter*, 1911], inverse distance weighting [*Shepard*, 1968], geostatstical methods [*Journel and Huijbregts*, 2003] and spline fitting [*Hutchinson*, 1998]. All these interpolation methods have their own associated uncertainties, which vary in space and time. In contrast to rain gauge rainfall, satellite-based rainfall data (e.g., using Tropical Rainfall Measuring Mission (TRMM) [*Kummerow*, 2000]) provide continuous rainfall in space and time that somewhat mitigates the uncertainties that would be introduced due to rain gauge rainfall interpolation. However, satellite-based rainfall have its associated uncertainty as well, as a result of temporal sampling and retrieval of rainfall rate from satellite signals [*Gebremichael et al.*, 2010].

A number of studies have estimated the uncertainties involved in gridded rainfall estimation [*Grimes et al.*, 1999; *Isaaks and Srivastava*, 1989; *Jeffrey et al.*, 2001; *Oke*,

2009]. Such studies have largely estimated the rainfall errors either in space (without considering the temporal variability) or in time (without considering the spatial variability). However, due to high variability of rainfall in space and time, the rainfall estimation errors also vary spatially and temporally. This research attempts to develop a method to quantify rainfall uncertainties that vary both in space and time. The method developed based on rain gauge and satellite rainfall will then be extended to GCM projection uncertainties (see, section 1.2.2).

Another interesting question regarding rain gauge and satellite rainfall data is: Whether or not merging of these two rainfall datasets reduces errors in rainfall estimation? In connection with this, a number of studies that merge rain gauge and TRMM-based rainfall have been carried out [*Grimes et al.*, 1999; *Huffman et al.*, 1995; *Li and Shao*, 2010]. These studies have used dense rain gauge networks and found that merging of the two reduces estimation errors only at locations where the rain gauge network is poor. It is, therefore, interesting to assess the extent of improvement that may be obtained using relatively sparse network of rain gauges. This thesis attempts to do this by developing a merging algorithm that combines rain gauge and satellite rainfall for three different sparse rain gauge networks across Australia (see, chapter 2). Focus is given to the estimation of the associated spatio-temporal errors as well as to the evaluation of the extent of error reduction after merging rain gauge and satellite rainfall.

#### **1.2.2.** Quantifying uncertainty in GCM simulations

#### **Uncertainty in GCM simulations**

Projections from GCMs are commonly used for climate change impact assessment on streamflows as well as other hydrologic variables (such as rainfall and ground water

level). Streamflows and other variables, however, are poorly simulated in GCMs [*Kuhl and Miller*, 1992] that the following indirect procedure is typically adopted to assess the impacts of climate change on water resources: (1) projection of future climate data (e.g., rainfall and temperature) using GCMs; (2) downscaling of coarse-scale GCM outputs to fine-scale data appropriate for hydrology and water resources studies; and (3) estimation of river flow and groundwater levels using hydrologic models. Although this procedure is considered reasonable, the reliability of the assessments and its usefulness for practical applications is questionable due to the various uncertainties introduced at each stage of the process.

According to the fourth assessment report (AR4) of the IPCC, there is a significant level of uncertainty in the sign of change of rainfall across different GCM projections using A1B scenario (Figure 1.1). One can expect much larger uncertainty in the magnitude of rainfall and more so if different emission scenarios are considered. Additional uncertainties are also introduced due to the downscaling methods and impact assessment models used. Figure 1.2 shows the propagation of uncertainties in the local climate change impacts and adaptation responses from various uncertainties introduced at different stages of the analysis. Multiple GCMs, emission scenarios, downscaling methods and impact models are used by *Chen et al.* [2011], *Deque et al.* [2007], and *Kay et al.* [2009] to evaluate these uncertainties. These studies estimated the uncertainties propagated from GCM projections to a given variable of interest (e.g. flow) and have found that GCM model structure is the largest source of uncertainty compared to all other sources. The outcomes of these studies offer some insights into the uncertainty introduced from GCMs to impact assessment; however, none of them have directly quantified the uncertainties

involved in the GCM projections themselves. Few studies, however, have attempted this, which are discussed below.



Figure 1.1: Relative changes in precipitation (%) for the period 2090-2099, relative to 1980-1999. Values are multi-model averages based on the SRES A1B scenario for (a) December to February and (b) June to August (right). White areas are where less than 66% of the models agree in the sign of the change and stippled areas are where more than 90% of the models agree in the sign of the change. (Source: *IPCC* [2007]).



Figure 1.2: The propagation of uncertainty in climate change impact studies. The increasing width of the pyramid indicates the expanding of the uncertainty envelope due to the various uncertainties introduced at each of the procedures (after, *Wilby and Dessai* [2010]).

#### **Quantifying GCM simulation uncertainty**

Uncertainty in GCM simulations arise from three sources: model structure (i.e., uncertainty due to inadequate representation of the climate system in models); scenario (i.e., uncertainty due to incomplete information about the greenhouse gas emission scenarios); and ensemble runs (i.e., uncertainty due to natural variability of the climate system) [*Yip et al.*, 2011]. These individual uncertainties as well as their total uncertainty vary spatially and temporally, depending on the GCM being assessed and on the variable of interest (e.g. rainfall or temperature) [*Johnson and Sharma*, 2009b; *Perkins et al.*, 2007].

Ideally, the uncertainties associated with GCM simulations should be provided by the modelling groups that provide the projection data. However, as of now, the GCM modelling groups do not provide the associated uncertainties, due to computational and/or time constraint of simulating thousands of realizations required to adequately characterise the uncertainty [*Murphy et al.*, 2004]. The modelling groups, however, provide few ensemble runs for each model and emission scenario. Using these few ensemble runs, different approaches have been used in the literature to evaluate skills of GCMs towards selecting the best models as well as to quantify GCM projection uncertainties.

Evaluation of GCM skills is commonly carried out by comparing the historical GCM runs with the observations. This approach, known as 'model performance', has largely been applied to select the best subset of models for simulating variables of interest as well as to estimate weighing factors to optimally combine different GCM outputs [*Dessai et al.*, 2005; *Hawkins and Sutton*, 2009; *Johnson and Sharma*, 2009b; *Perkins et al.*, 2007]. The assumption pertinent in the evaluation of GCM performance based on historical simulations is that the future skill of GCMs is similar to the historical period. However, this is not the case, as reported, for instance, by *Power et al.* [2011] and *Jun et al.* [2008], where weak accuracy is obtained between the historical and future simulations. To deal with such a problem, an approach, known as 'model convergence', which assesses GCM skills based on the agreement of future GCM projections with the ensemble mean has been used [*Dessai et al.*, 2005; *Giorgi and Mearns*, 2002; *Greene et al.*, 2006]. The above studies offer insights into the overall accuracy and uncertainty of the GCMs; however, they do not explicitly quantify the GCM uncertainties that vary in space and time.

There are indeed a number of studies that attempt to explicitly quantify GCM uncertainties [*Déqué et al.*, 2007; *Hawkins and Sutton*, 2009; *Hodson and Sutton*, 2008; *Yip et al.*, 2011]. These studies typically use the analysis of variance (ANOVA) to partition the total variance using multiple GCMs, emission scenarios and ensemble runs into the three sources of uncertainty mentioned above (i.e., model structure, scenario and ensemble runs uncertainties). An important limitation of all these studies is that the uncertainties are quantified for long-term mean ('long-term mean' refers here five years or more) of the GCM variable, and so they do not offer any information about the variability of the uncertainty at short time scales (such as monthly or annual).

Therefore, an appropriate framework that enables one to estimate GCM uncertainties that varies in space and time for any GCM output is lacking. This is further investigated in

this thesis and a method to quantify the spatio-temporal GCM uncertainties is developed in chapter 3. Provision of the GCM spatio-temporal uncertainty has important implications for subsequent modelling applications, i.e., the uncertainty information can be implemented in impact assessment models to assess regional changes together with their associated uncertainty. The existing literature towards implementation of GCM uncertainty for impact assessment on water resources is discussed next.

#### Implementation of GCM simulation uncertainty in impact assessment studies

In the previous section, review of various sources of GCM projection uncertainties as well as insights into quantifying them was described. With the knowledge that GCM projections are uncertain, an important question is: which and how many GCMs to use for impact assessment?

A number of studies suggest the use of one or a few GCMs having the best skills obtained through evaluation of model performance and/or convergence [*Johnson and Sharma*, 2009b; *Masson and Knutti*, 2011; *Pennell and Reichler*, 2010; *Perkins et al.*, 2007]. However, use of one or a few GCMs also has a disadvantage in that information from the GCMs that are not considered will be lost. One may argue that the GCMs excluded have less skill in simulating the variable of interest. Although this can be considered reasonable, there is a lack of reliable method to convincingly evaluate GCM skills [*Weigel et al.*, 2010]. Due to this, studies recommend the use of either numerous simulations from different GCMs, scenarios and ensemble runs [*Murphy et al.*, 2004] or thousands of simulation runs from a single GCM [*Stainforth et al.*, 2005] to precisely reproduce the uncertainty interval in the regional changes.

Despite these suggestions, many researchers still carry out impact assessments using only a single or a few GCM projections. Among others, the following could be important reasons for this: (1) Cost and/or time constraint to analyse large ensembles [*Perkins et al.*, 2007]; (2) The total number of available GCM projections, in the first place, are few [*KjellstrÖM et al.*, 2011; *Prein et al.*, 2011] that it is difficult to make statistically acceptable uncertainty interval.

In view of the above, it is important to develop an appropriate framework that helps to generate thousands of realizations for a single GCM applicable for water resources assessment. *Stainforth et al.* [2005] have carried out this through simulation of a single GCM, thousands of times, by perturbing selected model parameters and initial conditions. However, this method is computationally expensive, as it needs tens of thousands of computational machines around the world [*Stainforth et al.*, 2005], and thus makes the analysis difficult for practical applications..

Considering this, it is vital to develop a less computationally expensive stochastic method to generate GCM realisations through post-processing of the available GCM projections. In regard to stochastic data generation, extensive literature is available for generating climate data (especially rainfall) through parametric, semi-parametric and nonparametric methods [*Harrold et al.*, 2003; *Jones and Thornton*, 1993; *Mehrotra and Sharma*, 2007]. *Carpenter and Georgakakos* [2001] have applied a simple error model to generate ensemble streamflow forecasts by adding noise to the streamflow estimate, where the noise is estimated based on the uncertainty of the forecast. Due to its usefulness and simplicity, this method is of particular interest in this thesis.

Once a method to generate GCM realisations is developed, it can be used to reduce the influence of input uncertainty in impact assessment models. To this end, several statistical approaches have been developed in the literature: Integrated Bayesian uncertainty estimator (IBUNE) [*Ajami et al.*, 2007]; Bayesian total error analysis (BATEA) [*Kavetski et al.*, 2006a]; and Simulation extrapolation (SIMEX) [*Chowdhury and Sharma*, 2007]. The SIMEX, which attempts to reduce model parameter biases due to uncertainty in the input data, is implemented in this thesis for assessing and reducing uncertainty in future drought estimation (Chapter 4).

The GCM realizations can also be used to simulate the variable(s) of interest (such as streamflow or reservoir storage) with the associated uncertainty. This will be helpful for any alternative planning or decisions that could be made based on the GCM projections. A case study towards this is investigated at the Warragamba catchment, New South Wales (Australia) in Chapter 5.

#### **1.3.** Aims and objectives of the thesis

The above literature review reveals that while an extensive amount of research has already been carried out to understand and analyse the impacts of climate change on water resources, very less attention has been given to characterize and reduce the uncertainties introduced into impact assessment from the GCM simulation uncertainty. Thus, this thesis aims to develop an appropriate framework that is fine-tuned to quantify spatiotemporal GCM uncertainty as well as to implement such uncertainty information for water resources assessment. The specific objectives of the thesis, according to the topic presented in different chapters, are:

- To compare and merge rain gauge and remote sensing rainfall data as well as to estimate the associated spatio-temporal standard errors for Australian conditions;
- To develop a method that can quantify spatio-temporal GCM projection uncertainty;
- To implement spatio-temporal GCM projection uncertainty into water resources assessment using Simulation Extrapolation (SIMEX), with an example for drought analysis across the world;
- To develop methods that can be used to implement GCM projection uncertainty information for water resources assessment, with an example for reservoir storage analysis at the Warragamba Catchment in Sydney, Australia.

#### 1.4. Thesis outline

This thesis is presented as a series of chapters that are reproduced, with minor modifications, from journal papers either published or submitted for publication. The outline of the main chapters (Chapters 2 to 5) is given in Figure 1.3, which is arranged according to the specific objectives described in section 1.3, above. Each of these chapters can be read as a stand-alone document, and the notations used in each chapter are specific to that particular chapter. The thesis is organised in two parts: Part-1 and Part-2 (Figure 1.3). In Part-1 (Chapters 2 and 3), methods to quantify spatio-temporal uncertainties in climate datasets are discussed, whereas implementation of the spatio-temporal uncertainties for water resources assessment is presented in Part-2 (Chapters 4 and 5). In what follows, a brief overview of the main chapters (Chapters 2 to 5) is given.

Chapter 2 provides a preliminary study that compares and evaluates the uncertainties involved in the estimation of gridded rainfall using observed rainfall data based on two

different sources, i.e. rain gauge and remote sensing, across Australia. Both datasets have significant uncertainties due to various sources of errors, interpolation and retrieval errors, in either case. In an attempt to reduce these uncertainties, the study develops and implements a method to merge the two rainfall sources. Finally, a method to quantify the spatio-temporal standard error that varies in space and time is developed. The spatio-temporal standard error estimation method, developed based on observed rainfall, is then extended to estimate GCM projections uncertainty, which forms a basis for the remaining chapters (Chapters 3 to 5).



Figure 1.3: Flow chart showing the outline of chapters 2 to 5.

Chapter 3 develops a novel method to quantify GCM uncertainty at monthly timestep across the world. The method is implemented for rainfall and temperature projections from six GCMs and three scenarios using the CMIP3 datasets of the fourth assessment report (AR4) of the IPCC. Using the GCM projections and the new uncertainty estimates, two application studies towards assessing uncertainties involved in climate change impact assessments for water resources are carried out, which are discussed in chapters 4 and 5.

In chapter 4, drought assessment using Standardised Precipitation Index (SPI) for future climate, across the world, is discussed. The GCM uncertainty established in chapter 3 is implemented to analyse the influence of GCM uncertainty in the future SPI estimates. In addition, Simulation Extrapolation (SIMEX) method is applied to reduce SPI parameter bias that would otherwise occur due to the uncertainty in the GCM rainfall. A comprehensive assessment of water resources considering GCM uncertainties is then carried out in chapter 5. The study quantifies and evaluates the GCM uncertainties introduced in the assessment of climate change impacts on reservoir storage. The uncertainty estimation method developed in chapter 3 is used to quantify uncertainties in rainfall and evaporation projections, which are then used to estimate the uncertainties propagated into reservoir storage. This is carried out for the Warragamba catchment in New South Wales, Australia. An overall conclusion of the thesis as well as future research directions is discussed in chapter 6.
## **Chapter Two**

# 2. Merging gauge and satellite rainfall with specification of associated uncertainty across Australia

Accurate estimation of spatial rainfall is crucial for modeling hydrologic systems and planning and management of water resources. While spatial rainfall can be estimated either using rain gauge-based measurements or using satellite-based measurements, such estimates are subject to uncertainties due to various sources of errors in either case, including interpolation and retrieval errors. This chapter investigates the benefit of merging rain gauge measurements and satellite rainfall for Australian conditions as well as produces a database of retrospective rainfall along with a new uncertainty metric for each grid location at each timestep. The uncertainty metric estimation method, in this chapter, will be further extended in chapter 3 to estimate uncertainties of GCM projections. The content of this chapter is reproduced, with permission and minor changes, from a paper that is published in Journal of Hydrology, below.

Woldemeskel, F.M., B. Sivakumar, and A. Sharma (2013), Merging gauge and satellite rainfall with specification of associated uncertainty across Australia, *Journal of Hydrology*, 499, 167-176.

## 2.1. Introduction

Accurate estimation of spatial rainfall at fine scales is crucial for many practical hydrological and environmental modelling purposes, such as rainfall-runoff modelling, hydraulic structure design, and pollutant transport. There are two common methods for measuring rainfall: (1) using direct measurements (e.g. rain gauges); and (2) using remote

sensing techniques (e.g. weather radar or satellite-based techniques). The conventional way of obtaining spatial rainfall is through conversion (e.g. averaging or interpolation) of point rainfall measured at rain gauge locations. While the point rainfall itself is only a representation of average over an area, the approach is somewhat reliable if there is a dense network of rain gauges. However, in areas where there is only a sparse network of rain gauges, this approach to obtain spatial rainfall (as well as rainfall at other temporal scales) is subject to a large degree of uncertainty. Furthermore, rainfall measured using rain gauges is uncertain due to the effects of wind, flaws in rain gauge installation, wetting losses, and other random and systematic errors [e.g. *Ren and Li*, 2007; *Sevruk*, 1996].

Some of the above problems may be mitigated with the use of satellite-based techniques for rainfall measurements. Satellite-based techniques provide continuous rainfall at much finer temporal and spatial resolutions than ground-based rain gauges do. However, they are also uncertain due to temporal sampling and retrieval of rainfall rate from satellite signals [e.g. *Gebremichael et al.*, 2010]. There exist several satellite-based global rainfall products; however, the products from the Tropical Rainfall Measuring Mission (TRMM) rainfall estimates [e.g. *Kummerow*, 2000] are arguably the most extensive and most widely used for rainfall studies in tropical regions.

The TRMM was launched in November 1997 with an aim to measure tropical rainfall from space with combined passive and active microwave instruments [*Kummerow*, 2000]. Several studies have favourably assessed the utility of TRMM rainfall data by comparing them with rain gauge observations [e.g. *Chiu et al.*, 2006; *Chokngamwong and Chiu*, 2008; *Hughes*, 2006] as well as by using TRMM rainfall data for streamflow simulation [e.g. *Bitew*, 2010; *Collischonn et al.*, 2008; *Su et al.*, 2008]. Some efforts have also been made to merge TRMM rainfall data with rain gauge observations [*Grimes et al.*, 1999;

*Huffman et al.*, 1995; *Li and Shao*, 2010; *Oke*, 2009], including for Australia. For instance, *Li and Shao* [2010] showed that a nonparametric kernel merging of gauge and TRMM rainfall data improves Australian rainfall estimation in terms of biases when compared with other approaches. *Oke et al.* [2009] used TRMM data as a predictor in geostatistical estimation methods to estimate daily rainfall in Australia. It was demonstrated that incorporating TRMM data in rainfall estimation did not increase the overall accuracy, although some improvement was obtained in areas with sparse rain gauge network. They argued that the reason for the moderate performance of the merging is due to the poor correlation of TRMM data with gauge observations as well as to the existence of large bias in TRMM daily rainfall data, especially in coastal and high altitude regions.

The outcomes of these studies are encouraging as to the usefulness of merging satellite and rain gauge measurements, and there is certainly a great potential for further advances. This provides the motivation for the present study towards improving spatial rainfall estimation in Australia. More specifically, the study attempts to merge the high-quality monthly rainfall data measured using rain gauges and the accumulated monthly TRMM 3B42 data. Unlike the previous studies on merging such data for Australia [e.g. *Oke et al.*, 2009; *Li and Shao*, 2010], which have used relatively dense rain gauge network, we analyse three sparse rain gauge networks to specifically investigate the benefit of incorporating TRMM rainfall in data-limited areas. We also develop a new basis to assess uncertainty of the estimated gridded rainfall data at a monthly timestep for each grid. The analysis involves the following steps: First, a comparison of rain gauge rainfall and TRMM 3B42 data is carried out. Second, a methodology is described to estimate gridded monthly rain gauge rainfall using thin plate smoothing splines (TPSS) and modified inverse distance weight (MIDW) method. Third, the gridded rain gauge rainfall is merged with the monthly accumulated TRMM 3B42. Finally, cross validation (CV) errors at sampling locations as well as standard errors at grid points are estimated. We analyse a network of 230 rain gauges across Australia, which have high-quality rainfall data [*Lavery et al.*, 1997]. The CV error statistics indicate that merging of the two datasets improves the estimation of spatial rainfall, and more so where the rain gauge network is sparse. The provision of spatio-temporal standard errors with the retrospective dataset is particularly useful for subsequent modelling applications where input error knowledge can help reduce the uncertainty associated with modelling outcomes. This is particularly useful for distributed hydrological modelling where input data at each grid point is required. In such applications, the standard error at each grid point can be used as an input to study the propagation of rainfall uncertainty throughout the model as well as to reduce parameter bias due to input uncertainty in the parameter estimation.

#### 2.2. Study area and data

#### 2.2.1. Study area

The Australian climate varies from tropical in the north to arid in the middle to temperate in the south. The oceans surrounding Australia have a large impact on its climate. For instance, the El-Niño Southern Oscillation (ENSO), the western Pacific and the Indian Ocean sea surface temperatures (SST), and the Southern Ocean atmospheric variability influence the climates of different regions of Australia by varying degrees [*Taschetto and England*, 2009]. The country is largely dry, especially the middle and the west, with the rainfall highly variable in space and time. More than 80% of the country gets an annual rainfall of less than about 600 mm. However, the tropical region of the far north gets an annual rainfall as high as about 4000 mm. Rainfall is mainly monitored using the thousands of rain gauges installed at different parts of the country. However, the majority of these rain gauges have been installed only near the coasts of east, south east and south west of Australia, where much of the population is concentrated and in big cities. In the interior of the country, which is largely desert and very sparsely populated, the number of rain gauges is very few.

#### 2.2.2. Data

The rainfall data used in this study are high-quality monthly rain gauge rainfall as well as TRMM 3B42 products across Australia. The sources and features of these data are presented next.

