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Assessment of climatic vulnerability in the Upper Thames River basin: Downscaling with SDSM

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Assessment of Climatic Vulnerability in the Upper Thames River Basin:

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Executive Summary:

In recent years, an increased amount of carbon dioxide and other greenhouse gases generated by human activities have contributed a major effect on global climatic change. Understanding the effects of rising temperature is important in order to assess the wide scope of possible impacts on water resources management. Identifying the potential effects of climate change on the hydrologic cycle at a local scale is important in order to determine high risk areas and adapt the infrastructure appropriately. Atmosphere-Ocean coupled Global Circulation Models (AOGCMs) are a commonly used tool for predicting the effects of climate change based on the plausible emission scenarios developed by the IPCC. As these AOGCM models have a coarse spatial resolution, downscaling is required to determine the local scale hydrological impacts.

In this study, downscaling is achieved using a well-known multiple regression based decision support tool, the Statistical Down-Scaling Model (SDSM), developed in the UK by Dr. Robert Wilby and Dr. Christian Dawson. The SDSM model is used to produce 324 years of synthetic data for the 2050s time period. The performance of the model is evaluated by comparing a synthetic historical dataset to the observed data and with the output of two other weather generators LARS-WG and KnnCAD.

SDSM showed good results for maximum and minimum temperature for historical climate simulation. However, the performance for precipitation was not satisfactory as the simulated values did not capture historical trends for monthly wet days and the standard deviation of daily precipitation.. Comparing the SDSM results with the LARS-WG and

KnnCAD weather generators it is found that the performance of KnnCAD weather generator is preferable to LARS-WG and the SDSM for historical climate simulation.

For future climate simulations of precipitation, the variability between the weather generators is high. Most AOGCM models and downscaling tools agree that spring and early winter precipitation will increase although results vary depending on the weather generator and AOGCM used. SDSM simulations generally indicate an increase in summer precipitation while LARS-WG and KnnCAD predict a decrease. Most simulations predict an increase in mean daily precipitation amounts, indicating that more extreme rainfall events can be expected in the future. It is critical to consider a variety of these for comprehensive climate change impact assessments due to the high variability between AOGCM's and emission scenarios.

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1. Introduction

Rising average temperatures as a result of increasing greenhouse gas emissions will have a major impact on the global climate. According to the 4^{th} assessment report of the Inter-governmental Panel on Climate Change (IPCC), by the 2080's the average temperature will be 3°C warmer than in 1990 (IPCC, 2007). Human society and the natural environment are adversely affected by extreme weather conditions that could result from climate change. Rising average temperatures as a result of increasing greenhouse gas emissions will cause extreme events occur more frequently in future (Wilcox and Donner, 2007).

Atmosphere-Ocean integrated General Circulation Models (AOGCM's) are the tool for predicting the effects of climate change based on the probable emission scenarios developed by the IPCC (CCCSN, 2011).They are gridded predictions of the future climate based on the IPCC's greenhouse gas emission scenarios. These are developed by several research institutions around the world to predict the future global climatic variables. As these AOGCM models have a coarse spatial resolution (typically 100X100 km), downscaling is required to achieve local scale hydrological impacts (Prodanovic and Simonovic, 2007). Downscaling is a set of techniques that establishes a relationship with local and regional climate variables to large scale variables (Hewitson and Crane, 1996). In this study a well known multiple regression method based decision support tool, Statistical Down-Scaling Model (SDSM), developed in the UK by Dr. Robert Wilby and Dr. Christian Dawson (CCCSN, 2011) is employed to investigate the potential impact of climate change in the Upper Thames River Basin. Also, various techniques have been developed to downscale coarsely-gridded AOGCM data in order to predict future climate outcomes at a watershed scale. In these study the output of three different techniques, namely

SDSM, LARS-WG and KnnCAD are used to compare the downscaled the AOGCM data of the Upper Thames River basin.

2. Literature Review:

The fully coupled AOGCM's are the most reliable source for predicting global future climate change (Elmahdi et al., 2009). However, it is a common practice to use a single AOGCM for climate change impact assessments. Overreliance on a single model could lead to improper planning and adaption responses as each model has its own strengths and weaknesses (Wilby and Harris 2005). Also as the land and ocean has different thermal characteristics direct interpretation of AOGCM results is inadequate. In order to predict climate change impacts on smaller river basins or at a particular site, statistical downscaling of AOGCM data has evolved (Mearns et al., 2003).

There are several methods outlined in the literature for the downscaling of AOGCM data. These techniques are highly dependent on the region in which they are applied and the variables being considered (Dibike and Coulibaly, 2005). Each method has its strengths and drawbacks and results can differ greatly depending on the technique used. Downscaling techniques can be classified in two main categories, statistical downscaling and dynamic downscaling. In dynamic downscaling, a Regional Climate Model (RCM) is used with AOGCM outputs as the boundary conditions. While RCM's are able to more accurately simulate the climate for a specific region, there is a high amount of computational effort and cost associated with the development of these models and they are not readily available for application in most watersheds (Dibike and Coulibaly, 2005). Additionally, RCM's have a fairly high spatial resolution (approximately

40km X 40km), which may not be suitable for smaller watersheds (Islam et al, 2007). As RCM's are developed for a specific region, their availability is limited as well as their suitability for use with several AOGCM outputs.

Statistical downscaling is a popular method because of the reduced computational effort and ease of use. Statistical (linear and non-linear) relationships are used to produce synthetic datasets of any length representative of a specific time period. The major underlying assumption of these techniques is that the future climate is governed by the same relationships as the historical. There are a number of methods that can downscale the AOGCM data directly, however, they are not accurate for local-scale variables such as precipitation (Trigo and Palutikof, 2001). Moreover, monthly data is used instead of daily because of unavailability and poor quality of daily AOGCM data.

The three main types of statistical weather generators are parametric, semi-parametric (empirical) and non-parametric (Brissette et al., 2007).

Parametric weather generators typically use a Markov chain to calculate the probability of rainfall occurrence, and a given probability distribution to determine the amount of precipitation (Corte-Real et al., 1999). Probability of rainfall occurrence is determined through analysis of the historical records (Elshamy et al, 2006). The first such model, WGEN, was developed by Richardson in 1984. A disadvantage of WGEN is the inability to reproduce persistent weather situations such as droughts and wet spells due to the limited memory of the Markov chain (Sharif and Burn, 2007). As they are designed for short term projections (10-20 years) rare events cannot be identified properly (Brissette et al., 2007). Most other parametric weather generators use extensions of the Richardson approach, such as CLIGEN, SIMMENTO, WXGEN, GEM, WGENK (Kuchar 2004; Hanson and Johnson 1998; Soltani and Hoogenboom, 2003). Elshamy et al. (2006) employed SIMMENTO on the Nile river basin located in the UK and found that the model overestimates the variability of wet fractions and amounts. Hanson and Johnson (1998) used GEM on three sites in Idaho, USA and found that precipitation was underestimated for some months and average annual precipitation was considerably less than the historical observed values. The assumption of a probability distribution for precipitation amounts is a downside of the parametric approach as updated assumptions are required for each application of the model. Estimation of parameters and statistical verification makes the computational effort difficult. To overcome the limitations of parametric models, semi-parametric or empirical methods were introduced.

Semi-parametric or empirical methods are statistical downscaling techniques that can be categorized as either regression (transfer function) methods or stochastic weather generators and weather typing schemes (Dibike et al, 2007). Semi-parametric weather generating algorithms either use one or a combination of these schemes to downscale AOGCM data. The regression methods use a transfer function to make a direct quantitative relationship between local scale and large scale climatic variables using traditional linear and non-linear regression models (Mehrotra et al, 2006). The local scale variables (precipitation, temperature) are predictands and the large scale variables (pressure, specific humidity, and wind speed) are known as predictors. Linear regression, canonical correlation analysis (CCA) and principal component analysis (PCA) are examples of traditional regression-based downscaling methods to derive predictor and predictand relationships (Bannayan and Hoogenboom, 2008). The main advantage of regression-based models is their relative ease of application. However, as this type of model creates a stationary relationship between predictors and predictands (mainly for precipitation), it only explains a fraction of observed climate variability (Nicholas and Bttisti, 2010). Stochastic weather generators were developed in order to produce synthetic time series of any length that provide insight to the occurrence of extreme events (Wilks and Wilby, 1999). The observed weather series is used as an input for the algorithm to estimate a probability function of rare events. For modeling daily precipitation occurrence, two widely used approaches are the use of Markov chain or spell-length approach. Markov chains use the previous day's wet or dry state to predict the next day's state, and then a probability distribution is used to predict the amount of rainfall based on the day's wet or dry state. The spell length approach works by taking into account the observed dataset and using mixed exponential distributions to model dry/wet series first, then precipitation amounts conditional on the series state and length (Dibike et al., 2007). Weather typing works by grouping local and meteorological data with historical observed values. Re-sampling from the observed data distribution or the AOGCM-modified data is performed to construct future climate scenarios. The major limitation is that precipitation changes produced by changes in the frequency of weather patterns are seldom consistent with the changes produced by the host AOGCM (unless additional predictors such as atmospheric humidity are employed).

The two most well-known semi-parametric statistical downscaling models are the Statistical Downscaling Model (SDSM) and Long Ashton Research Station Weather Generator (LARS-WG) (Dibike et al., 2007).

The semi-parametric LARS-WG was developed by Semenov and Barrow (1997) for agricultural risk assessments. As a result of this LARS-WG is single site weather generator which has its limitations in the case of hydrologic risk assessment. LARS-WG was introduced to overcome the limitations of the Markov chain approach of the parametric models in that only wet/dry day occurrence is modeled instead of series of wet or dry days. It is important to derive these series for hydrologic impact assessments in order to identify rare events (droughts, floods, etc.) (Semenov and Barrow, 1997). The LARS-WG series approach derives a distribution of wet/dry day series from the past dataset. Kilsby et al., (2007) employed LARS-WG in agricultural and water system management in UK with UK Climate Impacts Programme (UKCIP02) scenarios and found that although the LARS-WG is an improvement over the Markov process, it fails to accurately simulate extreme events. Semenov and Barrow (1997) found that LARS-WG performed well in simulating extreme events in a study for agricultural application on crop production for two sites namely Rothamsted, UK and Seville, Spain with GCM equilibrium (UKHI) and transient (UKTI). These contradictory conclusions for similar watersheds show that the LARS-WG outputs are very sensitive to the input data used. As the LARS-WG is data intensive and GCM data for all the locations are not available, it can be uncertain (Semenov, 1997). The model uses an underlying probability distribution which is subjective and may be more suited for certain sites. Also because it is a single site application, spatial correlation must be assumed for multisite use.

Another well-known improved stochastic weather generator is SDSM, which is a hybrid between a stochastic weather generator and a regression based model (Koukids and Berg, 2009). It is capable of reproducing observed climate variability (Dibike et al., 2007) and is thus considered an effective statistical downscaling technique (Hashmi et al., 2011). A study done on the Clutha watershed, in New Zealand, by Hashmi et al. (2011), found that downscaled data for extreme precipitation events are reliable since AOGCM outputs are used only as large scale atmospheric predictors for changes in atmospheric circulation patterns instead of directly applying coarse outputs from the GCM to local scale variables such as precipitation and temperature. According to Koukids and Berg (2009) for any predictand (precipitation, maximum or minimum temperature) the choice of reanalysis data has a major effect on the calibration of

SDSM, and different datasets can produce very different results. Moreover, the choice of appropriate predictors for each predictand is a critical step in SDSM. Essentially downscaling is achieved through a modification of the historical dataset for some models. For SDSM downscaling is achieved using only modified predictor variables (not predictand variables). Percentage of variance and scatter plots are used (monthly, annually, seasonally) to investigate the predictors and finally predictors are chosen by considering their physical sensibility for that particular study area (Dibike and Coulibaly, 2005). Another noticeable factor for SDSM is the underlying probability distribution for each set of predictors and predictands, which requires screening of variables to identify the appropriate combination. This requires a lot of effort to calibrate and validate the model, as well as for each new location the entire process must be repeated. The choice of transfer function also affects the downscaled result as the transfer function establishes an empirical relationship between predictor and predictands. The limitation of the transfer function is that it sometimes explains a fraction of climate variability, mostly in case of precipitation (Wilby and Dawson, 2007). Expected increasing trend in the mean daily temperature as well as in mean and variability of precipitation value is observed with underestimation of wet spell lengths in Chute-du-Diable basin (Quebec, Canada) by SDSM (Dibike and Coulibaly, 2005). Another study showed a negligible difference at 95% confidence level between variance of observed value and downscaled value for daily maximum and minimum temperatures using SDSM, with NCEP reanalysis data as input (Khan et al., 2006). Philippe Gachon and Yonas Dibike (2007) declared SDSM a useful tool for temperature prediction for northern latitudes.

Non-parametric weather generators typically use a nearest neighbour technique. They are computationally simple and do not require any assumptions about the probability distributions of weather variables. The K-NN model is a non-parametric technique to produce weather data (Sharif and Burn, 2007), where K refers the number of nearest neighbours on which selection depends and NN refers to nearest neighbour (Brandsma and Buishand, 1998). The algorithm input is historical observed data which can be modified using change factors for AOGCM simulations. Simulation proceeds by essentially reshuffling the input file to produce a synthetic dataset with similar characteristics to the input file (Bannayan and Hoogenboom , 2008). This model relies on the assumption that the relationships governing the historical input data will also govern the simulated climate (Brandsma and Buishand, 1998). In this multi-site approach, spatial correlation is preserved as the values for each station are simulated concurrently (Mehrotra et al., 2006). The day to day variability is best reproduced with non-parametric weather generators (Brandsma and Buishand, 1998). Beersma et al., (2001) used a K-NN model in the Rhine Basin and found that spatial correlation and climate variability were well preserved. A major limitation of the K-NN approach is that it essentially reshuffles historical data, thus the output file has the same range as the input data (Sharif and Burn, 2007). In order to overcome the problem the K-NN was first modified by Sharif and Burn (2006) to obtain alternate extremes through the addition of a perturbation component (Eum et al., 2009). Later, it was modified by Eum and Simonovic (2009) and termed KnnCAD (Version 3) to include principal component analysis which allows the use of more variables in selection of the nearest neighbour (King et al., 2009). A modified dataset is established by multiplying or adding change factors from any AOGCM dataset to the historical observed data. These scenario-modified datasets are used as an input for the weather generators.

