

Multisite Multivariate Statistical Downscaling of Daily Extreme Temperature Series

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Abstract

General Circulation Models (GCMs) are considered as the most credible and potential sources of information for the study of climate change and variability. In particular, these GCMs have been commonly used for climate change impact assessment studies in engineering practice. However, the spatial resolution of GCM output is too coarse and thus has restricted its direct application to the relevant finer scales required by these climate change impact studies. Therefore, efforts have been made in the scientific and engineering communities to develop the “downscaling” techniques for bridging this gap of scales. Furthermore, while several downscaling methods have been developed, most of them considered downscaling of weather variables at individual sites independently ignoring the spatial dependency between sites. Hence, single-site downscaling methods are not capable to capture the observed spatial-temporal interactions between hydrologic processes at different locations. In this context, the present study proposes an improved multisite multivariate statistical downscaling (MMSD) approach, which is capable to downscale daily extreme temperature series at many locations concurrently. In this study, two MMSD models were introduced for the downscaling of daily maximum (T_{max}) and minimum (T_{min}) temperature at many different sites. The first model was based on a combination of the modeling of the linkages between local daily extreme temperature series and global climate predictors by a multiple linear regression model; and the modeling of its stochastic components by the combined singular value decomposition and multivariate autoregressive (SVD-MAR) model. The second method relied on a combination of a multiple linear regression model and a multivariate stochastic model (MSM). The feasibility and accuracy of both SVD-MAR and MSM models have been assessed using two sets of daily extreme temperature data obtained from two networks of weather stations located in two completely different climatic regions: the cold-climate southern Quebec-Ontario region in Canada, and the tropical-climate temperature extremes in Bangladesh.

Atmospheric variables from two independent GCMs, namely: CGCM (Canadian Centre for Climate Modelling and Analysis Coupled Global Climate Model, version 3.1) and HadCM (UK Hadley Centre Coupled Model, version 3) have been used as large-scale climate predictors in this study. The temperature scenarios were generated under four SRES scenarios (Special Report on Emission Scenarios) of the Intergovernmental Panel on Climate Change (IPCC). Those are

A1B and A2 emission scenarios of CGCM, and A2 and B2 emission scenarios of HadCM. In assessing the performance of the proposed downscaling models, firstly, the standard procedure was to calibrate and validate these downscaling models using observed daily temperature extreme data available at different weather stations and the large-scale climate variables given by the US National Center for Environmental Prediction (NCEP) reanalysis data for the study region. Secondly, climate predictors given by two GCMs were used to assess the performance of the calibrated MMSD models in the climate projections for future periods under different climate change scenarios.

Results of these illustrative applications using daily extreme temperature data for the southern Quebec-Ontario region and for Bangladesh have indicated that the proposed SVD-MAR and MSM models were able to describe accurately the spatio-temporal statistical properties inherent in the observed daily extreme temperature series at an individual site as well as at different locations concurrently. More specifically, both of the proposed models were found capable to reproduce the basic statistical properties of the daily extreme temperature processes, such as monthly mean and standard deviation of daily T_{max} and T_{min} , the 90th percentile of daily T_{max} and the 10th percentile of daily T_{min} accurately for all stations in both study regions. In addition, both models were able to capture accurately the spatial variability of the daily extreme temperature series in terms of both at-site and between-site correlations of daily T_{max} and T_{min} for different locations. Moreover, the results given by the MMSD models were compared with those obtained by the most popular single-site Statistical DownScaling Model (SDSM). It was found that both proposed SVD-MAR and MSM models were capable to reproduce more accurately the observed interstation correlations in the simulated series for both T_{max} and T_{min} as compared to the SDSM. Furthermore, along with preserving the spatial variability, both of the proposed methods accurately reproduced the observed autocorrelation coefficients up to lag3 for T_{max} as well as T_{min} for both study regions.

In addition to assessing the performance of the MMSD models and the single-site SDSM in terms of their accuracy in reproducing the statistical properties of the daily extreme temperature series, the present study also focuses on how multisite downscaling procedures can provide a significant improvement in the accuracy of impact assessment results as compared to single-site downscaling techniques. In this context, this study has demonstrated that the proposed multisite

multivariate statistical downscaling (MMSD) method can provide more accurate snowmelt estimations than those given by the single-site downscaling (SDSM) procedure using daily maximum and minimum temperature data in the southern Quebec-Ontario region.

Finally, daily T_{max} and T_{min} for future periods were predicted under four SRES scenarios from two CGMs: A1B and A2 scenarios from CGCM, and A2 and B2 scenarios from HadCM. Upward trends were detected in annual average of the daily T_{max} and T_{min} for future periods under all climate scenarios at all the studied stations in the southern Quebec-Ontario region and at majority of the stations in Bangladesh. In particular, the highest increase in annual average of T_{max} and T_{min} is predicted under HadCM-A2 scenario at the stations in the southern Quebec-Ontario region, whereas CGCM-A2 scenario shows the highest increase at the stations located in Bangladesh. Furthermore, trend analysis of other temperature indices indicated significant changes in most of the indices for the future 2041-2070 period as compared to the observed ones during the current period.

Résumé

On considère les modèles du climat global (MCG) comme les sources principales qui sont capables de fournir les informations fiables pour les études concernant le changement et la variabilité climatique. En particulier, ces modèles ont été fréquemment utilisés pour les études des impacts en pratique. Toutefois, les échelles spatiales de ces MCG sont très grandes et par conséquent limitent ses applications directes aux études d'impacts qui exigent des échelles plus fines. Donc, plusieurs méthodes de mise en échelle ont été élaborées dans les communautés scientifique et technique pour établir le lien entre ces différentes échelles. De plus, plusieurs de ces méthodes de mise en échelle ont été proposées, mais la majorité de ces méthodes concernent la mise en échelle des variables climatiques en un site donné sans considération de la dépendance spatiale entre les sites. Par conséquent, ces méthodes pour les sites individuels ne sont pas capables de capturer les interactions spatiales observées entre les processus hydrologiques en différents sites. Dans ce contexte, la présente étude propose une approche statistique de mise en échelle multisite et multivariable (MMSD) qui est capable de mettre en échelle des séries de températures extrêmes en plusieurs sites simultanément. Dans cette étude, deux modèles MMSD ont été élaborés pour les séries journalières de température maximale (T_{max}) et de température minimale (T_{min}). Le premier modèle a été basé sur la combinaison du modèle de régression linéaire multiple représentant les liens entre les températures journalières extrêmes en des sites et les prédicteurs climatiques globaux, et le modèle de décomposition de valeur singulière et autorégressif multivarié (SVD-MAR) décrivant sa composante aléatoire. Le deuxième modèle a été basé sur une combinaison du modèle de régression linéaire multiple et le modèle stochastique multivariable pour sa composante aléatoire. On a évalué la faisabilité et la précision de ces deux modèles SVD-MAR and MSM en utilisant des données journalières extrêmes provenant de deux réseaux différents de mesures météorologiques représentant deux régions climatiques distinctes : la région du climat froid du sud de Québec-Ontario au Canada et la région du climat tropique au Bangladesh.

Dans la présente étude, on a utilisé les données des variables climatiques provenant de deux modèles du climat global CGCM (Canadian Centre for Climate Modelling and Analysis Coupled Global Climate Model, version 3.1) and HadCM (UK Hadley Centre Coupled Model, version 3). Les scénarios de changement climatique considérés pour la température sont proposés par

Intergovernmental Panel on Climate Change (IPCC) : scénarios A1B et A2 pour le modèle CGCM, et scénarios A2 et B2 pour le modèle HadCM. Dans l'évaluation de la performance de deux modèles de mise en échelle proposés, la procédure standard consiste premièrement à la calibration et la validation de ces modèles en utilisant les données journalières observées de températures extrêmes disponibles aux divers stations météorologiques choisies et les données de réanalyse de US National Center for Environmental Prediction (NCEP) pour la région étudiée. Deuxièmement, les prédictors climatiques provenant de deux modèles du climat global différents ont été utilisées pour évaluer la performance des modèles MMSD proposés dans la prédiction du climat pour les périodes futures sous divers scénarios de changement climatique.

Les résultats de ces applications illustratives en utilisant les données journalières de températures extrêmes pour la région Québec-Ontario au Canada et pour le Bangladesh ont indiqué que les modèles SVD-MAR et MSM sont capables de décrire d'une façon précise les propriétés statistiques spatio-temporelles des données de températures extrêmes observées en un site et en plusieurs sites simultanément. Plus spécifiquement, ces deux modèles sont capables de capturer les propriétés statistiques de base des processus journaliers de températures extrêmes telles que la moyenne mensuelle et l'écart type des températures extrêmes journalières T_{max} et T_{min} ; la 90^{ième} percentile de T_{max} et la 10^{ième} percentile de T_{min} pour toutes les stations météorologiques dans les régions étudiées. En addition, ces deux modèles sont capables de capturer la variabilité spatiale des séries journalières de températures extrêmes en fonction de corrélations temporelle et spatiale de T_{max} et de T_{min} pour des divers sites. De plus, les résultats de ces modèles MMSD ont été comparés avec les résultats du modèle le plus populaire pour la mise en échelle en un site individuel SDSM. On a trouvé que les modèles MMSD sont capable de fournir des résultats plus précis au niveau de corrélations spatiales pour T_{max} et T_{min} . En plus, ces modèles MMSD sont capable de capturer précisément l'autocorrélation observée jusqu'à d'ordre 3 pour T_{max} et T_{min} pour les deux régions étudiées.