#### Rain gauge data

Rainfall data observed over a period of 10 years (January 1998–December 2007) at 230 rain gauges across Australia are considered (Figure 2.1). These 230 stations are selected from high-quality monthly rainfall measuring rain gauges, identified by *Lavery et al.* [1997] through detailed statistical tests of homogeneity as well as other quality-testing criteria (such as observational practice, site relocations and exposure of instruments). Where there are missing data (on average, just 1 % of the gauges have missing values in a given month during 1998–2007), they are filled by the long-term rainfall mean of the respective month.

#### TRMM data

The TRMM rainfall products are downloaded from the Goddard Distributed Active Archive Center (GDAAC). The Version 6 products of TRMM 3B42 for the period 1998–

2007 are considered in this study, and the available daily TRMM 3B42 data are used to calculate the accumulated monthly rainfall for analysis.



Figure 2.1: Location map of 230 rain gauge stations in Australia. The figure also shows five regions considered for leave-region-out cross validation (L-R-OCV) (numbers 1 to 5).

#### Latitude, longitude and elevation

Latitude, longitude and elevation at each rain gauge station are obtained from the Australian Bureau of Meteorology (BOM). Latitude and longitude at grid locations are determined by successively adding the grid size  $(0.05^{\circ})$  to the starting values of latitude and longitude. Elevation data at  $0.05^{\circ} \times 0.05^{\circ}$  latitude/longitude grid (about 5 km x 5 km) are obtained by aggregating 90 m Digital Elevation Model (DEM) of the Shuttle Radar

Topography Mission (SRTM), which is extracted from the Consortium for Spatial Information (http://www.cgiar-csi.org/).

### 2.3. Method

The methodology used in this chapter involves four important steps. First, the quality of the TRMM 3B42 rainfall data is assessed by comparing them with gauge observations at the sampling points. Second, rain gauge observations are interpolated to obtain rainfall data at  $0.05^{\circ} \times 0.05^{\circ}$  latitude/longitude grid. Third, merged rain gauge–TRMM data at  $0.05^{\circ} \times 0.05^{\circ}$  latitude/longitude grid are estimated. Finally, interpolation error at sampling points and standard error at grid locations are evaluated. We use the R statistical software to implement the methodology. Further details of these specific steps are presented next.

#### 2.3.1. Comparison of TRMM 3B42 and rain gauge data

The quality of TRMM 3B42 data is initially assessed to investigate whether the satellite data reasonably captures rainfall in Australia or not by comparing them with rain gauge data at the sampling points. Figure 2.2 shows the correlation between rain gauge and TRMM 3B42 rainfall data for all the 230 stations, plotted with respect to the corresponding latitude of the rain gauge stations. The figure indicates that TRMM 3B42 rainfall data reasonably agree with rain gauge observations, especially for stations within 39 degrees of the equator. However, the correlation is rather weak at more poleward locations (such as Tasmania) and other locations close to the coast, reflecting the uncertainty of TRMM rainfall estimates in coastal areas. A two-sample Kolmogorov-Smirnov (K-S) distributional test shows that significant difference in the statistical properties of rain gauge and TRMM 3B42 is found in about 10 % of the stations (see



Figure 2.3). These stations are mainly along the coast as well as at more poleward locations.

Figure 2.2: Correlation between rainfall data observed through rain gauges versus TRMM 3B42. The correlations are plotted with respect to the latitude of the rain gauge locations.

#### 2.3.2. Gridded rainfall estimation

Monthly rainfall values at  $0.05^{\circ} \ge 0.05^{\circ}$  latitude/longitude grid are estimated for both TRMM 3B42 and rain gauge rainfall to facilitate the merging of the two. For TRMM 3B42, the cell value corresponding to  $0.25^{\circ} \ge 0.25^{\circ}$  latitude/longitude grid is used. No error reduction is found when the inverse distance weighted (IDW) interpolation is used to estimate TRMM rainfall at  $0.05^{\circ} \ge 0.05^{\circ}$  latitude/longitude grid from  $0.25^{\circ} \ge 0.25^{\circ}$  latitude/longitude grid for details of the

IDW interpolation method). For rain gauge data, rainfall measured at 230 sampling points are interpolated to obtain gridded rainfall at  $0.05^{\circ} \times 0.05^{\circ}$  latitude/longitude grid. The interpolation is carried out for three different types of rain gauge networks, which are obtained by removing on average one, 10 % and 20 %, respectively, of the rain gauges from the total number of 230 during cross validation (see section 2.3.4 for more details about these three rain gauge networks and cross validation). The interpolation procedure involves the following four important steps.



Figure 2.3: A two-sample Kolmogorov-Smirnov (K-S) test between rain gauge and TRMM 3B42 rainfall data. Significance difference in the statistical properties of the data is observed only in the 10 % of the stations.

**Step 1** – **Normalisation**: Normality tests of the rainfall data using Lilliefors test [*Lilliefors*, 1967] show that the raw rainfall data can be considered normally distributed only at 5 % of the locations at 5 % significant level. We, thus, normalise the raw data by

raising to an appropriate fractional power; this helps to reduce the spatial and temporal skewness that exist in rainfall. *Hutchinson* [1998] and *Jeffrey et al.* [2001] used square root normalisation for daily rainfall in the USA and monthly rainfall in Australia, respectively. Based on their recommendations and considering its simplicity, we herein use the square root normalisation for monthly rainfall, given by:

$$P_{nor(i,n)} = P_{raw(i,n)}^{0.5}$$
(2.1)

where *i* is the month, *n* represents the station number,  $P_{nor}$  is the monthly normalised rainfall and  $P_{raw}$  is the monthly raw rainfall. This transformation step reduces the skewness of the rainfall data; i.e., at 5 % significant level, 65 % of the stations can be considered normal. The skewness coefficient of the remaining 35 % stations also becomes closer to zero, which is an indication that the transformed data can now be reasonably assumed to be normally distributed when compared to that of the raw data.

**Step 2 – Standardisation**: Standardised rainfall (hereafter referred to as 'residual') is estimated using:

$$r_{i,n} = \frac{P_{nor(i,n)} - \mu_{j,n}}{\sigma_{j,n}}$$
(2.2)

where *j* is the month in a given year, *r* is the monthly residual,  $\mu$  is the long-term monthly mean and  $\sigma$  is the long-term monthly standard deviation.

The standardisation is carried out to interpolate the normalised long-term mean and standard deviation separately from the residual. The spatial variability of rainfall, which is largely due to topographic influences, is effectively reduced as a result of the standardisation procedure. Therefore, the residual can be reasonably interpolated using observations of a few nearest neighbours. On the other hand, since the topographic influences are also, to a certain extent, depicted through the long-term mean and standard deviation [*Dai et al.*, 1997; *Jeffrey et al.*, 2001], topographic information is used as a predictor variable in the interpolation of the parameters. Thus, standardisation of rainfall data and interpolation of the parameters separately from the residuals help to achieve improved interpolation outcomes [*Chen et al.*, 2002].

Step 3 – Interpolation: During the past century, several interpolation methods have been developed and/or applied for rainfall estimation, such as Thiessen polygons [e.g. *Thiessen and Alter*, 1911], inverse distance weight [e.g. *Shepard*, 1968], geostatstical methods [e.g. *Journel and Huijbregts*, 2003] and spline fitting [e.g. *Hutchinson*, 1998]. In this chapter, a variant of the inverse distance weight and spline fitting are implemented, as follows. The long-term mean and standard deviation of the rainfall data are interpolated using the Thin Plate Smoothing Splines (TPSS), which is a regression approach that estimates a surface by minimising a certain penalty function [e.g. *Hastie et al.*, 2003]. Topographic information, such as latitude, longitude and elevation, are used as predictors for the TPSS model. On the other hand, the residual is interpolated using the Modified Inverse Distance Weight (MIDW) method that accounts for inter-gauge distance as well as direction, according to the method presented by *Shepard* [1968]. The TPSS and MIDW methods are selected in this research as they have been well investigated for spatial rainfall estimation and found to be useful. See Chapter 7 (Appendix A and B) for more details about the TPSS and MIDW methods, respectively.

**Step 4 – Back-transformation**: Rainfall at grid points are obtained using:

$$\hat{P}_{nor(i,n)} = \hat{r}_{i,n} \times \hat{\sigma}_{j,n} + \hat{\mu}_{j,n}$$
(2.3)

$$\hat{P}_{raw(i,n)} = \hat{P}_{nor(i,n)}^2 \tag{2.4}$$

where  $\hat{P}_{nor}$  is the estimated monthly normalised rainfall,  $\hat{r}$  is the estimated monthly residual,  $\hat{\sigma}$  and  $\hat{\mu}$  are the estimated long-term standard deviation and mean for each month, and  $\hat{P}_{raw}$  is the estimated monthly raw rainfall. Note that variables without hat (^) represent observed data or calculated values using observed data at rain gauge locations, whereas variables with hat represent interpolated values at grid points.

It has to be noted that interpolation of rainfall data in the normal space and then backtransformation introduce some bias in the statistical properties (such as mean and standard deviation) of the rainfall data [e.g. *Salas et al.*, 1980]. Albeit this limitation, the normalisation step is important to reduce the spatial and temporal skewness of the rainfall data which ultimately improves the gridded rainfall estimation. Gaussian Anamorphosis normalisation approach [*Wackernagel*, 1996] may be used to circumvent such bias introduced during back transformation. However, we have not applied the Gaussian Anamorphosis normalisation or any other bias reduction approach in this study.

#### 2.3.3. Merging

We estimate the merged rain gauge–TRMM rainfall by doing a linear weighted combination according to:

$$\hat{P}_{GSi} = \hat{g}_i \hat{P}_{Gi} + \hat{s}_i P_{si} \tag{2.5}$$

where  $\hat{P}_{GSi}$  is the merged rainfall estimate at the *i*<sup>th</sup> grid,  $\hat{P}_{Gi}$  (referred as  $\hat{P}_{raw}$  in Equation (2.4)) is the rain gauge rainfall at the *i*<sup>th</sup> grid,  $P_{Si}$  is the satellite rainfall at the *i*<sup>th</sup> grid,  $\hat{g}_i$ 

is the weight for rain gauge rainfall estimate at the *i*<sup>th</sup> grid, and  $\hat{s}_i$  is the weight for satellite rainfall estimate at the *i*<sup>th</sup> grid. A number of studies [*Gebregiorgis and Hossain*, 2011; *Grimes et al.*, 1999; *Huffman et al.*, 1995; *Marshall et al.*, 2006; *Sharma and Chowdhury*, 2011; *Wasko et al.*, 2013] utilise merging and model combination approaches somewhat similar to this. The weights ( $\hat{g}_i$  and  $\hat{s}_i$ ) are calculated based on the error variances of each estimate at a grid location according to:

$$\hat{g}_{i} = \frac{\hat{\varepsilon}_{si}^{2}}{\hat{\varepsilon}_{si}^{2} + \hat{\varepsilon}_{gi}^{2}}$$
(2.6a)

$$\hat{s}_{i} = \frac{\hat{\varepsilon}_{gi}^{2}}{\hat{\varepsilon}_{si}^{2} + \hat{\varepsilon}_{gi}^{2}}$$
(2.6b)

where  $\hat{\varepsilon}_{gi}^{2}$  is the rain gauge rainfall error variances at the *i*<sup>th</sup> grid and  $\hat{\varepsilon}_{si}^{2}$  is the satellite rainfall error variance at the *i*<sup>th</sup> grid.

We use thin plate smoothing splines (Chapter 7, Appendix A) to interpolate the error variance from sampling points to each grid location for both rain gauge and TRMM 3B42 rainfall estimates. Latitude, longitude, elevation and distance to nearest neighbour are used as predictors for rain gauge data. For TRMM 3B42, however, instead of distance to nearest neighbour, the overall monthly mean rainfall is used.

#### 2.3.4. Error estimation

Cross validation errors at sampling points

Cross validation is carried out to evaluate the estimated gridded rain gauge and merged rain gauge–TRMM rainfall data using mean error (ME), mean absolute error (MAE) and root mean square error (RMSE), calculated according to:

$$ME = \frac{1}{N} \sum_{n=1}^{N} (\hat{P}_n - P_n)$$
(2.7)

$$MAE = \frac{1}{N} \sum_{n=1}^{N} |\hat{P}_n - P_n|$$
(2.8)

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\hat{P}_n - P_n)^2}$$
(2.9)

where N is the total number of observations in the analysis and  $\hat{P}_n$  and  $P_n$  are the estimated and observed rainfall at a particular rain gauge, respectively.

In this study, we carry out three different cross-validation schemes: (1) leave-one-out cross validation (L-1-OCV); (2) leave-ten-out cross validation (L-10p-OCV); and (3) leave-region-out cross validation (L-R-OCV). In L-1-OCV, at each time, one rain gauge is removed from the analysis. In L-10p-OCV, at each time, 10 % of the rain gauges are randomly removed from the analysis. In L-R-OCV, the rain gauges are divided into five regions (numbered 1 to 5 in Figure 2.1), so that each region contains approximately 20 % of the total number of gauges. To estimate rainfall in any region, data from stations in the other four regions are considered. This, in some way, characterises an extreme case of ungauged basins and allows us to assess the utility of merging gauge and satellite data for large ungauged areas.

The TPSS is used to estimate the parameters (i.e. mean and standard deviation) for the three CV schemes, as follows. For L-1-OCV and L-10p-OCV, the parameters are estimated by consecutively removing one rain gauge and 10 % of rain gauges, respectively, from the analysis, which results in 230 and 23 parameter values in these two cases. We then use the average of these 230 and 23 values to obtain the parameters for L-1-OCV and L-10p-OCV, respectively. For L-R-OCV, the parameters in any region are estimated based on parameter values of other regions. Similarly, the MIDW is used to estimate the residuals for the three cases by removing one, 10 % and approximately 20 % (i.e. one out of five regions) of the rain gauges from analysis.

#### Standard error at grid points

The estimated cross validation errors at rain gauge locations are used to estimate the standard errors at grid points for each timestep (month). Here, 'standard error' is defined as the standard deviation of the estimated cross validation errors. We adopt the following procedure for estimating the standard errors:

- i. Standard deviation of the cross validation absolute errors and long-term mean rainfall at each rain gauge location is estimated for each month during 1998–2007.
- ii. Using long-term monthly mean rainfall as a predictor and monthly standard deviation as a response variable, a thin plate smoothing spline (TPSS) model is developed. This model is then used to predict standard error for each timestep at the rain gauge locations. Ideally, the mean of the predicted standard error and standard deviation at rain gauge locations should be equal. However, due to errors in the TPSS model, the predicted standard errors can be somewhat biased.

- iii. The bias in the standard error is corrected by multiplying with correctional factors. These factors are determined by dividing the standard deviation by the mean of the predicted standard errors at rain gauge locations for each month. Then, simple inverse distance weight interpolation is used to estimate the factors at grid points using six nearest neighbours.
- iv. Standard errors at grid points are predicted by using estimated rainfall as an input in the TPSS model in Step (2) and the bias is corrected by multiplying with the factors estimated in Step (3). The estimation of the standard error is carried out for L-1-OCV, L-10p-OCV and L-R-OCV as well as for their merged estimates with TRMM 3B42.



Figure 2.4: Monthly cross validation (a) root mean square error (RMSE) and (b) mean absolute error (MAE) for different number of nearest neighbours and power parameter. The figures show that number of stations equal to six as well as power parameter (k), Equation B2 (Appendix B), equal to 2 are optimal values to obtain the minimum RMSE and MAE.



Figure 2.5: Density plots of distances to first (a) and sixth (b) nearest neighbours under L-1-OCV, L-10p-OCV and L-R-OCV.

#### 2.4. Results

#### 2.4.1. Number of nearest neighbours

The optimum number of nearest neighbours for interpolation of residuals is selected by minimising the cross validation RMSE and MAE. Figures 2.4(a) and (b) show the RMSE and MAE for different power parameter values (*k*), Equation B2 (Appendix B), CVs and interpolation methods. In these figures, only the results for L-1-OCV and L-10p-OCV are shown, since they have better accuracy for selecting the optimum number of nearest neighbours than those of L-R-OCV. The figures show that the errors are large for the first few nearest neighbours. As the number of neighbours increases, the error decreases rapidly until the number of nearest neighbours is about six. After that, the error again increases slowly. This seems to be an indication that six nearest neighbours are optimal and, therefore, are used for interpolating the residuals. The density plots of the distances

to the first and sixth nearest neighbours for the three cases are shown in Figures 2.5(a) and (b), respectively. Under L-1-OCV and L-10p-OCV, the density plots have similar peaks and pattern; however, in the case of L-R-OCV, the peaks are shifted to the right. The average distances to the first and sixth nearest neighbours are, respectively, 170 km and 406 km for L-1-OCV, 178 km and 428 km for L-10p-OCV, and 227 km and 498 km for L-R-OCV. As for the power parameter (k), a value equal to two is used, as it gives the minimum value for both RMSE and MAE.

#### 2.4.2. Merging weights at grid points

The merging of rain gauge and TRMM 3B42 rainfall data is done using Equation (2.5), whereas the merging weights ( $\hat{g}_i$  and  $\hat{s}_i$ ) are calculated using Equations (2.6a) and (2.6b). Figures 2.6(a) to (c) show the calculated rain gauge weights at each grid point for leave-one-out cross validation (L-1-OCV), leave-ten-out cross validation (L-10p-OCV) and leave-region-out cross validation (L-R-OCV), respectively. The weights are stationary over time, but vary spatially from zero to one. The respective weights for TRMM 3B42 can also be estimated as one minus the weight for rain gauge. For L-1-OCV and L-10p-OCV (Figures 2.6(a) and (b)), the weights for rain gauge are greater than those for TRMM 3B42 in southwest and southeast Australia. This is essentially due to the dense network of rain gauges in these areas. On the other hand, due to the sparse network of rain gauges in the central and northern parts of the country, the weights for rain gauge are relatively smaller than those for TRMM 3B42. For L-R-OCV (Figure 2.6(c)), as large numbers of rain gauges are excluded during the cross- validation analysis, the rain gauge weights are significantly smaller when compared to those for L-1-OCV and L-10p-OCV, in almost all areas across Australia.



Figure 2.6: Rain gauge spatial weights for merging rain gauge and TRMM for (a) L-1-OCV, (b) L-10p-OCV and (c) L-R-OCV. The dots indicate rain gauge locations used in the analysis. Weights for TRMM 3B42 is one minus weights for rain gauge.

#### 2.4.3. Cross validation errors at sampling points

Figures 2.7 and 2.8 show the spatial root mean square error (RMSE) for rain gauge data as well as merged gauge–TRMM 3B42 for L-1-OCV and L-R-OCV, respectively; the results are for data averaged over the period 1998–2007 at the rain gauge locations (The

results for L-10p-OCV are not shown here, as they largely resemble that of L-1-OCV). The figures show that the RMSE of the merged rainfall estimate is reduced at the stations at longitudes between 122° and 130°, which is essentially due to the sparse network of rain gauges in this area (see Figure 2.1). The reduction in RMSE is more significant for merging TRMM 3B42 with L-R-OCV than that with L-1-OCV (Figure 2.8). The results also indicate that only little or even no improvement in RMSE is obtained for L-1-OCV in stations located in the eastern or western parts of Australia, likely due to the use of relatively dense rain gauge network for analysis in these areas. However, for L-R-OCV, considerable improvement is obtained by incorporating TRMM, as the gauge-only estimate is still uncertain in those regions due to the removal of all stations from that particular region.



Figure 2.7: RMSE of L-1-OCV as well as merged L-1-OCV and TRMM 3B42 at each rain gauge location averaged over the period 1998–2007. The RMSE values are plotted with respect to the longitude of the rain gauge locations.



Figure 2.8: Similar to Figure 2.7 but for L-R-OCV as well as merged L-R-OCV and TRMM 3B42.

Figures 2.9 and 2.10 show the time series of RMSE for rain gauge data as well as merged rain gauge–TRMM 3B42, averaged over the 230 rain gauges, for L-1-OCV and L-R-OCV cases, respectively. The results indicate that the merging increases RMSE in many of the timesteps in L-1-OCV (Figure 2.9). On the other hand, merging decreases RMSE in almost all the timesteps in L-R-OCV, which is a clear indication of the benefit of incorporating TRMM 3B42 for sparse rain gauge network. Figures 2.9 and 2.10 further show the seasonal fluctuation of the error, with larger errors observed whenever the accumulated rainfalls are larger.



Figure 2.9: Time series of RMSE of L-1-OCV as well as merged L-1-OCV and TRMM 3B42 averaged over 230 rain gauges.



Figure 2.10: Similar to Figure 2.9 but for L-R-OCV as well as merged L-R-OCV and TRMM 3B42.

Table 2.1: Summary of performance of different rainfall estimation methods (1998–2007): CV – cross validation; ME – mean error; MAE – mean absolute error;
RMSE – root mean square error.

Rainfall estimation	Rain gauges	ME	MAE	RMSE
method	omitted in CV	(mm)	(mm)	(mm)
L-1-OCV	1	-1.85	14.16	23.11
L-10p-OCV	10%	-1.90	14.15	23.02
L-R-OCV	~20% (Region)	-1.59	21.74	33.59
TRMM 3B42 & L-1-OCV	1	-2.25	14.45	23.34
TRMM 3B42 & L-10p-OCV	10%	-2.42	14.75	23.76
TRMM 3B42 & L-R-OCV	~20% (Region)	-2.65	18.30	28.24
TRMM 3B42	-	-3.42	18.26	27.80

Table 2.1 presents the overall error statistics (ME, MAE and RMSE) for the various interpolated and merged rainfall estimates. The error statistics for L-1-OCV and L-10p-OCV are comparable; however, the MAE and RMSE of L-R-OCV are much larger. Merging TRMM 3B42 and L-R-OCV decreases the overall MAE from 21.74 mm to 18.30 mm and RMSE from 33.59 mm to 28.24 mm. The mean error increases from –1.59 mm to –2.65 mm. The merged TRMM 3B42 and L-R-OCV has a slightly higher RMSE and MAE compared to that from TRMM 3B42 alone; however, TRMM 3B42 overestimates rainfall when compared to the merged TRMM 3B42 and L-R-OCV. The slight increase in the RMSE and MAE is due to a significantly large error obtained in the L-R-OCV estimate in heavy rainfall regions, particularly northern Australia, which increases the overall average RMSE and MAE in majority of the locations compared to the TRMM3B42.

