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ENVIRONMENTAL ENGINEERING**

Water Resources Research Report

**Assessment of Global and Regional Reanalyses
Data for Hydro-Climatic Impact Studies in the
Upper Thames River Basin**

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Executive Summary

This study evaluates NCEP-NCAR reanalyses hydro-climatic data as an initial check for assessment of climate change studies and hydrologic modeling on the basin scale. Reanalysis data set for daily precipitation, and temperature from the National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) (a) global (NNGR) and (b) regional (NARR) reanalysis project are used as input into the semi-distributed hydrologic model (HEC-HMS) during the period of 1980-2005. First, the precipitation and temperature data are interpolated to selected stations to check for their trends and similarity in means and variances. Although NARR shows some over-estimated values, mainly in estimating temperature during the summer months, it has been able to capture the trends. NNGR, on the other hand, has produced inferior results in many cases, especially in generating precipitation when compared with the observed values. With its improved atmospheric analytical ability, NARR appears to have performed better than the NNGR, suggesting that with coarse resolution NNGR may not be applied in climate change studies for medium or small watersheds. Next, an extensive analysis is performed for assessing the performance of the reanalysis data generated flows by comparing it with the observed inputs during May-November. The stream flows generated from the NARR dataset show encouraging results for simulating summertime low flows with less variability and error. NNGR dataset, have proven to be less accurate and highly variable. This study suggests that NARR can be adequately used as either an additional source of data or as an alternative to observations in data scarce regions.

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1. Introduction

1.1 Background

Hydro-climatic impact refers to the change in near surface climate elements that impact human sustenance: precipitation, surface temperature, soil moisture and stream flow (Joseph and Nigam 2006; Nigam and Ruiz-Barradas 2006). Nonetheless, precipitation and temperature have been used as two main inputs into the hydrologic models. Changes in the precipitation patterns, combined with natural and anthropogenically-induced climate variations, have enormous ecological, societal and economic impacts. An increased near surface temperature, on the other hand, increases the evaporation rates and accelerates the transport of water vapour in the atmosphere and thus causes change in the hydrologic cycle.

Analysis of river basins on the macro-scale aids in the quantification of global water cycle contributes to the knowledge of macro-scale hydrologic processes and assists in the coupling of atmospheric and hydrologic models to investigate the effects of global climate change (Haberlandt and Kite 1998). Despite substantial research efforts, present understanding of the local impacts of climate change and variability remain uncertain. Climatologists and hydrologists have faced challenges in understanding the link between climatic variability and stream flow.

1.2 Problem Definition

Analysis of hydro-climatic variability can provide an insight into the current climatic system, thereby supporting a wide range of scientific research studies and applications. These include an improved understanding of water budget and assessment of the state of the climate that ultimately leads to a satisfactory management of water resources and better emergency planning

for extreme events, e.g., floods and droughts (Silva, 2007). Hence, a well distributed hydrometric network is very important for capturing the present day climate situation. Unfortunately, progress in determining climatic variability and change suffers due to several limitations: (i) lack of spatial coverage over areas of interest, especially in mountainous and many high latitude regions, (ii) inaccessibility of sufficiently long data records at daily timescales, (iii) periods of missing information, and (iv) lack of consistent, high resolution, quality controlled analyses.

As a result, data obtained from weather stations have limited value for the efficient analysis of the entire climate system in a region. Moreover, only a few studies have compared daily gridded dataset with observed ones (Silva et al 2007; Higgins et al 2007). The present report thus focuses on evaluating the performance of the global and regional reanalysis data for (a) climate change and (b) hydrologic modeling in the Upper Thames River basin.

1.3 Reanalysis Project

On the above instances, gridded databases, such as, data generated by atmospheric-ocean coupled global and regional climate models (e.g., AOGCMs and RCMs), and reanalysis data such as the National Center for Environmental Prediction – National Center for Atmospheric Research (NCEP-NCAR) Global Reanalysis – NNGR (Kalnay et al. 1996) And North American Regional Reanalysis – NARR (Mesinger et al. 2006) can be viable additions and/or alternatives to alleviate these limitations of limited and inconsistent data, missing information and spatial bias resulting from the uneven and unrepresentative spatial domain (Robeson and Ensor 2006; Ensor and Robeson 2008).

The reanalyses are essentially diagnostic atmospheric models, which are used “in concert with observations via data assimilation” (Pielke 2002). The reanalysis data are advantageous

because they are based on the AOGCMs with a fixed dynamical core, physical parameterizations and data assimilation system (Castro et al 2007). A reanalysis is generally a model-run constrained by observations. The space and time resolution of the data generated through these reanalyses projects are independent of the number of observations, since the areas void of observations are filled with dynamically and physically consistent model-generated information. Although they provide datasets for any period of time, it is evident that their usefulness crucially depends on the quality and distribution of the observations in time and space. At the same time, it is important to note that to date, this is the most accurate way of interpolating data in time and space as well as a superior way to obtain dynamical consistency between different atmospheric variables. It is also more representative because it provides an opportunity to eliminate local effects, such as those caused by urbanization (Kalnay and Cai, 2003).

For any specific region if only few observations are available, the constraints to set for the model is considered weak and the model produces datasets based on its own variability. When enough observations are available, the model is more forced to follow the observed variability rather than its own built-in variability. Assuming that different datasets have their own variability, there may be instances where at least one of the reanalyses products do not represent the correct scenario. Comparing results from at least two reanalyses may offer a more correct evaluation of their performances. If the results agree, the observational constraint can be considered large enough to force the models to follow the real variability of the atmosphere. Conversely, a difference in the results indicates weak constraints set for that spatio-temporal domain, thereby indicating that at least one of the products does not represent the correct variability. So, a difference in two reanalyses products indicates lack of spatial coverage (Sterl, 2004).

With a satisfactory presentation of any region's variability, these gridded daily datasets can often be used to initialize climatic, ecological or hydrological models (Jolly et al 2005; Kittel et al 2004; Ensor and Robeson 2008). More information on the Global and Regional Reanalysis project is available in Kalnay et al. (1996) and Mesinger et al. (2006).

1.4 Outline of the report

The report is comprised of the following sections: chapter 2 contains the literature review; chapter 3 explains the methods applied for the hydrologic modeling; Chapter 4 presents a detailed analysis of the results. Finally, chapter 5 describes the conclusions and future possibilities of application.

2. Literature Review

Several studies have compared the global reanalysis precipitation and temperature data with other available databases at different locations around the globe. Neito et al. (2004) compared the NNGR data with ECHAM4/OPYC3 and HadCAM3 models to analyze the correspondences and/or the discrepancies within the observed winter precipitation data during 1949-2000 for the Iberian Peninsula. NNGR precipitation data effectively captured the spatial and temporal variability and showed a good agreement with the observed precipitation. Ruiz-Barradas and Nigam (2006) found a correlation coefficient of 0.99 when the NNGR data was compared with the observed summer precipitation to analyze the inter-annual precipitation variability over the Great Plains, United States. However, while Tolika et al. (2006) found an inferior agreement between NNGR and observations, they also found a closer inter-annual variability when NNGR was compared with the GCMHadAM3P data used in examining the suitability of the averaged distributions and the spatial and temporal variability of the winter precipitation in Greece. In many applications, the NNGR resolution appeared to be less satisfactory than the observed temperature and precipitation, especially in regions where a complex topography (Choi et al 2009; Tolika et al, 2006; Rusticucci and Kousky, 2002; Haberlandt and Kite, 1998) due to led to a coarse resolution (250 km X 250 km) and physical parameterizations (Castro et al 2007).

The recently released North American Regional Reanalysis (NARR) dataset, developed by Mesinger et al. (2006), designed to be “a long term, dynamically consistent, high-resolution, high frequency, atmospheric and land surface hydrology dataset for the North American domain”, is a major improvement upon the global reanalysis datasets in both resolution and accuracy. However, due to the fact that the NARR is a recent product, it has not been widely evaluated.

Nigam and Ruiz-Barradas (2006) have made an inter-comparison between two global [40 yr-ECMWF Re-Analysis (ERA 40) and NCEP] and regional (NARR) datasets to analyze the hydro-climatic variability over the Eastern United States and found that the NARR data provided a realistic spatial variation of summer and winter precipitation.

Most of the studies focused on the spatial distributions of the seasonal and/or inter-annual variability of hydro-meteorological data. There have been only a few studies relevant to hydrologic modeling. Woo and Thorne (2006) used temperature and precipitation data from the ERA 40, NNGR and NARR as input to a macro-scale hydrologic model to estimate the contribution of snowmelt to discharge in the Liard basin in the Subarctic Canada. They found (i) a cold bias resulting in later snowmelt peaks and (ii) that NARR provides a better representation of the relative flow contribution from different sections of the basin. Thorne and Woo (2006) also applied three sets of climate data: (i) in-situ data from weather stations, (ii) NCEP/NCAR Global reanalysis data, and (iii) weather forecast data produced by the Canadian Meteorological Centre (CMC) as inputs to a Semi-distributed Land Use-Based Runoff Processes (SLURP) model that was used to both simulate stream flow and to examine how the simulated flow for different parts of the basin relates to the measured discharge available for several sub-basins within the Liard sub-catchment. Choi et al. (2007; 2009) evaluated the monthly and daily reanalysis datasets to examine their potential as an alternative data source for hydrologic modeling in Manitoba. Their study revealed a satisfactory performance of the temperature data, but a weaker performance of the precipitation data. The study also found a superior performance of the NARR precipitation values when compared to that of their NNGR counterparts. Castro et al. (2007) applied 53 years of NNGR data with dynamic downscaling using the Regional Atmospheric Modeling System (RAMS) to generate regional climate model (RCM) climatology

of the contiguous US and Mexico. They compared the RAMS simulated data with that of the NARR, the observed precipitation and temperature data, and found a good agreement of the NARR data in some parts of the Great Plains. Zhang et al. (2008) applied NNGR data to investigate spatial and temporal patterns of the trends of precipitation maxima in the Yangtze River basin and found a significant increase in the summer precipitation intensity and changing rainfall frequency in the middle and lower reaches of Yangtze River.

The literature cited above clearly indicates the potentiality of the reanalysis data set to be used in hydrologic modeling and/or climate change for studies to replicate the current climate regime. The present study is conducted to evaluate the applicability of the global and regional reanalysis temperature and precipitation data for hydrologic modeling in the Upper Thames River (UTR) basin in Southwestern Ontario, Canada. The quality of the NNGR and NARR data is examined by applying them to a semi-distributed rainfall-runoff model based on the mechanism of Hydrologic Engineering Center's Hydraulic Modeling System (HEC-HMS) within the basin and then analyzing the performances of the generated output during May-November. This is, an important step towards examining the impact of climate change on water resources with the expectation that if a reanalysis data-driven hydrologic model is successful, it can be used interchangeably with station data to validate AOGCMs as a reference baseline in deriving the hydrologic impacts of climate change in the study area.

3. Methodology

3.1 Study Area

The Upper Thames River (UTR) basin (Figure 1) (42°35'24''N, 81°8'24''W), located in Southwestern Ontario, Canada, is a 3,500 km² area nested between the Great Lakes Huron and Erie. The basin often experiences major hydrologic hazards, such as floods and droughts. The basin has a well documented history of flooding events dating back to the 1700s (Prodanovic and Simonovic 2006).

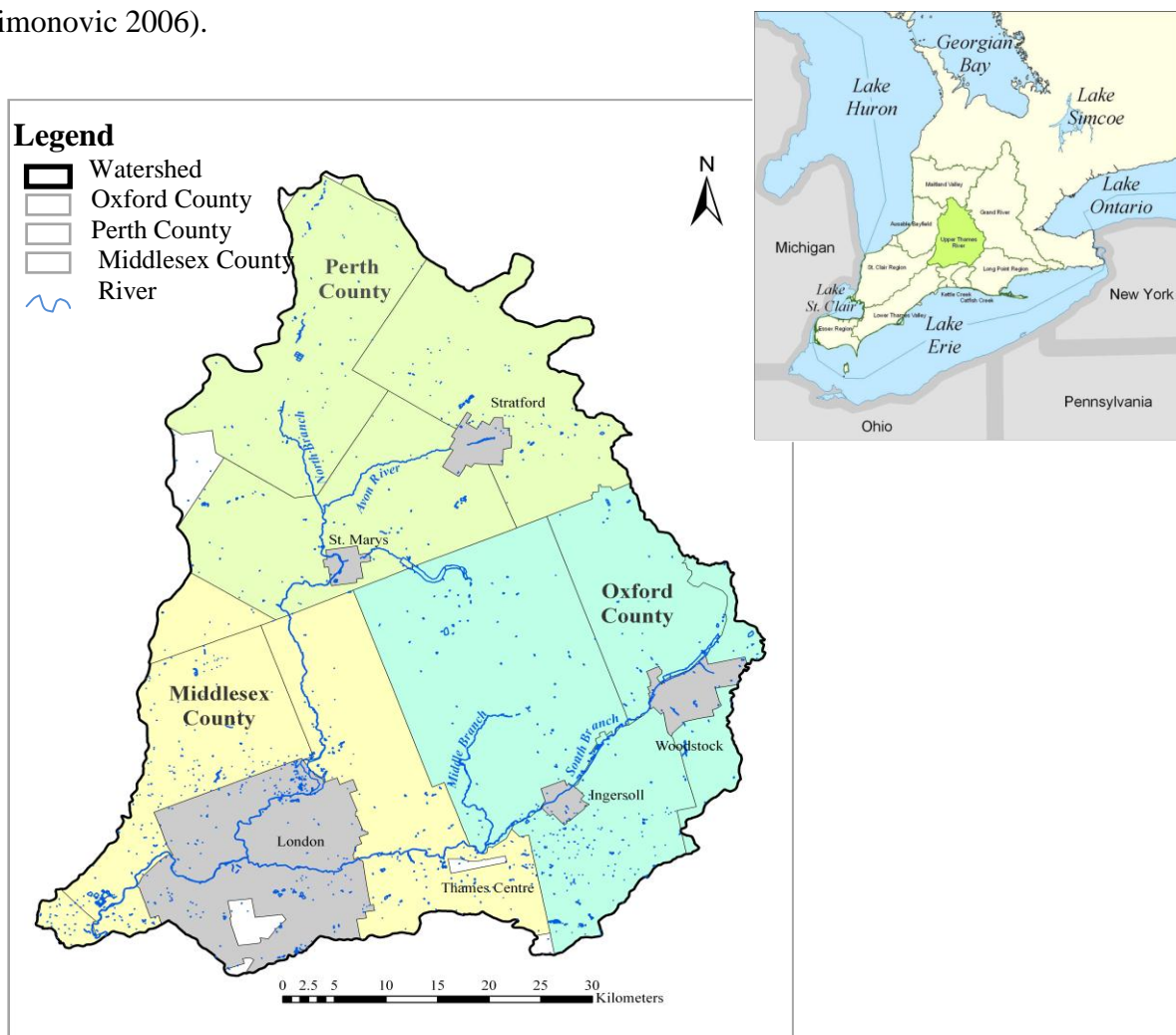


Figure 1: Map of the Upper Thames River Basin

High flows occur mostly in early March after snowmelt, and then again in July and August as a result of summer storms. Khaliq et al (2008) reported that in the Canadian regime, low flow conditions show a seasonal behaviour: summer low flow between June to November and winter low flow during the December and May periods. The UTR basin experiences frequent low flow conditions between June and September (Prodanovic and Simonovic 2006).

