Evaluation of Surface Climate Data from the North American Regional Reanalysis for Hydrological Applications in Central Canada

by

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Abstract

A challenge in hydrological studies in the Canadian Prairie region is to find good-quality meteorological data because many basins are located in remote regions where few stations are available, and existing stations typically have short records and often contain a high number of missing data.

The recently released North American Regional Reanalysis (NARR) data set appears to have potential for hydrological studies in data-scarce central Canada. The main objectives of this study are: (1) to evaluate and utilize NARR data for hydrologic modelling and statistical downscaling, (2) to develop methods for estimating missing precipitation data using NARR data, and (3) to investigate and correct NARR precipitation bias in the Canadian Prairie region.

Prior to applying NARR for hydrological modelling, the NARR surface data were evaluated by comparison with observed meteorological data over the Canadian Prairie region. The comparison results indicated that NARR is a suitable alternative to observed surface meteorological data and thus useful for hydrological modelling.

After evaluation of NARR surface climate data, the SLURP model was set up with input data from NARR and calibrated for several watersheds. The results indicated that the hydrological model can be reasonably calibrated using NARR data as input. The relatively good agreement between precipitation from NARR and observed station data suggests that NARR information may be used in the estimation of missing precipitation records at weather stations. Several traditional methods for estimating missing data were compared with three NARR-based estimation methods. The results show that NARR-based methods significantly improved the estimation of precipitation compared to the traditional methods.

The existence of NARR bias is a critical issue that must be addressed prior to the use of the data. Using observed weather station data, a statistical interpolation technique (also known as Optimum Interpolation) was employed to correct gridded NARR precipitation for bias. The results suggest that the method significantly reduces NARR bias over the selected study area.

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Contents

Abstract **i**

Acknowledgements **iii**

Contents **vi**

List of Tables **x**

List of Figures **xv**

1 INTRODUCTION **1**

1.1 Background 1

1.2 Objectives 10

1.3 Structure 10

2 CLIMATE CHANGE IMPACT ASSESSMENT STUDY **12**

2.1 Hydrological Modelling 14

2.1.1 Study areas 14

2.1.2 Hydrological modelling 21

2.1.3 Model calibration 32

2.2 Climate Change Impact Assessment 36

2.2.1 Statistical downscaling 36

2.2.2 Impact assessments using observations 41

3 EVALUATION OF NARR SURFACE CLIMATE 51

3.1 Reanalysis Data 51

3.2 Comparison of NARR and Gridded Observation Data 56

3.2.1 Spatial distribution of NARR precipitation 57

3.2.2 Gridded observation data sets 59

3.2.3 Data comparison 61

3.3 Comparison with Weather Station Data 66

3.3.1 Temperature 68

3.3.2 Precipitation 70

3.3.3 Comparison over the Prairie region 78

4 APPLICATION OF NARR FOR HYDROLOGICAL MODELLING AND CLIMATE CHANGE IMPACT ASSESSMENT 83

4.1 Introduction 83

4.2 Hydrological Modelling using NARR 85

4.2.1 Use of NARR as input to SLURP 85

4.2.2 SLURP calibration using NARR 89

4.3 Climate Change Impact Assessment using NARR 94
4.3.1 Downscaling GCM data using NARR 94
4.3.2 Runoff simulations of future scenarios using NARR 96

5 APPLICATION OF NARR FOR MISSING DATA ESTIMATION 99

5.1 Introduction 99
5.2 Preliminary Investigation 101
5.3 Estimation of Missing Precipitation Data 110
5.3.1 Traditional estimation methods 110
5.3.2 NARR-based methods 111
5.3.3 Comparison of methods 114

6 ASSIMILATION OF OBSERVED AND NARR PRECIPITATION 128

6.1 Introduction 128
6.2 Methodology: Statistical Interpolation 130
6.3 Assimilation of NARR Precipitation 135
6.3.1 Study area 135
6.3.2 Data preparation 137
6.3.3 NARR precipitation assimilation (NPA) model 140
6.3.4 Results of simulation and validation 141

7 CONCLUSIONS 148

Bibliography 154

A DETAILED RESULTS OF NARR EVALUATION 165

B DETAILED RESULTS OF MISSING DATA ESTIMATION 172

C DETAILED RESULTS OF NARR PRECIPITATION ASSIMILATION 177

List of Tables

2.1 Major hydrologic components of Manitoba Hydro's system. 15

2.2 Streamflow gauging stations located at selected large river basins in the Hudson and Nelson Drainage Areas. 18

2.3 Selected hydrometric gauging stations for the study. 19

2.4 Weather stations for SLURP modelling in the study areas. 26

2.5 Statistics of observed and simulated streamflow of the Sturgeon River and Taylor River watersheds for the combined periods of calibration and validation. 33

3.1 Daily temperature statistics of NARR, NNGR, ERA-40 and stations. (RMSE = root mean square error; R = correlation) 67

3.2 Average annual precipitation and daily precipitation RMSE of observations, NARR, NNGR, and ERA-40. 70

3.3 Daily (R_{day}) and monthly (R_{mon}) correlation between observations and NARR, NNGR, and ERA-40. 71

3.4 Comparison of daily temperature and precipitation averages and RMSEs of NARR and ERA-40 with observations. 80

3.5 Correlation comparison of temperature and precipitation from NARR and ERA-40 with observations. 82

4.1 Deviation of volume (D_v) and efficiency (E) of simulated runoff series from different runs. 87

4.2 Results from the SLURP model validation using observed and NARR data for each watershed. 91

4.3 Downscaled annual precipitation and temperature for 20C3M, A2, and B1. Changes from 20C3M are shown in parenthesis. 95

4.4 Mean annual runoff (in m^3/s) simulated by SLURP for 20C3M, A2, and B1. Changes from 20C3M are shown in parenthesis. 97

5.1 Wet-day match rate, total wet-dry-day mismatch rate, and correlations of neighbouring weather stations and NARR grids near Winnipeg, sorted by distances. 103

5.2 Same comparison as in Table 5.1, but with Brandon as the target station. 104

5.3 Same comparison as in Table 5.1, but with Dryden as the target station. 105

5.4 Same comparison as in Table 5.1, but with Thompson as the target station. 106

5.5 Same comparison as in Table 5.1, but with The Pas as the target station. 107

5.6 Statistics of missing data estimation results by two traditional methods using neighbouring observations (station-average (O_{SA}) and inverse distance weighting (O_{IDW})) and four NARR applications (direct inputation of NARR (N_{DI}), IDW of NARR (N_{IDW}), bias-factor using monthly data for NARR (N_{BFmon}), and bias-factor using quantiles for NARR (N_{BFQ})) at Winnipeg. 116

5.7 Precipitation match ratios in five amount ranges of missing data estimation results at Winnipeg. 117

5.8 Statistics of missing data estimation results by six methods at Brandon. 119

5.9 Precipitation match ratios in five amount ranges of missing data estimation results at Brandon. 119

5.10 Statistics of missing data estimation results by six methods at Dryden. 120

5.11 Precipitation match ratios in five amount ranges of missing data estimation results at Dryden. 122

5.12 Statistics of missing data estimation results by six methods at Thompson. 122

5.13 Precipitation match ratios in five amount ranges of missing data estimation results at Thompson. 123

5.14 Statistics of missing data estimation results by six methods at The Pas. 125

5.15 Precipitation match ratios in five amount ranges of missing data estimation results at The Pas. 125

6.1 List of 10 modelling stations and 10 validation stations. 137
6.2 Daily and annual mean precipitation of observation, NARR, NPA and IDW for each station group. The period is 1981-2000. 142
6.3 Observed and estimated daily mean precipitation of modelling and validation stations. 143
6.4 Average daily errors and RMSE of daily precipitation for NARR, NPA and IDW. 144
6.5 Average correlation of daily and monthly precipitation of NARR, NPA and IDW. 147

A.1 Average temperature and precipitation comparison at weather stations in Manitoba. 169
A.2 Average temperature and precipitation comparison at weather stations in north-western Ontario. 169
A.3 Average temperature and precipitation comparison at weather stations in Alberta. 170
A.4 Average temperature and precipitation comparison at weather stations in Saskatchewan. 171

B.1 Wet-dry-day match between neighbouring stations and Winnipeg. . . 172
B.2 Wet-dry-day match between observation and NARR at Winnipeg. . . 173
B.3 Wet-dry-day match between neighbouring stations and Brandon. . . . 173
B.4 Wet-dry-day match between observation and NARR at Brandon. . . . 173

B.5 Wet-dry-day match between neighbouring stations and Dryden. . . . 174

B.6 Wet-dry-day match between observation and NARR at Dryden. . . . 174

B.7 Wet-dry-day match between neighbouring stations and Thompson . . 175

B.8 Wet-dry-day match between observation and NARR at Thompson. . 175

B.9 Wet-dry-day match between neighbouring stations and The Pas. . . . 176

B.10 Wet-dry-day match between observation and NARR at The Pas. . . . 176

C.1 Mean monthly and annual precipitation of observations, NARR, NPA, and IDW for both MSG and VSG. 178

C.2 Correlation of daily and monthly precipitation of NARR, NPA and IDW. 179

C.3 RMSE and daily errors of precipitation for NARR, NPA and IDW. . 180

List of Figures

2.1 Mean monthly streamflow from selected large river basins in the Hudson and Nelson Drainage Areas (see Table 2.1 for station information). 17

2.2 Weather stations and streamflow gauges on study area. 20

2.3 SLURP vertical water balance (*Kite*, 2000). 24

2.4 AVHRR covers for the study area in northern Manitoba. 29

2.5 1971-2000 normals of daily mean temperature (curve) and precipitation (bar) at Red Lake and Thompson stations. 30

2.6 Annual precipitation (P), observed runoff (Q obs), and simulated runoff (Q sim) during the calibration and validation periods. 34

2.7 The observed and simulated daily runoff during the calibration and validation periods for Sturgeon and Taylor. 35

2.8 Projected changes by the 2050s and 2090s in annual mean temperature and precipitation for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods. 42

2.9 Projected changes by the 2090s in mean monthly temperature for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods. 43

2.10 Projected changes by the 2090s in mean monthly precipitation for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods. 44

2.11 Projected changes by the 2050s and 2090s in annual mean simulated runoff for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods. 45

2.12 Projected changes by the 2090s in mean monthly simulated runoff for the Taylor and the Sturgeon River watersheds derived from different downscaling methods. 47

2.13 Projected in mean daily simulated runoff by the 2090s for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods. 48

3.1 Distribution of surface observations assimilated in NARR (January 1988). Source: *Mesinger et al.* (2006). 54

3.2 Annual average NARR precipitation [unit: mm]. 57

3.3 Seasonal average NARR precipitation (Winter = DJF; Spring = MAM; Summer = JJA; Fall = SON) [unit: mm]. 58

3.4 Annual average CANGRID precipitation [unit: mm]. 59

3.5 Annual average ANUSPLIN precipitation [unit: mm]. 60

3.6 Differences between annual precipitation of NARR and CANGRID [unit: mm]. 62

3.7 Differences between annual precipitation of NARR and ANUSPLIN [unit: mm]. 63

3.8 Boxplots of annual and seasonal precipitation discrepancies between NARR and CANGRID and between NARR and ANUSPLIN for the full grid (left figures) and the trimmed grid that excludes the border band (right figures). 64

3.9 Mean monthly temperature from NARR, NNGR, ERA-40 and weather stations. 69

3.10 Scatter plot for NARR, NNGR, and ERA-40 against observation in Churchill (left) and Winnipeg (right) [unit: mm] (see Figure A.1 for other stations). 73

3.11 Q-Q plot for NARR, NNGR, and ERA-40 against observation in Churchill (left) and Winnipeg (right) [unit: mm] (see Figure A.2 for other stations). 74

3.12 Mean monthly precipitation from NARR, NNGR, ERA-40, and weather stations. 75

3.13 Mean Monthly RMSE for NARR, NNGR, and ERA-40. 76

3.14 Selected weather stations in Prairie regions. 79

3.15 Correlation coefficient of observed station and NARR and ERA-40 monthly precipitation. 81

4.1 Mean monthly precipitation and temperature at each watershed. . . . 86

4.2 Mean monthly observed runoff and simulated runoff with different input data sets. 88

4.3 The monthly mean precipitation of observation and NARR for period 1979-2004 in each watershed. 90

4.4 The recorded runoff, simulated daily runoff using NARR and observation, and precipitation of observation and NARR for validation period 2000-2004 in each watershed. 92

4.5 The simulated monthly runoff using NARR and observed runoff for a period 1981-2004 in each watershed. 93

4.6 Mean monthly precipitation and temperature obtained from CGCM and downscaled by NNR for 20C3M, A2, and B1. 96

4.7 Mean daily runoff simulated by SLURP with the downscaled CGCM3 output of control run, A2 and B1 scenarios for 2090s. 98

5.1 The correlation (R) and R_{WW} for each study area. 108

5.2 Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Winnipeg. 115

5.3 Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Brandon. . 118

5.4 Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Dryden. . . 121

5.5 Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Thompson 124

5.6 Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at The Pas. . 126

6.1 Selected weather stations for modelling (purple circles) and validation (yellow triangles). 136

6.2 Monthly precipitation difference of NARR against OBS at 42 stations for 1981-2000. 138

6.3 Fitted variogram. 141

6.4 Scatter plot (left) and Q-Q plot (right) of NARR, NPA, and IDW against observation at the validation station in Steinbach. 145

6.5 Mean daily error and RMSE of NARR, NPA, and IDW for the MSG and VSG data sets. 146

A.1 Q-Q plot for NARR, NNGR, and ERA40 against OBS. 166

A.2 Q-Q plot for NARR, NNGR, and ERA40 against OBS. 167

A.3 Correlation coefficient of observed station and NARR and ERA-40 daily precipitation. 168

C.1 Study area of NARR precipitation assimilation near Winnipeg. 177

C.2 Scatter plot of observations and NPA at 10 validation stations. 181

C.3 Q-Q plot of observations and NPA at 10 validation stations. 181

Chapter 1

INTRODUCTION

1.1 Background

Nine percents of the world's renewable freshwater is being processed in Canada (*Canada*, 2004), and water is one of Canada's greatest resources, used for domestic consumption, irrigation, energy and industrial production, transportation and recreation, and the maintenance of natural ecosystems. However, water is not evenly distributed across the country, and water availability varies both between years and with the changing seasons. Many regions of the country have experienced water-related problems such as droughts and floods, and associated water quality issues, which may be connected to climate change. Climate change has become a critical global issue as is easily seen from the discussion in the public media. An increasing number of initiatives and studies related to climate change issues, for instance the Kyoto Protocol and research activities by the Intergovernmental Panel on Climate

Change (IPCC), shows a growing public concern about the impact of climate change on human life. Understanding the vulnerability of water resources to climate change is vitally important.

To properly manage and protect water resources, it is essential to understand the hydrological processes in the region of interest. Hydrologic models are used to simulate runoff from a watershed by solving the equations that govern the hydrological processes within the watershed. Since hydrologic models are used to simulate the watershed response to a given input, these models are essential tools to assess the climate change impact on water resources. The simulation of hydrological processes using a model involves uncertainties from four sources: (1) errors in the input data such as precipitation and temperature, (2) errors in the recorded streamflow data, (3) errors due to non-optimal parameter values, and (4) errors due to an incomplete or biased model structure. Although the disagreement between simulation and observation is the combined effect of all four error sources, generally, only error source 3 is minimized in the calibration process. However, measurement errors, error sources 1 and 2, put a limit on the achievable agreement. Precipitation is usually the most important input variables required in hydrological modelling, and thus accurate knowledge of precipitation is essential for accurate runoff simulation. *Beven* (2001) noted that the well-established GIGO principle of 'garbage in garbage out' applies to rainfall-runoff modelling because no model will be able to produce accurate hydrograph predictions if the input to the model does not adequately characterize the actual precipitation. Also, the spatial distribution of the precipitation input to hydrological model can substantially influence the volume of storm runoff, peak runoff, and timing of the peak (*Wilson et al.*, 1979).

A common problem in many parts of the Prairie region is the lack of observed weather data. The weather data are required for hydrological modelling and climate change assessment. Ideally, the data must be measured at weather stations within or close to the watershed being modelled, over a long time period without gaps. However, because many watersheds are located in remote and unpopulated regions, there are often few weather stations in the vicinity. *Bárdossy and Das* (2008) investigated the influence of the spatial representation of the precipitation input, interpolated from rain gauge networks of different densities, on the calibration of a hydrological model and found that the overall model performances worsen substantially with an excessive reduction of rain gauges. They also found that the overall performance was not significantly improved by increasing the number of rain gauges above a certain threshold number, especially if stations around but outside the watersheds are considered. Thus, while interpolation is routinely used to deal with the lack of data in a watershed, there is a fair chance of poor spatial representation of the watershed conditions. While northern watersheds, due to their pristine condition, are prime candidates for climate change studies, the lack of climate data often limits their selection as study area. In remote regions such as the northern part of Prairies, climate data are generally interpolated using information from neighboring weather stations, although stations may be located several hundred kilometers from the watershed being modelled. The issue is also critical in statistical downscaling which depends on the quality and the length of the data series used for calibration (*Wilby and Wigley*, 1997). Statistical downscaling methods will be discussed in more detail in Chapter 2.

Over the past decade, there have been some efforts to produce retroactive records of global analyses in support of the needs of the research and climate monitoring communities, and these products, so-called reanalysis data, have become an important and widely utilized resource for the study of atmospheric and oceanic processes and predictability. The objective of reanalysis projects is to produce atmospheric analyses from historical data that can then be used for analyzing the spatial and temporal variability of the climate system (*Kalnay et al.*, 1996; *Gibson et al.*, 1997). Reanalysis products are used increasingly in many fields that require an observational record of the state of either the atmosphere or its underlying land and ocean surfaces. Since reanalysis data are produced using fixed, modern versions of the data assimilation systems developed for numerical weather prediction, they are suitable for use in studies of long-term variability in climate. The National Center for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) Global Reanalysis-1 (*Kalnay et al.*, 1996) and the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (*Gibson et al.*, 1997) are the most well known reanalysis products. There have been some attempts to overcome the lack of data availability by utilizing reanalysis data for macroscale hydrological modelling. A good example is the use of daily precipitation series from the NCEP-NCAR Reanalysis-1 for hydrological modelling over the Mackenzie River basin by *Haberlandt and Kite* (1998).

The NCEP-NCAR Global Reanalysis, henceforth denoted NNGR, is a joint effort of two institutes to produce new atmospheric analyses using historical data, as well as to produce analyses of the current atmospheric state using a state-of-the-art analysis/forecast system. NNGR data are available from 1948 to present. NNGR data are routinely used as predictors in statistical downscaling models (*Kalnay et al.*, 1996; *Kistler et al.*, 2001). NCEP has produced an improved version of the NCEP Reanalysis 1 model, the so-called NCEP-DOE Reanalysis 2, available for the years 1979 to present. More observations were added, assimilation errors were corrected and a better version of the climate model with updated parameterizations of physical processes was used.

It should be noted that the surface precipitation data of the NNGR are produced from an operational weather forecast model (*Haberlandt and Kite*, 1998) and global reanalysis products often contain biases originating from the forecast models (*Berg et al.*, 2003). In addition, global reanalysis products generally do not capture spatial variability at regional scales because of their coarse spatial resolution, typically in the order of 200 km. The quality of the various reanalysis products has been evaluated by many researchers around the world (*Rao et al.*, 2002; *Rusticucci and*

Kousky, 2002; *Tolika et al.*, 2006; *Nieto et al.*, 2004) and they generally conclude that the climate variables from global reanalysis products are reasonably close to the observed data when spatially and temporally averaged. In general, due to their coarse spatial resolutions and biases, global reanalysis products have been used mainly for forcing continental- to global-scale land surface models rather than for regional-scale hydrological modelling.

In parallel with NNGR efforts, ECMWF engaged in its first long reanalysis in collaboration with the University of California (PCMDI, Program for Climate Model Diagnosis and Intercomparison), the Japan Meteorological Agency (JMA), the World Climate Research Programme (WCRP) of the World Meteorological Organisation (WMO), the Centre for Ocean-Land-Atmosphere Studies (COLA), the NCAR and the NCEP. The first generation of reanalysis, the 15-year ECMWF reanalysis (ERA-15), was completed in 1995 and spans the period 1979-1993 when the observation system was relatively homogeneous. Data validations were performed by partners during 1994-1996 (*Gibson et al.*, 1997). Due to improvements in model resolution and in the parameterization of physical processes, the ECMWF model has been updated regularly over the years. Accordingly, the second extended reanalysis project, the ERA-40 (1958-2002), was produced by the ECMWF in 2002. Conventional observations for ERA-40 come from a much wider selection of sources and the period begins with the International Geophysical Year of 1958. The observation system has changed considerably over the reanalysis period with assimilable data provided by a succession of satellite-borne instruments from the 1970s onwards, supplemented by an increasing number of observations from aircraft, ocean-buoys and other surface platforms. Moreover, ERA-40 applied a new 3D-variational analysis method with a new model and made comprehensive use of historical observations and satellite data, most of them provided by NCAR (*Uppala et al.*, 2005).

Recently, NCEP has released a high-resolution reanalysis for the North American domain, the so-called North American Regional Reanalysis (NARR) (*Mesinger et al.*, 2006). NARR is a dynamically consistent, high resolution atmospheric and land surface hydrology data set covering the North American domain at a spatial resolution of 32 km. NARR data are available for the period 1979-present at a 3-hr temporal resolution. The accuracy of the major climate variables such as temperature, wind, and precipitation have been substantially improved compared to previous global reanalysis products (*Mesinger et al.*, 2006; *Nigam and Ruiz-Barradas*, 2006), and *Choi et al.* (2007b) found that the improvement is clear for temperature and precipitation in Manitoba. Primarily because it is a recently released product, NARR has not been widely evaluated or used for various applications. *Ruiz-Barradas and Nigam* (2006) evaluated it for the Great Plains and *Choi et al.* (2007a) explored its potential as input data for hydrological modelling in Manitoba. *Woo and Thorne* (2006b) used NARR temperature and precipitation data for the SLURP hydrological model for a western Canadian basin and obtained reasonable simulation results. Because of its high resolution and advanced data assimilation, it is reasonable to hypothesize that

NARR would be useful in hydrologic modelling, especially in the northern parts of Central Canada, where observed data are often not available. NARR could also be useful in statistical downscaling methods as reference data instead of weather station data.

The present thesis deals with the assessment and application of NARR for hydrologic modelling. The interest in using NARR data grew out of a climate change study funded by Manitoba Hydro and carried out over the years 2006-09 at the University of Manitoba. During the execution of this project, the lack of good climate data for hydrological modelling and statistical downscaling in the areas of interest became obvious. At the last stage of the project, NSERC funding was secured to assess the applicability of NARR in hydrologic studies of climate change. A preliminary evaluation of the NARR data and its application to hydrological modelling was conducted (*Choi et al.*, 2009). Further research, reported in this thesis, has focussed on a more thorough evaluation of NARR in the Prairie region, with particular emphasis on Manitoba, including a comparison of NARR surface variables with observations, other reanalysis products, and gridded interpolated data sets.

A common problem with observed climate records is missing data. This issue is particularly important in precipitation records. Traditional methods for missing data estimation rely on neighbouring stations, which in remote areas may be far away. As NARR data are spatially and temporally continuous, it is of interest to evaluate NARR for filling in the occasionally missing data in precipitation records.

Therefore, a missing data estimation approach using NARR is developed in this thesis and compared with the traditional methods.

It is well known that all climate models have inherent biases. Although the different reanalyses use information about observed precipitation, they do so in an indirect way and it is not uncommon to observe significant differences between observations and surface variables from reanalyses. This seems to be particularly an issue with precipitation. One way to overcome the disagreement between model data and observations is to adjust reanalysis precipitation fields with whatever observations are available in the region of interest. Geostatistical tools are suitable for this exercise. In this thesis, a technique is proposed to fine-tune NARR precipitation fields using observed station data. The technique employs a geostatistical method known as statistical interpolation. The choice of this approach is inspired by its use in the Canadian Precipitation Analysis (CaPA), developed recently at Environment Canada (*Mahfouf et al.*, 2007). CaPA combines short-term forecasts from Environment Canada's numerical weather prediction model GEM with observations from the synoptic network of weather stations to produce spatial estimations of precipitation. CaPA precipitation fields are only available for the last couple of years. For hydrologic modelling and climate change studies much longer records are needed. In our application, NARR essentially replaces GEM output and is used to produce long-term updated precipitation fields for the region of interest.

1.2 Objectives

The overall objective of this thesis is to evaluate the usefulness of NARR for hydrologic modelling and climate change studies in central Canada. Specific objectives of this study are:

- To evaluate the reliability of the NARR temperature and precipitation data against observations in the Prairie region.
- To evaluate the usefulness of NARR surface data for hydrological modelling and statistical downscaling through a comparison with the 'traditional' approach based on interpolated station data.
- To develop NARR-based methods for estimating missing precipitation records, and to compare the methods with traditional techniques for infilling missing data.
- To develop and evaluate a framework for combining NARR precipitation with observations, with the goal to improve the gridded precipitation estimates.

1.3 Structure

This thesis consists of five main chapters (Chapter 2 to Chapter 6). Chapter 2 describes the climate change project funded by Manitoba Hydro which provided motivation for the thesis. The project was conducted by students at the University of Manitoba and was divided into two parts: (1) statistical downscaling of GCM outputs, done by two Master students, *Lee* (2010) and *Koenig* (2008), and (2) runoff simulation of future climate scenarios using hydrological modelling, done by a post-doctorial fellow, *Dr. Woonsup Choi* and the author of this thesis.

In Chapter 3, NARR is introduced and evaluated by comparing temperature and precipitation data with observations. The NARR data are applied to hydrological modelling and statistical downscaling in Chapter 4, in order to investigate the feasibility of NARR for hydrological studies in a particular region of Canada. In Chapter 5, several NARR-based methods are proposed for estimating missing precipitation data. Chapter 6 describes and evaluates the proposed method for combining NARR precipitation with observations using statistical interpolation. Finally, Chapter 7 summarizes and discusses the overall findings of this study, highlighting the particular contributions of the thesis and making suggestions for future research.

Chapter 2

CLIMATE CHANGE IMPACT ASSESSMENT STUDY

Climate, freshwater, biophysical and socio-economic systems are interconnected, and a change in any one of these can induce a change in any other. Many regions are vulnerable to freshwater-related issues and the relationship between climate change and freshwater resources has become a major concern for society. Since the energy generation of a hydropower station is directly dependent on the availability of water, Manitoba Hydro is a notable beneficiary of water resources. Extended low flows or droughts reduce the system output and in extreme cases may make it impossible to supply the required energy demand. Hence, understanding the vulnerability and severity of change in water resource is important in order to quantify the reliability of the energy supply. Due to the need for a better understanding of climate change impacts on water resources in Manitoba, a climate change impact assessment study, funded by Manitoba Hydro in 2005-2009, was conducted by a research group at the University of Manitoba. The project investigated statistical downscaling methods for the assessment of climate change impacts on water resources in central Canada. Hydrological modelling is required to simulate streamflow responses to climate change and involves the selection of an appropriate model, the setup and calibration of the model for the study area, and the simulation of runoff for the control period and for future scenarios. To conduct a hydrological study of climate change, it is necessary to select one or more watersheds that properly represent the hydrologic regime locally and are representative of the greater area of interest. Several watersheds were selected based on Manitoba Hydro's interest in the water supply systems encompassed by the Nelson-Churchill River basins. A number of factors, including period of available climate data, location of weather stations and hydrometric gauging stations, and the availability of required climate variables, were considered in the selection of study areas and the hydrological model.

Because GCMs, the main tool for climate projections, have coarse resolutions, direct use of GCM data is not appropriate for regional-scale impact assessment. Hence, to generate future climate scenarios, statistical downscaling techniques must be applied to downscale the global climate model outputs for hydrological simulations. In the present study, GCM output was downscaled using three different statistical downscaling techniques (SDSM, LARS-WG, and Nearest Neighbour Resampling) and the three methods were compared in the context of hydrological modelling. Then the downscaled GCM data sets were applied as input to the selected hydrological model. The statistical downscaling was done by two Master students (*Koenig*, 2008; *Lee*, 2010).

2.1 Hydrological Modelling

2.1.1 Study areas

Manitoba Hydro's water supply system comprises the Nelson River and the Upper Churchill River drainage basins. At 1.2 million square kilometers, the Nelson River Basin is one of the largest basins on a global scale. The Nelson River drains Lake Winnipeg into Hudson Bay. Lake Winnipeg has several large rivers as contributaries, more specifically the Saskatchewan River, the Red River, and the Winnipeg River. The Upper Churchill River, which is naturally independent from the Nelson River, contributes water into the Nelson River via the diversion at Southern Indian Lake. The Nelson River generating stations provide approximately 80% of the hydropower production of Manitoba Hydro.

As shown in Table 2.1, the Winnipeg River, the Churchill River, and the local flows at the Nelson and Burntwood Rivers are important contributors to Manitoba Hydro's system, with 27.6%, 27.4%, and 11.4% of total flow, respectively. The Winnipeg River Basin drains over 130,000 km^2 in Ontario, Manitoba, and Minnesota. Al-

Table 2.1: Major hydrologic components of Manitoba Hydro's system.

Site	Av. Annual Flow (cfs)	Contribution to the System (%)
Winnipeg River (at Slave Falls)	31,650	27.6
Saskatchewan River (at Grand Rapids)	20,100	17.5
Churchill River (diverted from SIL)	31,390	27.4
Local Flows (at Nelson and Burntwood R.)	13,140	11.4
Known Flows (Red+Assiniboine+Fairford R.)	8,600	7.5
Unknown Flows (Lake Wpg tributaries-water loss)	9,900	8.6

though the Winnipeg River basin covers a relatively small area of Manitoba Hydro's system, the basin receives more annual precipitation compared to western Prairie watersheds and has a much higher runoff coefficient. It provides approximately 30% of the inflow to Manitoba Hydro's system. In contrast, the Saskatchewan River contributes only 17.5% of the inflow to Manitoba Hydro's system, even though the Saskatchewan River is about 2000 km long and has a drainage area of approximately 336,000 km^2. Different climatic zones and terrestrial ecozones cover the Saskatchewan River basin and the runoff in the river may not respond as uniformly to climate variation as the other three basins mentioned above. Therefore, the Winnipeg River, the Churchill River, and the local flows to the Nelson and Burntwood Rivers are the main basins of interest for this study, and the watersheds for assessments were selected within these basins.

Hydroclimatology of Manitoba

To select appropriate study areas, it is necessary to understand the hydroclimatology in the region. For this purpose, six weather stations across Manitoba, located in Churchill, Thompson, The Pas, Dauphin, Brandon, and Winnipeg, were investigated. The climatological characteristics of Manitoba are long and cold winters and mild summers with moderate precipitation. The highest mean monthly temperature is in July, while the minimum is in January. The mean July temperature is below 20°C during the period of 1979 to 2004 at the six stations across Manitoba, and the mean January temperature is below −20°C in Churchill and Thompson. In Thompson and Churchill, the mean April temperature is still below zero while it is above zero in the other cities. The mean annual temperature ranges from −6.6°C in the northern part of the province to −2.8°C in the southern part. Most of the precipitation occurs from late spring through early autumn across the province. The mean annual precipitation at the six stations ranges from 432 to 513 mm.

Figure 2.1 presents the mean monthly streamflow measured at selected gauging stations (see Table 2.2) in the aforementioned five major river basins. Spring snowmelt is one of the most significant hydrological characteristics of the basins. The timing and magnitude of peak flows vary by location. Figure 2.1 shows that there is a latitude gradient in terms of the average peak flow timing. In the Churchill and Nelson River basins, the surges generally start in May and the monthly peaks occur between June and July, while the surges start in April in the Assiniboine and

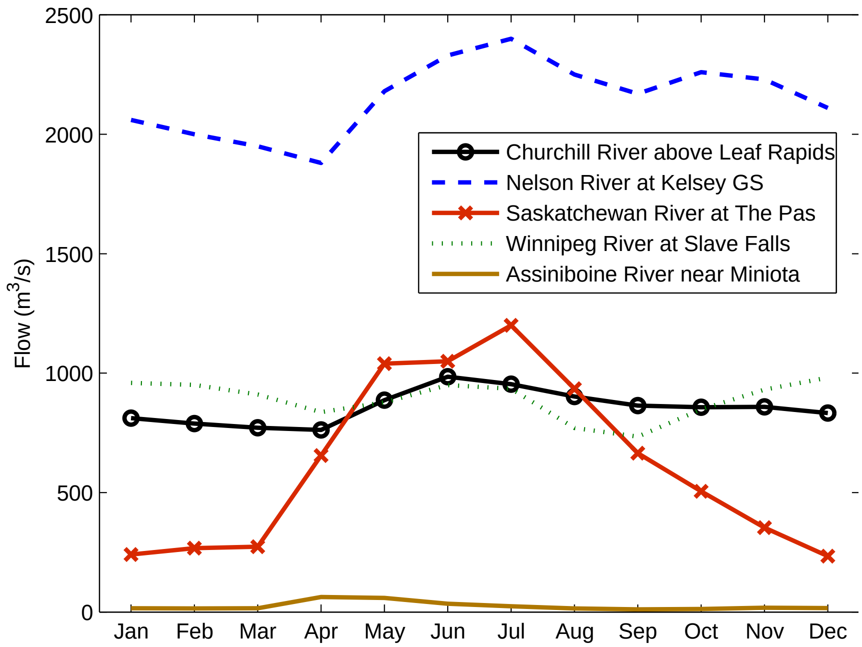

Figure 2.1: Mean monthly streamflow from selected large river basins in the Hudson and Nelson Drainage Areas (see Table 2.1 for station information).

Saskatchewan River basins. The below-zero April temperatures at Thompson and Churchill explain the latitude gradient in the timing of spring peak flow.

Watersheds selection

The watersheds for the climate change study were selected based on the availability of both hydrometric gauging stations and weather stations. The Water Survey of Canada (WSC) provides public access to both real-time and historical hydrometric information, which includes water level and streamflow data, collected at over 1200 locations in Canada. Most of the stations are located in the southern part of the country and it is often difficult to find an adequate network to describe hydrologic characteristics in the northern part of the country. The period of streamflow records

Table 2.2: Streamflow gauging stations located at selected large river basins in the Hudson and Nelson Drainage Areas.

Name	ID	Location	Period	Size (km^2)
Churchill River above Leaf Rapids	06EB004	56°29′37″N, 100°02′55″W	1973-2003	244,000
Nelson River at Kelsey GS	05UE005	56°02′20″N, 96°31′30″W	1960-2003	1,050,000
Saskatchewan River at The Pas	05KJ001	53°50′30″N, 101° 11′10″W	1913-2003	389,000
Winnipeg River at Slave Falls	05PF063	50°13′30″N, 95°34′15″W	1981-1999	126,000
Assiniboine River near Miniota	05ME006	50°06′39″N, 101°02′08″W	1961-2003	84,200

for a study basin needs to be long enough to perform hydrological modelling. As a rule of thumb, calibration and validation of a hydrological model require ten or more years of streamflow record, especially for climate-related studies. Another critical factor for the watershed selection is the regulation of streamflow. Hydrological models are based on the theory of water balance and the natural hydrological cycle. Since streamflow records are being used for calibration and validation of models, hydrometric stations with regulated flows must be avoided.

The availability and the quality of climate data for the study area are critical for hydrological modelling. In the regions of interest, it is generally difficult to find weather stations within unregulated watersheds. In practice, weather stations outside candidate watersheds must be considered, but in this research the distance from possible weather stations to a study watershed was limited to a maximum of 100 km in order to minimize misrepresentation of local weather, especially precipitation. In addition to the length of record, the availability of the required

Table 2.3: Selected hydrometric gauging stations for the study.

Station Name	Station No.	Latitude	Longitude	Drainage Area (km^2)	Period of Record
Sturgeon River at McDougall Mills	05QA004	50^o 10' 2"N	91^o 32' 26"W	4450	1961-Present
Troutlake River above big fall	05QC003	50^o 54' 20"N	93^o 5' 30"W	2370	1970-Present
Taylor River near Thompson	05TG005	55^o 29' 20"N	98^o 11' 10"W	886	1970-Present
Burntwood River above Leaf Rapids	05TE002	56^o 30' 00"N	99^o 13' 20"W	5810	1985-Present
Sapochi River near Nelson House	05TG006	55^o 54' 30"N	98^o 29' 20"W	391	1993-Present

climate variables, the continuity, and the temporal resolution (i.e. hourly or daily intervals) of climate data must also be considered in the selection of weather stations. The availability of certain essential climate variables, notably precipitation, temperature, relative humidity, and solar radiation, were considered even though all the variables are available only at a limited number of weather stations. Daily climate data for Canada can be downloaded from Environment Canada's website (`http://climate.weatheroffice.ec.gc.ca/climateData/canada_e.html`).

Based on the above considerations, three watersheds in northern Manitoba near Thompson and two watersheds in western Ontario near Sioux Lookout were selected as regional-scale watersheds (see Table 2.3 and Figure 2.2). Burntwood River, Taylor River, and Sapochi River hydrometric gauging stations in northern Manitoba are located within a 100 km range from the Thompson weather station. These three hydrometric stations have more than 10 years of streamflow records and remain active. The Thompson weather station contains all the required climate variables for hydro-

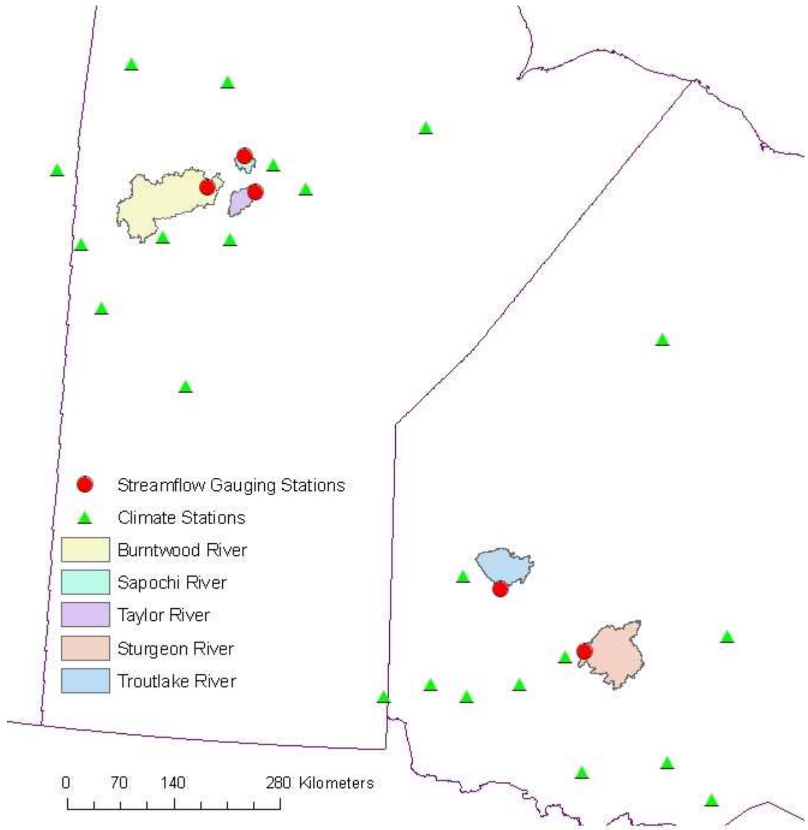

Figure 2.2: Weather stations and streamflow gauges on study area.

logical modelling from 1967 to the present. A few additional weather stations near Thompson were used to improve the representativeness of certain climate variables by interpolation.

Trout River and Sturgeon River hydrometric stations in the Winnipeg River basin are located within 50 km from the Redlake weather station with 74 years of records and the Sioux Lookout weather station with 66 years of records. Since other weather stations are located farther than 100 km from the two hydrometric gauges, only these two weather stations were used and no interpolation was done.

Since the results for watersheds located in the same basin were found to be quite similar, the procedures and assessment results are shown here only for the Sturgeon River and the Taylor River watersheds, representing the Winnipeg River basin and the northern Nelson River basin, respectively.

2.1.2 Hydrological modelling

Hydrological model selection

Climate change impact studies of water resources are typically conducted by simulating runoff and soil moisture using hydrological models under climate scenarios (e.g., *Gleick* (1989), *Kite* (1993)). A hydrological model simulates hydrological processes in a basin using weather input and a physiographical description of the basin. A number of hydrological models have been developed with different theoretical background, purpose, scale, and user interface.

In order to select an appropriate hydrological model among the numerous existing models, several considerations such as data availability, the intended use, and the required accuracy must be taken into account (*McKillop et al.*, 1999). In addition, a model should be able to simulate different climate scenarios for the future (*Frakes and Yu*, 1999). The spatial extent and temporal bounds as well as the availability of hardware and software need to be considered (*Chang*, 2001).