## 2.5. Discussion

The results from the present study generally indicate that merging rain gauge and TRMM 3B42 rainfall is not that beneficial for the L-1-OCV and L-10p-OCV rain gauge networks. Only little, and sometimes even no, improvement is observed in terms of MAE and RMSE at all the rain gauge locations considered for the analysis. This may be due to the uncertainties in the rain gauge and TRMM rainfall data as well as to the error introduced during the interpolation procedure. The rain gauge-based gridded data are subject to measurement errors, due to the effects of wind, wetting loss, interpolation errors and other factors, whereas the TRMM rainfall are also uncertain due to sampling and retrieval errors, among others. On the other hand, noticeable improvement is obtained by merging rain gauge and TRMM 3B42 for the L-R-OCV rain gauge network, despite the above uncertainties mentioned above, due to an exclusion of on average 20 % of the rain gauges from the same region from the analysis.

This suggests the particular importance of TRMM rainfall data for areas where the rain gauge network is sparse.

To gain the full benefit of the TRMM rainfall data in merging, it is vital to consider the uncertainties in the data measurements in both rain gauges and TRMM. This data uncertainty problem is not addressed in the present study; for instance, the original rainfall data themselves are considered for analysis. Furthermore, the TRMM rainfall products at 0.25° x 0.25° latitude/longitude grid are directly used to obtain rainfall at 0.05° x 0.05° latitude/longitude grid. This also introduces a certain degree of uncertainty, since it largely eliminates the local effects on rainfall estimation at the finer scale. We intend to extensively examine the data uncertainty problem in the future. To this end, we will also

consider an approach similar to the one adopted by *AghaKouchak et al.* [2009], who generated an ensemble of TRMM rainfall estimates by simulating error fields stochastically and imposing them in TRMM rainfall estimates. We will report the outcomes of such analysis in our future publications.

In the present study, the rainfall mean and standard deviation are interpolated separately from the residual field. The standard inverse distance weight (IDW) method is modified to more appropriately specify the weights for nearest rain gauge stations for interpolating the residuals. Consideration of only the horizontal distance and direction as influencing factors for calculating weights does not create a significant problem, since the effects of topography are already included in the mean and standard deviation interpolation. The analysis indicates that, in all cases considered, six nearest neighbours are optimal for residual interpolation (Figures 2.4(a) and (b)). For cases where the power parameter (k), see Equation (B2) in Appendix B (Chapter 7), equals two and as the number of nearest neighbours is beyond six, the cross validation errors continue to be almost constant, regardless of the number of neighbours. This outcome is acceptable, because, for k values of three or four, the calculated weights are very small for large values of inter-gauge distance (d) (see Equation (B2) in Appendix B (Chapter 7)), and thus the interpolation is again solely based on the first six nearest neighbours.

The present study reveals that merging of gridded rain gauge data and TRMM 3B42 improves spatial rainfall estimation especially for sparse rain gauge network. This is in accordance with the general conclusion drawn by *Oke et al.* [2009]. However, it is important to mention that, in the present study, we perform a far more elaborate analysis using three different densities of rain gauges networks formulated through cross

validation. This helps to assess the utility of merging for catchments/basins with varying degrees of rain gauge density. In addition, a new methodology is developed, in the present study, to estimate the standard error for the rain gauges based as well as merged gridded datasets that can be used to assess the propagation of error to models (such as hydrological models) that use rainfall as an input. The standard error estimation method developed herein can be extended to estimate uncertainties of simulated climate data, such as Global Climate Model (GCM) projections (For instance, *Woldemeskel et al.* [2012]). One can also use the improved rainfall data as a more reliable input to hydrological models to ultimately improve streamflow simulations. Further, the interpolation and merging procedure described here can be reproduced in other areas, especially in developing regions where rain gauge network is generally scarce; however, depending on the topography, climatic conditions and rain gauge networks in such areas, different findings may result.

#### 2.6. Conclusions

This study presented an approach to integrate rain gauge and TRMM 3B42 rainfall data for estimating monthly rainfall and associated standard errors at a finer spatial scale across Australia. Three different combinations of rain gauge networks were considered: leaveone-out cross validation (L-1-OCV); leave-ten-out cross validation (L-10p-CV); leaveregion-out cross validation (L-R-OCV). Rainfall was estimated from rain gauge observations using thin plate smoothing splines (TPSS) and modified inverse distance weight (MIDW) method. While thin plate smoothing splines was used for interpolating the mean and standard deviation rainfall field, MIDW was used for interpolating the residual field. The MIDW incorporated weights for direction as well as distance. This improved the interpolation, especially in situations where most of the rain gauges are concentrated in one direction and only a few in the other direction. The results indicate an increase in the overall errors (mean absolute error (MAE) and root mean square error (RMSE)) when the density of the rain gauge network decreases. The L-R-OCV method produced the largest error, since in this case many rain gauges were removed from the analysis from the same region. The errors in L-1-OCV and L-10p-OCV are comparable, however.

Rainfall estimates from TRMM are advantageous, as they are available in high spatial and temporal resolutions. However, they are also uncertain due to sampling and retrieval errors. The overall MAE and RMSE of TRMM 3B42 are found to be greater than those of the L-1-OCV and L-10p-OCV estimates, despite the fact that the rain gauge density of L-1-OCV and L-10p-OCV are already sparse compared to the total number of rain gauges (in thousands) that operate in Australia. The overall MAE and RMSE of TRMM 3B42 are smaller from L-R-OCV, in which about 20 % of the rain gauge stations were omitted from the analysis. Merging TRMM 3B42 with L-1-OCV and L-10p-OCV has only little benefit, if any. However, merging TRMM 3B42 with L-R-OCV improves rainfall estimation in most rain gauge stations considered. This suggests that integration of satellite rainfall with rain gauge data improves rainfall estimation, especially in areas with sparse rain gauge network. Assuming standard errors as a function of rainfall magnitude, a thin plate smoothing spline model was developed to estimate standard errors at each grid for all the timesteps. The estimated standard errors reveal that the errors are significantly large for the combination of large rainfall values and sparse rain gauge density. The provision of the gridded rainfall data together with the standard errors is useful for subsequent modelling applications, particularly where knowledge of the input error can help reduce the uncertainty associated with modeling outcomes.

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## **Chapter Three**

## 3. An error estimation method for precipitation and temperature projections for future climates

Precipitation and temperature projections from Global Climate Models (GCMs) are generally the basis for assessing the impact of climate change on water resources. The reliability of such assessments, however, is questionable, since GCM projections are subject to uncertainties arising from inaccuracies in the models, greenhouse gas emission scenarios, and initial conditions (or ensemble runs) used. The method to quantify uncertainties of observed rainfall data discussed in chapter 2 is extended here to estimate the spatio-temporal uncertainties involved in future GCM future projections. The content of this chapter is reproduced, with permission and minor changes, from a paper that is published in Journal of Geophysical Research: Atmospheres, below.

Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2012), An error estimation method for precipitation and temperature projections for future climates, *Journal of Geophysical Research: Atmospheres*, 117 (D22), D22104.

#### 3.1. Introduction

Global climate change is anticipated to have enormous impacts on our water resources. Although it is hard to make exact predictions of these impacts, a majority of studies suggests intensification of the global hydrologic cycle and occurrence of more-frequent and greater-magnitude extremes, such as floods and droughts [*IPCC*, 2007; *Kundzewicz et al.*, 2008; *Milly et al.*, 2002]. Recent increases in abnormal floods and droughts around the world seem to have only strengthened such findings. As a result, study of climate change impacts on water resources is at the forefront of scientific research today (see *Cleugh et al.* [2011], *Fowler et al.* [2007], *IPCC* [2007], *Obeysekera et al.* [2011], *Piao et al.* [2010], *Sahoo et al.* [2011], *Sivakumar* [2011], and *Towler et al.* [2010] for some recent accounts).

Towards assessing the impacts of climate change on water resources, the following steps are typically adopted: (1) projection of future climate data (e.g. precipitation, temperature) using Global Climate Models (GCMs); (2) downscaling of coarse-scale GCM outputs to fine-scale data appropriate for hydrology and water resources studies; and (3) estimation of river flow and groundwater levels using hydrologic models. Although this procedure is considered reasonable, there are also important questions about its reliability because of the various uncertainties involved in GCM projections, downscaling methods, and hydrologic models [*Sivakumar*, 2011; *Xu*, 1999]. The present study focuses on the quantification of uncertainties associated with outputs from GCMs.

Uncertainties in GCM outputs arise due to many factors, including uncertainty in the representation of the climate system in models, uncertainty in greenhouse gas emissions (GGE) scenarios, and the internal variability of the climate system itself. *Yip et al.* [2011] describe these as follows: "Model uncertainty arises because of an incomplete understanding of the physical processes and the limitation of implementation of the understanding. Scenario uncertainty arises because of incomplete information about future emissions. Internal variability is the natural unforced fluctuation of the climate system." Extensive research has already been carried out towards understanding of the overall uncertainties in climate change impact assessment using multiple GCMs/RCMs (Regional Climate Models), GGE scenarios, ensemble runs, downscaling methods, and

hydrologic models [e.g. *Chen et al.*, 2011; *Déqué et al.*, 2007; *Kay et al.*, 2009]. Such assessments give a wide range of values for a given variable of interest (e.g. flow), which can then be used for possible alternative planning and designing needed.

A major limitation of the above approach, however, is that the single or multiple GCM/RCM simulations are assumed to be a good representative of what will happen in the future. This is not a reasonable assumption, given the known/unknown uncertainties in GCM simulations, especially if only a single model and scenario are used. In view of this problem, an important question is if it is possible to explicitly quantify the uncertainty for any GCM output variable in space and time, by making use of estimates of simulations from multiple GCMs? Reliable quantification of these uncertainties indeed allows one to ask more sensible questions, general and specific, such as: (1) Are GCM estimates of precipitation over high altitudes less uncertain compared to those over coasts?; (2) Is the precipitation uncertainty associated with El-Niño events higher than that associated with other large-scale climatic events?; and (3) Where and how should the uncertainty associated with rainfall inputs be taken into account in planning, design, and management of water resources structures? Furthermore, one can also apply such information to investigate the propagation of GCM uncertainty to impact assessment models (e.g. hydrologic models) and to potentially reduce bias in model parameter estimation using methods such as simulation extrapolation [Chowdhury and Sharma, 2007] or Bayesian total error analysis [Kavetski et al., 2006a] that would otherwise occur due to GCM output uncertainty (see Wilby [2005] for details).

Quantification of uncertainties in GCM simulations requires utilization of many ensemble runs for each model and scenario. However, the climate modelling groups around the

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world produce, as of now, at the most only a few ensemble runs for each scenario. Using these limited number of ensemble runs, studies generally quantify the uncertainties in model, scenario, and internal variability in GCM projections and then add up these individual contributions to obtain the total uncertainty [*Déqué et al.*, 2007; *Hawkins and Sutton*, 2009; *Hodson and Sutton*, 2008; *Yip et al.*, 2011]. An important step in such studies is the use of multiple GCMs/RCMs, GGE scenarios, and ensemble runs as well as the application of the analysis of variance (ANOVA), which is a statistical method to partition variances between and within groups [e.g. *Harris*, 1994]. For instance, *Déqué et al.* [2007] use ten RCMs, two GGE scenarios, three GCMs for boundary forcing, and three ensemble runs to evaluate the uncertainty for mean change of precipitation and temperature, and report that uncertainty due to GCM is greater than other uncertainties, especially for temperature. *Hawkins and Sutton* [2009], fitting polynomial functions to temperature data, show that the relative importance of the above three sources of uncertainty varies in different regions and for different forecast lead times; the results are also shown to be comparable with those from the ANOVA analysis [*Yip et al.*, 2011].

Despite their usefulness, the above studies possess an important limitation, which is that the uncertainties in GCM simulations are quantified for long-term means of climate data, such as precipitation and temperature (here 'long-term' refers to five years or more). Although quantification of uncertainties for long-term mean offers insights on its magnitude, it does not offer any information about the variability of the uncertainty at shorter timescales (e.g. monthly, annual). The main reason behind the analysis for longterm mean is the disagreement of GCM simulations at shorter timescales. In the present study, we attempt to overcome this problem by estimating the uncertainties across space and time. The main purpose of this chapter is to develop an error estimation method that yields approximate quantification of the main sources of uncertainty in future GCM projections in both space and time. To this end, we analyse uncertainties in spatial and temporal patterns of GCM simulations at global and regional scales. We also discuss the issues of independence and choice of GCM(s) with regard to uncertainty estimation. More specifically, we formulate a method that estimates an uncertainty metric, which we call "Square Root Error Variance" (SREV), for future climate projections.

In this study, we estimate uncertainty for GCM precipitation and temperature simulations at a monthly time step across the world for the period 2001–2099. Our focus on precipitation and temperature is based on our specific interest in water resources assessment: precipitation is the most important input for hydrologic models (e.g. rainfallrunoff), whereas temperature forms a key input for estimation of evaporation and evapotranspiration. Nevertheless, our error estimation method is general and can be used for estimation of uncertainty in other GCM output variables (e.g. wind velocity, atmospheric pressure) as well.

The results indicate that, for both precipitation and temperature, uncertainty due to model structure is the largest source of uncertainty. Scenario uncertainly increases, especially for temperature, in future due to divergence of the three emission scenarios analysed. It is also found that ensemble run uncertainty is more important in precipitation simulation than in temperature simulation. Estimation of uncertainty in both space and time sheds lights on the spatial and temporal patterns of uncertainties in GCM outputs. The generality of this error estimation method also allows its use for uncertainty estimation in any other

output from GCMs, providing an effective platform for risk-based assessments of any alternate plans or decisions that may be formulated using GCM simulations.

The rest of this chapter is organized as follows. Section 3.2 describes the GCM datasets, and section 3.3 presents details of the proposed error estimation method. Section 3.4 presents the uncertainty estimation results. A discussion of these results is made in section 3.5, and conclusions are given in section 3.6.

#### **3.2.** Data

Monthly precipitation and temperature outputs from six GCMs of the World Climate Research Programme (WCRP) Coupled Model Inter-comparison Project phase 3 (CMIP3) multi-model datasets are considered for analysis in the present study. The multimodel datasets are downloaded from the Earth System Grid (ESG) website (https://esg.llnl.gov:8443/index.jsp). We use the CMIP3 datasets as an example (as they are already established well) to demonstrate the applicability of the error estimation method; however, the method can be applied to CMIP5 or other datasets as well. The GCMs are selected on the basis of availability of at least three ensemble runs for three Special Report on Emission Scenarios (SRES) emission scenarios (B1, A1B, and A2), so as to allow estimation of all three sources of uncertainty (i.e., model, scenario, and ensemble runs) as well as to be confident of interpretations of results and conclusions.

The above three scenarios (B1, A1B, and A2) are carefully chosen to represent a wide range of emission scenarios, i.e., low, medium, and high forcing effects, respectively, as they are based on different assumptions about population growth, economic development, energy use, and globalisation [*IPCC*, 2007; *Knutti et al.*, 2008]. The scenarios are more

specifically characterized as follows: B1 represents a convergent world with low population growth, rapid changes in economic structures toward a service and information economy, reduction in materials intensity, and the introduction of clean and resource efficient technologies; A1B represents a future world of very rapid economic growth and rapid introduction of new and more efficient technology; A2 represents a very heterogeneous world with economic development primarily regionally oriented and per capita economic growth and technological change more fragmented.

Overall, six GCMs, three scenarios, and three ensemble runs for the period 2001–2099 are considered, resulting in a total of 54 ( $3 \times 3 \times 6$ ) monthly time series. Table 3.1 presents some basic information about the groups that have developed these GCMs and the spatial resolutions of these models. Figure 3.1 shows an example of the projections of global mean precipitation (left) and temperature (right) for the three scenarios (B1, A1B, and A2) with a single ensemble run; the mean values are obtained by smoothing values over five years using lowess smoother. The figure reveals that the projections for both precipitation and temperature corresponding to the three scenarios diverge in the future (especially after 2040). Global mean and standard deviation of precipitation and temperature for the six GCMs during two different time periods (i.e., 2011-2030 and 2071–2090) are given in Table 3.2. The mean precipitation increases during 2071–2090 in comparison to 2011–2030 for all the scenarios considered (B1, A1B, and A2); however, B1 scenario shows larger standard deviation than A1B and A2 scenarios. Similarly, mean temperature also shows an increase during 2071–2090 in comparison to 2011–2030 under A1B and A2 scenario. Further, A2 scenario, which is the most extreme scenario considered, gives the largest temperature increase during 2071–2090.


Figure 3.1: Global mean precipitation and temperature smoothed over five years using lowess smoother. The light colors show precipitation and temperature for six GCMs and three SRES scenarios (B1, A1B, and A2). The bold colors show mean of precipitation and temperature for six GCMs for each scenario. A single ensemble run (run 1) is shown for each SRES scenario.

Table 3.1: List of GCMs and their atmospheric horizontal resolutions [*IPCC*, 2007]. The horizontal resolutions are expressed in triangular spectral truncation as well as degrees of latitude/longitude.

GCM	Modeling Group(s), Country	Atmospheric horizontal resolution	
PCM (Parallel Climate Model)	National Center for Atmospheric Research (NCAR), USA	T42 (~ 2.8°×2.8°)	
CCSM3 (the Community Climate System Model, version 3)	National Center for Atmospheric Research (NCAR), USA	T85 (~1.4°×1.4°)	
MIROC3.2 (medres) (a Model for Interdisciplinary Research On Climate, version 3.2)	Centre for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Centre for Global Change (JAMSTEC), Japan	T42 (~ 2.8°×2.8°)	
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group, Germany/Korea	T30 (~ 3.9°×3.9°)	
ECHAM5/MPI-OM	Max Planck Institute for Meteorology , Germany	T63 (~1.9°×1.9°)	
CGCM3.1 (T47) (Coupled Global Climate Model, version 3.1)	Canadian Centre for Climate Modelling & Analysis, Canada	T47 (~3.75°×3.75°)	

Table 3.2: Global mean (μ) and standard deviation (σ) of precipitation and temperature for six GCMs under B1, A1B, and A2 scenarios for two future time periods (2011–2030 and 2071–2090).

	В	B1		A1B		.2
Year		Statistic				
	μ	σ	μ	σ	μ	σ
	<b>Precipitation</b> (mm/month)					
2011-2030	87	5.7	87	4.5	87	4.5
2071-2090	89	5.2	90	4.6	90	4.7
	Temperature (K)					
2011-2030	288	0.4	288	0.7	288	0.7
2071-2090	288	0.9	289	1.0	290	1.0

## 3.3. Methodology

The proposed method for uncertainty estimation involves four important steps: (1) data interpolation to common grid; (2) data conversion to percentiles; (3) uncertainty estimation; and (4) translation of the estimated uncertainty to time series. The procedure for conversion of data to percentiles and estimation of uncertainty for each quantile is somewhat similar to the quantile regression approach [*Koenker and Bassett*, 1978], which estimates functional relationships of variables at any quantile of a distribution. However, unlike quantile regression, our approach estimates uncertainty of GCMs simulations at any and every percentile. The above four steps are discussed in more detail below.



Figure 3.2: Percentile plots of precipitation (left) and temperature (right) at a point in Southeast Australia (latitude = -32.5°, longitude = 147.5°). Each color shows different GCMs and consists of nine precipitation and temperature values (For three SRES scenario and three ensemble runs). The names of the GCMs are indicated by P (PCM), CC (CCSM3), M (MIROC3.2 (medres)), EG (ECHO-G), EM (ECHAM5/MPI-OM), and CG (CGCM3.1 (T47)).

Step 1 – Data interpolation to a common grid: Precipitation and temperature data gathered from the above six GCMs (at different spatial resolutions) are interpolated to a common grid, i.e. at  $3^{\circ}$  x  $3^{\circ}$  latitude/longitude grid. To achieve this, an inverse distance weight interpolation method using four nearest grid cells is applied, after *Nawaz and Adeloye* [2006].

**Step 2 – Data conversion to percentiles:** The common-gridded data are ranked in ascending order from the beginning to the last time step (which is 1188, corresponding to the number of values in the time series = 99 x 12). Figure 3.2, for instance, shows the percentile plots for precipitation (left) and temperature (right) for all the six GCMs, three scenarios, and three ensemble runs at a grid cell in Southeast Australia (-32.5° latitude

and 147.5° longitude). The figure clearly reveals the variability of precipitation and temperature at different percentiles. However, greater variability across simulations can be seen particularly at small percentiles for temperature than for precipitation.