Faisant suite à l'évaluation de la performance de deux modèles MMSD et du modèle SDSM en fonction de leur précision dans la description des propriétés statistiques des séries journalières de températures extrêmes. La présent étude examine également comment la mise en échelle en multisite peut fournir une amélioration significative des résultats des études d'impact en comparant à la mise en échelle en un site individuel. Dans ce contexte, cette étude a démontré que les modèles MMSD proposés peuvent fournir une estimation plus précise de la fonte de neige

par rapport du modèle SDSM en utilisant les données journalières de températures extrêmes pour la région du sud de Québec-Ontario,

Finalement, on a effectué les prédictions de températures journalières extrêmes T_{max} et T_{min} pour les périodes futures pour des divers scénarios climatiques pour les deux modèles du climat global : A1B et A2 pour le modèle CGCM et A2 et B2 pour le modèle HadCM. On avait observé une tendance d'augmentation dans la moyenne annuelle des températures extrêmes T_{max} et T_{min} pour les périodes futures sous tous les scénarios de changement climatiques pour toutes les stations dans la région Québec-Ontario et pour la plupart des stations au Bangladesh. En particulier, l'augmentation la plus élevée a été observée sous le scénarios HadCM-A2 pour la région Québec-Ontario, tandis que le scénarios CGCM-A2 avait indiqué l'augmentation la plus élevée pour les stations au Bangladesh. De plus, l'analyse des tendances d'autres indices de température avait indiqué des changements significatifs pour la plupart de ces indices pour la période future 2041-2070 par rapport aux indices observés durant la période courante.

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List of Abbreviations

ANN	Artificial Neural Network
AOGCM	Atmospheric Ocean General Circulation Model
BCCAQ	Bias Correction Constructed Analogues with Quantile Mapping Reordering
BCCI	Bias Correction and Climate Imprint
BCSD	Bias Correction and Spatial Downscaling
BMD	Bangladesh Meteorological Department
CCA	Canonical Correlation Analysis
CCCma	Canadian Centre for Climate Modelling and Analysis
CCCSN	Canadian Climate Change Scenarios Network
CDF-t	Cumulative Distribution Function Transform
CGCM	Canadian Centre for Climate Modelling and Analysis Coupled Global Climate Model
CLIGEN	CLimate GENerator
CMIP5	Coupled Model Intercomparison Project Phase 5
CNN	Convolutional Neural Network
CO ²	Carbon Dioxide
CRCM	Canadian Regional Climate Model
CRU	Climate Research Unit
CSDI	Cold Spell Duration Indicator
DAI	Data Access Integration
DTR	Diurnal Temperature Range
EC	Empirical Copula

ECCC	Environment and Climate Change Canada
EOF	Empirical Orthogonal Functions
ETCCDI	Expert Team on Climate Change Detection and Indices
Fr-Th	Freeze and Thaw cycle
GBM	Ganges, Brahmaputra and Meghna
GCM	General Circulation Models
GHLM	Generalized Hierarchical Linear Model
GLM	Generalized Linear Model
GP	Genetic Programming
GSL	Growing Season Length
HadCM	Hadley Centre Coupled Model
IPCC	Intergovernmental Panel on Climate Change
KDE	Kernel Probability Density Estimation
KNN	K Nearest Neighbor
LARG-WG	Long Ashton Research Station Weather Generation
LS-SVM	Least Square Support Vector Machine
LSTM	Long Short Term Memory
MAD	Mean absolute Differences
MAE	Mean Absolute Error
MAR	Multivariate Autoregressive
MaxTmax	Annual maximum value of daily maximum temp
MaxTmin	Annual maximum value of daily minimum temp

MinTmax	Annual minimum value of daily maximum temp
MinTmin	Annual minimum value of daily minimum temp
ML	Machine Learning
MLP	Multi Layer Perceptron
MMLR	Multivariate Multiple Linear Regression
MMSD	Multisite Multivariate Statistical Downscaling
MSM	Multivariate Stochastic Model
NCEP	National Center for Environmental Prediction
NNHMM	Nonparametric Nonhomogeneous Hidden Markov Model
NOAA	National Oceanic and Atmospheric Administration
N-PLS	N-way Partial Least Squares
NSRP	Neyman Scott Rectangular Pulses
PCA	Principal Component Analysis
PLS	Partial Least Square
PRECIS	Providing Regional Climates for Impacts Studies
QM	Quantile Mapping
R^2	Coefficient of Determination
RBF	Radial Basis Function
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RegCM2	Second-Generation Regional Climate Model
RMSD	Root Mean Square Differences

RMSE	Root Mean Square Error
SDSM	Statistical DownScaling Model
SPSS	Statistical Package for the Social Sciences
SRES	Special Report on Emission Scenarios
STD	Standard Deviation
SVD	Singular Value Decomposition
SVD-MAR	Singular Value Decomposition and Multivariate Autoregressive
SVM	Support Vector Machine
TavgMean	Annual Mean of daily average temp
TLFN	Time Lagged Feed Forward Network
Tmax	Daily maximum temperature
TmaxMean	Annual Mean of daily maximum temp
Tmax90p	90th percentile of daily Tmax
Tmin	Daily minimum temperature
TminMean	Annual Mean of daily minimum temp
Tmin10p	10 th percentile of daily Tmin
VIF	Variance Inflation Factor
VIP	Variable Importance in the Projection
WGEN	Weather Generator
WSDI	Warm Spell Duration Indicator

Chapter 1

INTRODUCTION

1.1 Statement of problems

Climate change has been regarded as one of the greatest issues in recent decades. Nowadays, there are growing evidences that increased atmospheric concentrations of greenhouse gases have caused the anthropogenic enhancement to greenhouse effect resulting in global warming and climate change (Mikhaylov et al., 2020; Houghton, 2009). Congruous observational evidences are also manifesting the increase in global mean temperature. For instance, National Oceanic and Atmospheric Administration (NOAA) ranked 2023 as the warmest year in its global temperature record since 1850 at 1.18°C above the 20th century average of 13.9°C (<https://www.ncei.noaa.gov/news/global-climate-202312>). In the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) it is reported that the globally averaged combined land and ocean surface temperature has shown a warming of 0.85°C [0.65 – 1.06°C] over the period 1800 to 2012 (IPCC, 2013), and an increase of 0.74°C [0.56 – 0.92°C] during the last hundred years ranging from 1906 to 2005 (IPCC, 2007). The Sixth Assessment Report (AR6) stated that the emissions of greenhouse gases have unequivocally caused global warming reaching global surface temperature 1.1°C above 1850-1900 average in 2011-2020 (IPCC, 2023). Warming of global temperature can induce a radical alteration in the variability of hydrologic processes. In addition, climate change can potentially exacerbate the type, intensity and frequency of extreme weather and climate events (Meehl et al., 2000), among which temperature related events are heat waves, severe winter, freezing spells, prolonged hot and cold spells, wildfires and summer storms etc. (Mastrandrea et al., 2011). The AR5 has pointed out that the number of cold days and nights has decreased while the number of warm days and nights has increased on a global scale since about 1950. Besides, the frequency of heat waves has increased in some parts of the world (IPCC, 2013). According to the AR6 the occurrences of climate-related food-borne and water-borne diseases have increased and extreme heat events have caused human mortality and morbidity (IPCC, 2023). Complying with the findings of IPCC, some other studies also have reported about extreme temperature events, such as European heat wave in 2010 (Miralles et al., 2014), summer heat wave in western Russia in 2010 (Dole et al., 2011), extreme heatwaves producing large societal impacts in 2003 in Europe, 2010 in Russia, 2015 in the Middle East, 2016 in Southeast

Asia (Horton et al., 2016), increased heat-related mortality and health issues (Mitchell et al., 2016; Walsh, et al., 2020) etc. Some recent extreme weather events in Canada include historic record wildfires in June 2023 which was seven times the 10-year average and 184,493 square kilometres of woodland were in smoke resulting in choking smoke filling the air across Canada. July 2023 was the warmest month ever recorded globally having the 1.5°C above the 1850 to 1900 average, and the hottest summer was observed on Earth as well as in Canada. In 2021 the drought across Western Canada was one of the worst in history. In the same year in September, British Columbia experienced flood of floods after an extraordinary warm and dry spring and summer abruptly switched from drought to floods. In 2020 Fort McMurray observed the flood of a century caused by severe ice jamming on a 25-km stretch of the Athabasca River, and Calgary experienced Canada's costliest hailstorm and the fourth most expensive insured natural disaster in history on June 13 (<https://www.canada.ca/en/environment-climate-change/services/top-ten-weather-stories.html>). Changes in temperature can engender direct or indirect impacts on nearly every aspect of human well-being, such as agriculture and food security (e.g., reduction in crop production if the temperature goes beyond the tolerance limits, negative impacts on dairy and cattle industry, altering the biogeochemical cycle etc.); hydrology and water resources (e.g., changes in timing and magnitude of floods due to early snowmelt, impacts on water quantity and quality etc.); natural ecosystem and resources (e.g., loss of coastal resources due to sea level rise, increased wildfires etc.); public health (e.g., heat related sickness and casualties, transmission of infectious diseases, air quality issues etc.); socio-economic condition (e.g., decline in agrarian economy, increased pressure on energy demand etc.) etc. Therefore, understanding the variability of current weather and accurate prediction of the possible future changes in climate and hydrologic processes are crucial for management, design and planning, mitigation and adaptation purposes in order to cope with the changing climate in a better way.