There were a number of factors to consider in the model selection for this study. First, the model should be suitable for large basins. The selected model was set up for small basins, but it was anticipated at the time of the study that the model would be applied over large basins in northern Manitoba in subsequent research. Second, the study aimed to investigate long-term impacts of climate change on water resources. In this context, the scope of models to consider could be narrowed. As the model was going to be run under different climate scenarios, the ability of a model to represent hydrology in different climatic conditions was important. It was reasonable to require that the model be physically based or at least conceptual, and empirical models were therefore eliminated. Models designed for simulating single-event storms were also eliminated, considering the purpose of this study. Since northern Manitoba is mostly remote, data availability was a critical issue in the project. Hence, models were required to not be too data-intensive. A model already applied in other climate change impact studies was preferred. Also, considering the hydroclimatology of Manitoba the model had to be able to model snow melt processes. Ideally, the model should have a good graphic user interface and good documentation and be available to the public at minimal cost.

Given the aforementioned constraints, several models were considered, including the Soil and Water Assessment Tool (SWAT), the Hydrologic Simulation Program-FORTRAN (HSPF), the Regional Hydro-Ecologic Simulation System (RHESSys), the UBC Watershed Model, the Semi-distributed Land Use-based Runoff Processes (SLURP) model, the WatFLOOD model, the Variable Infiltration Capacity (VIC) model, and PnET-II. Each model has its own pros and cons, however some models could be quickly eliminated. They included HSPF, UBC Watershed Model, and

PnET. HSPF has too many parameters to calibrate and has not been tested for large basins. The UBC Watershed Model has features (e.g. elevation bands) unnecessary for northern Manitoba basins and does not have special advantages over other models. With regard to PnET, it is difficult to conclude that it is a suitable model for climate change studies based on its past applications. It leans towards biogeochemical modelling and hydrological modelling is only a part of it. Of the remaining models, SWAT has some advantages in terms of ease of use, user support, and previous applications. However, it has been applied mostly in temperate climate regions and has never been tested in subarctic regions. It also requires detailed soil information, which generally is not available in the study regions.

SLURP has been applied to several basins in Canada by *Kite* (1998), *Su et al.* (2000), *Thorne and Woo* (2006), *van der Linden and Woo* (2003), *St.Laurent* (2003), and *Woo and Thorne* (2006a), although the studies were not necessarily for climate change impact assessment. In the context of climate change studies, SLURP was used to examine the effects of land cover change caused by climate change in the Rocky Mountains of British Columbia (*Kite*, 1993). Another study used gridded GCM output as distributed meteorological data input to SLURP for the Mackenzie River Basin (*Kite*, 1995). Such a wide range of applications in Canada gives confidence in the model for the Canadian environment. Therefore, SLURP was selected for use in this study.

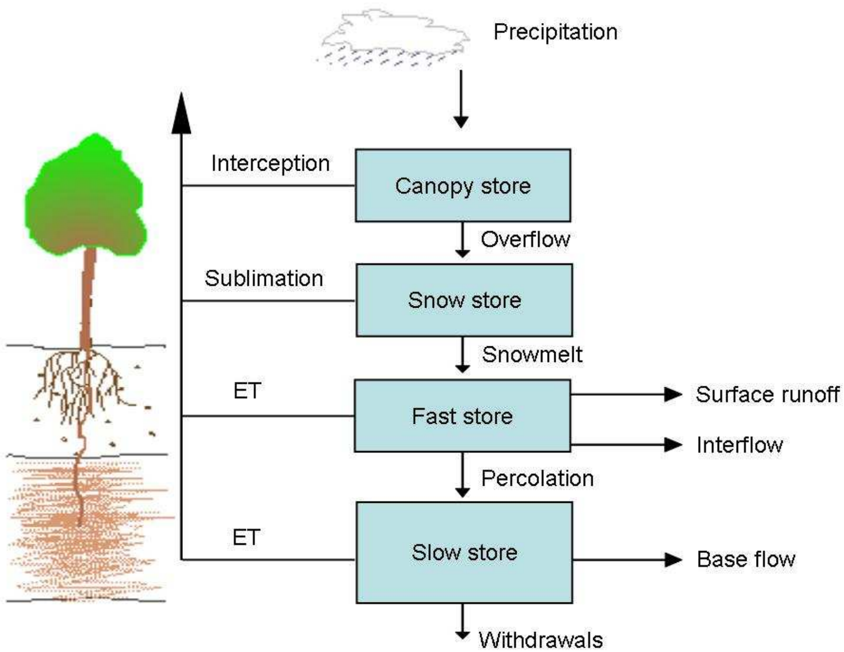

Figure 2.3: SLURP vertical water balance (*Kite*, 2000).

The SLURP model

SLURP is a semi-distributed basin-scale hydrological model that simulates runoff based on daily weather input data and physiographic data (land cover and elevation). Complete information is available in *Kite* (2000), but a brief description is given below.

In the SLURP model, a basin is divided into a number of aggregated simulation areas (ASAs). An ASA contains certain types of land cover, and the vertical water balance is calculated in each land cover in each ASA. Then runoff water is routed to the outlet of each ASA and become input to downstream ASA's. An ASA is described by the percentage of each land cover, but not by their locations.

SLURP simulates the vertical water balance with four storage tanks in each land cover in each ASA: canopy store, snow store, fast store, and slow store (Figure 2.3). Precipitation is provided as input of water to ASAs, and fluxes such as interception, sublimation, evapotranspiration (ET), surface runoff, interflow, and base flow are calculated from the storage tanks. Four different methods for estimating ET are available in SLURP, and Spittlehouse's method was selected for this study since *Barr et al.* (1997) found that it is more physically sound and results in better agreement between simulated and observed streamflow.

Outflow from each land cover is aggregated over each ASA, and outflow from each ASA is routed to downstream ASAs and eventually to the outlet of the basin. Users can choose one of three routing methods: no routing, Muskingum routing, and Muskingum-Cunge routing. Except for the no routing option, the user must assign appropriate routing parameters or use default values.

Meteorological data

SLURP requires four types of meteorological time series data: daily mean air temperature, total precipitation, mean relative humidity, and solar radiation or hours of bright sunshine. The meteorological time series data were obtained from Environment Canada weather stations in and around the watersheds of interest. Most of them are available at the Environment Canada website (`http://www.climate.weatheroffice.ec.gc.ca/climateData/canada_e.html`) at the daily or hourly scale, and the bright sunshine hours (BSH) data were purchased from Ontario Climate Centre. The weather stations used for hydrologic modelling are listed in Table 2.4. It

Table 2.4: Weather stations for SLURP modelling in the study areas.

Station name	Station ID	Location	Elev.(m)	Period	Variables
Red Lake A	6016975	51° 4.2′ N, 93° 47.4′ W	385.6	1953-present	P, T, RH
Sioux Lookout A	6037775	50° 7.2′ N, 91° 54′ W	383.4	1953-present	P, T, RH
Thompson A	5062922	55° 48′ N, 97° 52′ W	222.2	1967-present	P, T, RH, BSH
Snow Lake	5062706	54° 52′ N, 100° 1′ W	295.7	1983-1998	P, T
Wabowden	5063041	54° 55′ N, 98° 39′ W	231.6	1982-2001	P, T
South Indian Lake A	5062736	56° 48′ N, 98° 54′ W	289.0	1989-1998	P, T
Lynn Lake A	5061646	56° 51′ N, 101° 4′ W	356.6	1959-2005	P, T
The Pas A	5052880	53° 58′ N, 101° 6′ W	270.4	1953-present	P, T, RH, BSH
Gillam A	5061001	56° 21′ N, 94° 42′ W	145.1	1970-present	P, T
Pikwitonei A	5062111	55° 34′ N, 97° 10′ W	192.0	1987-1995	P, T
Flin Flon A	5050960	54° 40′ N, 101° 40′ W	303.9	1954-present	P, T, RH
Island Falls	4063560	55° 31′ N, 102° 21′ W	299.3	1929-2004	P, T

*Note: P denotes precipitation, T temperature, RH relative humidity, and BSH bright sunshine hours.

should be mentioned that a deliberate decision was made not to use the homogenized precipitation data by *Mekis and Hogg* (1999). The decision was based on the fact the homogenized data are not available at all sites used in the study and because Environment Canada's data are the official release of weather data in Canada.

It is generally desirable for a hydrologic study that a certain number of weather stations are located inside the watershed of interest. However, during the selection of study areas, it was found that few and sometimes no stations were available in the candidate watersheds. Therefore, data from the closest stations were used. In some cases, interpolation of an expanded set of stations was used to fill gaps in meteorologic records. Most weather stations listed in the Table 2.4 contain missing records, for periods ranging from a few days to several months. *Dingman* (2002) outlines several methods to estimate missing records using data from nearby stations, including the station-average method, the inverse-distance weighting (IDW) method, and the regression method. Different methods were adopted to infill missing records. For precipitation, inverse distance weighting (IDW) interpolation was employed. A linear regression model was used to infill missing temperature records. Linear regression models were built using the data from nearby stations as explanatory variables and the data from the station with missing records as the dependent variable. Then the data from nearby stations during the missing periods were plugged into the model to predict the temperature values for the station. When missing temperature records appear sparsely and isolated, the mean temperature of the previous and the following day was used to fill the missing records.

Because bright sunshine hour data were not available at the weather stations in this region, solar radiation data obtained from NARR were used instead. Some missing records in precipitation and relative humidity were also infilled with NARR data. Missing records in RH and BSH data series were estimated by simply averaging the records on the previous and the following day of the missing periods because they could not be estimated by interpolation due to lack of station data. Because SLURP is fairly insensitive to RH and BSH according to our sensitivity test for the Sapochi River watershed, this approach was regarded as acceptable. Changes of $\pm 20\%$ in RH and BSH resulted in under 4% change in streamflow.

After the missing records were filled in, the meteorological time series were spatially interpolated to the locations of the watersheds using the IDW method. The centroid of each basin was calculated and the IDW method was applied to create times series at the centroids. The weather stations at Thompson and The Pas were used as main input sources for the watersheds in northern Manitoba, and the weather stations at Redlake and Sioux Lookout were used for the watersheds in the Winnipeg River basin.

GIS data

SLURP also requires GIS data sets of digital elevation (DEM) and land cover to derive physiographic parameters. DEM data from the National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM) data were obtained from the U.S. Geological Survey (USGS) data distribution website (`http://seamless.usgs.gov/`) with 3 arc second resolution (about 90 m resolution).

The land cover data sets were derived from the Advanced Very High Resolution Radiometer (AVHRR) sensor operating on board the United States National Oceanic and Atmospheric Administration (NOAA) satellites. These land cover data sets are available at the GeoGratis website (`http://geogratis.cgdi.gc.ca/geogratis/`

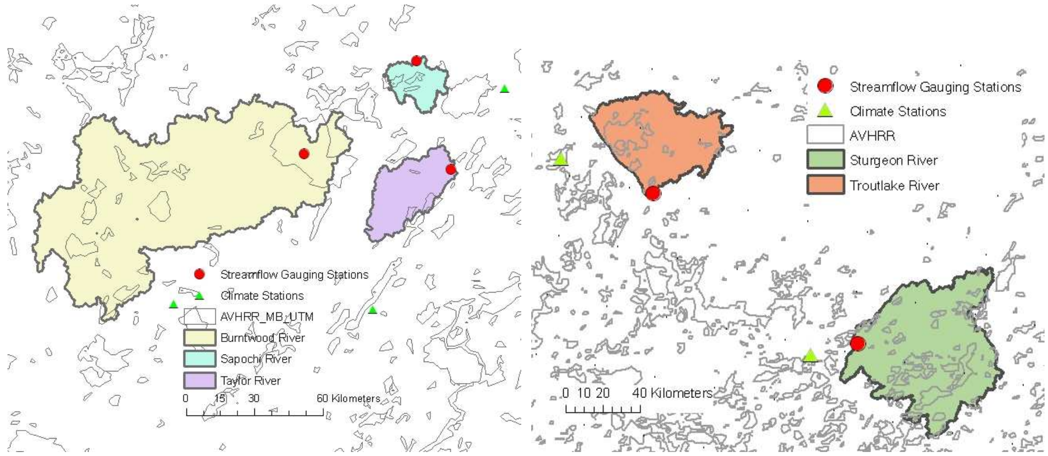

Figure 2.4: AVHRR covers for the study area in northern Manitoba.

en/index.html). GeoGratis is managed by the Earth Sciences Sector (ESS) of Natural Resources Canada (NRCan) and provides geospatial data at no cost. The scale of the AVHRR data is 1:2,000,000 and the data represents the land cover around the years 1992 and 1993 (Figure 2.4).

Streamflow data

Daily historical streamflow records for the selected hydrometric gauging stations (listed in Table 2.3) were extracted from HYDAT and used to calibrate the SLURP model.

Model setup

SLURP has a number of parameters that can be adjusted as part of the model calibration. In order to properly adjust the parameters, it is important to understand the climatological and geological environments of the study areas.

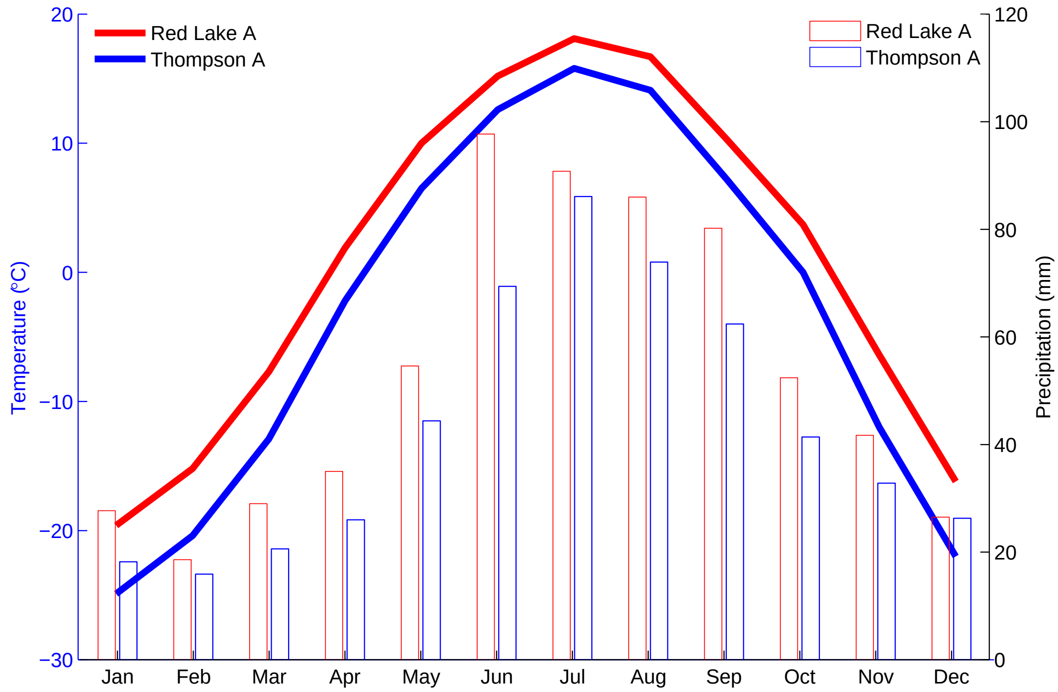

Figure 2.5: 1971-2000 normals of daily mean temperature (curve) and precipitation (bar) at Red Lake and Thompson stations.

Figure 2.5 presents the 1971-2000 climate normals measured at the Red Lake and Thompson weather stations. The climate in the Winnipeg River basin region is warmer and wetter than in the Nelson River region. The December and January average temperature drops below zero at Thompson but not at Red Lake, and the months form June to September are the wettest period at both locations. Annual mean precipitation at Red Lake is 640.2 mm, which is about 24% more than at Thompson.

The Sturgeon River watershed in the Winnipeg River basin is located in north-western Ontario, just east of the Manitoba border between the cities of Winnipeg and

Thunder Bay. There are a few communities around them with very small populations such as Sioux Lookout, Dryden, and Red Lake. The landscape is characterized by rugged wilderness, low and rolling terrains, and many lakes (*St. George*, 2007).

The Taylor watershed in the northern Nelson River basin is located in northern Manitoba. Nearby communities include Thompson, The Pas, and Flin Flon, and human activities in the watersheds of interest are minimal. This region belongs to the boreal forest and is characterized by coniferous trees such as spruce, hemlock, fir, and pine, and depressions, bogs, and lakes hidden among the trees (*de Blij and Muller*, 1996).

The region has a humid cold climate with short, cool summers. As shown in Figure 2.5, precipitation is highest during the summer season, but remains around 20 mm per month during the winter. The mean annual total precipitation is around 520 mm. Daily average temperature is the highest at 15.8°C in July, and the lowest at -24.9°C in January.

The SLURP model was set up and calibrated for each of the selected watersheds. The Sturgeon River watershed was divided into seven ASAs with an average size of 637 km^2. Water occupies about 19% of the watershed, ranging from 7.7 to 32.1% by ASA and the percentage of water land cover is much higher than for the watersheds in the northern Nelson River basin. The most dominant land cover is coniferous forest, ranging from 58.8 to 82.9% by ASA.

The Taylor River watershed was divided into seven ASAs with average size of 128 km^2. Coniferous forest and muskeg are the main land cover types occupying more than 60% of the watershed. The two SLURP models will in the following be referred to as the 'Sturgeon-model' and the 'Taylor-model'.

2.1.3 Model calibration

After the SLURP model was set up for each watershed with DEM and digital land cover data, each model was calibrated using streamflow data measured at the hydrometric gauges listed in Table 2.3. The key parameters adjusted during the calibration include maximum infiltration rate (mm/d), retention constant for the fast store (RCFS; in days), maximum capacity of fast store (MCFS; in mm), retention constant for slow store (RCSS; in days), maximum capacity of slow store (MCSS; in mm), rain/snow division temperature (in °C), canopy capacity (in mm), albedo, snowmelt rate (in mm/day), and evaporation-related parameters such as wilting point and field capacity.

The calibration criteria used for evaluating model performance, as suggested and explained by *ASCE* (1993) and *Legates and McCabe Jr* (1999), include the deviation of volume (D_v) of mean runoff, the Nash-Sutcliff Efficiency (E) of daily runoff series, and the mean absolute error (MAE). These criteria measure volumetric error, goodness-of-fit, and daily average error between simulation and observation, respec-

Table 2.5: Statistics of observed and simulated streamflow of the Sturgeon River and Taylor River watersheds for the combined periods of calibration and validation.

	Sturgeon	Taylor
Mean observed streamflow (m^3/s)	39.59	4.29
Mean simulated streamflow (m^3/s)	40.11	4.33
E	0.69	0.75
D_v (%)	1.33	1.08
MAE (m^3s^{-1})	10.63	1.90

tively. D_v, E, and MAE are calculated as follows:

$$D_v = \frac{\bar{S} - \bar{O}}{\bar{O}} \times 100 \tag{2.1}$$

$$E = 1 - \frac{\sum (S_i - O_i)^2}{\sum (O_i - \bar{O})^2} \tag{2.2}$$

$$MAE = \frac{\sum \mid S_i - O_i \mid}{N} \tag{2.3}$$

where $\bar{S}$ is mean streamflow simulated by the model, $\bar{O}$ is mean observed streamflow, S_i is simulated streamflow at time i, O_i is observed streamflow at time i, and N is the number of records during the period.

The Sturgeon-model was calibrated for 1995-1997 and validated for 1991-2004, while the Taylor-model was calibrated first for the year 1996 and validated over the period of 1985-2000.

Table 2.5 shows the goodness-of-fit statistics of the simulation results for the combined calibration-validation periods. It should be noted that periods with missing data in the streamflow records and corresponding periods in the simulations were

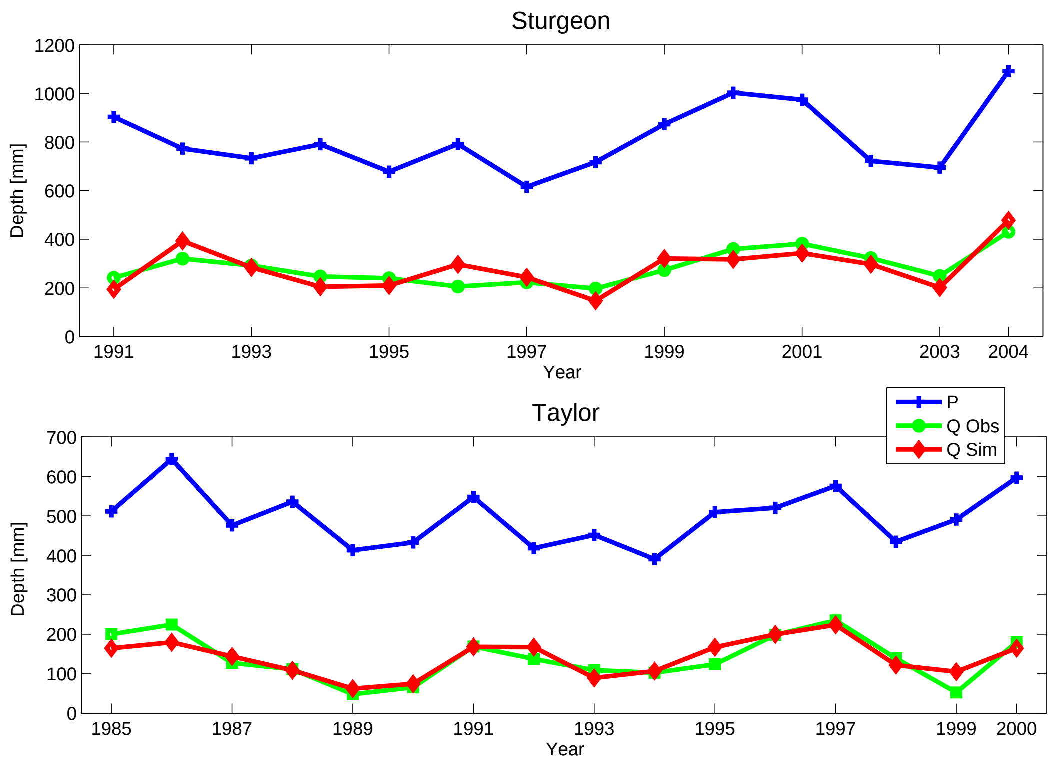

Figure 2.6: Annual precipitation (P), observed runoff (Q obs), and simulated runoff (Q sim) during the calibration and validation periods.

excluded from the calculation.

The D_v values of both models are close to zero, indicating the model's proficiency in reproducing mean runoff. However, the model generally overestimates April runoff and underestimates May runoff, which partly explains the E values of 0.69 and 0.75. MAE values are 27% and 44% of the observed mean streamflow in the Sturgeon-model and the Taylor-model, respectively. The simulation results of both models are satisfactory in terms of volumetric error and goodness-of-fit.

Figure 2.6 presents the annual water balance of the SLURP models. By visually inspection, the Sturgeon-model and Taylor-model both show reasonably good agree-

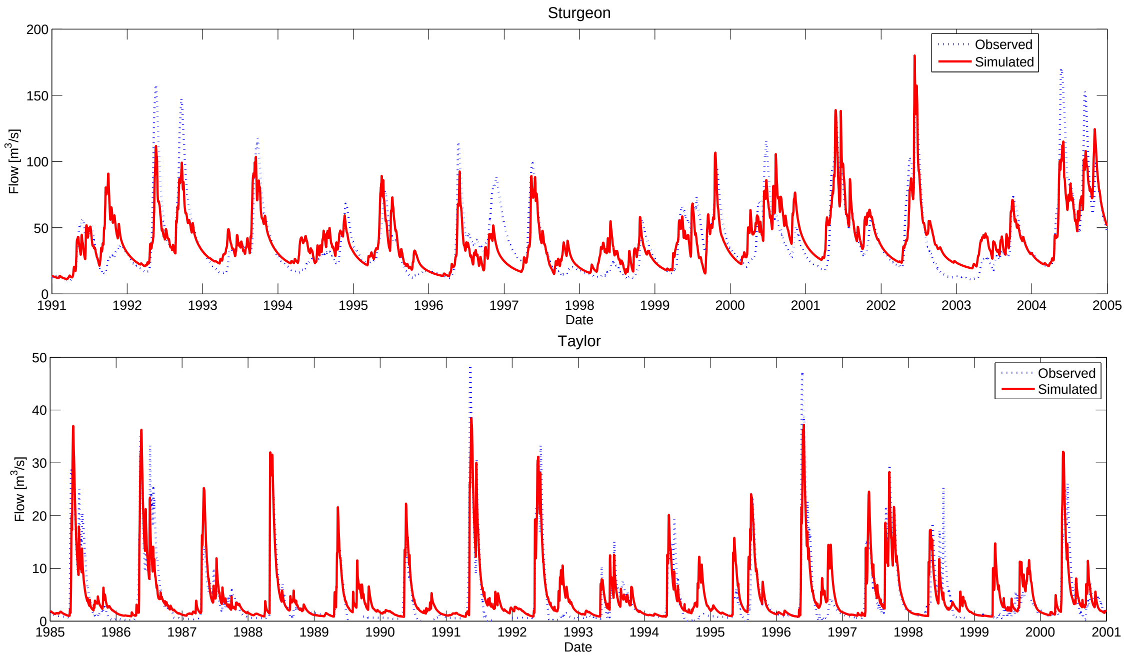

Figure 2.7: The observed and simulated daily runoff during the calibration and validation periods for Sturgeon and Taylor.

ment in most of the years. Discrepancies are noticeable in 1992, 1996, and 1998 in the Sturgeon-model, while for the Taylor-model, the years of 1986, 1992, 1995, and 1999 are noticeable. Generally, the simulation results of both models present the hydrologic water balances quite well.

Figure 2.7 shows the observed and simulated daily runoff for the combined periods of calibration and validation for each watershed. The Sturgeon-model and Taylor-model properly presents the timings of snowmelt and spring peak flows in general. The Sturgeon-model slightly underestimates the spring peak flow in 1992 and 2004, while the Taylor-model slightly underestimates it in 1991 and 1996. The peak flows are somewhat better represented in the Taylor-model. It should be noted that the Sturgeon-model used only climate data from the Sioux Lookout weather station located about 40 km from the watershed, while the Taylor-model used interpolated climate data from several neighbouring stations. Hence, input to the Sturgeon-model is more likely to misrepresent events in the watershed. For example, the underestimated runoff in 1996 autumn and the overestimated runoff in 2003 autumn can likely be linked to errors in meteorologic input. The recession curves after the spring peaks show quite good agreements with observations when the timing and magnitude of the peak are correctly captured. The low flows in the Sturgeon-model are in good agreements with observations except for the above mentioned abnormal years. The low flows in the Taylor-model are overestimated in 1989, 1990, and 1992, but observed streamflow records are missing so it is somewhat difficult to assess the simulation results. In general, the low flows of the Taylor-model show fairly good agreement with observations. Although the peak flows are sometimes slightly underestimated, the total volumes are generally close to the observations, as shown in Figure 2.6. Therefore, the calibration results are deemed to be satisfactory for representing the hydrological regimes in both watersheds.

2.2 Climate Change Impact Assessment

2.2.1 Statistical downscaling

Output from the Canadian Global Climate Model (CGCM) is used in the following to define scenarios of changed weather patterns. Due to the coarseness of GCM output, it is necessary to downscale GCM data for practical assessment of climate change in smaller watersheds. Three statistical downscaling methods were employed in this study: the Statistical Downscaling Model (SDSM: *Wilby et al.*, 2002), the Long Ashton Research Station Weather Generator (LARS-WG: *Semenov and Barrow*, 1997), and the nearest neighbor resampling (NNR: *Gangopadhyay et al.*, 2005). Statistical downscaling was implemented using the daily output from the third-generation Canadian Coupled General Circulation Model (CGCM3.1). The CGCM3.1 output was obtained at the T47 resolution (roughly 3.75 degrees latitude/longitude) for three different greenhouse gas emission scenarios from the Special Report on Emissions Scenarios (*Nakićenović et al.*, 2000): B1, A1B, and A2, which represent 'low', 'medium' and 'high' emissions, respectively.

SDSM

SDSM is a statistical downscaling technique based on multiple regression models between large-scale atmospheric variables (predictors) and local-scale variables (predictands), and a stochastic component is also included. Three predictands, daily maximum temperature, minimum temperature and precipitation, were modelled with SDSM for the reference and future periods. The general procedure to set up SDSM is as follows (*Wilby and Dawson*, 2004): (1) select appropriate predictor variables from gridded data sets (e.g. GCMs and reanalysis data sets) (2) re-grid the predictor variables to the same resolutions; (3) calibrate and validate the model against observed climate data; and (4) generate an ensemble of synthetic daily weather series given predictor variables for either reference or future climate.

SDSM was set up for each selected weather station using three different daily meteorological/atmospheric data sets. First, the maximum temperature, minimum temperature, and precipitation data were obtained from the weather stations and used for calibration and validation of the SDSM results. Second, the NCEP-NCAR global reanalysis data (NNGR) were used to obtain predictor variables for the period 1961-2000. Finally, CGCM3.1 was used to obtain predictors, both for the control period and future periods. Data from the NNGR and CGCM3.1 were obtained from the grid point closest to the weather station and then standardized to reduce the impact of biases in the climate model. The GCM data (control as well as future) were standardized using statistics from the control period. The SDSM model was calibrated with predictors from the reanalysis data for the period 1961-1990. Parameters of the model were adjusted to obtain the best statistical agreement between the weather station data and the downscaling variables. Then the model was validated for the period 1991-2000. Details of the climate scenarios generated by SDSM for use in this study can be found in *Koenig* (2008).

LARS-WG

LARS-WG is a stochastic weather generator that can produce synthetic daily time series of precipitation, maximum temperature, minimum temperature, and solar radiation. In LARS-WG, the occurrence of daily precipitation is modelled as alternating sequences of dry and wet spells. The daily maximum and minimum temperature, solar radiation and precipitation amount are then modelled conditional on whether precipitation occurs or not. In LARS-WG, the lengths of the wet and dry spells are drawn randomly from a semi-empirical distribution of observed wet and dry spell lengths, with allowance for seasonality. The general procedure to implement LARS-WG is as follows (*Semenov and Barrow*, 2002): (1) the model determines the statistical properties of the observed weather data and generates parameter files; (2) the model generates synthetic weather series based on the statistical properties; (3) climate scenarios are generated by perturbing the parameter files and running the model. LARS-WG was implemented for the location of the Sioux Lookout and Thompson weather stations to generate maximum and minimum temperature, and precipitation. LARS-WG requires the same observed weather station data as input as SDSM. Data from 1961-1990 were used for the calibration of the model. One hundred series of synthetic values were then generated to compare with observed climate data. After calibration, LARS-WG was validated over the 1991-2000 period (*Koenig*, 2008). Climate scenarios were generated by perturbing the parameters related to monthly precipitation, length of wet and dry spells, maximum and minimum temperature, standard deviation of temperature, and mean radiation simulated by CGCM3.1. Details of the application of LARS-WG for the study regions can be found in *Koenig* (2008).

Nearest Neighbor Resampling (NNR)

Nearest neighbor resampling (NNR) is a non-parametric method that has the advantage of avoiding the complex parameterization in other statistical downscaling methods. It produces local weather data by resampling from the record of observed weather variables (daily maximum temperature, minimum temperature and precipitation), based on the similarity of the daily large-scale atmospheric patterns of a GCM and the corresponding observed patterns. The basic idea is that by comparing large-scale atmospheric variables from a GCM for a given simulation day with the same variables in the historical record, days with similar large-scale variables (nearest neighbors) can be identified in the historical record. The comparison between the simulation day and the historical record is done using a vector of variables referred to as the feature vector. The elements of the feature vector must be carefully selected and must have a strong relationship with the surface variables of interest. The number of variables included in the vector may vary from a few (*Buishand and Brandsma*, 2001) to many (*Gangopadhyay et al.*, 2005). Using a pre-defined metric, the distance between the feature vector for a given simulation day and feature vectors in the historical record can be determined, and the group of the k most similar days can be identified. One of these is selected at random to provide the local weather data for the simulation day. The process is repeated for each GCM simulation day to generate time series of local weather.

The NNR method requires large-scale atmospheric variables for the feature vector and corresponding historical weather data relevant for a particular application, in this case input variables for SLURP. The large-scale variables considered here were surface temperature, 500 hPa temperature, 850 hPa temperature, 500 hPa geopotential height, and 850 hPa geopotential height covering a significant area over west-central Canada. The reanalysis and CGCM3.1 data were standardized to remove biases. Principal component analysis was used to reduce the number of variables in the feature vector.

It is worth reiterating that the downscaled climate scenarios used in this thesis were produced by *Koenig* (2008) and *Lee* (2010). Both of these Master theses as well as the present thesis were part of the climate change project funded by Manitoba Hydro in 2005-2008. The specific contribution of the present thesis is the application of the downscaled scenarios as input to the SLURP model, and the evaluation of the corresponding simulation results. A summary of the findings for the Taylor River and the Sturgeon River watersheds are given in the following.

2.2.2 Impact assessments using observations

Figure 2.8 shows the changes of annual temperature and precipitation with each downscaling method and with each emission scenario, for the 2050s and 2090s. In Figure 2.8, the circles, squares, and triangles represent downscaling results for SDSM, LARS-WG (denoted WG in figures), and NNR, respectively, while emission scenarios B1, A1B, and A2 are shown as green, blue, and red, respectively. The empty

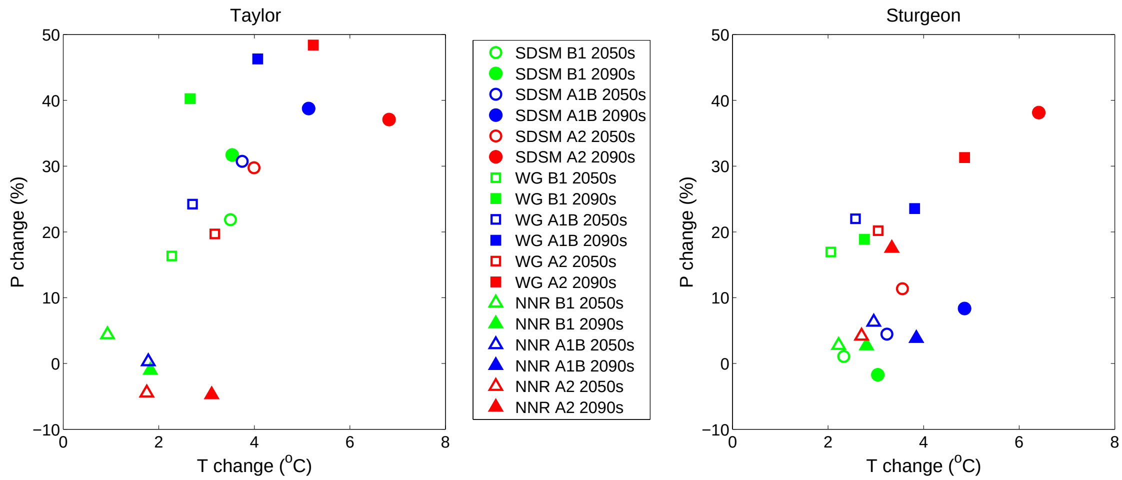

Figure 2.8: Projected changes by the 2050s and 2090s in annual mean temperature and precipitation for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods.

shapes represent the period of 2050s and the filled shapes are for 2090s. The temperature changes are positively correlated with precipitation changes in each of the two watersheds. Temperature is projected to increase in every case, and most of the projected precipitation changes are positive as well, except for a few NNR cases for Taylor. The magnitude and the range of changes between Taylor and Sturgeon are noticeably different. The changes of precipitation in Taylor range from -10% to 50%, while the changes in Sturgeon are in the range of -2% to 25% for precipitation and of 2 to 5 °C for temperature, with two outliers corresponding to the A2 scenario with SDSM and LARS-WG. The changes in the 2090s (filled shapes) are generally larger than the 2050s (empty shapes) in both watersheds. The A2 scenario (red) leads to more severe changes than the other scenarios. Among the statistical downscaling methods, the SDSM (circles) shows the largest changes in both annual precipitation and temperature for the same scenario and period.

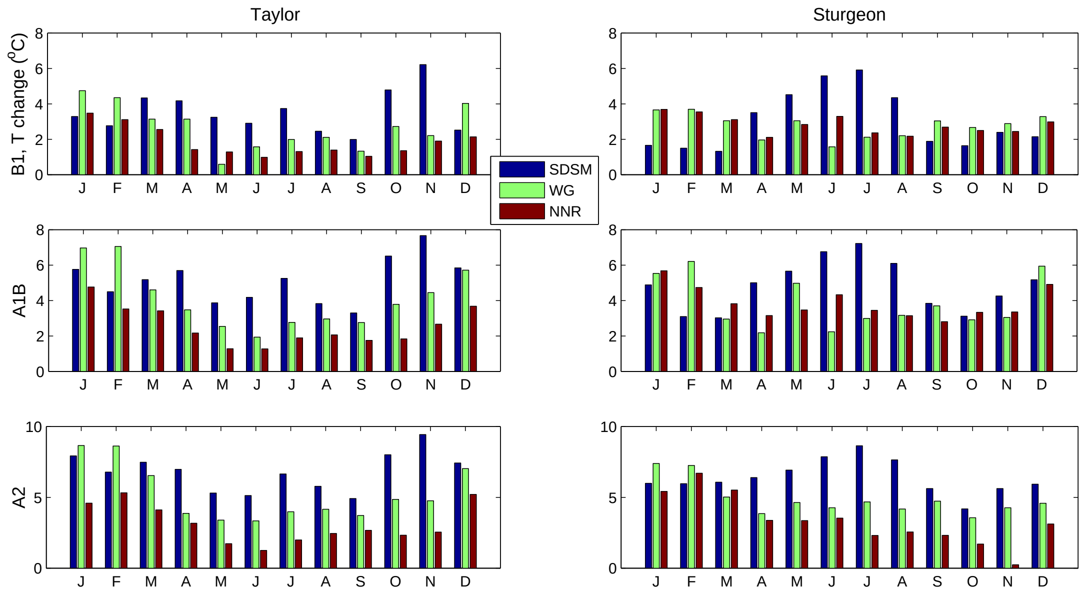

Figure 2.9: Projected changes by the 2090s in mean monthly temperature for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods.

Figure 2.9 shows the changes in mean monthly temperature for three scenarios and three statistical downscaling methods in Taylor and Sturgeon for the period 2090s. In Taylor, the LARS-WG and NNR show larger changes in temperature during winter, while the changes of SDSM are more evenly spread out over the year with the most significant changes in October and November for all three scenarios. However, in Sturgeon, the SDSM shows significant temperature increases in the summer months, while the LARS-WG and NNR shows more changes during the winter months, especially January and February.

Figure 2.10 shows the changes in mean monthly precipitation for the three scenarios and the three statistical downscaling methods in Taylor and Sturgeon for the

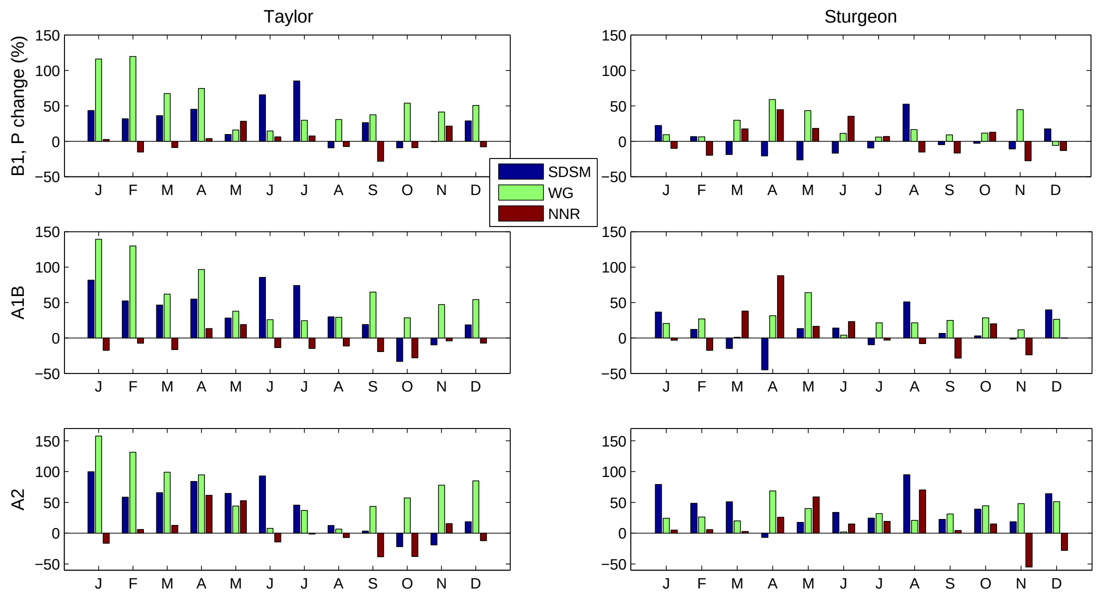

Figure 2.10: Projected changes by the 2090s in mean monthly precipitation for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods.

period 2090s. The LARS-WG shows significant precipitation increases during the winter months (more than 100% in January and February), but the relative changes are smaller between May and August for all three scenarios. This may partly be due to the fact that there is less precipitation in the winter months, so the same absolute amount of change will produce higher relative changes in winter. The SDSM generally shows precipitation increases from January to July, while the changes are minimal or negative in other months. It is noticeable that the NNR yields negative precipitation changes for roughly half of the months, with particularly significant decreases in September and October. NNR in Taylor shows significant increases only in April and May for the A2 scenario. The overall precipitation changes in Taylor are

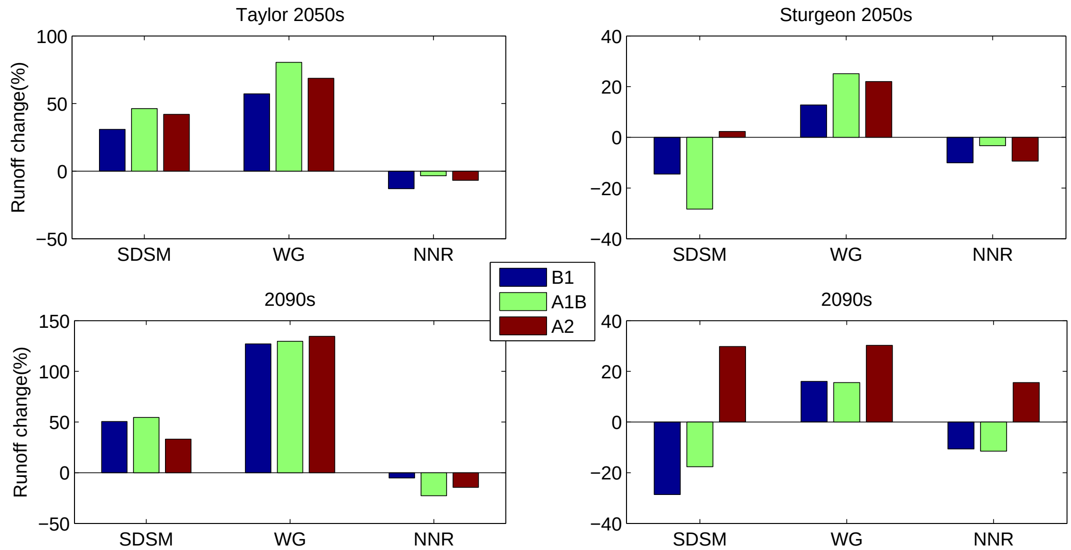

Figure 2.11: Projected changes by the 2050s and 2090s in annual mean simulated runoff for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods.

significantly larger than the changes in Sturgeon. In Sturgeon, there are some negative precipitation changes of SDSM and NNR in the B1 and A1B scenarios, while LARS-WG yields consistently positive changes. For A2 scenarios, all three methods project positive changes and the changes are more evenly spread out over the year.