**Step 3 – Calculation of uncertainty:** Uncertainty in GCM simulations can be assessed by either analysing the consistency between different GCM projections or comparing historical GCM simulations with observed data [*Dessai et al.*, 2005; *Raisanen*, 2007]. The former approach is chosen in this study, as our interest herein is to assess the uncertainty of future climate projections. Standard deviation at a particular percentile is used as a measure of uncertainty, as it calculates variability between equally possible climate projections of multiple GCMs. Here we apply the standard deviation in a novel way, which we call "Square Root Error Variance" (SREV), to estimate model, scenario, and ensemble run uncertainty individually as well as their total. Equations (3.1) to (3.3) are used to calculate the model, scenario, and ensemble run uncertainty at each percentile (*p*), denoted as  $SREV_p^M$ ,  $SREV_p^S$ , and  $SREV_p^E$ , respectively (*M* – model, *S* – scenario, and *E* – ensemble run):

$$SREV_{p}^{M} = \left[ var(M_{p} | S_{p}, E_{p}) \right]_{2}^{1} = \left[ \frac{1}{S(M-1)} \sum_{1}^{S} \sum_{1}^{M} (V_{MSE^{r}} - \overline{V}_{SE^{r}})^{2} \right]^{\frac{1}{2}}$$
(3.1)

$$SREV_{p}^{S} = \left[ var(S_{p} \mid M_{p}, E_{p}) \right]_{2}^{\frac{1}{2}} = \left[ \frac{1}{M(S-1)} \sum_{1}^{M} \sum_{1}^{S} \left( V_{MSE'} - \overline{V}_{M.E'} \right)^{2} \right]^{\frac{1}{2}}$$
(3.2)

$$SREV_{p}^{E} = \left[ var(E_{p} \mid M_{p}, S_{p}) \right]_{2}^{1} = \left[ \frac{1}{MS(E-1)} \sum_{1}^{M} \sum_{1}^{S} \sum_{1}^{E} (V_{MSE} - \overline{V}_{MS.})^{2} \right]^{\frac{1}{2}}$$
(3.3)

where *var* is variance,  $M_p | S_p, E_p$  is precipitation/temperature values for a given scenario and ensemble run at p,  $S_p | M_p, E_p$  is precipitation/temperature values for a given model and ensemble run at p, and  $E_p | M_p, S_p$  is precipitation/temperature values for a given model and scenario at p. For clarity of presentation, the notations of grid cell indexes are excluded. Further, the units for the SREV values are similar to those for precipitation and temperature, as the case may be (i.e. 'mm' for precipitation and degree 'K' for temperature).

As mentioned earlier, M = 6, S = 3, and E = 3 (representing number of GCMs, scenarios, and ensemble runs) are considered in the present study. The parameter  $E^r$  is an ensemble run chosen randomly from 1 to 3 (see Table 3.3) at about the median percentile (i.e. rank = 594 out of 1188); the superscript (r) is to indicate that  $E^r$  is a randomly chosen ensemble run. The table shows such ensemble runs used for calculating model and scenario SREV. For example, for calculating model SREV, ensemble runs 1, 2, 3, 1, 2, and 2 are used. The variability at this percentile among the different GCMs, scenarios, and ensemble runs is shown in Figure 3.3 for precipitation and temperature. At this percentile, the variance of precipitation, based on equations 3.1, 3.2 and 3.3, is equal to 3295, 47, and 4 mm<sup>2</sup> and of temperature is equal to 10, 1, and 0.01 K<sup>2</sup> for model, scenario, and ensemble runs, respectively. The reason behind using only a single combination of ensemble runs for the estimation of model and scenario uncertainty is this: since the variability across ensemble runs is much smaller than the model and scenario SREV, the choice of different combinations of ensemble runs does not really have any effect in the estimated values of the model and scenario SREV.



Figure 3.3: Variability of model, scenario, and ensemble at rank about 50th percentile for precipitation (a, b, and c) and temperature (d, e, and f) at grid cell similar to Figure 3.2. Whiskers show range from minimum to maximum values. Panels a and d show model variability for three scenarios (B1, A1B, and A2) and ensemble run 1; b and e show scenario variability for six models and ensemble run 1; and c and f show ensemble run variability for six GCMs and A2 scenario. The names of GCMs are same as given in Figure 3.2.

The symbol V is a variable representing precipitation/temperature, with  $V_{MSE}$  being the  $E^{th}$  observation for model M and scenario S. The symbols  $\overline{V}_{.SE^{r}}$ ,  $\overline{V}_{M.E^{r}}$ , and  $\overline{V}_{MS.}$  are precipitation/temperature values averaged over models, scenarios, and ensemble runs, respectively, and are given by:

$$\overline{V}_{SE^r} = \frac{1}{M} \sum_{1}^{M} V_{MSE^r}$$
(3.4)

$$\overline{V}_{M.E'} = \frac{1}{S} \sum_{1}^{S} V_{MSE'}$$
(3.5)

$$\overline{V}_{MS.} = \frac{1}{E} \sum_{1}^{E} V_{MSE}$$
(3.6)

Finally, total SREV ( $SREV_p^T$ ) is obtained by taking square root of sum of squares of individual SREV, as follows:

$$SREV_p^T = \left[ \left( SREV_p^M \right)^2 + \left( SREV_p^S \right)^2 + \left( SREV_p^E \right)^2 \right]^{\frac{1}{2}}$$
(3.7)

It is important to note that the SREV metric used in this study is equivalent to the conditional total standard deviation of the variables of interest conditional to specific percentiles and, thus, can be interpreted likewise (here 'standard deviation' (SD) refers to the standard deviation of all data points estimated by mixing data from different models, scenarios, and ensemble runs). Hence, it is indeed a reasonable and useful statistic for inferring uncertainty associated with the GCM outputs. The following short example helps explain how the SREV metric can be interpreted. Let us assume that the precipitation and total SREV for a given GCM output are 100 and 20 mm/month, respectively. With the assumptions that the precipitation data follow a Normal distribution and that the sample standard deviation represents the standard deviation of the population, one can say that the precipitation data may fall in the range 60–140 mm/month (=  $100 \pm 2 \times 20$ ) with a 95% probability.

Table 3.3: Randomly selected ensemble runs (from 1 to 3) used to calculate model and scenario square root error variance (SREV) at about median percentile. The numbers in the parentheses are used for scenario SREV estimation. Model SREV is calculated for each scenario, whereas scenario SREV is calculated for each model, and then mean uncertainty for either case is determined. The symbols used for GCMs are defined as P (PCM), CC (CCSM3), M (MIROC3.2 (medres)), EG (ECHO-G), EM (ECHAM5/MPI-OM), and CG (CGCM3.1 (T47)).

Models	Р	CC	М	EG	EM	CG
Scenarios						
B1	1 (3)	2 (3)	3 (3)	1 (3)	2 (3)	2 (3)
A1B	1 (3)	2 (3)	3 (3)	1 (3)	2 (3)	2 (3)
A2	1 (3)	2 (3)	3 (3)	1 (3)	2 (3)	2 (3)

An important assumption involved in this method of estimating uncertainty is that the non-exceedance probabilities of different GCMs are consistent. This is also closely related to the assumption in the quantile-based bias correction approach of *Li et al.* [2010] that matches GCM simulations with observations at the same percentile. However, unlike the quantile-based bias correction method, in the present study, we estimate SREV of model, scenario, and ensemble runs matching percentiles of GCM projections. We also assume that each of the six GCMs analysed is independent of the others, an assumption usually made in climate studies [*Pirtle et al.*, 2010]. A further assumption in this method is that all GCM projections analysed have equal uncertainty at any percentile, as is made in Equations (3.1) to (3.3).

At this point, it is also relevant to note that the method followed here to calculate the individual sources of uncertainty and the total uncertainty is similar in intent to the one adopted in the ANOVA approach [*Hodson and Sutton*, 2008; *Holtanova et al.*, 2010]. However, there are also notable differences between the two approaches in terms of the assumptions involved, as pointed out as follows. According to the ANOVA approach, variables are averaged across models, scenarios, and ensemble runs in the evaluation of model, scenario, and ensemble run variability. For instance, variables are averaged across scenarios and ensemble runs to obtain values (six values in the present case) for each GCM at a particular percentile, which are then used to calculate model variability. However, instead of averaging out variables across models and scenarios, we select, in our approach, the ensemble runs randomly (from 1 to 3). As a result of this assumption, equation (3.7) does not include the interaction term, which supposedly accounts for different model responses to the same forcing [*Hodson and Sutton*, 2008]. In our case, the interaction term is partially shared between model and scenario uncertainty.

**Step 4 – Translation of uncertainty to time series:** The estimated individual and total SREV conditional on the percentiles of simulations are converted to actual time series. The month and year of GCM simulations at any given percentile are used to obtain SREV value for that particular month and year of the time series. Each of the total, model, scenario and ensemble SREV are translated to time series.

## 3.4. Results

The proposed error estimation method is now applied to the monthly precipitation and temperature data from the six GCMs described above. Here, for the sake of brevity, we present results for only two of these six GCMs: ECHO-G and ECHAM5/MPI-OM. These two GCMs are selected mainly based on information and recommendations available from past studies, especially for Australian conditions: ECHO-G has been shown to have better skills in representing probability density function of precipitation and temperature [*Perkins et al.*, 2007] and ECHAM5/MPI-OM in representing persistence [*Johnson et al.*, 2011], compared to a host of other GCMs analysed. The spatial uncertainties are discussed in section 3.4.1 for two future time spans (2020s, i.e. mean of 2011 to 2030; and 2080s, i.e. mean of 2071 to 2090), whereas temporal uncertainties are discussed in section 3.4.2 for global and selected regional means.

#### 3.4.1. Spatial uncertainty

Figures 3.4 and 3.5 show the square root of error variances (SREV) of precipitation and temperature for ECHO-G and ECHAM5/MPI-OM models, respectively; these results correspond to scenario A2 and ensemble run 1.

For precipitation, the SREV values for 2020s show that the total uncertainty of ECHO-G is larger in mid-latitudes and reduces towards high and low latitudes (Figure 3.4a). This is in accordance with previous studies, which also report considerable uncertainty for precipitation change at mid-latitudes than at high and low latitudes [*IPCC*, 2007; *Miller and Yates*, 2006]. The results also indicate that model uncertainty is the main contributor to the total uncertainty in all regions and is much larger than scenario and ensemble run

uncertainties (see first row and columns 1 to 4 of Figure 3.4a). However, scenario and ensemble run uncertainties are also considerable in mid-latitudes, with scenario uncertainty being generally larger than ensemble run uncertainty. The results for 2080s are similar to those for 2020s, except that a slight increase in uncertainty is estimated in mid-latitudes, especially for scenario uncertainty (see second row and columns 1 to 4 of Figure 3.4a).



Figure 3.4: Maps of square root error variance (SREV) values for total, model, scenario, and ensemble uncertainty for precipitation and temperature for 2020s (2011–2030 mean) and 2080s (2071–2090 mean). The SREV values are shown for model ECHO-G, with A2 scenario and ensemble run 1.

As for temperature, unlike precipitation, uncertainty is large in high and low latitudes, with the maximum values obtained over the Arctic Ocean (see first row and first column of Figure 3.4b), which show large warming in the future due to a decrease in ice cover and thickness [*Raisanen*, 2007]. With regard to contributions of uncertainties, model uncertainty is still the main contributor to the total uncertainty, similar to that observed for precipitation; however, scenario uncertainty is more pronounced for temperature than for precipitation (see first row and columns 2 to 4 of Figure 3.4b). Further, scenario uncertainty increases for 2080s when compared to that for 2020s, which is likely due to the divergence of the three scenarios for 2080s than for 2020s (see second row and columns 1 to 4 of Figure 3.4b).



Figure 3.5: Same as Figure 3.4 but for ECHAM5/MPI-OM.

It is important to note that the total uncertainty does not show any noticeable increase for 2080s compared to 2020s, since model uncertainty, the main contributor, is almost constant. The results of ECHAM5/MPI-OM (Figures 3.5a and 3.5b) are comparable with ECHO-G, except that a decrease is observed for uncertainty in temperature in the Polar regions (see second row and first column of Figure 3.5b). The results are generally consistent with those observed for the other four GCMs as well (not shown).

#### **3.4.2.** Temporal uncertainty

#### **Global mean**

Estimates of global average SREV at monthly time scale are discussed next. Figures 3.6a and 3.6b present the temporal SREV values for precipitation for global five-year moving average for ECHO-G and ECHAM5/MPI-OM, respectively; these results correspond to scenario A2 and ensemble run 1. The results indicate that model uncertainty is the largest contributor to the total uncertainty, consistent with the results obtained for the spatial uncertainty case (section 3.4.1). Further, the SREV values of ECHO-G and ECHAM5/MPI-OM are also comparable, with the only exception being that the model uncertainty for precipitation from ECHAM5/MPI-OM is larger than that from ECHO-G (Figure 3.6b).

For temperature, scenario uncertainty is found to be significantly greater than ensemble run uncertainty, and it clearly shows an increasing trend due to the divergences of the different scenarios in the future (Figures 3.6c and 3.6d). The ensemble run uncertainties estimated here are also comparable with the results obtained by *Hawkins and Sutton* [2009], who report an overall uncertainty (i.e., mean of uncertainty in space and time) of

0.12 K. The scenario uncertainty estimates between the two studies are also generally comparable; however, the model uncertainty is underrepresented in *Hawkins and Sutton* [2009] compared to our results. Since uncertainties vary in different regions depending on precipitation and temperature magnitudes as well as on patterns of precipitation and temperature projections, spatial mean uncertainties of some selected regions are also estimated, as detailed next. The global mean monthly uncertainty estimates for the six GCMs are made available online (*http://hydrology.unsw.edu.au/downloads/data/*).



Figure 3.6: Global mean of total, model, scenario, and ensemble square root error variances for precipitation (top) and temperature (bottom). The first column is for ECHO-G and the second column is for ECHAM5/MPI-OM with A2 scenario, and

ensemble run 1. Five-year moving average using lowess smoother is shown. The vertical axis is in logarithmic scale.

#### **Regional means**

For studying uncertainties in regional means, three regions located at different geographic regions, and also with vastly different climatic conditions, land use characteristics, and socio-economic development are considered: Western Australia (WA), the Amazon (A), and Greenland (GL). The extent of each of these regions and the number of grid cells considered are shown in Table 3.4.

 Table 3.4. Temporal uncertainty analysis for regional means: Regions and their basic details.

Region name	Symbol	Latitude extent	Longitude	Number of cells
			extent	
West Australia	WA	13° S – 34° S	113° E – 131° E	49
Amazon	А	8° S –13° S	$49^\circ \mathrm{W} - 73^\circ \mathrm{W}$	64
Greenland	GL	$68^\circ$ N – $86^\circ$ N	$19^{\circ} \mathrm{W} - 58^{\circ} \mathrm{W}$	98



Figure 3.7: Regional mean of total, model, scenario, and ensemble square root error variances for precipitation (top) and temperature (bottom) with ECHO-G, A2 scenario, and first ensemble run. Five-year moving average using lowess smoother is shown. The vertical axis is in logarithmic scale.



Figure 3.8: Percentage of contribution of model, scenario, and ensemble run SREV to the total SREV for precipitation (left) and temperature (right) for two time spans (2020s and 2080s). EG (ECHO-G) and EM (ECHAM5/MPI-OM) with A2 scenario and first ensemble run are shown. The symbols used for the y-axis label are defined as follows: G (Global), A (the Amazon), WA (West Australia), and GL (Greenland).

Figures 3.7a to 3.7c show the precipitation SREV values for ECHO-G, scenario A2, and ensemble run 1. The results show that model uncertainty is largest in the Amazon (Figure 3.7b) and smallest in Greenland (Figure 3.7c). However, this is not the case for temperature, with the largest model uncertainty observed for Greenland (Figure 3.7f) followed by that for Western Australia (Figure 3.7d) and the Amazon (Figure 3.7e). These observations are even clearer in Figure 3.8, which shows that the relative contributions of model, scenario, and ensemble run uncertainties to the total uncertainty for the above

regions as well as for the global means. The relative contribution of ensemble run uncertainty for global mean is approximately 8% and 5% for precipitation and temperature, respectively. This is a clear indication that ensemble run uncertainty is more important in precipitation estimation than in temperature estimation, an observation also made by *Raisanen* [2001]. Unlike for precipitation, the relative contribution of scenario uncertainty for temperature increases for 2080s when compared to that for 2020s. Similar regional variations in the accuracy of GCMs for different variables have also been reported by *Johnson and Sharma* [2009a], although their study uses a variable convergence score approach for assessment of agreement between/among GCM projections.



Figure 3.9: Ratio of SREV to mean monthly precipitation and temperature for 2020s (top) and mean monthly 2020s precipitation and temperature (bottom) for ECHO-G under A2 scenario and ensemble run 1.

## 3.5. Discussion

Precipitation uncertainty is considerably large in mid-latitudes, which is also in accordance with the generally large magnitude of rainfall occurrence in these regions due to air masses that converge from both northern and southern hemispheres (Figures 3.4 and 3.5). Conversely, precipitation uncertainty is very small in latitudes close to the north and south poles as well as in arid and semi-arid regions that generally receive only a meager amount of rainfall throughout the year, such as Sahara and the Middle East. It is possible; therefore, that large uncertainty in wet regions and small uncertainty in dry regions could simply be an indication of the direct relationship between uncertainty in precipitation and magnitude of precipitation. This can indeed be seen from the percentile plots of GCM simulations presented in Figure 3.2; i.e., the variability between different projections is small at small percentiles, but it increases as the percentile increases.

To further examine the effects of precipitation and temperature magnitude on uncertainty, the SREV ratio is calculated by dividing the SREV values for 2020s by the mean monthly simulated precipitation and temperature (see first row and columns 1 to 2 of Figure 3.9). The results generally reveal that the spatial variability of SREV diminishes when divided by precipitation and temperature. There are a few exceptions to this observation, however, such as some areas in the Pacific Ocean, Atlantic Ocean, and Sahara, which have noticeably larger uncertainty with respect to the magnitude of precipitation; the observation of large uncertainty relative to precipitation magnitude for Sahara is also consistent with that reported by *Johnson and Sharma* [2009a]. For temperature, however,

the spatial pattern of SREV values is not affected when divided by the magnitude of temperature.

The reason behind the small uncertainty for temperature against large uncertainty in precipitation in mid-latitudes could be two-fold. First, the range of (or difference between) maximum and minimum values of temperature is significantly smaller when compared to that of precipitation. Second, there is considerable variability in the minimum temperature values (including below zero ones), unlike precipitation where it is generally zero. The mean SREV estimates of the regional 5-year moving average for Greenland are less variable in time than those for Western Australia and the Amazon for precipitation, whereas the reverse is true for temperature (Figure 3.7). Possible reasons for this are: (1) differences between the numbers of grid cells used for calculating mean SREV for different regions (Table 3.4), since a smoother mean is normally expected when the SREV is calculated for a large area; and (2) differences in the magnitude of precipitation and temperature between these regions. Further analysis is needed to substantiate the extent to which these two possibilities affect the temporal variability of SREV in different regions.

In this study, the evaluation of uncertainty in GCM precipitation and temperature projections is done at regional and global scales at a monthly time scale. Since none of the past studies, to our knowledge, have considered similar spatial and temporal scales for uncertainty estimation of GCM outputs, direct comparisons of the present results with others are not possible. However, some reliable comparisons between the results over a long-term timescale (i.e. five years or more) can be made. For instance, our study indicates that the uncertainty due to model is equal to about 80% and 75% for

precipitation and temperature, respectively. This is clearly in accordance with the studies by Déqué et al. [2007], Hawkins and Sutton [2009], and Yip et al. [2011], which report that the largest source of uncertainty is due to model, especially for projections until 2050. In our study, scenario uncertainty is the second largest followed by ensemble runs for both precipitation and temperature. Although scenario uncertainty slightly increases after 2050, the order of percentage contribution from the three sources stays the same throughout the 21<sup>st</sup> century. However, the studies by Yip et al. [2011] and Hawkins and Sutton [2009] report that the scenario uncertainty becomes greater than model uncertainty for temperature projection after about 2050. Hawkins and Sutton [2011] also report that ensemble runs is the largest uncertainty for precipitation projections until 2030 and model uncertainty dominates thereafter. These differences in the percentage contribution of different sources of uncertainty between our study and other studies could be due to the methods adopted. More specifically, our study ascertains uncertainty by focussing on a specific quantile in contrary to past studies which estimate uncertainty for temporal mean of the variable. As for spatial distribution of uncertainty, our results indicate that precipitation uncertainty is large in mid-latitudes and temperature uncertainty is large in the north and south poles. These results generally agree well with previous findings by Hawkins and Sutton [2011] and Miller and Yates [2006] for precipitation and by Hawkins and Sutton [2009] for temperature.

The large percentage contribution of model uncertainty suggests that climate processes are inadequately represented in the GCMs. This problem is expected, since GCM simulations have systemic deviations from observations that needs to be corrected. Applying statistical bias correction methods, such as Equidistant quantile mapping [*H Li et al.*, 2010] or Nested bias correction [*Johnson and Sharma*, 2012], prior to estimating

SREV values could significantly reduce model uncertainty. However, such uncertainty reduction is due neither to an advancement of our understanding of the climate processes nor to an improvement of the implementation of this understanding, but it is simply through post-processing of the statistical properties of GCM simulations to match with observations. We will investigate the extent of SREV reduction through bias correction in a future study.

Another important assumption in the proposed error estimation method for assessment of uncertainty in future climate projections is that the GCMs are independent. However, this assumption is imprecise, since the models (and modelling groups) share theoretical concepts, data information, literature, and even codes [Pirtle et al., 2010]. Justification for the independence of GCMs is a challenging topic in climate studies, and there have indeed been some efforts so far [Abramowitz and Gupta, 2008; Masson and Knutti, 2011; Pennell and Reichler, 2010; Power et al., 2011]. These studies evaluate independence mainly based on whether different GCM simulations differ from multi-model mean (or observations) significantly or not. However, as reported by Pirtle et al. [2010], this does not necessarily prove independence, as models could still share similar biases. Nonetheless, it is common to assume that GCMs are independent in climate studies [Pirtle et al., 2010], and thus the independence assumption for the six models is used in our study. It is relevant to note that the findings of Masson and Knutti [2011] and Pennell and Reichler [2010], albeit their limitations, are also in favor of this assumption, as each of the six GCMs analysed is less dependent on the other GCMs in their studies. Further, both these studies assess independence for the 20<sup>th</sup> century climate, but it is diffcult to guarantee whether the same is true for future projections [*Power et al.*, 2011].