3. Study Area

The Upper Thames River basin shown as the shaded region in Figure 1 is located in south-western Ontario, Canada. This basin is positioned between two major lakes, namely, Erie and Huron and consists of an area of 3500km^2. The total population of this basin is 420 000, in three different counties. The major urban center is London (in Middlesex County), with a population of 350,000. The length of the river is about 273km with an average annual discharge of 39.3 m^3/s. The two major tributaries of the Thames River are the north branch (1750 km^2) and the south branch (1360 km^2). The North branch flows through Mitchell, St. Mary's and then to London, where it meets the south branch which flows through Woodstock, Ingersoll and east London. The amount of precipitation the basin receives annually is 1000mm, about 60% of which is lost by evaporation/evapotranspiration, stored in ponds and wetlands or recharged as groundwater (Prodanovic and Simonovic, 2007).

The Upper Thames River basin has a long history of hydrological impacts such as flooding and droughts. Flooding typically occurs in early March due to snowmelt and in July and August as a result of summer storm events. Drought most frequently occurs in June or September.

A total of 15 stations around the basin are used in the study. These are selected based on the availability of data as well as the length and completeness of the record. All of the 15 stations are used as an input to the KnnCAD model whereas for LARS-WG and SDSM only the London data is used because these are single-site models. Figure 1 also shows 15 stations located in the basin.

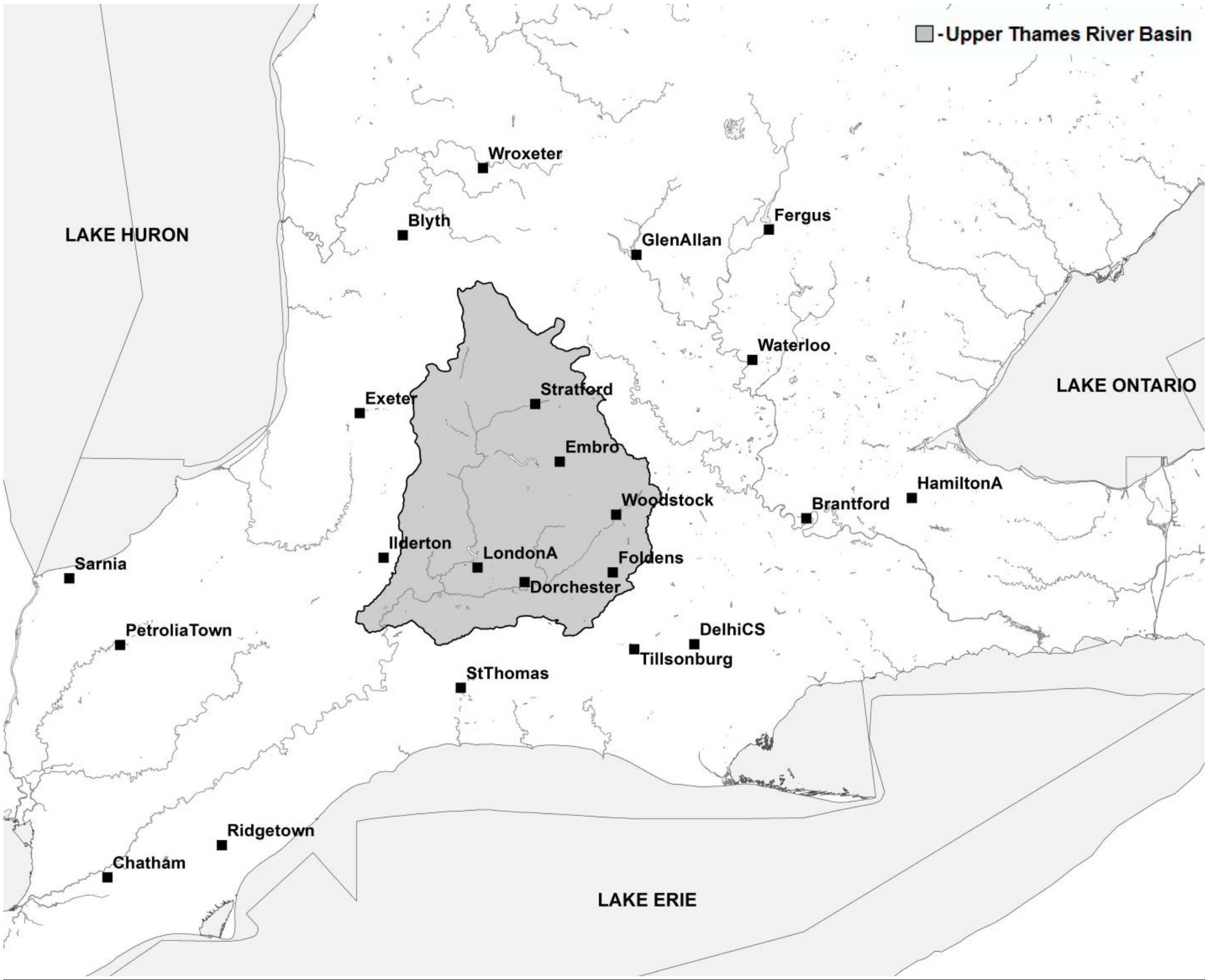


Figure 1: Schematic location map of Upper Thames River basin

<u>4. Data</u>

Three sources of data are used to provide input files for the weather generators. For each of the 15 stations listed previously precipitation and temperature data are collected from Environment Canada's Canadian Daily Climate Data (CDCD) archives. Several other variables are collected as well in order to better predict precipitation occurrence. The description of three sources used for the research is as follows:

- Daily weather data from Environment Canada's website: Three local scale variables precipitation, maximum temperature and minimum temperature for the period of 1979-

2005 are obtained from Environment Canada's website. (http://www.climate.weatheroffice.gc.ca/climateData/canada_e.html).The stations listed in Table 1 were chosen based on the completeness and length of the observed data.

- North American Regional Reanalysis (NARR): NARR is a climate data set for the North American domain which is a completed project of The National Center for Environmental prediction (NCEP). It was completed in 2004 and covers the 25- year period 1979-2003, and it will be continued later in near-real time as the Regional Climate Data Assimilation System, R-CDAS. The NARR is an extension of the global reanalyses and a long-term, dynamically consistent, high-resolution, high-frequency, atmospheric and land surface hydrology dataset which uses the Regional Data Assimilation System (RDAS) and very high resolution Eta model (0.3° × 0.3°, 32 km grid spacing, 45 layers spatially) . Most of the variables are collected 8 times daily; daily and monthly means are also available at 29 pressure levels. 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 and hence, 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 NARR data for over Canadian regions is that the daily gauge-based data it uses for assimilation are sparse (1 degree grid), which may be insufficient for the model to perform as expected (www.emc.ncep.noaa.gov/mmb/rreanl/narr.ppt). The application of NARR data for several stations in the UTRB has been researched by Solaiman and Simonovic (2010).

The results show that NARR can be used to generate precipitation more precisely and accurately. NARR data for this study has been made available through the Data Access Integration of the Canadian Climate Change Scenarios Network (CCCSN) of Environment Canada. For this study, the gridded data is interpolated for the stations of interest for Upper Thames River basin and used as inputs along with the observed data.

- The Canadian Climate Change Scenarios Network (CCCSN) provides access to several AOGCM models and emissions scenarios. The website allows the user to specify the range of geographical co-ordinates required, as well as the climatic variable and time period of interest. For the purpose of this study, the time slices collected were 1960-1990 (baseline), 2011-2040 (2050's). Seven variables were chosen: minimum temperature, maximum temperature, precipitation, specific humidity, northward wind component, southward wind component and mean sea level pressure. Six AOGCM models were collected, each with two to three emissions scenarios, as specified by the IPCC's Special Report on Emissions Scenarios (Nakicenovic et al, 2000). Full descriptions of the emissions scenarios can be found in Appendix A. Table 2 lists the AOGCM's along with the emissions scenarios available and their origin. Appendix B provides descriptions of each AOGCM.

4.1 AOGCM Data Description

For simulation six different AOGCM models with three scenarios are used for the three weather generators. Table 1 shows a list of the different AOGCM models along with the emission scenarios and atmospheric resolution.

Table 1: List of AOGCM Models and Emissions Scenarios used

AOGCM Models	Sponsors, Country	SRES Scenarios	Atmospheric Resolution	
			Latitude(deg)	Longitude(deg)
CGCM3T47, 2005	Canadian Center for Climate Modelling and Analysis	A1B,B1,A2	3.75	3.75
CGCM3T63, 2005			2.81	2.81
CSIROMK3.5, 2001	Commonwealth Scientific and Industrial Research Organization (CSIRO) Atmospheric Research Australia	A1B,B1,A2	1.875	1875
GISS-AOM, 2004	National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS), USA	A1B,B1	3	4
MIROC3.2 HIRES,2004	Centre for Climate Center Research (University of Tokyo), National Institute for Environmental Studies and Frontier Research Center for Global Change (JAMSTEC), Japan	A1B,B1	1.125	1.125
MIROC3.2 MEDRES,2004		A1B,B1,A2	2.8	2.8

The Canadian Climate Change Scenarios Network (CCCSN) website provides access to time series of meteorological variables as predicted by AOGCM models for different emission scenarios. The AOGCM used in his studies are the third generation Canadian Coupled Global Climate Model at T47 (CGCM3T47) and T63 (CGCM3T63) resolutions, Australia's Commonwealth Scientific and Industrial Research Organization generated MK3 Climate System Model (CSIROMK3.5), Goddard Institute for Space Studies provided Atmosphere Ocean Model (GISS-AOM), the Japanese Model for Interdisciplinary Research on Climate version 3.2 in high (MIROC3.2HIRES) and medium (MIROC3.2MEDRES) resolutions. IPCC developed the A1B, A2 and B1 scenarios for a special report on Emission Scenarios (SRES). Appendix A provides full descriptions of the emissions scenarios and Appendix B provides descriptions of each AOGCM.

5. Methodology

Pre-processing of the AOGCM data for each future time period is carried out in the following two steps described in Sections 5.1 and 5.2 below.

5.1 Spatial Interpolation of AOGCM outputs-

The Inverse distance weighing method (IDW) is used to interpolate the gridded AOGCM outputs to create a separate dataset for each station. Equations 5.1 and 5.2 are used to calculate the weighted average for each station using the four closest grid points.

$$w_1 = \frac{1/d_1^2}{1/d_1^2 + 1/d_2^2 + 1/d_3^2 + 1/d_4^2} \qquad (5.1)$$

$$p_i(t) = \sum_{j=1}^{4} \mathrm{w_j p_j}\,(\mathrm{t}) \qquad (5.2)$$

Where, d is the distance from the station to each point, w is the assigned weight for each gridded value (using Equation 5.1) and p is the weighted average of the variable for the station (using Equation 5.2). Subscripts, j represents the j^{th} grid point and the subscript i represents the number of station.

5.2 Change factor calculation from AOGCM output

Monthly averages are calculated for each variable from both the baseline (1960-1990) and the future time periods (2020's, 2050's and 2080's) using the AOGCM-interpolated datasets for each station. The monthly change factors are computed as the difference between the baseline and the future averages for maximum temperature, minimum temperature, northward wind speed, eastward wind speed and mean sea level pressure. The percent change between the baseline and the future averages are taken for precipitation and humidity (King et al., 2010).

The change factors for each AOGCM scenario are used to modify the observed daily data for each station gathered from Environment Canada. The monthly change factors for humidity and precipitation are multiplied by the observed daily values, and for all other variables the change factors are added. These AOGCM-modified datasets are used as predictor variable inputs for the Statistical Downscaling Model (SDSM) to produce simulations of 324 years for each future time period.

5.3 Application of SDSM

The Statistical Downscaling Model (SDSM) is a widely used downscaling tool that is a hybrid between a stochastic weather generator and a regression based downscaling model (Wilby et al 2002). SDSM develops an empirical relationship between a few selected large scale predictor variables (i.e. mean sea level pressure, wind velocity) and local scale predictands (i.e. precipitation and temperature) (Koukids and Berg, 2009). The model's ability to capture inter annual variability of this downscaling technique is improved when compared with other tools such as weather typing (Hashmi et al., 2011). This downscaling method is recommended by

Canadian Climate Impact Scenarios Project (CCIS) for climate change impact studies (Dibike et al., 2007).

The datasets for predictor variables are normalized for use as input parameters for SDSM. Selection of appropriate predictors and predictands in statistical downscaling is critical in ensuring the best possible calibration. Different combinations of variables are investigated through linear correlation analysis and scatter plots in order to select the best matched predictors for each individual predictand. As the results vary from month to month the most suitable variables are chosen through detailed investigation of the monthly outputs and by ensuring the combinations are physically sensible (Dibike et al., 2007). The predictands used in this analysis are precipitation, maximum temperature and minimum temperature

Once the selection of predictor variables is complete for each predictand, calibration of the model occurs. The twenty seven years of historical record are divided in two parts, where the first twelve years (1979-1990) are used for calibration and the remaining fifteen years (1991-2005) are used for validation with an independent dataset. Each predictand is used with various predictor combinations to calibrate the model in order to identify the best combination of predictors. Different values for bias correction and variance inflation are tested in order to choose the combination that provides the most robust output. Since the distribution of daily precipitation values is skewed, a conditional process is selected and a fourth root transformation applied (Khan et al., 2006). For precipitation, an annual model type is used as there are no distinct monthly or seasonal trends. For minimum and maximum temperatures, a monthly model type is selected.

Validation of the model is carried out through the use of boxplots of total precipitation, wet days and temperatures plotted against the historical observed values (1991-2005). Frequency plots of wet spell lengths are also used to examine precipitation characteristics. Through investigation of these plots, it was found that the standard value for the bias correction (1) and variance inflation (12) gives best validation. For precipitation, mean sea level pressure and medional wind velocity are chosen as the predictors which best simulate the historical climate. Medional velocity and specific humidity are selected as predictors for both minimum and maximum temperatures as these predictors provide a good calibration and are physically sensible.

5.4 Application of LARS-WG

Long Ashton Research Station Weather Generator (LARS-WG) is a stochastic weather generator that uses a spell-length approach to simulate daily weather (Semenov and Barrow, 1997). A stochastic weather generator is a statistical model that simulates synthetic weather series of any length which correspond to the observed climate statistics at a single site (CCSN 2011 and Dibike and Coulibaly, 2005). These synthetic climate series can be used to investigate the occurrence of extreme temperature and precipitation events which is beneficial for many hydrologic and agricultural applications. Stochastic weather generators can also be used to interpolate weather generator parameters in order to simulate a synthetic climate series for an unobserved location (Wilby and Dawson, 2007). LARS-WG uses semi-empirical distributions derived from the observed data to model the lengths of wet and dry spells, as well as daily precipitation and solar radiation amounts. Precipitation amounts are simulated conditional on spell length, similar to the conditional process used for precipitation simulation in SDSM. Downscaling of AOGCM data is achieved by applying monthly change factors to the historical data and using this as an input to LARS-WG.