The SLURP model was run with input data generated by each downscaling method for the control period 1970-2000 and the two future periods, 2050s and 2090s. The projected changes of mean annual runoff for the two periods for each emission scenario are depicted in Figure 2.11. Changes are defined as relative departures from the control run. The changes of annual mean runoff reflect the temperature and precipitation changes shown in Figure 2.8. For Taylor, LARS-WG results in the greatest runoff increases which is not surprising given that LARS-WG also projects the largest precipitation increase. NNR produces negative changes, a reflection of the negative precipitation changes. The LARS-WG also shows the largest difference between the two future periods, as the increase in runoff in the 2050s (70%) is sustained into the 2090s (120%). The results of SDSM and NNR vary little between the two periods. In Sturgeon, the negative changes appear in the NNR and SDSM results for the B1 and A1B scenarios, while most of results show positive changes in the A2 scenario, which are also reflections of the smaller annual precipitation changes. It is noticeable that even though the precipitation changes of NNR are all positive, the corresponding runoff changes in Sturgeon are negative. The seasonal temperature changes in Figure 2.9 are fairly uniform over the year for NNR and LARS-WG, and the precipitation changes are generally small with these methods. A substantial increase in temperature causes more evapotranspiration that more than offsets the increase in precipitation and affects the runoff negatively. It explains the smaller runoff changes in Sturgeon, especially the negative runoff changes associated with the SDSM results which generally yields the highest temperature increases during the summer (Figure 2.9). Overall, the variations between the projections by emission scenarios are less than between the projections by downscaling methods in Taylor, while the variations by emission scenarios are more pronounced in Sturgeon. It suggests that the uncertainty associated with the choice of statistical downscaling methods is more significant than the uncertainty related to emission scenarios.

Projected changes by the 2090s in mean monthly runoff are shown in Figure 2.12.

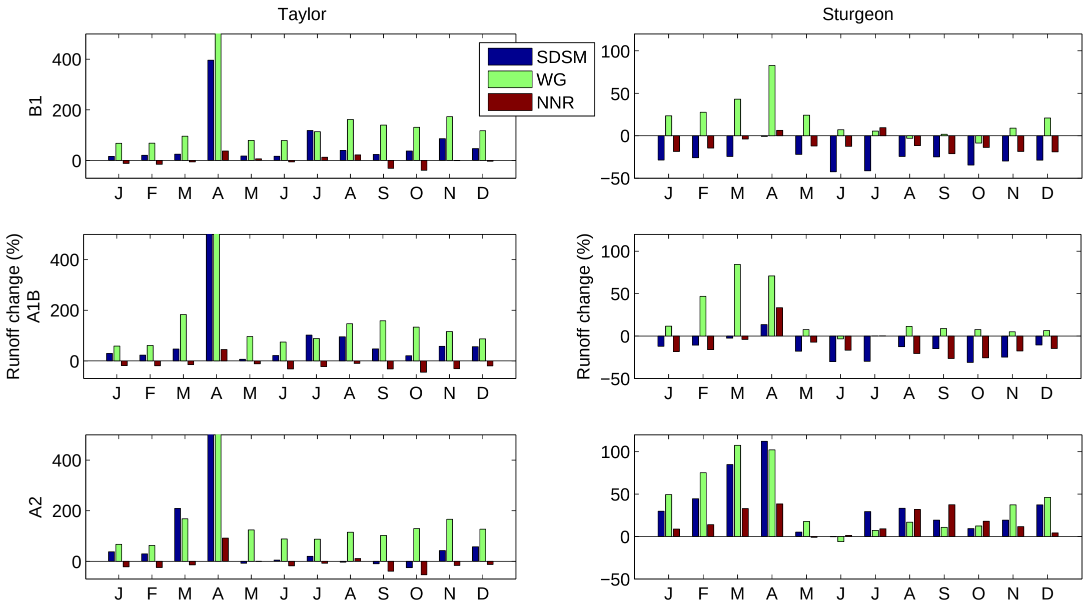

Figure 2.12: Projected changes by the 2090s in mean monthly simulated runoff for the Taylor and the Sturgeon River watersheds derived from different downscaling methods.

In most cases, the largest percentage increases occur in April, except with LARS-WG in Sturgeon for the A1B and A2 scenarios. Since the absolute amount of runoff is comparably smaller in Taylor than in Surgeon, the percentage of runoff change in April appears substantially higher in Taylor. In Taylor, the results of the three emission scenarios show a similar pattern, namely that runoff changes are smallest in winter and largest in spring. SDSM and LARS-WG show substantial runoff increase in April, while NNR shows no particularly extreme runoff change. This is primarily due to different seasonal patterns in the precipitation change. In Sturgeon, LARS-WG shows positive runoff changes for all emission scenarios, while SDSM and NNR show negative runoff changes in most months for the B1 and A1B scenarios. For the

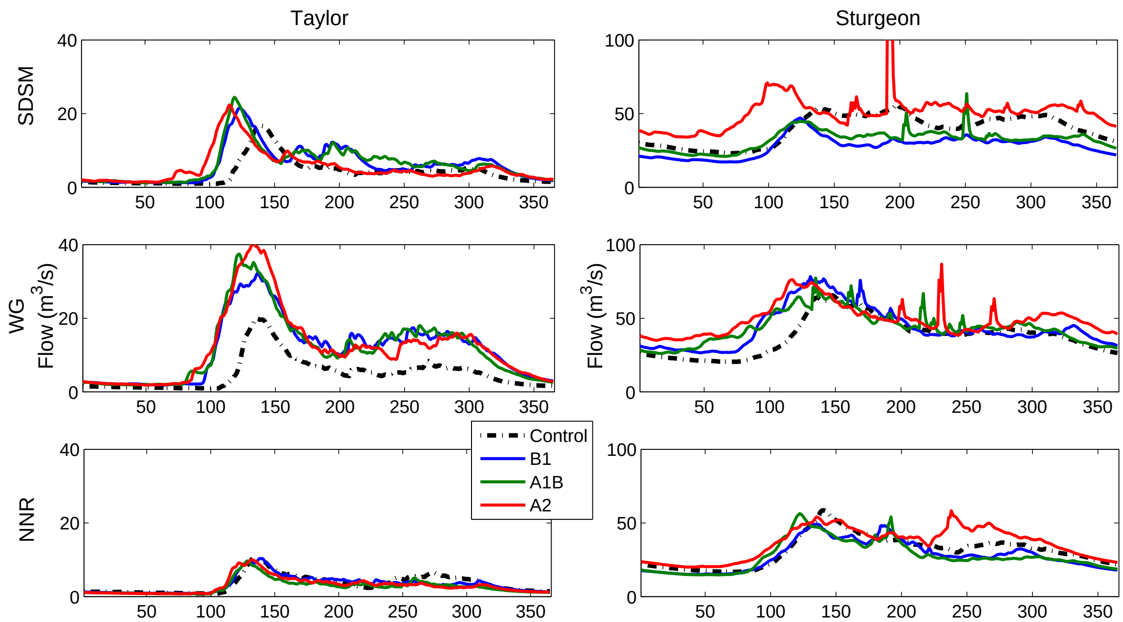

Figure 2.13: Projected in mean daily simulated runoff by the 2090s for the Taylor and the Sturgeon River watersheds derived from three different downscaling methods.

A2 scenario in Sturgeon, results of all three methods show noticeable changes except in May and June, and SDSM and NNR show even larger runoff increases between June and October.

Figure 2.13 shows the mean daily streamflow by the 2090s for each scenario and downscaling model. The streamflow regimes in the two watersheds show clearly distinguishable changes in the future projections. In Taylor, the spring freshets begin about 30 days earlier than in the current climate according to the SDSM and LARS-WG results, while the peak of spring runoff is almost twice as large with LARS-WG than with SDSM. In the comparison of projections by emission scenario, the A2 scenario shows somewhat earlier spring freshet due to the higher temperature changes, but the variations between the scenarios are not as significant as between the downscaling methods. As expected, the NNR results show little impact on streamflow, in part due to the negative precipitation changes in some months.

In Sturgeon, the spring freshet occurs earlier and the runoff volume is greater because of earlier snowmelt. The SDSM result for the A2 scenario shows the greatest increase of flows in early spring and some periods during the summer and autumn, while the results of other scenarios show a decrease in flows. The LARS-WG results show earlier increase of flows but the peak flows are similar to the current climate. It is noticeable that the results for the three scenarios fall in a close range, with a few spikes occurring during the summer in response to some heavy rainfall events. The NNR results show slight increase in flows, especially during the autumn in the A2 scenario, and the future mean flow scenarios are all close to the average for the current climate. In conclusion, the overall changes in the Taylor watershed are more significant than in the Sturgeon watershed.

The climate change impact assessments have uncertainties related to construction of emission scenarios, global climate modelling, and downscaling of GCM outputs. In this study, the uncertainties in two aspects (choice of emission scenarios and downscaling methods) have been investigated. The pattern of temperature changes are similar between the emission scenarios and the differences in the magnitude of change is a direct consequence of the classification of the emission scenarios: B1, A1B, and A2 represent 'low', 'medium' and 'high' emissions, respectively. For precipitation, the changes associated with different scenarios are similar in Taylor, albeit not as similar as for temperature. In Sturgeon, it is difficult to find the similarity in precipitation changes associated with different scenarios. However, the difference between the statistical downscaling methods is quite significant for both temperature and precipitation. It clearly indicates that the uncertainty related to the choice of downscaling method is significantly higher than the uncertainty related to emission scenarios.

Chapter 3

EVALUATION OF NARR SURFACE CLIMATE

3.1 Reanalysis Data

The availability of good-quality climate data is important for hydrological applications and research. However, hydrologists often face problems with lack of data, especially in remote areas such as northern Canada. As mentioned in the introduction, reanalysis products of past observations have emerged as a potential alternative to observations. In this chapter, the North American Regional Reanalysis (NARR) is investigated and compared with observed climate data in order to assess its reliability for hydrological modelling in Canada, or more specifically in the Prairie region. The chapter will also compare NARR with two other popular reanalyses, the NCEP-NCAR Global reanalysis (NNGR) and the ERA-40 from the European Centre for

Medium-Range Weather Forecasts (ECMWF).

NNGR is perhaps the most well-known first generation global reanalysis product. The NNGR uses a state-of-the-art analysis/forecast system to perform data assimilation using past data from 1948 to the present. It has a spatial resolution of 2.5° by 2.5° in the horizontal and 17 pressure levels and 28 sigma levels in the vertical, and 6-hourly temporal resolution over the entire globe. Many studies (*Mo and Higgins*, 1996; *Higgins et al.*, 1996; *Trenberth and Guillemot*, 1998; *Betts et al.*, 1999; *Roads et al.*, 1999; *Roads and Betts*, 2000) have examined this global reanalysis, focusing on energy and water budgets, and have typically found a number of noticeable differences and biases in the large-scale basin averages (*Berg et al.*, 2003). Nevertheless, many researchers have concluded that the climate variables from global reanalysis products are reasonably close to the observed data.

The ERA-40 is another global reanalysis product, available from September 1957 to August 2002 at a 6-hourly temporal resolutions over the entire globe. The ERA-40 is provided at two different horizontal resolution: 2.5° by 2.5° for public users with limited data processing resources and TL159 spectral fields and N80 Quasi-regular Gaussian grid with 60 levels in the vertical including a well-resolved boundary layer and stratosphere. The former data is available for free, while charges apply to the latter. ERA-40 uses a 3-D variational assimilation system which improved the model from its predecessor. *Betts et al.* (2003a,b) assessed the systematic biases in temperature and precipitation, and the surface water budget of ERA-40 for the Mackenzie

River basin by comparing with the Mackenzie GEWEX (Global Energy and Water Cycle Experiment) study (MAGS). They found that ERA-40 has a distinct seasonal temperature bias of 2 to 3°C from December to April and a cool bias of -1.5°C in summer. ERA-40 was found to overestimate precipitation in the northern and western mountainous basins and to have less variability of evaporation across the basins than the MAGS estimate.

The North American Regional Reanalysis (NARR) was developed as a follow-up to the NNGR project. NARR is a high-resolution climate data set for the entire North American domain, and it appears to be a major improvement upon the earlier NNGR data sets in both resolution and accuracy. The NARR is a reprocessing of the historical meteorological observations using NNGR and associated data assimilation systems (*Mesinger et al.*, 2006). The NARR data cover North America with a 32 km horizontal resolution and 45 layers in the vertical, from 1979 to present. NARR provides an improved analysis of land hydrology and land-atmosphere interaction, and *Mesinger et al.* (2006) expected good representation of extreme weather events in NARR. This data set would therefore interface well with hydrological models.

A major component of the NARR is the assimilation of precipitation using the Eta climate model, which is an operational model used primarily for regional weather prediction and NWP-type applications (*Mesinger*, 2001). The model has been very successful also in regional climate and seasonal prediction applications (e.g. *Altshuler et al.*, 2002; *Chou et al.*, 2005; *Katsafados et al.*, 2005). The precipitation data for

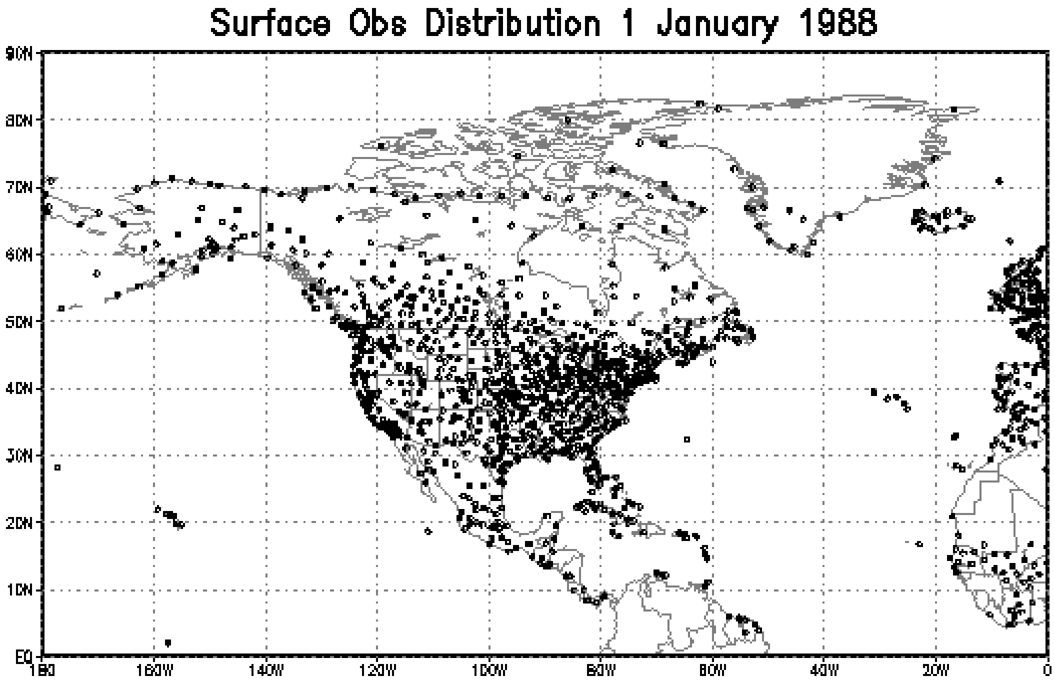

Figure 3.1: Distribution of surface observations assimilated in NARR (January 1988). Source: *Mesinger et al.* (2006).

the assimilation process come from a variety of sources. The data over the continental United States come from an interpolated 1/8°-grid gauge data set obtained using the PRISM-model (Parameter-elevation Regressions on Independent Slopes Model) (*Daly et al.*, 1994) and a least-squares distance weighting algorithm. Over Canada and Mexico where the station networks are less dense, the precipitation comes from 1-degree gauge-interpolated data sets. Also, in the US 24-hr accumulations are disaggregated to hourly precipitation using station data, while in Canada and Mexico 24-hr accumulations are disaggregated to hourly precipitation using Global Reanalysis

2 precipitation forecast. Much of the rest of the domain's precipitation comes from CMAP (Climate Prediction Center's Merged Analysis of Precipitation), a merged combination of satellite and gauge precipitation. *Mesinger et al.* (2006) found that NARR precipitation was quite similar to the observed precipitation used in the data assimilation. Figure 3.1 shows the distribution of surface observations for the NARR data assimilation process. A better performance of NARR precipitation in the US is to be expected given its higher density of weather stations.

Because the NARR data set is fairly recent, few studies have evaluated and applied the data. A recent independent examination of NARR precipitation found it to be superior to global reanalyses over the contiguous United States (*Bukovsky and Karoly*, 2007). *Becker et al.* (2009) examined the seasonal characteristics of daily precipitation over the US from NARR, and found that NARR mean seasonal amounts are very close to observations throughout the year, although NARR shows a slight systematic bias toward more-frequent, lighter precipitation. The study indicates that NARR underestimates extreme precipitation intensity and overestimates lighter events in the eastern half of the United States, particularly during summer. *Nigam and Ruiz-Barradas* (2006) examined the hydroclimatic representation in ERA-40, NNGR, and NARR of precipitation, evaporation, surface air temperature, and moisture flux distributions. Their study focused on the description of seasonal hydroclimatic variability in the NARR data. They concluded that reanalysis precipitation evolution appears realistic in winter and early spring. *Ruiz-Barradas and*

Nigam (2006) also examined the structure of precipitation and the role of evaporation and moisture fluxes. Both studies indicate that the assimilation of precipitation in NARR improves the representation of land-atmosphere interactions.

The above studies suggest that NARR has significant potential for hydrological modelling. A detailed evaluation of the NARR data in the Prairie region is therefore undertaken in this chapter, using observed data as baseline for the assessment.

3.2 Comparison of NARR and Gridded Observation Data

One of the benefits of using NARR is the grid structure of the data which covers the entire North American domain. To assess the reliability of NARR, it is necessary to evaluate the data both spatially and temporally. In Canada, there have been some efforts to develop gridded climate data sets using various statistical interpolation methods. Two data sets are considered here: CANGRID and ANUSPLIN. Although these interpolated gridded data sets are not precise observed data, they are based on quality-controlled data and have been used in a number of studies to represent Canadian climate data. In this section, NARR precipitation in the Prairie region is investigated through a comparison with CANGRID and ANUSPLIN, for a preliminary verification of the spatial representativeness of NARR precipitation.

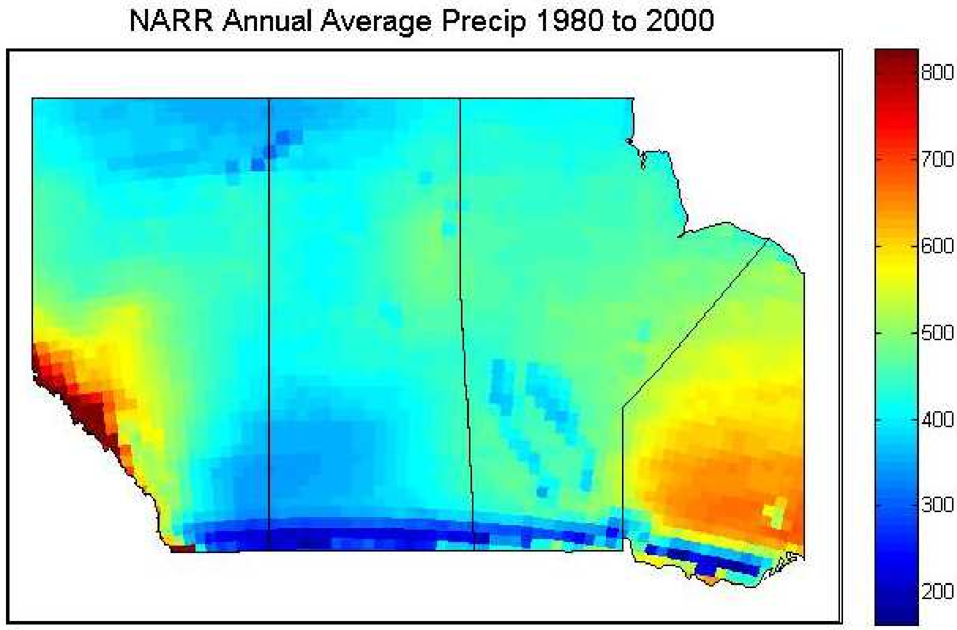

Figure 3.2: Annual average NARR precipitation [unit: mm].

3.2.1 Spatial distribution of NARR precipitation

Gridded average annual and seasonal NARR precipitation for the period of 1980 - 2000 are shown in Figures 3.2 and 3.3. The average annual precipitation plot shows a narrow band of a substantially lower precipitation in the southern part of the Prairie region along the border between Canada and the US. Considering the shape and the location of this anomaly, it seems reasonable to hypothesize that it is caused by a systematic error in the assimilation processes associated with the difference in observed precipitation input.

For further investigation of this issue, the average seasonal precipitation is plotted in Figure 3.3. The severity of the band anomaly appears to depend on the season. In the winter time, the band is weak although still recognizable. In spring and fall,

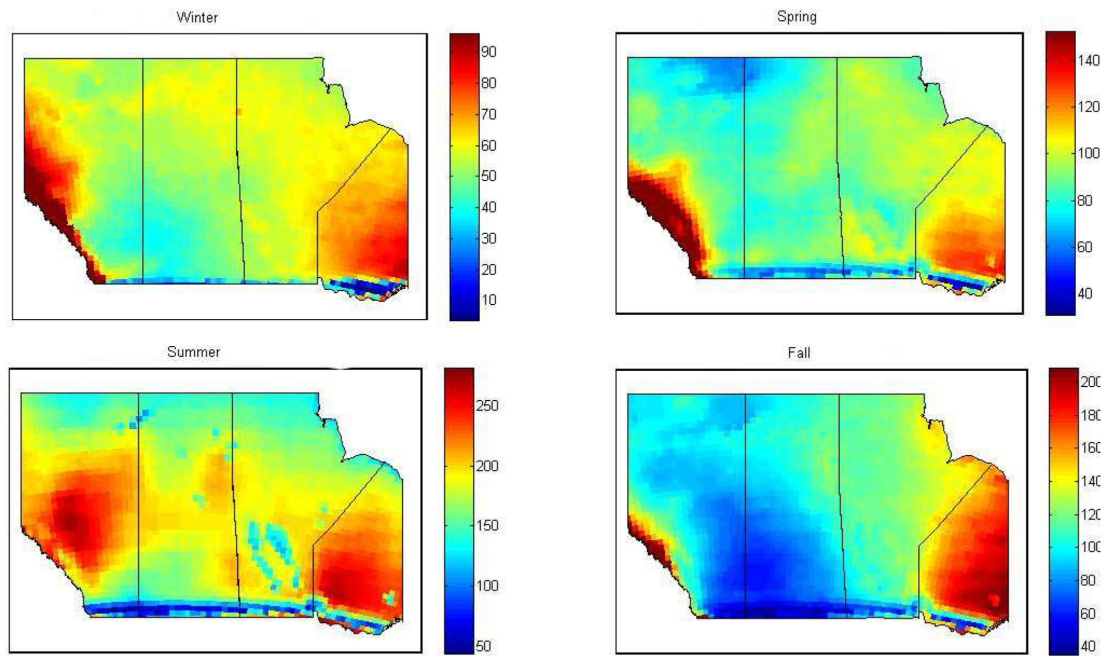

Figure 3.3: Seasonal average NARR precipitation (Winter = DJF; Spring = MAM; Summer = JJA; Fall = SON) [unit: mm].

the band is clearly distinguishable but less severe than summer. The precipitation input data sets used to construct NARR need to be disaggregated into hourly values, and, as mentioned earlier, the disaggregation process is different in Canada and the US. The CMAP data sets used in the US is reliable only up to about 50° N close to where the Canada-US border is located. In order to avoid the sharp discontinuity along the borders, *Shafran et al.* (2004) added a blending to the Eta code to adjust the influence of the CMAP data during the assimilation processes. The narrow band of bias most likely occurs as a result of the way different data sets were integrated into the assimilation.

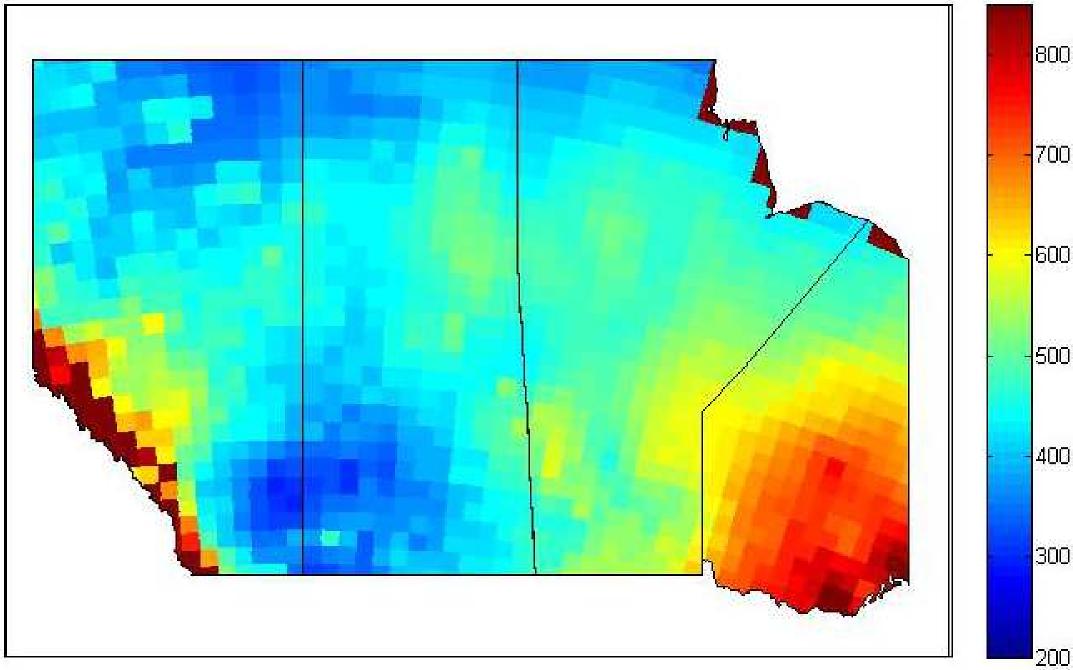

Figure 3.4: Annual average CANGRID precipitation [unit: mm].

3.2.2 Gridded observation data sets

Canadian Gridded Climate Data (CANGRID)

CANGRID is a Canadian climate archive data set of monthly total precipitation and mean temperature data, interpolated to 50 km grid scale and available from 1896 to present. CANGRID was developed for climate trend and variability studies and is based on statistical optimal interpolation of the Adjusted Historical Canadian Climate Data (AHCCD)[1]. This statistical optimal interpolation method is known to perform better than many empirical methods in sparsely and unevenly distributed climate networks. Recently, CANGRID has been combined with near real-time observations in the CTVB (Climate Trends and Variations Bulletin) for up-to-date

[1] http://www.ec.gc.ca/adsc-cmda/default.asp?lang=En&n=F3D25729-1

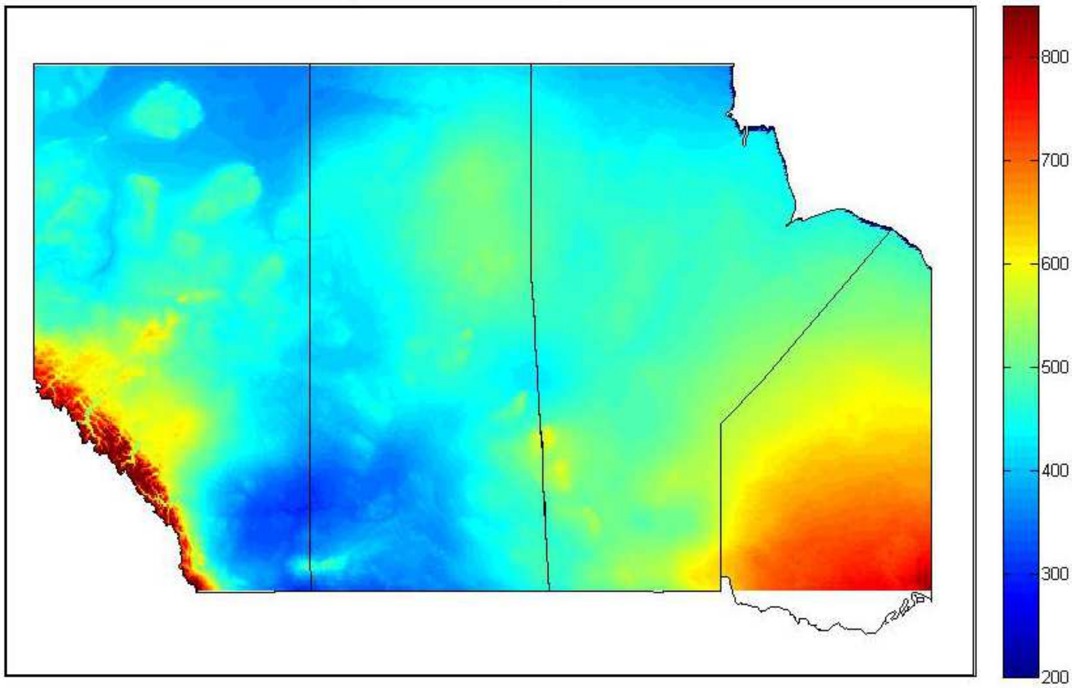

Figure 3.5: Annual average ANUSPLIN precipitation [unit: mm].

continuous climate monitoring on a monthly, seasonal, and annual basis. The CANGRID data is provided free of charge for public use under the copyright of Environment Canada. The average of annual CANGRID precipitation over the Prairie regions for the period 1980-2000 is shown in Figure 3.4.

ANUSPLIN

Agri-Geomatics, in collaboration with Natural Resources Canada (NRCan), Environment Canada, and the Australian National University, recently released a daily 10 km Raster-Gridded Climate data set called ANUSPLIN for the Canadian landmass south of 60°N. The ANUSPLIN contains gridded data of daily maximum and minimum temperature, and precipitation, interpolated from daily Environment Canada climate station observations using a thin plate smoothing spline surface fitting method. The model fits thin-plate smoothing spline surfaces to multivariate noisy data and uses a non-parametric version of standard multivariate linear regression. The model is fitted to observational data using generalized cross-validation (Agriculture and Agri-Food Canada[2]). Figure 3.5 shows the distribution of average annual precipitation over the Prairie regions. Because the data set was initially developed for the Prairie regions of Alberta, Saskatchewan, and Manitoba, some grid points are missing in the southern part of western Ontario.

3.2.3 Data comparison

First, the gridded average annual precipitation of NARR was compared with the same data from CANGRID and ANUSPLIN. Since the three data sets contain data at different grid resolutions, some regridding was required. For comparison of two data sets, the data set with the highest resolution was regridded to the larger grid size. For comparison of NARR and CANGRID, the NARR data (32 km) were regridded using linear interpolation unto the CANGRID grid (50 km). When comparing NARR with ANUSPLIN, the ANUSPLIN data (10 km) were interpolated unto the NARR grid (32 km).

Figure 3.6 shows the difference of average annual precipitation in NARR and CANGRID (NARR minus CANGRID). The annual precipitation difference in most of the Prairie region is within a ±50 mm range, except some regions such as the

[2] http://www4.agr.gc.ca/AAFC-AAC/display-afficher.do?id=1227620138144&lang=eng

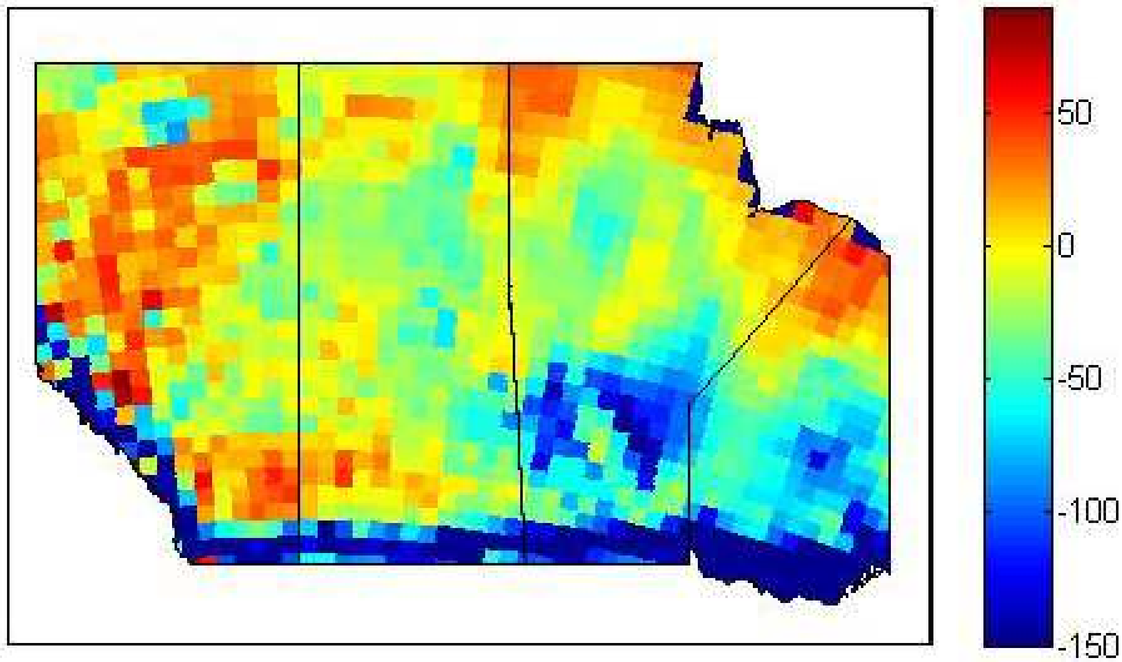

Figure 3.6: Differences between annual precipitation of NARR and CANGRID [unit: mm].

area around Lake Winnipeg and Lake Manitoba, the mountainous regions in western Alberta, as well as the Canada-US border line. In both Figures 3.2 and 3.3 showing NARR data, the shapes of the two lakes are distinguishable, but they are absent from CANGRID (Figure 3.4). Clearly, the lakes were not considered in the interpolation process. Also, there is no elevation adjustment in CANGRID so the gridded values in elevated terrain such as the Rockies are unlikely to reflect the full orographic influence, and it is generally recommended that the CANGRID data not be used in mountainous areas. Therefore, the NARR data is possibly more accurate in the lake and the mountainous regions than the CANGRID data. The aforementioned narrow band of underestimated precipitation bias clearly appears in the plot along the border line.

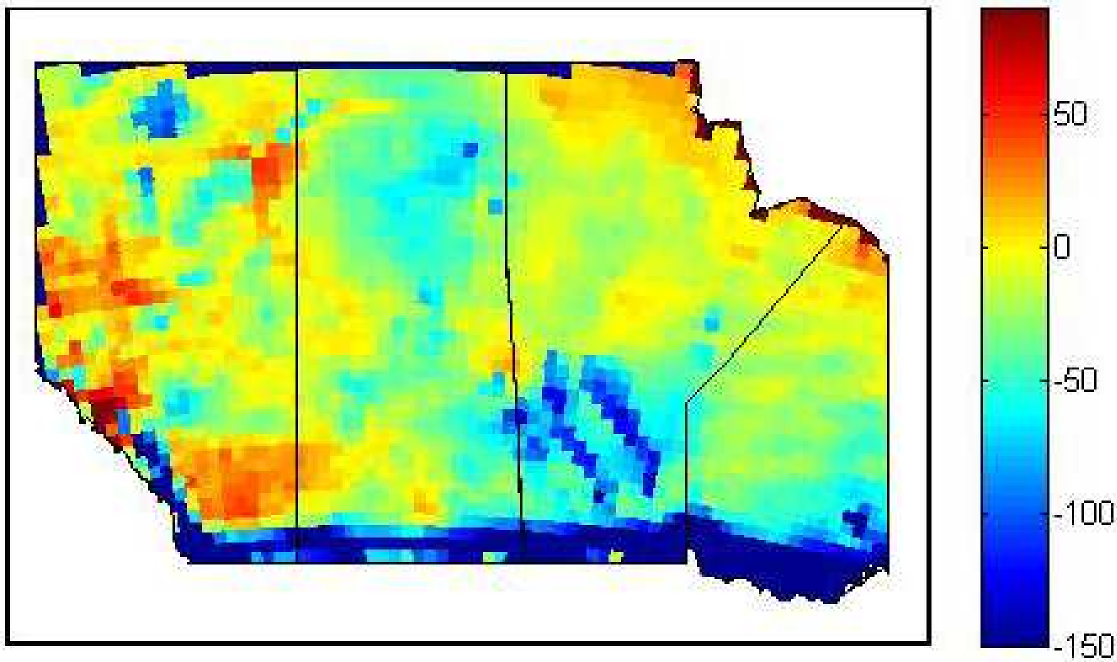

Figure 3.7: Differences between annual precipitation of NARR and ANUSPLIN [unit: mm].

Figure 3.7 depicts the difference of average annual precipitation between NARR and ANUSPLIN (NARR minus ANUSPLIN). The result is quite similar to the comparison with CANGRID. Again, the lake areas and the narrow band bias show the most significant differences. Apart from the above mentioned areas, the discrepancy is within a ±50 mm range. It should be noted that the southern part of north-western Ontario should be disregarded due to the absence of ANUSPLIN data for comparison.

There are some slight differences between the two comparison results, especially in the northern parts of the Prairies and near mountainous area. NARR precipitation appears slightly higher than CANGRID in the northern area, especially in northern Alberta and Manitoba, while this is less evident in the comparison with ANUSPLIN.

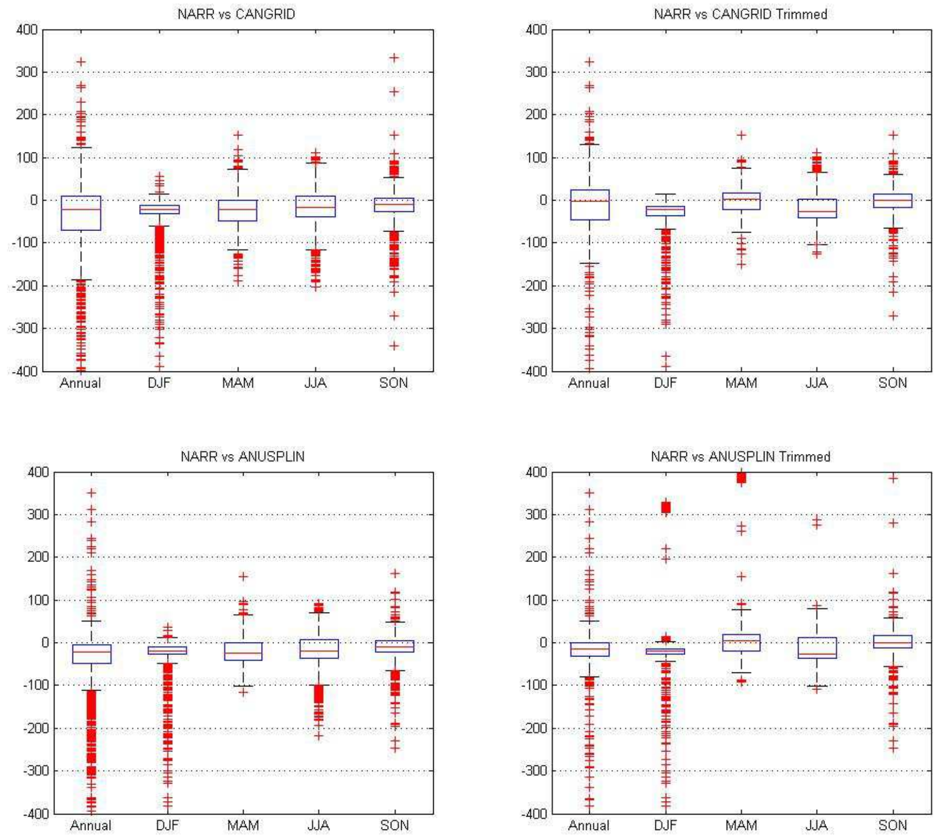

Figure 3.8: Boxplots of annual and seasonal precipitation discrepancies between NARR and CANGRID and between NARR and ANUSPLIN for the full grid (left figures) and the trimmed grid that excludes the border band (right figures).