To examine the effects of choice and independence of GCM on uncertainity estimation, a preliminary sensitivity analysis is carried out here. To this end, the SREV values are compared for four different combinations of GCMs, as follows: (1) Group-1 – comprises the six GCMs analysed in this study; (2) Group-2 – comprises 22 GCMs, each having at least a single ensemble run for the A1B scenario; (3) Group-3 – comprises 14 GCMs that are supposed to be independent according to *Pennell and Reichler* [2010]; and (4) Group-4 – comprises 14 GCMs, each having at least a single ensemble run for the A1B, and A2 scenarios.



Figure 3.10: Sensitivity of SREV for different combinations of GCMs for each grid cell along latitude averaged over all longitudes for precipitation (a) and temperature
(b). Group 1 – comprises all the six GCMs analysed in this study; Group 2 –

comprises 22 GCMs, each having at least a single ensemble run for the A1B scenario; Group 3 – comprises 14 GCMs that are presumed to be less dependent on each other, according to Pennell and Reichler[2010]; and Group 4 – comprises 14 GCMs, each having at least a single ensemble run for B1, A1B, and A2 scenarios. Model SREV sensitivity is shown for the four groups; however, scenario SREV sensitivity computation is possible only for Group 1 and Group 4.

Figure 3.10a presents the estimated SREV results for precipitation simulations, for each grid cell along latitude averaged over all longitudes. The four groups generally show similar patterns; however, some differences are also seen at the peak values close to the equator for the case of uncertainty in terms of model. The GCMs in Group-3, which are considered to be independent, result in larger SREV peak when compared to that in Group-4, although both groups use equal number of GCMs (i.e. 14). This could be due to the interdependence of some of the GCMs in Group-4, which results in an underestimation of SREV. The six GCMs in Group-1 also underestimate the peak SREV compared to Group-2 and Group-3.

The SREV results for the temperature simulations are presented in Figure 3.10b. Group-2 gives higher SREV than all other groups, especially at low and high latitudes. Group-3 and Group-4 have similar SREV in all latitudes, which is an indication that SREV is less sensitive to the independent GCMs categorized in Group-3. There is also no noticeable sensitivity of scenario SREV to model choice, regardless of whether the data is precipitation or temperature. These observations leads to an interpretation that the interdependence of GCMs could affect the estimation of SREV and, therefore, further investigation is required to obtain a good sub-set of independent GCMs for SREV

estimation. However, at this stage, evaluation of the interdependence of GCMs is premature, due to lack of a solid assessment framework as well as detailed information about internal structure of GCMs. Study of this is an interesting topic, especially for climate researchers, if detailed information about the models is made publicly available.

In this study, all the six GCMs analysed are assumed to have equal uncertainty at a particular percentile (Step 3 of the error estimation method). Several studies have suggested that the skill of the GCMs varies in reproducing the 20<sup>th</sup> century climate [e.g. *Johnson et al.*, 2011; *Perkins et al.*, 2007]. To address this issue, *Hawkins and Sutton* [2009] used multiplicative weights to account for varying accuracy of GCMs in their estimation of uncertainity for future projections. Introducing weights to account for accuracy of GCMs is meaningful only if the past accuracy of GCMs would be repeated for future projections as well. However, this is not the case, as reported, for instance, by *Power et al.*[2011] and *Jun et al.* [2008], where they discussed weak relationship between the accuracy of current and future GCMs simulations. In addition, lack of an accurate GCM skill measurement framework as well as limitation of length of verification data also complicate any attempt at finding reasonable weights [*Irving et al.*, 2011; *Weigel et al.*, 2010]. These issues have essentially led us to assume an equal uncertainity for all GCMs at a particular percentile.

## **3.6.** Conclusions

This study developed a new method for estimation of uncertainty in precipitation and temperature GCM simulations across space and time. The basis for this was six GCMs from CMIP3, selected so as to have at least 3 ensemble runs for the three emission scenarios considered. Monthly precipitation and temperature simulations for the period 2001–2099 from each of these models served as the basis for ascertaining the square root error variance (SREV), a measure equivalent to the standard deviation of the error conditional to the rainfall or temperature simulated. The SREV was calculated empirically, matching percentiles of different GCM simulations with an assumption that non-exceedance probabilities across models were consistent. Three main sources of uncertainty, namely model, scenario, and ensemble run, as well as the associated total uncertainty were evaluated for each of the six GCMs, three GGE scenarios, and three ensemble runs.

The results show that model uncertainty is the largest contributor to the total uncertainty followed by scenario and ensemble run uncertainty for both precipitation and temperature. Unlike uncertainty due to model and ensemble runs (which is almost constant), scenario uncertainty shows a significant increase in the far future due to divergence of the three emission scenarios. This increase is particularly more pronounced for temperature than for precipitation. The results also reveal that the patterns of precipitation and temperature uncertainties in space are different: for precipitation, large uncertainties are estimated in mid-latitudes close to the equator (which receive large amount of rainfall), whereas for temperature, large uncertainty is estimated in high and low latitudes. This suggests that the accuracy of GCMs in space varies on the type of variable analysed. The ensemble uncertainty is more pronounced for precipitation than for temperature globally as well as in certain regions. The estimated SREV values are generally less affected by GCM independence and model choice, although considerable sensitivity is observed at the peak values. Nevertheless, further investigations are required to categorically establish, and possibly confirm, the effects of GCM interdependence in uncertainty estimation.

The proposed error estimation method is an important contribution for improving climate models and climate change impact studies, since it is useful to improve climate models in locations where large uncertainty is revealed. The uncertainties at the monthly time step, together with GCM precipitation and temperature simulations, can also be used to mitigate parameter bias due to input uncertainty in climate change impact studies on water resources. Finally, the generality of the error estimation method allows its use for estimation of uncertainty for any other variable simulated from GCMs.

# **Chapter Four**

# 4. A framework to quantify GCM uncertainties for use in impact assessment studies

An uncertainty metric, square root error variance (SREV), to quantify uncertainties involved in precipitation and temperature projections from GCMs is developed in chapter 3. This chapter provides an application example of the SREV for drought assessment using the standard precipitation index (SPI). For this purpose, a new framework is proposed that involves quantification of GCM precipitation uncertainties as well as consideration of this uncertainty during the estimation of SPI parameters. The content of the chapter is reproduced from a paper submitted to Journal of Hydrology, below.

Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), A framework to quantify GCM uncertainties for use in impact assessment studies, *Journal of Hydrology, Submitted.* 

## 4.1. Introduction

Climate change is anticipated to intensify the global water cycle and affect the livelihood of people, economies and ecosystems [*Beaumont et al.*, 2011; *Hawkins and Sutton*, 2009; *Nicholas*, 2006; *Parmesan and Yohe*, 2003; *Sahoo et al.*, 2011; *Whitehead et al.*, 2009]. General Circulation Models (GCMs), developed in different parts of the world, are commonly used as a basis to study the climate of the future which helps to understand the impacts of climate change and develop strategies to adapt to or possibly mitigate these impacts [*Cleugh et al.*, 2011; *IPCC*, 2007; *Sivakumar*, 2011; *Towler et al.*, 2010].

Although GCMs exhibit the physical processes of the climate system, the outcomes from these models are highly uncertain, due to insufficient representation of the climate system, unknown greenhouse gas emission scenarios and initial conditions, and downscaling methods [*Bennett et al.*, 2012; *Groves et al.*, 2008; *Hawkins and Sutton*, 2009; *Yip et al.*, 2011]. As a result, a reliable projection of future climate and assessment of its impacts on water resources are difficult to make.

Studies report that predictions of hydrologic variables made using ensembles of GCMs have large spread due to uncertainties introduced at different stages. *Buytaert et al.* [2009], using climate projections from 20 GCMs and a hydrologic model, found that the simulated discharges widely diverge among themselves, reflecting the uncertainties in climate change impact assessment on river discharges. Many other researchers have also concluded that reliable predictions of extreme hydrologic variables (such as flood or drought) are difficult due to the uncertainties in climate projections and impact assessment models [*Burke and Brown*, 2008; *Ghosh and Mujumdar*, 2007; 2009; *Salas et al.*, 1980; *Wackernagel*, 1996].

Although accurate prediction of climate change impacts has been impossible so far, there are nevertheless demands, by policy makers, for reliable estimates for undertaking practical measures, such as the design of hydraulic structures and allocation of water for various uses. Therefore, consideration of uncertainties in GCM outputs and impact assessments is very important. Reducing uncertainties, at the minimum, requires improvement of models to enhance the quality of climate simulations (e.g., through regional climate modelling [*Ehret et al.*, 2012; *Wang et al.*, 2004] ) and/or implementation of methods to account for the GCM uncertainties during parameterisation of subsequent

modeling. *Beven and Cloke* [2012] and *Wood et al.* [2012] report that quantification of uncertainties in climate data and hydrologic models as well as development of methods to account for such uncertainties are among the most challenging and pressing issues in hydrology research today.

In view of these, it is necessary to formulate an appropriate framework that is fine-tuned to deal with the following two tasks: (1) quantification of uncertainty; and (2) consideration of this uncertainty in modelling applications. The former seeks to evaluate the amount of uncertainty that exists in climate data, which commonly serve as inputs for impact assessment models. The latter seeks to take into account the estimated uncertainty and make adjustments during the parameter estimation procedure. Although some previous attempts have been undertaken towards these, such have largely considered the two tasks separately, rather than jointly. For instance, Déqué et al. [2007], Hawkins and Sutton [2009; 2011], Hodson and Sutton [2008] and Woldemeskel et al. [2012] quantified uncertainties in GCM projections considering multiple GCMs, scenarios, and ensemble runs. However, they have offered no discussion as to how to apply this uncertainty information in subsequent modelling applications. On the other hand, many frameworks to account for input, model structure, and output uncertainties in the estimation of model parameters have been developed during the past couple of decades [Ajami et al., 2007; Chowdhury and Sharma, 2007; Cook and Stefanski, 1994; Kavetski et al., 2006a; b]. These studies have assumed synthetic uncertainty data or made a crude assumption about the uncertainty of the input and/or output data.

In this study, we address both the aforementioned tasks by developing a sound framework that combines quantification of uncertainty in the climate data and consideration of this

uncertainty during parameter estimation of subsequent models. In doing so, we seek answers to the following specific research questions: How does one quantify uncertainty in climate projections using outputs from an ensemble of GCMs? Does the uncertainty significantly reduce after correction of the biases in GCM outputs? Can one use a single GCM simulation and its associated uncertainty, instead of multiple GCMs without explicitly considering associated uncertainty, as a basis for climate change impact assessment?

To address these, monthly precipitation outputs from six GCMs of the Coupled Model Inter-comparison Project phase 3 (CMIP3) datasets are considered. Global gauge-based gridded rainfall data are used for correction of GCM biases using the nested bias correction (NBC) approach [*Johnson and Sharma*, 2011; 2012; *Rajeshwar Mehrotra and Sharma*, 2012]. Uncertainty estimation for raw as well as bias-corrected data is carried out using an uncertainty metric, the square root of error variance (SREV), recently developed by *Woldemeskel et al.* [2012]. Precipitation outputs from a single GCM and the associated uncertainty are then used to estimate the drought index through a 12-month Standard Precipitation Index (SPI-12). The uncertainties are incorporated in the estimation of SPI using a novel method, called simulation-extrapolation (SIMEX), [*Cook and Stefanski*, [1994], which corrects biases in the model parameters when the standard error (or uncertainty) associated with input data is known. Finally, drought frequencies for 2080s (2070–2090) are analysed and discussed for raw and bias-corrected precipitation data with and without using SIMEX.

The results reveal that model structural uncertainty is the main source of error in GCM outputs and that correction for biases significantly decreases this error. SPI model

parameters as well as the future drought frequency before and after implementation of the method differ widely. The proposed method allows quantifying and accounting for GCM uncertainties in climate change impact assessment more reliably.

The rest of the chapter is organised as follows. Section 4.2 discusses the details of the proposed methodology. Section 4.3 describes the different sources of data used in this study. Application to drought assessment is detailed in section 4.4, followed by the presentation of results in section 4.5. The results are discussed in section 4.6, while the conclusions are drawn in section 4.7.

#### 4.2. Method

Climate data projected using GCMs are uncertain due to errors in the model parameterisation, scenario and initial conditions. Therefore, using GCM outputs as inputs to any impact assessment model introduces biases in parameter estimation and prediction. Accounting for erroneous input data generally involves quantification of the uncertainty and consideration of this uncertainty in subsequent modelling applications. Here, we propose a framework to implement these two steps when impact assessment models are forced by uncertain GCM projections. The proposed method is summarised in Figure 4.1. Initially, the systemic biases in GCM outputs are corrected using a nested bias correction (NBC) approach [*Johnson and Sharma*, 2011; 2012; *Rajeshwar Mehrotra and Sharma*, 2012]. The NBC is selected here for its ability to fix the mean, standard deviation and lag-1 autocorrelation of the GCM outputs at multiple time scales. The remaining uncertainties are dealt with as follows. First, the amount of error in the GCM is quantified using the uncertainty metric, the square root error variance (SREV), developed by *Woldemeskel et al.* [2012]. Then, simulation-extrapolation (SIMEX) is used to specify

parameters of the impact assessment models, utilising the GCM outputs and the associated uncertainty. A brief account of the SREV and SIMEX procedures are given below. More details on SREV can be found in *Woldemeskel et al.* [2012] and on SIMEX in *Cook and Stefanski* [1994] with also an application in hydrology in *Chowdhury and Sharma* [2007]. An example application on how to use the method will be discussed in section 4.4 for drought analysis through the standard precipitation index (SPI).



Figure 4.1: Flow-chart of the framework used to estimate uncertainties of GCM projections and parameters of gamma distribution. Shaded boxes indicate method whereas empty boxes indicate data.

#### 4.2.1. Square root error variance (SREV)

The square root error variance (SREV), which is an empirical error estimation metric, is used to formulate the main uncertainties of GCM projections, namely model, scenario and initial condition uncertainties as well as their total magnitude. In this study, the uncertainties are estimated through the following steps. First, outputs from a host of GCMs for at least three scenarios and three ensemble runs are rearranged in ascending/descending order to convert to their percentiles. Second, standard deviation across models, scenarios and ensemble runs are separately calculated, conditional on their percentile (*p*), as shown in Equations 4.1 to 4.3 that we refer to as model SREV ( $SREV_p^M$ ), scenario SREV ( $SREV_p^S$ ) and ensemble runs SREV ( $SREV_p^E$ ). The total SREV ( $SREV_p^T$ ) is then calculated by taking the square root of the sum of the squares of individual SREV for model, scenario and ensemble runs (Equation 4.4). Finally, the SREV estimates at each percentile are translated to time series.

$$SREV_{p}^{M} = \left[ \operatorname{var}(M_{p} \mid S_{p}, E_{p}) \right]^{\frac{1}{2}} = \left[ \frac{1}{S(M-1)} \sum_{1}^{S} \sum_{1}^{M} \left( V_{MSE^{r}} - \overline{V}_{.SE^{r}} \right)^{2} \right]^{\frac{1}{2}}$$
(4.1)

$$SREV_{p}^{S} = \left[ var(S_{p} \mid M_{p}, E_{p}) \right]_{2}^{1} = \left[ \frac{1}{M(S-1)} \sum_{1}^{M} \sum_{1}^{S} (V_{MSE'} - \overline{V}_{M.E'})^{2} \right]^{\frac{1}{2}}$$
(4.2)

$$SREV_{p}^{E} = \left[ var(E_{p} \mid M_{p}, S_{p}) \right]_{2}^{1} = \left[ \frac{1}{MS(E-1)} \sum_{1}^{M} \sum_{1}^{S} \sum_{1}^{E} (V_{MSE} - \overline{V}_{MS.})^{2} \right]^{\frac{1}{2}}$$
(4.3)

$$SREV_p^T = \left[ \left( SREV_p^M \right)^2 + \left( SREV_p^S \right)^2 + \left( SREV_p^E \right)^2 \right]^{\frac{1}{2}}$$
(4.4)

where *var* is variance,  $M_p | S_p, E_p$  is GCM output for a given scenario and ensemble run at p,  $S_p | M_p, E_p$  is GCM output for a given model and ensemble run at p, and  $E_p | M_p, S_p$  is GCM output for a given model and scenario at p. In this study, M = 6, S =3, and E = 3 (representing number of GCMs, scenarios, and ensemble runs) are considered. The parameter  $E^r$  is an ensemble run chosen randomly from 1 to 3; the superscript (r) is to indicate that  $E^r$  is a randomly chosen ensemble member. The symbol
*V* is a variable representing GCM output, with  $V_{MSE}$  being the  $E^{th}$  simulation for model *M* and scenario *S*. The symbols  $\overline{V}_{.SE'}$ ,  $\overline{V}_{M.E'}$ , and  $\overline{V}_{MS}$  are GCM output values averaged over models, scenarios, and ensemble runs, respectively. Further, the units for the SREV values are similar to those for the GCM outputs.



Figure 4.2: Illustration of simulation-extrapolation (SIMEX) procedure for the shape parameter of a gamma distribution fitted for GCM precipitation data.

### 4.2.2. Simulation-Extrapolation (SIMEX)

Simulation-Extrapolation (SIMEX) is a method to correct bias in model parameters when inputs to the model are measured with uncertainty [*Cook and Stefanski*, 1994]. The method involves two steps – Simulation and Extrapolation – which are demonstrated in Figure 4.2, with a discussion using a gamma distribution parameter for precipitation data, as follows.

### Simulation

Let us assume that a precipitation value from a GCM is used to fit a gamma distribution function that has two parameters: shape and scale. The parameters will be biased if they are estimated using conventional methods that give no consideration to the uncertainties in the precipitation data. However, SIMEX helps to correct the biases in the parameters as follows.

- i. A parameter value is estimated using the original erroneous precipitation ( $P_{original}$ ) and through any conventional optimisation method. Such parameter estimates, called naïve estimate, are biased due to the uncertainties in the precipitation data. The naïve estimate of the shape parameter is shown in Figure 4.2 (top) corresponding to the zero error level ( $\lambda = 0$ ).
- ii. Additional parameters are then estimated for a new set of precipitation ( $P_{new}$ ) obtained by intentionally adding errors sampled from a normal distribution with mean zero and standard deviation  $\sigma$  (i.e.,N (0,  $\sigma$ )) multiplied by an error level ( $\lambda$ ) to the original precipitation data ( $P_{original}$ ), according to.

$$P_{new} = P_{original} + \lambda \times N(0, \sigma)$$
(4.5)

where  $\sigma$  is the total uncertainty (SREV) described in Equation 4.4 and  $\lambda$  is an error level ranging between 0 and 2, according to Cook and Stefanski [1994]. For  $\lambda =$ 0.25, several  $P_{new}$  and parameter values are estimated by randomly replicating the normal distribution  $N(0, \sigma)$  as shown in Figure 4.2 (top). In this study, the analysis is carried out for 50 random replicates. iii. Step 2 is then repeated for other error levels. Overall, we use λ = 0, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2. Note that λ = 0 corresponds to the naïve parameter estimator. The mean of the parameters at each error level (λ) is then calculated to develop a trend between λ and the parameter estimates to be used for the extrapolation step (Figure 4.2 (bottom)).

### Extrapolation

In the extrapolation step, a trend line is fitted between the parameter estimates and the error level ( $\lambda$ ). Linear, quadratic or nonlinear trend lines are suggested by *Cook and Stefanski* [1994] for the extrapolation. Following this, we use quadratic extrapolation, as it better represents our data structure (based on preliminary analysis). The quadratic trend line is finally extrapolated to  $\lambda = -1$  corresponding to an unbiased parameter value called 'SIMEX estimate' (Figure 4.2 (bottom)).

## **4.3.** Data

### 4.3.1. Observed data

Gridded monthly gauge precipitation data for the period 1950–1999 are obtained from the University of Delaware air temperature and precipitation archive provided by NOAA/OAR/ESRL PSD on their website at <u>http://www.esrl.noaa.gov/psd/</u>. The landonly precipitation data at a spatial grid of 1° x 1° latitude/longitude are used to obtain precipitation data at 3° x 3° latitude/longitude grid using simple averaging. The observed gridded data are utilised for correction of GCM biases.

### 4.3.2. GCM data

Precipitation outputs from six GCMs of the World Climate Research Programme (WCRP) Coupled Model Inter-comparison Project phase 3 (CMIP3) multi-model datasets are considered for analysis in the present study. Basic information of the GCMs and the groups that developed them are given in Table 4.1. The GCMs are selected on the basis of availability of at least three ensemble runs for three emission scenarios (B1, A1B, and A2). Overall, six GCMs, three scenarios and three ensemble runs for the period 2001–2099 are used to estimate uncertainties of future precipitation projections. The three scenarios are chosen as they represent a large range of forcing effects, i.e., low, medium, and high, respectively [*IPCC*, 2007; *Knutti et al.*, 2008]. The baseline scenario (20C3M) for the six GCMs for the period 1950–1999 is also considered for correction of GCM biases. The GCMs at different spatial scales are re-gridded to a common 3° x 3° latitude/longitude grid by coinciding with the observed gridded data (see section 4.3.1) using the inverse distance weight interpolation, after *Nawaz and Adeloye* [2006].

Table 4.1: List of GCMs and their atmospheric horizontal resolutions [*IPCC*, 2007]. The horizontal resolutions are expressed in triangular spectral truncation as well as degrees of latitude/longitude.