Calibration of LARS-WG is done using the first 14 years of data as an input to produce 324 years of synthetic climate data. The outputs are compared to the remaining 13 years of record through the use of the same boxplots and frequency distributions as for SDSM calibration.

5.5 Application of KnnCAD

The KnnCAD model is a non-parametric, multisite K-Nearest Neighbour technique to produce synthetic climate data of any length with the same characteristics as the observed record (Sharif and Burn, 2007). Downscaling is achieved by using AOGCM-modified datasets for each station as inputs to produce synthetic weather data.

KnnCAD works by selecting the next day's weather from a subset days within a temporal window centred on that day, essentially reshuffling the data. The only parameter which must be set for calibration is the length of this temporal window. The model is calibrated using the first 14 years of data as an input and comparing the result to the last 15 years of historical data through the use of box plots and frequency distributions.

6. Results

In this study, AOGCM data is downscaled for London Ontario, using three different weather generators namely SDSM, LARS-WG and K-NN WG. A historical record of 27 years (1979-2005) of data is used along with AOGCM data from a total of 15 scenarios to create synthetic datasets of 324 years as well as a historical simulation. In the following section the results for the SDSM model are investigated, and a comparison of outputs from all three weather generators is presented.

6.1 SDSM Performance Evaluation

SDSM is used to produce 324 years of synthetic historical data for a comparison with the observed historical values in order to ensure that the outputs are statistically similar to the observed climate. Three predictand variables, precipitation, maximum and minimum temperature along with chosen combinations of predictor variables are used to produce 324 years of synthetic historical data. Box-plots are used for comparison of total monthly precipitation and monthly wet days. The upper and lower edge of the box indicates the 75th percentile and 25th percentile respectively. All the values within 1.5 times of the inter-quartile range are represented by a straight line extending from the top and bottom of the box. Values ranges beyond that are called outliers and are shown as dots.

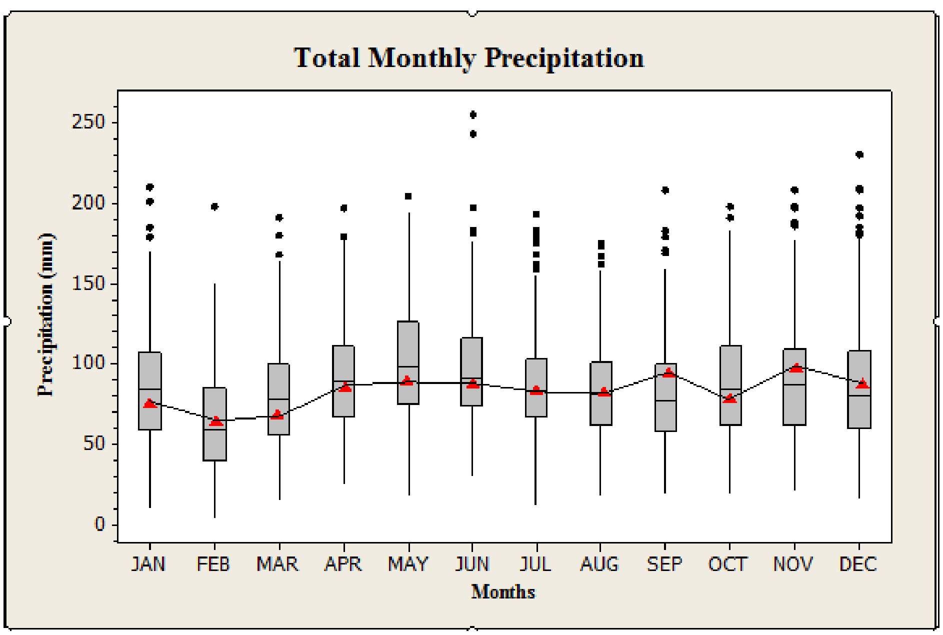


Figure 2: Total monthly precipitation box plot for historical simulated data, with the observed means shown as a line plot and outliers as black dots.

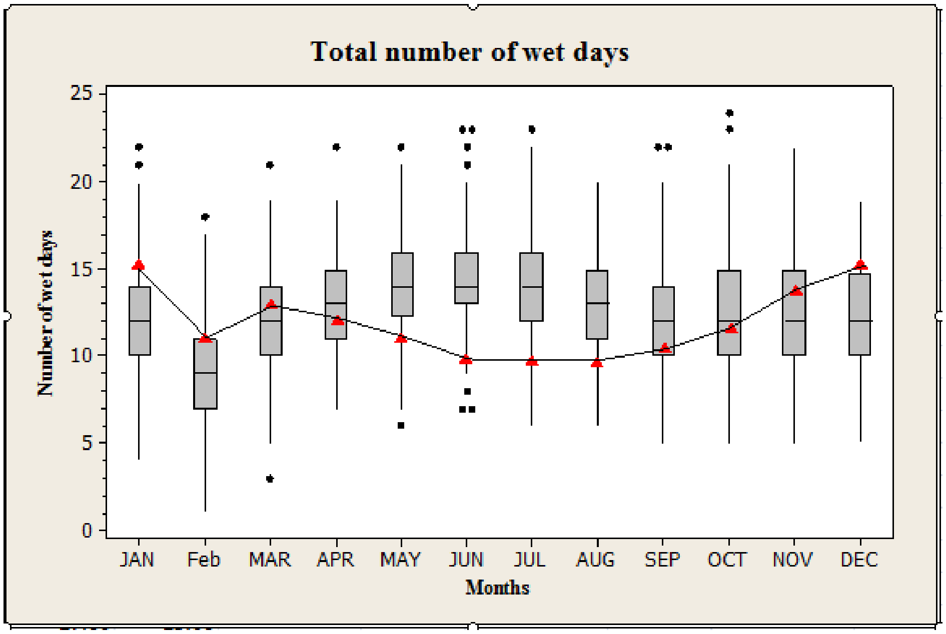


Figure 3: Total number of wet days box plot for historical simulated data, with the observed means shown as a line plot and outliers as black dots

Total monthly precipitation is shown in the box plots in Figure 2 with the observed average value plotted as a line. The median of the simulated value is very close to the observed value, except for some months. February, September, November and December are slightly overestimated while March, May and October are slightly under estimated. Overall simulation for precipitation is well downscaled by SDSM. However, for wet days the simulation is less satisfactory. Figure 3 shows the total number of wet days per month and the observed means are shown as a line. From the figure, it can be seen that SDSM could not adequately simulate monthly wet days for most months. Only the months March, April and October are close to the median.

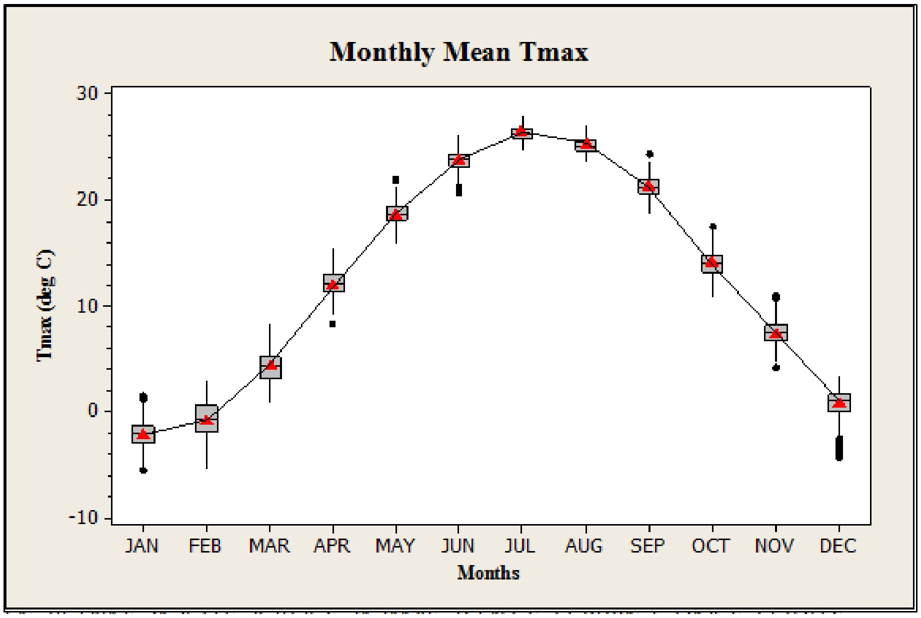


Figure 4: Monthly mean maximum temperature box plot for historical simulated data, with the observed means shown as a line plot in red and outliers as black dots

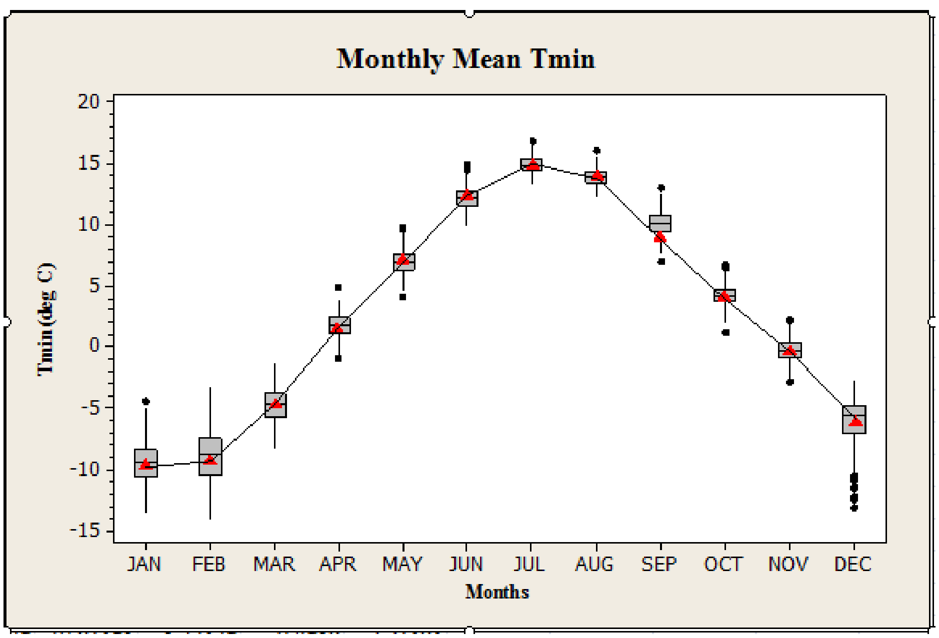


Figure 5: Monthly mean minimum temperature box plot for historical simulated data, with the observed means shown as a line plot in red and outliers as black dots

Figures 4 and 5 show boxplots of the simulated monthly averages for maximum and minimum temperature, respectively. The line plot shows the observed average value for the months in that period. For all months the maximum temperature values are well simulated as they are very close to the observed value. Minimum temperature simulated values are also satisfactory except for September, where the historical observed value is overestimated by SDSM and falls below the interquartile range. This indicates SDSM is able to reproduce the historical values satisfactorily.

6.2 Generation of Future Climate Variables

6.2.1 Total Monthly Precipitation

Figures 6 through 11 show box plots of the simulated total monthly precipitation for the 2050's.The outliers from the box plots are shown as black dots and are indicative of the stochastic component in SDSM. Figure 9 shows the total monthly precipitation for the CGCM3T47 model scenarios A1B, A2 and B1. All three scenarios predict an increase in precipitation from January to May and rest of the year there is a decrease. The total monthly precipitation for CGCM3T63 is shown in Figure 10. Scenarios A1B, A2 and B1 follow the same trend as CGCM3T47 scenarios except that the increase in precipitation is observed from January till April. Unlike the CGCM models, CSIROMK3.5 for scenario B1 is predicting a fluctuation in precipitation throughout the year. However, the A2 scenario of the same model shows similar trends to the CGCM3T47 and CGCM3T63 models where an increase in seen from January to July and decreases are predicted in the remaining months. Again variability in the predictions for total monthly precipitation is found for both the A1 and B1 scenarios of GISSAOM model, including increases in precipitation from March to August for Scenario A1 and March to July for scenario B1. MICRO3.2HIRES models shows a different trend than others, where for A1 scenario the amount of precipitation from May through August including January is increasing, and precipitation amounts for the rest of the year are decreased from the historical values. Whereas for the B1 scenario, lowered values of precipitation are predicted for the months of April and September through November and increases are predicted for the remaining months. This model shows higher variability in precipitation amounts than others. The last model MIROC3.2MEDRES has a different trend for each scenario. For A1 there is again a variation of increasing and decreasing precipitation totals. The A2 scenario follows the trend as for the CGCM3T47, CGCM3T63 and GISSAOM models, where a higher than observed precipitation totals are seen from January to August and lower totals from September to December. Finally, for the B1 scenario the MIROC3.2MEDRES model predicts decreases in the month of February and increases in month of September, November and December. The rest of the months predict values similar to the historical observed series.