Moreover, as ANUSPLIN takes into account the elevation in its interpolation scheme, the discrepancies in the mountainous area are within the general range of ± 50 mm.

In order to summarize the data discrepancy between grid point values in two different spatial data sets, a boxplot representation is used, see Figure 3.8. To better appreciate the significance of the narrow band bias, the box plot comparison was performed in two ways. The data were first compared at all grid points (left panels in Figure 3.8), and then a reduced set of grid points that excluded the narrow band was compared (right panels in Figure 3.8).

When all grid points are considered in the comparison with CANGRID, the medians of annual and seasonal precipitation discrepancies are overall negative. The central 50% of the distribution, represented by the box, of the annual precipitation discrepancies lies between -75 mm and 5 mm and 99.3% (range of the whiskers) lies between -200 mm and 110 mm. The seasonal precipitation data show a similar pattern. Overall, it is clear that NARR precipitation has a significant negative bias relative to CANGRID. When the grid points in the border band are excluded, the medians of precipitation discrepancies move up to 0 mm in annual, spring, and fall, while the medians in winter and summer are still negative. 50% of the distribution of the annual precipitation discrepancies lies between -50 mm and 15 mm and 99.3% lies between -150 mm and 120 mm. It is clear that the border band is associated with significant negative biases. The seasonal precipitation show that the boxes in winter and summer stays almost the same and that the boxes in the annual, spring, and fall distributions move up.

The comparison results of ANUSPLIN are similar to the results from CANGRID, except for the ranges of boxes and whiskers. The box range of annual precipitation discrepancies in the full grid is between -50 mm and 0 mm, and the whiskers lie between -110 mm and 50 mm, which is significantly narrower than what was found in the CANGRID comparison. The results for the seasonal comparison of the border-excluded data set with ANUSPLIN are similar to the CANGRID comparison, but the change of annual median in ANUSPLIN is minimal compared to the CANGRID comparison. Again, the noticeable differences by excluding the narrow bias band indicate that the bias is specifically localized in the area. The relatively small discrepancies in areas other than the bias band indicate that the NARR precipitation reasonably represents the climatology in the Prairie region.

Considering the sophisticated nature of ANUSPLIN, the data set is most likely better than CANGRID. The narrower range of discrepancy between NARR and ANUSPLIN provides a basis for confidence in NARR precipitation, at least in terms of seasonal means and spatial distribution.

The main motivation for studying NARR in this thesis is to assess its reliability in remote regions such as the northern part of the Prairie provinces, approximately above 55°N. Thus, the comparison results that exclude the narrow border band provide an appropriate validation. Nonetheless, further evaluation of the bias problem is required.

3.3 Comparison with Weather Station Data

To assess the reliability of NARR as a proxy for observed climate data at station scale, the NARR data was compared to information from selected weather stations. The evaluation was conducted for two climate variables, temperature and precipitation, which are key input to hydrological models. As an improved version of NNGR (NCEP-NCAR Global Reanalysis), NARR is expected to show better agree-

Table 3.1: Daily temperature statistics of NARR, NNGR, ERA-40 and stations. (RMSE = root mean square error; R = correlation)

	OBS	NARR			NNGR			ERA-40		
Station	Avg	Avg	RMSE	R	Avg	RMSE	R	Avg	RMSE	R
Brandon	2.2	3.9	3.37	0.98	2.4	2.92	0.98	3.0	2.25	0.99
Churchill	-6.6	-5.9	3.56	0.97	-7.1	3.64	0.97	-6.0	2.72	0.99
Dauphin	2.3	3.2	3.46	0.97	2.0	3.48	0.97	2.4	3.06	0.98
The Pas	0.4	1.4	2.90	0.98	0.2	2.82	0.98	0.5	2.00	0.99
Thompson	-2.9	-1.1	3.50	0.98	-4.4	3.55	0.98	-2.0	2.38	0.99
Winnipeg	3.0	4.0	3.02	0.98	2.1	2.94	0.98	3.2	2.20	0.99
Average	-0.2	0.9	3.30	0.98	-0.8	3.23	0.98	0.2	2.44	0.99

ment with observations on a regional scale due to the higher spatial resolution and general reliability. In order to verify the better agreement of NARR compared to other reanalysis products, the NNGR and ERA-40 were included in the analysis. The comparison was conducted for daily, monthly, and annual time scales based on basic statistics such as averages, root mean square errors (RMSE), and correlation coefficients (R) for each time scale.

The observed data sets were obtained from six Environment Canada weather stations: Winnipeg, Brandon, Dauphin, The Pas, Thompson, and Churchill. The comparison period was chosen as 1981-2000 because ERA-40 covers only the period from mid-1957 to mid-2002. The NARR, NNGR, and ERA-40 data sets were retrieved from the grid points closest to each weather station and interpolated to the locations of the weather stations using a linear interpolation scheme.

3.3.1 Temperature

The average daily temperature of observations, NARR, NNGR, and ERA-40 are compared in Table 3.1. NARR and ERA-40 overestimate daily temperature in general while NNGR underestimates at most stations. NARR temperature is approximately 1°C higher than observed temperature, while NNGR and ERA-40 are approximately 0.8°C lower and 0.2°C higher, respectively. Table 3.1 also shows the RMSE and daily correlation, R, values of the daily temperature. ERA-40 has the lowest average RMSE of 2.4 °C for the six stations, while NARR and NNGR has RMSEs of 3.3 °C and 3.2 °C. The correlations of daily average temperature for each reanalysis are between 0.97 and 0.99 for all stations, with ERA-40 consistently showing the highest correlation.

The mean monthly temperatures for all data sets are compared in Figure 3.9. All reanalysis data sets appear in reasonable agreement with observations. The NARR temperature shows the best agreement with observations in Churchill for all months, but overestimates temperature in summer at other locations, especially in Brandon and Winnipeg. NNGR shows significant underestimation in spring and autumn at many stations while ERA-40 shows better agreement for all seasons at most of the stations. In summary, all three reanalysis products have temperature biases of less than 1°C, average RMSE values of less than 3.3 °C, and a high daily correlation of over 0.97. These results suggest that temperature data from reanalyses, in general, are highly reliable and suitable for use in hydrological studies.

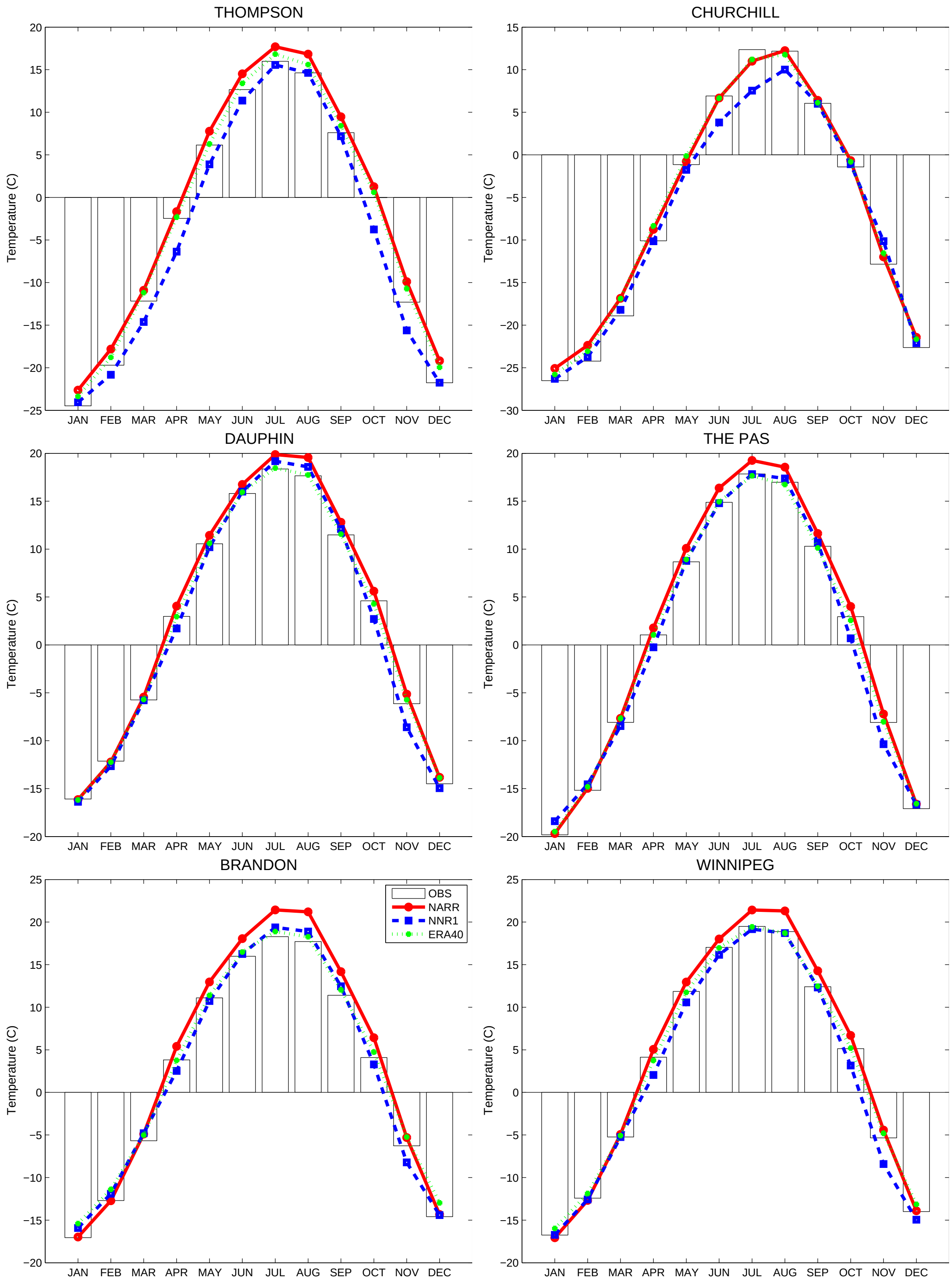

Figure 3.9: Mean monthly temperature from NARR, NNGR, ERA-40 and weather stations.

3.3.2 Precipitation

Table 3.2 compares the annual mean precipitation and daily precipitation RMSE of reanalysis data sets with observations at the six reference sites. The annual average precipitation of NARR and ERA-40 are, respectively, about 6% and 2% less than observed precipitation overall, while NNGR overestimates than observed annual average precipitation by 25%. In the comparison of individual stations, the difference of annual average precipitation between NARR and observations in Brandon, Dauphin, and Winnipeg is more than 50 mm; indeed, NARR precipitation is substantially lower than other reanalyses and observations at these locations. Winnipeg and Brandon are located within the bias band identified in Section 3.2 and the significant underestimation concurs with the bias issue. However, except for Dauphin the annual average precipitation of NARR at stations located outside of the bias band show only small differences (less than 4%). ERA-40 appears to better estimate

Table 3.2: Average annual precipitation and daily precipitation RMSE of observations, NARR, NNGR, and ERA-40.

	Annual mean precipitation (mm)				RMSE (mm)		
Station	OBS	NARR	NNGR	ERA-40	NARR	NNGR	ERA-40
Brandon	472.1	421.1	609.4	465.6	3.50	4.34	3.87
Churchill	448.8	450.2	467.3	431.8	2.44	2.97	2.78
Dauphin	516.6	460.6	640.4	472.9	4.06	4.48	4.06
The Pas	440.5	445.3	684.9	476.2	2.67	3.52	3.05
Thompson	497.1	477.8	562.4	471.5	3.34	3.85	3.00
Winnipeg	523.7	455.6	671.5	530.2	3.76	4.86	4.32
Average	483.1	451.8	606.0	474.7	3.29	4.00	3.51

Table 3.3: Daily (R_{day}) and monthly (R_{mon}) correlation between observations and NARR, NNGR, and ERA-40.

Station	Correlation (R_{day})			Correlation (R_{mon})		
	NARR	NNGR	ERA-40	NARR	NNGR	ERA-40
Brandon	0.59	0.45	0.50	0.90	0.72	0.77
Churchill	0.72	0.55	0.61	0.90	0.57	0.77
Dauphin	0.54	0.46	0.53	0.81	0.71	0.74
The Pas	0.73	0.56	0.62	0.95	0.68	0.80
Thompson	0.57	0.47	0.67	0.81	0.76	0.83
Winnipeg	0.64	0.42	0.50	0.90	0.72	0.81
Averaged	0.63	0.48	0.57	0.88	0.69	0.79

precipitation at the two stations located within the bias band and in Dauphin; however, worse agreement is observed at the other stations compared to NARR. NNGR overestimates the annual average precipitation overall, up to as much as 240 mm in The Pas.

The daily precipitation of NARR has the lowest RMSE of 3.3 mm which suggests daily precipitation differences are less than other reanalyses. It is notable that the RMSE statistic gives a relatively high weight to large errors. Therefore, the RMSE comparison may suggest that NARR estimates large daily precipitation events better than NNGR and ERA-40.

The daily and monthly precipitation correlations between reanalysis and observations are compared in Table 3.3. The averages of daily and monthly correlations of NARR precipitation are 0.63 and 0.88, respectively, and both correlations are significantly higher than the correlation averages of NNGR and ERA-40. At most of the stations, the correlation of NARR is about 0.2 and 0.1 higher than the correlations of NNGR and ERA-40, respectively, except in Thompson where the daily and monthly correlations of ERA-40 precipitation are higher than NARR. The higher correlations of NARR compared to other reanalyses in the band bias area should not be a surprise since bias and correlation measure largely different aspects. The higher correlations and lower RMSE of NARR precipitation may indicate that the NARR daily precipitation agree better with larger daily precipitation events despite of the general underestimation in the bias band.

A scatter plot is a useful way to visualize the day-to-day match of daily precipitation. Figure 3.10 shows scatter plots of daily precipitation, with markers representing different reanalysis data: red circles for NARR, blue crosses for NNGR, and green triangles for ERA-40. The monthly and annual averages of NARR precipitation in Churchill are almost the same as observations, and the daily precipitation of NARR (red circles in left panel of Figure 3.10) in the scatter plot are found near the 45°-line. Moreover, at higher values NARR is generally closer to the 45°-line than NNGR and ERA-40.

A Q-Q (quantile-quantile) plot is useful for comparing the shapes of two distributions. Figure 3.11 shows Q-Q plots of observations and reanalysis data sets, using the same marker representation as in the scatter plots. In Figure 3.11 (left panel), the NARR precipitation at Churchill lies on the left side of the 45°-line, suggesting an underestimation of precipitation compared to observations. However, the dots for NARR lie nearer the line than the dots of NNGR and ERA-40, indicating

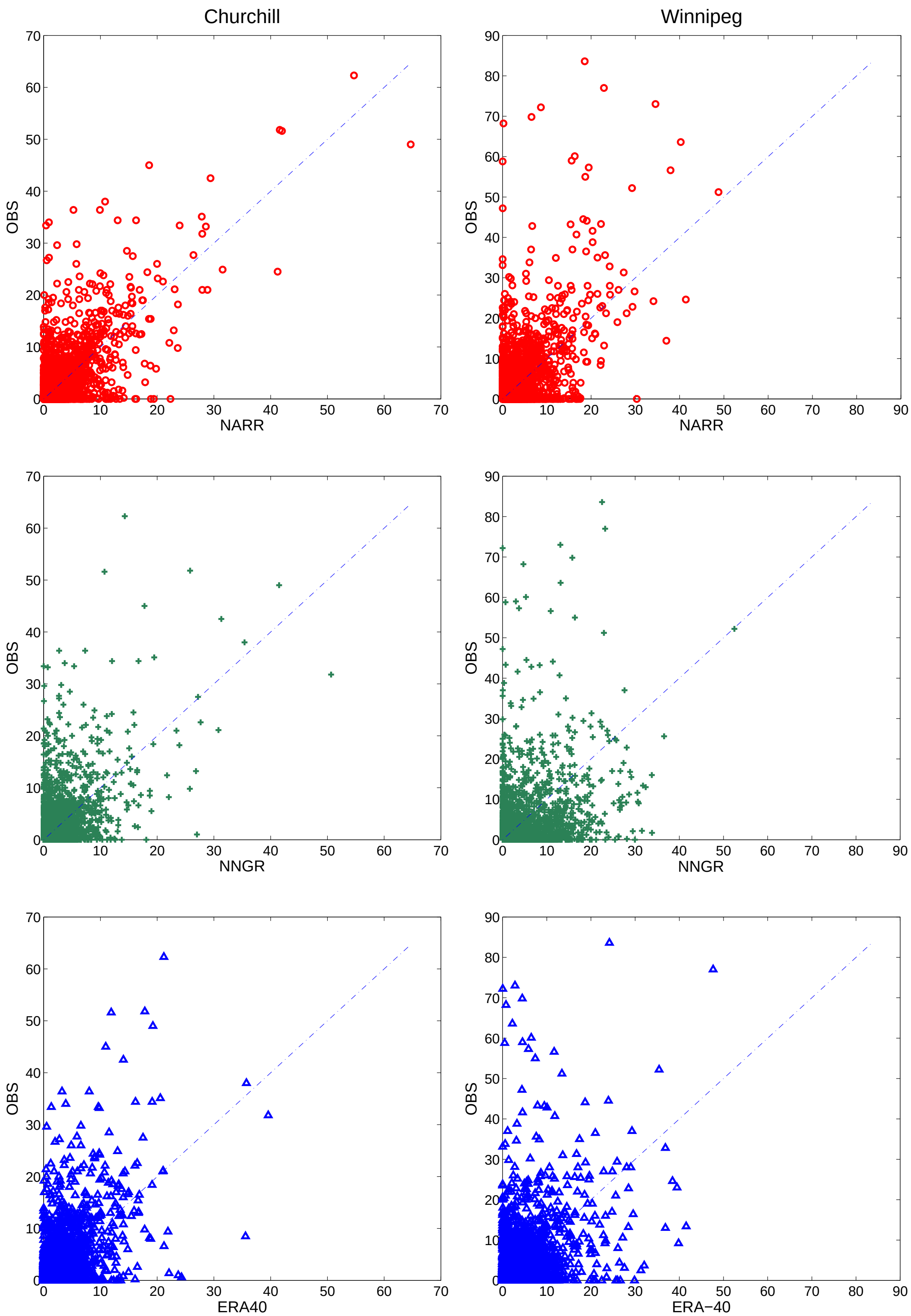

Figure 3.10: Scatter plot for NARR, NNGR, and ERA-40 against observation in Churchill (left) and Winnipeg (right) [unit: mm] (see Figure A.1 for other stations).

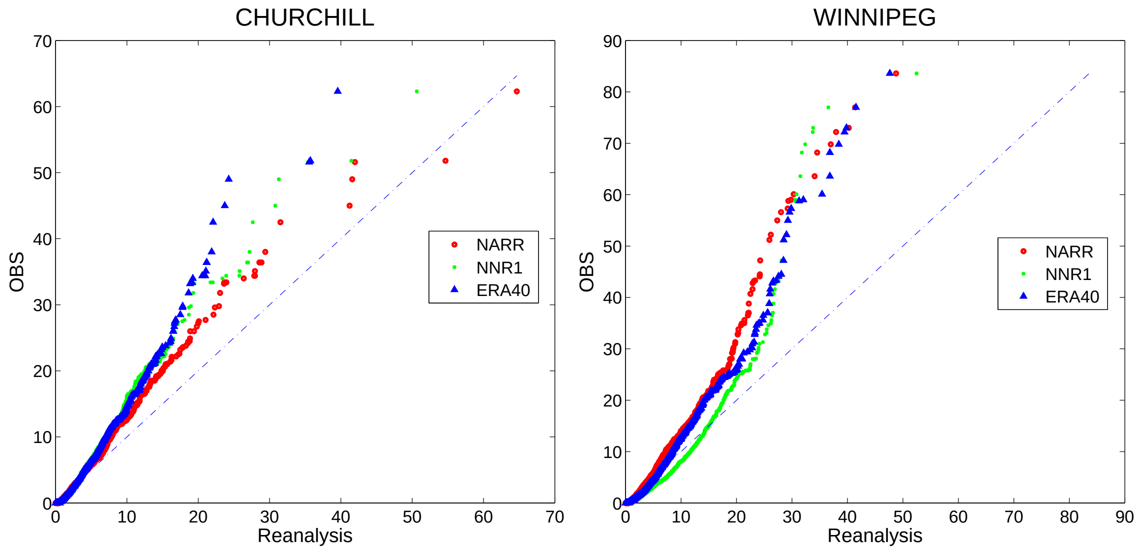

Figure 3.11: Q-Q plot for NARR, NNGR, and ERA-40 against observation in Churchill (left) and Winnipeg (right) [unit: mm] (see Figure A.2 for other stations).

that NARR estimates larger precipitation events better than NNGR and ERA-40 at Churchill. On the other hand, in Winnipeg (Figure 3.11, right panel) NARR and NNGR significantly underestimate daily precipitation, while the ERA-40 lies closer to the 45°-line. However, precipitation of all reanalysis at higher quantiles appear to be similar to each other.

An investigation of seasonal precipitation is also an important component of the evaluation of reanalysis products. Figure 3.12 shows that NNGR significantly overestimates precipitation in spring and summer at most stations, except in Churchill where the summer precipitation is significantly underestimated. It is reasonable to suspect that due to the coarse resolution of NNGR, the influence of the ocean is not well-captured at the grid points near Churchill. NARR precipitation shows significant improvement over NNGR at all stations. In Winnipeg, Brandon, and Dauphin,

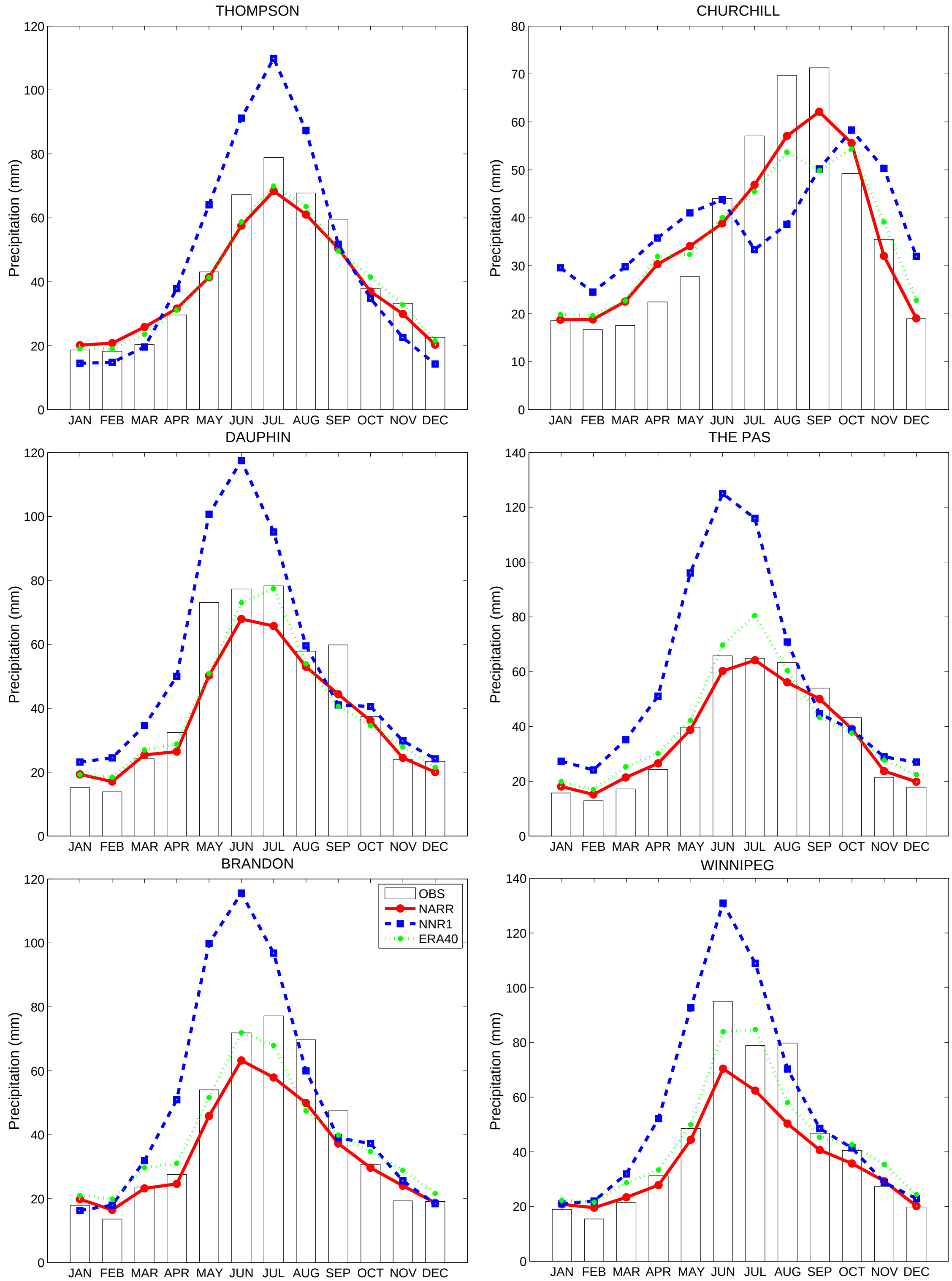

Figure 3.12: Mean monthly precipitation from NARR, NNGR, ERA-40, and weather stations.

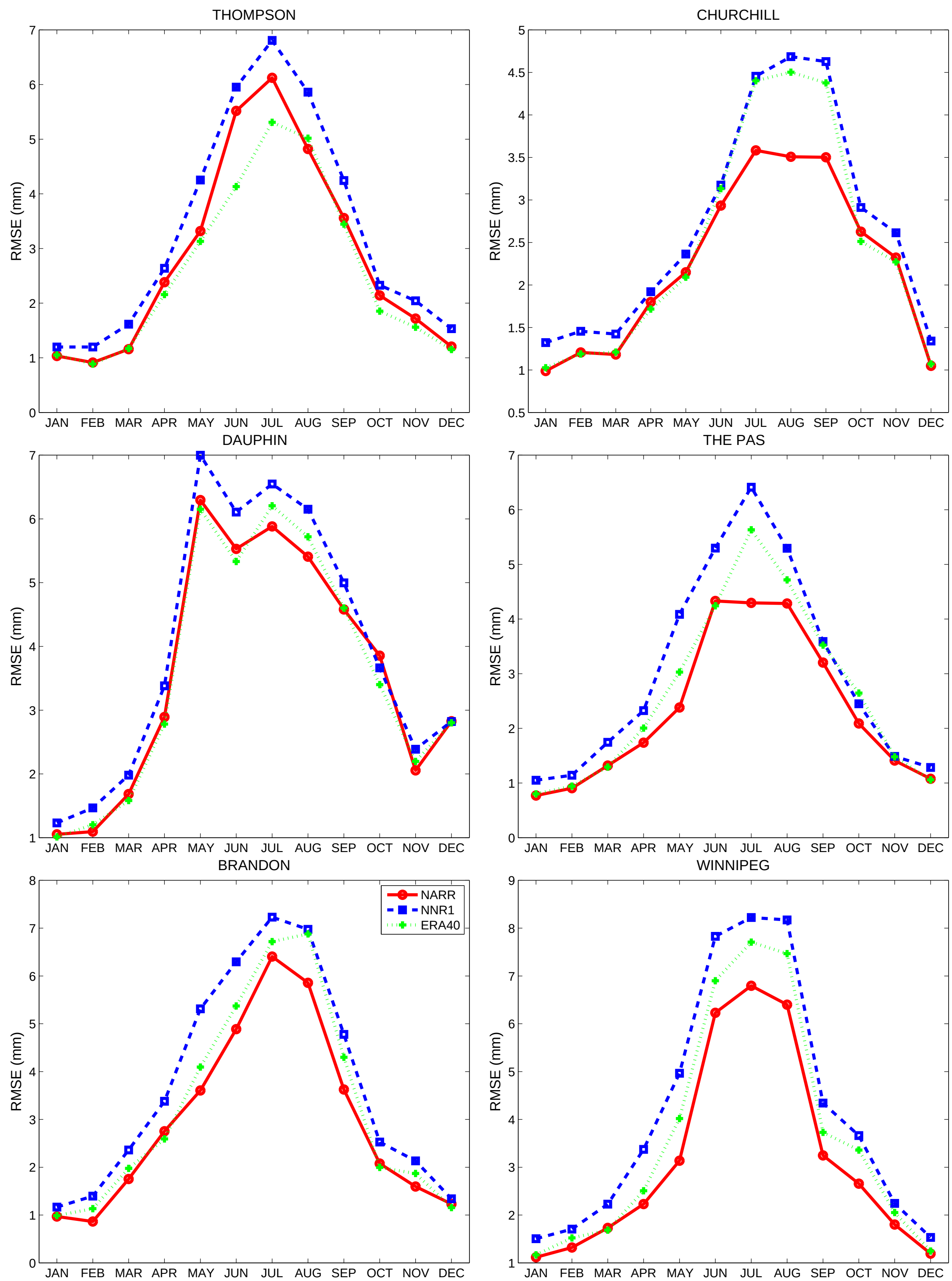

Figure 3.13: Mean Monthly RMSE for NARR, NNGR, and ERA-40.

NARR precipitation during the summer months is lower than observations which in the case of Winnipeg and Brandon is a product of the bias of NARR precipitation in the band area. NARR precipitation is also lower than observations in other seasons, particularly fall and early winter. In terms of mean monthly precipitation, the ERA-40 precipitations agree better with observations than NARR in the bias band area and show similar agreement as NARR at other stations.

As mentioned before, although some averages of ERA-40 precipitation agree better with observations than averages of NARR, it does not necessarily imply that ERA-40 precipitation estimate the day-to-day match better. Figure 3.13 shows the mean monthly RMSE of daily precipitation. The NNGR clearly has higher RMSEs in all seasons compared to NARR and ERA-40. The monthly RMSEs of NARR are lower than ERA-40 in the summer and the two are fairly close to each other in other seasons. Although the mean monthly precipitation of ERA-40 may be closer to observations than NARR, the day-to-day errors of NARR appear to be less than ERA-40, indicating that NARR may represent the day-to-day precipitation events better than ERA-40. Based on the above comparison, it can be concluded that NARR considerably improves upon the NNGR precipitation in all respects. The ERA-40 precipitation also shows significantly better agreement with observations than NNGR and even NARR for some cases in the narrow bias band area. However, in the comparisons of RMSE and correlations, NARR appears to be better than ERA-40.

3.3.3 Comparison over the Prairie region

The Prairie provinces, i.e. Alberta, Saskatchewan, and Manitoba, contain geologic and climatologic similarities over vast areas, but also contain unique features such as the Canadian Rockies, the Prairie Pothole region stretching from Alberta through the middle and lower portion of Saskatchewan to the southern portion of Manitoba, the Boreal Plains found in central Alberta, extending east through the center of Saskatchewan and into the center of Manitoba, and the Boreal Shield extending from northern Saskatchewan east to Newfoundland, passing north of Lake Winnipeg, the Great Lakes and the St. Lawrence River. An assessment of NARR over the entire Prairie regions with its diverse ecozones will provide a broader understanding of its reliability, consistency, and usability in central Canada.

In this section, the area for assessment is expanded to the three Prairie provinces, Alberta, Saskatchewan, and Manitoba, and to a section of north-western Ontario. The diversity of geological and geographical characteristics was considered for station selection. In the first part of this chapter, it was found that NNGR clearly overestimates precipitation amounts compared to NARR and ERA-40. Thus, only ERA-40 is included in the assessment in this section. The weather stations were selected considering the length and quality of the records. The NARR data is available from 1979 to present and the ERA-40 data is available from 1957 to 2002. The period of 1981 - 2000 was selected for the assessment. Initially, weather stations in central Canada with historical climate records for the assessment period were identified.

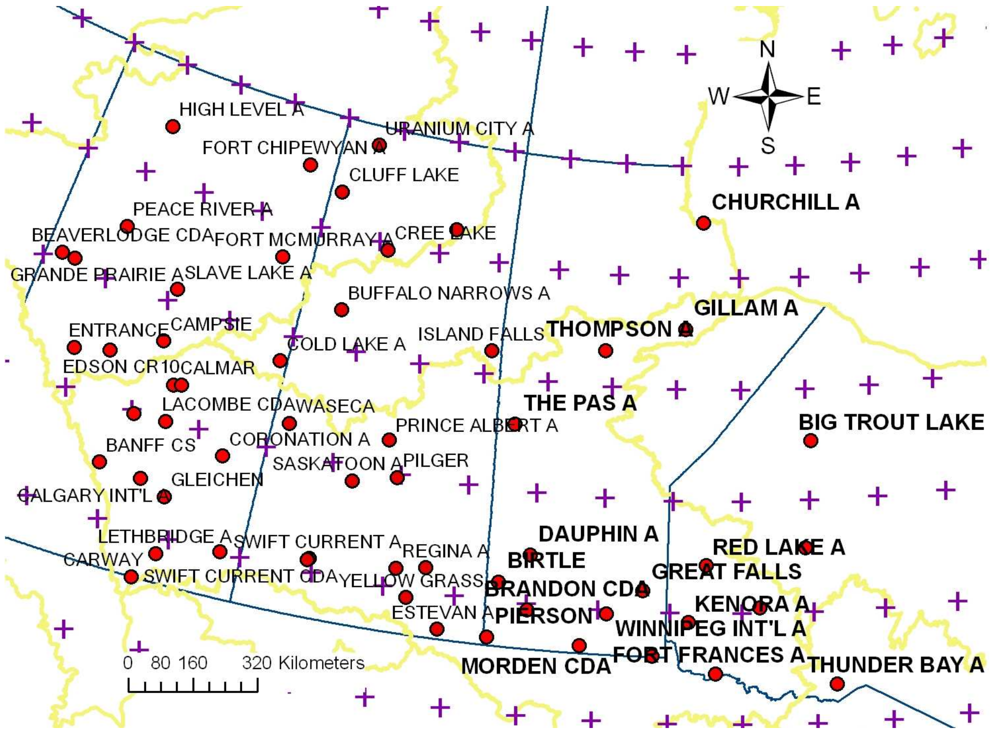

Figure 3.14: Selected weather stations in Prairie regions.

Stations with more than 30 % missing records were removed. Some further screening led to 50 weather stations over the Prairie region, including 10 stations in Manitoba, 5 stations in Ontario, 15 stations in Saskatchewan, and 20 stations in Alberta (see Figure 3.14). The NARR and ERA-40 data were collected at the grid points nearest to each selected station following the same procedure as in the previous section.

Table 3.4 shows the averaged RMSEs of daily mean temperature and precipitation for each province (see Table A.1, A.2, A.3, and A.4 for each station in each province, respectively). The averaged temperature RMSEs of NARR is higher than the average of ERA-40 by 0.7 overall and is also higher in all individual provinces. On the other hand, the averaged RMSEs of NARR precipitation is lower than ERA-40 by 0.2 overall and in all individual provinces. In Table 3.5 it is seen that the

Table 3.4: Comparison of daily temperature and precipitation averages and RMSEs of NARR and ERA-40 with observations.

Province	Daily Mean Temperature (°C)					Daily Precipitation (mm)				
	OBS	NARR		ERA-40		OBS	NARR		ERA-40	
		Avg	RMSE	Avg	RMSE		Avg	RMSE	Avg	RMSE
MB (10)	0.1	1.2	3.3	0.5	2.7	1.3	1.1	3.4	1.3	3.9
ON (5)	2.3	3.1	2.8	2.0	2.5	1.9	1.2	4.5	1.7	4.7
SK (15)	2.1	2.9	3.1	2.4	2.5	1.1	1.0	3.0	1.2	3.4
AB (20)	3.0	3.0	3.2	2.8	3.0	1.2	1.3	3.2	1.3	3.5
Total	1.9	2.6	2.9	1.9	2.7	1.4	1.2	3.5	1.4	3.9

mean temperature correlations between observation and both NARR and ERA-40 are above 0.97 for the daily time scale and almost 1.00 for monthly in all Prairie provinces. The daily precipitation correlations, averaged over all provinces, are 0.6 for NARR and 0.5 for ERA-40. The monthly precipitation correlations average 0.9 and 0.78 for NARR and ERA-40, respectively. The correlations of ERA-40 for temperature are slightly higher than NARR, but for precipitation NARR clearly shows better correlations with observations at most stations. In all provinces, the precipitation correlations of NARR are 0.1 higher than ERA-40 at both daily and monthly time scales.

In order to identify spatial patterns in precipitation correlations, the precipitation correlations of NARR and ERA-40 are displayed on maps. Figure 3.15 depicts the correlations of monthly precipitation from NARR (above) and ERA-40 (below) with observations (see Figure A.3 for daily precipitation). The monthly correlations of NARR are around 0.9 from the US border to above the central part of each province

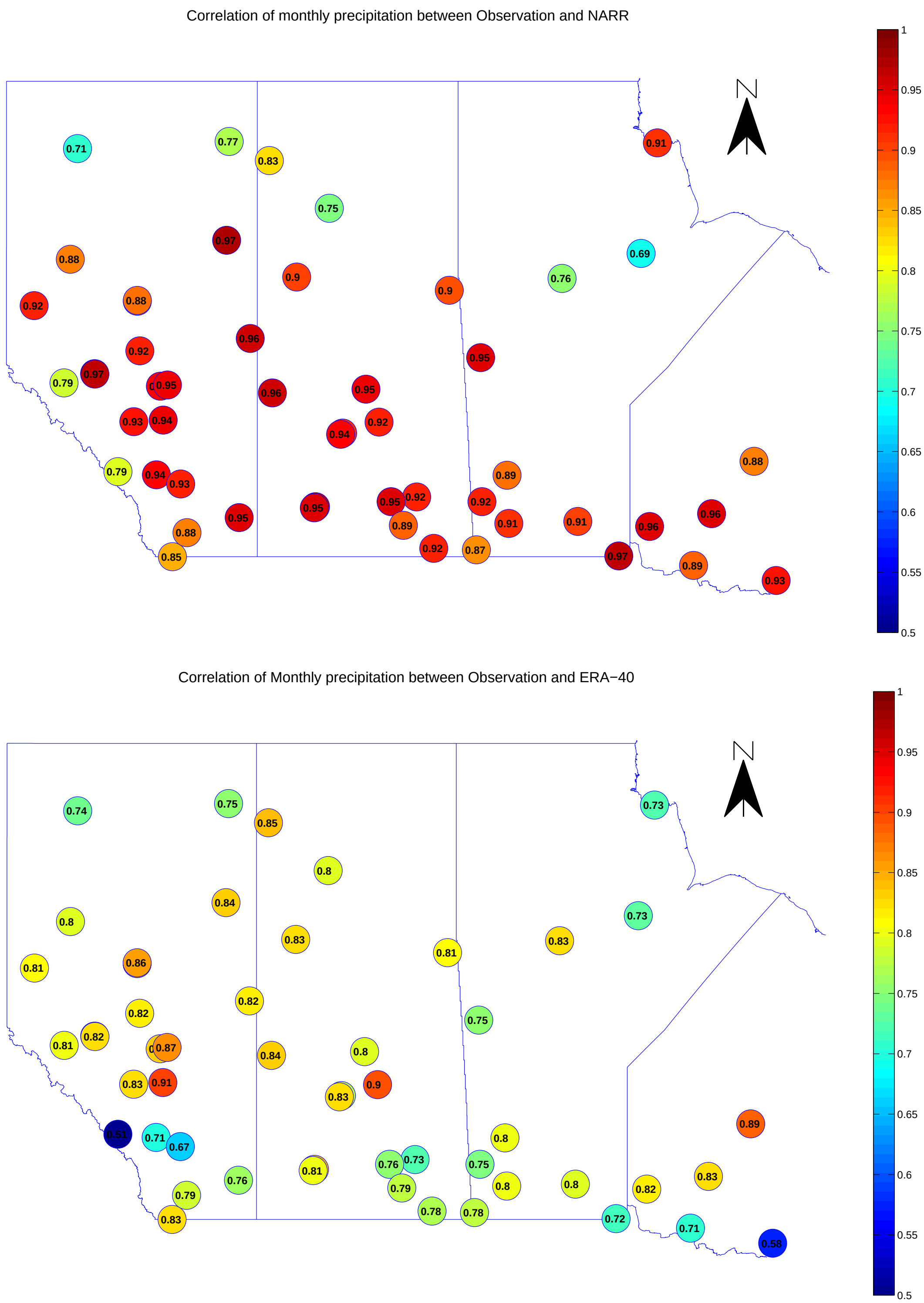

Figure 3.15: Correlation coefficient of observed station and NARR and ERA-40 monthly precipitation.