The population of the basin is 450,000 (2006), of which 350,000 are the residents of the City of London. The Thames river basin consists of two major tributaries of the river Thames: the North Branch (1,750 km²), flowing southward through Mitchell, St. Mary's, and eventually into London, and the South Branch (1,360 km²), flowing through Woodstock, Ingersoll, and east London. The Upper Thames River basin receives about 1,000 mm of annual precipitation, 60% of which is lost through evaporation and/or evapotranspiration, stored in ponds and wetlands, or recharged as groundwater (Prodanovic and Simonovic 2006). Several weather stations around the basin provide point measurements of weather variables including daily temperature and precipitation. Unfortunately, over the years only a few studies have been conducted for the purpose of making a reliable database and providing an adequate spatial coverage of variable climatic conditions within the basin. The spatial distribution of the weather stations is also sparse, especially in the west side of the basin, and does not cover the entire basin (Figure 2).

3.2 Data Description

For comparison, the following data sources were taken into account:

3.2.1 Observation

Daily observed precipitation and temperature data covering the UTR basin (Table 1 and Figure 2) for the period of 1980 – 2005 has been collected from Environment Canada (http://climate.weatheroffice.ec.gc.ca/climateData/canada_e.html).

3.2.2 NCEP-NCAR Global Reanalysis (NNGR)

The NCEP-NCAR Global Reanalysis (NNGR) is ‘an assimilated dataset using a state-of-the-art analysis/forecast system and past data since 1948’ (Kalnay et al. 1996). One interesting feature of the data set is that there are no precipitation estimates of sufficient spatial resolution or length, and hence no station precipitation data are assimilated directly into the model (Reid et al. 2001). It is provided 4 times daily at 6 hour interval, daily and monthly values of over 80 climatic variables on $2.5^{\circ} \times 2.5^{\circ}$ grid. The global reanalysis data for this project is made available through the Physical Sciences Division of the Earth System Research Laboratory of the National Oceanic and Atmospheric Administration (NOAA) (<http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis.html>).

Table 1: Weather Stations in Upper Thames River Basin

Serial	Station Name	Location			Variables
		Latitude ($^{\circ}$ N)	Longitude ($^{\circ}$ W)	Elevation (m)	
1	Blyth	43.72	81.38	350.50	Prec, Tmax, Tmin, Tmean
2	Dorchester	43.00	81.03	271.30	Prec
3	Exeter	43.35	81.50	262.10	Prec, Tmax, Tmin, Tmean
4	Foldens	43.02	80.78	328.00	Prec, Tmax, Tmin, Tmean
5	Glen Allan	43.68	80.71	400.00	Prec, Tmax, Tmin, Tmean
6	London A	43.03	80.15	278.00	Prec
7	St. Thomas	42.78	81.17	209.10	Prec, Tmin, Tmean
8	Stratford	43.37	81.00	345.00	Prec, Tmax, Tmin, Tmean
9	Waterloo-Wellington	43.46	81.38	317.00	Prec, Tmax, Tmean
10	Woodstock	43.14	80.77	281.90	Prec, Tmax, Tmin, Tmean
11	Wroxeter	43.86	81.15	335.00	Prec

Data source: National Climate Data and Information Archive of Environment Canada (http://climate.weatheroffice.ec.gc.ca/climateData/canada_e.html)

3.2.3 North American Regional Reanalysis (NARR)

The NARR is an extension of the global reanalysis, which uses a very high resolution Eta model ($0.3^{\circ} \times 0.3^{\circ}$, 32 km grid spacing, 45 layers) spatially) with the Regional Data Assimilation System (RDAS). Most of the variables are collected 8 times daily; daily and monthly means are also available at 29 pressure levels. Unlike its global counterpart, the NARR dataset has been developed by assimilating high quality and detailed precipitation observations into the atmospheric analysis, which consequently made the forcing to the land surface model component of the system more accurate. As such, a much improved analysis of land hydrology and land-atmosphere interaction has been become possible (Nigam and Ruiz-Barradas 2006). However, one significant weakness of the NARR data when applied in Canadian regions is that the daily gauge-based data it uses for assimilation is sparse (1 degree grid), which is may be insufficient for the model to perform as expected

(www.emc.ncep.noaa.gov/mmb/rreanl/narr.ppt). NARR data for this study has been made available through the Data Access Integration of the Canadian Climate Change Scenarios Network of Environment Canada.

In order to assess the reanalysis data, the daily accumulated precipitation rate and the daily maximum, minimum and mean temperatures have been considered. Data for each variable has been collected for the period 1980 – 2005. The NNGR and NARR precipitation rate ($\text{kg m}^{-2} \text{s}^{-1}$) data has been converted to the daily total (mm day^{-1}). As suggested by Reid et al. (2001) and Choi et al. (2007), precipitation values less than 0.5 mm/day^{-1} have been considered zero in order to compare with the observed precipitation.

Figure 2 and Table 1 present the details of 11 stations located within and around the Upper Thames river basin. Some parts of the basin are poorly covered due to the lack of weather stations in those areas. In some cases, stations are missing records over several months of the entire study period. For any station with more than 15% of missing records for a specific month, that month has been eliminated from both station and reanalysis datasets in order to maintain consistency.

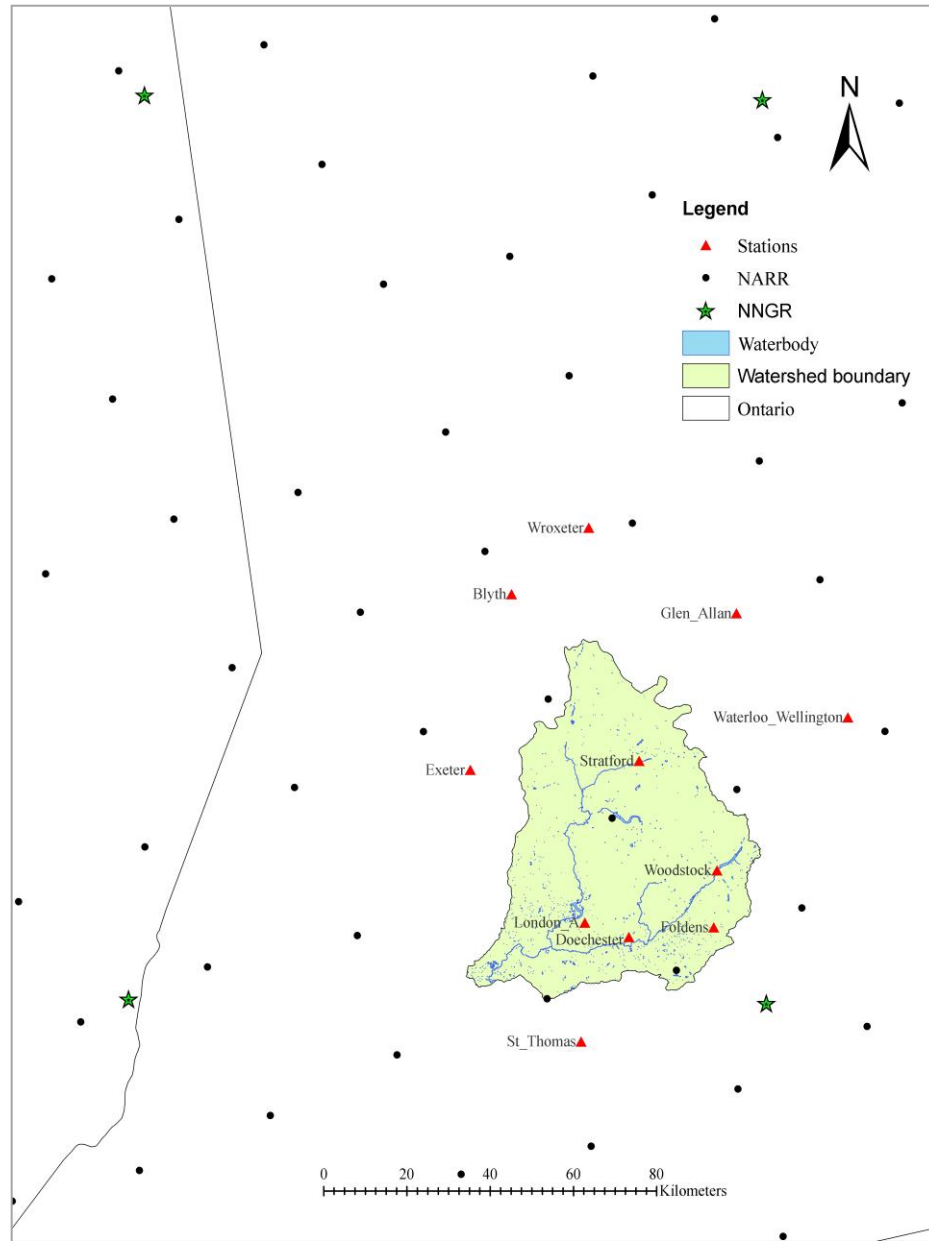


Figure 2: Location of the Weather Stations, NNGR and NARR Grid Points within the Upper Thames River Basin

3.3 Continuous Hydrologic Model

The continuous based hydrologic model captures land based physical processes of the hydrologic cycle (Bennett 1988). It takes the soil moisture balance into consideration over a long term period and is useful mostly for simulating the daily, monthly and seasonal rainfall runoff processes for the basins with a large amount of pervious lands (Ponce 1989). The

continuous model needs detailed information of long term moisture losses due to evaporation and evapotranspiration. A typical continuous hydrologic model constitutes a combination of methods to describe conversion of excess rainfall into direct runoff, baseflow, channel/reservoir routing, together with losses due to movement of water through vegetation, surface, soil and ground water (Ponce 1989). The continuous hydrologic model component used in this study is based on the United States Army Corps of Engineers, Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS).

The HEC-HMS is designed for rainfall-runoff modeling for solving a wide range of problems at diverse geographic locations, although most of its applications have been limited to North American basins. HEC-HMS has been successfully used for around three decades and is recognized by the hydrologic community (Prodanovic, 2008). The model consists of three modules: (i) meteorologic module (which includes methods describing precipitation and/or evaporation); (ii) basin module (consisting of methods describing the physical properties of a catchment); and (iii) control module (where start and end times of a simulation are specified). The meteorologic and basin modules consist of a collection of methods allowing the user to specify and describe climatic and physical properties of the basin. For example, different loss methods (i.e., representing evaporation and/or evapotranspiration) are available depending on whether the user wishes to study the short (event) or long (continuous) term hydrologic characteristics of the basin. Detailed information about the structure of the model is available in USACE (2006).

3.4 Model Setup

The hydrologic model applied to the Upper Thames River basin is described in Cunderlik and Simonovic (2004, 2005). Figure 3 presents the model structure with each box representing each module that captures physical processes acting in the basin.

The snow module: Precipitation and temperature from various sources are used as inputs in the hydrologic model. The regularly spaced reanalysis database is interpolated to the irregularly spaced sub-catchments within the basin that take precipitation as input. In this study, the Inverse Distance Weighting (IDW) method has been used for interpolating precipitation and temperature reanalysis data from their respective grids to station grids. This method is widely used and recommended by the United States Army Corps of Engineers (Prodanovic and Simonovic 2007). The interpolated precipitation and temperature data is integrated into the snow module to separate the solid (snow) and liquid (rainfall) forms of precipitation. The snow module uses the meteorological data to compute snow accumulation and melt by degree-day method (Cunderlik and Simonovic 2004). The interpolated sub-basin precipitation and temperature values are separated into their solid and liquid forms of precipitation in the snow module. The snowfall is subjected to an accumulation and melt algorithm and produces snowmelt. It is then added to the liquid precipitation (or rainfall) and thus produces a new variable: ‘adjusted precipitation’. The following sets of equations are used in this process:

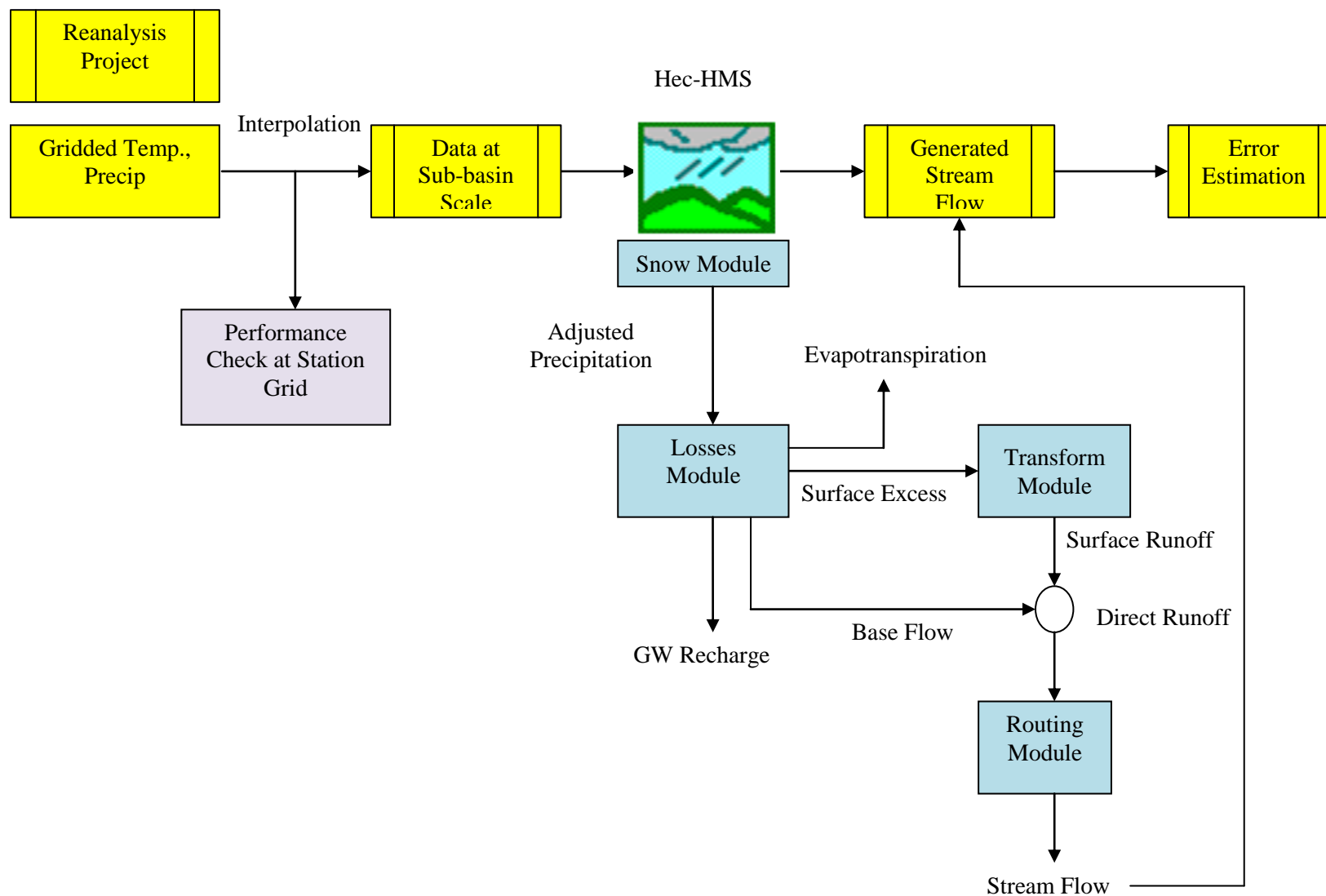


Figure 3: Flow Chart of Continuous Hydrologic Modeling using Reanalyses Data

The measured amount of precipitation (mm/day) P_i is categorized as rain and snow by the following equation:

$$\left. \begin{matrix} S_i = P_i \\ R_i = 0 \end{matrix} \right\}, T_i < T_{min} \dots \dots \dots (3.1)$$

$$\left. \begin{matrix} S_i = P_i \cdot \left[\frac{T_{max} - T_i}{T_{max} + T_i} \right] \\ R_i = P_i - S_i \end{matrix} \right\}, T_{min} < T_i < T_{max} \dots \dots \dots (3.2)$$

$$\left. \begin{matrix} S_i = 0 \\ R_i = P_i \end{matrix} \right\}, T_i > T_{max} \dots \dots \dots (3.3)$$

Where, S_i and R_i represent the measured amount of snow and rain, respectively (mm/day), $i = 1, 2, 3, \dots \dots n$ represents number of days with precipitation, while $T_{min} = -4^{\circ}C$ and $T_{max} = -2^{\circ}C$ refer to the minimum and maximum temperature for snowfall and snowmelt, respectively.