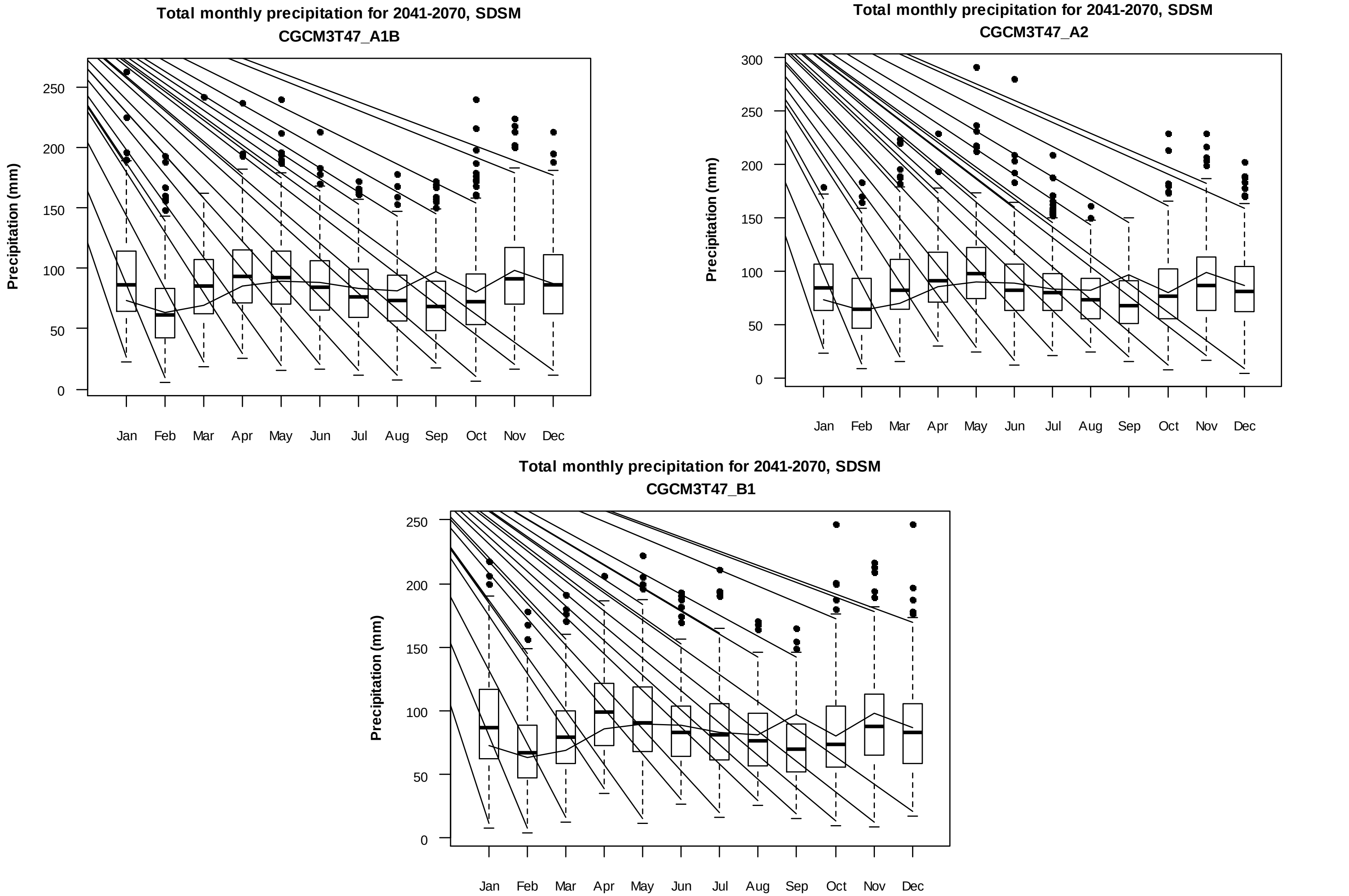


Figure 6: Total monthly precipitation box plots of CGCM3T47 A1B, A2 and B1 for the years 2041-2070 with observed historical averages as a line.

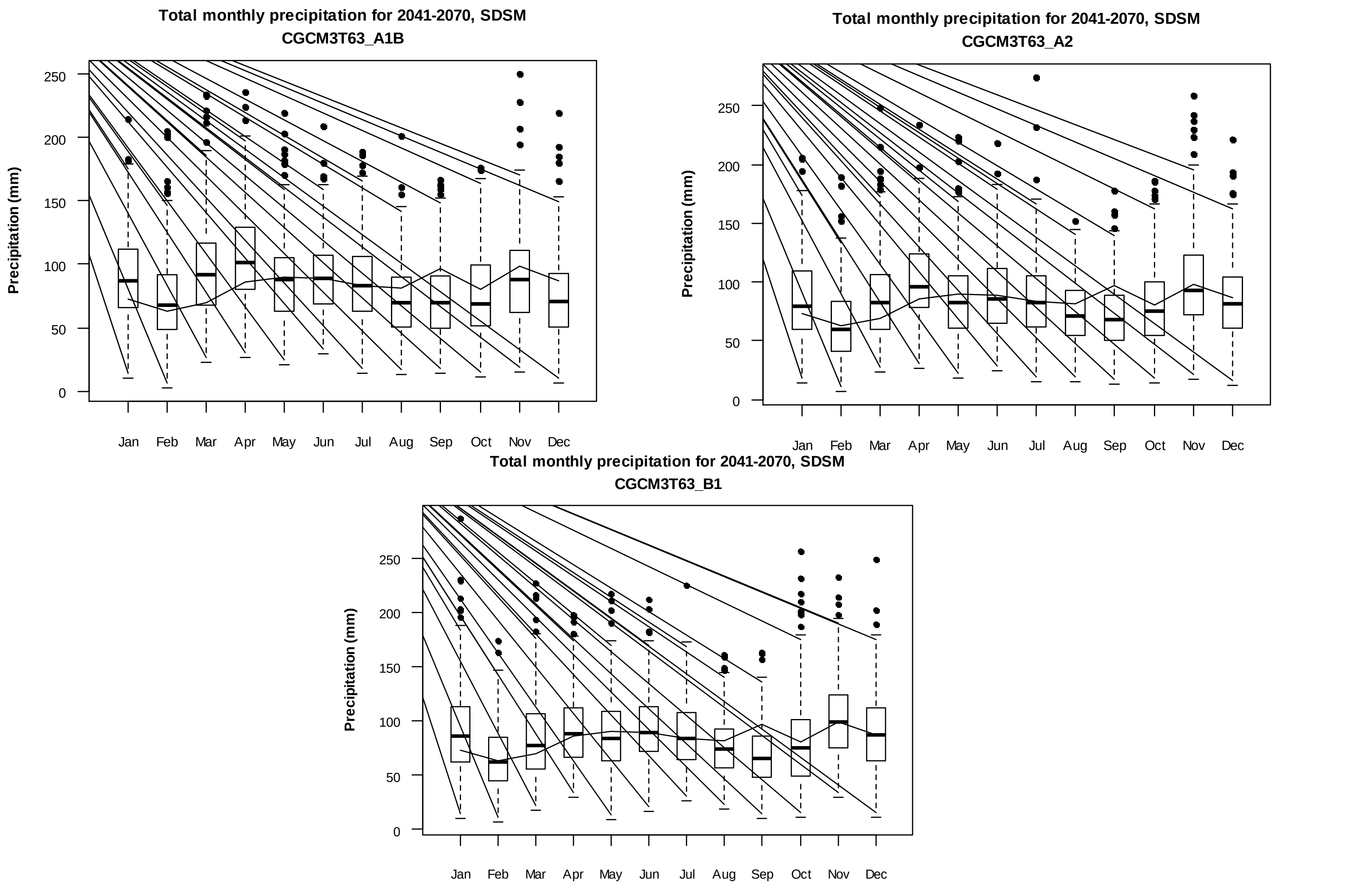
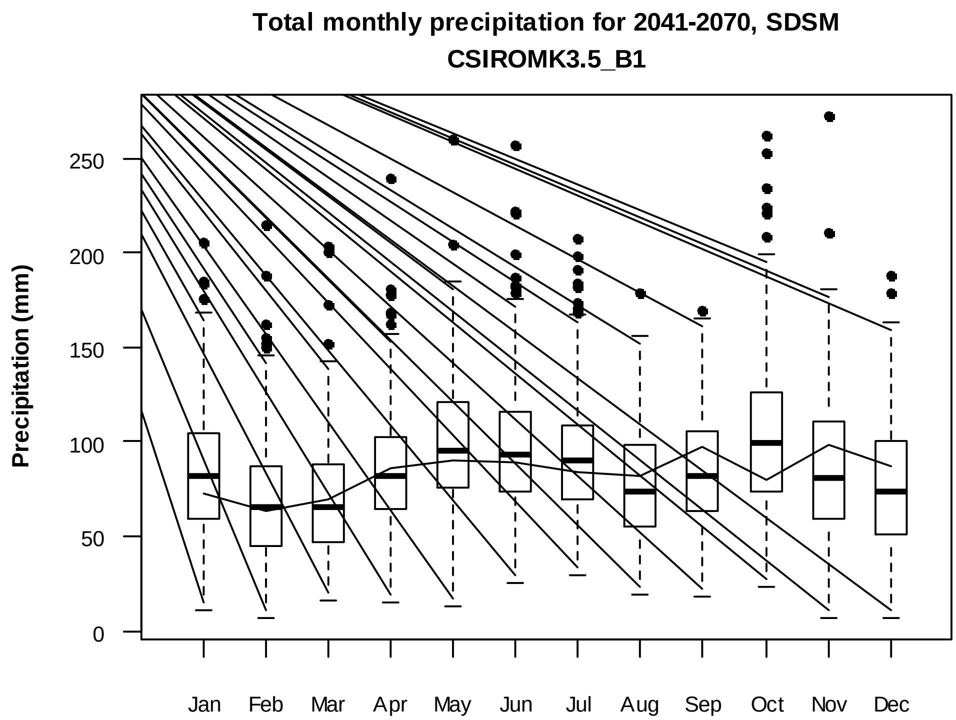


Figure 7: Total monthly precipitation box plots of CGCM3T63 A1B, A2 and B1 for the years 2041-2070 with observed historical averages as a line



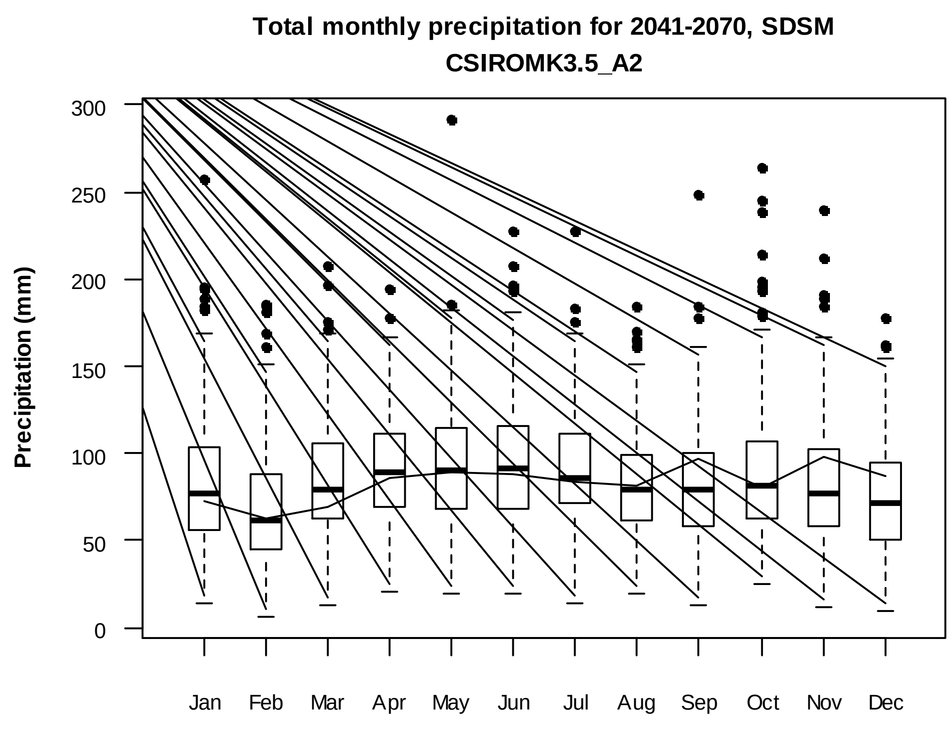
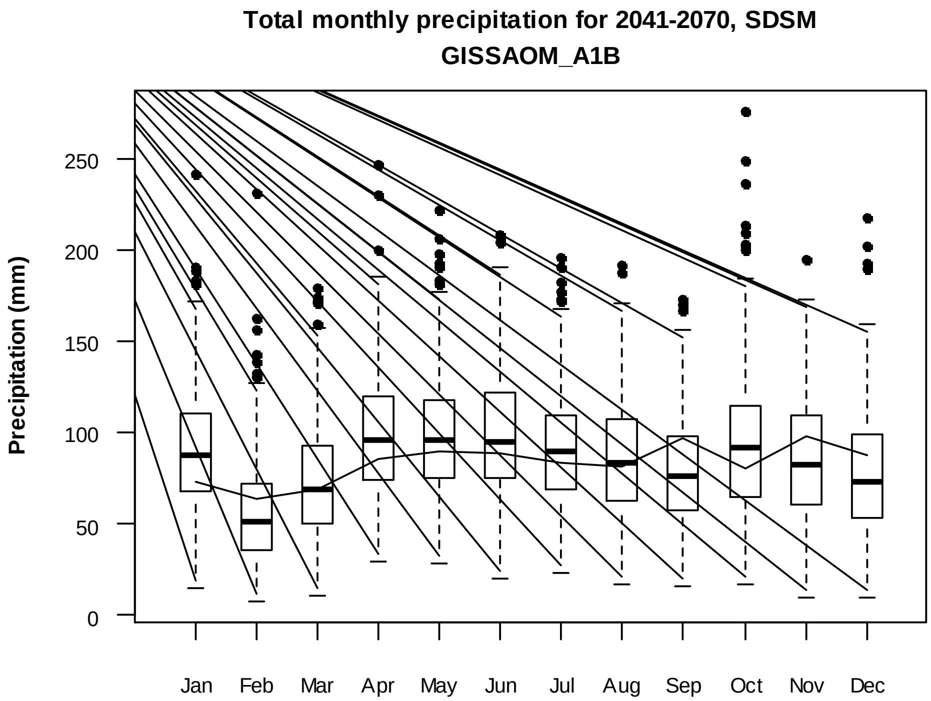


Figure 8: Total monthly precipitation box plots of CSIROMK_3.5 A2 and B1 for the years 2041-2070 with observed historical averages as a line.