General Circulation Models (GCMs) are considered as the most credible and potential primary sources of information for the study of climate change and variability. These GCMs have been developed to simulate the current climate processes and to estimate plausible climate change in future. These numerical coupled models demonstrate significant skill to represent a large proportion of the complexity of various earth systems including the atmosphere, oceans, land surface etc. at the continental and hemispheric spatial scales (Xu, 1999). Nevertheless, the GCM simulations are inherently incapable to represent local or regional scale features and variability

due to their coarse spatial resolution (hundreds of kilometers) (Wigley et al., 1990; Xu, 1999; Chu et al., 2010). Thus, the coarse spatial resolution of GCM output has restricted its direct application in climate change impact models since there is a mismatch of scales between GCM simulations and the scale of interest for regional or local impacts. This scale mismatch problem has led to the necessity of establishing the linkage between large-scale climate variables and the local hydro-meteorological parameters (e.g., precipitation and temperature) in order to account for the climate change effects at local or regional levels (Nguyen et al., 2006). Consequently, considerable efforts have been made in the climate research community to develop innovative techniques to bridge this gap of scales, known as ‘downscaling’ (Fowler et al., 2007; Willems et al., 2012; Nguyen, 2019).

To date, a number of studies have been conducted to develop and evaluate the effectiveness of various downscaling techniques. However, most of them have been conducted for downscaling of weather variables at a single site and for a single variable. One of the major limitations associated with single-site downscaling is that they downscale weather variables at an individual site independently ignoring the spatial relationship with other sites (Mehrotra et al., 2006a). But in reality, weather data at different sites over an area are not independent of each other, and exhibit some sort of correlations among them since the neighbouring sites over a given area experience the same weather on the same day due to common exposure to a single weather system (Yang et al., 2005). Thus, if weather data having strong correlations (e.g. daily temperature) are downscaled individually at a single station without accounting for the spatial coherence among the stations, the downscaled series will not be able to adequately represent the actual weather condition over the given area; thus, leaving the scope of inaccurate assessment of climate change impacts. For example, comparing the effectiveness of a multisite weather generator with a single-site weather generator in hydrological modeling Khalili et al. (2011a) showed that single-site weather generator could result in a significant underestimation of extreme streamflow especially in summer and autumn seasons. Again, the study by Zareie et al. (2015) showed that multisite temperature downscaling approach outperformed the single-site downscaling especially in simulating the timing of streamflow during peak flow season. In a recent study, Rahman and Nguyen (2024) compared the accuracy of the multisite and single-site downscaling techniques in snowmelt computations and found that multisite downscaling produced more accurate snowmelt estimations than single-site downscaling. Therefore, in downscaling procedures preserving spatial dependence among a set of stations is essential for water resources studies, especially for the areas where an

accurate description of the spatial and temporal variations of weather variables is required. These issues associated with single-site downscaling have triggered the necessity of multisite downscaling, which is capable to downscale the weather variables at many stations concurrently preserving the spatial dependence between the stations. In concert with the spatial dependency in temperature series in a network of stations, there also exists some degree of relationship between the daily maximum and minimum temperature at a given site. For example, if daily maximum temperature (T_{max}) is higher on a given day, daily minimum temperature (T_{min}) also tends to be usually higher on the same day at the same location. These inherent characteristics of temperature should be well addressed in downscaling procedures in order to achieve an accurate and reliable simulation of daily T_{max} and T_{min} . In fact, in most cases the downscaling of weather variables does not end in itself but provides data or information for impact assessment studies (Maraun et al., 2010). Hence, one of the fundamental necessities of downscaling procedures stems from the requirements of climate scenarios at finer resolution, which could be used as input parameters in hydrologic and climate change impact models. So, the downscaled series is required to be a true representative of the weather variables over a given area for a meticulous assessment of climate change impacts.

Although multisite downscaling has been the interest of some studies, the preponderance is about the downscaling of precipitation and there is a dearth of meaningful efforts for multi-site downscaling of temperature (Srinivas et al., 2013), despite the fact that temperature exhibits a strong correlation among the neighbouring stations. In addition, even though some studies developed different techniques for multisite downscaling, but the number of studies about evaluating the efficacy of multisite versus single-site downscaling at the application level is very limited. More specifically, the studies related to multisite downscaling were focused on the accuracy of these procedures in capturing the observed spatio-temporal characteristics of the selected weather series; but these studies did not demonstrate the significant impact of multisite downscaling on the application results as compared to those given by single-site downscaling approaches.

1.2 Objectives of the study

In view of the aforementioned issues, an efficient multisite multivariate downscaling technique is needed to describe accurately the inherent spatial and temporal consistencies of daily T_{max} and T_{min} series (that is, daily maximum and minimum temperature) at different locations concurrently. This could provide an accurate simulation of daily extreme temperature series for the current period as well as reliable projections of the extreme temperature for the future at a finer resolution for accurate assessment of climate change impacts. In this context, the present study aims to develop statistical models for multisite multivariate downscaling of daily extreme temperature series, which are capable to establish the linkages between GCM outputs and the observed daily temperature extremes at different locations concurrently. The specific requirements for the proposed statistical downscaling models over other existing models are their ability to describe accurately the following main characteristics: i) interstation correlations of both daily T_{max} and T_{min} (spatial variability); ii) at-site correlation between daily T_{max} and T_{min} ; and iii) at-site autocorrelation (temporal dependence) of daily T_{max} and daily T_{min} . The specific objectives of this study can be described as follows:

1. To develop Multisite Multivariate Statistical Downscaling (MMSD) procedures for downscaling daily T_{max} and T_{min} series concurrently at different locations, which are capable to reproduce the spatial variability and temporal dependence inherent in daily temperature series, along with preserving the correlation between daily T_{max} and T_{min} .
2. To evaluate the feasibility and effectiveness of the proposed MMSD procedures by applying to two sets of daily extreme temperature data obtained from two networks of weather stations located in two completely different climatic regions: cold-climate southern Quebec-Ontario region in Canada and tropical-climate region in Bangladesh.
3. To provide the predictions of the daily extreme temperature series for future periods under different climate change scenarios and to compare the changes in the trends of temperature indices during future periods due to climate change with the observed trends during the current period in both of the studied regions.

4. To demonstrate the significant improvement in the accuracy of snowmelt computations in practice using the multisite downscaling methods as compared to the single-site downscaling technique.

Therefore, this study which aims to compare the effectiveness of multisite downscaling with single-site downscaling methods in preserving spatial dependencies in temperature data across different locations, would provide valuable insights for selecting the appropriate downscaling method for more accurate climate change impact assessments. In addition, the predictions of the daily extreme temperature series for future periods would provide decision-makers with the necessary information for policy-making, planning, developing adaptation and mitigation strategies related to climate change etc.

1.3 Organization of the thesis

The remaining chapters of this thesis are organized as follows: Chapter 2 provides an overview and classification of existing downscaling methods and summarizes a review of the studies conducted for downscaling of climate variables. Chapter 3 presents the detailed methodology of the proposed MMSD procedures and the criteria for assessing the performance of the proposed methods. Descriptions of predictors and predictands used in this study are also given in this chapter. Chapter 4 provides the statistical characterization of temperature extremes and detailed statistical analysis of the observed daily extreme temperature series in the southern Quebec-Ontario region and Bangladesh. Applications of the proposed MMSD procedures to daily extreme temperature series in the southern Quebec-Ontario region and Bangladesh are provided in chapters 5 and 6, respectively. Chapter 7 gives the conclusions drawn from this study and the recommendations for further studies. Finally, the statements of originality are presented in Chapter 8.

Chapter 2

LITERATURE REVIEW

This chapter begins with an overview and classification of existing downscaling methods as well as studies conducted for downscaling of temperature. At last, some recent advances in multisite downscaling processes are outlined.

2.1 Overview and classification of downscaling methods

All the existing downscaling procedures are broadly categorized into two fundamental categories (Xu, 1999; Fowler et al., 2007): limited area models or dynamical downscaling techniques and statistical or empirical downscaling procedures. Both methods basically rely on GCMs for the information on the atmospheric circulation at large-scale, but the downscaling techniques are substantially different for two of the methods (Mearns et al., 1999). Both of the methods are described below.

2.1.1 Dynamic downscaling

Dynamical downscaling, more commonly known as regional climate modeling (RCM), involves the extraction of regional scale information from large-scale GCM data by the modeling of regional climate dynamical processes (Xu, 1999). Dynamic downscaling produces spatially complete fields of climate variables by nesting a finer scale climate model in a coarse scale model and preserves some spatial correlations as well as physically plausible relationships between the variables (Maurer and Hidalgo, 2008). The following three approaches of dynamic downscaling have been described by Rummukainen (1997) (taken from Xu, 1999):

- 1) Running a regional-scale limited-area model with coarse GCM data as the geographical or spectral boundary conditions, which is known as one-way nesting.
- 2) Performing global-scale experiments with high-resolution Atmosphere GCMs (AGCMs), using GCM data as initial conditions.
- 3) Using a variable-resolution global model; using the highest resolution over the area of interest.