The snowmelt is then subjected to an accumulation and melt algorithm and is eventually converted into snowmelt. The daily amount of snow melt is calculated as:

$$M_i = MR \cdot (T_i - T_c) \dots \dots \dots (3.4)$$

Where MR represents a parameter for melt rate (mm/⁰C/day) set to 4.0. T_c is a critical parameter for melt and is set to zero.

Previously obtained snowmelt is then accumulated with the converted snowmelt by the following equation:

$$S_i = S_i + S_{i-1} \dots\dots\dots (3.5)$$

If snowmelt occurs (i.e. if $M_i > 0$) and if the accumulated snowmelt $S_i > M_i$, implying that only a portion of the accumulated snow melts, it is represented by:

$$S_i = S_i - M_i \dots\dots\dots (3.6)$$

$$P_a = R_i + M_i \dots\dots\dots (3.7)$$

Where, P_a represents adjusted precipitation [mm/day].

If all accumulated snow melts,

$$P_a = R_i + S_i \dots\dots\dots (3.8)$$

Lastly, if no snowmelt takes place,

$$P_a = R_i \dots\dots\dots(3.9)$$

The loss module: The adjusted precipitation is further used as input into the precipitation loss module to obtain losses. Among the different methods of calculating losses available in HEC-HMS, the five layer soil moisture accounting (SMA) algorithm, developed by Leavesley et al. (1983), is chosen for continuous modeling of complex infiltration and evapotranspiration environments. The loss module is the most complicated component as it simultaneously takes a large number of processes into consideration.

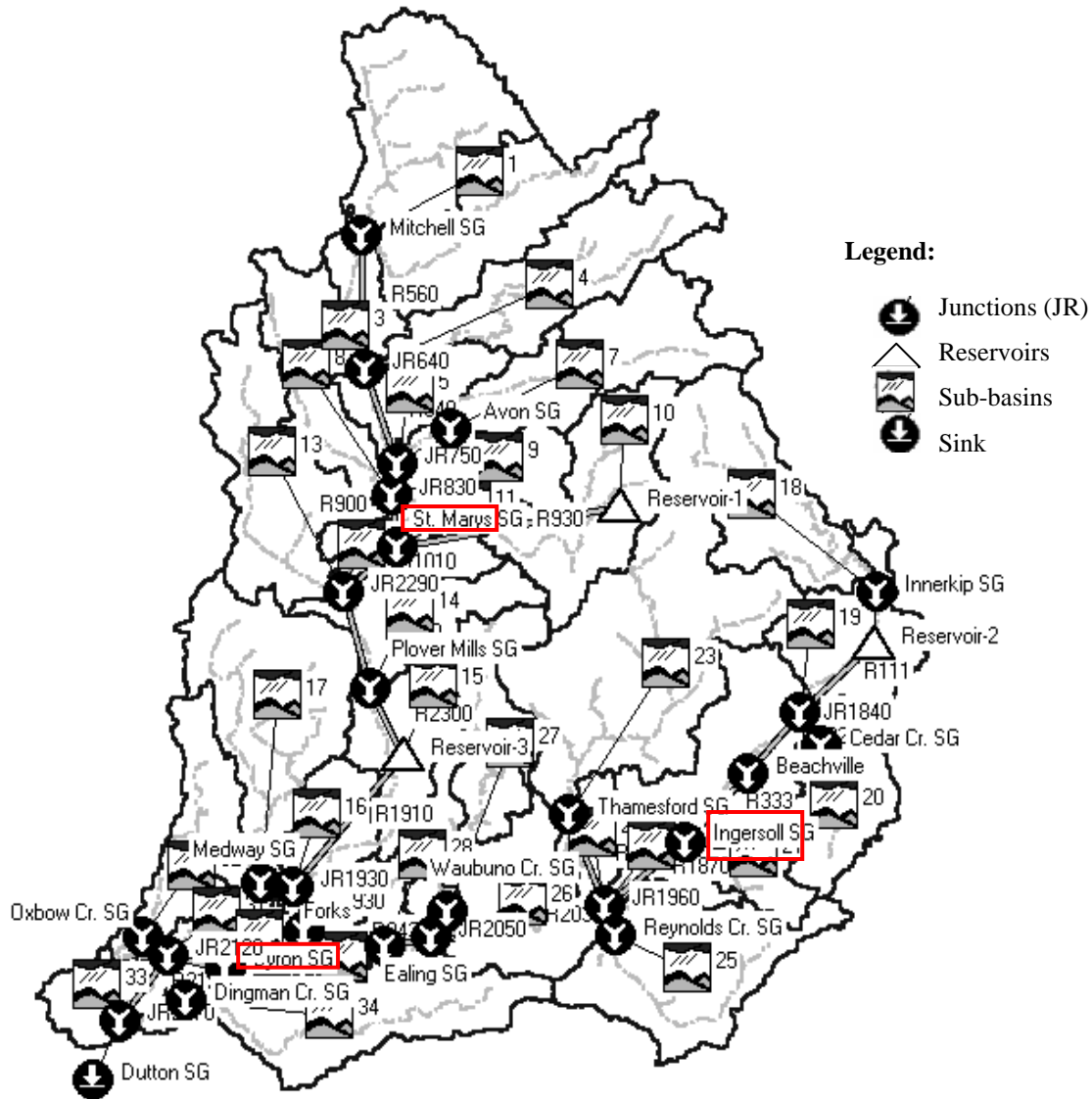


Figure 4: HEC-HMS Continuous Hydrologic Model at Upper Thames River Basin

The losses module (Figure 4) uses a series of conceptual reservoirs to represent the storage and movement of water in each sub-catchment of the basin. The storage reservoirs are: (i) canopy interception; (ii) surface interception; (iii) soil profile; and (iv) a number of ground water

layers (only two shown here). The inflow and outflow rates between the reservoirs regulate the amount of water stored in each conceptual reservoir. These include evapotranspiration, infiltration, percolation, surface runoff and ground water flow.

The canopy storage layer includes the precipitation captured by vegetation (such as trees, shrubs, bushes, grasses, etc); furthermore, precipitation is the only inflow that can fill this storage volume. When precipitation occurs, it fills this storage layer first, provided it is not already at capacity. The only process that can remove the moisture out of this layer is the process of evapotranspiration. After filling the canopy layer, precipitation begins to fill the surface storage, and/or to infiltrate into the soil. The surface storage layer represents the volume of water held by shallow depressions and cracks on the ground surface. The storage of water in this layer (in addition to precipitation excess from the canopy) is capable of infiltrating the soil, provided the soil is not fully saturated. The inflow to the surface storage layer refers to water that does not infiltrate the soil layer; it is a combination of the precipitation excess from the canopy layer, and its own volume that is left over after infiltration has taken place. The outflow from this layer consists of evaporation and surface runoff. Surface runoff refers to the flow produced when the surface storage layer is at capacity, and thus it cannot absorb water that has not already been infiltrated. During large precipitation events, the canopy and surface storage layer fill quickly, thus producing high amounts of surface excess (as infiltration alone is not usually sufficient for absorbing all surplus precipitation). The soil profile storage corresponds to the top layer of the soil. Water that infiltrates is the only inflow to this layer, while the outflows represent percolation to the lower ground water layer and evapotranspiration. The soil storage is further divided into two zones: the upper zone and the tension zone. The former is that portion of the soil layer that can lose water to both percolation and evapotranspiration, while the latter is one

that loses water only through evaporation, but not percolation (Bennett, 1998). This is because the upper zone represents water held in the pores of the soil (which can freely percolate and/or evaporate), while the tension zone constitutes water held by capillary tension, thus making it difficult to flow and move but can evaporate. It should be mentioned that evapotranspiration rates from the soil vary, as it is more difficult to remove water held by capillary tension than water held between the pores of the soil.

Evapotranspiration is the process that removes moisture from canopy, surface, and soil profile storage. In the Soil Moisture Accounting algorithm, evapotranspiration can only occur during periods free of precipitation. Potential evapotranspiration is calculated based on maximum regional monthly evapotranspiration rates (specified by the user), multiplied by a pan coefficient. Actual evapotranspiration rates are realized through a loss of moisture, first from the canopy, second from the surface, and lastly from the soil storage. However, actual evapotranspiration rates can never exceed their potential value. The water that percolates from the soil profile storage is used as an input to the ground water layer immediately beneath it. The outflows from this layer represent the ground water flow (one that is returned to the stream channel as baseflow), and a further percolation to either another ground water layer or as deep percolation— representing water entering a deep aquifer.

The equations for the Soil Moisture Algorithm are well documented and can be found in Bennett (1998).

Transform and Routing Modules: The transfer module uses Clark’s Method (USACE 2006) to convert the surface excess obtained from the SMA algorithm into the direct runoff. The resultant surface runoff is joined with the baseflow to produce direct runoff. The direct runoff is then added into the flood routing module to calculate the generation of a flood wave by using

modified plus method ultimately producing channel stream flow (USACE 2006). A series of linear reservoir method is used to transform lateral ground water flow (obtained from SMA algorithm) into baseflow.

The hydrologic model applied to the Upper Thames River basin has been properly calibrated and verified with extensive sensitivity analyses [Cunderlik and Simonovic (2004, 2005)]. The model consists of thirty-two special units, twenty one river reaches and three flood control reservoirs (Wildwood, Fanshawe and Pittock) (Figure 4). Each sub-basin in Figure 4 is represented by rectangles and is provided with interpolated reanalyses data. The outputs of each sub basin are flow hydrographs joined by junctions (circles) where the flows are added together. River reaches represent the major rivers and streams in the basin and are shown as thick lines connected between two junctions. The routing module described above is applied to each river reach, and thus acts as a passage of a flood wave as it moves through the river system. Reservoirs are depicted as triangles and the same routing rules are applied here.

The model is seasonal in nature with different parameters referring to the summer and winter seasons. The parameter sets for the summer and winter seasons are presented in Cunderlik and Simonovic (2004) and Prodanovic and Simonovic (2007).

3.5 Performance Evaluation and Uncertainty Estimation

Quantitative assessments of the degree to which the simulated data match the observed data are used to provide an evaluation of the model's predictive abilities. It utilizes numerous statistics and techniques. Goodness-of-fit (correlation coefficient, r and coefficient of determination, R^2) or relative error measurements are mostly used to assess the ability of the model. Unfortunately, they only describe the degree of collinearity between the observed and

predicted values and provide a biased presentation of the efficiency of the model (Willmott 1981; Willmott et al. 1985; Kessler and Neas 1994; Legates and Davis 1997). Furthermore, they are oversensitive to extreme values and insensitive to additive and proportional differences between predicted and observed values (Legates and McCabe 1999). As a result, other statistics such as absolute error measures (root mean square, RMSE or mean absolute error, MAE) in terms of the units of the variables are developed to examine the association between observed and simulated data. In order for a complete assessment of the model performance, it is important to include at least one goodness-of-fit measure (r or R^2) and at least one absolute error measures (RMSE or MAE) along with additional supplemental information such as a comparison between the observed and simulated mean and standard deviations (Legates and McCabe 1999; Willmott et al. 1985). In this study, apart from RMSE, MAE and r , normalized mean square (NMSE) and relative bias have also been used to assess the accuracy of the estimates. The NMSE measures the average magnitude of the errors in the predicted dataset without considering their direction, whereas the relative bias provides the deviation of the simulations from observations.

Because of the existing model and data errors, it is necessary to use appropriate criteria for estimating the relevant uncertainties (Sorooshian et al. 1993). In this study, only data uncertainty arising from the (i) inconsistency and non-homogeneity and (ii) inadequate representation of the reanalysis data due to space and time limitations has been assessed. The Probability Density Function (PDF) provides the most complete and ideal description of uncertainty. However, in most practical problems such a probability function cannot be derived precisely (Tung 1996). Another well known approach to characterize uncertainties is to express it in terms of a reliability domain, such as the confidence interval or quartile plot with some specific probabilistic confidence. The estimation of uncertainties in terms of the model errors and

quartiles around the mean and variances has been conducted by several authors for the purpose of analysis (Khan et al. 2006). However, the confidence interval has inherent limitation due to its inability to directly combine the confidence intervals of individual contributing random components to provide an overall confidence interval of the system (Tung 1996). Hence, a useful alternative is used by calculating the variance and mean, as a measure of the dispersion of the variable of interest. In this study, the uncertainty in the simulated discharges has been assessed in terms of model errors and percentile plots in the estimates of mean and variances. The process consists of several steps. Twenty six years of daily discharge during May-November obtained from the observed, NNGR and NARR hydro-climatic data have been taken into consideration. At first, the presentation of the uncertainties has been plotted using box and whisker plots where the bottom and top end of the box indicate the 1st quartile (25th percentile) and 3rd quartile (75th percentile) of the dataset for the low flows during May-November, with their median in between. This is a common approach for assessing the data quality and model capability and has been used by Prodanovic (2008) and Sharif and Burn (2006). Next, errors in the estimates of means and variances of low flows have been evaluated using a non-parametric statistical hypothesis test at a 95% confidence interval. One of the best non-parametric methods for constructing a hypothesis test p value for the difference of two population means is the Wilcoxon rank-sum test (Khan et al. 2006). It is used to check if the two sets of observations come from the same distribution. For hypothesis testing, both samples are combined into a single ordered sample and ranks are then assigned to the sample values from smallest to the largest, irrespective of the source of the samples. A smaller sum of the samples provides the indication that the values of that specific population tend to be smaller than the other population and hence, the null hypothesis of no differences between populations may be rejected (Conover, 1980). The second test to be applied

is the modified version of Levene's test (Levene 1980) for testing the equality of two sample population variances as proposed by Brown and Forsythe (1974). This method considers the distances of the observations from their sample median rather than their sample mean, which makes the test more robust with data following a skewed distribution.

4. Results and Discussion

The analyses of the results are divided into two parts: Firstly, the performances of the temperature and precipitation data interpolated to the stations around the Upper Thames River basin from the NNGR and NARR datasets are examined; Secondly, a trend analysis has been performed to see whether the reanalysis dataset is capable of capturing the yearly temperature trend of the observations. Student's t and F tests are performed to check for the similarity of means and variances for both data types with respect to observations. Next, changes in temperature anomalies over the years are compared. For precipitation, the performances of both datasets have been analyzed in terms of goodness-of-fit. The cumulative precipitation of selected stations during the year of 2000 is computed.

The second part of the analysis contains an evaluation and comparison of the daily discharge generated by the HEC-HMS model. The results for three stream gauges within the basin: Byron, Ingersoll and St. Mary's are presented. First, performances of the NNGR and NARR inputs into the hydrologic model have been compared with the statistical goodness-of-fit measures: the root mean square error (RMSE), correlation coefficient (r), normalized mean squared error (NMSE), mean absolute error (MAE) and relative bias (RB). The outputs (daily discharge) have been assessed by flow comparison graphs, scatter plots and confidence interval plots. Because of the existing model and data errors, it is necessary to use appropriate criteria for estimating the relevant uncertainties (Sorooshian, 1993). In this study, only data uncertainty arising from (i) the inconsistency and non-homogeneity and (ii) the inadequate representation of the reanalysis data due to space and time limitations has been assessed. The errors arising from the data sources are evaluated by estimating the means and variances.

4.1 Reanalyses Data Performance Results

The abilities of the NNGR and NARR to capture the inter-annual variability of temperature and precipitation are presented in this section on a station-by-station basis. These stations are situated within and around the Upper Thames River basin.

4.1.1 Temperature

Table 2 presents the quality of daily temperature data from NNGR and NARR with respect to the observations in terms of bias and correlation. Correlations are above 0.95 in the case of both datasets, which indicates that the values are closer to the observations in terms of goodness-of-fit. For all stations, the biases between the datasets are within 20%.