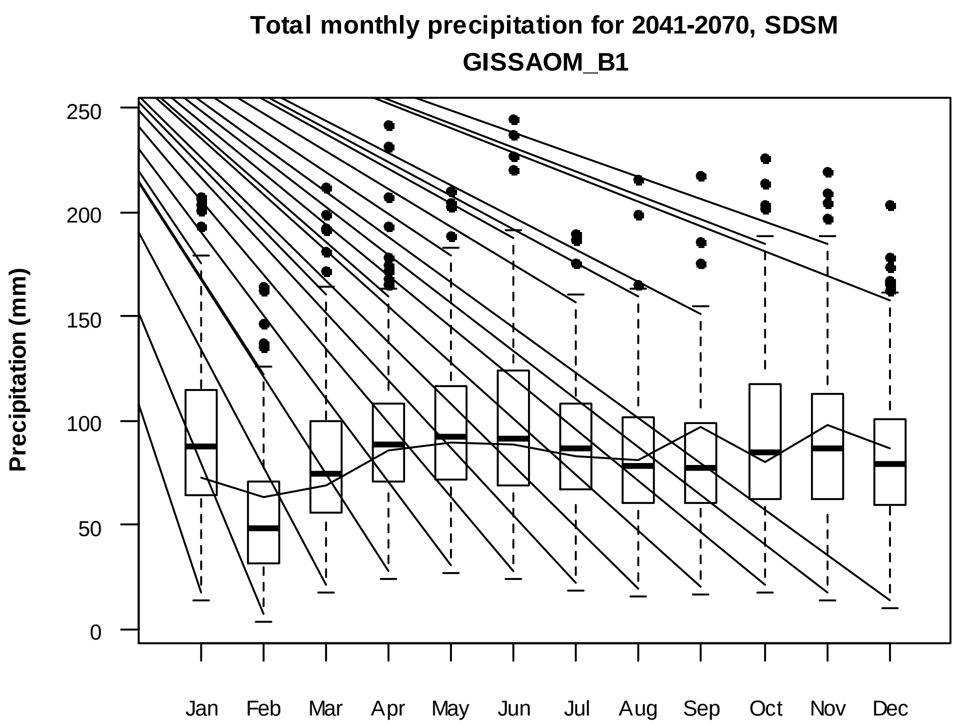


Figure 9: Total monthly precipitation box plots of GISSAOM A1B and B1 for the years 2041-2070 with observed historical averages as a line.

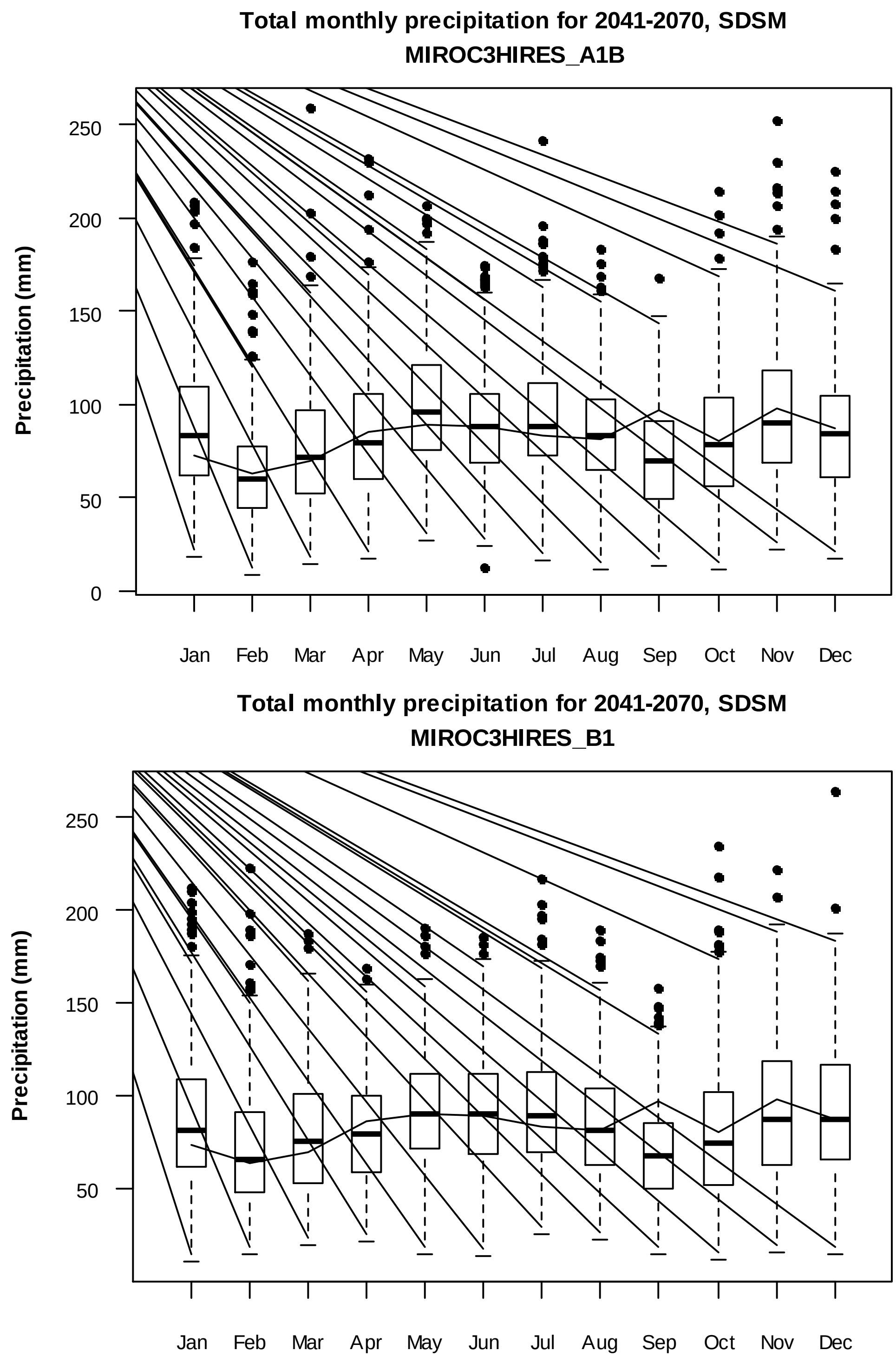


Figure 10: Total monthly precipitation box plots of MIROC3HIRES A1B and B1 for the years 2041-2070 with observed historical averages as a line.

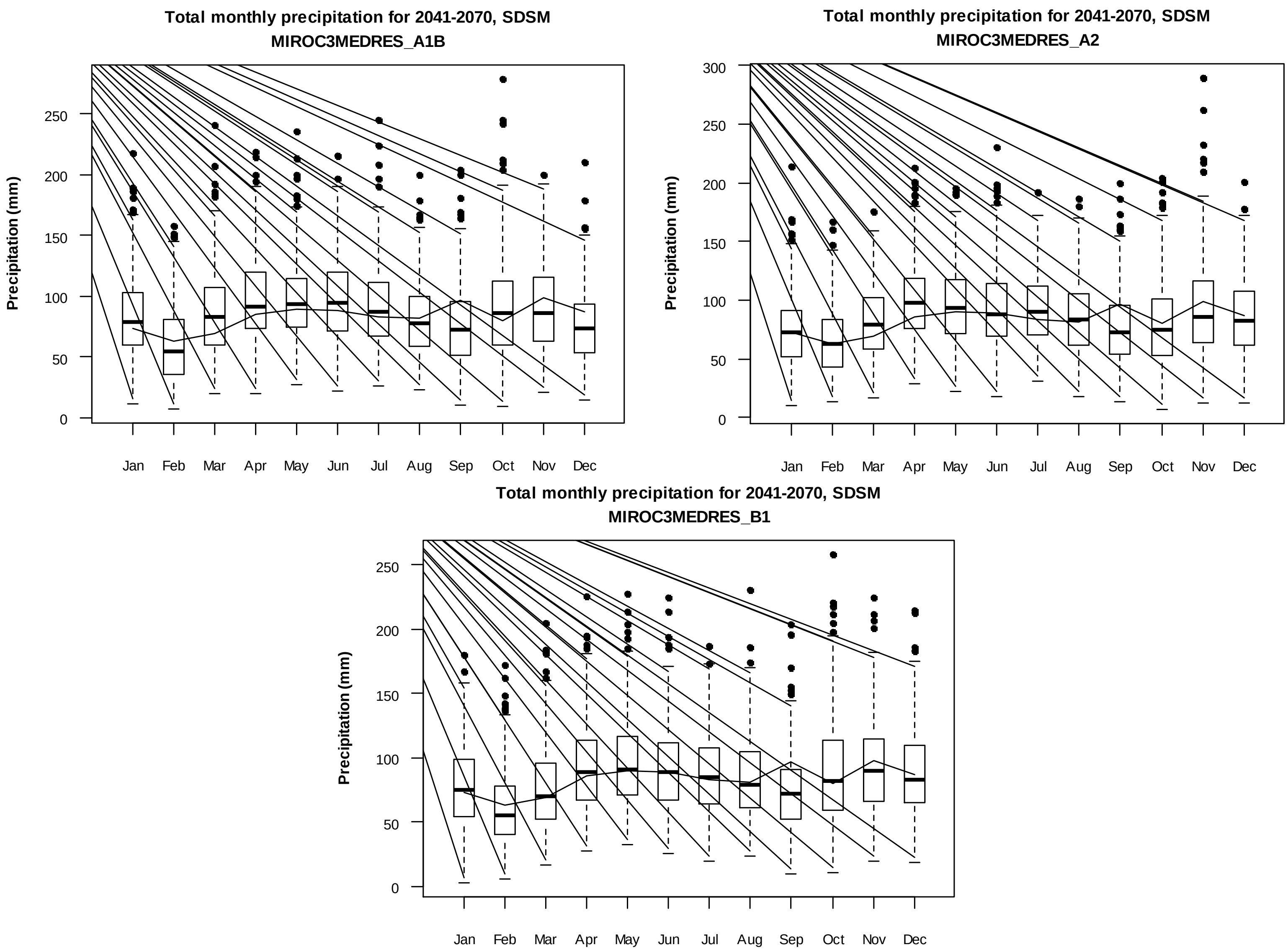


Figure 11: Total monthly precipitation box plots of MIROC3MEDRES A1B, A2 and B1 for the years 2041-2070 with observed historical averages as a line.

6.2.2 Temperature

Figure 12 illustrates the average monthly maximum temperatures for the 2050's compared with the historical averages, plotted in black. Figures 12(a) and 12(b) and 12(c) represent the A1B, A2 and B1 scenarios, respectively. All simulations indicate a rise in average temperature of approximately 3°C from the historical observed value for the entire year. Each model has a different prediction for monthly temperature increase. A1B and B1 scenarios show the highest variability in temperature change between models. For both A1B and A2 scenarios MIROC3.2MEDRES is indicating an increase of around 5°C greater than the GISSAOM A1B scenario and the CSRIOMK3.5 A2 scenario for March. On the other hand, for B1 scenarios in Figure 12(c) the highest difference of maximum temperatures is observed in winter with an increase of 1-3 degrees and 1-4 degrees in the summer. Among all three scenarios the smallest variability between models is observed from May to July of the A2 scenarios. These predicted rises in temperature at the end of winter period when snowmelt begins can result in increased runoff for the basin.

The minimum temperatures for 2050's are shown in Figure 13(a), 13(b) and 13(c) where all models for the AIB and A2 scenarios predict increases of 1-5°C while B1 scenarios show the smallest increase of 1-3° C. The highest increase was predicted for February by CGCM3T63 for A1B scenario and the highest variability between predictions exists with GISSAOM and MIROC3.2MEDRES model (3-5°C) during fall and in the beginning of spring. For the A2 scenario, the highest temperature increase is 5°C predicted by the CGCM3T63 model in February. B1 models show similar outputs except for MIROC3.2MEDRES models.

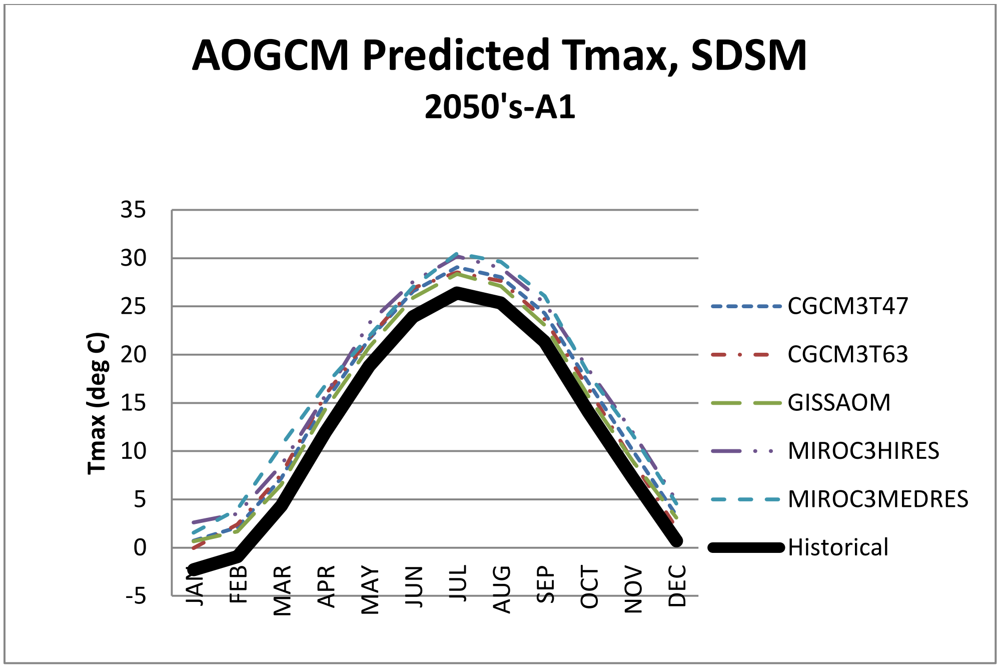


Figure 12(a): AOGCM predicted average monthly maximum temperature compared to historical averages for A1 scenario

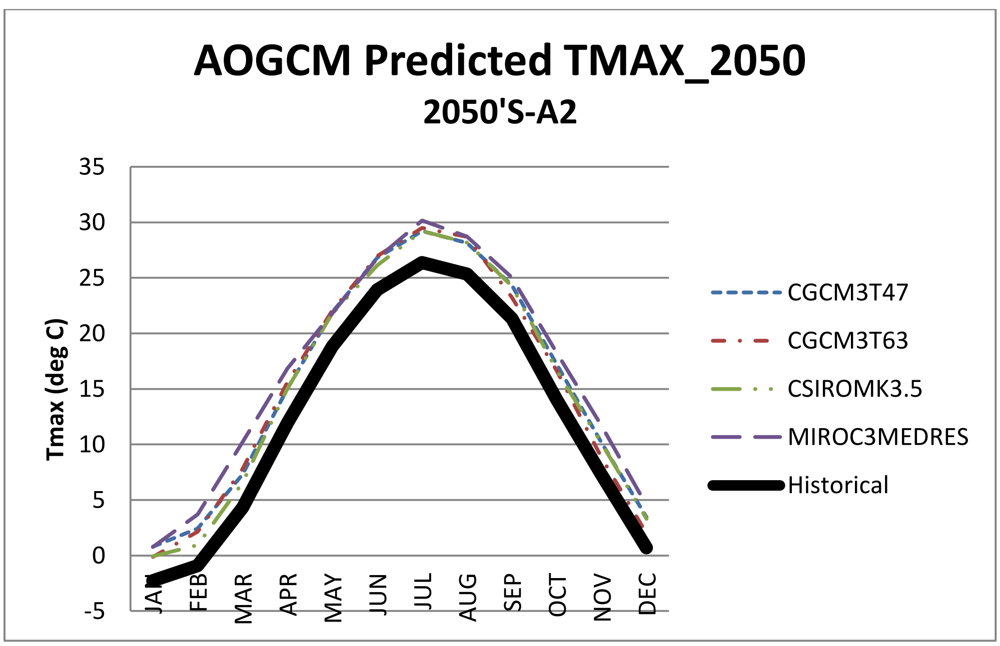


Figure 12(b): AOGCM predicted average monthly maximum temperature compared to historical averages for A2 scenario