Table 3.5: Correlation comparison of temperature and precipitation from NARR and ERA-40 with observations.

Province	Mean Temperature (°C)				Total Precipitation (mm)			
	Daily		Monthly		Daily		Monthly	
	NARR	ERA-40	NARR	ERA-40	NARR	ERA-40	NARR	ERA-40
MB (10)	0.98	0.99	1.00	1.00	0.59	0.49	0.88	0.77
ON (5)	0.98	0.98	1.00	1.00	0.63	0.52	0.92	0.76
SK (15)	0.98	0.99	1.00	1.00	0.58	0.46	0.91	0.81
AB (20)	0.97	0.97	0.99	1.00	0.62	0.52	0.90	0.79
Total	0.98	0.98	1.00	1.00	0.60	0.50	0.90	0.78

and then gradually decreases northward to 0.7. The correlations at stations located in southern central Alberta and Saskatchewan are noticeably higher, around 0.95. This is a region where the station network is dense and the quality of station records is presumably better than in the remote regions. The correlations in the northern Boreal Shield area and the nearby Rocky mountain area are between 0.7 and 0.8 at some stations. These relatively low correlations suggest that the density of weather station network and the geographical characteristics such as variation of elevation may considerably affect the performance of NARR. The ERA-40 correlations of monthly precipitation shows a similar spatial pattern but are generally around 0.1 lower than NARR.

The spatial evaluation suggest that the high correlation and low RMSE of NARR precipitation is fairly consistent across the Prairie regions. Although the quality deteriorates northward, the results are still quite good and certainly hold promise for hydrologic modelling.

Chapter 4

APPLICATION OF NARR FOR HYDROLOGICAL MODELLING AND CLIMATE CHANGE IMPACT ASSESSMENT

4.1 Introduction

The uncertainty of input data for hydrological modelling significantly affects the model performance. *Sun et al.* (2002) demonstrated that the spatial distribution of precipitation and the representation of spatial conditions across a watershed affect errors in storm-runoff simulation and found that the accuracy of storm-runoff prediction considerably depends on the extent of spatial precipitation variability. *Michaud and Sorooshian* (1994) found that inadequate rain gauge densities can cause significant errors in simulated peaks, including a consistent reduction in simulated peaks due to the spatial averaging of precipitation. *Moulin et al.* (2009) investigated the influence of mean areal precipitation estimation errors in hydrological modelling and found that the mean areal precipitation estimations induce large uncertainties in hydrological simulations. They also affirmed that even in an optimal situation (good quality data sets and intensive effort in hydrological model selection and calibration), reducing runoff simulation errors can be difficult without a significant improvement of the precipitation measurement networks and techniques. *Bárdossy and Das* (2008) investigated the influence of the spatial resolution of the precipitation input on hydrological model calibration and found that models using different raingauge networks might need re-calibration of the model parameters.

As mentioned in Chapter 2, due to the lack of weather stations, it can be a challenge to perform hydrologic modelling of Northern Canadian watersheds. In Chapter 3, NARR was shown to be in good agreements with observed meteorological data at weather stations and thus may potentially be used in lieu of observed station data. The relatively good representation of precipitation in NARR suggests that the data can be used to improve the calibration and validation of hydrological models in areas where climate stations are limited in number or even non-existent. NARR may also be useful in statistical downscaling models. In this chapter, NARR will be applied to hydrological modelling and statistical downscaling.

4.2 Hydrological Modelling using NARR

4.2.1 Use of NARR as input to SLURP

Based on the findings in Chapter 3, it is reasonable to assume that NARR will be useful in hydrologic studies where observed climate data are lacking or of poor quality. As a preliminary evaluation of the reliability of NARR for hydrological modelling, the NARR data were applied to the three calibrated watershed models in northern Manitoba (Taylor, Burntwood, and Sapochi watersheds). The observed data of nearby weather stations (listed in Table 2.4) were interpolated to the centroid of each watershed for the model calibration and compared with the NARR data at the grid point closest to the centroid of each watershed. The observed mean monthly precipitation and temperature were compared with the corresponding statistics from NARR for each watershed as shown in Figure 4.1. NARR precipitation during the summer months is significantly lower than what is observed at weather stations. NARR precipitation is also lower than measured precipitation in fall and early winter. The goodness-of-fit is reasonable on a monthly time scale, but is low at the daily scale ($R \approx 0.5$). Average NARR temperatures between May and October are higher than observations. However, when annually averaged, the difference between NARR and stations temperature is negligible, and the goodness-of-fit of the daily series is

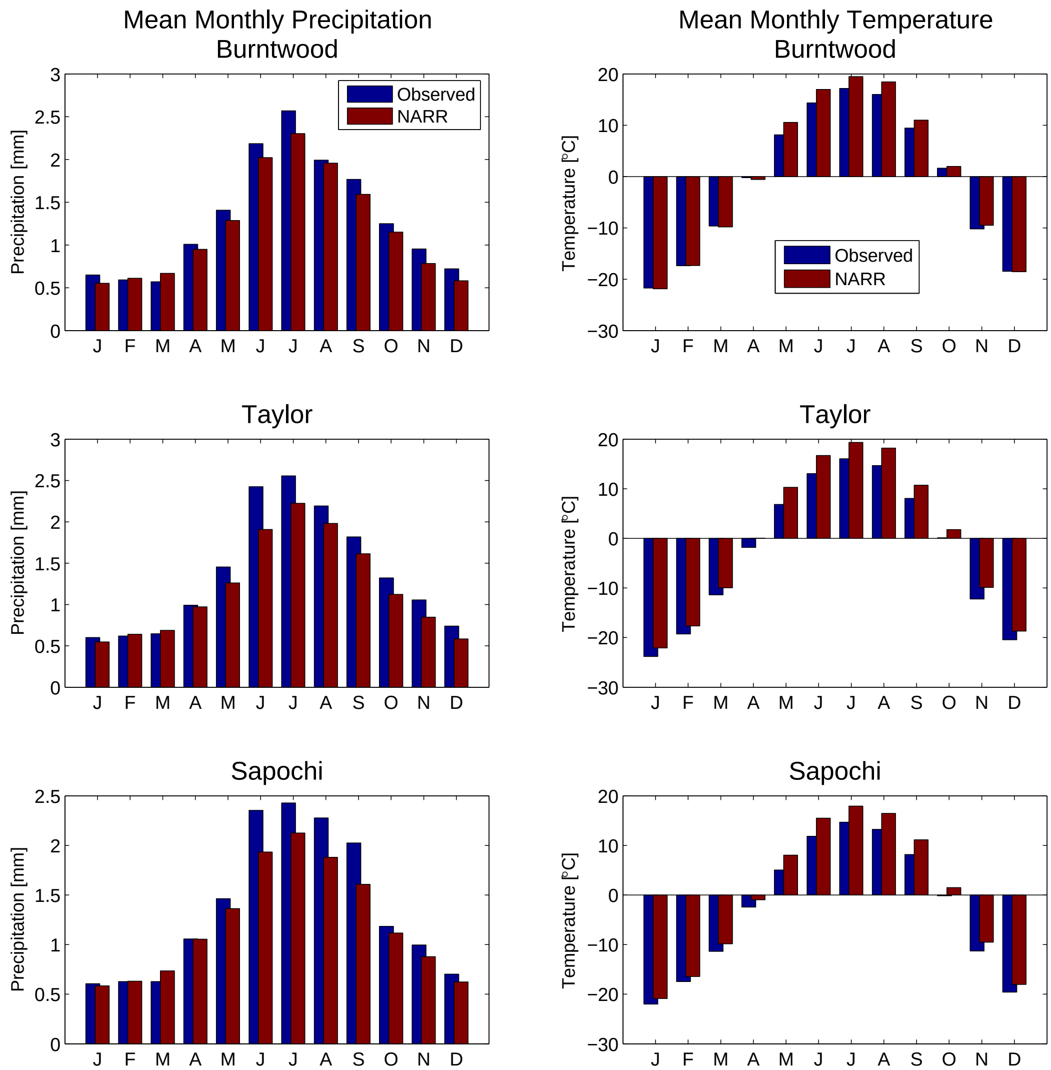

Figure 4.1: Mean monthly precipitation and temperature at each watershed.

high ($R > 0.9$). The daily NARR temperature is off the station data by a few degrees on average.

A series of experiments were designed to test the use (sensitivity) of NARR temperature and precipitation data as input to the SLURP models already calibrated with observed data. For each watershed, four different SLURP runs were performed for the period 1979-2004, using different combinations of input variables. The first

Table 4.1: Deviation of volume (D_v) and efficiency (E) of simulated runoff series from different runs.

	Station		NARR T		NARR P		NARR PT	
	D_v	E	D_v	E	D_v	E	D_v	E
Burntwood	0.1	0.47	-0.1	0.44	-19.7	0.36	-20.6	0.38
Taylor	1.1	0.75	4.2	0.67	-22.2	0.55	-21.7	0.47
Sapochi	4.3	0.41	-0.7	0.53	-28.1	0.49	-28.2	0.51

Notes: (1) the Taylor and Burntwood results were calculated for the period 1985-2000 with missing streamflow records excluded; (2) the Sapochi results were calculated for the period from 1995 through September 2002 except 1999 with missing streamflow records excluded.

run, referred to as 'Station', employed solely observed data from weather stations as inputs. The second run used NARR precipitation while the remaining data were from weather stations (denoted 'NARR P'). The third run used NARR temperature with the remaining data from weather stations (denoted 'NARR T'). The forth run used both precipitation and temperature of NARR (denoted 'NARR PT'). The output from each run was compared to the observed streamflow and the agreement was measured in terms of absolute deviation D_v and efficiency E.

Table 4.1 indicates that the runs with NARR precipitation data underestimated runoff in all watersheds. The average annual precipitation of NARR is about 6% lower than the observed precipitation in Thompson (shown in Table 3.1) which explains the D_v values in Table 4.1 for the NARR P and NARR PT runs. The runoff from the NARR T run differs from the Station run only by a few percent. The E values indicate that the SLURP runs with the NARR precipitation data (NARR P and NARR PT) result in slightly worse goodness-of-fit at the daily time scale for Burntwood and Taylor while being slightly better for Sapochi. Overall, the goodness-

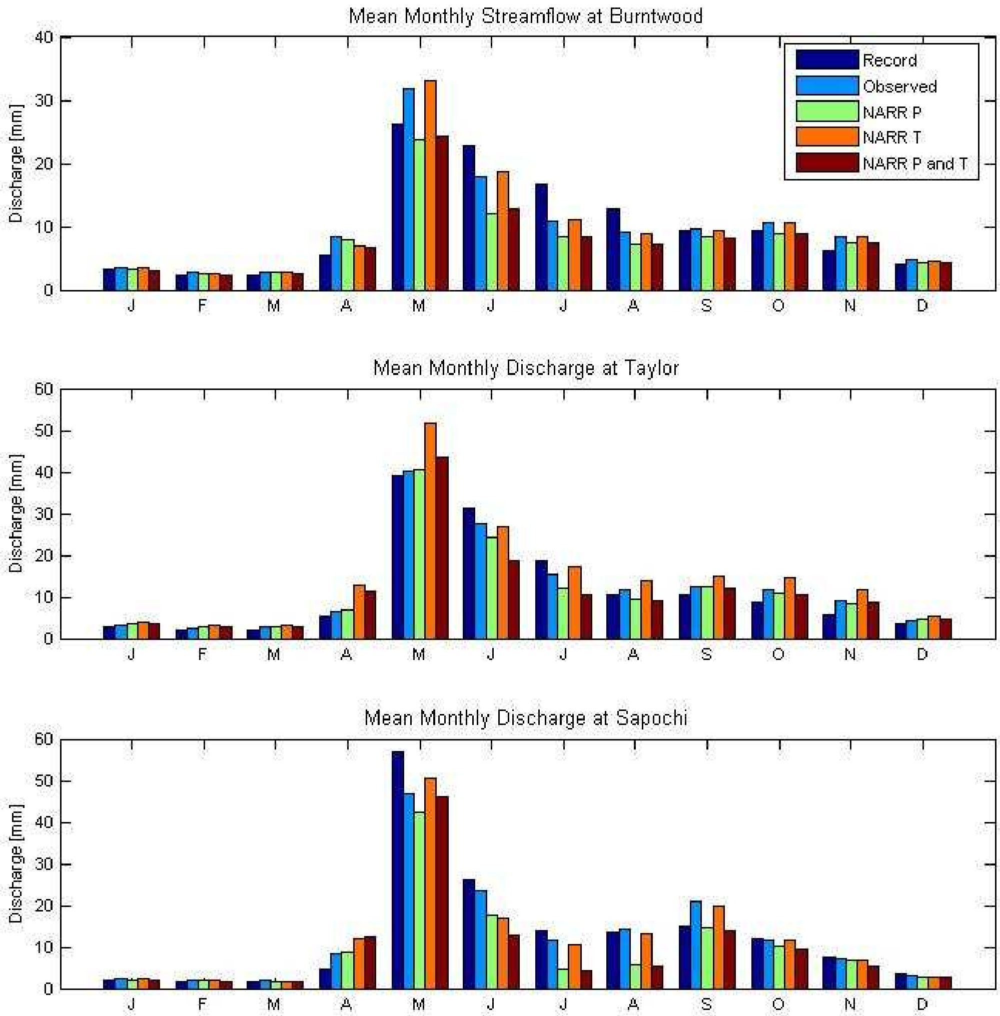

Figure 4.2: Mean monthly observed runoff and simulated runoff with different input data sets.

of-fit from the NARR P and PT runs is better than anticipated, considering the low correlation coefficients with the station precipitation data (Table 3.5 in Chapter 3).

Figure 4.2 presents the mean monthly runoff in each watershed from the four different SLURP runs for the period 1980-2004. The year 1979 was used as 'warm-up' period. The runoff from the NARR P run is lower than the runoff from the Station run, especially in late spring and summer. This result is consistent with the fact that the NARR precipitation is lower than the observed precipitation during summer. For the NARR T run, the most noticeable feature is that the runoff in May is higher than for the Station run due to the higher NARR temperature.

4.2.2 SLURP calibration using NARR

As precipitation has the most influence on hydrological modelling, the precipitation data of observations and NARR were compared in more detail. In practice, the observed climate data from weather stations outside from the watershed are often used for hydrological modelling in remote regions although they may not be fully representative of the watershed conditions. Therefore, the difference between NARR data and observations from outside of a watershed do not necessarily represent the error of NARR precipitation in the watershed. Nevertheless, the average precipitation data of observations and NARR grid points were compared in order to investigate bias of NARR precipitation prior to hydrological modelling. The average annual precipitation for the period 1979 - 2004 in Sturgeon is 748.5 mm (at the Sioux Lookout station) and 660.9 mm based on the average of NARR grid points in the watershed, while the averages for the same period in Troutlake are 641.4 mm (Red Lake) and 601.5 mm (average of NARR grid points in the watershed). The difference of annual average precipitation between observation and NARR in Sturgeon (87.6 mm) is noticeably greater than in Troutlake (39.9 mm), and it indicates that the band bias of NARR precipitation affects in Sturgeon as the watershed is closer to the US bor-

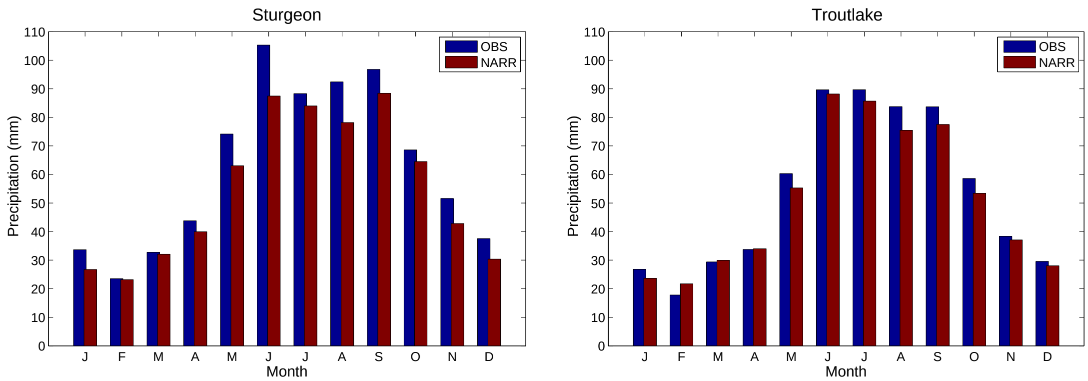

Figure 4.3: The monthly mean precipitation of observation and NARR for period 1979-2004 in each watershed.

der than the Troutlake watershed. As shown in Figure 4.3, the differences of mean monthly precipitation between observation and NARR in Sturgeon are significant in spring and summer while the differences in Troutlake are minimal.

To verify the reliability of NARR for hydrological modelling, the SLURP model was calibrated using solely the NARR data and the simulation results were compared with the observed streamflow records. Each model was calibrated using streamflow records measured at the Sturgeon River and the Troutlake River. Since all weather stations and streamflow gauges have missing data, the calibration and validation were conducted over the periods with best quality records in each watershed. The Sturgeon-model was calibrated first for the period of 1992-1995 and validated for the period 2000-2004, while the Troutlake-model was calibrated for the period 1994-1997 and validated for the period 2000-2004. Since NARR does not contain any missing data, the calibration and validation with NARR data can be conducted using any period. However, for fair comparison with simulation using observed data, the same

Table 4.2: Results from the SLURP model validation using observed and NARR data for each watershed.

	Sturgeon		Troutlake	
	Observed	NARR	Observed	NARR
Observed mean runoff (m^3/s)	46.13		20.68	
Simulated mean runoff (m^3/s)	49.14	45.04	19.86	19.86
D_v of mean runoff (%)	6.51	-2.38	-3.96	-3.99
E of daily runoff series	0.77	0.64	0.65	0.61

validation period (2000-2004) was used. The calibration procedure used in this study is the same as the one used in Chapter 2. Table 4.2 shows a summary of model performances of NARR and observed climate data for the validation periods. The performance statistics using NARR data are close to the statistics obtained using observed data. In both simulations, the averages of simulated runoff are close to the streamflow record and daily E-values are at an acceptable level.

Figure 4.4 shows the recorded daily streamflow, and the simulated streamflows using observed climate data and NARR data for the validation period 2000-2004. Since the calibration process forces the model to fit the recorded streamflow, the comparison will focus on the validation period rather than the calibration period. At Sturgeon, both runoff simulations generally reproduce the timing of spring snowmelt and the shape of runoff recession. The NARR simulation underestimates the quantity of recession in 2004 and the simulation using observed climate data overestimates in 2002. The peaks of NARR simulated spring runoffs are lower than the observed peaks in 2001, 2002, and 2004. The simulation using observed climate data estimates

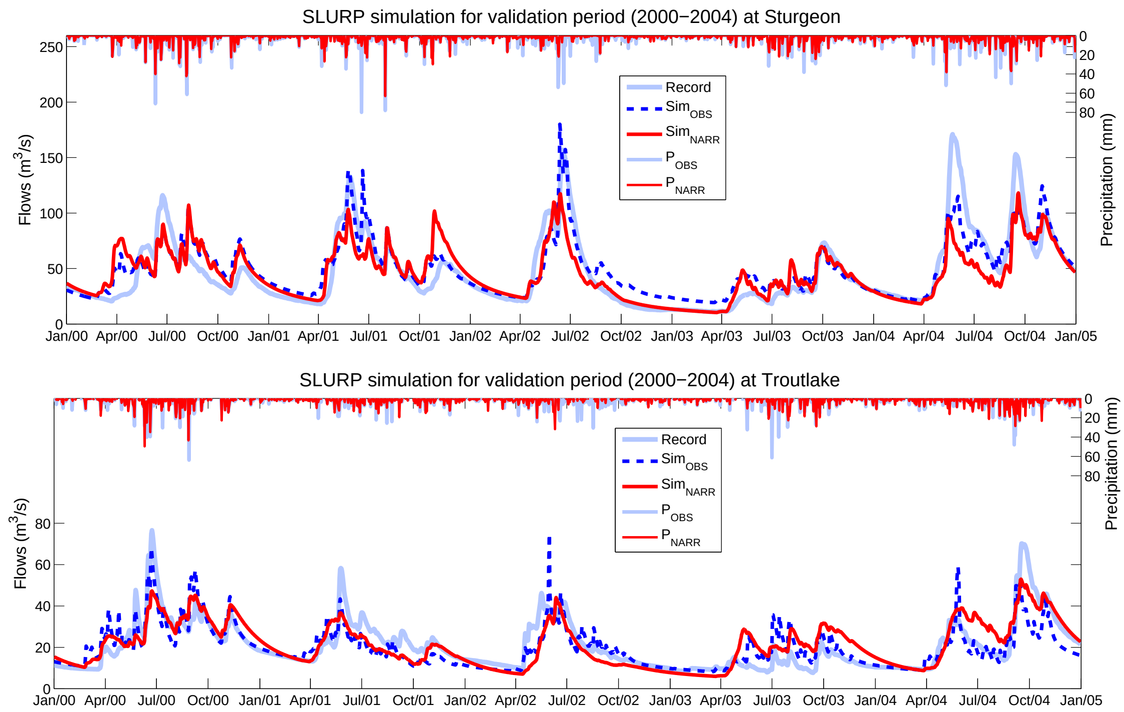

Figure 4.4: The recorded runoff, simulated daily runoff using NARR and observation, and precipitation of observation and NARR for validation period 2000-2004 in each watershed.

the peaks better than the NARR simulation in 2001 and 2002, due to the larger observed precipitation. It is noticeable that the underestimation of peaks in NARR simulations generally occurs when NARR precipitation is particularly lower than observations. In autumn 2001, the shape of recession is similar to the recorded streamflow but due to the higher NARR precipitation in that period, the simulated recession curve is higher. The same phenomenon is seen in autumn 2002 where the observed precipitation causes a slight rise at the end of recession and the ensuing simulated runoff stayed higher than the record streamflow until the next spring. However, the shape of the recession curve is similar to the record. This indicates that

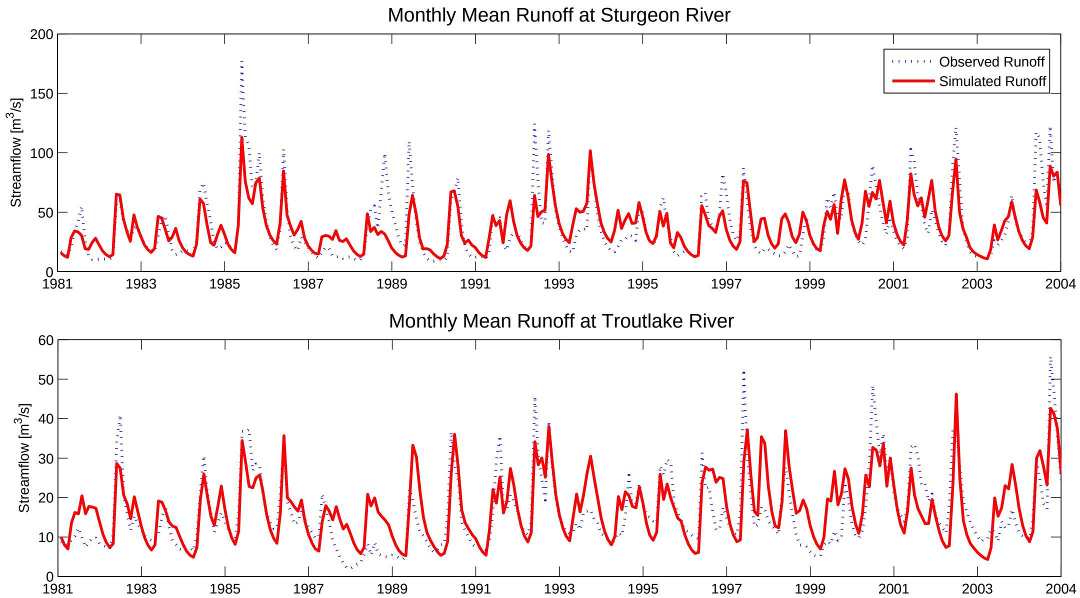

Figure 4.5: The simulated monthly runoff using NARR and observed runoff for a period 1981-2004 in each watershed.

errors in precipitation estimates can affect simulation errors over longer periods, and considering the general good fit of snowmelt-timing and the shape of recession curves, most of the simulation errors may be attributed to inaccurate representativeness of precipitation in the watershed. It should be noted that the band bias of NARR precipitation is located near the Sturgeon watershed and appears to be the main cause for the underestimated runoff simulation using NARR. Although the simulation using observed climate data estimated the peaks somewhat better than the NARR simulation due to the NARR precipitation bias, the simulation using NARR data is in good agreement with recorded streamflow.

The SLURP was then run for the extended period of 1981-2004, using the NARR data at Sturgeon River and Troutlake River watersheds as input. Figure 4.5 shows the monthly mean runoff of SLURP simulations compared with observed streamflow records in the two watersheds. The simulation results show generally good agreement with streamflow records in terms of timing and overall magnitude, although some months with high runoff are underestimated and some months in dry years are overestimated (1987, 1988, and 1989). It is again noticeable that more cases of underestimation are seen in Sturgeon than in Troutlake due to the influence of the NARR band bias in the Sturgeon watershed.

4.3 Climate Change Impact Assessment using NARR

4.3.1 Downscaling GCM data using NARR

Statistical downscaling methods often require data such as specific humidity and shortwave solar radiation which are available at few weather stations in the Prairie region. On the other hand, NARR contains most of these climate variables, making NARR potentially useful for statistical downscaling in remote regions.

A statistical downscaling technique is used here to downscale the output from the CGCM3 using the NARR data. Of the three statistical downscaling methods used in Chapter 2, only the NNR method will be used in this part of the study. The downscaling procedure for this application is the same as the one applied in Chapter 2 under the SRES A2 and B1 emission scenarios for the period 2081-2100 (2090s).

CGCM data were downscaled to produce time series data of mean daily tem-

Table 4.3: Downscaled annual precipitation and temperature for 20C3M, A2, and B1. Changes from 20C3M are shown in parenthesis.

	Sturgeon			Troutlake		
	20C3M	A2	B1	20C3M	A2	B1
Annual Precipitation (mm)	634	687 (+8.4%)	622 (-1.9%)	576	597 (+3.6%)	585 (+1.6%)
Average Temperature (°C)	3.22	5.67 (+2.45°C)	5.63 (+2.41°C)	2.77	5.62 (+2.85°C)	5.30 (+2.53°C)

perature, relative humidity, solar radiation, and daily accumulated precipitation at NARR grid points located at the centroid of each watershed. Twenty-six years (1979-2004) of NARR data are available to use as historical data of local climate.

The NNR model was first used to downscale the CGCM for a control run period and cross validated with the local NARR climate data. Then the model was used to downscale the A2 and B1 emission scenarios at two grid points located in the center of the Sturgeon River and the Troutlake River watersheds. The NNR model used the large scale climate variables provided by the CGCM to resample days from the historical NARR data.

Table 4.3 shows the downscaled annual precipitation and averages for the two watersheds. Both scenarios show increase of annual precipitation at Troutlake, while annual precipitation at Sturgeon increases in the A2 scenario but decreases in the B1 scenario. As expected, both scenarios show increases in temperature and the average temperature increases by approximately 2.5°C in both watersheds (see Table 4.3). As shown in Figure 4.6, both scenarios show higher increases of temperature in the

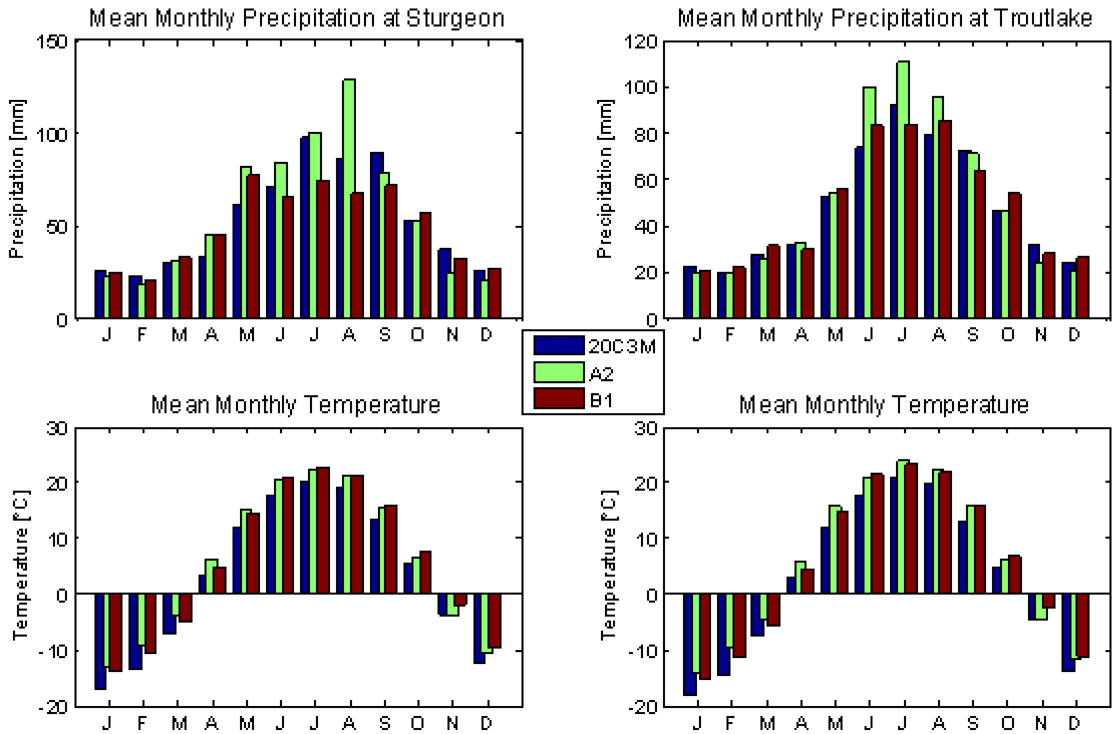

Figure 4.6: Mean monthly precipitation and temperature obtained from CGCM and downscaled by NNR for 20C3M, A2, and B1.

winter than in the summer. The precipitation for the A2 scenario increases during the summer months in both watersheds, while the precipitation significantly decreases for the B1 scenario in Sturgeon. This concurs with the results found in Chapter 2.

4.3.2 Runoff simulations of future scenarios using NARR

The downscaled CGCM3 data are used as input data to the calibrated SLURP model using NARR for assessing the future climate change impact on water resources. Downscaled CGCM3 data for the two scenarios and the control run are applied in the SLURP model for each watershed. As expected, simulated future runoffs reflects the projected change in future precipitation. In the B1 scenario at

Table 4.4: Mean annual runoff (in m^3/s) simulated by SLURP for 20C3M, A2, and B1. Changes from 20C3M are shown in parenthesis.

	20C3M	A2	B1
Sturgeon	31.2	34.7 (+11.2%)	28.9 (-7.4%)
Troutlake	14.9	16.1 (+8.1%)	15.3 (+2.7%)

Sturgeon, as precipitation decreases runoff also decreases. However, runoff increases as precipitation increases in the A2 scenario at Sturgeon River and in both scenarios at Troutlake. The increasing rate of runoff is proportional to the rate of precipitation. For instance, runoff increases the most (Table 4.4) in the A2 scenario at Sturgeon, just as precipitation does (Table 4.3).

Figure 4.7 shows the simulated daily mean runoff for the control run period and both emission scenarios. The temperature increases in the winter advance the spring snowmelt runoff by almost 30 days in both watersheds. The increased summer precipitation in the A2 scenario results in increased runoff in summer and in early autumn. On the other hand, the B2 scenario shows decrease in summer runoff at Sturgeon but minimal changes at Troutlake (Figure 4.7). It is noticeable that in both scenarios the magnitude of spring runoff at Sturgeon is similar to the control run period, while the spring runoff slightly decreases at Troutlake.

The results of hydrological modelling and climate change assessments using solely NARR instead of observation from weather stations are generally similar to the results found in Chapter 2. The timing and magnitude changes in the spring runoff as well as the runoff changes in summer and early autumn for both scenarios are almost

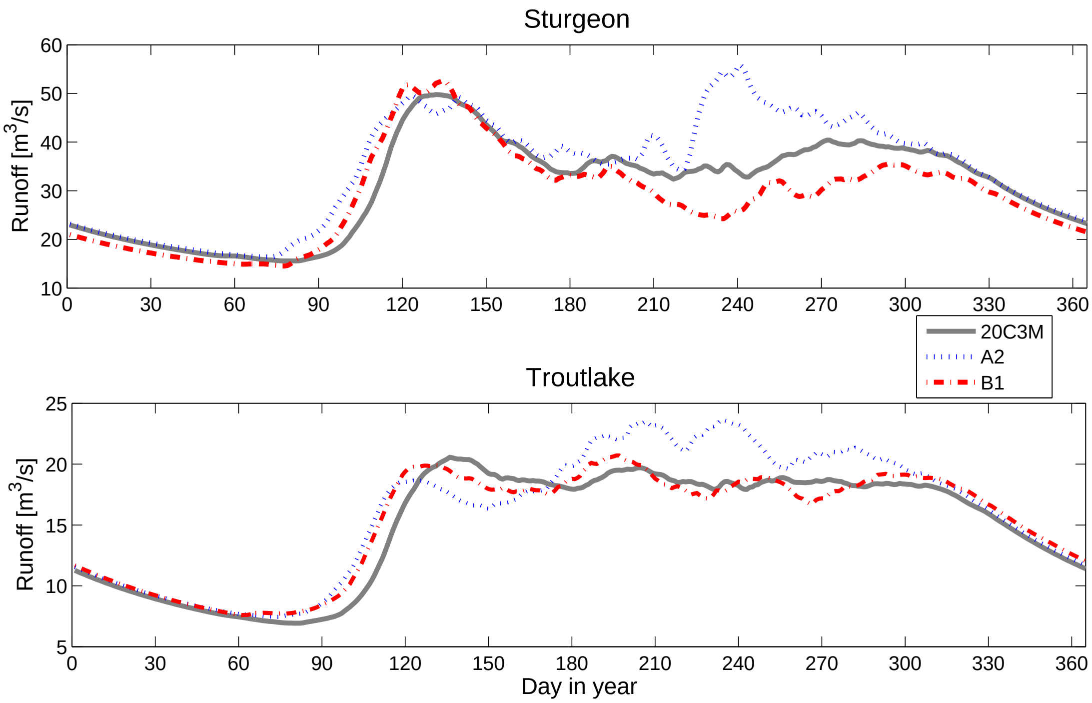

Figure 4.7: Mean daily runoff simulated by SLURP with the downscaled CGCM3 output of control run, A2 and B1 scenarios for 2090s.

identical. This suggests that NARR is useful for both the hydrological modelling and statistical downscaling in climate change related studies.

Chapter 5

APPLICATION OF NARR FOR MISSING DATA ESTIMATION

5.1 Introduction

A climate normal is defined as the average of an observed climate variable at a given location over a specified time period. It is an important concept in climate-related studies and is used routinely to determine how much a given observation departs from average conditions. *World Meteorological Organization* (1989) recommended that the data record for the calculation of climate normals, ideally, should be 30-years long, be free of any inconsistencies (e.g. due to changes in station location, instrumentation, time of observation, surrounding environment, observing practice, sensor drift, etc.) and be serially complete (i.e., no missing values). *World Meteorological Organization* (1989) indicated that inconsistencies can lead to a non-climatic bias in one period of a station's record relative to another, and the series is then said to be inhomogeneous.

The requirement of 30 years of climate data to define normals has been adopted in many climate change and hydrological studies. However, many observed climate data sets, especially precipitation, contain missing records which poses problems for hydrological modelling studies. The availability of weather stations with no missing data is generally low in the Prairie region, especially in the northern-most parts of the Prairie provinces, and it is therefore difficult to properly conduct hydrologic modelling in those areas. Also, although some climate stations have more than twenty years of records, the record may not cover the desired period.

Despite the small number of reliable stations in the northern Prairie region, there are some stations containing a suitable period of records, with the occasionally missing data. The ability to fill in the missing data would increase the number of useable weather stations for hydrological modelling and research. The traditional methods for filling in missing data in hydrological studies generally use climate data from neighbouring weather stations. However, in the northern parts of the Prairie, weather stations are often more than 200 km apart, which is too far to obtain reliable in-filled data. Moreover, the climate data of weather stations also have some quality issues. *Metcalfe et al.* (1997) quantified the systematic errors in rain gauge catch such as wetting loss, wind-induced error, and trace precipitation due to method of observation and gauge design. They found that the combined magnitude of the adjustments for the systematic errors can exceed 7%. *Madsen* (1994) found the normal-exposed

Hellmann rain gauge only catches about 85% of the true annual precipitation. Such studies indicate that the observed precipitation at weather stations possibly contains some errors. The performance of traditional methods for estimating missing precipitation data can therefore be affected if neighbouring stations are not carefully corrected for bias.

In the previous chapters, it was found that the NARR precipitation has a fairly high correlation with observations and therefore has potential for filling in missing observations, keeping in mind that NARR has certain biases that must be accounted for. In this chapter, the usefulness of NARR precipitation for missing data estimation is investigated. Four different estimation methods using NARR are developed and compared with traditional methods.

5.2 Preliminary Investigation

The benefit of using NARR for estimating missing precipitation must be evaluated relative to traditional methods based on neighbouring stations. In order to achieve this goal, it is necessary to understand the relationship between precipitation at neighbouring stations. Here the relationship between neighbouring stations in weather networks of different density is investigated. Three study areas, located around Winnipeg, Dryden, and Thompson, were selected based on the density of the weather station network in each area. The three locations represent as fairly dense area (Winnipeg), a moderately dense area (Dryden), and a remote area (Thompson).

To assess neighbouring weather stations and NARR for estimating missing precipitation events, the wet/dry-day-match and correlation between a target weather station and a neighbouring station or NARR were investigated and compared. Two types of NARR estimates were considered: (1) the nine grid points closest to a target station, and (2) a NARR value interpolated to the target station location. The wet day match ratio R_{WW} is defined as the number of days where both the target station and the neighbouring station or NARR is wet, divided by the total number of wet days at the target station.

Reanalysis products are known to contain a high number of days with precipitation because they produce the precipitable water from atmospheric variables. However, many days have very small, insignificant amounts of precipitation. To remove this effect, a cutoff threshold was set to 0.5 mm for NARR precipitation. All days with precipitation less than 0.5 were assumed dry. A total wet-dry-day mismatch ratio (WD_{mR}), defined as the number of days where the wet-dry condition of a neighbouring station (or NARR) is opposite to the target station divided by the total number of days at the target station, was additionally compared in order to identify problems with NARR's wet-day frequency. For instance, when the WD_{mR} of NARR is significantly higher than the one at a neighbouring station but the R_{WW} of NARR is similar to the value at the neighbouring station, then this would indicate that NARR contains substantially more wet-days than the neighbouring station on dry-day events at the target station. However, it should be noted that the WD_{mR}

Table 5.1: Wet-day match rate, total wet-dry-day mismatch rate, and correlations of neighbouring weather stations and NARR grids near Winnipeg, sorted by distances.

Station	Dist(km)	R_{WW}	WD_{mR}	R
Winnipeg	0.0	1.00	0.00	1.00
Steinbach	54.6	0.70	0.17	0.60
Miami Thiessen	90.3	0.62	0.20	0.54
Altona	94.1	0.60	0.21	0.49
St. Alphonse	139.3	0.61	0.22	0.44
Cypress River	139.5	0.56	0.22	0.43
Neepawa Water	163.7	0.51	0.23	0.37
Brandon	195.3	0.60	0.18	0.41
Turtle Mountain 11	226.8	0.48	0.24	0.34
Turtle Mountain 6	233.6	0.49	0.25	0.32
Virden	267.5	0.46	0.26	0.29
Pierson	303.6	0.41	0.27	0.21
Nearest NARR grid	7.1	0.76	0.23	0.62
Average of NARR 9grid	36.0	0.75	0.23	0.61
Interpolated NARR	0.0	0.73	0.26	0.62

comparison is a relative measure to identify the bias in wet-day frequency and not an absolute error measure of NARR.

The dense study area near Winnipeg include the Winnipeg weather station, considered here to be the target station, and the 11 neighbouring stations listed in Table 5.1. The stations were selected considering the percentage of missing records and the length of record. The nearest neighbouring station, Steinbach, is located at 54.6 km from Winnipeg and, as expected, the R_{WW} value of 0.7 and the correlation (R) of 0.6 are the highest among the neighbouring stations. The other stations are more than 90 km from Winnipeg and as the distance between stations and the target station increases, the correlations and R_{WW} decreases in a fairly systematic way. The R_{WW}

Table 5.2: Same comparison as in Table 5.1, but with Brandon as the target station.