Table 2: Comparison of Mean Daily Temperature from Observations and Reanalyses Data for 1980-2005

Stations	Mean		Mean Bias		Correlation		
	Observed	NNGR	NARR	NNGR	NARR	NNGR	NARR
Exeter	7.76	8.18	9.25	5.46	19.25	0.98	0.97
Foldens	7.93	8.43	9.21	6.42	16.15	0.98	0.98
Glen Allan	6.70	7.97	7.72	19.00	15.31	0.98	0.98
St. Thomas	8.60	8.59	9.32	-0.18	8.33	0.98	0.97
Stratford	7.42	8.26	8.48	11.39	14.30	0.98	0.98
Waterloo-Wellington	6.96	8.13	8.62	16.87	23.81	0.98	0.98
Woodstock	7.77	8.37	8.70	7.69	11.96	0.98	0.98

Figure 5 presents mean monthly temperature at selected stations in the basin. Both reanalysis datasets demonstrate a tendency to over-estimate the observed values, especially during summer.

NNGR has repeatedly under-predicted temperature during early spring and winter, thereby indicating higher biases. Except spring and summer, they seem to be in fairly close agreement with observed temperature. NNGR shows a comparatively higher degree of consistency during late spring and fall. Although NARR overestimates throughout the year, it has been able to capture the monthly trend for all stations with a bias within 20%, except for March where biases are very high. Except for the above discrepancies, the agreement confirms the findings from previous studies and shows that both NNGR and NARR satisfactorily capture the observed intra-seasonal and annual fluctuations (Kalnay and Cai, 2003, Kalnay et al., 2006, Pielke et al., 2007).

Next, statistical tests are performed on the monthly temperature to determine whether the reanalyses data produces monthly climatological data and yearly trends that are representative of the true climatology and trends. To test the null hypothesis that the reanalysis and observations render consistent monthly means and variances, student's t test and the F test are performed. If the test indicates a rejection of the null hypothesis at the $p=0.05$ level, then the means or variances are considered to be statistically different. This procedure uses the null hypothesis that the difference between two population means is equal to a hypothesized value $H_0: \mu_1 - \mu_2 = \mu_0$.

For the purpose of the test, the following hypotheses are established:

$H_0: \mu_1 - \mu_2 = 0$ (the mean temperature from both observations and NNGR (G) or NARR (R) are equal)

$H_0: \mu_1 - \mu_2 \neq 0$ (the mean temperature from both observations and NNGR (G) or NARR (R) are different)

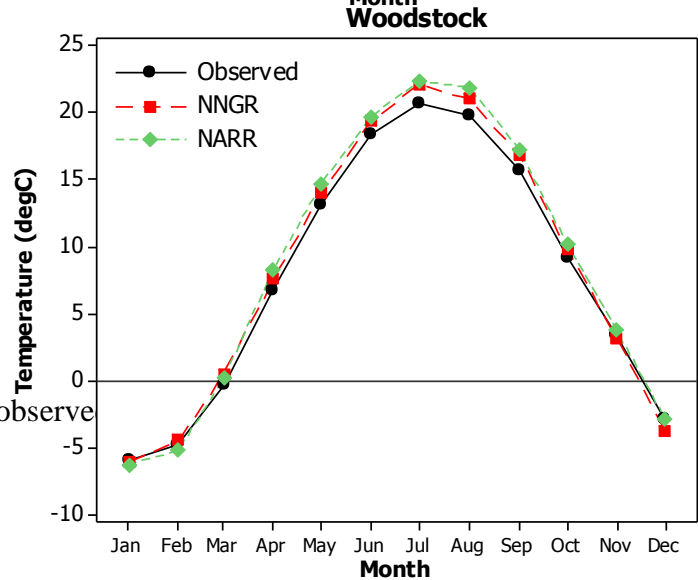
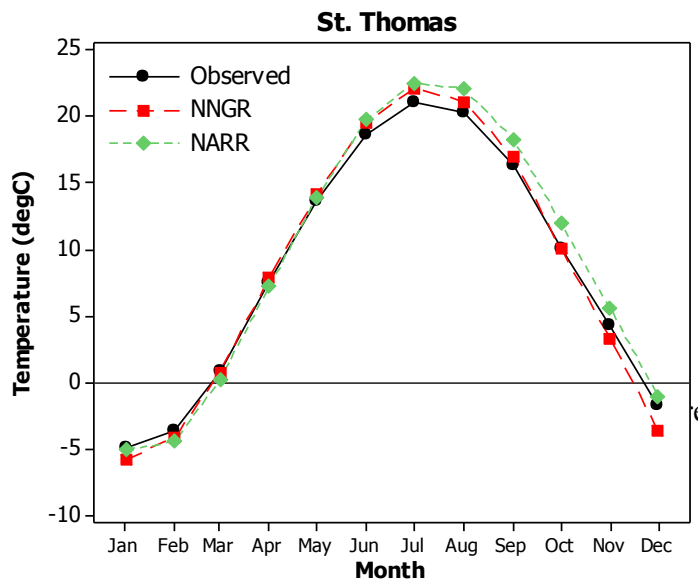
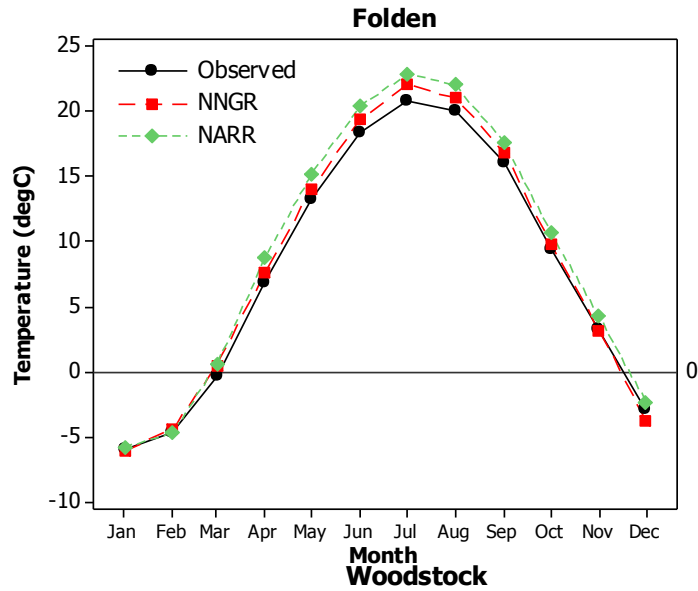
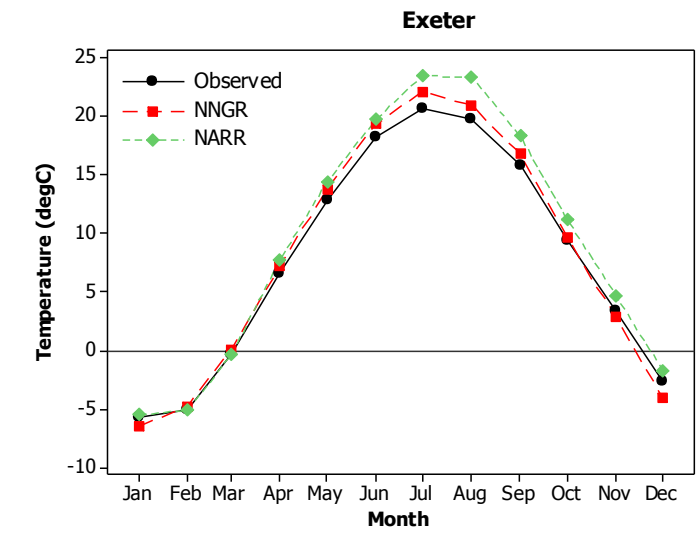


Figure 5: Mean Monthly Temperature between Observed (EC) and NNGR/NARR

Table 3 (a) presents the student's t test static results for the similarity of means, assuming equal variances for all three datasets. The results are presented in terms of the estimates of differences between the observed and NNGR/NARR means, the 95% confidence interval for the differences and the hypothesis results (t and p values). Confidence intervals are calculated for the selected stations. The range includes 0 values suggesting that there are no differences in means. The probability (p) values for all cases are greater than the chosen α level (0.05), which indicates that there is no evidence of a different mean in the three datasets.

The t test performed above assumes equal variances for all datasets to be tested. It is more powerful than the unequal variance assumptions, but can result in serious errors if the variances are not equal. Therefore, it is important to test whether the variances of all datasets are equal. Accordingly F tests are subsequently performed to determine whether the variances of two different datasets are significantly different. This procedure uses the null hypothesis that the two variances are equal, i.e. $H_0: \sigma_1^2 = \sigma_2^2$

The following hypotheses are thus established:

$H_0: \sigma_o^2 = \sigma_{G/R}^2$ (the observations and the NNGR (G) or NARR (R) have equal variances)

$H_0: \sigma_o^2 < \sigma_{G/R}^2$ (the observations have variances less than the NNGR (G) or NARR (R))

Table 3 (b) presents the hypothesis test results of the F test for both reanalyses datasets. Like the t test results, the p values for the F test also appear to be greater than 0.05, which fails to reject the null hypothesis of the variances being equal. Thus, it is reasonable to assume that the observations and NNGR/NARR have equal variances in F test.

Table 3(a): t Test Static Results for Mean Monthly Temperature during 1980-2005

Station	Modified t-Test Static							
	Difference	95% CI for differences NNGR	T	<i>p</i>	Difference	95% CI for differences NARR	T	<i>p</i>
Woodstock	-0.597	(-2.154, 0.960)	-0.75	0.452	-0.597	(-2.154,0.960)	-0.75	0.452
St. Thomas	0.016	(-1.511, 1.543)	0.02	0.983	-0.71	(-2.229, 0.810)	-0.92	0.359
Folden	-0.509	(-2.069, 1.051)	-0.64	0.522	-1.275	(-2.852, 0.302)	-1.59	0.113
Exeter	-0.424	(-1.992, 1.143)	-0.53	0.595	-1.484	(-3.074, 0.106)	-1.83	0.067
Glen Allan	-1.274	(-2.858, 0.310)	-1.58	0.115	-1.02	(-2.618, 0.577)	-1.25	0.21
Stratford	-0.844	(-2.399, 0.712)	-1.07	0.287	-1.052	(-2.635, 0.531)	-1.3	0.192
Waterloo-Wellington	-1.174	(-2.738, 0.391)	-1.47	0.141	-1.649	(-3.241, -0.057)	-2.03	0.042

Table 3(b): F Test Static Results for Mean Monthly Temperature during 1980-2005

Station	F test static			
	NNGR		NARR	
	Test static	P value	Test static	P value
Woodstock	1.71	0.191	2.74	0.099
St. Thomas	3.49	0.062	3.36	0.067
Folden	1.05	0.437	2.01	0.157
Exeter	2.54	0.112	4.17	0.052
Glen Allan	1.45	0.23	1.63	0.203
Stratford	2.85	0.092	4.98	0.06
Waterloo-Wellington	2.97	0.085	4.97	0.06

A trend analysis has also been tested to determine whether the reanalyses database is consistent with the true trend based on the observations. Although reanalysis trends cannot provide reliable estimates of the true atmospheric trends, it is important to check whether the distribution of the reanalyses trends provide a reasonable representation of the expected range of atmospheric trends. Comparison of yearly temperature trends in Table 4 shows that in case of NNGR, for all stations but Exeter, a weak negative trend per year (-0.0085 to -0.1577) is prominent indicating a slow cooling trend. It is just opposite of the observations.

NARR, on other hand, has been able to capture the increased temperature trend with less than 25% error except for Exeter.

Table 4: Comparison of Trend Analysis Results for 1980-2005

Station	Trends				
	Observed	NNGR	NARR	% Bias NNGR	% Bias NARR
Folden	0.0452	-0.0085	0.0525	-118.81	16.15
Glen Allan	0.0356	-0.005972	0.0443	-116.78	24.44
Exeter	0.0543	0.0011	0.0334	-97.97	-38.49
Stratford	0.0611	-0.007048	0.0495	-111.54	-18.99
St. Thomas	0.0456	-0.006348	0.0556	-113.92	21.93
Waterloo-Wellington	0.0341	-0.003548	0.0361	-110.40	5.87
Woodstock	0.0428	-0.01577	0.0407	-136.85	-4.91

Next, temperature anomaly charts are compared (Figures 6 a through c) for the summer (June-July-August) and winter (December-January-February) months to check the yearly differences that obtain during the period of 1980-2005. The values below 0 represent the years when the mean temperature was underestimated by the reanalysis data, whereas the values above 0 years represent the years in which the temperatures were over-estimated. Anomaly charts are particularly useful to assess the magnitudes of temperature changes. The results from different stations are consistent with the evaluated performances shown above which indicate an over-prediction during summer months and variable predictions during winter.

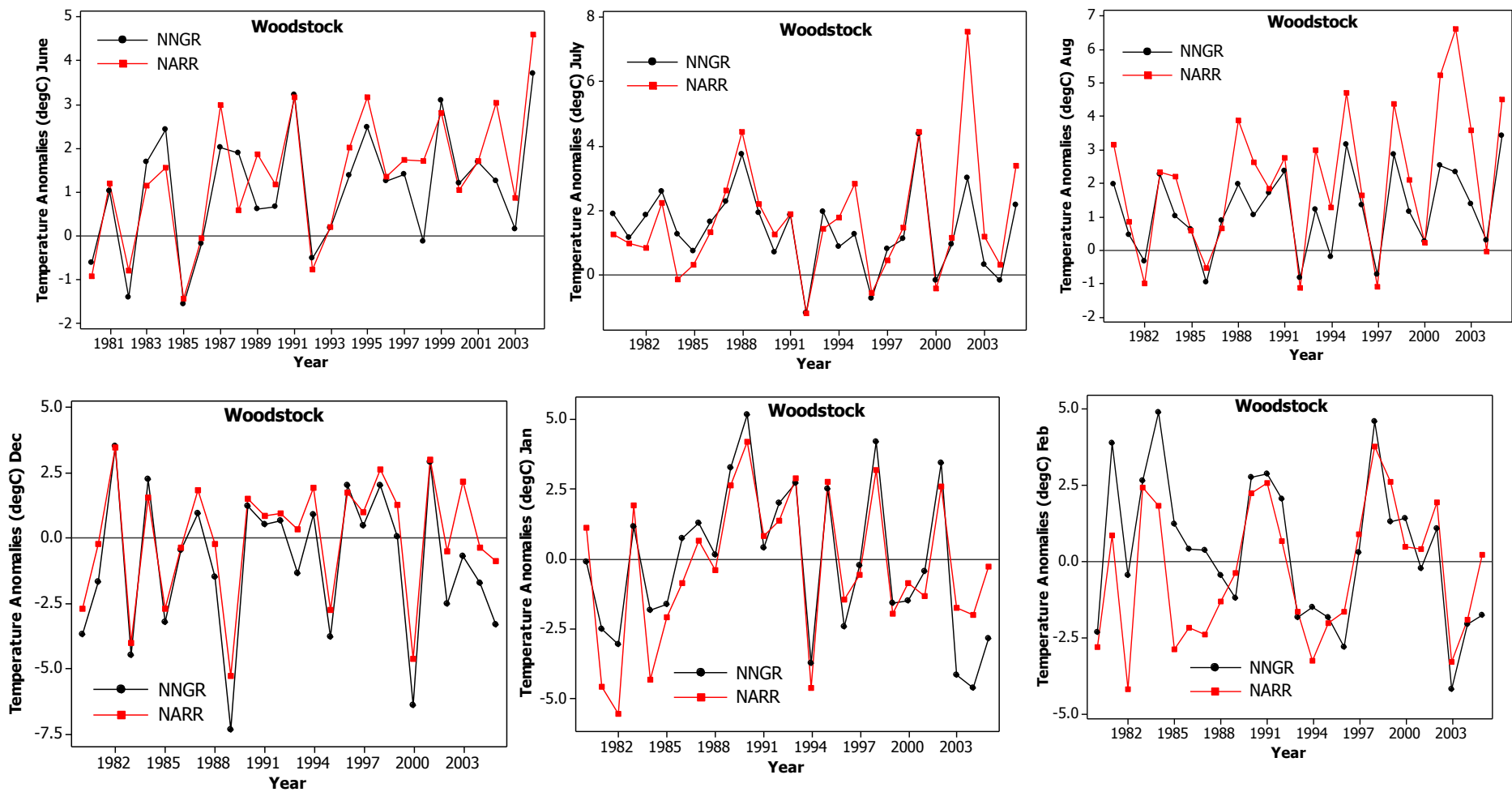


Figure 6 (a): Changes in Temperature Anomalies over Woodstock during June-July-August and December-January-February during 1980-2005