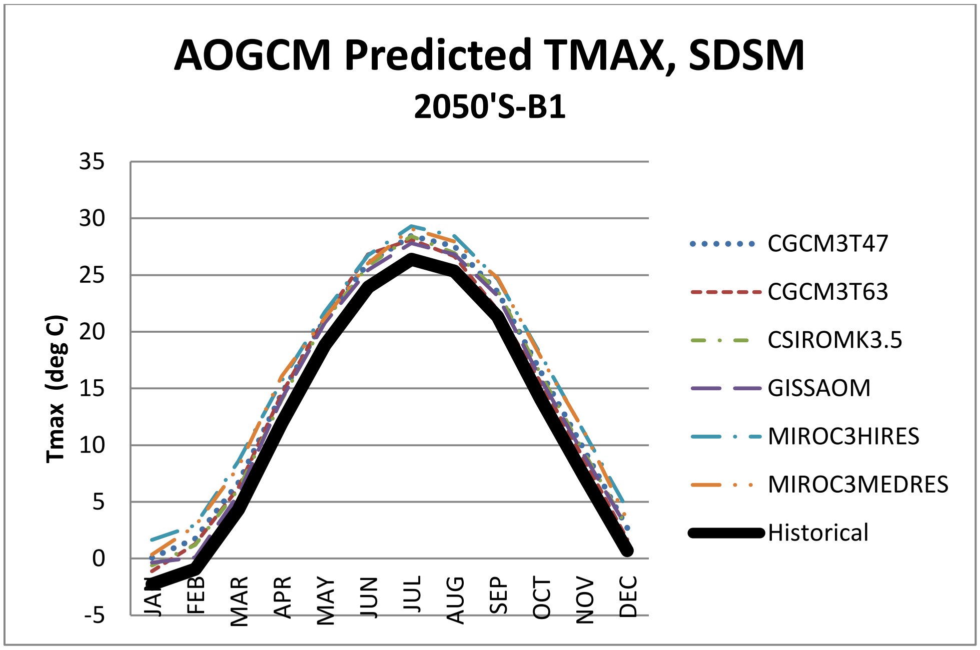


Figure 12(c): AOGCM predicted average monthly maximum temperature compared to historical averages for B1 scenario

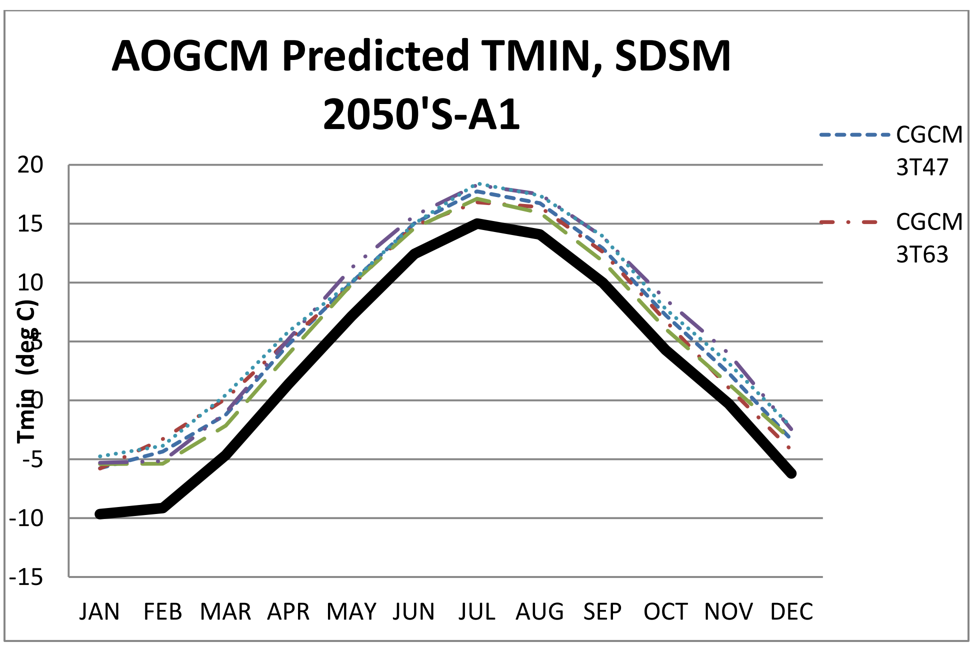


Figure 13(a): AOGCM predicted average monthly minimum temperature compared to historical averages for A1 scenario

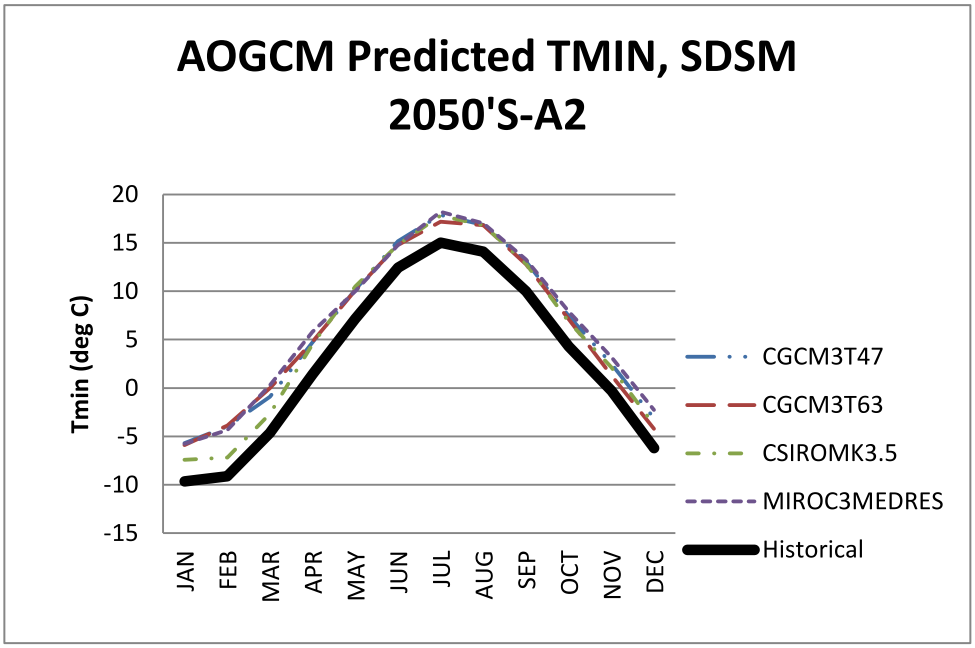


Figure 13(b): AOGCM predicted average monthly minimum temperature compared to historical averages for A2 scenario

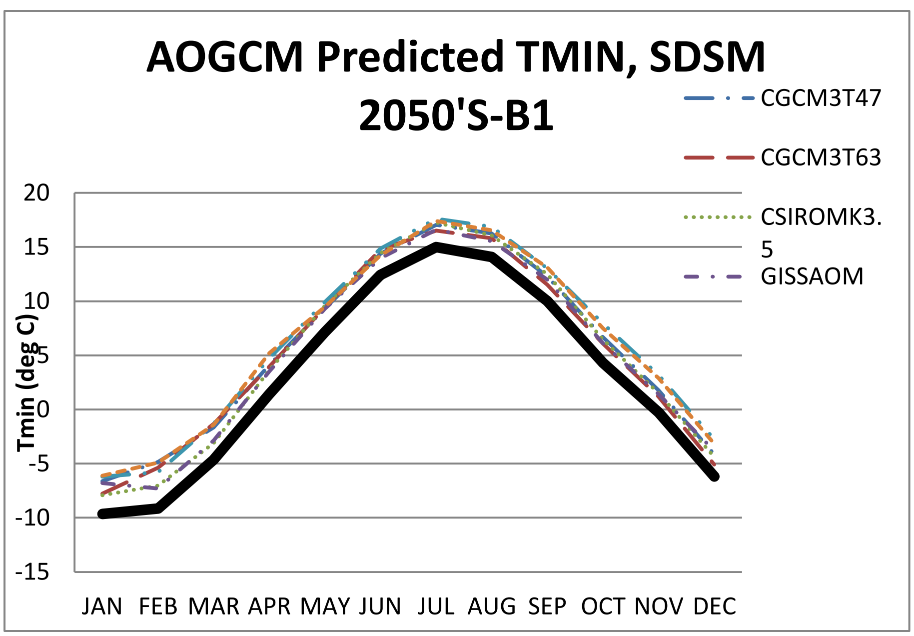


Figure 13(c): AOGCM predicted average monthly minimum temperature compared to historical averages for B1 scenario

7. Comparison Between LARS-WG, SDSM, KnnCAD

The comparison among SDSM, LARS-WG, and KnnCAD for percent change for total seasonal precipitation is shown in Table 2. Also the absolute minimum and maximum temperatures, total monthly precipitation, and the mean and standard deviation of daily precipitation are plotted in Figure 14. Here the weather generators are assessed based on their ability to reproduce historical climate statistics. Among these variables precipitation is given the highest priority as it is a very crucial part of hydrologic modeling.

Table 2 shows the AOGCM-predicted percent change in total seasonal precipitation as predicted by the three models as well as the change in mean daily precipitation and the seasonal average for each scenario. According to emission scenario A1B for winter, the models predict an increase ranging on average from 11-14%. For SDSM and LARS-WG, MIROC3.2HIRES predicts the highest percent increase for the A1B winter scenario. CGCM3T47 predicts the highest increase in winter precipitation of 18.7% for KnnCAD and the lowest increase for SDSM (10.5%). For spring, results were variable with some models predicting increases and other models predicting a decrease in total precipitation. KnnCAD simulations all show an increase in spring precipitation while LARS-WG predicts a decrease for the MIROC3.2HIRES scenario and SDSM predicts a decrease from three of the models. Values predicted ranged from -8 to 20.5% change in spring precipitation. In the summer for all three weather generators both increasing and decreasing changes in total precipitation are observed.

7.1 Comparative Performance Evaluation of LARS-WG, SDSM, KnnCAD

Figure 14 includes three graphs which present SDSM, LARS-WG, and KnnCAD temperature and precipitation results. For absolute maximum and minimum monthly temperatures the historical values are shown as solid lines and simulated results are shown as dashed lines. KnnCAD-simulated absolute maximum and minimum temperatures are very close to the observed values with very little difference. For LARS-WG the historical and simulated values coincide for the months of January, March, April, May, July, and September. As a result it can be said that LARS-WG also reproduces the temperatures successfully with some minor differences in historical and simulated values from October to December. Minimum temperatures are simulated less accurately by LARS-WG but the seasonal trend is well captured and there is still a fairly close agreement. SDSM consistently overestimates maximum temperatures except for the month of August. The model also simulates cooler minimum temperatures for all months, indicating that SDSM has some difficulty in the simulation of extreme temperature values.

Box plots of simulated total monthly precipitation values are plotted for each weather generator in Figure 14. The straight lines represent historical median values. SDSM overestimates the historical precipitation medians for January to May and August and underestimates them for September, November and December. For LARS-WG, precipitation totals are close to the historical values except for slight overestimations in August to October. For KnnCAD the precipitation totals in March, April and September are slightly overestimated while June and November values are underestimated. To conclude in case of precipitation all three models shows satisfactory performance in the simulation of total monthly precipitation values.

The final row in Figure 14 shows the standard deviation (top) and mean (bottom) of simulated and historical daily precipitation values, by month. The solid line shows the historical trend while the dashed line represents simulated data. Results from LARS-WG and KnnCAD are closer to the historical values and better capture the seasonal trends than SDSM outputs. SDSM output is poor for such precipitation characteristics, particularly for the standard deviation of daily precipitation which is significantly underestimated between the months of June to September.