The major advantage of dynamic downscaling is their skill to explicitly treat many of the physical processes that control the regional climate phenomena (Hellstrom et al., 2001). However, dynamic downscaling is computationally demanding, which makes its use limited in climate change impact studies (Maurer and Hidalgo, 2008). The developments of state-of-the-art RCMs, their potentials and limitations were outlined by Rummukainen, 2010.

2.1.2 Statistical downscaling

The statistical downscaling procedures basically involve defining an empirical relationship between global-scale atmospheric variables and local scale observed surface environmental parameters such as temperature and precipitation (Nguyen, 2002; Sunyer et al., 2012). The practical advantage of easiness to apply and low computation demand have made statistical downscaling more promising option in climate impact studies (Wilby et al., 2002; Lee and Jeong 2014). However, the major weakness of this method is stationary assumption, which assumes the statistical relationship between predictors and predictands constructed at current period will be valid under different forcing conditions of future climate. But this assumption is not verifiable under present climate condition (Wilby et al., 2004). Although statistical methods are more straightforward than dynamical downscaling, sometimes fail to represent extreme events adequately. In addition, it needs long and reliable historical data for accurate calibration (Fowler et al., 2007), which may not always be available for the intended location. Moreover, the results are sensitive to the selection of predictor and the transfer scheme chosen to build the empirical predictor-predictand relationship (Wilby et al., 2002).

Statistical Downscaling can be classified into three groups according to the computational techniques: stochastic weather generators, weather typing approaches and regression based methods (Fowler et al., 2007; Wilby et al., 2004).

Stochastic weather generators

Stochastic weather generators produce synthetic time series of weather data depending on the specific weather parameters derived from the statistical characteristics of observed local weather. Thus, the statistical properties of the simulated daily weather series are controlled by the parameters which are the statistical encapsulation of the climate of that location. Weather

generators provide a stochastic approach in downscaling, which is achieved through changes model parameters consistent with the corresponding variable changes in the GCM (Wilks, 2010). The main advantage of this technique is that it can exactly reproduce many observed climate statistics and enable the efficient production of large ensembles of scenarios which are particularly useful for risk analysis (Wilby et al., 2002). The key issue associated with the weather generator is that it requires adjusting the model parameters in a physically realistic and internally consistent way; otherwise, the unanticipated effect can occur when the parameters are varied (Wilby and Wigley, 1997). Another disadvantage includes their low ability in reproducing interannual to decadal climate variability (Fowler et al., 2007; Wilks and Wilby, 1999). The best known stochastic weather generators are Richardson type weather generator like WGEN (Richardson and Wright, 1984) and Long Ashton Research Station Weather Generation (LARS-WG) (Semenov and Barrow, 1997). These two types of weather generators differ mainly in choosing the distributions used for describing daily values of weather elements (Semenov et al., 1998). However, the use of semi-empirical structure of LARS-WG imposes more complex conditioning requiring more parameters than WGEN (Brissette et al., 2007). Comparative performance of different weather generators in terms of their ability to reproduce the observed statistical characteristics was assessed by Semenov et al. (1998) and Qian et al. (2004) among others.

Weather typing

Weather typing approaches involve grouping of local (at station level or area average) meteorological variable into finite number of discrete weather classes relating the prevailing patterns of atmospheric circulation (Wilby and Wigley, 1997; Wilby et al., 2004). The classification scheme can be either objective, subjective or hybrid depending on the need of research and nature of the data (Wilby and Wigley, 1997; Enke et al., 2005). Objective or automated classification includes principal component analysis (PCA), canonical correlation analysis (CCA), correlation-based pattern recognition techniques, composting, neural network etc. (Wilby and Wigley, 1997; Yarnal et al., 2001). European Grosswetterlagen and British Isles Lamb Weather Type are the examples of subjective classification (Enke et al., 2005; Wilby and Wigley, 1997). After being classified into a particular group, the local surface variables are conditioned on the respective weather pattern. Climate change is estimated by assessing the change in the frequency of the corresponding weather classes simulated by the GCM (Fowler et al., 2007). The

advantages of weather classification methods are the consideration of the physical sensible linkages between global scale climate and weather at the local scale as well as its versatile applicability for a wide variety of environmental variables and multi-site simulation (Wilby et al., 2002, 2004). However, the method assumes that the characteristics of the relationship between local variables and weather classes will remain valid in future periods (Fowler et al., 2007). Another limitation of this method is its inadequacy to describe intra-type variation of surface climate (Wilby et al., 2004). Different categories of weather typing approaches are well discussed by Huth et al. (2008).

Regression based methods

The regression based downscaling methods generally involve establishing empirical relationships between large-scale global predictors and local scale predictand. The relation type may be linear or nonlinear (Wilby et al., 2002; Wilby and Wigley, 1997). Different approaches of regression models prevail according to the choice of the mathematical function for describing the predictor-predictand relationship, the computational technique used, or the selection process of the predictor variables. They range from the simplest form to sophisticated linear and non-linear procedures involving the use of principal components (Kidson and Thompson, 1998; Huth, 2002), Artificial Neural Network (ANN) (Zorita and Von Storch, 1999; Crane and Hewitson, 1998; Nourani et al. 2019), Canonical Correlation Analysis (CCA) (Busuioc et al., 2008; Karl et al., 1990), Singular Value Decomposition (SVD) (Khalili and Nguyen, 2012, 2018), Support Vector Machine (SVM) (Danandeh et al. 2019) etc. The main advantages of the regression based downscaling methods are that these procedures are computationally less demanding compared to other methods and are able to establish a direct linkage between large-scale climate predictors and local surface parameters. However, similar to weather typing methods, the regression-based downscaling methods also assume the validity of predictor-predictand relationship in future climate conditions. Regression-based downscaling is highly sensitive to predictors' selection and statistical fitting process and sometimes fails to represent future extreme events, as these types of extreme events mostly lie at the outlier or beyond the range of the calibration data set (Wilby et al., 2002).

Both dynamic and statistical downscaling techniques have their relative strengths and weaknesses, which are elaborately described by Wilby et al. (2002, 2004) etc. In addition to these studies, some other studies have investigated the skills, potentials and limitations of statistical and

dynamic downscaling methods in downscaling temperature and precipitation and the example includes the studies by Hellstrom et al. (2001), Kidson and Thompson (1998), Mearns et al. (1999), Murphy, (1999), Wilby et al.(2000), Haylock et al. (2006a), Hewitson et al. (2014), Trzaska and Schnarr (2014), Widmann, et al. (2019) etc.

2.2. Studies related to downscaling of temperature series

Numerous approaches have been applied in different studies to downscale weather variables over different regions of the world. The following sections summarize some of the studies which are related to downscaling of temperature along with other climate variables, mostly precipitation.

Regression based downscaling approaches have been paid attention in many studies for downscaling of temperature. For example, Huth (2002) compared the performance of several linear statistical downscaling methods using different predictor sets for daily mean winter temperature in central Europe. Those methods are CCA prefiltered by PCA, SVD analysis, and multiple linear regressions. Multiple linear regressions were performed either directly with grid point data or principal components (PCs) of predictor fields with or without screening. Here, the observed variability of temperature series was restored in two methods: randomization and variance inflation. The study showed that, the temporal structure was preserved better by the pointwise regression, whereas, the spatial structure was best reproduced by CCA. And, in general the inflation method performed better than the randomization process. Schoof and Pryor (2001) compared ANNs with regression methods for downscaling the daily maximum and minimum temperature during two seasons, the growing season and the non-growing season. For growing season, the performance of the ANNs outperformed regression methods for maximum temperature when the autoregressive term was not included. However, during non-growing season, both models produced similar results and did not perform well like the growing season. For minimum temperature also, neural networks performed slightly better than the regression models. However, this study showed that adding an autoregressive term could improve the performance of both of the models. Benestad (2001) used empirical orthogonal functions (EOFs) for downscaling monthly mean temperature and compared it with a conventional CCA method. Although both methods produced similar results, the EOF method was found to be more robust with respect to the choice of predictor domain. The study showed that climate scenarios derived using the EOF approach

were associated with smaller errors than the conventional method. In a separate study by Imbert and Benestad (2005), a combined approach of downscaling was suggested, which involved the use of analog method with a combination of regression-based model. In this method the trend from a linear model was superimposed onto the results of the analog model. Comparing the linear, analog and combined methods this study suggested that the combined method was capable to extrapolate the values outside the range of calibration period by shifting the analog-derived distribution towards higher values, while the linear model could not always give the strongest trend. Coulibaly et al. (2005) investigated the applicability of temporal neural network, called time-lagged feed-forward network (TLFN) as a downscaling method. TLFN has the advantage of incorporating several lagged predictor values as input along with their concurrent values and the temporal processing is achieved without any additional computational cost. Thus, this method has the potential to be an effective downscaling technique especially for the climate variables whose current weather state is associated with their previous weather state. Application of TLFN in north-eastern Canada showed that it produced comparable results in downscaling daily maximum and minimum temperature with respect to existing SDSM during current period of validation. A different type of statistical downscaling method, genetic programming (GP) was proposed by Coulibaly (2004) to downscale maximum and minimum temperatures in northeastern Canada. The GP involved the use of a context-free grammar along with Powell optimization method. Here, the grammar was used for building the equations to relate predictand and predictors while Powell optimization was used as optimization process to find the better values of the variables and the constants within the equation. Comparison of this method with the SDSM showed that GP produced better results than SDSM especially for maximum temperature. The advantage of GP is that it automatically selects the most relevant predictor variables and does not require a preliminary screening for input variables. Some other examples of regression based downscaling include the studies conducted by Hofer et al. (2010) and Kettle and Thompson (2004). The first study downscaled air temperature in a glacier environment at a high temporal resolution with the use of EOF and multiple linear regressions. The latter study was carried out in European mountains to reconstruct daily mean, minimum and maximum temperature by using regression models with the PCs of temperature and pressure variables. The concept of defining homogeneous regions in statistical downscaling has been used in some studies for the regions where regional and seasonal differences are more pronounced. For example, Matulla (2005) used region and season-specific

combinations of predictor variables for downscaling of temperature in a complex structured landscape in Australia where differences in elevation are very large. In the study by Matulla (2005), the downscaling procedure was accomplished through PCA for dimension reduction, and CCA to link the statistical relation between large and local scale variables.