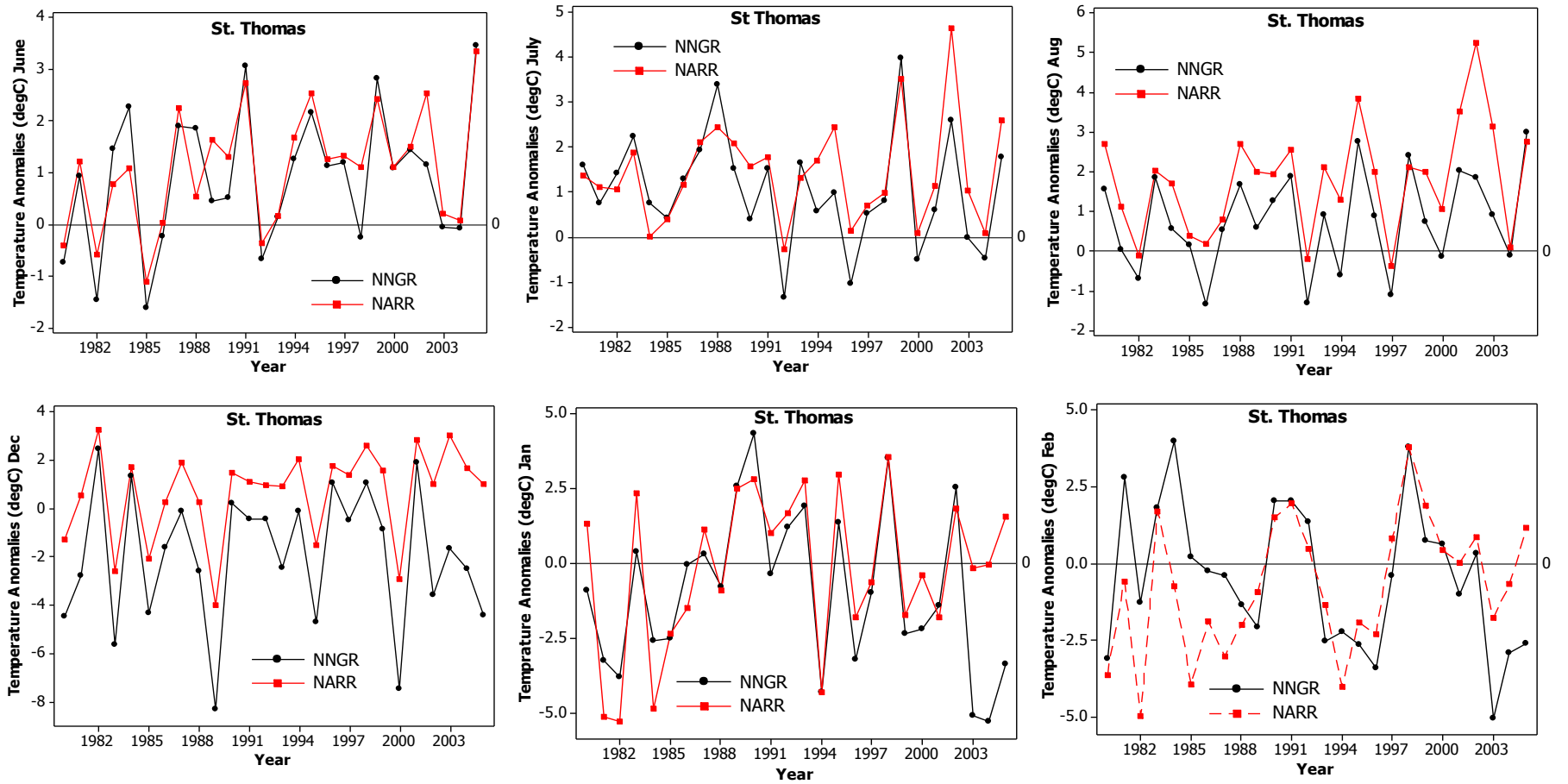


Figure 6 (b): Changes in Temperature Anomalies over St. Thomas during June-July-August and December-January-February during 1980-2005

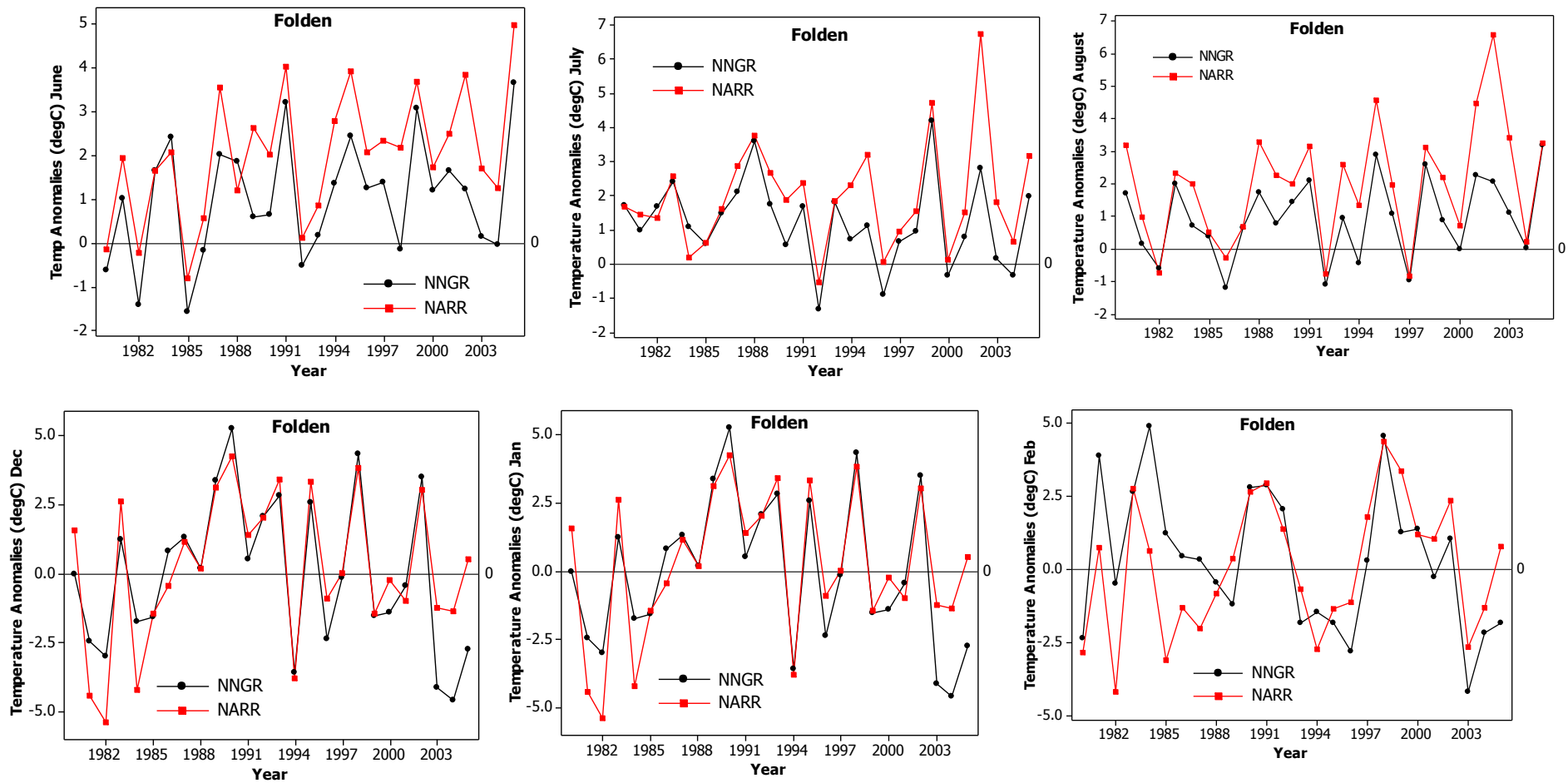


Figure 6 (c): Changes in Temperature Anomalies over Folden during June-July-August and December-January-February during 1980-2005

Table 5: Comparison of Mean Daily Precipitation from Observations and Reanalyses Data for 1980-2005

Station	Mean			Variance			Mean Bias		Correlation	
	Obs	NNGR	NARR	Obs	NNGR	NARR	NNGR	NARR	NNGR	NARR
Dorchester	7.76	6.53	7.17	75.00	30.00	67.68	-15.81	-7.64	0.36	0.48
Blyth	8.77	5.95	5.99	73.91	24.67	43.43	-32.10	-31.64	0.33	0.40
LondonA	7.95	6.00	6.46	78.03	45.79	29.47	-24.52	-18.71	0.50	0.50
Exeter	7.96	6.11	6.23	65.60	25.73	46.17	-23.25	-21.73	0.35	0.42
Foldens	7.99	6.69	6.93	75.28	31.83	62.92	-16.28	-13.22	0.36	0.51
Glen Allan	7.29	6.12	6.84	64.48	25.54	56.06	-16.07	-6.11	0.37	0.46
St. Thomas	8.28	6.47	6.03	77.21	29.68	44.33	-21.89	-27.23	0.32	0.48
Stratford	7.80	6.32	7.35	59.81	27.35	71.33	-18.98	-5.75	0.37	0.45
Woodstock	8.19	6.62	7.15	76.65	31.03	68.13	-19.22	-12.78	0.37	0.51

4.1.2 Precipitation

Precipitation, generally have higher variances than temperature and is more difficult to simulate. Table 5 presents the statistics of mean daily precipitation calculated for selected stations around the Upper Thames River basin. The variance within the observed precipitation ranges from 64.48 to 78.03, while the variance of NNGR varies from 24.67 to 45.79.

The and mean bias from NNGR varies between -15.81% and -32.10% with respect to observations, suggesting that it is not able to capture the variability of the precipitation in the region. For NARR, the variance is much higher with values ranging between 29.47 and 71.33 and a mean bias of -5.75 to -31.64%.

The correlation values are much lower than the temperature, and they also show greater variability by station. The correlation values between observation and NNGR is also below 0.4 except for London station. While for NARR, the correlation appeared higher than the NNGR which implies a higher station-to-station correlation around the grid points in terms of

the goodness-of-fit measure. The inter-station variability in the mean bias and correlation may be related to the individual station locations with respect to local geographic features.

Figures 7 (a), (b), and Appendix A present the cumulative daily precipitation graphs of NARR and NNGR at different stations for the year 2000. In Stratford, Woodstock and Waterloo-Wellington, NARR is fairly close to the observed precipitation. In London, however, NNGR data perform slightly better. Interestingly, the gap between the observed and estimated data widens from summer for London, Stratford, St. Thomas, Wroxeter while in Folden, Waterloo-Wellington and Woodstock the datasets followed the observed values closely throughout the year.

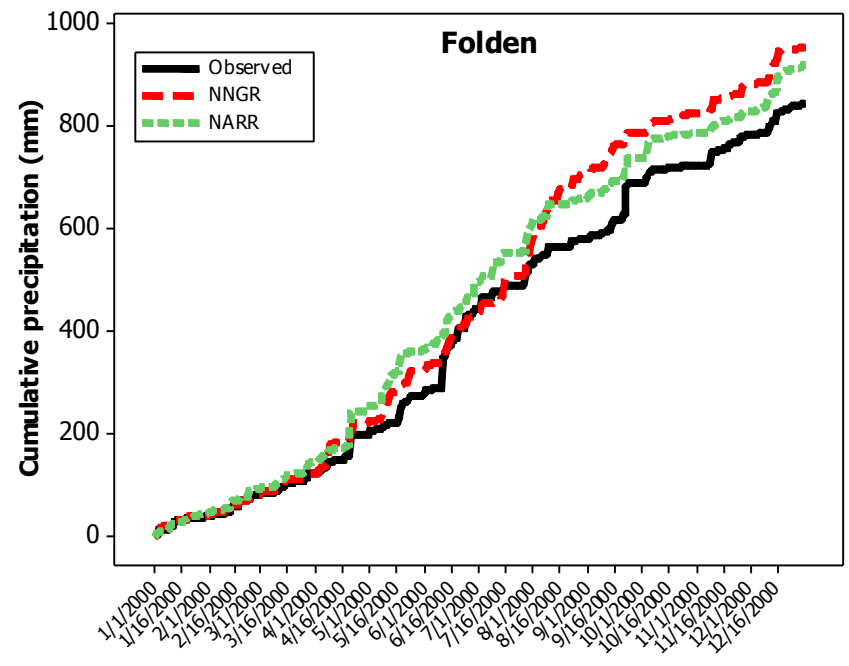
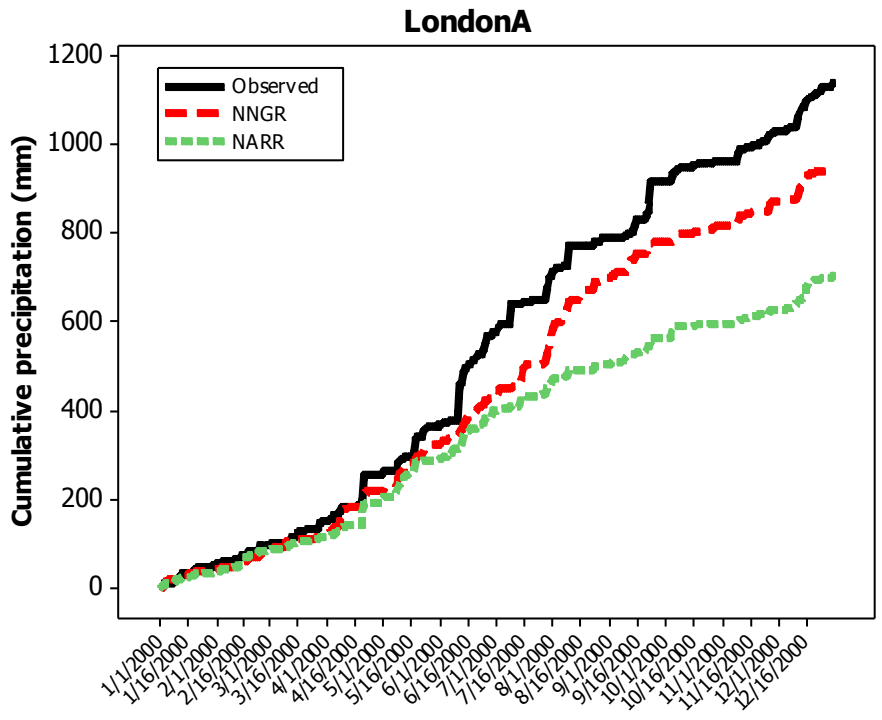


Figure 7 (a): Comparison of Cumulative Daily Precipitation in 2000 for London (Top) and Folden (Bottom)