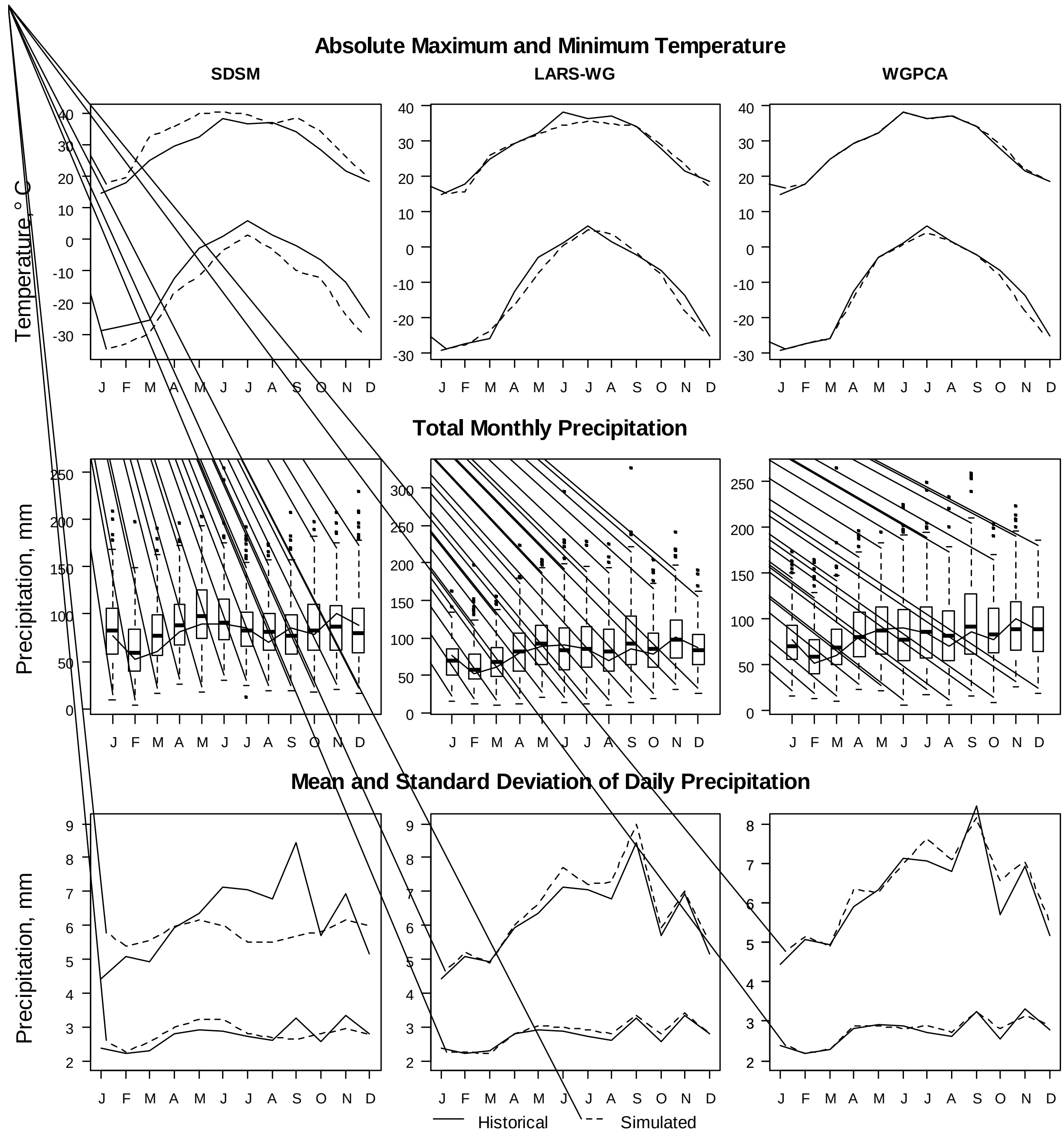


Figure 14: Comparative performance evaluation results for LARS-WG, SDSM, and KnnCAD. The top row shows the absolute maximum (top) and minimum (bottom) simulated and observed emperatures. The second row shows box plots of total monthly precipitation values with the historical median plotted as a line. The third row shows the standard deviation (top) and mean (bottom) of daily precipitation values.

7.2 Comparative Generation of Future Daily PPT by SDSM, LARS-WG, KnnCAD

The largest increase in summer precipitation is predicted by SDSM for GISSAOM with a value of 14.2% and the largest decrease from KnnCAD for MIROC3.2MEDRES (-17.8%). In fall for SDSM, all models show a decreasing trend with CGCM3T63 predicting the largest decrease of -19.3%. However, for all models LARS-WG and KnnCAD show increasing precipitation with only one decrease for KnnCAD from MIROC3.2MEDRES. For CGCM3T63 both LARS-WG and KnnCAD predict large increases in fall precipitation, with change values of 41.5% and 38.8% respectively. For changes in mean daily precipitation values, all the weather generators show increasing percent changes except for MIROC3.2MEDRES in KnnCAD. This indicates more extreme rainfall events are predicted to occur. The models predicted increases on average of 2-9% for the A1B scenario with some models predicting up to an 18% increase.

The A2 scenario has on average an increasing percent change trend in total precipitation for all seasons but LARS-WG and KnnCAD show decreases in summer and for SDSM in fall. The decreasing percent change is simulated mostly by MIROC3.2MEDRES for all models. The largest increase in winter precipitation is predicted by KnnCAD, with values ranging from 5.6-24.8% from the different AOGCMs. LARS-WG shows a decrease for MIROC3.2MEDRES with a value of -0.9%. In spring all three weather generators produces an increase in percent change ranging from 8.4 to 15.2% but SDSM shows comparatively lower increases (1-4%) than the other models. This indicates that the different techniques to achieve downscaling perhaps have an effect on the resulting output from an AOGCM. In summer there is a decreasing trend observed for most of the KnnCAD simulations with only one increasing scenario predicted by CSIROMK3.5. In contrast, the SDSM outputs all predict an increase in summer precipitation. LARS-WG has both increasing and decreasing values. During fall the SDSM simulations predict decreases in precipitation while the other downscaling tools show increasing trends except in MIROC3.2MEDRES. In case of the mean percent change all of models predict an increase of 1.9-16.3 %.

For the B1 scenarios for winter, LARS-WG predicts increases in most scenarios with two decreases. SDSM shows the highest percent change ranging from 7 to 26.5%. The highest percent change predicted for this season is 26.5% by SDSM for CGCM3T63 and lowest value of percent change of 2.2% is predicted by LARS-WG is 3.2% for MIROC3.2MEDRES. In spring a variation of increases and decreases in seasonal precipitation are predicted. The highest percent change is an increasing trend of 23% predicted by LARS-WG for the MIROC3.2MEDRES model and the highest decrease is predicted by SDSM of -7.4% for GISSAOM model. The highest increase in summer precipitation is 27.4% and the lowest value is 1.2% according to LARS-WG. In fall all the SDSM models predict a decrease in precipitation whereas LARS-WG and KnnCAD predict increasing precipitation amounts except by MIROC3.2MEDRES. The change in mean is mostly increasing for KnnCAD with highest of 16.9% and lowest percent change of 3%. The range of percent change for precipitation is narrow for SDSM with a highest percent change of 3.4% for GISSAOM model.

Table 2: The AOGCM-predicted percent change in total seasonal precipitation

Emission Scenario	AOGCM	Winter			Spring			Summer			Fall			Change in Mean		
		SDSM	LARS-WG	Knn CAD	SDSM	LARS-WG	Knn CAD	SDSM	LARS-WG	KnnCAD	SDSM	LARS-WG	KnnCAD	SDSM	LARS-WG	KnnCAD
A1B	CGCM3T47	10.5	16.5	18.7	13.1	20.5	17.6	-3.6	0.6	-3.9	-11.0	6.3	7.2	1.6	10.7	9.5
	CGCM3T63	13.7	13.0	13.2	11.5	15.8	10.1	4.7	-1.1	-5.1	-19.3	41.5	38.8	1.8	18.0	14.8
	GISSAOM	14.3	5.5	7.6	-7.0	13.1	4.7	14.2	13.1	7.0	-6.2	11.5	10.4	3.4	11.1	7.5
	MIROC3.2HIRES	20.8	18.4	16.2	-8.1	-6.0	1.0	11.1	-3.0	-16.0	-12.5	9.7	7.3	2.0	4.6	1.8
	MIROC3.2MEDRES	11.2	0.4	2.9	-0.1	12.9	12.6	12.7	-14.5	-17.8	-10.2	2.7	-4.7	2.9	0.4	-2.1
Average A1B		14.1	10.8	11.7	1.9	11.3	9.2	7.8	-1.0	-7.2	-11.8	14.3	11.8	2.3	9.0	6.3
A2	CGCM3T47	18.1	21.7	24.8	4.0	15.0	22.1	6.2	1.2	-9.9	-17.2	10.6	6.6	1.9	11.9	10.3
	CGCM3T63	21.8	4.9	5.6	3.6	11.0	8.4	3.5	-1.2	-3.8	-17.8	46.2	39.4	1.7	16.3	13.2
	CSIROMK3.5	7.4	9.8	13.5	0.1	15.2	14.1	10.2	20.9	10.1	-8.4	7.6	2.3	1.9	13.4	9.7
	MIROC3.2MEDRES	13.6	-0.9	2.5	1.4	7.5	13.5	11.2	-8.2	-15.5	-12.0	-4.1	-4.5	2.9	-1.5	-1.3
Average A2		15.0	9.2	11.6	2.2	12.0	13.5	7.8	2.3	-5.2	-13.4	14.9	11.1	2.2	9.8	7.6
B1	CGCM3T47	20.4	11.9	16.1	2.1	18.4	14.8	4.2	-2.4	-5.9	-15.4	6.3	6.0	1.9	8.4	7.4
	CGCM3T63	26.5	12.9	22.7	-1.3	-3.4	-4.5	5.3	11.9	5.8	-17.8	54.6	41.6	2.0	20.2	16.9
	CSIROMK3.5	7.0	4.1	7.3	-7.1	16.1	13.7	13.0	27.4	22.5	-4.2	9.2	4.4	3.2	14.4	11.9
	GISSAOM	18.4	-1.2	8.4	-7.4	-0.5	-0.9	12.8	12.8	11.0	-7.9	6.2	6.6	3.4	4.7	6.3
	MIROC3.2HIRES	21.0	5.2	5.3	-5.1	-0.6	2.7	10.0	-5.9	-15.1	-14.2	-2.3	-3.6	2.1	-1.0	-3.0
	MIROC3.2MEDRES	16.1	-2.2	3.2	-5.8	23.0	20.7	8.9	1.2	-3.7	-9.6	1.1	-3.4	1.8	5.8	3.9
Average B1		17.8	3.8	9.4	-5.3	6.9	6.3	10.0	9.5	4.1	-10.8	13.8	9.1	2.5	8.8	7.2

8. Conclusion

An investigation of the potential impacts of climatic change on the Upper Thames River basin using six AOGCM's, each with up to three emission scenarios is performed. Downscaling of the AOGCM data is achieved using the SDSM model and results are compared with two other weather generators, namely LARS-WG and KnnCAD. Each downscaling approach has various strengths and weaknesses. The weather generators are used to produce 324 years of synthetic data for the historical climate as well as the AOGCM models for London.

The ability of the weather generators to reproduce historical precipitation and temperature characteristics is investigated. Considering the high spatial and temporal variability of precipitation, the performance of the weather generators is deemed satisfactory through the investigation of total monthly precipitation and temperature box plots as well as the mean and standard deviations of daily precipitation amounts. In the reproduction of historical data, weather generator performance by all three models is satisfactory however the KnnCAD performance is preferable to the SDSM and LARS-WG results in terms of temperature extremes.

The SDSM's future climatic output includes box plot for historical simulated data, with the observed means for the total monthly precipitation, total monthly number of wet days, and minimum and maximum temperatures. Also box plot outputs of total monthly precipitation and average monthly minimum temperature compared to historical averages for 2050's for six AOGCM model and three SRES scenario has been analyzed. The historical simulated data for total monthly precipitation shows good match with the observed mean values for summer and spring season. However, the winter and fall seasons predicted precipitation is a bit off from the range. Also, there is no consistency with observed and simulated wet days. Although, historical simulated data for maximum and minimum temperatures are almost identical with the observed means. A mixed result of increase and decrease with some fluctuations has been observed in all AOGCMs for precipitation between baseline and 2050 time periods. Overall, a decrease of precipitation is observed in summer and fall for 2050 period compared to the baseline. A result for total number of wet days for 2050 period is ignored as the simulated historical value shows no correlation with the observed mean value. The predicted maximum and minimum temperature for 2050 shows an increase for all AOGCM models and all scenarios compared with the historical averages. Among all models GISSAOM and MIROC3.2MEDRES shows the highest temperature differences.

The AOGCM-predicted percent changes in mean and total seasonal precipitation amounts show highly variable results from the different downscaling approaches. The AOGCM data is found to be highly variable as one model could predict a decrease in precipitation, while others predict an increase. The variability between weather generators is also high as for the same AOGCM one tool could predict an increase in precipitation while another tool predicts a decrease. However, some distinct trends are noticed during analysis. Most simulations showed an increase in mean daily precipitation amounts, indicating that more extreme rainfall events can be expected in the future. Most AOGCMs agree that average fall and early winter precipitation will increase. The climate models also generally agree that summer precipitation totals will decrease. Spring results are less conclusive, with different combinations of AOGCM's and downscaling tools predicting very different percent change values. Because of the high variability between AOGCM's and emission scenarios, it is crucial to consider a variety of these for comprehensive climate change impact assessments.

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APPENDIX A: AOGCM DATA DESCRIPTION

Coupled Global Climate Model: The third generation Coupled Global Climate Model (CGCM3) is an atmospheric-ocean model used in the IPCC's Fourth Assessment Report (2007) to produce extensive model simulations. It was developed by the Canadian Centre for Climate Modeling and Analysis (CCCma), which is a division of the Climate Research Branch of Environment Canada. The model runs at two resolutions, T47 and T63. The lower resolution model, CGCM3T47, has a grid size of 3.75° latitude by 3.75° longitude and 31 vertical layers. The CGCCM3T63 model provides a slightly higher resolution of 2.8° x 2.8° also with 31 vertical layers, (CCCma, 2010). Both versions are driven by A1B, A2, and B1 emissions scenarios which each provide potential, yet divergent, atmospheric greenhouse gas concentrations for the future.

Commonwealth Scientific and Industrial Research Organizations Mk3.5 Climate Systems Model: Commonwealth Scientific and Industrial Research Organization (CSIRO) is located in Australia and is one of the largest and diverse scientific agencies in the world. The Marine and Atmospheric research division of CSIRO developed a coupled global climate model with atmosphere, land surface, ocean, polar ice components known as CSIRO Mk3.5. Its predecessor (CSIRO Mk3.0) appeared in the IPCC's Fourth Assessment Report and improvements were made to create CSIRO Mk3.5. Such improvements include reduced drift in the global mean temperature. CSIRO Mk 3.5 has a spatial resolution of 1.875° x 1.875° with 18 vertical levels, (Collier, Dix, and Hirst, 2010). Emissions scenarios A2 and B1 are used as input as scenario A1B is not available for this AOGCM on the CCCSN database.

Goddard Institute for Space Studies Atmospheric Ocean Model: NASA's Goddard Institute for Space Studies (GISS) explores the global effects of natural and human induced change to our environment on various time scales. In 2004 they released their own global climate model, GISS-AOM. It has a spatial resolution of 4° longitude and 3° latitude, 12 atmospheric layers, and up to 16 oceanic layers, (Atmosphere-Ocean Model, 2007). Emissions scenarios A1B and B1 are used to drive this model.

Model for Interdisciplinary Research on Climate 3.2: The Model for Interdisciplinary Research on Climate 3.2 (MIROC3.2) was developed at the Centre for Climate System Research at the University of Tokyo, National Institute for Environmental Studies, and the Frontier Research Centre. This model runs at two resolutions MIROC3.2HIRES and MIROC3.2MEDRES. MIROC3.2HIRES (high resolution) has a spatial resolution of 1.125° x 1.125° and is driven by emissions scenarios A1B and B1. MIROC3.2MEDRES (medium resolution) differs from MIROC3.2HIRES only in resolution as it has a courser grid size of 2.8° x 2.8°, (PCMDI, 2005). All three emissions scenarios (A1B, A2, B1) are available and used as input to the MIROC3.2MEDRES version.