Machine learning (ML) techniques have been considered as one of the promising options for statistical downscaling due to their ability to simulate complex nonlinear relationships. (Hernanz et al., 2022a). For example, Vaughan et al. (2022) proposed a deep learning based technique for downscaling of temperature and precipitation using convolutional conditional neural processes (convCNPs). This model allowed deep learning techniques to apply to off-the-grid spatio-temporal data. Thus, convCNPs was capable to generate multisite predictions at an arbitrary set of locations, regardless of the availability of training data by using sub-grid-scale topographic information of local predictions. In other recent studies by Hernanz et al. (2022b; 2022c) five statistical downscaling methods, such as, (1) Analog, (2) Regression, (3) ANN, (4) SVMs and (5) Kernel Ridge Regression were compared using perfect predictors (reanalysis) and imperfect predictors (global climate model experiment) respectively in 2022b and 2022c in Spain. Here, all the methods were found capable to capture maximum and minimum temperature, although maximum temperature was better simulated than minimum temperature for their mean values with slight biases on the extremes. For precipitation, the total precipitation amount was reproduced well by most of the methods, but Analog method produced more accurate intense precipitation amounts and occurrences. Li et al. (2020) investigated the performance of machine learning (long short-term memory (LSTM) networks and SVM; and, statistical (arithmetic ensemble mean (EM) and multiple linear regression (MLR)) at twelve meteorological stations in Ontario, Canada. The study showed that although both machine learning and statistical techniques performed well for downscaling daily temperature, but had difficulties in capturing extreme values for temperature especially below -10°C and above 20°C . Baghanam et al. (2020) assessed three statistical methods, such as, LARS-WG, SDSM, and ANN for downscaling precipitation, maximum and minimum temperature. This study showed that temperature series were better simulated by ANN model, while precipitation was best represented by SDSM.

Examples of weather classification based downscaling of temperatures include the study by Bárdossy et al. (2002), in which an automated objective circulation pattern classification has

been proposed. The classification method was based on the concept of fuzzy-rules combined with simulated annealing algorithm as an optimization procedure. Here, the purpose of the classification process was to define the circulation pattern which causes warm or cold local conditions depending on the information of large-scale pressure distribution. The method proposed by Bárdossy et al. (2002) was further used by Panagoulia et al. (2008), in which daily temperature series were downscaled by using a simple autoregressive model conditioned on atmospheric circulation and local daily precipitation status. Application of this model over a mountainous catchment in Central Greece showed overall a good agreement between the simulated and historical mean annual cycle of temperature.

Wilks (1992) involved weather generator in climate change studies in order to describe daily weather variability in present day climate and generate synthetic daily time series consistent with assumed future changes. In the approach by Wilks, the characteristics of present day climate were represented in terms of some parameters of daily stochastic process and the synthetic weather sequences for changing climate were produced by adjusting these parameters based on the information from GCM integration. The proposed approach was applied for generating a couple of weather variables like precipitation occurrence and amount, maximum and minimum temperature and solar radiation. Huth et al. (2003) investigated the ability of weather generator to capture the third and fourth order statistical moments (that is, skewness and kurtosis) of daily maximum and minimum temperature distributions. Among other statistical methods the weather generator reproduced the observed skewness better in winter and summer seasons. Comparing several statistical methods Huth et al. (2003) concluded that different methods have their relative strengths and drawbacks in simulating observed statistical properties, and the causes of a good correspondence with or differences from observations depend on the treatment of physics in the models, imperfections in physical parameterizations, or types of the linear functions chosen to transfer the properties from predictors onto predictands.

Some comparative studies have investigated the relative performance of statistical and dynamic downscaling techniques. For example, Wilby et al. (2000) compared the performance of semi empirical statistical method and RegCM2 (Second-Generation Regional Climate Model) for downscaling daily maximum, minimum temperatures and precipitation in Animas River basin, Colorado. It was found that statistical downscaling was more skilful than the RegCM2 for monthly precipitation, maximum and minimum temperature. Moreover, the study suggested that the

advantage of requiring very few parameters makes the statistical downscaling procedure more attractive in hydrological applications compared to computationally demanding RCM. Similar type of conclusion was drawn by Kidson and Thompson (1998) that, although statistical and dynamical methods have comparable skill in estimating daily and monthly anomalies of temperature and rainfall, the statistical technique requires considerably less computational effort and thus is preferable for many applications. However, Hay and Clark (2003) showed that statistical downscaling performed better than dynamic downscaling to capture the daily variability of temperature in three mountainous basins in the western United States. Application of the downscaled climate data as an input in hydrologic model demonstrated that in a snowmelt-dominated basin where the variability of runoff is much more strongly controlled by daily variations in temperature rather than precipitation, statistical downscaling based simulations were capable to represent the daily runoff more accurately than those of dynamic downscaling. Again the findings from Murphy (1999) indicate that, although dynamical and statistical models were found to produce similar skill when applied under present climate conditions, prediction for future period showed large differences in the climate change scenarios produced by two models (Murphy, 2000). Mearns et al. (1999) also identified the analogous findings by showing substantial differences in future seasonal cycle of mean temperature derived by the RegCM2 and a semi-empirical statistical model.

This present study considers Bangladesh as one of its study areas and this paragraph provides some examples of downscaling studies conducted in this region. Being located at the confluence of the Ganges, Brahmaputra and Meghna (GBM) rivers, Bangladesh is a disaster-prone country and suffers from floods, tropical cyclones, storm surges, coastal erosion and droughts (Ali, 1999; Mirza, 2002). Geomorphological conditions, geographic location, the low-lying elevation from sea level, high population density and other issues have made Bangladesh one of the most vulnerable countries in combatting the challenges of climate change and global warming (Al-Amin et al., 2013). Climate change is likely to exacerbate the frequency and intensity of climatic hazards especially floods, frequent storms, sea level rise and heat waves (Kim et al., 2014; Mirza, 2002; Younus, 2013; Harmeling, 2008; Ali, 1999) among others. The IPCC warns about the exposure of the mega delta of GBM basins to a greatest risk of increased floods and variability of water availability induced by climate change (IPCC 2007, 2014). The adverse effects on the hydrology and water resources of the GBM basins ultimately have the potential to lead to more serious floods

in Bangladesh threatening its agrarian economy leaving especially coastal regions of Bangladesh most susceptible to climate change-induced impacts, like sea-level rise, increased storm damages, loss of wetlands, salinity intrusion (Dasgupta et al. 2015; Rakib et al. 2019). Examples of downscaling studies in Bangladesh include the studies by Rahman et al. (2015) and Nury and Alam (2013), both of which used SDSM for downscaling the weather variables. The first study applied SDSM to downscale maximum and minimum temperature and precipitation over eight hydrological regions in Bangladesh. In this study, the projection under A2 emission scenario of HadCM3 shows an increasing trend in average monthly maximum and minimum temperature with respect to the base period. This study shows that the dry season will become warmer and high temperature zone will shift from the northern region to the southwest region. The latter study was conducted in the north-eastern region of Bangladesh to investigate the performance of SDSM to downscale rainfall and temperature using the predictors of HadCM. A recent study by Shahriar et al. (2021) presented downscaling daily mean temperature and precipitation under different scenarios of three GCMs, namely HadCM3, CanESM2, and CGCM3 in the south-eastern region of Bangladesh. Some other recent studies include Alamgir et al. (2019), which studied spatiotemporal changes in annual and seasonal temperatures of Bangladesh by downscaling of Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs using SVM. This study predicted a rapid rise in temperature in the northern part of Bangladesh, which is already historically observing temperature extremes, and thus further rise in temperature may result in an increased frequency of temperature-related extremes in that region.