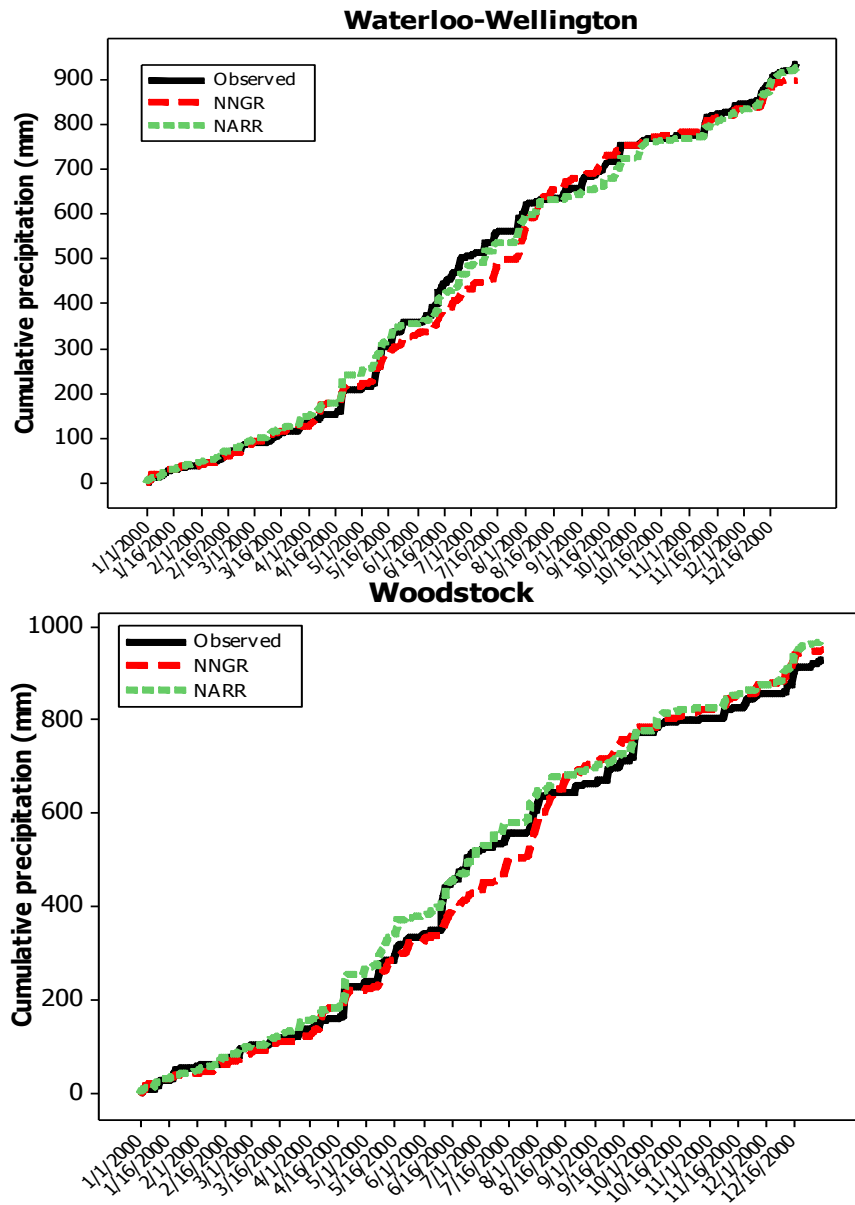


Figure 7 (b): Comparison of Cumulative Daily Precipitation in 2000 for Waterloo-Wellington (Top) and Woodstock (Bottom)

4.2 Hydrological Model Results

4.2.1 Performance Evaluation

Table 6 compares the statistical performance measures of the daily discharge obtained during January 1980- December 2005 for evaluating the performances of the reanalyses data. The root-mean-square-error for both NNGR and NARR varies considerably, from 4.00 m³/s (NNGR) and 3.44 m³/s (NARR) at Ingersoll to 28.1 m³/s (NNGR) and 24.37 m³/s (NARR) at Byron. The correlation coefficients produced by NARR (0.59-0.65) are significantly higher than those produced by NNGR (0.41-0.44). The normalized mean square error is also slightly higher in the case of NNGR. The absolute mean error is differentiable both in terms of the data types and locations. NNGR produces higher errors. It also appears that the MAE measure is lowest at locations where more than one sub-basin is contributing to the total runoff. The values of the relative bias differ greatly at the selected locations, with the NARR, unlike its counterpart, producing a negative bias. The bias produced by the NNGR data is much higher, ranging from 26% to 45% to that of -12% to -7% from NARR. Apparently, Byron is the outlet of the basin with a contributing area of 3,110 km² (Cunderlik and Simonovic, 2004) and with 32 sub-basins. The poor model performance at Byron can be attributed to the fact that this part suffers from inadequate meteorological data, which may have restricted a more satisfactory representation of the daily discharge values.

Table 6: Comparison of Performance Statistics at Selected Locations within the Basin

Locations	NNGR					NARR				
	RMSE (m ³ /s)	r	NMSE (1/ m ³ /s)	MAE (m ³ /s)	RBias (%)	RMSE (m ³ /s)	r	NMSE (1/ m ³ /s)	MAE (m ³ /s)	RBias (%)
Byron	28.097	0.44	1.03	15.73	31	24.37	0.65	0.77	9.95	-12
Ingersoll	4.2875	0.41	1.25	2.62	45	3.44	0.63	0.80	1.57	-7
St. Marys	10.08	0.44	0.97	5.23	26	10.04	0.59	0.97	3.72	-9

4.2.2 Flow Comparison Plots

Figures 8 and 9 present flow comparison graphs during June-August, 2001-2005. The modeled hydrograph from the reanalysis data does not provide a good fit to the observed data. Peaks are not captured by using either NNGR or NARR, though some biased peaks are generated by NNGR during the low flow periods. The hydrographs generated by the NARR data for low flows are better than the NNGR data. NNGR produces more biased results in both locations, even for low flows. The model performance for low flow improves with the increase of contributing area. NNGR has systematically overestimated the peaks during summer; NARR has not shown systematic bias in most of the periods except for the year 2002.

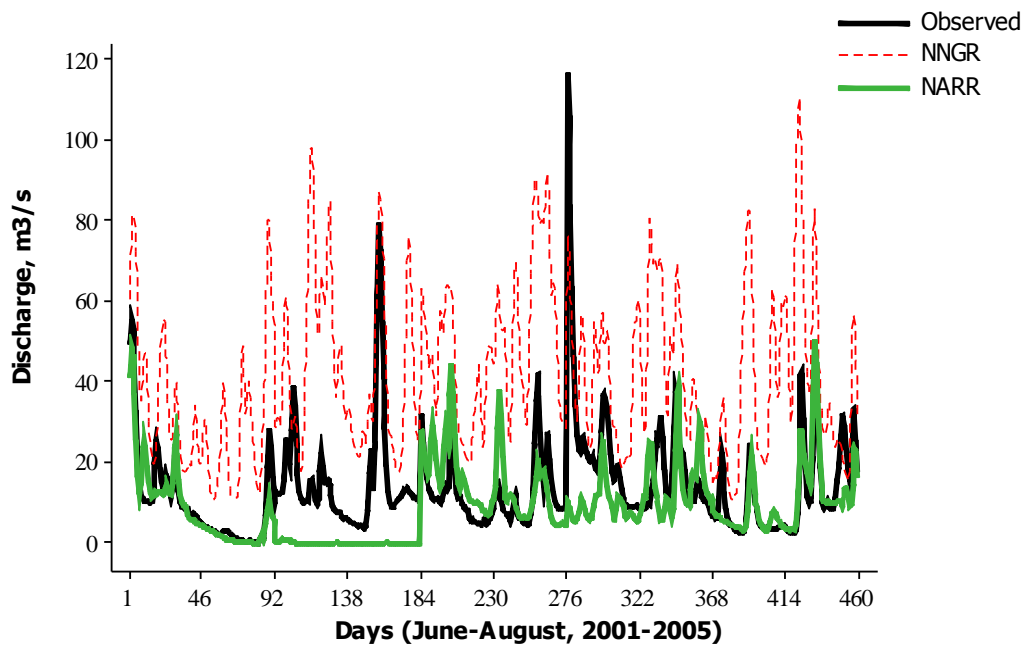


Figure 8: Daily Hydrographs Obtained from Various Data Sources during June-August, 2001-2005 at Byron

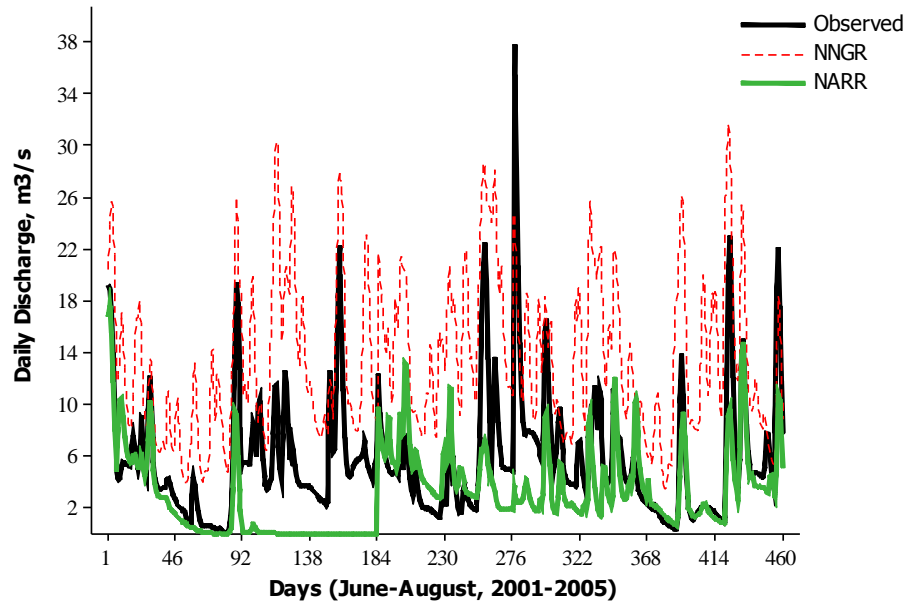


Figure 9: Daily Hydrographs Obtained from Various Data Sources during June-August, 2001-2005 at St. Marys

Figures 10 (a), (b), and Appendix B present a comparison of the scatter plots between precipitation and associated flows during May-August, 1980-2005 at Byron, Ingersoll and St. Mary's. The higher flows show significantly scattered patterns; low flows are in better agreement with precipitation because the low flows are more directly linked with the deficit of precipitation. NNGR generated flows, however, show relatively less concurrence than NARR. This may be explained by the level of bias present in the dataset.

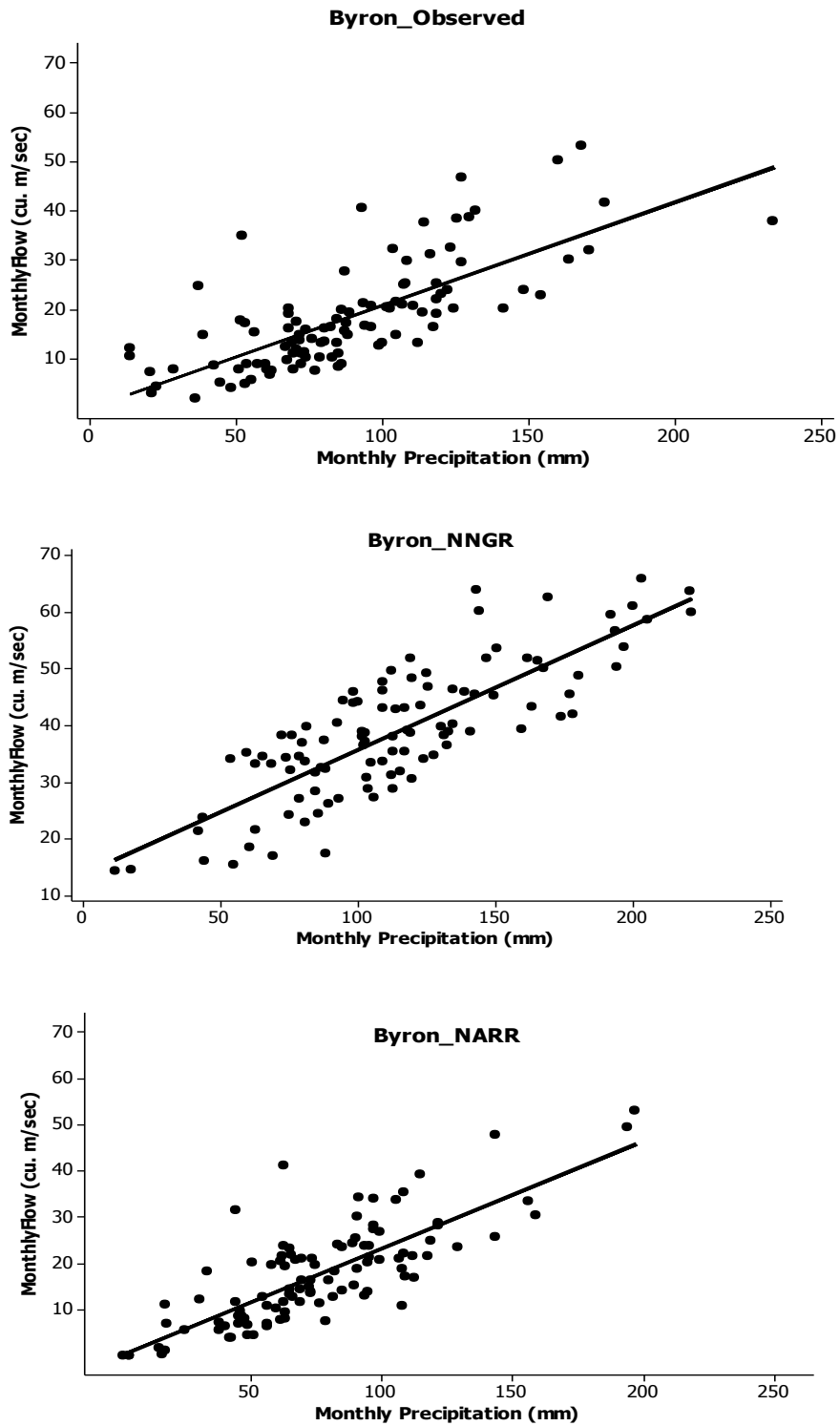


Figure 10 (a): Scatter Plots of Precipitation and Flow (May-August, 1980-2005) at Byron