GCM	Modeling Group(s), Country	Atmospheric horizontal resolution	
PCM (Parallel Climate Model)	National Center for Atmospheric Research (NCAR), USA	T42 (~ 2.8°×2.8°)	
CCSM3 (the Community Climate System Model, version 3)	National Center for Atmospheric Research (NCAR), USA	T85 (~1.4°×1.4°)	
MIROC3.2 (medres) (a Model for Interdisciplinary Research On Climate, version 3.2)	Centre for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Centre for Global Change (JAMSTEC), Japan	T42 (~ 2.8°×2.8°)	
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group, Germany/Korea	T30 (~ 3.9°×3.9°)	
ECHAM5/MPI-OM	Max Planck Institute for Meteorology , Germany	T63 (~1.9°×1.9°)	
CGCM3.1 (T47) (Coupled Global Climate Model, version 3.1)	Canadian Centre for Climate Modelling & Analysis, Canada	T47 (~3.75°×3.75°)	

# 4.4. Application to drought analysis

A number of drought monitoring indices have been developed in the literature, e.g., Palmer drought severity index (PDSI) [*Palmer*, 1965]; Standard precipitation index (SPI) [*McKee et al.*, 1993]; Crop moisture index (CMI) [*Palmer*, 1968]. Standard precipitation index (SPI) is a meteorological drought index used to determine dry or wet events from precipitation records alone. The SPI is estimated by first aggregating monthly precipitation dataset into a moving 3-, 6-, 12-, 18- or 24-month total precipitation, depending on the timescale of interest. Each of these datasets is then fitted to a gamma probability distribution, as.

$$f(x;\alpha,\beta) = \frac{1}{\beta^{\alpha}} \frac{1}{\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}$$
(4.6)

where x > 0 is the precipitation amount,  $\alpha, \beta > 0$  are the shape and scale parameters, respectively, and  $\Gamma(\alpha)$  is the gamma function given by.

$$\Gamma(\alpha) = \int_{0}^{\infty} y^{\alpha - 1} e^{-y} dy$$
(4.7)

The property of the gamma distribution indicates that the product of the shape and scale parameters gives the precipitation mean. Once an appropriate estimate for the shape and scale parameters is obtained, the probability of a given precipitation event gives an indication of the extent of dryness or wetness of that particular precipitation event relative to the average precipitation. Generally, lower probabilities indicate dryness whereas higher probabilities are associated with the occurrence of wet events. As precipitation varies highly in space, the magnitude of precipitation that produces dry or wet events at different location also varies significantly. This makes it difficult to compare droughts in different regions. The SPI, however, estimates drought index consistent in different regions by calculating the score value (i.e., the number of standard deviations from the mean) of a hypothetical standard normal distribution for the same gamma distribution probability of a given precipitation. The score value of the standard normal distribution gives the SPI estimate for that particular location and timescale. Table 4.2 presents the drought categories based on SPI estimate, as suggested by *McKee et al.* [2006].

SPI value	Drought Category		
0 to -0.99	Mild drought		
-1 to -1.49	Moderate drought		
-1.5 to -1.99	Severe drought		
≤-2.0	Extreme drought		

Table 4.2: Drought categories based on SPI value, as suggested by McKee et al. [2006].

Conventionally, the shape and scale parameters are estimated using least squares method or other optimisation techniques without due consideration to precipitation uncertainties. This approach produces unbiased parameters only if the precipitation data are accurate. However, since accurate precipitation records are seldom available, the parameters estimated using this procedure are biased, leading to an uncertain SPI value. For instance, the GCM precipitation outputs used, in this study, to estimate future droughts across the world are highly uncertain and, therefore, produce biased SPI estimate if the uncertainties are not given due consideration during fitting of gamma distribution parameters. To deal with such a problem, we use a framework, discussed in section 4.2, that accounts for the uncertainties of precipitation data during parameter estimation. The method involves estimation of the uncertainties involved in the GCM precipitation data (using SREV) and application of the SIMEX method for parameter estimation of the gamma distribution. We estimate the shape parameter using the SIMEX procedure with the scale parameter being determined from the relationship between the two (i.e., the scale parameter is calculated by dividing the mean precipitation and the shape parameter). This way, the long-term mean precipitation is maintained. We also note that estimation of the shape parameter suing the other way around (i.e., using SIMEX for the scale parameter and the shape parameter being estimated from their relationship) produce worse results than the former and, therefore, we use only the former approach for further analysis. The uncertainty estimation as well as drought assessment is carried out at a monthly timescale across the world for a spatial scale of 3° x 3° latitude/longitude grid, which has important implications for large scale water resources management and planning.

The SPI values are used to determine frequency of severe droughts for 2080s (2070–2090). Severe drought frequency is defined here as the percentage of times in which a severe drought (i.e.,  $-1.99 \le \text{SPI} \le -1.5$ ) occurs within a given time period. The six GCMs, three scenarios and three ensemble runs, discussed in section 4.3.2, are used for the overall analysis. However, for the sake of brevity, main results (i.e., uncertainty values, parameter estimates, and drought frequency analysis) for only a single GCM and scenario (i.e., ECHAM5/MPI-OM with A2 scenario) are discussed below. The ECHAM5 model is selected for its better skills, compared to a host of others, in representing rainfall persistence, especially for Australian conditions [*Johnson et al.*, 2011]. It should be noted that, since the variability across different GCMs in the drought assessment is considered

through the uncertainty estimate, results of the other GCMs are also comparable with those of ECHAM5.

# 4.5. Results

### 4.5.1. GCM precipitation uncertainty

The precipitation outputs from six GCMs and three scenarios are converted to their percentiles to estimate the uncertainties using the square root of error variance (SREV) metric. The results are shown in Figure 4.3 for a grid point in Southeast Australia (= – 32.5 °S latitude and 147.5 °E longitude). In these plots, the precipitation percentiles are plotted against the magnitude for the baseline scenario (20C3M) and three future scenarios (A2, A1B and B1) for a single simulation run. The top plot corresponds to precipitation data before bias correction while the plot at bottom is obtained after using the nested bias correction (NBC) method. The pre-NBC results show that a large variability is observed across different GCMs for a given percentile, while the post-NBC results reveal a significant decrease in variability. Thus the large uncertainties in raw GCM precipitation dataset can be reduced through bias correction. The large variability across different models for raw data and its significant reduction after bias correction is not particular to either the first simulation run or different scenarios, as similar results are also observed for A2 scenario and other simulation runs (Figure 4.4).



Figure 4.3: Percentile plots of baseline and future scenarios for precipitation data before (top) and after (bottom) bias correction. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and post-NBC is for precipitation data after bias correction. 'O' in the legend refers to observed rainfall data.



Figure 4.4: Percentile plots of baseline and A2 scenario for three ensemble runs for precipitation data before and after bias correction. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and –post-NBC is for precipitation data after bias correction.

The square root of error variance (SREV) is first estimated at each percentile and then translated to time series. Figure 4.5 shows the time series of global mean SREV for different sources of uncertainty using raw and bias-corrected precipitation data. The figure reveals that for pre-NBC data, the model uncertainty is the main source of error, which is followed by scenario and ensemble run uncertainties. This is clearly in accordance with the observation made by several other studies, such as *Déqué et al.* [2007], *Hawkins and Sutton* [2009] and *Woldemeskel et al.* [2012]. Some seasonal fluctuation can also be seen in the model uncertainty, as the estimates are generally smaller in the early months and middle of the years than those in other months.

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Figure 4.5: Global mean square root of error variance (SREV (mm/month)) for precipitation before and after bias correction using ECHAM5/MPI-OM. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and post-NBC is for precipitation data after bias correction.

For the bias-corrected data, the model uncertainty significantly reduces in all the timesteps due to the correction of the systematic biases. This is expected, since bias correction increases the agreement of model outputs with observations as well as among the different models [*Ehret et al.*, 2012; *Johnson and Sharma*, 2012; *Watanabe et al.*, 2012]. Following this some reduction is also observed in the scenario and ensemble run uncertainties. As a result of the reduction of individual uncertainties, the total uncertainty also decreases significantly after bias correction.

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Figure 4.6: The shape parameter estimates of gamma distribution for different cases using precipitation outputs of ECHAM5/MPI-OM and A2 scenario. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and post-NBC is for precipitation data after bias correction. Pre-SIMEX is without using SIMEX and post-SIMEX is using SIMEX.

### 4.5.2. Gamma distribution parameters

The shape parameter is estimated with and without SIMEX for both pre- and post-NBC precipitation data to allow comparison of results for all of these four cases (i.e., with and without SIMEX for raw and bias corrected GCM precipitation simulation). The scale parameter for the four cases is obtained through the relationship between the shape and scale parameter with the mean precipitation (i.e., dividing the mean precipitation by the shape parameter). The results of shape parameter for ECHAM5 and A2 scenario for the four cases are shown in Figure 4.6. As seen, the shape parameter is large in some regions, such as Canada, the Amazon, Central Africa, for both pre- and post-SIMEX using pre-

NBC data. Wide differences are observed between the pre- and post-NBC results in many grid locations, such as South America, North and South Africa, Antarctica, the Middle East and Australia. These differences are even more clearly visible in Figures 4.7a and 4.7c, which show the ratio of pre-NBC and post-SIMEX as well as post-NBC and post-SIMEX parameters divided by pre-NBC and pre-SIMEX, respectively. The large difference between Figures 4.7a and 4.7c show the impact of using GCM bias correction on the shape parameter. This indeed is expected, as the statistical properties of the precipitation data are corrected during bias correction, which, in turn, lead to improved parameter estimates than the original data. Another reason could be this: in some locations where precipitation magnitude is very small, negative precipitation values are obtained during bias correction, which are then replaced by zero as negative rainfall is meaningless. To maintain the long-term mean, however, the precipitation series is multiplied by an appropriate factor. Although this seems reasonable, other properties (such as standard deviation) of the time series are modified resulting in large difference in the parameter values in such locations. Comparison of Figure 4.7c with 4.7b, which show the ratio of post-NBC and pre-SIMEX divided by pre-NBC and pre-SIMEX, reveals that the impact of SIMEX is minimal in contrast with NBC. However, Figure 4.7d, which shows the ratio of post- and pre-SIMEX for post-NBC data, indicates that the implementation of SIMEX produces significant increase in the parameter estimates. The scale parameter values or the four cases are shown in Figure 4.8. The parameter is generally large in the midlatitude, where the rainfall is high, and reduces in the high and low latitudes.



Figure 4.7: Ratio of shape parameters of gamma distribution for different cases; a) pre-NBC and post-SIMEX divided by pre-NBC and pre-SIMEX, b) post-NBC and pre-SIMEX divided by pre-NBC and pre-SIMEX, c) post-NBC and post-SIMEX divided by pre-NBC and pre-SIMEX, d) post-NBC and post-SIMEX divided by post-NBC and pre-SIMEX using ECHAM5/MPI-OM. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and Post-NBC is for precipitation data after bias correction. Pre-SIMEX is without using SIMEX and post-SIMEX is using SIMEX.



Figure 4.8: The same as figure 4.6 but for scale parameter. Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and Post-NBC is for precipitation data after bias correction. Pre-SIMEX is without using SIMEX and post-SIMEX is using SIMEX.

### 4.5.3. Drought Frequency

Using the shape and scale parameters obtained above, gamma distribution is fitted at all the grid locations. The distribution is then converted to standard normal distribution using approximate methods to formulate the 12-month standard precipitation index (SPI-12). The drought frequency is finally estimated by calculating the percentage of drought events within a fixed time span. The change in drought frequency of the future (2070-2090) relative to the current (1970-1999) is shown in figure 4.9 for three scenarios (A2, A1B and B1). The figure reveals that drought frequency increases in some parts of the world and decreases in others as a result of global warming. Significant increase is observed over most of the United States, South America, North Africa, and South Asia whereas significant decrease being obtained in Central and Northern Eurasia, Canada and Antarctica. These results are clearly in accordance with previous studies by *Burke et al.* [2006] and *Dai* [2011], which found comparable changes in the future drought using Palmer Drought Severity Index (PDSI). Figure 4.9 further shows that the intensity of change in the drought frequency is different for different emission scenarios with the intensity somewhat decreasing in the following order: A2, A1B and B1. This is as a result of the different assumptions in the forcing effects of the three scenarios as they are based on high, medium and low greenhouse gas emissions, respectively.



Figure 4.9: Change in drought frequency (%) during 2070-2099 relative to 1970-1999 for three future scenarios (A2, A1B and B1). The figure shows results of ensemblemean of six GCMs (table 4.1) for bias corrected data using NBC.

Figure 4.10 shows the frequency of severe droughts for 2080s (i.e., the percentage of time in which a severe drought occurs in any given year during 2070–2090) using ECHAM5/MPI-OM and A2 scenario with and without SIMEX for raw and bias-corrected data. Looking at Figure 4.10a, a large percentage (up to 10 %) of the severe drought frequency is generally observed in dry areas, such as some parts of North America, North Africa, and South Asia. On the other hand, in wet regions, such as Canada and Europe, the frequency of severe droughts is relatively low. The drought frequency estimates using SIMEX (Figure 4.10b and 4.10d) show more or less similar spatial trends as the pre-SIMEX estimates, although the drought frequency is more pronounced in the former case.



Figure 4.10: Severe drought frequency for different cases using ECHAM5/MPI-OM in 2080s (2070–2090). Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and Post-NBC is for precipitation data after bias correction. Pre-SIMEX is without using SIMEX and post-SIMEX is using SIMEX.

Figure 4.11 shows the box-plots of severe and moderate drought frequency for all grid points across the world. Severe drought frequency estimates at the 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> percentiles with and without SIMEX are somewhat similar for both pre- and post-NBC data. However, the post-NBC results differ from the pre-NBC in that the drought frequency values for the former have smaller range between the 25<sup>th</sup> and 75<sup>th</sup> percentiles as compared to the later for both pre- and post-SIMEX. In addition, the post-NBC results

reveal higher severe drought frequency values than the pre-NBC. For the moderate drought, unlike the severe drought, the drought frequencies are much larger. In addition, the post-SIMEX results show smaller drought frequency estimate at the 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> percentiles than the pre-SIMEX results for both pre- and post-NBC.



Figure 4.11: Box-plots of severe ( $-1.99 \le SPI \le -1.5$ ) and moderate ( $-1.49 \le SPI \le -1$ ) drought frequency for grid points across the world using ECHAM5/MPI-OM in 2080s (2070–2090). Pre-NBC is for precipitation data before bias correction using the nested bias correction (NBC) and Post-NBC is for precipitation data after bias correction. Pre-SIMEX is without using SIMEX and post-SIMEX is using SIMEX. The horizontal lines of each box-plot show the 25th, 50th and 75th percentiles, whereas points outside the whiskers are outliers.

## 4.6. Discussion

An important assumption in the proposed method is that the GCMs, developed by different climate modelling groups around the world, are independent of each other. Although this assumption is not just limited to the present study but is common to climate studies, it is nevertheless difficult to justify, since the climate modelling groups generally share theoretical concepts, literatures, and data information [*Pirtle et al.*, 2010]. The implication of this assumption is that, if the models used to formulate the uncertainty are interdependent, then the uncertainty will be underestimated, as the variability across such models will be small.

The different cases considered to estimate the gamma distribution parameters in this study (i.e., with and without using SIMEX for pre- and post-bias corrected data) suggest that the parameter values as well as the drought frequency estimates differ widely. The utility of SIMEX, to obtain unbiased model parameters when uncertain inputs are used, has been favourably reported across different disciplines, such as hydroclimatology [*Chowdhury and Sharma*, 2007], applied statistics [*Guolo and Brazzale*, 2008] and biometrics [*Marschner*, 2006]. To evaluate the performance of the SIMEX for drought estimation, we analysed drought frequency during 1960-1999 is calculated for six GCMs and 20C3M scenario as well as observed rainfall. Then, mean absolute error (MAE) across the world is calculated for severe ( $-1.5 \le SPI < -1.99$ ) and extreme (SPI  $\le -2.0$ ) drought events. The results (summarised in table 4.3) show a consistent reduction in MAE after implementation of the SIMEX procedure, except MIROC3.2 and ECHO-G (severe

drought). Therefore, the use of the SIMEX procedure with the bias- corrected data is the novel aspect of this study and the results are also far more reliable.

Table 4.3: Global mean absolute error (MAE) of severe  $(-1.5 \le \text{SPI} \le -1.99)$  and extreme (SPI  $\le -2.0$ ) drought frequency before (Pre-SIMEX) and after (Post-SIMEX) using SIMEX during 1960 to 1999 for six GCMs and 20C3M scenario. The MAE reduces consistently after implementing the SIMEX.

	Severe drought (%)		Extreme drought (%)	
	Pre-SIMEX	Post-SIMEX	Pre-SIMEX	Post-SIMEX
GCM				
РСМ	4.4	4.3	2.5	2.3
CCSM3	4.5	4.4	2.6	2.4
MIROC3.2	4.3	4.3	2.4	2.4
ECHO-G	4.1	4.2	2.9	2.5
ECHAM5/MPI-OM	4.4	4.3	2.5	2.3
CGCM3.1 (T47)	4.4	4.2	2.5	2.3

The proposed framework emphasises two themes – quantification of uncertainty and consideration of this uncertainty in modelling applications – in dealing with the issue of uncertainty in GCM outputs for impact assessment studies. The framework is applied to study an assessment of droughts across the world only to show its utility for hydrologic studies. It is important to mention that the framework is also applicable for other water resource studies, which use parametric models, as well. One example of such applications is the probabilistic design of reservoir storage by considering the precipitation data as a

stochastic process. Another useful application of the GCM uncertainty estimates is one can use a single GCM simulation with the associated uncertainty for climate change impact assessments instead of using multiple GCMs. This simplifies and reduces the effort and time required to assess climate change impacts using multiple GCMs.

As SIMEX is relatively new to the hydroclimatology discipline, some issues still need further investigation. One of the issues is that the parameter estimation through extrapolation is somewhat sensitive to the type of the function used. In this study, we use a quadratic function, as it is recommended by *Stefanski and Cook* [1993] and also somewhat represents our data structure; however, detailed analysis will help to identify the most plausible extrapolant function suitable for hydrologic studies. Another issue that needs further consideration is the implementation of SIMEX when multivariate parameters are involved. In this study, only two parameters are involved; however, in rainfall-runoff models, and many other environmental models for that matter, where several parameters need to be optimised, the SIMEX needs to be modified to accommodate the optimisation of multivariate parameters.

# 4.7. Conclusions

A new framework is developed in this study to obtain unbiased estimates of model parameters when uncertain GCM outputs are used in impact assessment models. The uncertainty in the raw and bias-corrected GCM data is first estimated using the square root error variance (SREV) metric, considering the variability in the precipitation outputs of six GCMs, three scenarios and three ensemble runs. Then, the GCM data together with the associated uncertainty are used to optimise model parameters with a novel method, called simulation-extrapolation (SIMEX). The method is applied to estimate the shape and scale parameters of gamma distribution, which are then used to estimate the frequency of droughts across the world using the standard precipitation index (SPI).

The results indicate that the uncertainty in precipitation comes mainly from structural uncertainty followed by scenario and initial condition errors. The model uncertainty considerably decreases after bias correction, as the systematic biases are reduced. The shape and scale parameters estimated for raw and bias-corrected data show significant differences in areas where the rainfall is generally low. This is because some negative precipitation values are replaced by zero during bias correction which possibly alters the statistical properties of the data. However, effort is made to maintain the long-term mean value of precipitation at such areas by multiplying with an appropriate factor. Estimates of frequency of severe droughts in 2080s (2070–2090) for the four cases studied (i.e., with and without using SIMEX for raw and bias-corrected data) also differ widely.

As the actual frequency of severe droughts in the future are not known, it is difficult to make an absolute recommendation; however, the results from the SIMEX for the biascorrected data can be considered as more plausible ones, as SIMEX takes into consideration the various uncertainties in GCM precipitation outputs. The framework proposed and implemented in this study provides a new approach to dealing with uncertainties in climate change impact assessment. There is clearly room for improving the framework further. For instance, analysis of GCM interdependence prior to uncertainty quantification and modification of the SIMEX algorithm to accommodate multivariate parameter estimation are just two of the possible areas for improvement. We are currently conducting research in these directions, and will report the details in the future.

# **Chapter Five**

# 5. A new framework for incorporating GCM uncertainty for reservoir storage estimation for future (warmer) climates

Having shown an application example of the SREV for drought assessment in chapter 4, this chapter provides an additional example for reservoir storage assessment. Whether or not water availability and reservoir storage requirement is affected as a result of climate change is a question of great interest to water managers and policy makers. Among other factors, uncertainties in GCM projections make accurate assessment of climate change impacts on reservoir storage estimation extremely complicated. This chapter investigates the influence of GCM uncertainty on the estimation of reservoir storage. The content of the chapter is reproduced from a submitted paper to Journal of hydrology, below.

Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2013), A new framework for incorporating GCM uncertainty for reservoir storage estimation for future (warmer) climates, *Journal of Hydrology, submitted*.

# 5.1. Introduction

Population growth and the many associated activities have and continue to necessitate large-scale storage of water to meet our various water demands. Dams and reservoirs are often a suitable means for large-scale water storage, so that water can be supplied to different places and at different times, as needed. A normal practice in the estimation of storage capacity of reservoirs is to use the historical streamflow records as the main input, with an inherent assumption that similar characteristics of streamflow will also occur in the future. This assumption, however, can no longer be reliably justified in the face of global climate change (caused by greenhouse gas emissions) and its effects on hydrology and water resources [*IPCC*, 2007]. According to the Intergovernmental Panel on Climate Change [*IPCC*, 2007], global average surface temperature has increased by 0.74°C during the last century (1906 to 2005) and an increase of up to 4°C (based on high greenhouse gas emission scenario) is also projected for the end of the 21st century. As a result of this change, more-frequent and greater-magnitude extreme hydroclimatic events (e.g. floods, droughts, sea level rises) are also anticipated to occur [*IPCC*, 2007; *Kundzewicz et al.*, 2008; *Milly et al.*, 2002]. These projected changes in surface temperature and extreme hydroclimatic events will likely affect future water availability and demands. This will, in turn, likely influence the future role of reservoirs and their functions in different parts of the world, including need for additional reservoirs, removal of some existing ones, and the reliability of established reservoir operation policies.