Besides statistical downscaling, RCM has also been used in some studies to perform regional simulations of rainfall and temperature scenarios in Bangladesh (e.g., Islam et al., 2008; Islam, 2009b; Rajib and Rahman, 2012; Rahman et al., 2012). The RCM called Providing REgional Climates for Impacts Studies (PRECIS) was used in some studies for simulating of high resolute regional-scale climatology in Bangladesh. In this context, Islam (2009b) suggested that although the PRECIS simulated outputs are not directly useful for application purposes, after performing appropriate calibration with observations acceptable results are achievable. Islam et al. (2008) investigated the performance of grid-to-grid and point-to-point basis calibration methods for PRECIS. In the grid-to-grid basis method, observational data collected at all locations are gridded using the Kriging average technique while in point-to-point basis method the observed data at a particular site is considered as the representative of that location. It was found that the

regional analysis with grid-to-grid method provided an overestimation of PRECIS due to asymmetric low-density data network of weather stations in Bangladesh. On the other hand, better performance of PRECIS was achieved when model data was extracted using point-to-point method. Rouf et al. (2011) assessed the past, present and future pattern of temperature and rainfall in Bangladesh based on MRI-AGCM, which is a very high resolution Atmospheric Ocean General Circulation Model (AOGCM) with the horizontal grid size of about 20 km developed by the Meteorological Research Institute and Japan Meteorological Agency. The calibration of MRI-AGCM was performed on point-to-point basis and the projections were made for near future (2015-2034) and future (2075-2099) periods in two disaster prone areas over north-western and south-western parts in Bangladesh. The projection indicates that the mean temperature in Bangladesh is expected to rise at a much higher rate than present time during both near future and future periods and the rate of increasing is slightly higher at the stations located in north-western zone than those in south-western zone.

2.3 Multisite generation processes of climate variables

As the present study focuses on multisite downscaling techniques, the recent advances in multisite simulation of weather variables are outlined in the following two subsections and listed in Table 2.1. It should be mentioned that all the multisite modeling approaches that are described here may not deal with climate change. Because multisite generation approach simulates time series of weather variable depending on the properties extracted from the segments of historical data. Thus the multisite generation approaches without linked to climate model outputs or atmospheric predictors of climate models do not incorporate climate change features, as the climate change signal is not ascribed.

2.3.1 Multisite generation of precipitation

This section mainly encompasses the studies related to multisite simulation of precipitation. Wilks (1998) developed a stochastic weather generator for simultaneous simulation of precipitation occurrence and amounts at multiple sites. In this stochastic model the spatial correlation structure was imparted through the use of serially independent but spatially correlated random numbers. However, Wilks approach requires the development of empirical curves to link the random number correlations with precipitation occurrence and amounts for all possible pairs

of stations and for each month. The procedure of constructing the curves has made this approach computationally intensive and difficult to use specially for a network of large number of stations despite its potentials to reproduce the main statistics of multi-site precipitation processes adequately. However, the computational burden associated with Wilks approach was circumvented in the study by Brissette et al. (2007), which was conducted for the stochastic generation of precipitation at multiple locations. In fact, this study followed Wilks approach but involved automatic determination of correlation matrix of random numbers instead of drawing the empirical curves for all possible station pairs used in Wilks approach. The suggested method in Brissette et al. (2007) is simpler, but was found to perform well for reproducing the correlation structure of precipitation at multiple sites. In a separate study by Wilks (1999a), a stochastic model was used to downscale daily precipitation by means of disaggregating precipitation statistics from area-average to individual constituent station. The procedure involved the characterization of the precipitation climate in terms of a set of few stochastic weather model parameters. The relationships between the parameters representing the features of weather series at different spatial scales were used to disaggregate the precipitation statistics from large to local scales.

Wilby et al. (2003) involved two distinct steps for multi-site downscaling of daily precipitation, where the first step constituted the generation of a ‘marker’ precipitation series for areal average amounts across multiple sites conditional on a set of large-scale atmospheric predictor variables; and the second step employed the resampling of observed daily precipitation from constituent sites, conditional on the downscaled precipitation series of the marker site. In this study, three sets simulation methods were performed: (1) a deterministic model in which daily precipitation occurrence and amounts are conditioned by atmospheric predictor variables (2) a hybrid model combining regression based deterministic model and stochastic components and (3) an unconditional procedure involving random sampling of daily precipitation amounts with replacement. Application of these methods over Eastern England and the Scottish Borders region showed that deterministic model underestimated the variance of daily precipitation amounts and N -day totals, and over-estimated observed autocorrelation with poor representations of spatial dependency. On the other hand, unconditional resampling procedure was able to reproduce the distribution of daily amounts and inter-site correlations, but yielded poor representations of N -day exceedances for large N . However, the hybrid procedure explored the opportunity to overcome the weaknesses associated the deterministic model and stochastic resampling approaches and

produced better results than the remaining two. Another study conducted by Harpham and Wilby (2005) compared three downscaling models for heavy daily precipitation occurrences and amounts at multiple sites. These are: a Radial Basis Function (RBF) ANN, Multi Layer Perceptron (MLP) ANN, and a conditional resampling method (SDSM). In that study, the ANNs produced better result than SDSM for most of the indices related to seasonal-series of heavy precipitation but it overestimated the inter-site correlations for the precipitation amounts. Although SDSM provided better results for the inter-site correlation and daily precipitation quantiles than ANNs, but convective precipitations were not well reproduced by it.

Fowler et al. (2000) developed a single site rainfall model using a semi-Markov based weather generator coupled with Neyman Scott Rectangular Pulses (NSRP) stochastic model. The model was further extended by Fowler et al. (2005) to allow multi-site generation of rainfall in order to accurately represent the rainfall statistics at several sites simultaneously along with reproducing their spatial consistency. In this procedure the multi-site stochastic model first generates a uniform spatial-temporal NSRP model with different parameters corresponding to distinct weather states and then a scale factor is applied to the time series of each site depending on the particular weather state. Here, Monte-Carlo simulation and sampling techniques were combined to produce long synthetic rainfall series at multiple sites preserving the monthly cross-correlation statistics. Although the suggested methodology allows for a spatially varying mean and variance; with a uniform standard error, the autocorrelation and dry period probabilities remain uniform. This assumption of uniformity of dry period probabilities restrict its usefulness only for small region, where rainfall does not vary significantly with orography. In order to develop the multisite generation model for daily precipitation Khalili et al. (2007) introduced the concept of spatial autocorrelation, which is the correlation between values of a single variable through space. The proposed approach was based on the use of the spatial moving average process and weather generator approach. Here, the spatial moving average process was used for generating spatially autocorrelated random numbers to be used in a stochastic weather generator in order to reproduce the observed daily spatial autocorrelations in the synthetic precipitation processes. Application of the suggested method at the stations located in Canadian province of Quebec showed that it was able to simulate the precipitation processes accurately in terms of preserving daily spatial autocorrelations and monthly interstation correlations but failed to preserve the spatial intermittence property.

Table 2.1 Examples of studies involving multisite generation processes.

Authors	Method/Technique	Region	Predictand
Abbasian et al. (2020)*	Generalized Hierarchical Linear Model	Iran	Precipitation
Buishand and Brandsma (2001)	K-nearest-neighbor resampling	German	Precipitation
Brissette et al. (2007)	Stochastic weather generator	Canada	Precipitation
Charles et al. (1999a) *	Nonhomogeneous hidden Markov model	Australia	Precipitation
Chandler (2020)	Weather generation using generalised linear models	Iberia	Precipitation Temperature
Fowler et al. (2005) *	Semi-Markov based weather generator, conditioned by weather type	UK	Precipitation
Harpham and Wilby (2005)*	Artificial Neural Network, Conditional resampling	England	Precipitation
Hughes et al. (1999)	Nonhomogeneous hidden Markov model	Australia	Precipitation
Hundecha and Bardossy (2008)*	Multiple linear regression and multivariate autoregressive approach	German	Precipitation Temperature
Jeong et al. (2012)*	Multivariate multiple linear regression, Stochastic weather generator	Canada	Precipitation
Jeong et al. (2013) *	Multivariate multiple linear regression	Canada	Temperature
Khalili et al. (2007)	Weather generator Spatial autocorrelation	Canada	Precipitation
Khalili et al. (2011b)*	Multiple regression and Spatial moving average	Canada	Temperature
Khalili and Nguyen (2012, 2018)*	Multiple linear regression Singular value decomposition Quantile mapping, Stochastic weather generator and Empirical Copula	Canada North China	Temperature Precipitation Temperature
Li and Babovic (2019)*	K-nearest-neighbor based nonparametric nonhomogeneous hidden Markov model	Australia	Precipitation occurrence
Mehrotra and Sharma (2005)*	Kernel probability density estimation based nonparametric nonhomogeneous hidden Markov model	Australia	Precipitation
Mehrotra and Sharma (2006b)*	Stochastic generation-modified Markov model	Australia	Precipitation
Mehrotra and Sharma (2010)*	Circulation-typing approach, First-order Markov chain	Spain, Italy	Precipitation Temperature
Palutikof et al. (2002)*	Multiple linear regression		
Rahman and Nguyen (2022)*	Singular value decomposition and Multivariate Auto Regressive	Bangladesh	Temperature
Srinivas et al. (2013)*	least-square support vector machine	India	Temperature
Su et al. (2020)*	Stochastic Weather Generators and modified shuffle procedure	Huangfuc-huan Basin	Precipitation