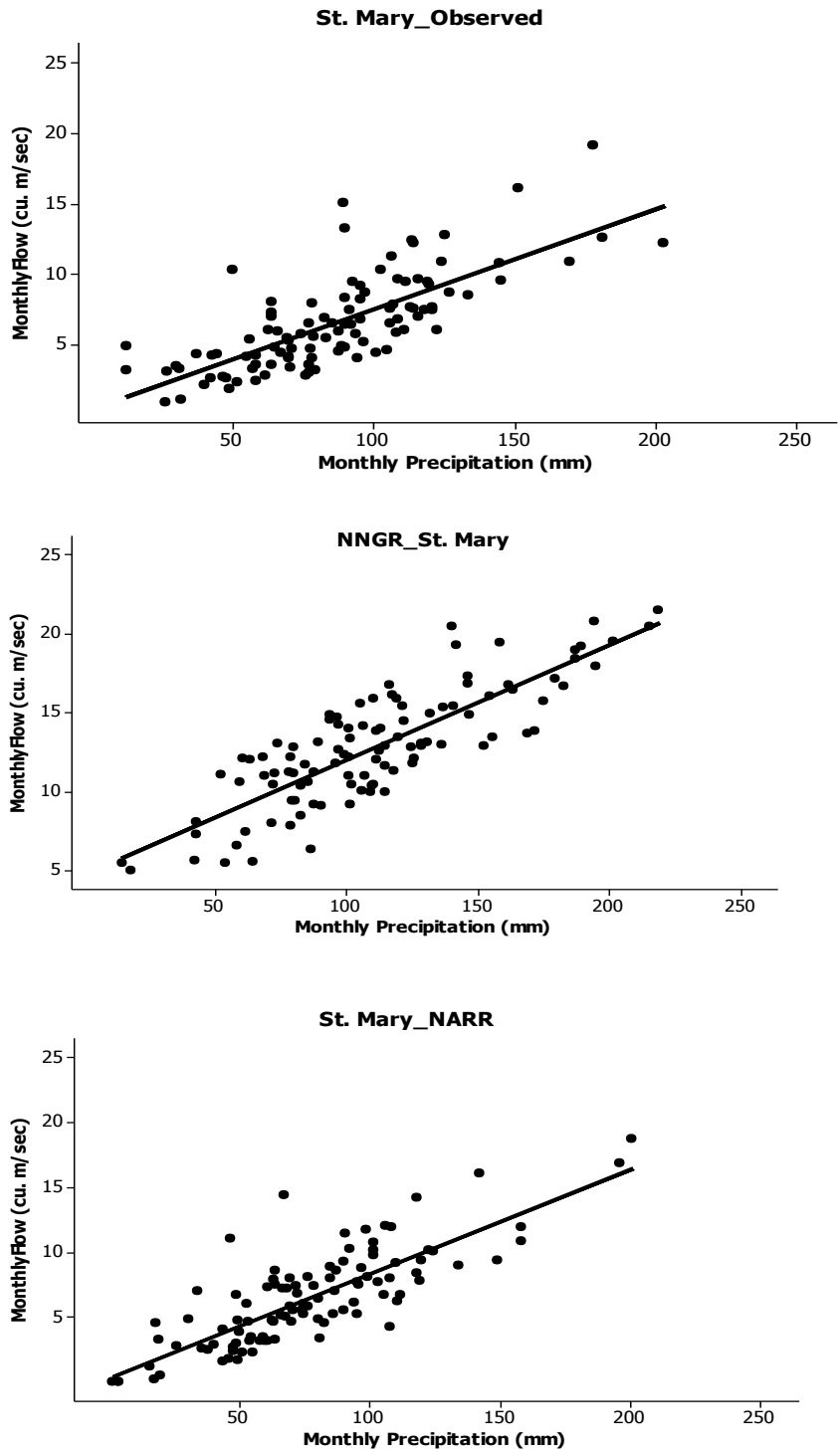


Figure 10 (b): Scatter Plots of Precipitation and Flow (May-August, 1980-2005) at St. Mary

4.2.3 Error Evaluation in terms of Box and Whiskers plot

Figures 11 (a) and (b) present the box plots of the monthly discharge at Byron and St. Mary's during May-November, 1980-2005. Although the model has been applied on daily data, the statistics from the daily data have been aggregated into a monthly scale to facilitate the presentation of results. Summer discharge shows variability in the estimated means. From the plots of Byron, it can be seen that the historical mean of the mean discharge deviates significantly from the median for NNGR except for October for NNGR. While NARR has been consistent and has been able to adequately present the observed discharge. NNGR, however, has suffered from a significant overestimation during most of the months considered in the study (excluding October and November). Some values during September through November are above the top whiskers, i.e., considered as outliers. In most months, the monthly average discharge from the observed dataset falls below the 25th percentile value of NNGR flows. The performance of NARR is, however, very satisfactory and suffers from only minor underestimations. In most cases, the mean observed discharge is close to the NARR median (except in October). Although in few years the NARR discharge appeared outside the top whisker's range (outliers), those are, however, very few compared to the entire dataset.

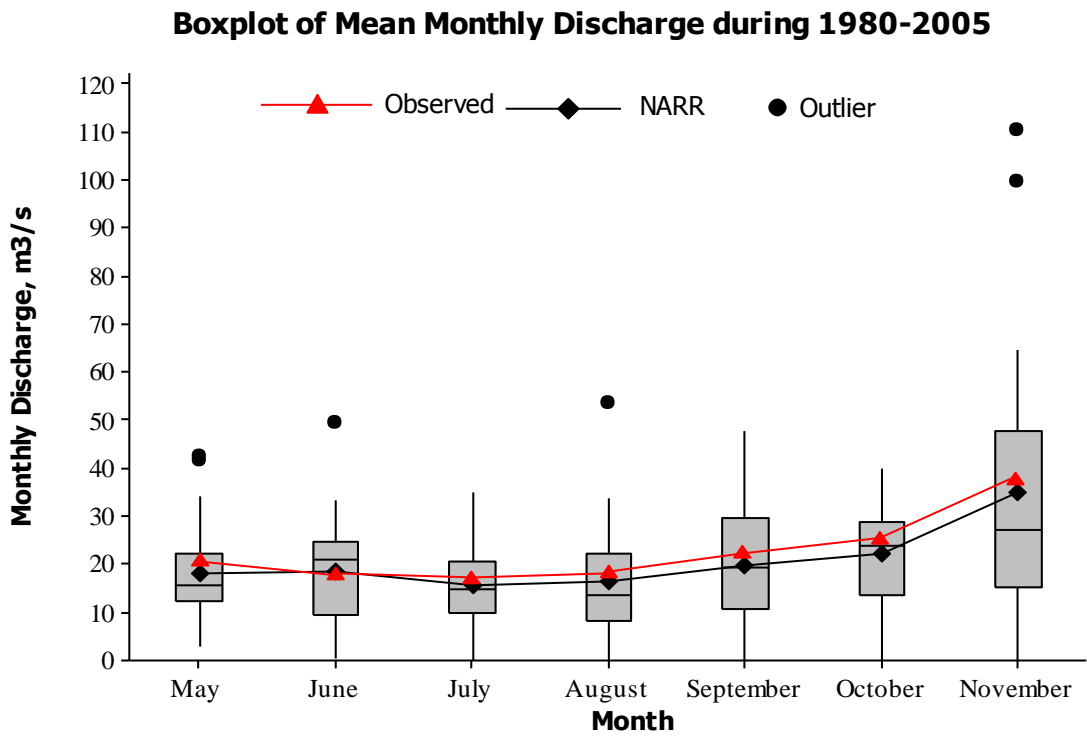
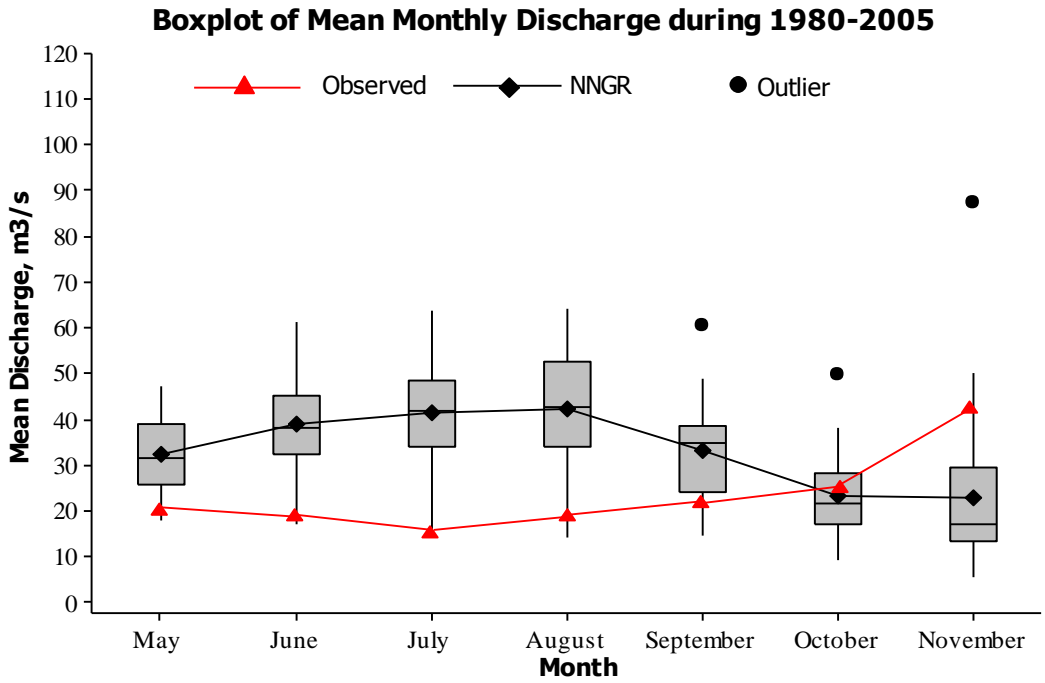


Figure 11 (a): Box Plots of Monthly Discharge during May-November, 1980-2005 at Byron

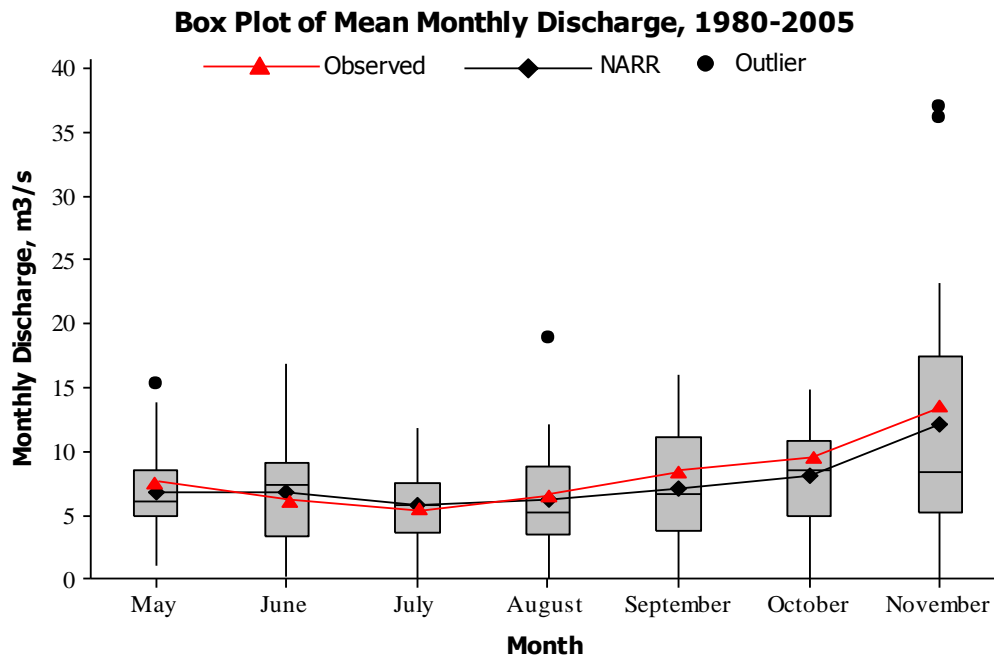
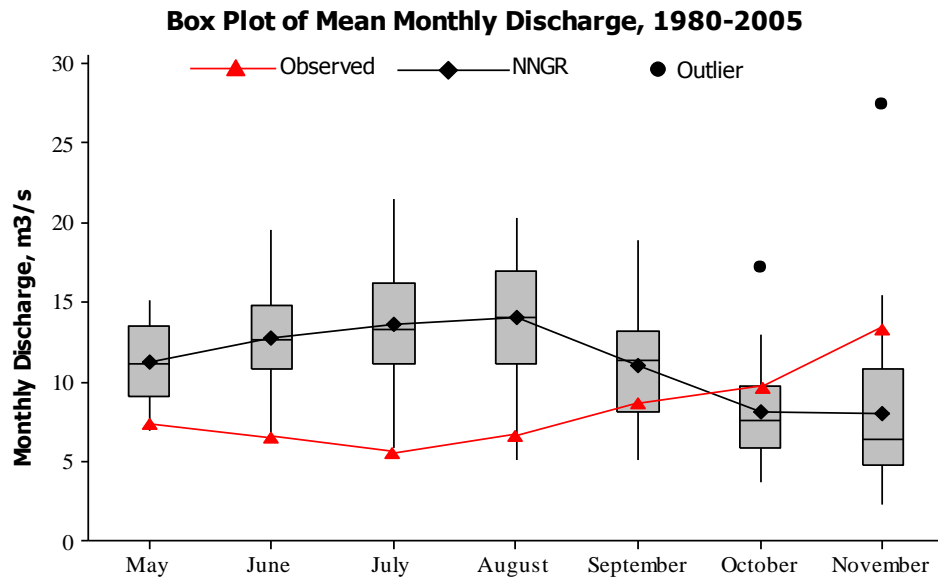


Figure 11 (b): Box Plots of Monthly Discharge during May-November, 1980-2005 at St. Marys

4.2.4 Error Evaluation in terms of Means and Variances

Table 7 presents the results of the non-parametric Wilcoxon rank-sum test performed for evaluating errors in the estimation of the mean daily flow values for May-November, 1980-2005. The statistical significance test results (p values) reveal that at a 95% confidence level, errors at the Byron location are higher in NNGR for all months ($p < 0.05$) except during October, and in NARR the errors are significant during only three months. Similar results can be seen at St. Mary's as well, where NARR produced higher errors in three months while NNGR errors were high in all seven months.

Table 7: Test Results (p values) of the Wilcoxon Rank Test at 95% Confidence Level

Month	Byron		St. Marys	
	NARR	NNGR	NARR	NNGR
May	0.08	0.00	0.76	0.00
Jun	0.87	0.00	0.23	0.00
Jul	0.53	0.00	0.13	0.00
Aug	0.00	0.00	0.02	0.00
Sep	0.76	0.00	0.31	0.00
Oct	0.01	0.95	0.00	0.00
Nov	0.00	0.00	0.00	0.00

Next, Levene's test is used at the Byron and St. Mary's locations to evaluate the quality of the variances between the flows generated by the observed and reanalysis data at a 95% confidence interval. The results are presented in Table 8. In the case of Byron, the variance test results of NNGR reveal that for all months except two, all the p values fall below 0.05; the case is even worse in St. Mary's, with only one month above the threshold p level (>0.05), suggesting that the observed and NNGR generated flow variances are statistically different. For NARR, however, the p values for five months are found to be above 0.05, indicating the equality of variances for those months. These test results confirm that the

variability of the NARR generated flows can be considered equal to the observed flows in general, but NNGR generated flows cannot be considered equal at the 95% confidence level.

Table 8: Test results (p values) of the Levene's Test at 95% Confidence Level

Month	Byron		St. Marys	
	NARR	NNGR	NARR	NNGR
May	0.04	0.77	0.04	0.09
Jun	0.10	0.00	0.02	0.00
Jul	0.44	0.00	0.47	0.00
Aug	0.65	0.00	0.10	0.00
Sep	0.08	0.91	0.02	0.02
Oct	0.00	0.00	0.00	0.00
Nov	0.99	0.00	0.91	0.00

5. Conclusion

In mountainous, remote regions, or even in stations with large amounts of missing data, the task of hydrologic modeling continues to be a major challenge due to the overall lack of observed data. In a rapidly changing climate, this is becoming a major concern because to investigate the hydrologic impact of climate change it is important to model the present climate accurately in order to account for future changes. With their more refined spatial and temporal coverage, the NCEP reanalysis data have the potential to be used effectively in data scarce regions (Reid et al. 2001). In order to take advantage of these data, there is, however, a need for accurate synopsis of the climate conditions. Because the reanalysis dataset is produced by assimilating observed weather information, including surface temperature, into a numerical weather forecast system, it can be thought of as the product of an advanced interpolation scheme (numerical weather model) which takes into account important factors, such as topography and land cover (Choi et al. 2009). In this paper, the performance of the NCEP global and regional reanalysis data under present climate conditions for precipitation and temperatures are verified with selected stations around the Upper Thames River basin in Southwestern Ontario, Canada. NARR has been able to capture the real scenario over 1980-2005 by capturing the temperature trends, with some over-estimation during the summer months. The means and the variances of both datasets do appear to be similar when evaluated by t and F tests. The results for computing precipitation at several stations show variable results. While in some stations the reanalysis dataset performed well, for a couple of stations both of them appeared to suffer from underestimation and overestimation, thereby

necessitating a careful check before their application. The overall goodness of fit results indicate a better performance by NARR when compared to NNGR.