APPENDIX B: SRES EMISSIONS SCENARIOS

The IPCCs Special Report on Emissions Scenarios (SRES) contains scenarios with both greenhouse gas and sulphate aerosol forcings. In general, emissions scenarios provide input to the AOGCMs for evaluating climatic and environmental consequences of future greenhouse gas emissions, (IPCC, 2000). Greenhouse gases are considered positive forcings, and sulphate aerosols are negative forcings as they scatter and absorb solar radiation. Nevertheless, they negatively impact the environment by indirectly altering cloud properties and longevity.

Several divergent scenarios are used when simulating global climate data as recommended by the IPCC to ensure a wide range of future variables are considered in analysis, thus reducing uncertainty. The IPCCs Fourth Assessment Report (2007) uses three primary emission scenarios in their multi-model ensemble which include A1B, A2, and B1. All three scenarios are separately used as input to the AOGCMs for this study.

A1B: The SRES A1 storyline has three sub-categories that all describe a future with alternative development of energy technology. These sub-scenarios include A1FI, A1B, and A1T which represent fossil-fuel intensive, balanced, and predominantly non-fossil fuel technological advances, respectively. The A1B scenario was used in the IPCC's Fourth Assessment Report as well as in this study. It illustrates an integrated world of rapid economic and population growth on a global scale. The population peaks at approximately 9 billion mid-century and declines thereafter. New technologies consume a combination of clean non-fossil fuels and fossil fuels that are a major contributor to greenhouse gas emissions.

A2: The SRES A2 emissions scenario is similar to A1 as it portrays an economic future, but it is more heterogeneous. Countries are self-reliant and the feeling of nationalism is strong. As a result technological change and economic growth per capita is slower than in other storylines. It is understood that globalisation would increase these rates of growth.

B1: As in the A1 emissions scenario the SRES B1 scenario describes a world with a global population that peaks mid-century and declines after. As a result of globalisation, there have been rapid changes in economic structure. It is a positive outlook of a future with reduced material consumption and the introduction of clean, resource-efficient technologies.

APPENDIX C: PREVIOUS REPORTS IN THE SERIES

ISSN: (print) 1913-3200; (online) 1913-3219

(1) Slobodan P. Simonovic (2001). Assessment of the Impact of Climate Variability and Change on the Reliability, Resiliency and Vulnerability of Complex Flood Protection Systems. Water Resources Research Report no. 038, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 91 pages. ISBN: (print) 978-0-7714-2606-3; (online) 978-0-7714-2607-0.

(2) Predrag Prodanovic (2001). Fuzzy Set Ranking Methods and Multiple Expert Decision Making. Water Resources Research Report no. 039, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 68 pages. ISBN: (print) 978-0-7714-2608-7; (online) 978-0-7714-2609-4.

(3) Nirupama and Slobodan P. Simonovic (2002). Role of Remote Sensing in Disaster Management. Water Resources Research Report no. 040, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 107 pages. ISBN: (print) 978-0-7714-2610-0; (online) 978-0-7714- 2611-7.

(4) Taslima Akter and Slobodan P. Simonovic (2002). A General Overview of Multiobjective Multiple-Participant Decision Making for Flood Management. Water Resources Research Report no. 041, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 65 pages. ISBN: (print) 978-0-7714-2612-4; (online) 978-0-7714-2613-1.

(5) Nirupama and Slobodan P. Simonovic (2002). A Spatial Fuzzy Compromise Approach for Flood Disaster Management. Water Resources Research Report no. 042, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 138 pages. ISBN: (print) 978-0-7714-2614-8; (online) 978-0-7714-2615-5.

(6) K. D. W. Nandalal and Slobodan P. Simonovic (2002). State-of-the-Art Report on Systems Analysis Methods for Resolution of Conflicts in Water Resources Management. Water Resources Research Report no. 043, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 216 pages. ISBN: (print) 978-0-7714-2616-2; (online) 978-0-7714-2617-9.

(7) K. D. W. Nandalal and Slobodan P. Simonovic (2003). Conflict Resolution Support System – A Software for the Resolution of Conflicts in Water Resource Management. Water Resources Research Report no. 044, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 144 pages. ISBN: (print) 978-0-7714-2618-6; (online) 978-0-7714-2619-3.

(8) Ibrahim El-Baroudy and Slobodan P. Simonovic (2003). New Fuzzy Performance Indices for Reliability Analysis of Water Supply Systems. Water Resources Research Report no. 045, Facility for Intelligent Decision

Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 90 pages. ISBN: (print) 978-0-7714-2620-9; (online) 978-0-7714- 2621-6.

(9) Juraj Cunderlik (2003). Hydrologic Model Selection for the CFCAS Project: Assessment of Water Resources Risk and Vulnerability to Changing Climatic Conditions. Water Resources Research Report no. 046, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 40 pages. ISBN: (print) 978-0-7714- 2622-3; (online) 978-0-7714- 2623-0.

(10) Juraj Cunderlik and Slobodan P. Simonovic (2004). Selection of Calibration and Verification Data for the HEC-HMS Hydrologic Model. Water Resources Research Report no. 047, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 29 pages. ISBN: (print) 978-0-7714-2624-7; (online) 978-0-7714-2625-4.

(11) Juraj Cunderlik and Slobodan P. Simonovic (2004). Calibration, Verification and Sensitivity Analysis of the HEC-HMS Hydrologic Model. Water Resources Research Report no. 048, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 113 pages. ISBN: (print) 978- 0-7714-2626-1; (online) 978-0-7714- 2627-8.

(12) Predrag Prodanovic and Slobodan P. Simonovic (2004). Generation of Synthetic Design Storms for the Upper Thames River basin. Water Resources Research Report no. 049, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 20 pages. ISBN: (print) 978- 0-7714-2628-5; (online) 978-0-7714-2629-2.

(13) Ibrahim El-Baroudy and Slobodan P. Simonovic (2005). Application of the Fuzzy Performance Indices to the City of London Water Supply System. Water Resources Research Report no. 050, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 137 pages. ISBN: (print) 978-0-7714-2630-8; (online) 978-0-7714-2631-5.

(14) Ibrahim El-Baroudy and Slobodan P. Simonovic (2006). A Decision Support System for Integrated Risk Management. Water Resources Research Report no. 051, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 146 pages. ISBN: (print) 978-0-7714-2632-2; (online) 978-0-7714-2633-9.

(15) Predrag Prodanovic and Slobodan P. Simonovic (2006). Inverse Flood Risk Modelling of The Upper Thames River Basin. Water Resources Research Report no. 052, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 163 pages. ISBN: (print) 978-0-7714-2634-6; (online) 978-0-7714-2635-3.

(16) Predrag Prodanovic and Slobodan P. Simonovic (2006). Inverse Drought Risk Modelling of The Upper Thames River Basin. Water Resources Research Report no. 053, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 252 pages. ISBN: (print) 978-0-7714-2636-0; (online) 978-0-7714-2637-7.

(17) Predrag Prodanovic and Slobodan P. Simonovic (2007). Dynamic Feedback Coupling of Continuous Hydrologic and Socio-Economic Model Components of the Upper Thames River Basin. Water Resources Research Report no. 054, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 437 pages. ISBN: (print) 978-0-7714-2638-4; (online) 978-0-7714-2639-1.

(18) Subhankar Karmakar and Slobodan P. Simonovic (2007). Flood Frequency Analysis Using Copula with Mixed Marginal Distributions. Water Resources Research Report no. 055, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 144 pages. ISBN: (print) 978-0-7714-2658-2; (online) 978-0-7714-2659-9.

(19) Jordan Black, Subhankar Karmakar and Slobodan P. Simonovic (2007). A Web-Based Flood Information System. Water Resources Research Report no. 056, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 133 pages. ISBN: (print) 978-0-7714-2660-5; (online) 978-0-7714-2661-2.

(20) Angela Peck, Subhankar Karmakar and Slobodan P. Simonovic (2007). Physical, Economical, Infrastructural and Social Flood Risk – Vulnerability Analyses in GIS. Water Resources Research Report no. 057, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 80 pages. ISBN: (print) 978-0- 7714-2662-9; (online) 978-0-7714-2663-6.

(21) Predrag Prodanovic and Slobodan P. Simonovic (2007). Development of Rainfall Intensity Duration Frequency Curves for the City of London Under the Changing Climate. Water Resources Research Report no. 058, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 51 pages. ISBN: (print) 978-0- 7714-2667-4; (online) 978-0-7714-2668-1.

(22) Evan G. R. Davies and Slobodan P. Simonovic (2008). An integrated system dynamics model for analyzing behaviour of the social-economic-climatic system: Model description and model use guide. Water Resources Research Report no. 059, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 233 pages. ISBN: (print) 978-0-7714-2679-7; (online) 978-0-7714-2680-3.

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(24) Rajesh Shrestha and Slobodan P. Simonovic (2009). A Fuzzy Set Theory Based Methodology for Analysis of Uncertainties in Stage-Discharge Measurements and Rating Curve. Water Resources Research Report no. 061, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 104 pages. ISBN: (print) 978-0-7714-2707-7; (online) 978-0-7714-2708-4.

(25) Hyung-Il Eum, Vasan Arunachalam and Slobodan P. Simonovic (2009). Integrated Reservoir Management System for Adaptation to Climate Change Impacts in the Upper Thames River Basin. Water Resources Research Report no. 062, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 81 pages. ISBN: (print) 978-0-7714-2710-7; (online) 978-0-7714-2711-4.

(26) Evan G. R. Davies and Slobodan P. Simonovic (2009). Energy Sector for the Integrated System Dynamics Model for Analyzing Behaviour of the Social- Economic-Climatic Model. Water Resources Research Report no. 063. Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada. 191 pages. ISBN: (print) 978-0-7714-2712-1; (online) 978-0-7714-2713-8.

(27) Leanna King, Tarana Solaiman, and Slobodan P. Simonovic (2009). Assessment of Climatic Vulnerability in the Upper Thames River Basin. Water Resources Research Report no. 064, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 61pages. ISBN: (print) 978-0-7714-2816-6; (online) 978-0-7714- 2817-3.

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(29) Leanna King, Tarana Solaiman, and Slobodan P. Simonovic (2010). Assessment of Climatic Vulnerability in the Upper Thames River Basin: Part 2. Water Resources Research Report no. 066, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 72pages. ISBN: (print) 978-0-7714-2834-0; (online) 978-0-7714-2835-7.

(30) Christopher J. Popovich, Slobodan P. Simonovic and Gordon A. McBean (2010). Use of an Integrated System Dynamics Model for Analyzing Behaviour of the Social-Economic-Climatic System in Policy Development. Water Resources Research Report no. 067, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 37 pages. ISBN: (print) 978-0-7714-2838-8; (online) 978-0-7714-2839-5.

(31) Hyung-Il Eum and Slobodan P. Simonovic (2009). City of London: Vulnerability of Infrastructure to Climate Change; Background Report 1 – Climate and Hydrologic Modeling. Water Resources Research Report no. 068, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 102pages. ISBN: (print) 978-0-7714-2844-9; (online) 978-0-7714-2845-6.

(32) Dragan Sredojevic and Slobodan P. Simonovic (2009). City of London: Vulnerability of Infrastructure to Climate Change; Background Report 2 – Hydraulic Modeling and Floodplain Mapping. Water Resources Research Report no. 069, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 147 pages. ISBN: (print) 978-0-7714-2846-3; (online) 978-0-7714-2847-0.

(33) Tarana A. Solaiman and Slobodan P. Simonovic (2011). Quantifying Uncertainties in the Modelled Estimates of Extreme Precipitation Events at the Upper Thames River Basin. Water Resources Research Report no. 070, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 167 pages. ISBN: (print) 978-0-7714-2878-4; (online) 978-0-7714-2880-7.

(34) Tarana A. Solaiman and Slobodan P. Simonovic (2011). Assessment of Global and Regional Reanalyses Data for Hydro-Climatic Impact Studies in the Upper Thames River Basin. Water Resources Research Report no. 071, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 74 pages. ISBN: (print) 978-0-7714-2892-0; (online) 978-0-7714-2899-9.

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(36) Dejan Vucetic and Slobodan P. Simonovic (2011). Water Resources Decision Making Under Uncertainty. Water Resources Research Report no. 073, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 143 pages. ISBN: (print) 978-0-7714-2894-4; (online) 978-0-7714-2901-9.

(37) Angela Peck, Elisabeth Bowering and Slobodan P. Simonovic (2010). City of London: Vulnerability of Infrastructure to Climate Change, Final Report - Risk Assessment. Water Resources Research Report no. 074, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 66 pages. ISBN: (print) 978-0-7714-2895-1; (online) 978-0-7714-2902-6.

(38) Akhtar, M. K., S. P. Simonovic, J. Wibe, J. MacGee, and J. Davies, (2011). An integrated system dynamics model for analyzing behaviour of the social-energy-economic-climatic system: model description. Water Resources Research Report no. 075, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 211 pages. ISBN: (print) 978-0-7714-2896-8; (online) 978-0-7714-2903-3.

(39) Akhtar, M. K., S. P. Simonovic, J. Wibe, J. MacGee, and J. Davies, (2011). An integrated system dynamics model for analyzing behaviour of the social-energy-economic-climatic system: user's manual. Water Resources Research Report no. 076, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 161 pages. ISBN: (print) 978-0-7714-2897-5; (online) 978-0-7714-2904-0.

(40) Millington, N., S. Das and S. P. Simonovic (2011). The Comparison of GEV, Log-Pearson Type 3 and Gumbel Distributions in the Upper Thames River Watershed under Global Climate Models. Water Resources Research Report no. 077, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 53 pages. ISBN: (print) 978-0-7714-2898-2; (online) 978-0-7714-2905-7.

(41) Andre Schardong and Slobodan P. Simonovic (2012). Multi-objective Evolutionary Algorithms for Water Resources Management. Water Resources Research Report no. 078, Facility for Intelligent Decision Support,

Department of Civil and Environmental Engineering, London, Ontario, Canada, 167 pages. ISBN: (print) 978-0-7714-2907-1; (online) 978-0-7714-2908-8.

(42) Samiran Das and Slobodan P. Simonovic (2012). Assessment of Uncertainty in Flood Flows under Climate Change: the Upper Thames River basin (Ontario, Canada). Water Resources Research Report no. 079, Facility for Intelligent Decision Support, Department of Civil and Environmental Engineering, London, Ontario, Canada, 67 pages. ISBN: (print) 978-0-7714-2960-6; (online) 978-0-7714-2961-3.