Sun and Lan (2021)*	Convolutional neural network, Generalized Linear regression, Quantile mapping	China	Precipitation Temperature
Yang et al (2005)	Generalized linear models	England	Precipitation
Yang et al (2019)*	Quantile mapping reordering and the cumulative distribution function transform method	China	Precipitation Temperature
Wilby et al. (2003)*	Regression based deterministic model, Semi-stochastic, Unconditional resampling	England and Scotland	Precipitation
Wilks (1998)	Stochastic weather generator	New york	Precipitation
Wilks, (1999)	Stochastic weather generator	USA	Precipitation

* denotes the studies which dealt with downscaling procedures

The method of nearest-neighbor resampling method has been used in some studies for simulating the weather variables at multiple locations (e.g., Buishand and Brandsma, 2001; Mehrotra and Sharma, 2005 etc. among others). In the study by Mehrotra and Sharma (2005) the K-nearest-neighbor (KNN)-based nonparametric nonhomogeneous hidden Markov model (NNHMM) was developed in order to downscale precipitation occurrence at a network of 30 stations in Australia. Here the rainfall occurrence was generated depending on the average rainfall occurrence of previous day and continuous weather state, which is conditional to the previous day weather state and selected atmospheric variables. The spatial distribution was defined in terms of an areal averaged value of precipitation occurrence at stations and relative location of the station from a fixed origin. In a further study conducted by Mehrotra and Sharma (2006b), kernel probability density estimation (KDE) based NNHMM approach was implemented to downscale both precipitation occurrence and amounts at the stations over the same region. Here, at site rainfall occurrences were downscaled by involving the use of NNHMM, while nonparametric KDE approach was adopted to downscale rainfall amounts on the wet days. Some other studies explored the use of generalized linear models (GLMs) to generate precipitation sequences at individual as well as multiple sites. For example, Yang et al (2005) illustrated the application of GLM for multisite simulation of rainfall. In this study, a GLM was fitted with appropriate incorporation of intersite dependence structure that enables the simulation of multisite sequences of rainfall with realistic joint distributional properties. Some other examples of application of GLM include the studies conducted by Chandler and Wheeler (2002), Chandler (2005), etc. An overview of Nearest-neighbor resampling, NHMM and GLM along with other methods, as well as the developments in downscaling techniques, their skills and gaps were elaborately discussed by Maraun et al. (2010).

In a latter study, Chandler (2020) presented a methodology for simulating daily weather variables at multiple locations based on generalised linear models and weather generation. In that method the local weather structures like spatial, temporal, and inter-variable dependencies were represented by multivariate weather generation. This methodology was implemented in a software tool called Rglimclim.

In a study by Jeong et al. (2012), a hybrid statistical downscaling procedure was developed, combining regression based and stochastic weather generation approaches for multisite downscaling of daily precipitation. In that study Multivariate Multiple Linear Regression (MMLR) was used to obtain the deterministic series of daily precipitation occurrence and amount, while multivariate normal distribution, the first-order Markov chain model, and the probability distribution mapping technique were used for reproducing temporal variability and spatial dependency among the stations. Here, the stochastic weather generating technique was employed for complementing the unexplained temporal variability and spatial dependency of the MMLR. Although this method was found capable to capture the temporal variability and spatial dependency among many stations, it overestimated lag1 auto-correlations of precipitation occurrences and slightly underestimated cross-site correlation coefficients of precipitation amounts. Mehrotra and Sharma (2010) proposed a stochastic multisite downscaling framework of daily rainfall occurrences and amounts at a network of 45 rain gauges around Sydney, Australia. Here rainfall occurrences were modeled using a variation of the stochastic generation-modified Markov model, in which the exogenous atmospheric predictors and local low frequency variability indicators were used to preserve year-to-year variation and reproduce the extreme events. At site rainfall amounts on wet days were simulated using a KDE based approach, whereas, spatial dependence in rainfall occurrence and amounts was preserved by using spatially correlated and serially independent random numbers.

Some recent studies include Su et al., 2020, which proposed a multi-site downscaling method for downscaling daily precipitation from GCM-Based monthly data using stochastic weather generators, CLIGEN (CLimate GENerator) and modified shuffle procedure to reconstruct the spatial correlation. Application to ten stations in arid to semi-arid Huangfuchuan Basin showed the model was capable to produce the inter-station correlation among the stations and daily, monthly, and annual precipitation accurately. Abbasian et al. (2020) proposed a Generalized Hierarchical Linear Model (GHLM) to downscale precipitation at multiple sites in Lake Urmia

basin in northwestern Iran. GHLM was an extension of generalized linear model and is structured into data level and group level. Here, data level explained precipitation variability at stations, i.e., precipitation variability at stations while precipitation variability between sites were described at group level. Basu and O'Connor (2020) applied a support vector regression (SVR)-based downscaling approach to downscale rainfall at several locations in Ireland, and compared with relevance vector machine and deep learning based downscaling techniques. This study suggested that the rainfall generation mechanisms are not same for all the sites and hence, same rainfall generation mechanism should not be used for all the sites. Thus, this study proposed dividing the study area into several climatological regions and developing different downscaling models for each of the climatological regions.

2.3.2 Multisite generation of temperature series

This section provides the examples of the studies which include the multisite downscaling of temperature series (sometimes with other weather variables). Palutikof et al. (2002) downscaled daily temperature and precipitation series at several locations in Mediterranean catchments. In the study by Palutikof et al. (2002), at first the precipitation occurrence was generated based on a circulation-typing approach combined with a conditional first-order Markov chain. After that, the rainfall scenarios at multiple sites were constructed by sampling from a benchmark file containing the information on observations at multiple sites, circulation weather type and the status of dry or wet day at the reference station. And at last, the temperature scenarios were constructed using deterministic transfer functions initialized by free atmosphere variables and depending on the wet and dry days. Hindecha and Bardossy (2008) implemented multiple linear regression and multivariate autoregressive approach to downscale precipitation and temperature at multiple locations in German part of Rhine basin. Here, the multiple linear regressions were used to downscale the seasonal indices of precipitation and temperature from seasonal measures of a set of large-scale predictors, where each index was expressed as a linear function of the principal components of potential large-scale predictors. The multivariate autoregressive approach was applied to generate daily series of weather variables at multiple locations simultaneously maintaining their spatial covariance structure. In this study, the temperature was downscaled based

on large-scale atmospheric circulation patterns as well as the precipitation status on the same day and the temperature on the previous day.

Example of other studies includes multi-site multivariate statistical downscaling approach proposed by Khalili et al. (2011b), where daily maximum and minimum temperature at many locations were downscaled simultaneously. In that study spatial moving average method was used to simulate the stochastic components of multiple regression models. Khalili et al. (2011b) showed that the proposed multi-site statistical downscaling approach was capable to accurately describe various characteristics of maximum and minimum temperature including their spatial and temporal variation. Moreover, comparison of the results indicated that the suggested statistical downscaling approach was able to describe the spatial and temporal characteristics of extreme temperature series at the regional scale better than the Canadian Regional Climate Model (CRCM). The characteristics of daily temperature series were well addressed by Jeong et al. (2013), where a statistical downscaling model was proposed for simultaneous downscaling of daily maximum and minimum temperature at multiple sites. Here MMLR was used to construct the deterministic part of the model making the relationship with large-scale atmospheric variables. Spatial correlation structure of maximum and minimum temperatures, and at-site temporal correlation between maximum and minimum temperatures were preserved by adding the spatially correlated random numbers as unexplained variance of the predictands. Srinivas et al. (2013) used a least-square support vector machine (LS-SVM)-based methodology for multi-site downscaling of daily temperature series in the catchment of Beas river basin, India. This study involved clustering of the sites based on correlation structure of the predictands. In each cluster one representative site was selected at which downscaling of large-scale atmospheric predictor variables was performed at monthly time scale. Then the downscaled monthly information was translated from the representative site to other remaining sites using LS-SVM inter-site regression relationships. The monthly information was further transformed to daily time scale using KNN disaggregation methodology. The method was found effective in downscaling the maximum and minimum temperature at daily time scale maintaining the correlation structure among stations and produced comparable results with those two downscaling methods proposed Jeong et al. (2013) and Khalili et al. (2011b).

In a more recent study by Yang et al. (2019) four statistical downscaling techniques, such as, bias-correction and spatial downscaling (BCSD), bias-correction and climate imprint (BCCI), and

bias correction constructed analogues with quantile mapping reordering (BCCAQ), and the cumulative distribution function transform (CDF-t) method were evaluated for precipitation and surface temperature. Here, the quantile mapping based techniques were better capable than CDF-t to produce spatial correlation; and BCSD was found to perform better for frequency distributions of daily temperature, precipitation, but showing larger biases in temperature-related extremes. Li and Babovic (2019) proposed a hybrid multi-site multivariate downscaling model combining quantile mapping (QM), stochastic weather generator (WG) and Empirical Copula (EC) approaches for temperature and precipitation. In this model, the QM was used for downscaling the monthly large-scale climate model outputs to a finer scale; WG was used for temporal downscaling of monthly data to daily data; and EC was applied to incorporate the observed inter-site, inter-variable dependencies as well as the temporal persistences in the simulated series. The methods proposed by Li and Babovic (2019) were further applied by Li, et al. (2019) to predict the projected changes in precipitation and temperature in Singapore. Projection for periods 2021–2050 and 2071–2100 under two emission scenarios, such as representative concentration pathway RCP 4.5 and RCP8.5 scenarios indicated an increase in average temperature of daily maximum and minimum temperatures. Sun and Lan (2021) used Convolutional neural network (CNN) models of different configurations to downscale daily temperature and precipitation in China and compared with Generalized Linear regression Model (GLM) and two quantile mapping based techniques including bias correction and spatial disaggregation (BCSD); and bias correction and climate imprint (BCCI). CNN performed better than GLM in reproducing seasonal cycle of temperature and frequency distributions of daily precipitation and has a better potential for downscaling application over a large region. However, bias correction methods captured temporal correlations better than other models especially for precipitation.