The present study has demonstrated that the NARR data can be a feasible substitute to the observed weather stations data. It is, however, important to keep in mind the limitation of NARR data: (i) the daily gauged data NARR uses for assimilation, comes in 1 degree grid which may be insufficient for the model to perform well; (ii) The weather station data represent point information while NARR provides areal averages in 32 km X 32 km grid; even within these area, there can be considerable variations of climate, which can be, however, more prominent in complex topographies. The latter is, however, not considered a major drawback as in hydrologic modeling where it is more important to get an areal representation rather than a point precipitation (Choi et al, 2009).

For this study, the meteorological inputs from the above data sources are used with the semi-distributed continuous rainfall-runoff model developed based on the computational engine of HEC-HMS for the period 1980-2005. The differences between the two datasets appear to be more prominent from the following analysis: first, the comparison of their relative bias shows that NNGR is associated with a more significant bias than its NARR counterpart. The NARR, correlatively, produced an insignificant negative bias at all locations, which may be due to insufficient meteorological inputs that have restricted the representation of the real basin conditions. Secondly, the flow hydrographs show that NNGR is associated with some biases that lead to shifts at the peaks away from their original time of occurrence. This can be the result of (a) the continuous model calibration for low flow conditions, and/or (b) the sparse grid points, especially from NNGR. In the case of NARR, the model performance for low flow improves at downstream locations with the increase of

the contributing basin area. Although there are under- and over-estimations, NARR has not shown any systematic bias. The comparisons of the precipitation and flow scatter plots support the above explanation: higher flows are scattered from their fitted lines while the precipitation and low flows appeared to be in better agreement. Thirdly, the box plots present a clear distinction between the two reanalysis datasets: the NARR have successfully followed the trend, while the performance of NNGR has been inferior. The errors associated with the generated flows and that are derived from estimating means and variances have been further tested using the non-parametric Wilcoxon rank sum test and Levene's test. Both tests indicate that NARR leads to less error. Its variability is also shown to be closer to the observed variability for most of the months at the 95% confidence level.

Based on the following observations, it can be concluded that the differences in simulating discharge using NARR and NNGR data sets lies in their inherent process of generating precipitations. NARR data are produced by assimilating high quality and detailed precipitation observations into the atmospheric analysis, thus making the forcing into the land surface model component of the system more accurate by enabling the interaction of the land hydrology and land-atmosphere, which has not been considered in NNGR. The coarser grid of NNGR may also have limited its performance. Considering the satisfactory performance of NARR, and also the drawbacks of NARR data over some parts of the Canadian landscape, it is suggested that a thorough investigation should be carried out for its application in both climate and hydrologic impact studies. Future work aims at including other atmospheric variables from NARR data for climate change modelling to improve its performance in generating any future impacts of climate change. From a hydrologic modelling point of view, it will be interesting to compare results from NARR with the newly

developed 10-km gridded Canadian daily dataset (Hutchinson et al. 2009) to achieve a more accurate source of alternative database for hydrologic modeling in the study area.

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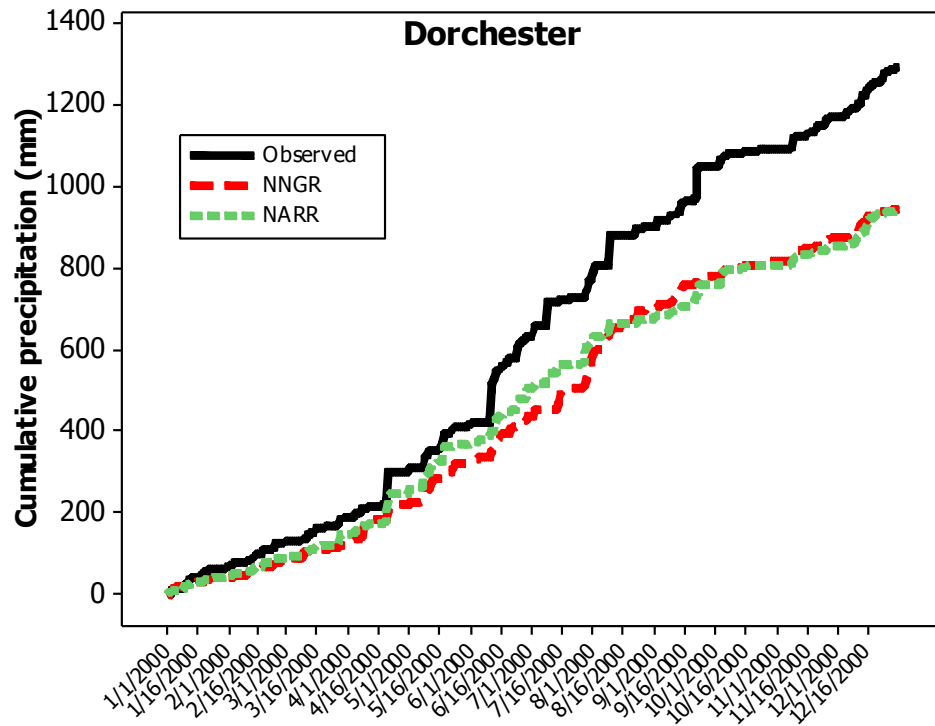
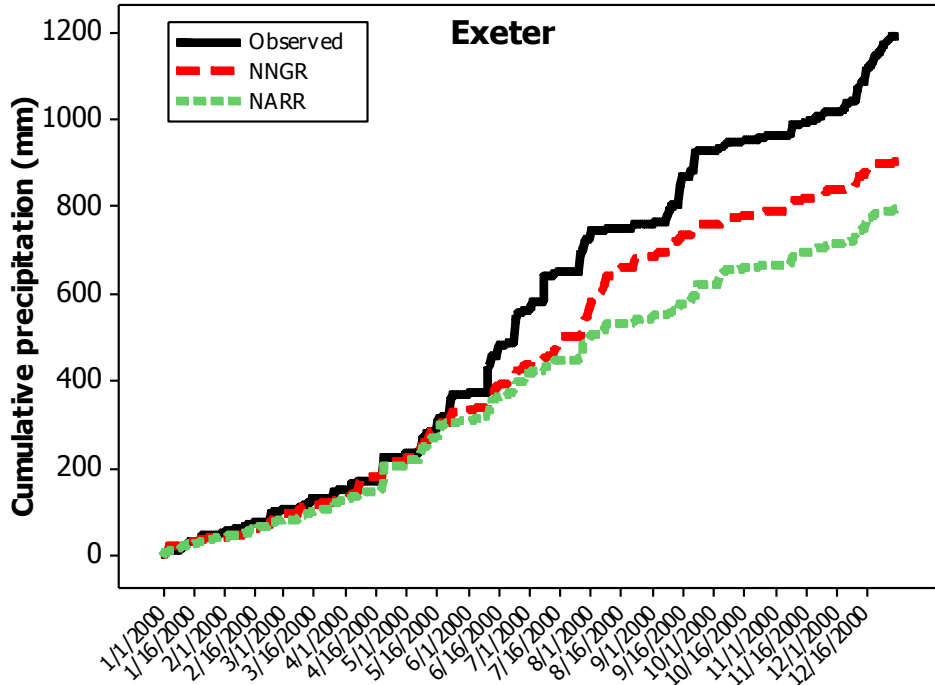
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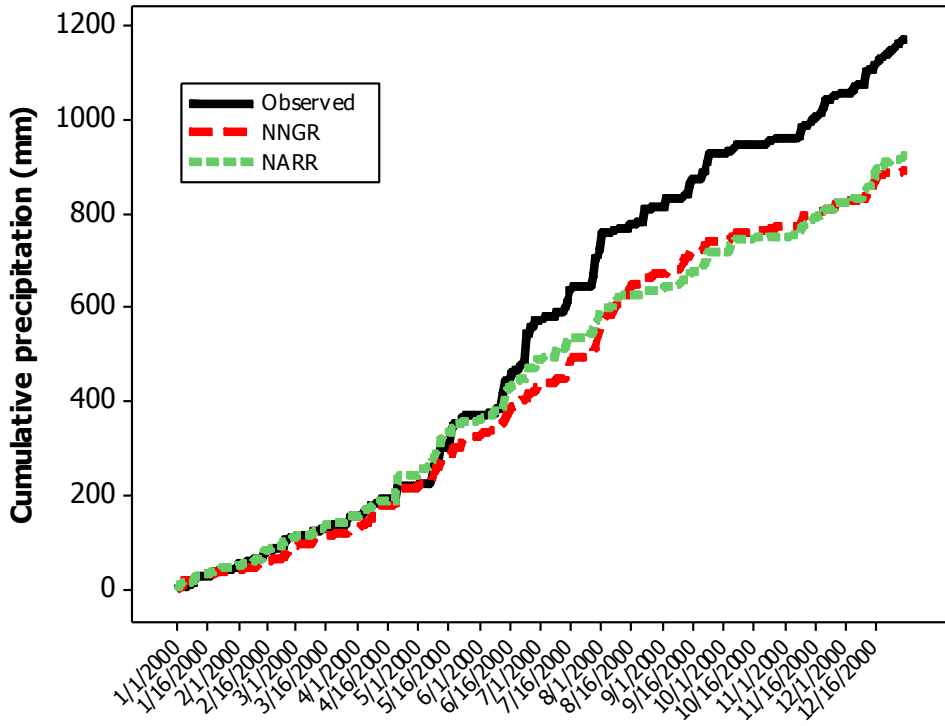
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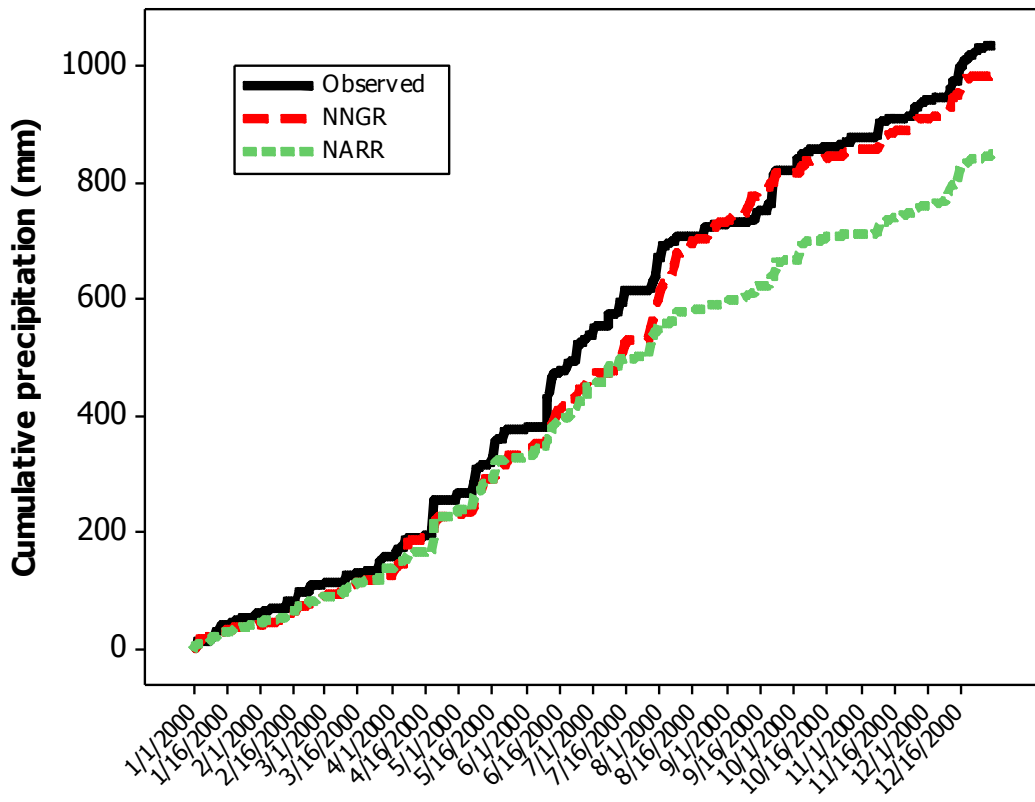
APPENDIX A: Cumulative Precipitation for 2000



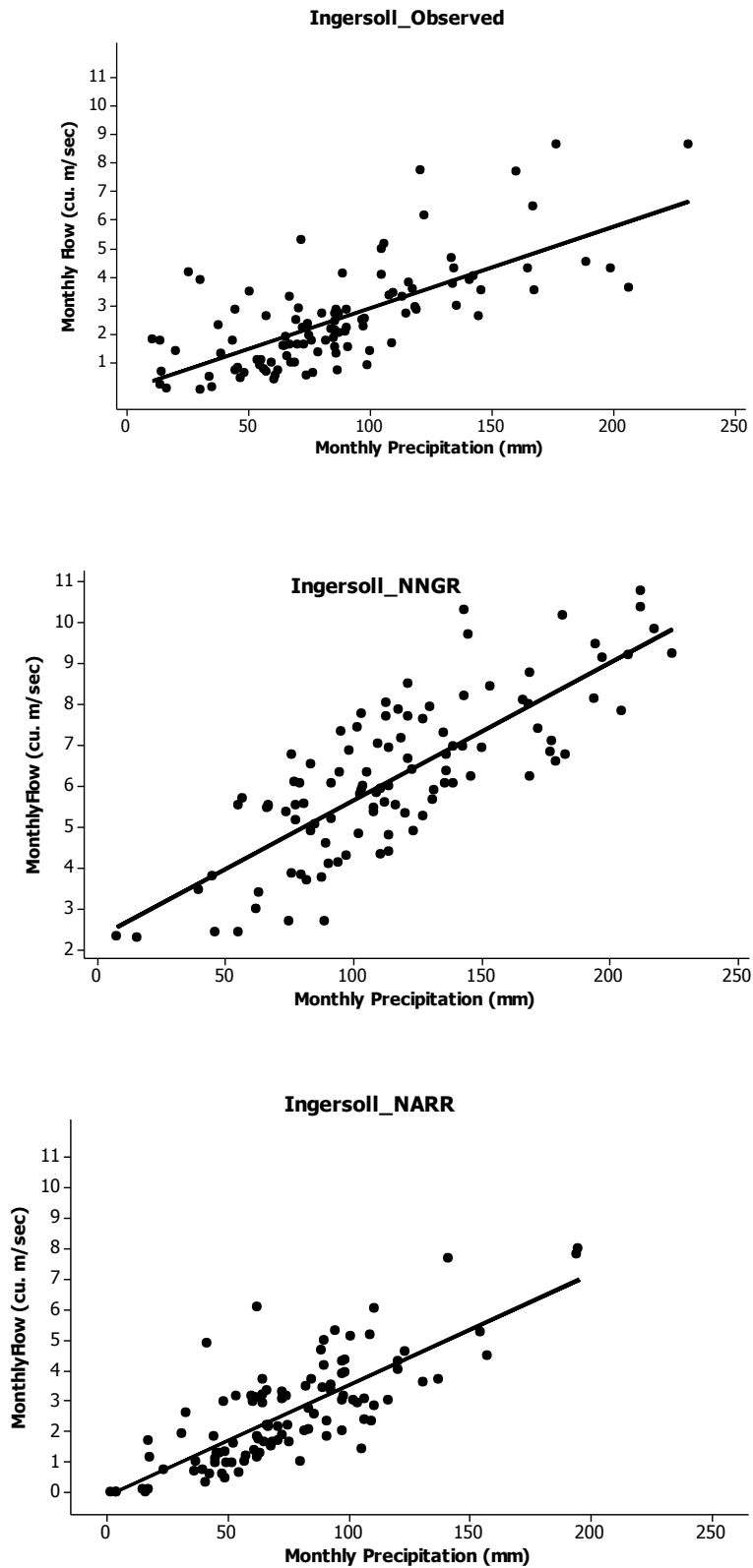
Glen Allan



St. Thomas



APPENDIX B: Scatter plots of precipitation and flow (May-August, 1980-2005) at Ingersoll



APPENDIX C: Previous Reports in Series

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