Occurrences of more floods, in some areas of the world, bring more sediment to the reservoirs, thereby reducing their storage capacities [*Peizhen et al.*, 2001]. On the other hand, increased drought events, in other areas, induce water stress [*Arnell*, 1999; *Harding*, 2012; *Piao et al.*, 2010]. Further, climate change will also likely alter seasonal streamflow sequences. For example, *Barnett et al.* [2005] estimate that, for the western United States, the peak spring flow in the future will be observed about a month earlier than usual. Reservoir storages, estimated based on historical flows alone, will not be able to accommodate such peak flows that occur earlier than normal [*Barnett et al.*, 2005]. As a result, water shortage will occur during low flows later in the year. A number of other studies have also found that the benefits of reservoirs will likely reduce as a result of climate change [*Ashofteh et al.*, 2013; *Christensen and Lettenmaier*, 2007; *Thomas A.* 

*McMahon et al.*, 2010; *Raje and Mujumdar*, 2010]. These studies have indeed improved our understanding of the impacts of climate change on reservoir storages. However, none of these studies have explicitly considered the uncertainties associated with global climate model (GCM) projections, which commonly serve as the basis for climate change impact assessment. Since uncertainties in GCM projections can play a key role in the assessment of our future water resources, the existing studies cannot be considered to offer reliable assessments on the implications of climate change on reservoir storage requirements. Regarding this an important question is: how is reservoir storage influenced by GCM projection uncertainties? This can be evaluated by first quantifying GCM projection uncertainties and then considering such uncertainties in the estimation of reservoir storage.

A number of studies were carried out to quantify GCM projection uncertainties and their influence in impact assessment models [*Chen et al.*, 2011; *Déqué et al.*, 2007; *Hawkins and Sutton*, 2009; *Kay et al.*, 2009; *Yip et al.*, 2011]. Most recently, *Woldemeskel et al.* [2012] developed an uncertainty metric, square root error variance (SREV), to quantify GCM uncertainties that vary in space and time. It was found that GCM model structure is the main source of uncertainty followed by uncertainties in greenhouse gas emission scenario and internal variability. To consider such uncertainties of GCM in water resources assessment, studies recommend the use of numerous projections from different models, scenarios and ensemble runs in order to precisely reproduce the uncertainty interval [*IPCC*, 2007; *Murphy et al.*, 2004]. Although this seems reasonable, there are challenges with regard to its implementation.

First, researchers commonly make water resources assessment using a single or a multimodel mean of a few model projections, despite the above recommendation that such assessments fail to reproduce the full range of regional changes [*IPCC*, 2007]. The reluctance to consider numerous projections for impact assessment could be due to the extensive computational time and effort needed to analyze large datasets from many GCMs, scenarios and ensemble runs [*Perkins et al.*, 2007]. Second, although one makes water resources assessments based on all the available GCM projections, the numbers of such projections are limited that it is impossible to infer statistically acceptable uncertainty intervals, which require thousands of realizations [*KjellstrÖM et al.*, 2011; *Stainforth et al.*, 2005].

In this chapter, we address both the aforementioned challenges by developing a framework to generate thousands of realizations of each model and scenario projection towards characterization of GCM uncertainties into reservoir storage estimation. By doing so, we provide answers to the key research question presented above; that is, how are reservoir storages influenced by GCM projection uncertainties? The method proposed here involves three important steps. First, GCM uncertainties are quantified in space and time using the square root of error variance (SREV) metric [*Woldemeskel et al.*, 2012]. Second, multiple GCM realizations are generated based on an additive error model for a selected GCM projection. Third, the GCM realizations are used to estimate reservoir storage requirements as well as the associated uncertainty.

The proposed method is applied to quantify uncertainties in rainfall and temperature projections using six GCMs, three scenarios and three ensemble runs for the Warragamba Catchment in New South Wales, Australia. The biases in the GCM projections are corrected first using the Nested Bias Correction (NBC) [*Johnson and Sharma*, 2011; 2012; *Mehrotra and Sharma*, 2012]. Multiple rainfall and temperature realizations are generated then for a selected GCM and scenario. The temperature realizations are used to obtain evaporation realizations, which are then used as input (together with rainfall realizations) to a rainfall-runoff model for estimating streamflow. Finally, these streamflow realizations are used to quantify reservoir storage requirements with the associated uncertainty, using reservoir behavior analysis.

The results suggest that GCM uncertainties will be significantly large for the future period than the current period for both rainfall and temperature. Large uncertainty in the future reservoir storage is also estimated. Comparison of influences of rainfall and evaporation uncertainty suggests that reservoir storage uncertainty is mainly introduced from rainfall than evaporation. Finally, the proposed method provides an effective framework to quantify and incorporate GCM uncertainties in climate change impact assessment on water resources

The rest of the chapter is organized as follows. Section 5.2 discusses the details of the proposed methodology. Section 5.3 describes the study area and different sources of data used in this study. Results are discussed in section 5.4, followed by conclusions in sections 5.5.

# 5.2. Method

The methodology proposed is discussed by grouping into three sections. Section 5.2.1 describes the method to generate rainfall, temperature and evaporation realizations. The

rainfall-runoff model used to simulate streamflows is then presented in section 5.2.2. Finally, the reservoir storage estimation method is given in section 5.2.3.

### 5.2.1. Rainfall, temperature and evaporation realizations

The method to generate rainfall, temperature and evaporation realizations involves the following steps. First, uncertainty in bias-corrected multi-GCM, scenario and ensemble runs is estimated using the square root of error variance (SREV) [*Woldemeskel et al.*, 2012]; the GCM bias correction is carried out using the nested bias correction (NBC) approach [*Johnson and Sharma*, 2012]. A brief account of the SREV metric is given in below, and the reader is referred to *Woldemeskel et al.*[2012] for more details. Second, an error model is developed to generate thousands of rainfall and temperature realizations for a single GCM (referred as 'reference GCM' from now on), as explained below. The temperature realizations are finally used to estimate evaporation realizations.

### Square root error variance (SREV)

The SREV is estimated by aggregating standard deviation of each source of GCM uncertainty (i.e., model, scenario and ensemble run) at every percentile (Equation 5.1).

$$SREV_p^T = \left[ \left( SREV_p^M \right)^2 + \left( SREV_p^S \right)^2 + \left( SREV_p^E \right)^2 \right]^{\frac{1}{2}}$$
(5.1)

Where  $SREV_p^T$ ,  $SREV_p^M$ ,  $SREV_p^S$ , and  $SREV_p^E$  are square root of error variances of total (*T*), model (*M*), scenario (*S*) and ensemble runs (*E*) at each percentile (*p*), respectively. Square root error variance for any of the individual sources of uncertainties (i.e.,  $SREV_p^M$ ,  $SREV_p^S$ , or  $SREV_p^E$ ) are estimated by calculating standard deviation of multi-GCM, scenario and ensemble run projections, at each percentile, conditional on the other two. For example, model SREV ( $SREV_p^M$ ) at each percentile is estimated by calculating standard deviation of many model projections for a given scenario (e.g., A2) and a randomly selected ensemble run (e.g., run1). This is then repeated for other scenarios (e.g., A1B, B1, etc...) and the average of the SREV estimates conditional on all the scenarios is considered as the model uncertainty (i.e.,  $SREV_p^M$ ). Similarly, scenario SREV is estimated by conditioning on models and ensemble runs whereas ensemble runs SREV is calculated by conditioning on models and scenarios. Finally, the SREV at each percentile for any GCM projection is translated to time-series to obtain SREV at each time-step based on the month and year of the GCM projection at that percentile.

### **Error model**

Global climate modeling groups around the world produce, at most, only a few climate projections for each emission scenario, due to computational expensiveness in simulating many realizations. These few climate projections are not enough to infer a statistically acceptable uncertainty interval, which typically needs thousands of realizations. Considering this, an error model, which uses the reference GCM projections and its associated uncertainty, is developed here to generate the GCM realizations. The model is described as follows.

Let us denote the reference GCM projection for a given scenario at any timestep (t) and a certain grid location by v(t); for simplicity here, let us exclude the notation for the grid. The value v(t) is a deterministic estimate of the GCM variable under consideration, which is also uncertain. A Gaussian noise is, therefore, added to v(t) for obtaining thousands of possible realizations of the variable that enables us to incorporate the uncertainty associated with the variable for any subsequent application, as:

$$V(t; \omega) = v(t) + \varepsilon(t; \omega)$$
(5.2)

Where  $V(t; \omega)$  is a GCM variable at time-step (t) with  $\omega$  denoting a particular realization,  $\varepsilon(t; \omega)$  is a noise sampled from Gaussian distribution with mean equal to zero and standard deviation equal to the total SREV value estimated above. *Carpenter and Georgakakos* [2001] used an error model in intent similar to this for streamflow forecasting; however, they used a different approach to estimate the standard deviation of the noise.

Equation 5.2 is used to obtain thousands of rainfall and temperature realizations for the current (1960 to 1999) and future climate (2001 to 2099) periods for the reference GCM. The temperature realizations are then used to obtain evaporation realizations, as described next.

### **Evaporation realizations**

A number of potential evaporation (PE) estimation methods have been proposed in the literature: Penman [*Penman*, 1948], Penman-Monteith [*Monteith*, 1965] and Thornthwaite [*Thornthwaite*, 1948], to mention a few. These methods generally require several climate and aerodynamic data that sometimes may not be directly available. *Oudin et al.* [2005] developed a simplified method, which uses only temperature and extraterrestrial radiation data, to estimate potential evaporation at the daily timestep, given by:

$$PE = \frac{R_e}{\lambda \rho} \frac{T_a + 5}{100}, \text{ if } T_a + 5 > 0$$
(5.3)

PE = 0, Otherwise

where *PE* [mm day<sup>-1</sup>] is the rate of potential evaporation,  $R_e$  [MJ m<sup>-2</sup> day<sup>-1</sup>] is the extraterrestrial radiation,  $\lambda$  [MJ kg<sup>-1</sup>] is the latent heat flux,  $\rho$  [kg m<sup>-3</sup>] is the density of water, and  $T_a$  [°C] is the mean daily air temperature. We use Equation 5.3 to estimate the potential evaporation at the monthly timestep, following the reasonably good results presented by *Kay and Davies* [2008]. It should be mentioned that although both temperature and extraterrestrial radiation are used as an input in Equation 5.3, many realizations are considered only for the case of temperature while a single GCM projection is being employed for radiation. This is because, GCMs simulate extraterrestrial radiation fairly well and so the uncertainty associated with radiation is ignored in the analysis.

#### 5.2.2. Rainfall-Runoff model

The relationship between rainfall and runoff is recognized as highly non-linear, especially during extreme flood events [e.g., *Liu and Brutsaert*, 1978]. Therefore, a nonlinear datadriven rainfall-runoff model, nonlinear autoregressive Exogenous (NARX) model, widely used in system identification, is developed in this study to estimate streamflows. The NARX model has also been well investigated for rainfall-runoff modeling and found to produce reasonable outcomes [e.g., *Ali*, 2009; *Amisigo et al.*, 2008; *Previdi et al.*, 1999]. The model can be written as follows (Equation 5.4):

$$y(t) = f\left(y_{t-1}, y_{t-2}, \dots, y_{t-n_y}, u_t, u_{t-1}, u_{t-2}, \dots, u_{t-n_u+1}, x_t, x_{t-1}, x_{t-2}, \dots, x_{t-n_x+1}\right)$$
(5.4)

where y(t) is the output signal at time t (e.g., streamflow), u(t) and x(t) are exogenous input variables at time t (e.g., rainfall, evaporation) and f is a nonlinear function. We use a wavelet network function for representing the nonlinear function (f) [Billings and Wei, 2005]. The model is calibrated to obtain the values of the input ( $n_u$  and  $n_x$ ) and output ( $n_y$ ) lags to reduce the prediction error. For the Warragamba catchment studied here (see section 3),  $n_y = n_u = n_x = 1$  produce the best outcomes. Therefore, using these parameter values, rainfall and evaporation realizations are used in Equation 5.4 to obtain streamflow realizations. The potential evaporation is multiplied by coefficient of 0.7, somewhat reasonable according to [Richard, 2007], to convert the potential evaporation to actual evaporation of the catchment.

### 5.2.3. Reservoir capacity estimation

Reservoir behavior analysis is carried out at monthly timestep to estimate reservoir storage capacity. Behavior analysis is based on the water balance of input to and output from the reservoir, as given by [*McMahon and Mein*, 1986].

$$S_{t+1} = S_t + Q_t - D_t - a_t \times E_t$$
(5.5)

$$0 \le S_{t+1} \le S_{max}$$

where  $S_t$ ,  $Q_t$ ,  $D_t$ , and  $E_t$  are reservoir storage, streamflow (inflow), demand (or release) and evaporation at time *t*, respectively;  $a_t$  is the top surface area of water in the reservoir at time *t*;  $S_{t+1}$  is reservoir storage at time t + 1; and  $S_{max}$  is the maximum capacity of the reservoir. Streamflow and evaporation realizations are used to estimate storage capacity stochastically by assuming different demand values. To convert evaporation flux to volume, it is assumed that the reservoir has cylindrical shape with the absence of any depth-area-volume relationship for the reservoir (i.e., *a* is considered constant for all timesteps in Equation 5.5). Reservoir storage values, for current and future climates, are estimated and the uncertainties associated with them are evaluated.



Figure 5.1: Location map of the Warragamba catchment in New South Wales (NSW), Australia. The nearest GCM grids to the catchment are shown in c and points 1 and 2 show the centers of these GCM grids.

# 5.3. Study area and data

### 5.3.1. Study area

The study is carried out for the Warragamba catchment, located in New South Wales (NSW), Australia (Figure 5.1). The catchment has an area of 9050 km<sup>2</sup> and receives an average annual rainfall of 840 mm. The Warragamba dam in this catchment is one of the largest water supply dams in the world. The storage reservoir, Lake Burragorang, which has a volume of about 2000 GL and maximum depth of 105 m, provides 80 % of the water supply to Sydney [*Cox et al.*, 2003], the capital of NSW and the largest city in Australia. Figure 5.1c shows the two nearest GCM grids to the Warragamba catchment. Grid-2, which indicates a higher correlation between GCM rainfall and the observed rainfall, is selected for the analysis, after *Carpenter and Georgakakos* [2001].

### 5.3.2. Data

Data from observations, reanalysis and GCM projections are used for this study. Monthly rainfall data observed during 1960–1999 at 45 rain gauges in and around the Warragamba catchment are used to calculate the weighted average rainfall, is used as an observed rainfall estimate for bias correction of GCM rainfall outputs as well as calibration of the rainfall runoff model. Similarly, monthly streamflow, for the same time period, is considered for this study. Monthly average temperature data is obtained from the University of Delaware air temperature and precipitation archive provided by NOAA/OAR/ESRL PSD on their website at <a href="http://www.esrl.noaa.gov/psd/">http://www.esrl.noaa.gov/psd/</a>. Whenever observed data is not available, reanalysis data from the NCEP/NCAR reanalysis project is considered. Thus, reanalysis data for the period 1960 to 1999 are used for extraterrestrial radiation. The observed and reanalysis data are used to correct biases in
GCM as well as to develop the rainfall-runoff model. Climate projections for rainfall, temperature and extraterrestrial radiation for two time periods, current (1960 to 1999) and future (2001 to 2099), are obtained from CMIP3 datasets for six GCMs (see Table 5.1 for details), three scenarios (B1, A1B and A2) and three ensemble runs. The GCM outputs as well as the reanalysis data are interpolated to a common  $3^{\circ}$  x  $3^{\circ}$  latitude/longitude grid. Among the six GCMs, we consider ECHAM5/MPI-OM as the reference GCM, since it has been found to have better skills in representing persistence across Australia [*Johnson et al.*, 2011]. As for the scenarios, we select the three scenarios carefully to represent a wide range of greenhouse gas emissions, i.e., low (B1), medium (A1B) and high (A2) [*IPCC*, 2007].

Table 5.1: List of GCMs and their atmospheric horizontal resolutions [*IPCC*, 2007]. The horizontal resolutions are expressed in triangular spectral truncation as well as degrees of latitude/longitude.

GCM	Atmospheric horizontal resolution
PCM (Parallel Climate Model)	T42 (~ $2.8^{\circ} \times 2.8^{\circ}$ )
CCSM3 (the Community Climate System Model, version 3)	T85 (~1.4°×1.4°)
MIROC3.2 (medres) (a Model for Interdisciplinary Research On Climate, version 3.2)	T42 (~ $2.8^{\circ} \times 2.8^{\circ}$ )
ECHAM5/MPI-OM	T63 (~1.9°×1.9°)
ECHO-G (Coupled climate model ECHAMA4 and ocean model HOPE-G)	T30 (~3.9°×3.9°)
CGCM3.1 (T47) (Coupled Global Climate Model, version 3.1)	T47 (~ 3.75°×3.75°)

## 5.4. Results and Discussion

#### 5.4.1. Rainfall and temperature uncertainty

The uncertainty estimates, in terms of square root error variance (SREV), of current and future rainfall and temperature projections for the reference GCM (ECHAM5/MPI-OM) and A2 scenario are shown in Figure 5.2. For both rainfall and temperature, the uncertainty is larger in the future as compared to the current. This is expected as the model outputs, in general, are more accurate in the current period than the future. However, there is another reason, in addition to this, as follows. For the current period, only a single greenhouse gas emission scenario (i.e., 20C3M) based on observations during the 20<sup>th</sup> century is considered [*IPCC*, 2007], and, as a result, uncertainty due to emissions is not included in the current period. For the future, however, uncertainty due to three different emission scenarios (i.e., B1, A1B and A2) is examined. Therefore, the total uncertainty for the future will, in all likelihood, be significantly larger than that for the current.

The ratio of the overall mean future SREV divided by the current SREV is 1.6 and 10.3 for rainfall and temperature, respectively. This indicates that the relative increase in the future uncertainty in temperature is significantly larger than rainfall. The reason for this could be that temperature is fairly well projected for the current period, while it is highly uncertain for the future period. On the other hand, rainfall is generally poorly simulated in both periods due to its high variability in space and time [*Johnson and Sharma*, 2009a]. Figure 5.2 further shows that there is a particularly increasing trend in SREV after 2060 for temperature while such is not observed for rainfall. This is in accordance with the studies by *Yip et al.* [2011] and *Woldemeskel et al.* [2012], which show that temperature

simulation uncertainty increases for the future period due to divergence of greenhouse gas emission scenarios.



Figure 5.2: Rainfall and temperature square root error variance (SREV) for current and future time periods at the Warragamba Catchment in Australia. The result is for ECHAM5/MPI-OM under A2 scenario and 20C3M for future and current time periods, respectively.

#### 5.4.2. Potential evaporation and streamflow simulations

Thousands of potential evaporation realizations for the current and future are estimated for the reference GCM projection using temperature realizations and radiation data (results not shown). Figure 5.3 illustrates the current and future long-term mean monthly potential evaporation results for the reference GCM (ECHAM5/MPI-OM) and A2 scenario. Overall, potential evaporation is large during summer (December to February) and low during winter (June to August). Figure 5.3 further shows that potential evaporation slightly increases in the future during summer and decreases during winter. Actual evaporation values, estimated by multiplying the potential evaporation by a factor 0.7, are used as inputs to the nonlinear autoregressive exogenous (NARX) rainfall-runoff model. Figure 5.4 shows the observed and simulated streamflow values obtained using this rainfall-runoff model. As seen for the current period, the model estimates streamflow fairly well, except an underestimation of peaks during some months. The rainfall-runoff model is used to simulate thousands of streamflow realizations for the current and future period (results not shown), which are then used to estimate reservoir storage with its associated uncertainty.



Figure 5.3: Long-term monthly mean potential evaporation for current (1960 to 1999) and future (2001 to 2099) periods. The result is for ECHAM5/MPI-OM and A2 scenario.



Figure 5.4: Monthly observed and simulated streamflow using the nonlinear autoregressive exogenous (NARX) model for 1960 to 1999. The simulations reproduce the observed streamflow fairly well.

## 5.4.3. Storage estimation

Reservoir behavior analysis is used to estimate and evaluate storage at the Warragamba dam for four different datasets:

- (i) Observed data;
- (ii) Projections from the reference GCM (ECHAM5/MPI-OM) with the A2 scenario;
- (iii) Thousands of realizations from the reference GCM (ECHAM5/MPI-OM) with the A2 scenario; and
- (iv) Projections from five additional GCMs with the A2 scenario.

The thousands of storage realizations (case-iii above) are used to estimate the 5<sup>th</sup> and 95<sup>th</sup> percent storage uncertainty intervals for the reference GCM. The storages estimated using the other five GCM projections (case-iv) are used to validate the uncertainty interval. Ideally, it is expected that about 90 % of the storage estimates using the five GCMs be within the uncertainty interval.

Figure 5.5 illustrates the current and future storage requirements at different demand levels for the above four cases. For both time periods, i.e. current and future, the storage requirement increases as the demand increases, with a sharp increase when the demand reaches about 300 GL/year. The upper and lower bounds around the reference GCM indicate the 5<sup>th</sup> and 95<sup>th</sup> percent uncertainty intervals. The uncertainty interval for the current period is narrower than that for the future, which reflects that future storage estimation is more uncertain than the current one. For the current period, although storages of some of the five other GCMs fall within the uncertainty range, a number of them are still outside of the interval, even when the demand levels are smaller. However,

for the future, most of the five GCM storage estimates fall within the uncertainty range, except some storage estimates which are outside at larger demand levels (i.e. over 300 GL/year).



Figure 5.5: Estimated storage for current (1960 to 1999) and future (2001 to 2099) periods established using observed data, reference GCM, reference GCM realizations and five other GCMs under A2 scenario for different demand levels. Refer table 5.1 for all the GCMs considered.