Station	Dist(km)	R_{WW}	WD_{mR}	R
Brandon A	0.0	1.00	0.00	1.00
Neepawa Water	48.7	0.67	0.16	0.62
Virden	72.4	0.64	0.18	0.57
Turtle Mountain 6	72.9	0.63	0.18	0.52
Cypress River	74.4	0.69	0.17	0.59
St Alphonse	84.4	0.71	0.18	0.51
Turtle Mountain 11	87.6	0.61	0.19	0.48
Pierson	125.3	0.55	0.21	0.39
Miami Thiessen	132.9	0.69	0.17	0.48
Winnipeg A	195.3	0.63	0.18	0.41
Altona	195.7	0.61	0.20	0.39
Steinbach	233.1	0.64	0.20	0.39
Nearest NARR grid	15.9	0.74	0.23	0.59
Average of NARR 9grid	38.1	0.74	0.23	0.58
Interpolated NARR	0.0	0.71	0.25	0.59

and correlation of the nearest NARR grid point are higher than all neighbouring stations ($R_{WW} = 0.76$ and $R = 0.62$). The average R_{WW} and correlation of the 9 NARR grid points are close to the results for the nearest grid point, while the interpolated NARR has slightly lower R_{WW} value although still higher than any of the neighbouring stations. The WD_{mR} of Steinbach is lower than NARR and, for the other stations, the mismatch ratio is similar, around 0.23 (see Table B.1 and B.2 for details of wet-dry-day match information).

The same analysis was conducted with Brandon as the target station, and the results are shown in Table 5.2. Overall, the results are similar to the comparison for Winnipeg as R_{WW} and correlations show a fairly consistent relationship with distance. Since the distances in Table 5.2 are somewhat smaller than in Table 5.1,

Table 5.3: Same comparison as in Table 5.1, but with Dryden as the target station.

Station	Dist(km)	R_{WW}	WD_{mR}	R
Dryden A	0.0	1.00	0.00	1.00
Sioux Lookout A	69.0	0.79	0.14	0.79
Rawson Lake	72.7	0.65	0.21	0.54
Kenora A	116.6	0.74	0.16	0.65
Red Lake A	156.4	0.71	0.19	0.52
Nearest NARR grid	17.3	0.79	0.24	0.66
Average of NARR 9grid	38.6	0.78	0.24	0.65
Interpolated NARR	0.0	0.79	0.24	0.66

the R_{WW} and correlations are generally higher and the WD_{mR} are lower than in the Winnipeg comparison (see Table B.3 and B.4 for details of wet-dry-day match information). The correlations and R_{WW} for NARR are higher than most of the stations. On the other hand, the WD_{mR} of neighbouring stations are for the most part higher than NARR. The correlations with NARR and with stations within a 80-km range are similar, and NARR is significantly higher beyond the 80 km range.

In the moderately dense study area near Dryden, 5 stations were found to have appropriate precipitation records for the study and Dryden was selected as the target station. The stations in this study area are located within a radius of 156 km from the target site. The comparison results in Table 5.3 also are consistent with the results for Winnipeg and Brandon, with R_{WW} and correlations values that are generally higher at closer distances. Only the nearest station, Sioux Lookout, has a higher correlation (0.79) than NARR and a similar R_{WW} value of 0.79 (see Table B.5 and B.6 for details of wet-dry-day match information).

Table 5.4: Same comparison as in Table 5.1, but with Thompson as the target station.

Station	Dist(km)	R_{WW}	WD_{mR}	R
Thompson A	0.0	1.00	0.00	1.00
Gillam A	188.0	0.64	0.22	0.55
Norway House A	205.9	0.64	0.22	0.48
Lynn Lake A	231.4	0.62	0.22	0.46
Flin Flon A	273.0	0.47	0.28	0.35
Island Lake A	281.4	0.61	0.24	0.36
The Pas A	290.9	0.48	0.26	0.36
Churchill A	353.1	0.46	0.32	0.20
Nearest NARR grid	5.7	0.81	0.27	0.55
Average of NARR 9grid	35.5	0.80	0.28	0.54
Interpolated NARR	0.0	0.81	0.28	0.55

The study area near Thompson in northern Manitoba represents a remote area with 8 neighbouring stations generally located at distances of more than 200 km from the target station. The nearest station, Gillam, is 188 km away from Thompson and the R_{WW} and correlation are 0.64 and 0.55, respectively, which are the highest among the neighbouring stations. The R_{WW} of neighbouring stations are in a range of 0.46 - 0.64 and the correlations between 0.2 and 0.55. The NARR correlation of 0.55 is similar to Gillam, but the NARR R_{WW} value of 0.81 is significantly higher than all neighbouring stations (see Table B.7 and B.8 for details of wet-dry-day match information).

An additional comparison using The Pas as target station in the same area is investigated in Table 5.5. It is noticeable that Flin Flon, the second nearest station 87 km away from The Pas, shows higher R_{WW} and correlation values than the nearest

Table 5.5: Same comparison as in Table 5.1, but with The Pas as the target station.

Station	Dist(km)	R_{WW}	WD_{mR}	R
The Pas A	0.0	1.00	0.00	1.00
Island Lake A	32.4	0.53	0.29	0.27
Flin Flon A	87.6	0.67	0.19	0.57
Norway House A	213.2	0.67	0.21	0.48
Gillam A	267.2	0.43	0.33	0.17
Thompson A	290.9	0.54	0.26	0.36
Lynn Lake A	321.7	0.53	0.27	0.24
Churchill A	534.8	0.32	0.38	0.03
Nearest NARR grid	14.6	0.78	0.22	0.71
Average of NARR 9grid	37.7	0.79	0.23	0.70
Interpolated NARR	0.0	0.76	0.24	0.72

station, Island Lake. The correlation and R_{WW} of neighbouring stations except Island Lake show a similar pattern as in the Thompson comparison. The very low R_{WW} of 0.32 and lack of correlation with Churchill indicate that a station located more than 500 km from a target station is not useful for missing data estimation. The R_{WW} and correlation values of NARR in The Pas are significantly higher than at all neighbouring stations and also higher than NARR at the other target locations (Tables 5.1 - 5.4). This result indicates that the NARR correlation and R_{WW} vary by the location of a target station and a careful comparison is required prior to using NARR to estimate missing data (see Table B.9 and B.10 for details of Wet-dry-day match information).

Figure 5.1 shows, for each study area, the correlation (circles) and R_{WW} (squares) of all stations as a function of distances, and the average correlation and R_{WW} of the nearest NARR grid points for each station as lines. In the Winnipeg and Dryden

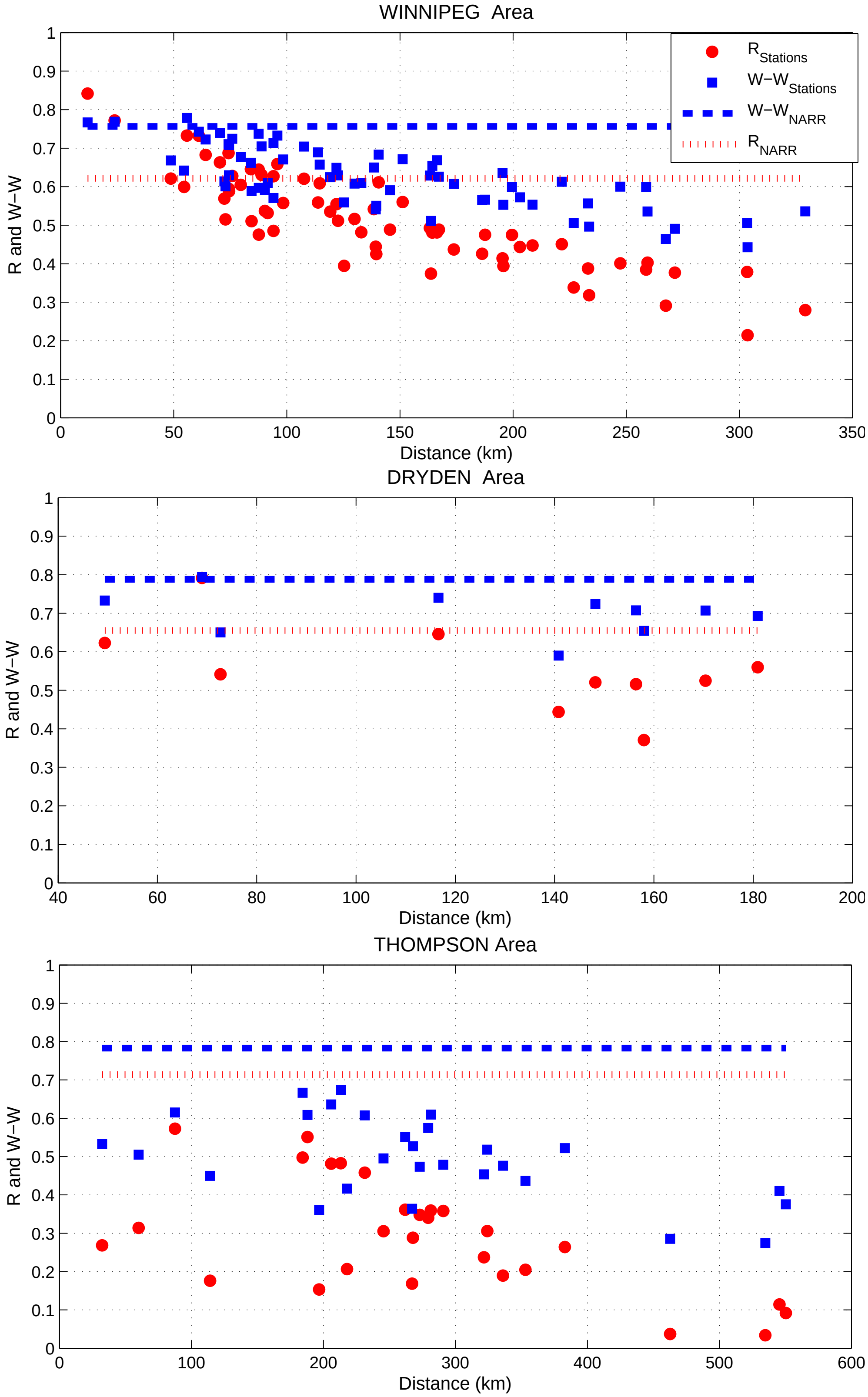

Figure 5.1: The correlation (R) and R_{WW} for each study area.

areas, the NARR R_{WW} is higher than the station R_{WW} in most cases and only a few stations, all within 100 km range, have R_{WW} values of similar magnitude to the NARR. The average correlation of NARR is generally lower than correlations with stations within a 50-km range and, for stations in the 50-100 km range, the NARR correlation is close to the average correlation with stations. In the Thompson area, the NARR R_{WW} is higher than R_{WW} of all stations and the highest R_{WW} of stations is 0.1 lower than the NARR R_{WW}. Also, the average correlation of NARR in the Thompson area is significantly higher than correlations with stations and more than 0.1 higher than the highest station correlation of 0.58.

In conclusion, a distance of 100 km between stations is found to be the dividing point where the NARR precipitation becomes better in terms of both correlation and wet day matching ratio. Stations located more than 200 km from the target station are not particularly useful for missing data estimation as the correlations are typically lower than 0.5, and R_{WW} values are lower than 0.6. In comparison, the average NARR correlation is higher than 0.6 and the R_{WW} is higher than 0.75. The comparison results indicate that NARR precipitation is useful for estimating missing precipitation at weather stations in remote regions where weather stations often are located 100 km or more apart.

5.3 Estimation of Missing Precipitation Data

5.3.1 Traditional estimation methods

Two traditional methods for estimating missing precipitation data are used here as a baseline for validating methods based on NARR. Missing data at a weather station are usually estimated either using the available data at the station itself or using data from neighboring stations. The station-average method (SA) and the inverse-distance weighting method (IDW) are commonly used methods for missing data estimation. The station-average method simply computes the missing data as the average of the values at the nearby stations, i.e.:

$$\hat{p} = \frac{1}{G}\sum_{g=1}^{G} p_g \tag{5.1}$$

where p_g is the daily precipitation value at station g, and G is the number of neighbouring stations considered. The inverse distance weighted (IDW) method is based on the idea that the weight of a neighbouring station should depend on its distance from the target. The IDW method weights the p_g value at station g by its inverse distances, d_g^{-1}, from the target station. There are several variations of the IDW method and it is perhaps more common to consider the inverse squared distance as weights. In this study, precipitation is estimated as

$$\hat{p} = \frac{1}{D}\sum_{g=1}^{G} d_g^{-2} \cdot p_g \tag{5.2}$$

where $D = \sum d_g^{-2}$.

5.3.2 NARR-based methods

Four different methods based on NARR will be applied here for estimating missing precipitation and will be compared with the traditional methods. In the first method, the missing values in an observed precipitation data set are directly replaced by the corresponding NARR precipitation data from the grid point closest to the station (N_{DI}). In the second method, the precipitation data from the nearest 9 NARR grid points are interpolated to the target station location using inverse distance weighting (N_{IDW}).

Since NARR precipitation contains biases (Chapter 3), two additional methods, designed to account for possible biases, were devised. In order to take seasonality into account, the ratios of monthly mean precipitation for the calendar month with missing data at stations and from NARR for the longest overlapping period were calculated. These ratios will be referred to as bias-factors. The bias-factors were used to correct the NARR bias prior to imputing the NARR data into the missing period:

$$P^*_{NARR} = P_{NARR} \times \frac{\bar{P}_{OBS,j}}{\bar{P}_{NARR,j}}, \quad j = 1, \dots, 12 \tag{5.3}$$

where P^*_{NARR} is the estimated, bias-corrected daily precipitation, P_{NARR} is the original daily NARR precipitation value for the day with missing observation, $\bar{P}_{OBS,j}$ is the observed monthly mean precipitation in month j at a target location, and

$\bar{P}_{NARR,j}$ is the monthly mean NARR precipitation in month j. This method is denoted N_{BFmon}.

The relationship between quantiles of the observed precipitation data and the corresponding quantiles of the NARR precipitation data provide more specific information about the differences in the distribution of precipitation. Since proper estimation of extreme precipitation events is important when filling in missing data, consideration of quantile ratios seems useful. Thus, bias-factors were applied to quantile ranges instead of just monthly mean precipitation ratios (N_{BFQ}). The quantiles of observations and NARR were calculated for calendar month j for the longest overlapping period. Then, for that month the ratios of corresponding quantiles were calculated. These ratios will be denoted quantile bias-factors (BFQ). The quantile bias-factors were then used to adjust the NARR precipitation in the corresponding quantile range prior to imputing the NARR data into the missing record:

$$P^{*}_{NARR} = P^{NARR} \times \frac{P^{OBS}_{Q\%}}{P^{NARR}_{Q\%}} \tag{5.4}$$

where P^{*}_{NARR} is the estimated, bias-corrected daily precipitation, P^{NARR} is the original daily NARR precipitation falling in a given quantile range, $Q\%$, at the target station, and $P^{OBS}_{Q\%}$ and $P^{NARR}_{Q\%}$ are the precipitation quantiles of observation and NARR, respectively. For instance, to adjust a NARR precipitation event in the month of August (j=8) corresponding to, say, the 90 percentile in the observed distribution of precipitation during the month of August, the 90 percentile values of

NARR and observed precipitation in the same month are sought, and the ratio of the two values is calculated as the 90% quantile range bias-factor. The NARR precipitation is then multiplied by the calculated bias-factor for correction. The bias-factors of each quantile range can be precalculated and multiplied by the NARR precipitation event lying in the corresponding quantile range. Because the percentage of wet days is approximately 25%, five different quantile ranges were defined as 60-75%, 75-90%, 90-95%, 95-99%, and 99-100%. It should be noted that Q-Q plots show the distribution match but not the day-to-day quantity match. In the low quantiles (e.g., 60% and 75%), the precipitation amount differences (amount intervals) between quantiles are smaller, while the amount intervals in the high quantiles (above 90%) are substantially larger. There are three quantile ranges above 90% to reflect the importance of large precipitation events.

Missing data estimation results by the two traditional methods (station-average (O_{SA}) and inverse distance weighting (O_{IDW})) and the four NARR-based methods (direct imputation of NARR (N_{DI}), IDW of NARR (N_{IDW}), bias-factor using monthly data for NARR (N_{BFmon}), and bias-factor using quantiles for NARR (N_{BFQ})) are compared in the following section.

5.3.3 Comparison of methods

The six methods described above are compared using cross-validation. Cross-validation is a standard statistical method used to evaluate the estimation error of a prediction model. It is implemented here by removing selected periods from the observed record at the target station and using the different methods for infilling missing data to reconstruct the period. The reconstructed values can then be compared to the actual observations and performance statistics can be calculated. The validation period was selected as 1979-2004 where both observations and NARR data are available. Days where neighbouring stations had missing data were simply excluded in the analysis. The statistics for the entire period and the matching ratios for five precipitation amount ranges were used in the comparison.

Winnipeg area

Table 5.6 shows the statistics of missing data estimation results at Winnipeg. The N_{BFmon} result shows the best daily and annual mean precipitation agreement with observations, while the N_{BFQ} and O_{SA} overestimate precipitation. The MAE values are slightly better with NARR-based methods than with traditional methods, and the same conclusion applies to correlation values. The correlation values are quite similar to the values found in Table 5.1.

Figure 5.2 shows the precipitation events at Winnipeg, with the corresponding estimated precipitation in four quantity ranges: 10-20 mm, 20-30 mm, 30-40 mm,

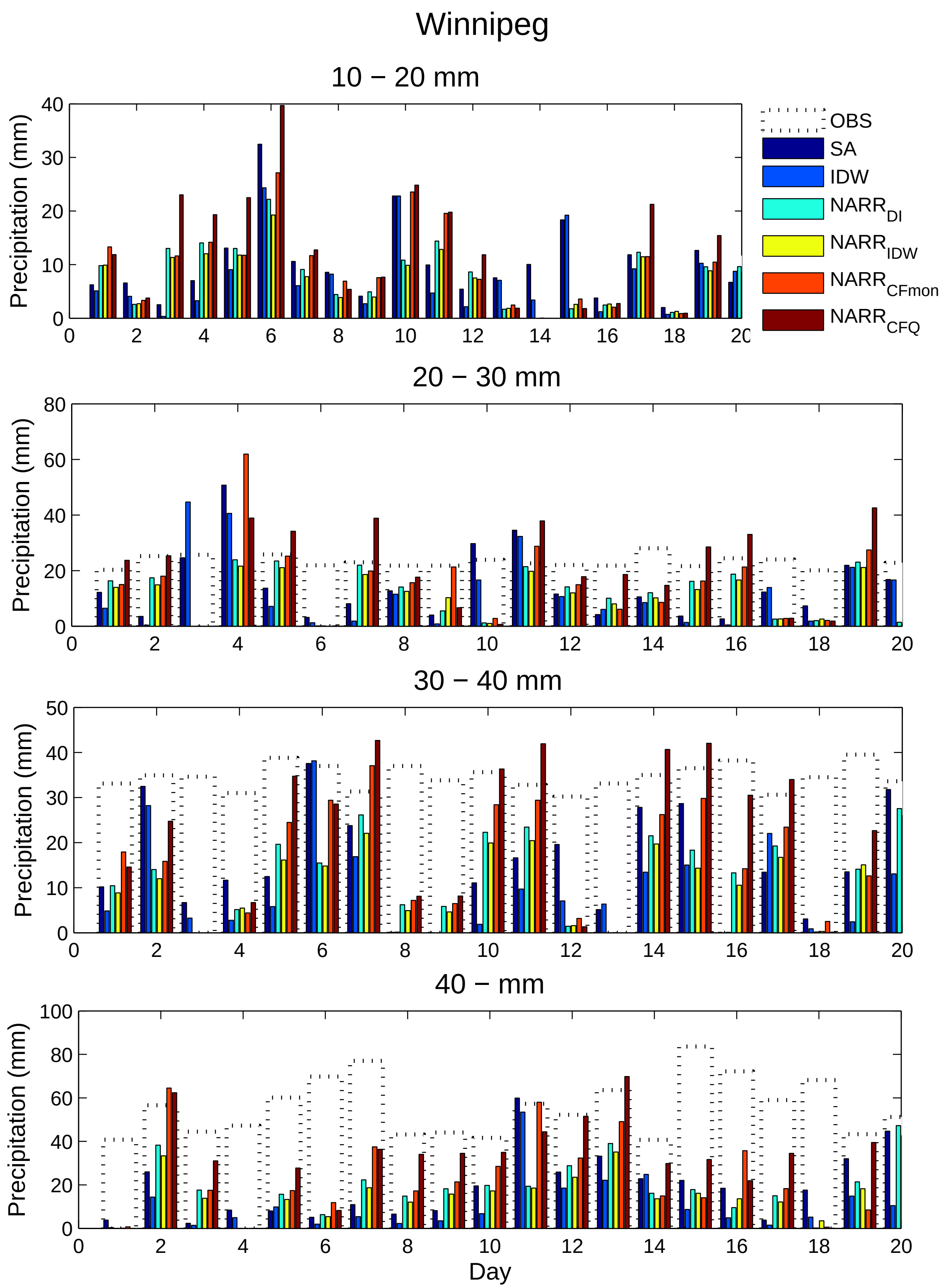

Figure 5.2: Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Winnipeg.

Table 5.6: Statistics of missing data estimation results by two traditional methods using neighbouring observations (station-average (O_{SA}) and inverse distance weighting (O_{IDW})) and four NARR applications (direct inputation of NARR (N_{DI}), IDW of NARR (N_{IDW}), bias-factor using monthly data for NARR (N_{BFmon}), and bias-factor using quantiles for NARR (N_{BFQ})) at Winnipeg.

	OBS	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
Annual Avg	517.7	530.8	487.8	447.8	420.6	514.3	578.8
MAE		1.36	1.62	1.27	1.26	1.32	1.42
R		0.59	0.41	0.62	0.62	0.62	0.62

and more than 40 mm. Only the first 20 events are shown for each category (fewer in cases where the actual number of events are less than 20). The estimations with both traditional and NARR-based methods show a tendency of underestimation in the 10-20 mm range, while a few cases of overestimation. In the 20-30 mm range, the traditional methods estimate slightly more wet days, but the estimated precipitation by NARR-based methods match the quantity of precipitation better. In the higher ranges of 30-40 mm and above 40 mm, the N_{BFmon} and N_{BFQ} methods clearly estimate the precipitation amounts better than other methods. It is noticeable that the precipitation of N_{DI} and N_{IDW} are also better than traditional methods in quite a number of cases.

Table 5.7 shows the number of wet-days in the five quantity ranges at Winnipeg and the quantity-match-day ratios of estimated precipitation by each method. The quantity-match-day ratio is calculated as the number of days when the estimated daily precipitation amount lies within a range of the target station, divided by the

Table 5.7: Precipitation match ratios in five amount ranges of missing data estimation results at Winnipeg.

	OBS	Traditional		NARR-based			
	(days)	O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
5-10mm	354	0.26	0.16	0.25	0.24	0.25	0.24
10-20mm	234	0.26	0.13	0.21	0.20	0.26	0.20
20-30mm	79	0.11	0.06	0.15	0.13	0.20	0.22
30-40mm	21	0.14	0.05	0.00	0.00	0.05	0.24
40mm >	29	0.07	0.03	0.03	0.03	0.21	0.28

total number of days in the range at the target station. It describes how many days of estimated precipitation events closely match the target precipitation events. In the lower range of 5-10 mm, most methods estimate precipitation in that range around 25% of cases and as the ranges become higher, the matching ratios get lower. The exception is the N_{BFQ} precipitation match which remain high in the higher precipitation ranges. This indicates that the N_{BFQ} method estimates precipitation events above 20 mm significantly better than other methods at Winnipeg. The precipitation of N_{BFmon} also shows quite good matching ratios.

At Brandon, all NARR-based methods are closer to the observation than the traditional methods (Table 5.8). The correlations are around 0.6, with the O_{SA} method showing the highest value of 0.65.

Figure 5.3 shows the precipitation events at Brandon with the corresponding estimated precipitation in the four quantity ranges. A tendency of underestimating precipitation appears in most ranges and it is more significant than at Winnipeg. Nevertheless, the N_{BFmon} and N_{BFQ} precipitation estimates show better agreement

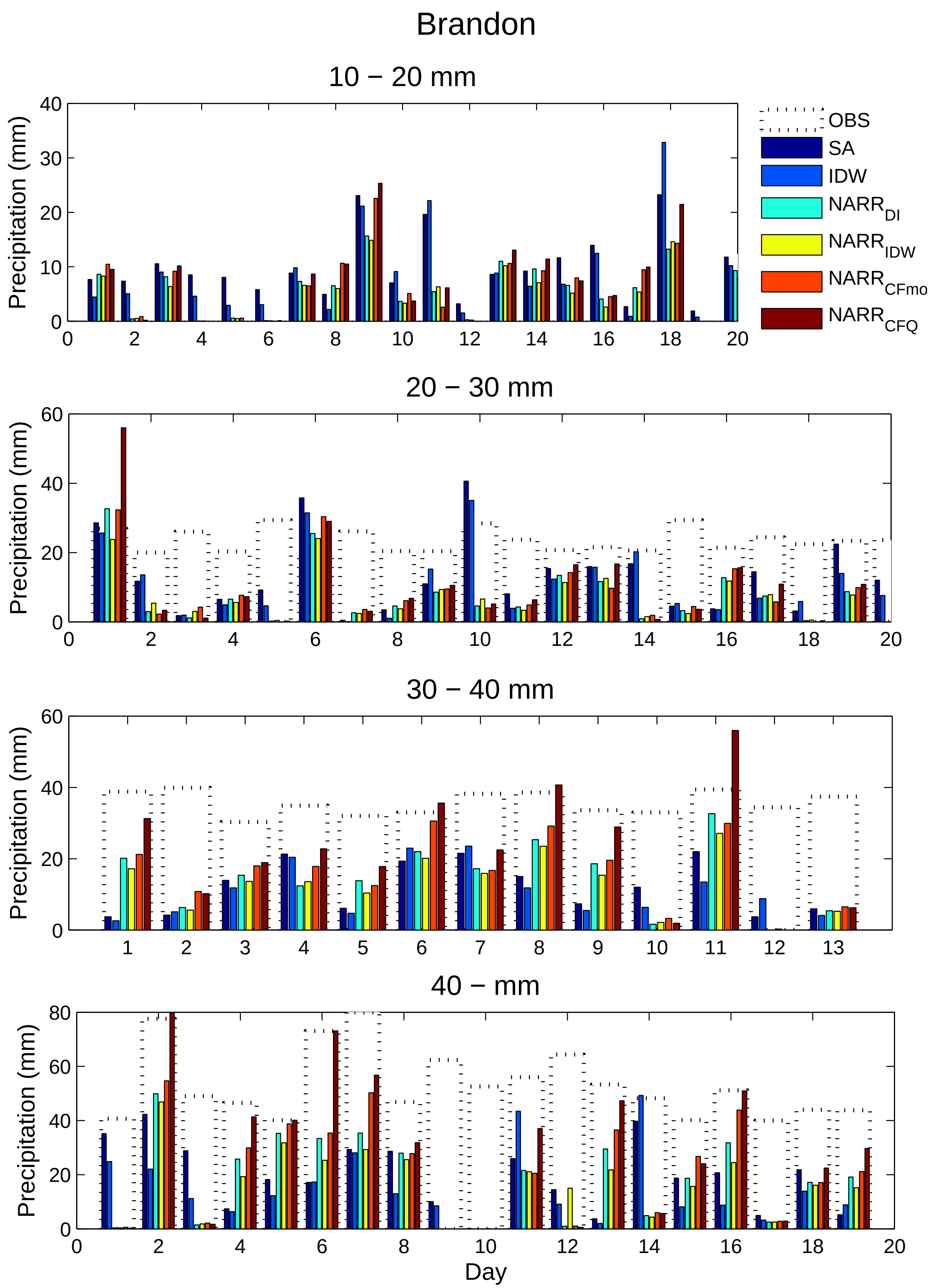

Figure 5.3: Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Brandon.

Table 5.8: Statistics of missing data estimation results by six methods at Brandon.

	OBS	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
Annual Avg	458.4	515.0	536.0	441.0	423.5	455.3	507.8
MAE		1.15	1.31	1.22	1.21	1.25	1.30
R		0.65	0.54	0.59	0.60	0.58	0.58

with the target station in the ranges above 30 mm. The NARR-based methods seem to misestimate a few more wet-days than the traditional methods. However, it should be noted that the 20 events shown in the figures are a subset of all events.

Table 5.9 shows that the NARR-based methods properly estimate the wet-day frequency and the quantity better than the traditional methods for the precipitation events higher than 30 mm. For the precipitation events less than 30 mm, traditional methods are slightly better than the NARR-based methods, while the NARR-based methods, especially the N_{BFmon} and N_{BFQ}, estimate precipitation of more than 30 mm substantially better than the traditional methods.

Table 5.9: Precipitation match ratios in five amount ranges of missing data estimation results at Brandon.

	OBS	Traditional		NARR-based			
	(days)	O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
5-10mm	337	0.36	0.28	0.26	0.26	0.26	0.27
10-20mm	238	0.29	0.24	0.26	0.21	0.24	0.34
20-30mm	63	0.21	0.16	0.10	0.14	0.05	0.19
30-40mm	13	0.00	0.00	0.08	0.00	0.08	0.15
40mm >	19	0.05	0.11	0.05	0.05	0.16	0.37

Table 5.10: Statistics of missing data estimation results by six methods at Dryden.

	OBS	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
Annual Avg	709.8	696.4	670.9	642.0	604.7	706.9	792.1
MAE		1.22	1.38	1.61	1.59	1.65	1.77
R		0.79	0.72	0.66	0.65	0.65	0.65

Dryden area

In the Dryden study area, the daily mean precipitation of all six methods shows good agreement with the observed daily mean precipitation. The O_{SA} and N_{BFmon} annual mean precipitation are quite close to the observations, while O_{IDW}, N_{DI}, and N_{IDW} underestimate and N_{BFQ} overestimates the annual precipitation (Table 5.10). The MAE and correlation values of traditional methods are better than the NARR-based methods. This indicates that the traditional methods using neighbouring stations located within 100 km are likely to be better than NARR-based methods.

Figure 5.4 shows the precipitation event match between the observations and the precipitation for the four quantity ranges at Dryden. The precipitation of traditional methods shows somewhat better agreements than the NARR-based methods in the range below 20 mm, but the differences are smaller than those found at Winnipeg and Brandon. In the 20-30 mm range, it is difficult to conclude which method performs best because the precipitation of the six methods are quite similar. The precipitation of NARR-based methods show slightly better agreement with the precipitation above 30 mm, but the differences are minimal and it varies from case to case. Table 5.11

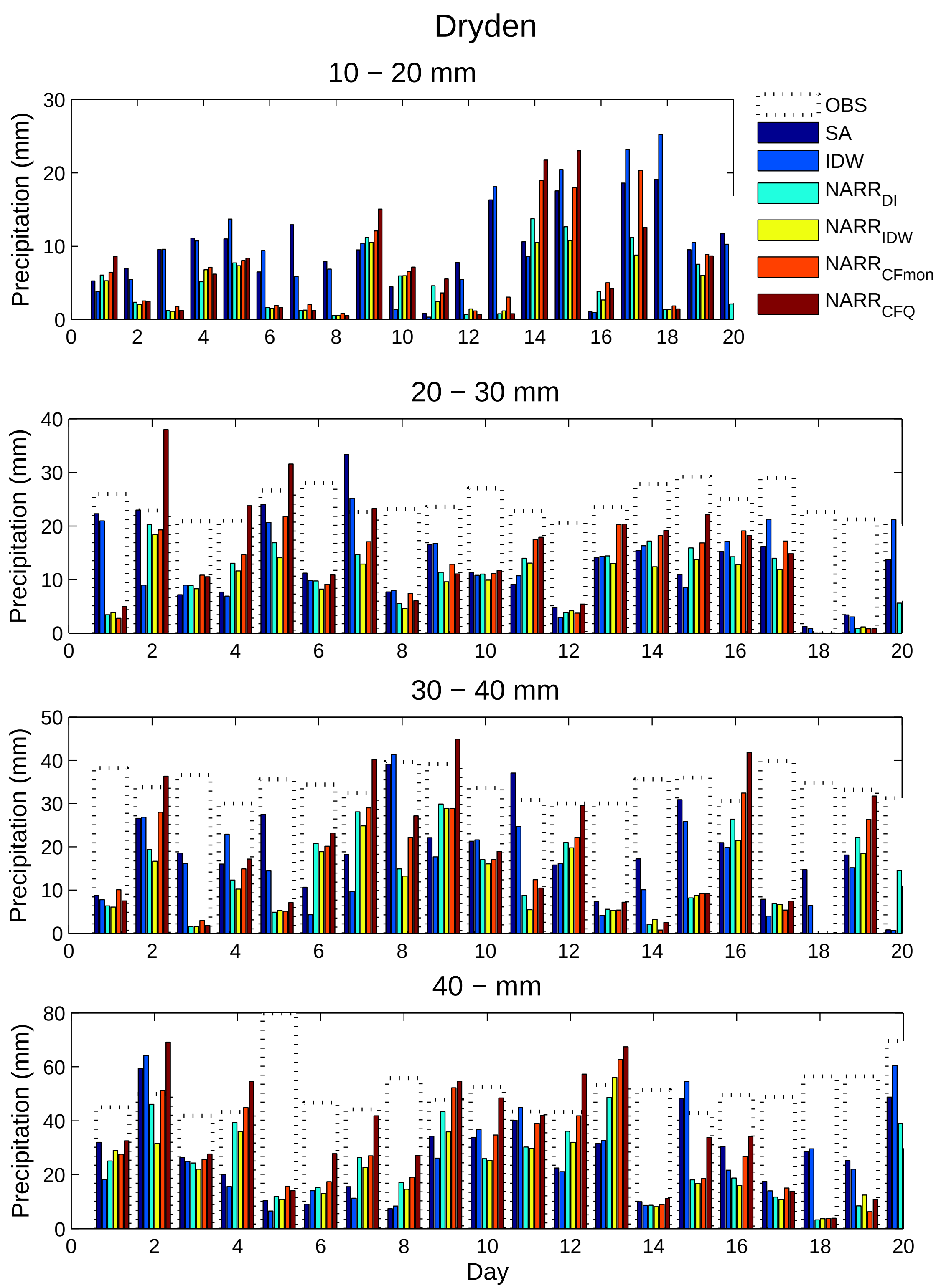

Figure 5.4: Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Dryden.

Table 5.11: Precipitation match ratios in five amount ranges of missing data estimation results at Dryden.

	OBS	Traditional		NARR-based			
	(days)	O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
5-10mm	531	0.38	0.35	0.28	0.25	0.29	0.31
10-20mm	350	0.45	0.31	0.30	0.27	0.30	0.27
20-30mm	96	0.18	0.16	0.16	0.14	0.19	0.19
30-40mm	37	0.11	0.05	0.05	0.03	0.08	0.11
40mm >	33	0.24	0.18	0.18	0.09	0.33	0.52

corroborates the findings from Figure 5.4, showing that for a given range, there is limited differences in the match ratio of the six methods. At Dryden, the traditional methods estimate precipitation of more than 40 mm quite well which is in contrast to the results found at Winnipeg and Brandon. Nevertheless, the N_{BFmon} and N_{BFQ} methods still estimate the precipitation above 40 mm better than the traditional methods.

The remote area

The statistics shown in Table 5.12 are quite similar to each other in all respects, except for the higher daily and annual mean precipitation of N_{BFQ}. It is noticeable

Table 5.12: Statistics of missing data estimation results by six methods at Thompson.

	OBS	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
Annual Avg	490.5	485.0	476.1	473.8	472.5	486.2	567.3
MAE		1.35	1.32	1.31	1.33	1.31	1.44
R		0.55	0.60	0.55	0.54	0.56	0.53

Table 5.13: Precipitation match ratios in five amount ranges of missing data estimation results at Thompson.

	OBS	Traditional		NARR-based			
	(days)	O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
5-10mm	396	0.22	0.23	0.27	0.26	0.26	0.34
10-20mm	206	0.25	0.12	0.19	0.17	0.23	0.25
20-30mm	72	0.14	0.01	0.14	0.11	0.15	0.15
30-40mm	22	0.18	0.00	0.00	0.05	0.05	0.05
40mm >	12	0.25	0.00	0.08	0.00	0.17	0.17

that the difference between observed and estimated annual mean precipitation is small (<20 mm) for all methods.

In Figure 5.5, the traditional methods, particularly the O_{SA}, is seen to estimate precipitation better than other methods for many events at Thompson. The performance of O_{SA} is significantly better in the range above 40 mm. This is also seen in Table 5.13 and it is distinctively different than the results obtained at other stations. The precipitation quantity-match ratios of O_{IDW}, N_{DI}, and N_{IDW} are similar, while for O_{SA}, N_{BFmon} and N_{BFQ} they appear better in all ranges above 10 mm. For the range above 30 mm, the O_{SA} estimates precipitation significantly better than other methods.

The results for The Pas, located in the same general study area as Thompson, are substantially different than the results for Thompson. The Pas follows a pattern similar to other stations. Table 5.14 shows that the statistics of NARR-based methods are significantly better than the ones of traditional methods in all aspects. It is noticeable that the precipitation of N_{DI} and N_{IDW} shows the best agreement with

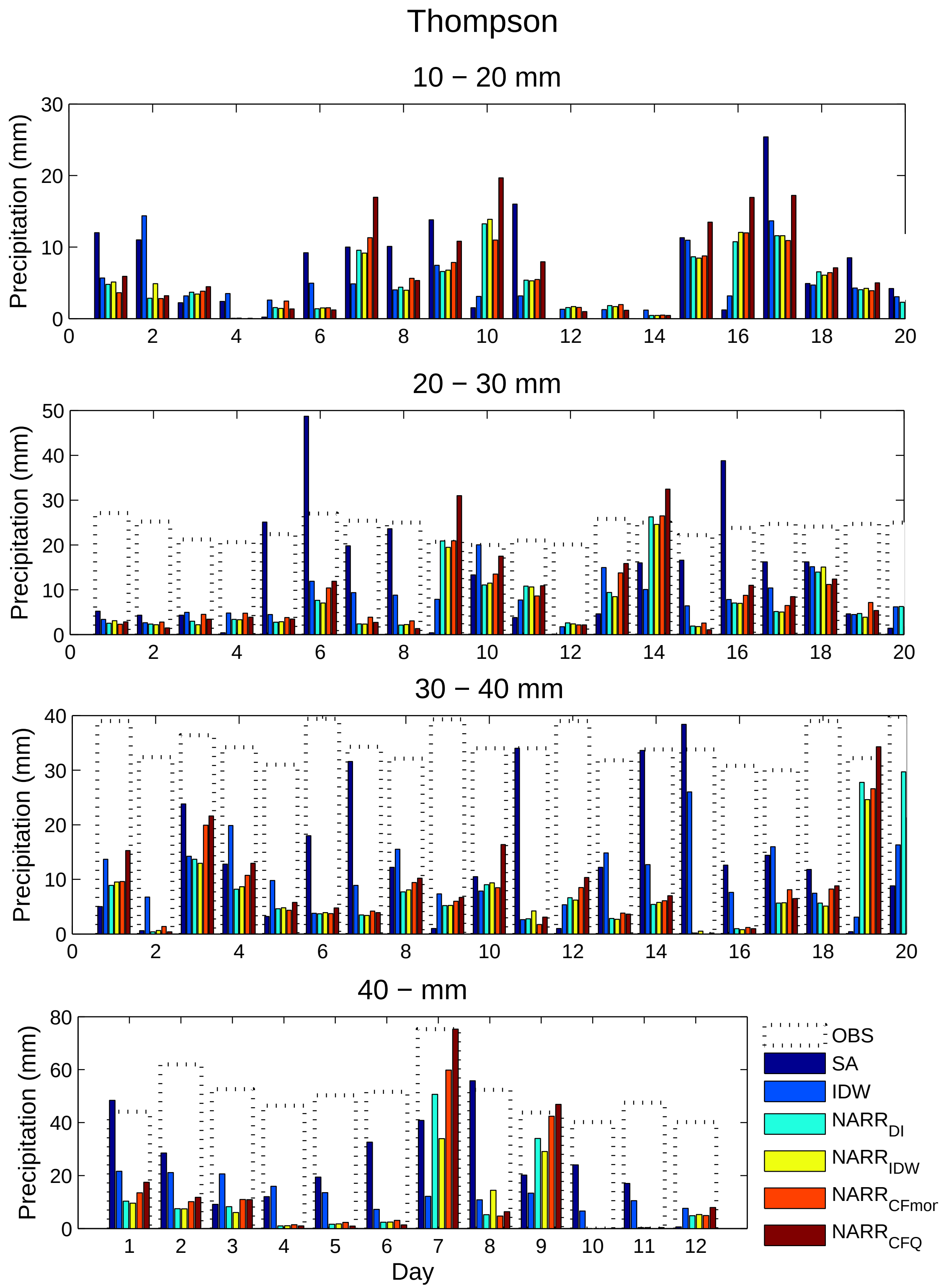

Figure 5.5: Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at Thompson

Table 5.14: Statistics of missing data estimation results by six methods at The Pas.