In the above analysis, we have focused only on the uncertainties from GCM projections, as they are the main sources of error in the impact of climate change on water resources [*Chen et al.*, 2011; *Déqué et al.*, 2007; *Kay et al.*, 2009]. However, both rainfall-runoff models and reservoir behavior analysis introduce additional uncertainty in the storage estimation. Although we do not aim here to specifically ascertain the uncertainties in the rainfall-runoff model and in the reservoir behavior analysis, a preliminary bias correction using an approach similar to delta change [*Hay et al.*, 2000] is carried out to reduce

storage biases that would be introduced as a result of these two. The correction is carried out as follows. Initially, delta change factors are estimated by calculating the ratio of the future storage divided by the current one, at each demand level. Then, the storages estimated using observed data are then multiplied by these factors to obtain bias-corrected future storage estimates. Figure 5.6 shows the results of the storage bias correction for the future. It is clear that most of the estimates from the additional five GCMs now fall within the uncertainty interval, especially at lower demand levels. Nevertheless, at higher demand level, three of the five GCMs still fall outside of the uncertainty interval.



Figure 5.6: Estimated storage for future (2001 to 2099) periods established using reference GCM, reference GCM realizations and five other GCMs under A2 scenario after correcting rainfall-runoff and reservoir behavior analysis biases using delta change approach. Refer table 5.1 for all the GCMs considered.

With the above uncertainty estimates based on rainfall and evaporation together, it would also be interesting to look at the extent of reservoir storage uncertainty contributed from these two individual sources. Figure 5.7 illustrates these for the current and future time periods. The results indicate that, for both time periods, the storage uncertainty originating from evaporation is significantly smaller than that from rainfall. This is commensurate with other studies that have also found that, in general, GCMs simulate surface temperature (hence evaporation) fairly well when compared to rainfall [*Gleckler et al.*, 2008; *Johnson and Sharma*, 2009a; *Perkins et al.*, 2007].



Figure 5.7: Storage uncertainty originating from rainfall and evaporation for current (1960 to 1999) and future (2001 to 2099) periods for different demand levels. The result is for ECHAM5/MPI-OM and A2 scenario.

In this study, we have analyzed only a single reservoir at the Warragamba catchment. However, it is a common practice to combine multiple reservoirs as a single system in establishing reservoir operation policies. For example, the Sydney water supply headworks system consists of several interconnected reservoirs that draw water from four catchments [*Cui and Kuczera*, 2005]. Our future research will examine the influences of GCM uncertainties in multi-reservoir systems as well as optimization of water systems for future climate considering GCM uncertainties using methods, for example, by *Georgakakos and Marks* [1987].

## 5.5. Conclusions

Global climate model projections are highly uncertain that they, if used as an input for impact assessment studies without due consideration to uncertainties, produce biased outcomes. In this study, we have evaluated the influence of uncertainties in GCM outputs in reservoir storage estimation for the current (1960 to 1999) and future (2001 to 2099) climates, with the Warragamba catchment in Australia as a case study. After estimating the uncertainties in rainfall and temperature projections from six GCMs and three scenarios, thousands of rainfall and temperature realizations are generated for a selected reference GCM (ECHAM5/MPI-OM) and scenario (A2). The temperature realizations are then used to estimate potential evaporation, which together with rainfall, form inputs for simulation of streamflow and reservoir storage.

The results indicate comparatively larger uncertainties in rainfall, temperature and reservoir storage for the future time period than for the current period. Future reservoir storages estimated using the reference GCM (ECHAM5/MPI-OM) and scenario (A2) at different water supply demand levels are generally of the same order of magnitude as the storage estimated using the observed data. However, the 5<sup>th</sup> and 95<sup>th</sup> percent uncertainty interval is significantly large, especially at larger demand levels. Storage estimates using five other GCMs fall reasonably well within the uncertainty interval, especially for the

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future projections, suggesting that the estimated uncertainty bounds capture uncertainties in GCM projections. Results also indicate that storage estimation uncertainty largely originates from rainfall projections from GCMs than evaporation realizations based on temperature. This is mainly due to the greater skill of GCMs in simulating temperature than in simulating rainfall.

In concluding remarks, this study reveals that a significant amount of uncertainty is introduced to the reservoir storage estimation from GCM projection uncertainties. Therefore, it is important to give due consideration of GCM projection uncertainties during water resources assessment. An effective framework to carryout this is proposed herein that quantifies and incorporates GCM projection uncertainties into water reservoir estimation. The method can be simply extended to any other assessment of climate change impacts on water resources

# **Chapter Six**

# 6. Synthesis

## 6.1. Overview

Climate change, caused by greenhouse gas emissions, is anticipated to have significant impacts on our water resources. Accurate estimation of these impacts, however, is extremely challenging, due to the various uncertainties involved both in the projections from GCMs and the assessment of their impacts on water resources. A thorough literature review, in this thesis, revealed that an appropriate framework to quantify the uncertainties associated with GCM projections, which are commonly used as inputs to impact assessment models, is clearly lacking. In particular, a reliable method to quantify GCM projection uncertainties that vary in both space and time, which is crucial for proper assessment of climate change impacts on water resources, is almost non-existent. Since development of an appropriate method to incorporate such uncertainty into impact assessment models is crucial for future water planning and management, two important research questions were identified in the present research:

- i. How can we explicitly quantify the uncertainty of any GCM output variable that varies in space and time?
- ii. How can the uncertainty associated with GCM projections be taken into account in the assessment of the impacts of climate change on hydrologic systems?

These questions were investigated in this thesis, which led to the development of an error estimation method that quantifies spatio-temporal uncertainties in GCM projections. Further, the thesis illustrated various methods to implement the estimated spatio-temporal uncertainties into water resources assessment through case studies in Australia and around the world. The details of the methods and conclusions drawn from the case studies were documented in chapters 2 to 5. In what follows, a brief summary and conclusions from the present research are given. The main limitations and future research avenues in this area will also be highlighted towards the end.

## 6.2. Summary and conclusions

Summary and conclusions of the thesis are grouped below into two sections, according to the content of the thesis. Summary of chapters 2 and 3, which deal with quantification of uncertainties in climate data, is presented in section 6.2.1. Section 6.2.2 provides summary of chapters 4 and 5 that deal with the application of the estimated GCM projection uncertainty for water resources assessment.

#### 6.2.1. Quantifying spatio-temporal uncertainties in climate data

Climate data (such as, rainfall and temperature that have significant importance for water resources assessment) vary significantly in space and time. This variability is particularly significant in rainfall due to the influence of various factors. For instance, in Australia, the El-Nino Southern Oscillation (ENSO), the western Pacific and the Indian Ocean sea surface temperatures (SST), and the Southern Ocean atmospheric variability influence the climate (in general) and rainfall (in particular) by varying degrees [*Taschetto and England*, 2009]. Different techniques are used to measure or simulate rainfall for water resources assessment; however, all the methods have their associated uncertainty that varies in space and time.

Chapter 2 provided a detail study of the spatio-temporal uncertainties associated with observed rainfall based on rain gauge and satellite data, which was extended to GCM projection uncertainty later in the thesis. The chapter illustrated a method to estimate gridded rainfall from gauge measurements at sample locations and proposed an approach to merge gauge and satellite rainfall, in an attempt to reduce errors and enhance the quality of spatial rainfall estimation.

It was generally found that integration of satellite rainfall with rain gauge data improves rainfall estimation, especially in areas with sparse rain gauge network. An important contribution of this study is the development of spatio-temporal standard errors along with retrospective rainfall datasets. This has significance for subsequent modelling applications (e.g. rainfall-runoff modelling), where input knowledge can help reduce the uncertainty associated with modelling outcomes. Although analysis towards this last step has not been carried out in this study, the logic of estimating spatio-temporal error estimation has been extended to quantify uncertainties involved in GCM projections, and then applied for water resources assessment.

Global climate model projections, which are commonly used for climate change impact assessment on water resources, suffer from uncertainties that arise from model structure, scenario and ensemble runs. Although GCMs have large uncertainty, climate modelling groups around the world do not provide the associated uncertainties with the projections, but only provide few simulation runs, for all the models and each emission scenario. Using these few simulation runs, chapter 3 developed a novel uncertainty metric, square root error variance (SREV), that quantifies GCM projection uncertainty for each location and time step. The methodology was implemented to quantify uncertainties associated with rainfall and temperature projections of six GCMs, three scenarios and three ensemble runs.

It was found that GCM model structural error is the largest source of uncertainty followed by scenario and ensemble runs, for both rainfall and temperature. Scenario uncertainty shows a significant increase in the future, unlike model structural and emission scenario, which are almost constant. It was also found that the spatial distribution of uncertainty is different for rainfall and temperature. For rainfall, large uncertainties are obtained in midlatitudes close to the equator, whereas for temperature, large uncertainties are obtained at high and low latitudes close to the equator. Further, uncertainty due to ensemble runs is more pronounced in rainfall projections than that of temperature.

The spatio-temporal uncertainties estimated in chapter 3 provoke a number of research questions. The following two questions were investigated in chapters 4 and 5, which are summarised in section 6.2.2:

- Is it possible to improve parameter estimation of impact assessment models, given knowledge of the uncertainties in the GCM projections?
- How do uncertainties in GCM rainfall and temperature projections affect assessment of reservoir storage requirements?

#### 6.2.2. Incorporating GCM uncertainties into water resources assessment

Chapter 4 provided an assessment of future droughts using standardised precipitation index (SPI), across the world. Emphasis was given to the development of a method that can reduce drought estimation parameter bias, which would otherwise occur due to the GCM uncertainties. To this end, simulation extrapolation (SIMEX), which tries to estimate error free parameters, when input errors are known, was used as a tool to estimate the parameters of the SPI. Further, biases in the raw GCM projection were corrected using the Nested Bias Correction (NBC) approach [*Johnson and Sharma*, 2012]. It was found that the model structural uncertainty of rainfall projections considerably decreases after bias correction, as the systemic biases are reduced. It was also found that future drought frequencies estimated for four cases (i.e., with and without using SIMEX for raw and bias-corrected data) differ widely. Finally, the drought estimates based on SIMEX for the bias-corrected data were recommended as the most plausible one, as the SIMEX and bias correction steps take into consideration the various uncertainties involved in GCM precipitation outputs.

Chapter 5 implemented a method to incorporate GCM rainfall and temperature uncertainties into reservoir storage assessment. To this end, an error model was proposed to generate thousands of rainfall and temperature realizations based on a single GCM projection and its associated uncertainty. Then, the rainfall and temperature realizations were used to estimate uncertainties propagated to reservoir storage estimation using rainfall-runoff model and reservoir behavior analysis. This was implemented for the Warragamba catchment in Australia, for different demand levels. A significant uncertainty in the future reservoir storage requirement was found, especially at larger demand levels. The uncertainty of the storage mainly propagated from the rainfall than temperature, which is reasonable as GCM rainfall projection is highly inaccurate compared to temperature.

## 6.3. Limitation and future work

Assumptions and limitations of the thesis have been discussed in each of the chapters. In this section, the main assumptions and future research directions towards improving them are discussed. One of the assumptions, in the development of the GCM uncertainty in chapter 3, is that the six GCMs considered are independent. These models are selected from the CMIP3 datasets based on a criterion that each model should have at least three ensemble runs for three future emission scenarios, to enable us to estimate the uncertainty associated with the ensemble runs. The criterion, therefore, does not consider whether the selected GCMs are independent or not. Studies, however, suggest that the assumption of independence is imprecise as climate modelling groups share theoretical concepts, data information and even codes [*Pirtle et al.*, 2010]. A preliminary analysis carried out in chapter 3 showed that the interdependence of the six models has minor effect on the outcomes. However, further study about this is necessary towards improving the analysis in this thesis (in particular) as well as towards developing a generic framework that can be used for selection of independent models for any other impact assessment study.

In this thesis, quantification of uncertainty was mainly carried out at a large spatial scale, commensurate with the GCM spatial resolution. This, however, has an important limitation for water resource assessment, which commonly needs evaluation at a much finer scale. To reduce biases that are introduced as a result of this, nested and quantile-based bias correction methods were used in chapter 5. Another alternative, which has not been attempted in this thesis, is to downscale larger-scale GCM outputs to smaller scale appropriate for water resource assessment. The uncertainty quantification method, developed in this thesis, can be easily modified to evaluate uncertainties in the

downscaled GCM output. To this end, dynamic downscaling outcomes using Regional Climate Models (RCMs), which have higher spatial resolutions, can be used to estimate uncertainty in a similar manner to that of the method described in chapter 2. It is necessary to use several RCM outputs in order to incorporate the additional uncertainty that will be introduced as a result of the downscaling method. Some attempts have already been made towards this in the literature [e.g. *Déqué et al.*, 2007; *Rowell*, 2006], although such studies have mainly been carried out for long-term mean, rather than monthly timescale. Statistical downscaling methods, which are less computationally demanding than RCMs, can also be used as an alternative to downscale large-scale GCM projections to local scale. Several statistical downscaling methods should also be considered to account for the uncertainties introduced as a result of downscaling. Reviews of different statistical downscaling methods can be found in, for example, *Wilby and Wigley* [1997] and *XU* [1999].

Further research is also necessary to deal with uncertainties associated with impact assessment models. The main uncertainties in this regard are those due to model structure, parameter estimation as well as input and outputs. Extensive research has already been carried out towards quantification and reduction of these uncertainties [e.g. *Ajami et al.*, 2007; *Beven and Binley*, 1992; *Chen et al.*, 2011; *Jeremiah et al.*, 2012; *Kavetski et al.*, 2006a]. Therefore, it is important to combine the uncertainties of impact assessment models with the GCM uncertainties towards a more comprehensive assessment of climate change impacts on water resources.

In this thesis, monthly rainfall data from different sources (rain gauge, satellite based and GCM output) are used for development of the uncertainty quantification method. Monthly

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rainfall data has a number of applications for short- to medium-term water resources planning and management, particularly for water supply, reservoir operation and environmental flows assessment. However, it has also limitation for some hydrologic applications, such as assessment of extremes and flood events. The uncertainty quantification methods developed in this thesis can easily be applied to quantify uncertainties involved in daily rainfall data as well.

The provision of spatio-temporal GCM uncertainties, in this thesis, provides several research opportunities towards climate change impact assessment on water resources. Two application examples have been demonstrated: assessment of future drought and reservoir storage requirements. The former was carried out using Simulation Extrapolation (SIMEX) approach, whereas an additive error model was developed for the latter. These application examples provide initial attempts to characterise GCM projection uncertainties into water resources assessment; however, further research can also be done towards incorporating GCM uncertainties in the planning, design and management of water resources. To this end, one can carry out future water resources system optimization by incorporating the associated uncertainty using methods, for example, proposed by Georgakakos and Marks [1987] and Carpenter and Georgakakos [2001]. In regards to this, the following research questions (both specific and general) need further investigation: How can one incorporate GCM uncertainty in impact assessment of multi-reservoir systems? Does any planning or decisions that may be formulated based on GCM projections change after incorporating the uncertainties? and Would reservoir operating rules be affected or reservoir benefits reduce because of climate change and associated uncertainty? Further, the analysis in this thesis was carried out using CMIP3 datasets as the CMIP5 datasets were not well established during the study period of this research. As CMIP5 data are readily available now, it is interesting to evaluate and compare the uncertainties with that obtained for CMIP3. These issues and other related ones will be investigated in future.

In closing, rainfall and temperature projections have a significant level of uncertainty that should be given due consideration in the assessment of their impacts on water resources. This thesis developed frameworks to quantify spatio-temporal GCM uncertainties and offered application examples towards incorporating these uncertainties in impact assessment models, thus providing an effective platform for risk-based assessments of any alternate plans or decisions that may be made based on impact assessments.

## Chapter 7

## 7. Appendix

#### **Appendix A: Thin plate smoothing spline**

The Thin Plate Smoothing Spline (TPSS) interpolation is a regression approach to estimate a continuous surface by minimising a certain penalty function [e.g. *Hastie et al.*, 2003]. Depending on the number of predictors used, thin plate smoothing splines is also called bivariate thin plate smoothing splines (two predictors) or trivariate thin plate smoothing splines (three predictors) or, in general, multivariate thin plate smoothing splines. This study uses the trivariate thin plate smoothing splines to interpolate long-term normalised monthly mean rainfall and standard deviation at a 0.05° x 0.05° latitude/longitude grid. The trivariate thin plate smoothing splines model can be written as:

$$\hat{O}_n = f(x_n, y_n, z_n) + \varepsilon_n \quad n = 1, \dots, N$$
(A1)

where *N* is the total number of rain gauges,  $\hat{O}_n$  is the response variable representing either the long-term normalised monthly mean rainfall or its standard deviation,  $x_n$ ,  $y_n$  and  $z_n$ are the predictors corresponding to latitude, longitude and elevation, respectively, and  $\varepsilon_n$ is the random error assumed to be normally distributed with mean zero and standard deviation  $\sigma$ . The TPSS estimates optimum surface *f* by minimising a penalty function (Equation A2) that makes a compromise between calibration and prediction errors (i.e., errors that result when the estimated surface *f* is used to predict the response variable).

$$\frac{1}{N}\sum_{n=1}^{N} \{O_n - f(x_n, y_n, z_n)\}^2 + \lambda J_m(f)$$
(A2)

where *N* is the total number of rain gauges,  $\hat{O}_n$  is observed response variable representing either the long-term normalised monthly mean rainfall or its standard deviation,  $x_n$ ,  $y_n$ and  $z_n$  are predictors corresponding to longitude, latitude and elevation, respectively,  $f(x_n, y_n, z_n)$  is the value of the fitted surface at the  $n^{th}$  rain gauge,  $\lambda$  is the smoothing parameter and  $J_m$  is  $m^{th}$  order roughness penalty function. In this study, m = 2 is used and the roughness penalty function  $(J_2)$  is given by [*Wahba*, 1990] :

$$J_{2}(f) = \int \int \int \left( f_{xx}^{2} + f_{yy}^{2} + f_{zz}^{2} + 2 \times [f_{xy}^{2} + f_{xz}^{2} + f_{yz}^{2}] \right) dx dy dz$$
(A3)

The parameter  $\lambda$  (Equation A2) controls the amount of smoothness provided for fitting surface *f*. As  $\lambda$  approaches zero, the interpolated surface passes through all the rain gauge points, whereas as  $\lambda$  approaches infinity, the interpolated surface approaches to least squares plane [*Hastie et al.*, 2003]. Neither of these values of  $\lambda$  is appropriate, because either the prediction error or/and calibration errors will be large. An optimal value of  $\lambda$  is determined by minimising the prediction error through Generalised Cross Validation (GCV) [*Hastie et al.*, 2003].

## Appendix B: Modified inverse distance weight

A modified inverse distance weight (MIDW) method is employed for interpolating the residual of the normalised rainfall. The MIDW, unlike the conventional inverse distance weight that considers weights only for distance, improves the interpolation by also incorporating directional factors, according to the method presented by *Shepard* [1968]. The MIDW method has been extensively used and found to be appropriate for rainfall interpolation [e.g. *Chen et al.*, 2002; *Dirks et al.*, 1998; *Yatagai*, 2008]. A brief account of this interpolation method is presented below, and the reader is directed to *Shepard* [1968] for additional details.

The interpolation method at any grid can be written as:

$$\hat{r} = \frac{\sum_{n=1}^{n=N} w_n r_n}{\sum_{n=1}^{n=N} w_n}$$
(B1)

where  $\hat{r}$  is the interpolated residual at 0.05° x 0.05° latitude/longitude grid,  $r_n$  is the known residual at rain gauge n and  $w_n$  is the interpolation weight, which is calculated by considering inter-gauge horizontal distance and direction.

The interpolation weight  $(w_n)$  is calculated according to:

$$w_n = \begin{bmatrix} \left(\frac{1}{d_n}\right)^k \times (1+t_n) & \text{if } d_n \neq 0\\ \\ \frac{1}{n} & \text{if } d_n = 0 \end{aligned} \tag{B2}$$

$$t_{n} = \frac{\sum_{n^{*}=1}^{n^{*}=N-1} \left(\frac{1}{d_{n^{*}}}\right)^{k} \left(1 - \cos(\alpha_{n^{*}})\right)}{\sum_{n^{*}=1}^{n^{*}=N-1} \left(\frac{1}{d_{n^{*}}}\right)^{k}}$$
(B3)

where k is the power parameter (to be chosen),  $t_n$  is the factor for direction,  $d_{n^*}$  is the distance from nearest neighbours to the point of interest and  $\alpha_{n^*}$  is the inter-gauge angle between nearest rain gauges (nearest neighbours). The difference between n and  $n^*$  is this: n denotes a nearest neighbour where  $t_n$  is to be calculated, whereas  $n^*$  represents other nearest neighbours than denoted by n. For example, if six nearest neighbours are considered (i.e. N = 6), to calculate  $t_n$  for first nearest neighbour (i.e., n = 1), then  $n^*$  will be from 2 to 6 consecutively. The cosine of the angle  $\alpha_{n^*}$  in Equation (B3) is calculated by the inner product as:

$$\cos \alpha_{n^*} = \frac{\left[ (x - x_n)(x - x_{n^*}) + (y - y_n)(y - y_{n^*}) \right]}{d_n d_{n^*}}$$
(B4)

where x and y are the cartesian coordinates of the reference point at which the residual is to be estimated,  $x_n$  and  $y_n$  are the cartesian coordinates of a rain gauge for which the directional factor is to be calculated,  $x_{n^*}$  and  $y_{n^*}$  are the cartesian coordinates of nearest neighbours other than rain gauges denoted by  $x_n$  and  $y_n$ ,  $d_n$  is the distance between the reference point and a rain gauge station for which the directional weight is to be calculated and  $d_{n^*}$  is the distance between the reference point and other nearest neighbours. For instance, if two nearest neighbours to a certain point are in the same direction, then  $\alpha_n = 0^\circ$  and  $t_n = 0$ ; if they are in opposite directions, then  $\alpha_n = 180^\circ$  and  $t_n = 2$ . Note that at  $t_n = 0$ , MIDW is the same as inverse distance weight (IDW) interpolation.

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