	OBS	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
Annual Avg	436.3	506.2	470.7	444.7	446.2	432.9	495.2
MAE		1.30	1.66	1.02	1.03	1.07	1.06
R		0.54	0.26	0.71	0.71	0.66	0.71

observations. The differences of annual mean precipitation of NARR-based methods are within 10 mm, while the MAE values are about 1.0 and the correlation values are around 0.7.

Figure 5.6 also shows that the precipitation of NARR-based methods yield the best match for most events for all quantity ranges. The precipitation quantity-match ratios of the N_{BFQ} (Table 5.15) are significantly higher than the ones of other methods in all ranges.

In conclusion for the study areas considered in this chapter, the NARR-based methods, particularly the ones using bias-factors, estimate daily precipitation better than traditional methods, with Thompson being the exception. More specifically,

Table 5.15: Precipitation match ratios in five amount ranges of missing data estimation results at The Pas.

	OBS (days)	Traditional		NARR-based			
		O_{SA}	O_{IDW}	N_{DI}	N_{IDW}	N_{BFmon}	N_{BFQ}
5-10mm	353	0.27	0.13	0.32	0.30	0.28	0.31
10-20mm	189	0.28	0.07	0.33	0.32	0.30	0.33
20-30mm	57	0.09	0.02	0.19	0.18	0.16	0.37
30-40mm	19	0.11	0.00	0.11	0.11	0.05	0.21
40mm >	12	0.00	0.00	0.00	0.00	0.08	0.42

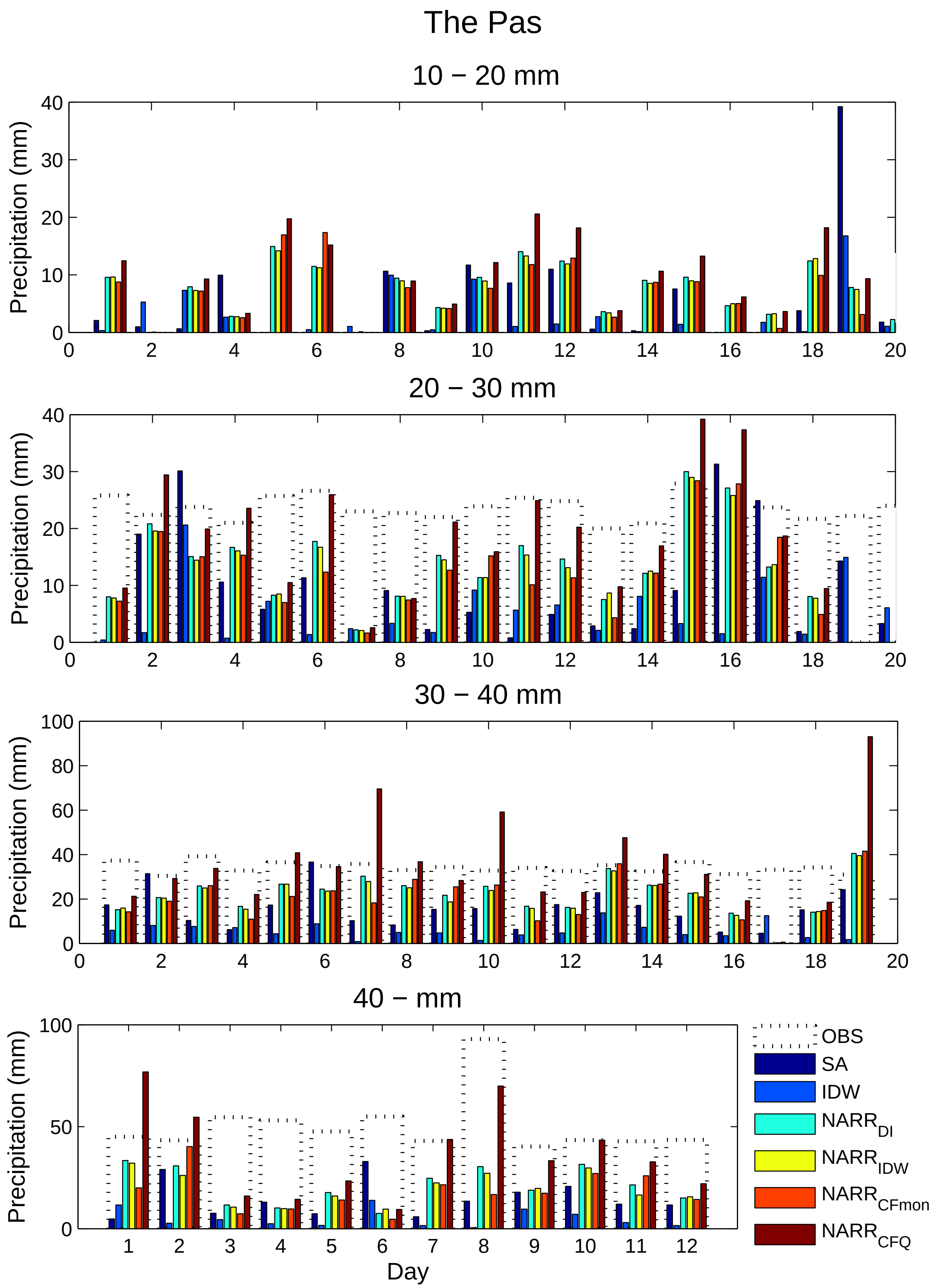

Figure 5.6: Missing data estimation results of four precipitation amount ranges (10-20mm, 20-30mm, 30-40mm, and more than 40mm) at The Pas.

the performances of the N_{BFmon} and N_{BFQ} methods are significant better for precipitation events above 30 mm. The performances of traditional methods, as expected, vary based on the distances from neighbouring stations. The N_{DI} and N_{IDW} often perform as well as the traditional methods. The results indicate that the NARR-based methods for estimation missing precipitation data are promising, especially in remote regions.

Chapter 6

ASSIMILATION OF OBSERVED AND NARR PRECIPITATION

6.1 Introduction

Data assimilation is a key component in reanalyses and is applied in many fields of geosciences, especially in weather forecasting and hydrology. Data assimilation combines observations at point locations with a background field, typically in the form of output from a numerical weather prediction model, to produce an analysis on a regular grid.

Mesinger et al. (2006) mentioned that the most important data addition in NARR was the assimilation of observed precipitation. Notwithstanding the successful assimilation using a sophisticated physical model, the NARR precipitation is not produced by direct assimilation of precipitation observations but instead by derivation of vertical latent heat flux profiles from precipitation analyses (*Mesinger et al.*, 2006). Hence, there is a possibility of further improving NARR precipitation by direct assimilation of precipitation from the network of gauges. As mentioned in Chapter 3, the NARR assimilation process is different for different countries. The assimilation of observed precipitation for NARR use a simple daily gauge-based data set on a 1° grid over Canada and Mexico, while over the US, a combined data set from a variety of sources such as NCDC daily cooperative stations, River Forecast Center stations, and daily accumulations of the Hourly Precipitation Data (HPD) set analyzed using the Parameter-elevation Regressions on Independent Slopes Model (PRISM, *Daly et al.* (1994)) is used. It is obvious that lack of rain-gauges negatively affects the performance of the assimilation in Canada. In the NARR assimilation process, the border regions between different countries are blended together to minimize the discontinuity caused by the different precipitation sources, but as mentioned in Section 3.2, a critical bias was found along the border between Canada and the US, suggesting problems with the transition zone. The blending process along the borders likely explains the significant bias observed in these regions. The aforementioned issues suggests that further improvements of NARR precipitation in Canada can be achieved by performing additional assimilation.

In this chapter, an assimilation model using the statistical interpolation technique is developed to allow direct integration of station precipitation into NARR. The results are compared with the traditional inverse-distance-weighting method.

6.2 Methodology: Statistical Interpolation

Statistical Interpolation is a minimum variance method that is closely related to the kriging technique (*Daley*, 1991). Statistical Interpolation uses observations of a variable to supplement a set of simulated values of the same variable. In general, the simulated output is in the form of a gridded data set whereas observations are located irregularly in space. The Statistical Interpolation aims to combine the two data sets in a way that minimizes the overall variance.

The following is a brief outline of the procedure for assimilating precipitation from a network of stations into NARR via the Statistical Interpolation scheme. Daily precipitation is assumed to be available at K sites and the observations at time t are denoted by $O_k,\ k = 1, \ldots, K$. The time index is omitted to simplify notation. The background field values, i.e. the gridded NARR precipitation, on day t is denoted $B_i,\ i = 1, \ldots, n$. The true value of precipitation at any point (NARR grid or station) is denoted T_i. Finally, we let $A_i,\ i = 1, \ldots, n$ be the analysis result at grid point i, obtained by combining NARR and station data.

For the Statistical Interpolation to yield optimal results, both the NARR field and the station data must be climatologically unbiased. If one assumes that stations are unbiased, then station averages can be used to remove systematic biases from NARR. This is an important step in obtaining good results. The assumption of unbiasedness can be stated as:

$$E[B_i] = T_i \quad \text{and} \quad E[O_k] = T_k \tag{6.1}$$

It is assumed that both the NARR precipitation and the station observations have errors, i.e. differs from the true value, T_k. Error in station precipitation refers both to instrument error and to errors of representation, i.e. representing areal (grid cell) precipitation by a point value.

The analysis value at grid point i is obtained by updating the NARR value with a weighted sum of innovations, where innovations mean the difference between station values and model values interpolated to the station locations:

$$A_i = B_i + \sum_{k=1}^{K} W_{ik}(O_k - B_k) \tag{6.2}$$

The weights W_{ik} must be determined in such a way that the variance of the analysis error at grid point i is minimized. The analysis error is defined as

$$[A_i - T_i] = [B_i - T_i] + \left[\sum_{k=1}^{K} W_{ik}(O_k - B_k)\right] \tag{6.3}$$

Squaring the left- and right-hand sides and taking expectation yield:

$$\begin{aligned} E[(A_i - T_i)^2] =& E[(B_i - T_i)^2] + 2\sum_{k=1}^{K} W_{ik} E[(O_k - B_k)(B_i - T_i)] \\ &+ \sum_{k=1}^{K}\sum_{\ell=1}^{K} W_{ik} W_{i\ell} E[(O_k - B_k)(O_\ell - B_\ell)] \end{aligned} \tag{6.4}$$

Since both background and observations are assumed unbiased, the analysis will be unbiased as well so $E[(A_i - T_i)^2] = \mathrm{Var}(A_i - T_i)$. We seek weights that will minimize the variance of the analysis error so the partial derivatives are equated to zeros:

$$\frac{\partial E[(A_i - T_i)^2]}{\partial W_{ik}} = 2E[(O_k - B_k)(B_i - T_i)] + 2\sum_{\ell=1}^{K} W_{i\ell} E[(O_k - B_k)(O_\ell - B_\ell)] = 0 \tag{6.5}$$

for $k = 1, \ldots, K$, or

$$\sum_{\ell=1}^{K} W_{i\ell} E[(O_k - B_k)(O_\ell - B_\ell)] = -E[(O_k - B_k)(B_i - T_i)], \quad k = 1, \ldots, K \tag{6.6}$$

Under the assumption that there is no correlation between background errors and station errors, the above expression can be further simplified. For example, by adding and subtracting T_i on the right-hand side one finds that

$$\begin{aligned} E[(O_k - B_k)(B_i - T_i)] &= E[\{(O_k - T_k) - (B_k - T_k)\}(B_i - T_i)] \\ &= E[(O_k - T_k)(B_i - T_i)] - E[(B_k - T_k)(B_i - T_i)] \\ &= -E[(B_k - T_k)(B_i - T_i)] \end{aligned} \tag{6.7}$$

since the assumption of no correlation between background and observation errors implies that $E[(O_k - T_k)(B_i - T_i)] = \mathrm{Cov}(O_k - T_k, B_i - T_i) = 0$. Using a similar technique for the left-hand side, we find:

$$\begin{aligned} E[(O_k - B_k)(O_\ell - B_\ell)] &= E[((O_k - T_k) - (B_k - T_k))((O_\ell - T_\ell) - (B_\ell - T_\ell))] \\ &= E[(O_k - T_k)(O_\ell - T_\ell)] - E[(O_k - T_k)(B_\ell - T_\ell)] \\ &\quad - E[(B_k - T_k)(O_\ell - T_\ell)] + E[(B_k - T_k)(B_\ell - T_\ell)] \\ &= E[(O_k - T_k)(O_\ell - T_\ell)] + E[(B_k - T_k)(B_\ell - T_\ell)] \end{aligned} \tag{6.8}$$

Substituting Eq.6.7 and Eq.6.8 into Eq.6.6 yields:

$$\sum_{\ell=1}^{K} W_{i\ell} \left\{E[(O_k - T_k)(O_\ell - T_\ell)] + E[(B_k - T_k)(B_\ell - T_\ell)]\right\} = E[(B_k - T_k)(B_i - T_i)], \quad k = 1, \ldots, K \tag{6.9}$$

This defines a system of K linear equations with K unknown weights. If we define $\mathbf{\Sigma}_B$

to be the $(K \times K)$-covariance matrix of background errors at the station locations, $\boldsymbol{\Sigma}_O$ to be the $(K \times K)$-covariance matrix of the station errors, and $\boldsymbol{\Sigma}_{Bi}$ to be the K-dimensional vector with elements $E[(B_k - T_k)(B_i - T_i)]$ containing the covariances of errors at the analysis point and at the K stations, then the system of equations can be written in matrix form as:

$$[\boldsymbol{\Sigma}_B + \boldsymbol{\Sigma}_O]\boldsymbol{W}_i = \boldsymbol{\Sigma}_{Bi} \tag{6.10}$$

which can easily be solved if $\boldsymbol{\Sigma}_B$, $\boldsymbol{\Sigma}_O$, and $\boldsymbol{\Sigma}_{Bi}$ are known. These covariances must be estimated via spatial correlation analysis. It is reasonable to assume that station errors are spatially uncorrelated, so $\boldsymbol{\Sigma}_O$ can be assumed diagonal. Furthermore, if the stations in the network are of the same type, one can assume that error variances are identical so that $\boldsymbol{\Sigma}_O = \sigma_o^2 \boldsymbol{I}$.

Since the true value is never known, the elements of $\boldsymbol{\Sigma}_B$, $\boldsymbol{\Sigma}_{Bi}$, and σ_O^2 must be estimated from knowledge of the innovations. It is clear from Eq.6.8 that $[\boldsymbol{\Sigma}_B + \boldsymbol{\Sigma}_O]$ is exactly the covariance of innovations. With the assumption of spatially uncorrelated observation errors, Eq.6.8 may be written as

$$\begin{aligned} E[(O_k - B_k)(O_\ell - B_\ell)] &= \mathrm{Cov}(O_k - B_k, O_\ell - B_\ell) \\ &= \begin{cases} \sigma_0^2 + \mathrm{Var}(B - T) & \text{if } k = \ell \\ \mathrm{Cov}(B_k - T_k, B_\ell - T_\ell) & \text{if } k \neq \ell \end{cases} \end{aligned} \tag{6.11}$$

This formulation shows that σ_0^2 can be represented as a nugget effect in the model for the spatial covariance of innovations. We can estimate σ_0 by fitting a covariance model to all data for which $k \neq \ell$. The fitted model can then be used to determine $\mathrm{Var}(B - T)$ and σ_0^2 will finally be known from the estimation of $\mathrm{Var}(O - B)$.

A variogram analysis function was developed using a nonlinear least-squares regression fitting model. $\mathbf{\Sigma}_{B_i}$ in Eq.6.10 is assumed to be a function of distance alone (isotropic) and its elements are modelled in this study by the following function:

$$C(r) = \sigma_b^2 \left(1 + \frac{r}{L}\right) \exp\left(-\frac{r}{L}\right) \tag{6.12}$$

where r is the distance between two points, L is a characteristic horizontal scale, and σ_b is the standard deviation of background error. The characteristic horizontal scale, L, is determined by fitting the model to data. Nonlinear least-squares regression, which estimates the coefficients of a nonlinear regression function using least squares estimation, is used to determine L and σ_b^2.

6.3 Assimilation of NARR Precipitation

6.3.1 Study area

In order to properly assimilate precipitation observations into NARR, a set of weather stations with good-quality precipitation records are required. Southern Manitoba, in particular the area near Winnipeg, has the highest density of weather stations in the

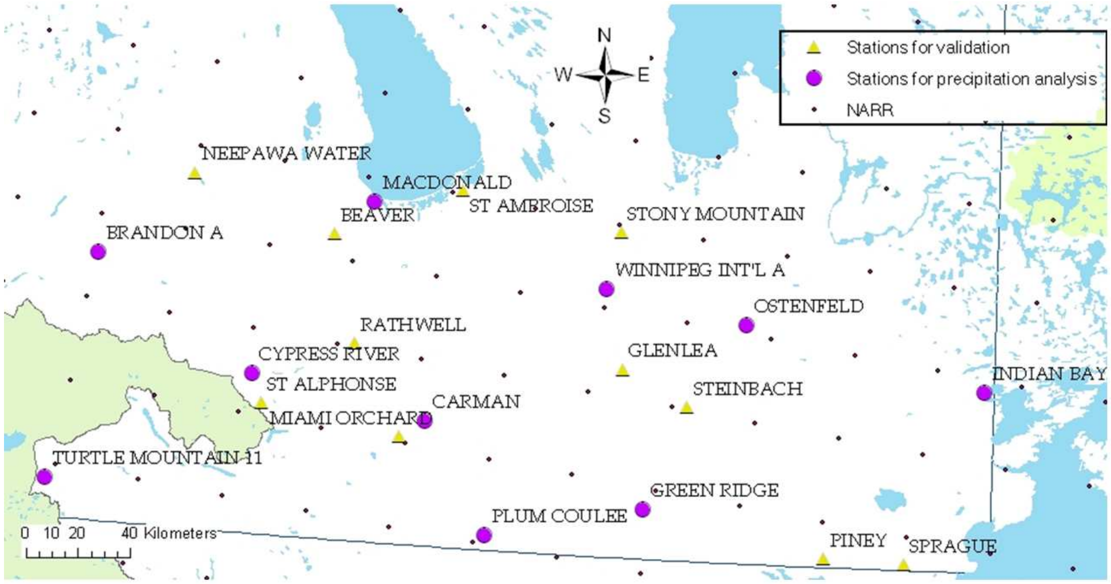

Figure 6.1: Selected weather stations for modelling (purple circles) and validation (yellow triangles).

province. Hence, the area shown in Figure 6.1 was selected for this part of the study. In Chapter 3, an evaluation of NARR precipitation was performed focusing on the spatial representation over the entire prairie region, and a systematic bias along the border between Canada and the US was discovered. Therefore, it is necessary to evaluate the NARR precipitation bias more accurately in the study area used in this chapter.

Initially, 42 weather stations were selected for detailed comparison with NARR (shown in Figure C.1). However, because many stations have missing records, a subset of 10 stations with the least amount of missing records were selected for the assimilation study (henceforth denoted 'MSG', Modelling Station Group). An additional 10 stations were selected, considering their percentage of missing records and location, for validation purpose (henceforth denoted 'VSG', Validation Station

Table 6.1: List of 10 modelling stations and 10 validation stations.

Modelling Station Group (MSG)		Validation Station Group (VSG)	
No.	Station Name	No.	Station Name
M1	Brandon A	V1	Beaver
M2	Carman	V2	Glenlea
M3	Cypress River	V3	Miami Orchard
M4	Green Ridge	V4	Neepawa Water
M5	Indian Bay	V5	Piney
M6	Macdonald	V6	Rathwell
M7	Ostenfeld	V7	St Alphonse
M8	Plum Coulee	V8	St Ambroise
M9	Turtle Mountain 11	V9	Steinbach
M10	Winnipeg Int'l A	V10	Stony Mountain

Group). The validation stations were chosen to be evenly spread out between the modelling stations and they were not included in the assimilation modelling. The list of selected stations is provided in Table 6.1.

6.3.2 Data preparation

Daily precipitation data were extracted for the 91 NARR grid points (shown as dots in Figure 6.1) covering the study area. A requirement of the Statistical Interpolation technique in Eq. 6.1 is that both background and observations must be unbiased. Because the band of NARR precipitation bias found in Section 3.2 overlaps the study area, the NARR bias was investigated through a comparison with the 42 stations initially selected. As seen in the upper part of Figure 6.2, the median monthly precipitation of NARR is lower than observations by roughly 10 mm, and about 75% of monthly precipitation differences between NARR and observations are negative.

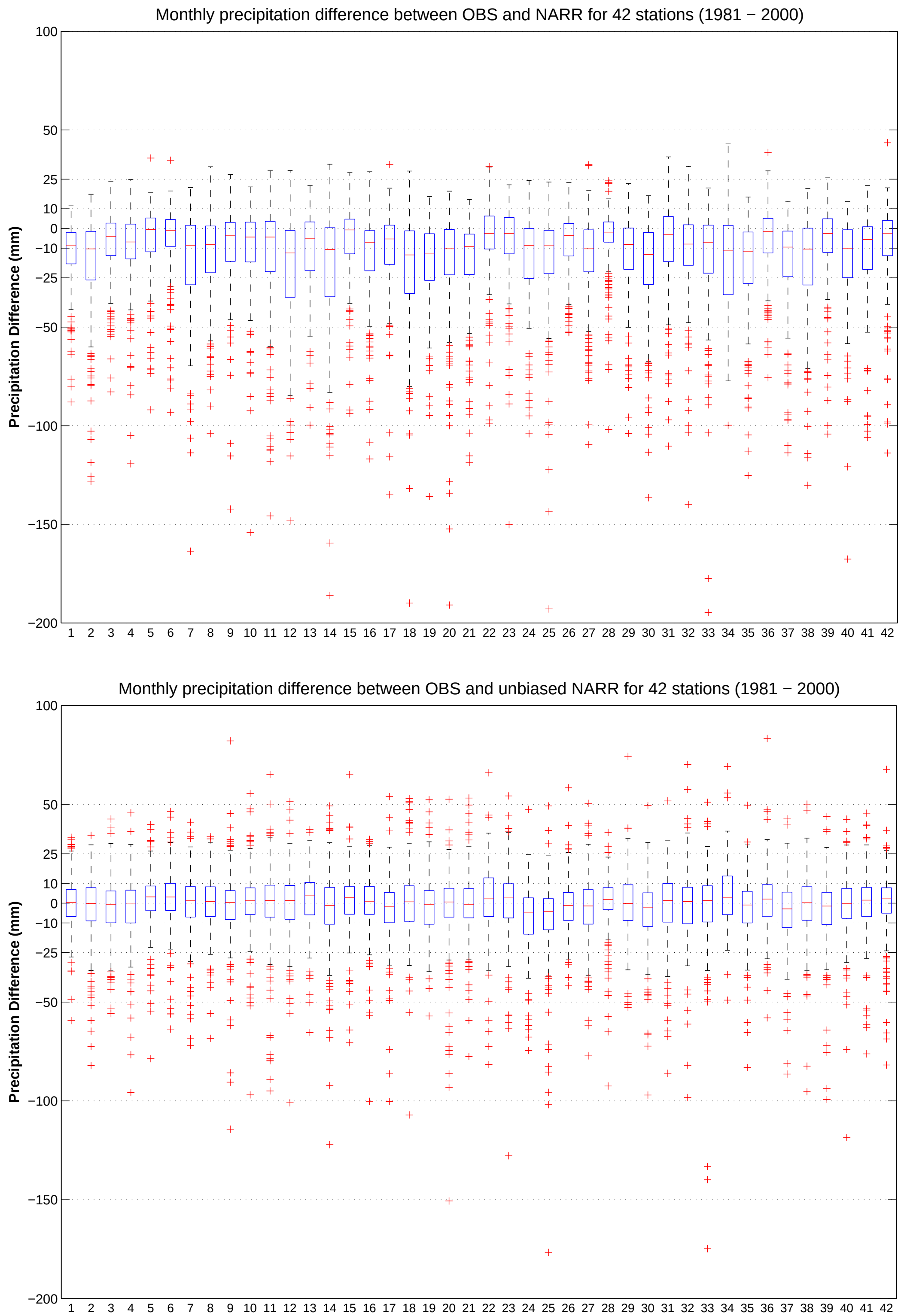

Figure 6.2: Monthly precipitation difference of NARR against OBS at 42 stations for 1981-2000.

This bias necessitates correction measures in order to proceed with the modelling.

To correct bias of a spatially distributed data set such as NARR precipitation, it is desirable to have an observed precipitation data set in gridded format. The CANGRID data appears to be a useful data set for correcting bias spatially, because CANGRID is a high-quality interpolated gridded data set. A simple bias-factor method based on NARR and CANGRID was applied for bias correction. First, monthly precipitation of NARR and CANGRID were extracted for the period of 1981-2000. Because the resolution of the two data sets are different, the CANGRID data were re-gridded unto the NARR grid using triangle-based linear interpolation. Second, the mean monthly precipitation for each grid point was calculated for both data sets, and the percentage difference of monthly precipitation for each month and at each grid point was determined. Finally, NARR daily precipitation was corrected by multiplying by the monthly bias-factor for each grid.

The bias-factor method using CANGRID significantly reduces the bias in NARR precipitation. As shown in the upper part of Figure 6.2, most of the monthly precipitation differences of the uncorrected NARR are negative. The bias-corrected NARR shows that the medians of the differences generally fall in the ± 5 mm range while the edges of each box, which represent the 25th and 75th percentiles, appears around the ± 10 mm range. Also, the differences of the bias-corrected NARR are evenly distributed on the positive and negative sides. The outliers represent extreme differences of data and most of them are repositioned in a range between +50 mm and

-100 mm, where the range for uncorrected NARR was between +25 mm and -150 mm. The observations in this study were assumed unbiased because the publicly released observed data from weather stations are quality controlled by Environment Canada.

6.3.3 NARR precipitation assimilation (NPA) model

The NARR precipitation assimilation (henceforth denoted as 'NPA') based on Statistical Interpolation was implemented in Matlab and observations in the MSG data set (Table 6.1) were used for assimilation. The NPA procedure requires estimation of the weights in Eq.6.10 which in turn requires estimation of the covariances of background errors, station errors, and errors at the analysis point, i.e. $\mathbf{\Sigma}_B$, $\mathbf{\Sigma}_O$, and $\mathbf{\Sigma}_{Bi}$, respectively. The required variogram was obtained by fitting Eq.6.12 to the data using nonlinear least-squares regression fitting. The data consisted of distances between station locations and the covariance of NARR errors at the station locations. The fitted model produced the optimized L and σ_b^2 (i.e. $\mathrm{Var}(B-T)$) as 56.5 km and 13.62, respectively. The covariance matrix of background errors, $\mathbf{\Sigma}_B$, was computed by Eq.6.12 using the optimized values of L and σ_b^2. For estimating $\mathbf{\Sigma}_{Bi}$, the same procedure was applied using distances between station locations and NARR grid points. For the variogram analysis, $\mathrm{Var}(O-B)$ was also obtained as shown in Figure 6.3, and σ_0^2 was estimated as 8.36 by subtracting σ_b^2 from $\mathrm{Var}(O-B)$. The covariance matrix of station errors, $\mathbf{\Sigma}_O$, was assumed diagonal so $[\mathbf{\Sigma}_B + \mathbf{\Sigma}_O]$ was

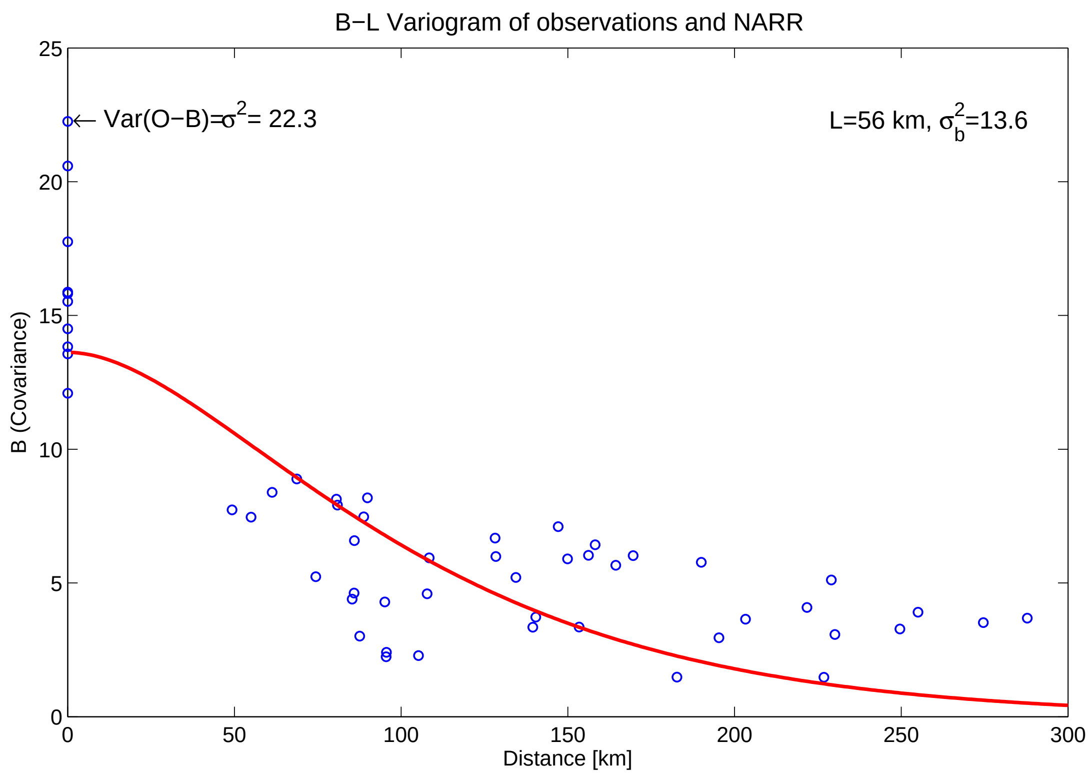

Figure 6.3: Fitted variogram.

estimated as $[\mathbf{\Sigma}_B + \sigma_o^2 \boldsymbol{I}]$. The weights were then determined by solving Eq.6.10 for W_{ik}. In the final step, the assimilated NARR precipitation (the analysis value A_i in Eq. 6.2) was computed using observed precipitation data from the 10 modelling stations (O_k), NARR precipitation from the 91 grid points (B_i), and the weights (W_{ik}). In summary, the NPA model requires observed precipitation data, NARR precipitation, and the optimized parameters L, σ_b^2, and σ_0^2 as input.

6.3.4 Results of simulation and validation

The performance of the NPA model was assessed by comparison with a traditional station interpolation method based on inverse distance weighting. Only the MSG

Table 6.2: Daily and annual mean precipitation of observation, NARR, NPA and IDW for each station group. The period is 1981-2000.

Model	Daily		Annual	
	MSG	VSG	MSG	VSG
OBS	1.49	1.48	542.9	540.0
NARR	1.07	1.08	390.8	395.7
NPA	1.53	1.52	557.9	554.7
IDW	1.46	1.48	533.7	540.2

observations were used in the IDW model to allow for a fair comparison with the NPA model.

The simulation results were assessed by analyzing statistics such as averages at different time scales, root mean square errors (RMSE), daily data differences (errors), and correlations at different time scale. Also, basic plotting techniques including scatter plot, Q-Q plot, and box plot were used.

Table 6.2 shows averages of daily mean precipitation at daily and annual time scales, averaged over all stations in each station group (see Table C.1 for each station result). The assessments for MSG represent simulation performance against the observations used for estimation, while the VSG results are independent, validation results based on stations that were not involved in the assimilation process. Because the stations in the two groups (MSG and VSG) were selected to be evenly distributed across the study region, averages of daily precipitation for the two groups are almost the same. Although NARR preciptiation was bias corrected, NARR underestimates daily average precipitation by -0.4 mm for both station groups. The NPA estimation

Table 6.3: Observed and estimated daily mean precipitation of modelling and validation stations.

Station	MSG				Station	VSG			
No.	OBS	NARR	NPA	IDW	No.	OBS	NARR	NPA	IDW
M1	1.3	1.1	1.4	1.7	V1	1.5	1.2	1.4	1.3
M2	1.5	0.9	1.5	1.4	V2	1.5	1.1	1.6	1.4
M3	1.4	1.0	1.5	1.3	V3	1.5	0.8	1.5	1.5
M4	1.5	0.8	1.6	1.4	V4	1.4	1.2	1.4	1.6
M5	1.7	1.0	1.7	1.5	V5	1.6	1.2	1.7	1.6
M6	1.4	1.2	1.4	1.6	V6	1.4	1.0	1.5	1.4
M7	1.8	1.2	1.7	1.6	V7	1.5	0.9	1.5	1.4
M8	1.5	1.3	1.5	1.6	V8	1.3	1.2	1.5	1.5
M9	1.5	0.9	1.5	1.4	V9	1.6	1.0	1.6	1.6
M10	1.4	1.2	1.5	1.2	V10	1.4	1.3	1.5	1.5

significantly improves the underestimation problem of NARR as the averages are close to the target values (overestimation by 0.04 mm for both groups). In the comparison with the IDW simulation, Table 6.2 shows that daily mean precipitation averaged over all stations is better with IDW than with NPA, although the NPA results are still very close to observations.

A comparison of daily mean precipitation for each individual station reveals some additional insight. As seen in Table 6.3, although station averages of IDW were better than NPA, NPA shows better agreement with observation of daily mean precipitation at 8 of 10 stations in the MSG data set, while 3 stations showed better agreement and 4 stations appeared the same in the VSG data set. Table C.1 further shows that the NPA monthly and annual mean precipitation of individual stations agrees better with observation than IDW at each station, although the station averages are

Table 6.4: Average daily errors and RMSE of daily precipitation for NARR, NPA and IDW.

Station	Average Daily Errors			RMSE		
Group	NARR	NPA	IDW	NARR	NPA	IDW
MSG	-0.42	0.04	-0.03	4.04	2.37	3.98
VSG	-0.40	0.04	0.00	4.16	3.33	4.23

better for IDW. It is obvious that the average of spatially distributed data need to be carefully assessed because spatial variations may be concealed by averaging. In summary, it is concluded here that NPA performes better than IDW in terms of averages.

An assessment using root mean square error (RMSE) and average daily precipitation errors was conducted for investigating the day-to-day precipitation agreement. Station averages of NARR mean daily errors are in the order of -0.4 for both station groups and are clearly worse than NPA and IDW. Station averages of mean daily errors for IDW and NPA are fairly close to zero. The lower average RMSEs of NPA in the MSG group of station compared with the VSG group indicates that the assimilation performance is affected by the distance from stations involved in the process. Compared to NARR and IDW, NPA results are significantly better in terms of RMSEs. The RMSEs of IDW and NARR are quite close while average daily errors are distinctively different. Although NARR underestimates precipitation in terms of average, the error in daily precipitation, as measured by the RMSE, is relatively similar to IDW.

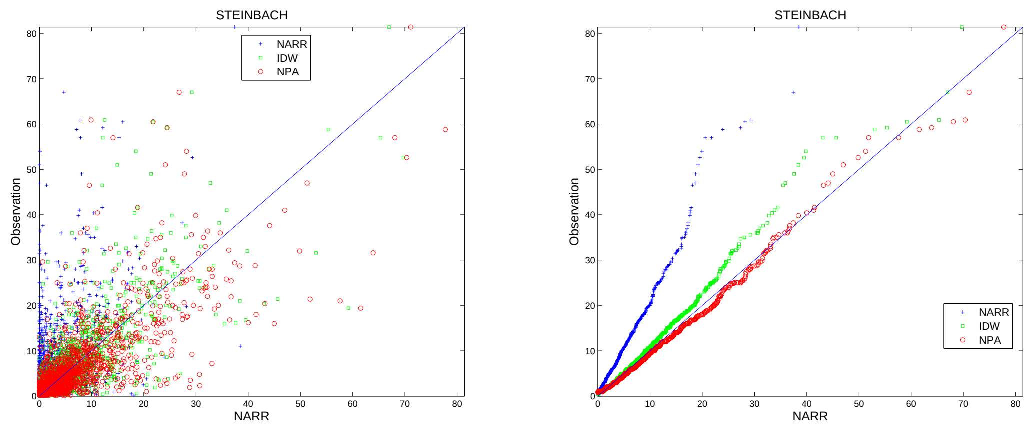

Figure 6.4: Scatter plot (left) and Q-Q plot (right) of NARR, NPA, and IDW against observation at the validation station in Steinbach.

A scatter plot is another way to present the day-to-day match of two precipitation data sets. For instance, the scatter plot shown in Figure 6.4 (left panel) depicts the day-to-day match between observations and estimations of daily precipitation for NARR, NPA, and IDW at Steinbach (a station in the VSG data set, see Figure C.2 for all stations). NARR appears to underestimate daily precipitation overall and to poorly represent the extreme precipitation. The NPA simulation seems to agree more satisfactorily with observations, especially for the extreme precipitation as many red dots appear near the 45°-line at high values. IDW also shows a good agreement with observations, but NPA appears better for the extreme values.

The distributional aspects of data sets can be examined by a Q-Q plot. Figure 6.4 (right panel) shows the three model simulations (see Figure C.3 for all stations). Most of the NPA points are founded along the 45°-line. IDW quantities are generally lower than observation quantities.

Seasonal performance of each model is an important aspect to assess in estimation

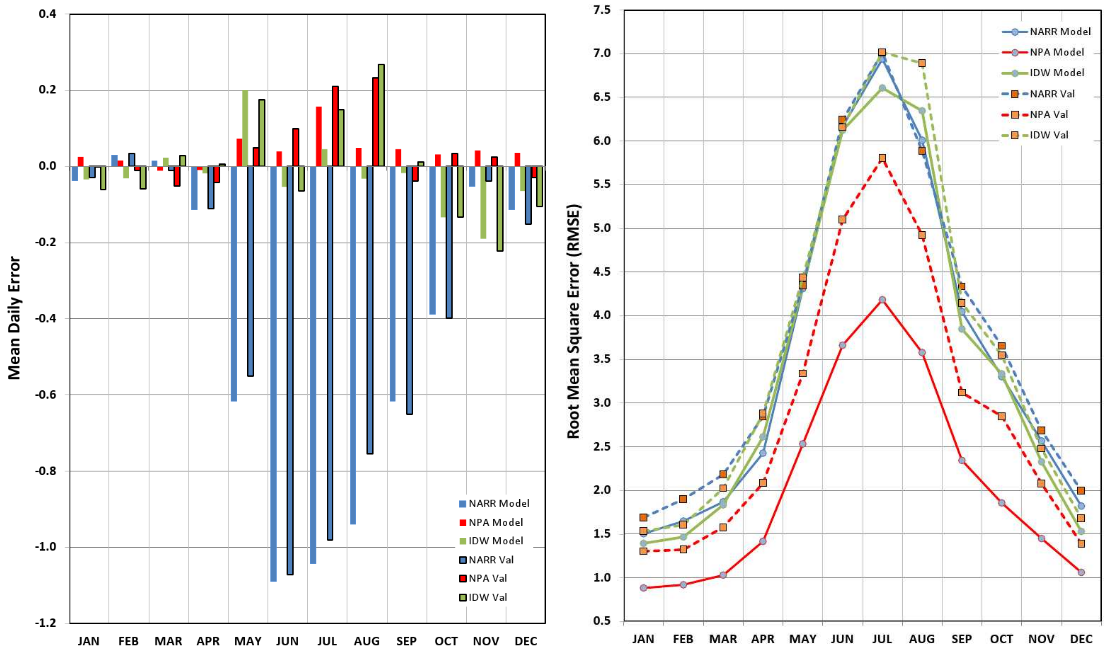

Figure 6.5: Mean daily error and RMSE of NARR, NPA, and IDW for the MSG and VSG data sets.

of precipitation, because it is difficult to estimate extreme rainfall events in reanalysis products. Figure 6.5 depicts the RMSE and daily precipitation errors for each month (see Table C.3 for each station result). The negative bias of NARR is particularly significant in the summer until October, which corresponds to the findings in Chapter 3. NPA and IDW show a slight overestimation between May and August. In other months, NPA shows minimal mean daily errors, while NARR and IDW shows some underestimation. Overall, the RMSEs of NPA for all months are noticeably lower than the other two models. Similar to the station average assessment of RSME, the RSMEs of IDW are almost identical to the NARR results for each month. This implies that the differences of IDW against observation in the summer months are as large as with NARR.

Table 6.5: Average correlation of daily and monthly precipitation of NARR, NPA and IDW.

Model	Daily		Monthly	
	MSG	VSG	MSG	VSG
NARR	0.55	0.53	0.88	0.85
NPA	0.86	0.75	0.96	0.90
IDW	0.58	0.57	0.80	0.78

Finally, averages of correlation between observations and model simulations for each station group were assessed (Table 6.5, see Table C.2 for details). NPA also shows the best correlation among the models for all time scales. The NPA model improved raw NARR daily precipitation from an average correlation of 0.53 to 0.75 in VSG, while the IDW model yields 0.57. The monthly correlation of NPA (0.90) is high and, noticeably, the IDW (0.78) is even shown lower than NARR (0.85). The correlations are obviously presenting similar features as the previous RMSE assessments of IDW. Although the average precipitation assessment of IDW performance appears better than NARR and similar to NPA, the RMSE and correlation assessments show that the IDW performance when considering the day-to-day match is worse than NPA and comparable to NARR.

Chapter 7

CONCLUSIONS

This thesis has investigated the usefulness of the North American Regional Reanalysis for hydrologic modelling. In regions that have few climate stations, NARR precipitation and temperature may constitute a useful data alternative. The thesis has in particular focussed on NARR for continuous streamflow simulation, estimation of missing precipitation records, and climate model downscaling.

Any conclusion on the usefulness of NARR will depend on the alternative to which it is compared. The thesis has attempted to assess NARR for use in central Canada, with the main focus on Manitoba. Northern and Eastern Manitoba are known to have a sparse network of climate stations. The conclusions drawn from the thesis are specific to this particular region and results will be different for other regions.

The major findings in this thesis are:

- For the study region, the spatial representativeness of NARR precipitation is generally good, as demonstrated by comparison with two interpolated gridded climate data sets, CANGRID and ANUSPLIN, except for a band of systematic underestimation along the border with the US. The bias band is clearly visible on spatial maps and must be attributed to problems with reconciling different input data sets north and south of the border.

- The NARR precipitation and temperature show good statistical agreement with observations at six weather stations in Manitoba, across a range of time scales (daily, monthly, seasonal and annual). The NARR precipitation has a correlation of more than 0.8 at the monthly time scale and 0.6 at the daily time scale.

- NARR precipitation generally shows better agreement with observations than NNGR and ERA-40, two other popular reanalysis data sets. ERA-40 temperature shows somewhat better agreement with observations than the other two reanalyses; the temperature of NARR and NNGR are similar.

- The NARR climate data were found to be useful alternatives to station data in a climate change study. For the particular case studies considered in the thesis, the hydrological modelling and statistical downscaling of GCMs using solely the NARR climate data gave simulation results similar to those obtained using observations. The case study watersheds had climate observation in reasonable proximity. The results suggests that NARR can be used in situations where no observational data are available.

- The NARR precipitation data show reasonable day-to-day match with observations at weather stations and may therefore be useful for estimating missing records of daily observed precipitation. Several NARR-based methods for estimating missing data were proposed and demonstrated to generally perform better than traditional methods using observations from neighbouring stations when the distance to neighbouring stations is more than 100 km.

- The NARR precipitation can be combined with station data using statistical interpolation. Such re-assimilation corrects the NARR precipitation bias along the border as well as other deficiencies in NARR and generally results in an improved product.

- A climate change study has found that the uncertainty related to the choice of downscaling method is significantly higher than the uncertainty related to emission scenarios. The pattern of temperature changes between emission scenarios is similar and the difference in the magnitude of change is a direct consequence of the classification of the emission scenarios. However, the difference between the statistical downscaling methods is quite significant for both temperature and precipitation.

As already mentioned, the conclusion in this thesis are valid only for the regions and time scales investigated. NARR was compared with CANGRID and ANUSPLIN to assess spatial properties of biases, with observations and other reanalyses at six weather stations to assess performance at point scale, and with fifty weather stations across the Prairie region to assess both point and distributed scales for daily, monthly, seasonal, and annual time steps. The comparison results for monthly, seasonal, and annual precipitation indicate that NARR has an agreement with observations that is better than NNGR and ERA-40. The daily correlation of NARR precipitation (average of 0.6 for 50 weather stations in the Prairie regions) is noticeably lower than the monthly correlation (average of 0.9 for 50 weather stations in the Prairie regions), but the difference of average precipitation and RMSE values are quite small. A hydrological study of long-term climate conditions does not necessarily require day-to-day match of precipitation; the high values of monthly correlation and the relatively small bias (outside the bias band) imply that the NARR precipitation is suitable for long-term assessments.

Due to a significant negative bias band along the border with the US, NARR must be used with caution in this region. The issue must be linked to a systematic error in the NARR assimilation process. NARR precipitation outside the bias band can be used with little or no bias correction but inside the band, a bias correction is required, for example using the re-assimilation procedure proposed in the thesis.

The day-to-day match of NARR daily precipitation and observations within grid cells was compared to the match between pairs of climate stations. A distance of 100 km from a target weather station appears to be the point beyond which the daily precipitation of NARR agrees better than the ones at the neighbouring weather station. Several NARR-based methods for infilling missing precipitation records were proposed. The NARR-based estimation methods, particularly the scale-factors methods (N_{BFmon} and N_{BFQ}), correct the NARR bias and the estimated precipitation quantities are generally more accurate than those based on traditional methods, in many cases even when neighbouring stations are within 100 km. This suggests that the NARR-based methods are useful for infilling missing observations. The N_{BFQ} method can be further improved by including information about the year-to-year differences in dryness and wetness. In order to more accurately apply the missing data estimation methods to a weather station, the local climatic characteristics near the station need to be thoroughly understood. The missing data estimation using NARR will increase the number of reliable weather stations with full records which will be useful in hydrologic modelling studies.

While NARR has a useful role to play in filling holes in observation records, observations also can be used to improve the gridded NARR precipitation fields. This was demonstrated using statistical interpolation. The re-assimilation of observed precipitation records into NARR correct much of the internal biases in NARR, including the bias band along the border. The corrected NARR precipitation fields will be useful in hydrological modelling of large basins.

The NARR climate data were validated by hydrological modelling. The simulation results were quite close to the results obtained using observations at weather stations. Generally, the uncertainty of conventional input data is disregarded in the calibration of hydrologic models. However, precipitation data from weather stations may not always represent actual precipitation in the watershed, leading to errors in runoff simulations as well as in calibrated model parameters. Although NARR surface climate data include some biases, the NARR data do not seem to be any worse than observed data in this regard, at least for the watersheds modelled in this thesis.

In order to validate the reliability of NARR for a climate-related study, the NARR data were also used for statistical downscaling. The assessment of climate change impacts was conducted using solely the NARR data and compared with the results of a project that employed observational data, and very similar results were obtained.

The evaluation and various applications of NARR surface variables have demonstrated its consistency and potential for hydrological studies, including studies related to long-term climate issues.

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Appendix A

DETAILED RESULTS OF NARR EVALUATION

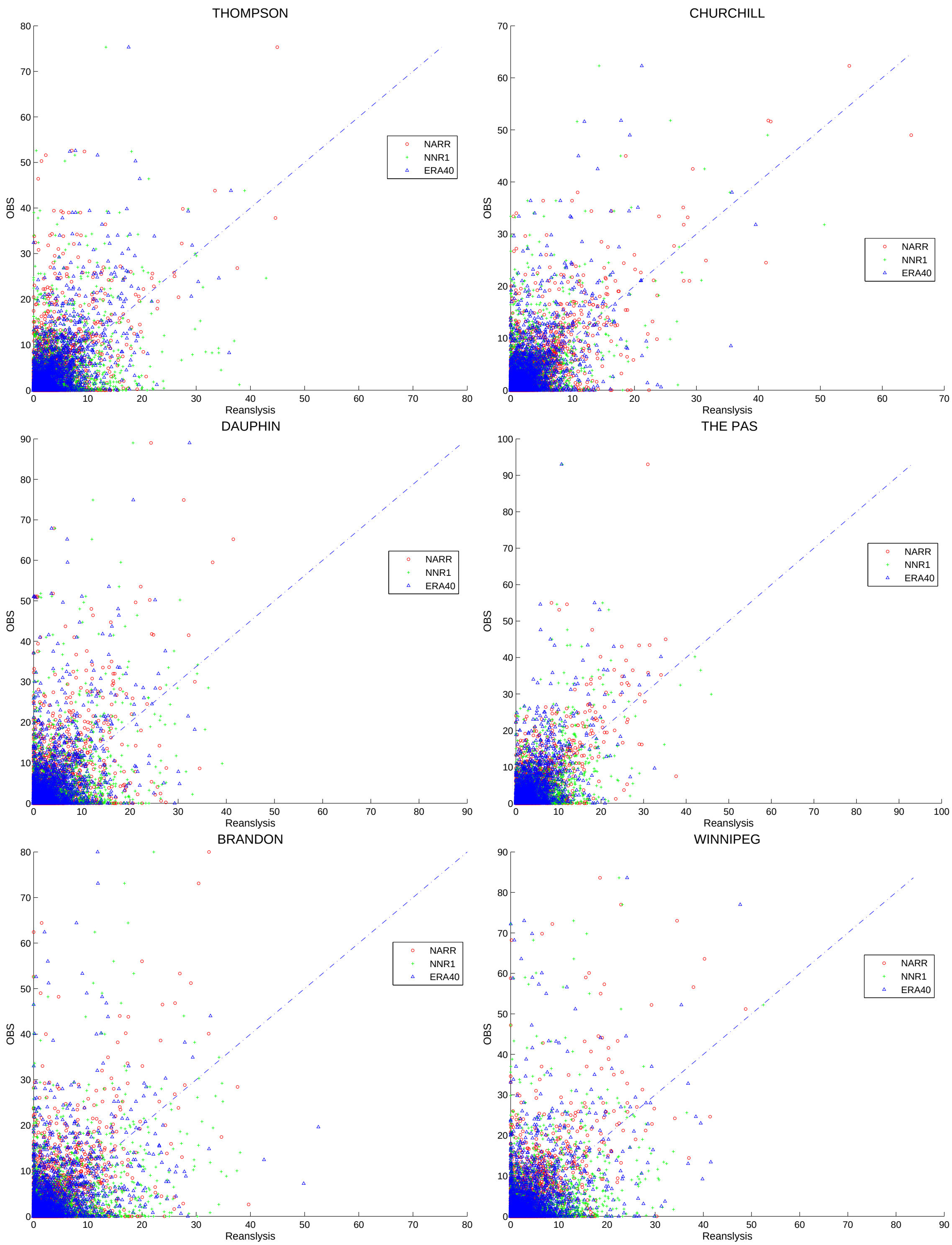

Figure A.1: Q-Q plot for NARR, NNGR, and ERA40 against OBS.

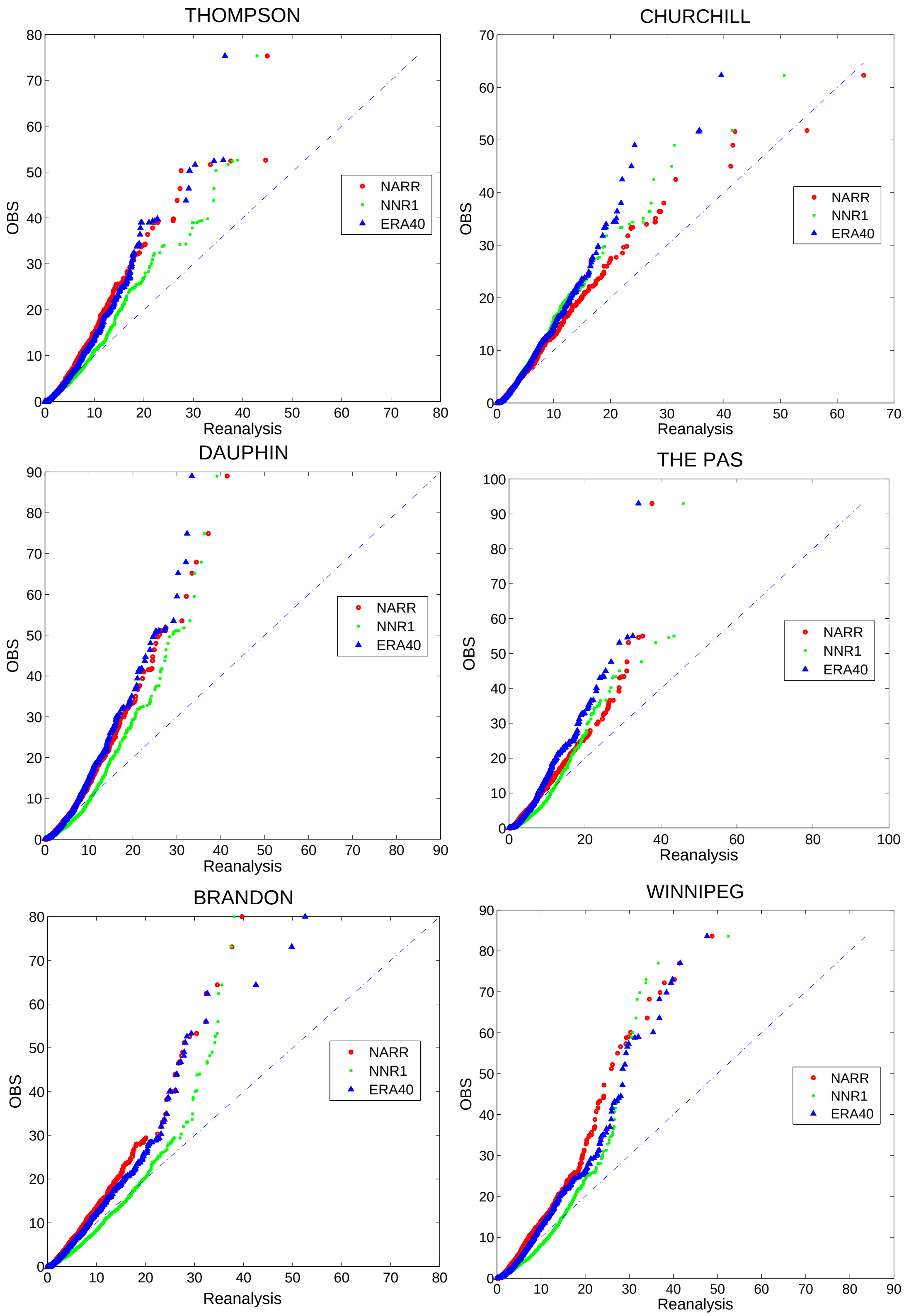

Figure A.2: Q-Q plot for NARR, NNGR, and ERA40 against OBS.

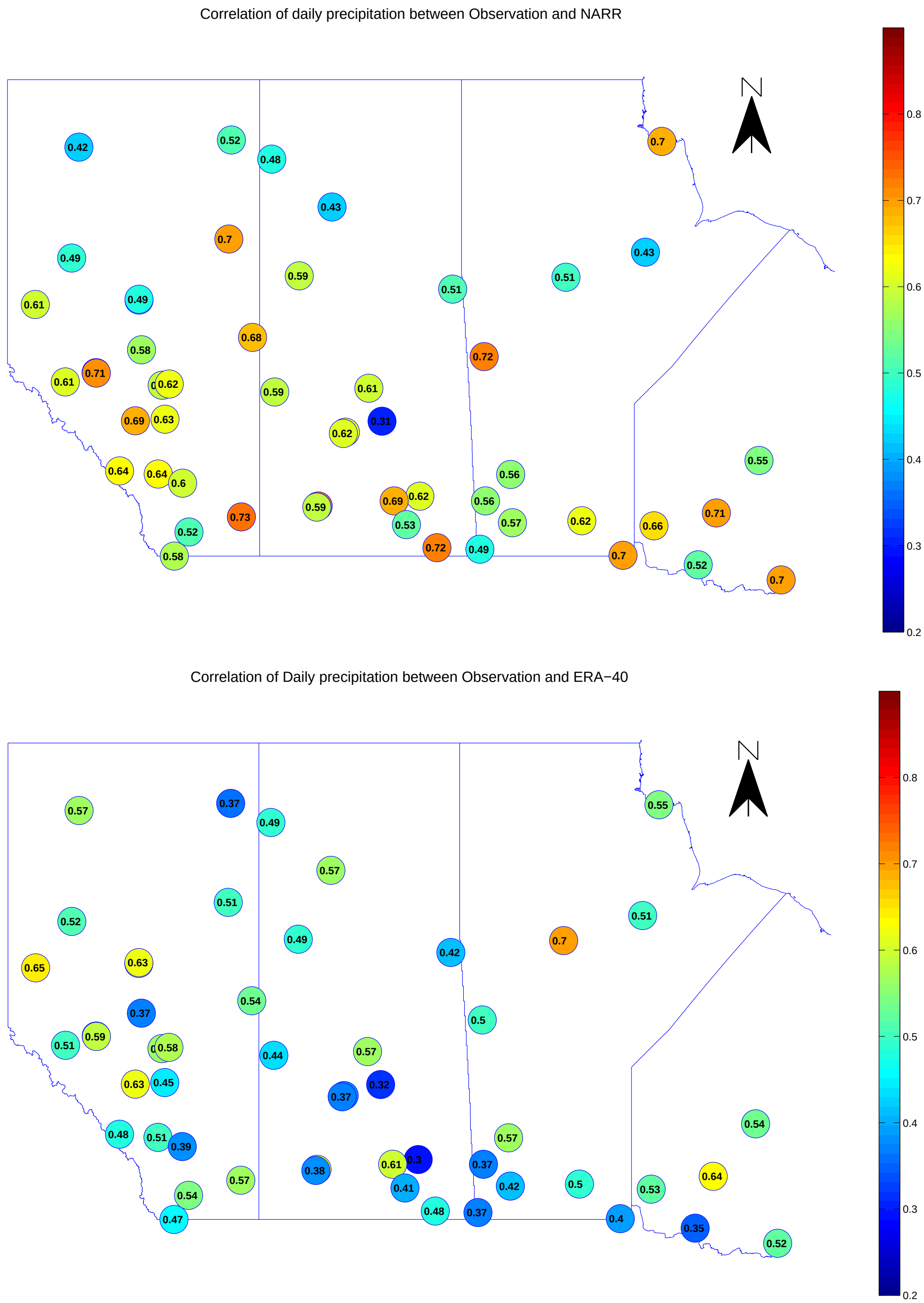

Figure A.3: Correlation coefficient of observed station and NARR and ERA-40 daily precipitation.

Table A.1: Average temperature and precipitation comparison at weather stations in Manitoba.

Station	Mean Temperature			Daily Precipitation		
MANITOBA	OBS	NARR	ERA40	OBS	NARR	ERA40
Birtle	1.5	3.5	2.7	1.2	1.2	1.0
Brandon CDA	3.1	4.4	3.5	1.3	1.2	1.4
Churchill A	-6.6	-5.1	-4.7	1.2	1.3	1.3
Dauphin A	2.5	3.7	3.1	1.4	1.3	1.1
Gillam A	-4.2	-2.6	-5.1	1.3	1.3	1.3
Pierson	4.4	5.3	3.6	1.3	0.7	1.3
Sprague	3.4	5.1	3.8	1.7	1.3	2.0
The Pas A	0.3	2.0	-0.8	1.2	1.2	1.2
Thompson A	-3.1	-0.6	-1.2	1.4	1.3	1.3
Winnipeg A	2.9	4.7	3.1	1.4	1.2	1.5

Table A.2: Average temperature and precipitation comparison at weather stations in north-western Ontario.

Station	Mean Temperature			Daily Precipitation		
Kenora A	2.8	3.8	2.6	1.9	1.4	1.6
Mine Centre	3.2	4.9	2.3	2.1	0.9	1.8
Pickle Lake A	-0.3	1.8	-0.8	1.9	1.9	1.8
Sioux Lookout A	1.8	2.7	1.9	2.0	1.9	1.8
Thunder Bay A	2.6	1.8	2.9	1.9	1.2	1.9

Table A.3: Average temperature and precipitation comparison at weather stations in Alberta.

Station	Mean Temperature			Daily Precipitation		
ALBERTA	OBS	NARR	ERA40	OBS	NARR	ERA40
Banff CS	2.3	2.0	3.4	1.0	1.4	1.2
Calgary A	4.3	4.2	3.3	1.1	1.3	1.5
Calmar	3.2	3.7	2.9	1.4	1.4	1.6
Campsie	2.4	3.7	3.0	1.3	1.4	1.1
Carway	4.7	5.8	5.9	1.5	1.1	1.0
Cold Lake A	2.0	2.5	1.8	1.1	1.2	1.2
Edmonton Intl A	2.8	3.6	3.3	1.3	1.3	1.1
Edson A	2.3	2.1	0.5	1.5	1.7	1.9
Entrance	2.8	2.5	0.2	1.5	1.8	1.9
Fort Chipewyan	-1.9	0.1	-2.7	1.1	1.1	1.1
Fort Mcmurray	1.0	1.2	0.2	1.2	1.2	1.2
Gleichen	3.8	5.7	5.8	0.9	1.0	1.0
Grande Prairie	2.2	3.2	2.5	1.2	1.4	1.5
High Level A	-1.3	0.3	1.0	1.1	1.1	1.2
Lacombe CDA	3.0	4.0	3.0	1.2	1.3	1.6
Lethbridge A	5.9	7.6	6.0	1.0	0.9	1.0
Medicine Hat A	6.0	6.8	5.8	0.9	0.9	0.9
Peace River A	1.7	2.5	3.3	1.1	1.3	1.2
Rocky MTN House	1.5	3.1	3.1	1.8	1.6	1.6
Slave Lake A	2.1	2.7	2.9	1.3	1.4	1.2

Table A.4: Average temperature and precipitation comparison at weather stations in Saskatchewan.

Station	Mean Temperature			Daily Precipitation		
SASKATCHEWAN	OBS	NARR	ERA40	OBS	NARR	ERA40
Buffalo Narrow	1.2	1.6	1.6	1.3	1.2	1.2
Cluff Lake	-0.6	-0.3	0.0	1.3	1.2	1.2
Cree Lake	-2.2	-0.5	-1.2	1.2	1.2	1.2
Estevan A	3.9	5.4	3.1	1.1	0.8	1.3
Indian Head CDA	3.0	4.2	3.2	1.2	1.1	1.1
Island Falls	-1.7	-1.4	-0.2	1.3	1.3	1.2
Pilger	1.6	3.1	1.6	1.0	1.1	1.4
Prince Albert	1.2	2.6	1.9	1.2	1.1	1.2
Regina A	3.2	4.5	3.9	1.1	1.1	1.0
Saskatoon SRC	4.1	4.4	3.1	1.0	1.0	1.1
Saskatoon Water	4.6	4.5	3.1	0.9	1.0	1.0
Swift Current	4.1	6.4	4.7	1.1	1.0	1.0
Swift Current	4.3	6.3	4.7	0.9	1.0	1.0
Waseca	2.2	2.6	2.8	1.2	1.1	1.0
Yellow Grass	4.4	4.9	4.4	1.3	1.1	1.2

Appendix B

DETAILED RESULTS OF MISSING DATA ESTIMATION

Table B.1: Wet-dry-day match between neighbouring stations and Winnipeg.

Station No.	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S10	S11	S12
W-W	1398	1132	956	1149	1467	1437	1638	1324	1075	1400	2349	1201
D-D	6096	6042	5945	5982	6133	5929	6234	6067	5908	6343	7148	6120
W-D	951	1217	1393	1200	882	912	711	1025	1274	949	0	1148
D-W	1052	1106	1203	1166	1015	1219	914	1081	1240	805	0	1028
W-W Ratio	0.60	0.48	0.41	0.49	0.62	0.61	0.70	0.56	0.46	0.60	1.00	0.51
W missing%	0.40	0.52	0.59	0.51	0.38	0.39	0.30	0.44	0.54	0.40	0.00	0.49
Total Err%	0.21	0.24	0.27	0.25	0.20	0.22	0.17	0.22	0.26	0.18	0.00	0.23
OBS (W-D)%	0.10	0.13	0.15	0.13	0.09	0.10	0.07	0.11	0.13	0.10	0.00	0.12
(D-W)%	0.11	0.12	0.13	0.12	0.11	0.13	0.10	0.11	0.13	0.08	0.00	0.11

Table B.2: Wet-dry-day match between observation and NARR at Winnipeg.

	NARR int.	G1	G2	G3	G4	G5	G6	G7	G8	G9
W-W	1709	1804	1803	1775	1788	1777	1750	1724	1711	1689
D-D	5603	5526	5477	5415	5619	5548	5499	5737	5724	5647
W-D	640	545	546	574	561	572	599	625	638	660
D-W	1545	1622	1671	1733	1529	1600	1649	1411	1424	1501
W-W Ratio	0.73	0.77	0.77	0.76	0.76	0.76	0.74	0.73	0.73	0.72
W missing%	0.27	0.23	0.23	0.24	0.24	0.24	0.26	0.27	0.27	0.28
Total Err%	0.23	0.23	0.23	0.24	0.22	0.23	0.24	0.21	0.22	0.23
NARR(W-D)%	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.07
(D-W)%	0.16	0.17	0.18	0.18	0.16	0.17	0.17	0.15	0.15	0.16

Table B.3: Wet-dry-day match between neighbouring stations and Brandon.

Station No.	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S10	S11	S12
Total #Day	9462	9493	9467	9433	9436	9492	9400	9495	9467	9452	9497	9436
W-W	1355	1336	1207	1391	1514	1563	1420	1514	1421	2205	1400	1473
D-D	6162	6352	6297	6326	6290	6170	6126	6367	6361	7247	6311	6500
W-D	850	869	998	814	691	642	785	691	784	0	805	732
D-W	1085	895	950	921	957	1077	1121	880	886	0	936	747
W-W Ratio	0.61	0.61	0.55	0.63	0.69	0.71	0.64	0.69	0.64	1.00	0.63	0.67
W missing %	0.39	0.39	0.45	0.37	0.31	0.29	0.36	0.31	0.36	0.00	0.37	0.33
Total Err %	0.20	0.19	0.21	0.18	0.17	0.18	0.20	0.17	0.18	0.00	0.18	0.16

Table B.4: Wet-dry-day match between observation and NARR at Brandon.

	NARR int.	G1	G2	G3	G4	G5	G6	G7	G8	G9
W-W	1555	1667	1654	1647	1639	1621	1634	1592	1585	1586
D-D	5532	5517	5558	5501	5652	5666	5637	5766	5762	5677
W-D	573	538	551	558	566	584	571	613	620	619
D-W	1478	1730	1689	1746	1595	1581	1610	1481	1485	1570
W-W Ratio	0.71	0.76	0.75	0.75	0.74	0.74	0.74	0.72	0.72	0.72
W missing %	0.29	0.24	0.25	0.25	0.26	0.26	0.26	0.28	0.28	0.28
Total Err %	0.25	0.24	0.24	0.24	0.23	0.23	0.23	0.22	0.22	0.23

Table B.5: Wet-dry-day match between neighbouring stations and Dryden.

Station No.	S 1	S 2	S 3	S 4	S 5
Total #Day	9405	9475	9402	9481	9434
W-W	3170	2516	2061	2346	2242
D-D	6235	5555	5374	5582	5419
W-D	0	654	1109	824	928
D-W	0	680	861	653	816
W-W Ratio	1.00	0.79	0.65	0.74	0.71
W missing %	0.00	0.21	0.35	0.26	0.29
Total Err %	0.00	0.14	0.21	0.16	0.19

Table B.6: Wet-dry-day match between observation and NARR at Dryden.

	NARR int.	G1	G2	G3	G4	G5	G6	G7	G8	G9
W-W	2511	2515	2519	2494	2485	2498	2473	2445	2428	2446
D-D	4631	4681	4603	4549	4696	4618	4557	4752	4714	4621
W-D	659	655	651	676	685	672	697	725	742	724
D-W	1604	1554	1632	1686	1539	1617	1678	1483	1521	1614
W-W Ratio	0.79	0.79	0.79	0.79	0.78	0.79	0.78	0.77	0.77	0.77
W missing %	0.21	0.21	0.21	0.21	0.22	0.21	0.22	0.23	0.23	0.23
Total Err %	0.24	0.23	0.24	0.25	0.24	0.24	0.25	0.23	0.24	0.25

Table B.7: Wet-dry-day match between neighbouring stations and Thompson

Station No.	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8
Total #Day	9497	9463	9481	9467	9346	9496	9493	9473
W-W	1212	1657	1696	2656	1258	1271	1689	1619
D-D	5260	5742	5732	6811	5531	5747	5685	5533
W-D	1444	999	960	0	1398	1385	967	1037
D-W	1551	1069	1079	0	1280	1064	1126	1278
W-W Ratio	0.46	0.62	0.64	1.00	0.47	0.48	0.64	0.61
W missing %	0.54	0.38	0.36	0.00	0.53	0.52	0.36	0.39
Total Err %	0.32	0.22	0.22	0.00	0.28	0.26	0.22	0.24

Table B.8: Wet-dry-day match between observation and NARR at Thompson.

	NARR int.	G1	G2	G3	G4	G5	G6	G7	G8	G9
W-W	2150	2156	2156	2126	2161	2160	2112	2127	2116	2127
D-D	4679	4722	4670	4571	4739	4710	4631	4781	4721	4651
W-D	501	500	500	530	495	496	544	529	540	529
D-W	2112	2089	2141	2240	2072	2101	2180	2030	2090	2160
W-W Ratio	0.81	0.81	0.81	0.80	0.81	0.81	0.80	0.80	0.80	0.80
W missing %	0.19	0.19	0.19	0.20	0.19	0.19	0.20	0.20	0.20	0.20
Total Err %	0.28	0.27	0.28	0.29	0.27	0.27	0.29	0.27	0.28	0.28

Table B.9: Wet-dry-day match between neighbouring stations and The Pas.

Station No.	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8
Total #Day	9497	9463	9481	9467	9346	9496	9493	9473
W-W	762	1238	1014	1271	1567	2349	1583	1252
D-D	5134	5657	5375	5762	6166	7147	5900	5489
W-D	1587	1111	1335	1078	782	0	766	1097
D-W	2013	1490	1772	1385	981	0	1247	1658
W-W Ratio	0.32	0.53	0.43	0.54	0.67	1.00	0.67	0.53
W missing %	0.68	0.47	0.57	0.46	0.33	0.00	0.33	0.47
Total Err %	0.38	0.27	0.33	0.26	0.19	0.00	0.21	0.29

Table B.10: Wet-dry-day match between observation and NARR at The Pas.

	NARR int.	G1	G2	G3	G4	G5	G6	G7	G8	G9
W-W	1796	1866	1845	1835	1839	1839	1837	1853	1846	1844
D-D	5452	5435	5534	5525	5489	5550	5539	5402	5482	5522
W-D	493	483	504	514	510	510	512	496	503	505
D-W	1556	1712	1613	1622	1658	1597	1608	1745	1665	1625
W-W Ratio	0.76	0.79	0.79	0.78	0.78	0.78	0.78	0.79	0.79	0.79
W missing %	0.24	0.21	0.21	0.22	0.22	0.22	0.22	0.21	0.21	0.21
Total Err %	0.24	0.23	0.22	0.22	0.23	0.22	0.22	0.24	0.23	0.22

Appendix C

DETAILED RESULTS OF NARR PRECIPITATION ASSIMILATION

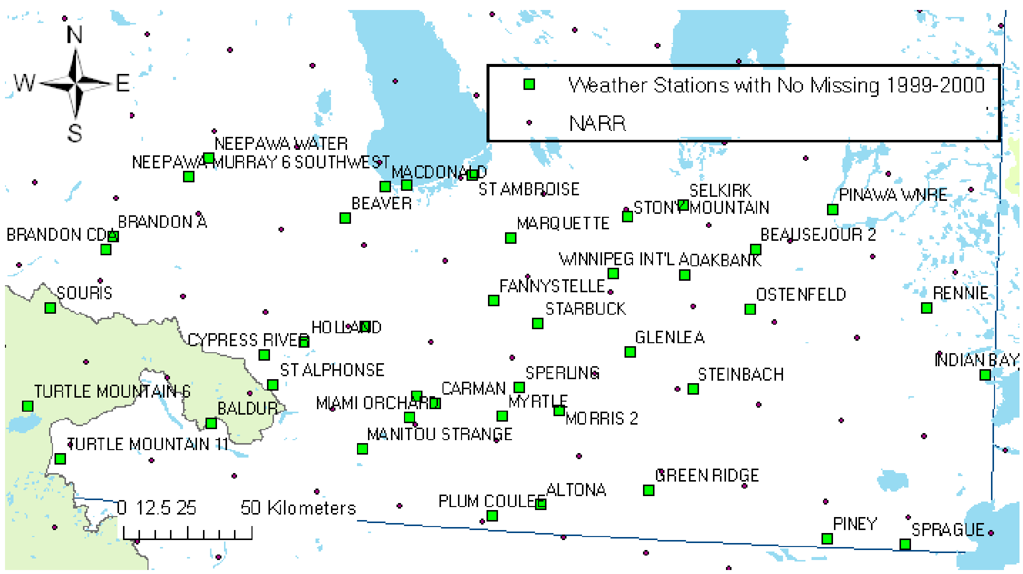

Figure C.1: Study area of NARR precipitation assimilation near Winnipeg.

Table C.1: Mean monthly and annual precipitation of observations, NARR, NPA, and IDW for both MSG and VSG.

Station	Monthly Mean				Annual Mean			
No.	OBS	NARR	NPA	IDW	OBS	NARR	NPA	IDW
Modelling Station Group (MSG)								
M1	39.3	33.9	42.4	50.4	472.1	406.2	508.7	605.1
M2	45.1	28.7	45.7	43.0	540.8	344.1	549.0	515.6
M3	43.5	29.5	44.5	38.5	521.9	354.1	533.9	462.6
M4	46.1	25.4	48.7	42.7	553.2	304.5	583.9	513.0
M5	50.6	30.7	50.3	45.4	606.7	368.2	603.7	544.6
M6	42.0	36.1	43.8	47.2	504.5	433.0	525.8	566.5
M7	53.5	37.4	51.7	47.4	641.9	449.3	619.9	568.2
M8	44.4	39.3	46.2	50.1	532.7	471.9	554.3	600.7
M9	44.3	28.7	44.7	42.9	531.2	344.5	537.0	514.4
M10	43.6	36.0	46.9	37.2	523.7	431.7	562.6	445.9
Validation Stations Group (VSG)								
V1	45.6	36.0	44.0	38.9	547.8	432.4	528.4	466.5
V2	45.5	32.3	47.8	42.8	546.0	388.2	573.3	513.1
V3	44.7	24.1	45.8	46.3	536.2	289.6	549.2	555.6
V4	42.8	36.8	43.9	48.1	513.9	441.5	526.7	577.0
V5	50.2	35.7	51.4	49.5	602.1	428.7	617.1	594.0
V6	44.1	31.7	45.0	42.7	529.4	380.8	539.8	512.4
V7	45.8	27.0	44.7	42.7	549.6	324.6	536.2	512.7
V8	40.5	36.0	44.2	45.1	486.3	432.1	531.0	541.0
V9	47.2	30.0	50.1	47.7	566.3	360.6	601.3	572.4
V10	43.6	39.9	45.3	46.4	522.7	478.5	544.0	557.0

Table C.2: Correlation of daily and monthly precipitation of NARR, NPA and IDW.

Station	Daily			Monthly		
No.	NARR	NPA	IDW	NARR	NPA	IDW
Modelling Station Group (MSG)						
M1	0.60	0.65	0.56	0.89	0.91	0.80
M2	0.56	0.89	0.62	0.87	0.96	0.80
M3	0.53	0.88	0.69	0.89	0.97	0.86
M4	0.51	0.91	0.49	0.85	0.97	0.74
M5	0.46	0.95	0.42	0.79	0.98	0.68
M6	0.57	0.90	0.67	0.88	0.96	0.85
M7	0.50	0.97	0.45	0.87	0.99	0.71
M8	0.58	0.88	0.53	0.93	0.97	0.79
M9	0.56	0.79	1.00	0.88	0.91	1.00
M10	0.64	0.74	0.40	0.90	0.93	0.71
Validation Stations Group (VSG)						
V1	0.58	0.82	0.61	0.88	0.92	0.79
V2	0.51	0.77	0.38	0.86	0.90	0.65
V3	0.51	0.74	0.50	0.77	0.92	0.75
V4	0.54	0.69	0.68	0.85	0.87	0.88
V5	0.56	0.68	0.45	0.90	0.90	0.72
V6	0.54	0.82	0.71	0.87	0.92	0.87
V7	0.49	0.80	0.74	0.83	0.92	0.88
V8	0.52	0.67	0.58	0.84	0.87	0.79
V9	0.55	0.80	0.54	0.87	0.91	0.76
V10	0.50	0.72	0.55	0.82	0.84	0.68

Table C.3: RMSE and daily errors of precipitation for NARR, NPA and IDW.

Station No.	RMSE NARR	RMSE NPA	RMSE IDW	Mean Daily Errors NARR	Mean Daily Errors NPA	Mean Daily Errors IDW
Modelling Stations						
M1	3.44	3.57	4.44	-0.18	0.10	0.36
M2	4.03	2.19	3.92	-0.54	0.02	-0.07
M3	3.83	2.16	3.30	-0.46	0.03	-0.16
M4	4.30	2.04	4.53	-0.68	0.08	-0.11
M5	4.79	1.67	5.21	-0.65	-0.01	-0.17
M6	3.70	1.93	3.51	-0.20	0.06	0.17
M7	4.62	1.35	5.06	-0.53	-0.06	-0.20
M8	3.98	2.43	4.86	-0.17	0.06	0.19
M9	3.94	2.95	0.25	-0.51	0.02	-0.05
M10	3.75	3.44	4.75	-0.25	0.11	-0.21
Validation Stations						
V1	3.98	2.77	4.05	-0.32	-0.05	-0.22
V2	4.50	3.40	5.46	-0.43	0.07	-0.09
V3	4.42	3.63	4.65	-0.68	0.04	0.05
V4	3.96	3.48	3.56	-0.20	0.04	0.17
V5	4.39	4.04	5.29	-0.47	0.04	-0.02
V6	3.80	2.74	3.27	-0.41	0.03	-0.05
V7	4.17	2.93	3.19	-0.62	-0.04	-0.10
V8	4.06	3.64	4.11	-0.15	0.12	0.15
V9	4.07	3.17	4.36	-0.56	0.10	0.02
V10	4.26	3.47	4.32	-0.12	0.06	0.09

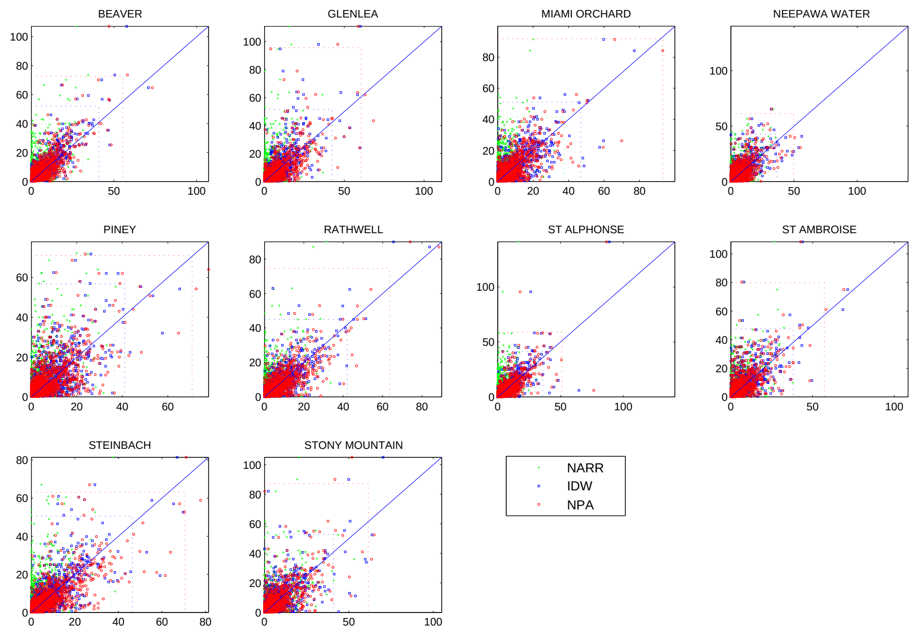

Figure C.2: Scatter plot of observations and NPA at 10 validation stations.

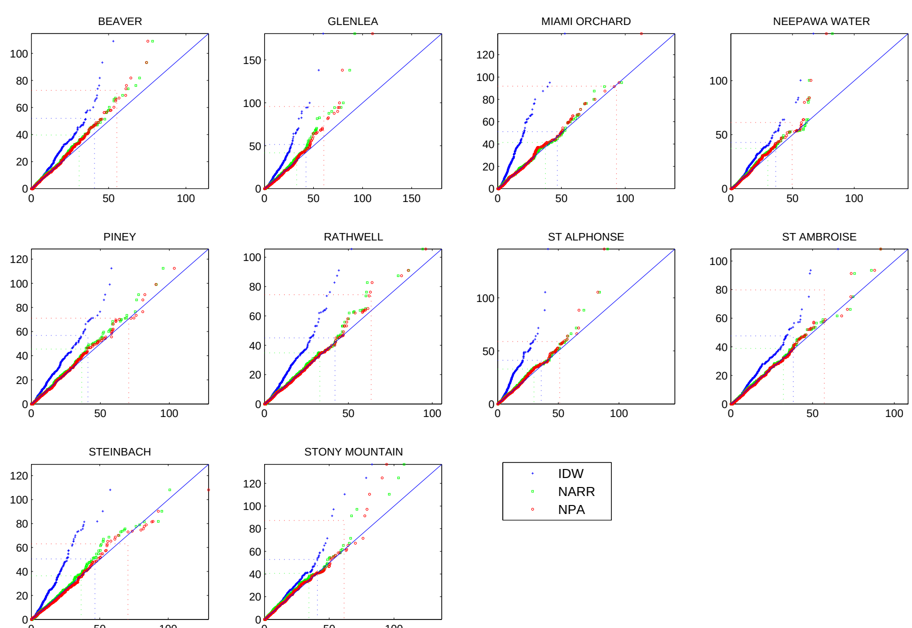

Figure C.3: Q-Q plot of observations and NPA at 10 validation stations.