Examples of other recent multisite multivariate downscaling studies include the statistical procedure by Khalili and Nguyen (2012, 2018) for downscaling of daily temperature extremes using a combination of a multiple regression model and the Singular Value decomposition (SVD) technique. This method was further applied by Rahman et al. (2013) to daily temperature extremes in Bangladesh, which represents completely a different climatic condition from Canada. Further, a more general multisite downscaling method was proposed by Rahman and Nguyen (2022), which applied the multivariate autoregressive (MAR) model combined with the SVD technique for the modeling the space-time variabilities of daily extreme temperature processes more

effectively. In a later study by Rahman and Nguyen (2024) this method was applied to compare the accuracy of multisite downscaling techniques in snowmelt estimation over single-site downscaling in the southern Quebec-Ontario region in Canada.

Although several multisite downscaling methods have been developed, the preponderance of existing multisite downscaling studies is about the downscaling of precipitation processes. Moreover, very few studies have compared the accuracy of multisite and single-site downscaling in real-world applications. While most of the existing research focused on evaluating how well these methods captured the observed spatio-temporal characteristics of weather variables, there has been little emphasis on comparing the practical usefulness of multisite downscaling in impact assessments (Rahman and Nguyen, 2024). Therefore, more research is needed to evaluate the advantages of multisite downscaling for climate-related impact modeling and decision-making.

Chapter 3

METHODOLOGY

This study presents statistical methods of multisite multivariate downscaling of daily extreme temperature series, which is capable to downscale GCM outputs at many locations simultaneously reproducing the spatial dependence among them. The proposed approach consists of a combination of multiple regression models to represent the linkage between global climate predictors and local T_{max} and T_{min} series, and singular value decomposition and multivariate autoregressive model (SVD-MAR) to describe the observed statistical properties of the regression model stochastic components. Besides this approach, another multisite multivariate statistical downscaling technique has been suggested, which is a combination of multiple linear regression and multivariate stochastic model (MSM). This chapter provides detailed methodology for each of the proposed Multivariate Statistical Downscaling (MMSD) procedures. At first the conceptual approach for MMSD procedures is presented and then detailed description of each step is provided for both of the methods. The proposed MMSD methods have been applied to two sets of daily temperature data obtained from two networks of weather stations located in two different climatic regions: southern Quebec-Ontario region in Canada and Bangladesh. Descriptions of both data sets are given in this chapter.

3.1 Conceptual approach for MMSD procedures

A conceptual approach of the MMSD procedures is illustrated by a schematic diagram in Figure 3.1. The conceptual diagram is generalized for each of two proposed MMSD methods. The fundamental concept of MMSD is that, large-scale atmospheric variables are related to local scale temperature through a statistical model, in which large-scale GCM simulations are used as inputs (or “predictors”) to downscale the local scale temperature (or “predictands”) at many sites concurrently.

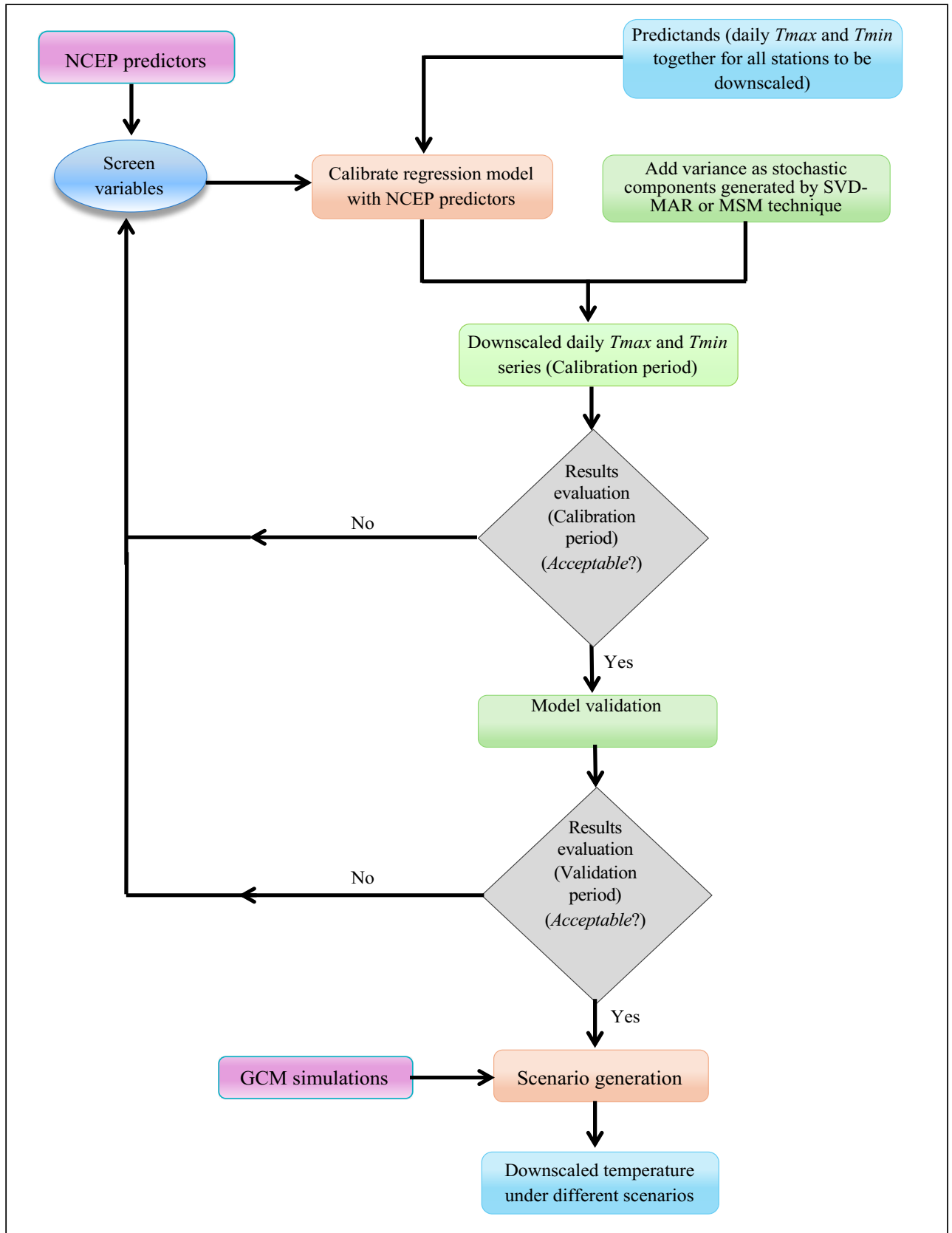


Figure 3.1: Conceptual approach for MMSD procedures.

The proposed MMSD models consist of two components: deterministic components and stochastic components. The deterministic part involves building the quantitative relationship between global climate predictors and local T_{max} and T_{min} series. In this study multiple linear regression was used to formulate the deterministic part of the model. In this case, few significant variables from a set of 26 large-scale predictors were selected to use as the representative explanatory variables in regression models. The residuals in the regression model are the stochastic components of the downscaling models, which represent the unexplained variance of the predictands. In this present study, two different techniques for generating the stochastic components have been proposed. These are: (i) combination of singular value decomposition and multivariate autoregressive model (hereafter referred as SVD-MAR) (ii) multivariate stochastic model (hereafter referred as MSM).

The available dataset was split into two halves. One-half of the observed temperature records were used for estimating the regression parameters during calibration period. The other half was used as an independent dataset representing an “unknown” climate for model validation purposes. The performance of the model was tested by comparing the simulated results with the observations during both calibration and validation periods. In Figure 3.1 it has been shown that, proceed to next step from calibration to validation, and validation to scenario generation was performed only if the model was found capable to produce acceptable results by preserving the observed basic statistical properties of daily temperature in downscaled series at each step. Otherwise, iteration was made from very early stage of the model starting with re-screening of the predictor variables (Figure 3.1).

In downscaling process, the standard procedure is to calibrate the downscaling model with observed coarse-resolution large-scale climate variables before generating climate scenarios with GCM simulations. In this study the variables of US National Center for Environmental Prediction (NCEP) reanalysis data have been used as observed large-scale climate variables which have been described below. Hence, at first the proposed MMSD models were calibrated using NCEP predictors. After the calibration with NCEP predictors, the synthetic series of daily T_{max} and T_{min} for current and future periods was generated using the GCM simulations. Daily temperature series was generated under four scenarios from two CGMs (A1B and A2 scenarios from CGCM, and A2 and B2 scenarios from HadCM).

Each of the proposed MMSD procedures was applied separately to two sets of daily temperature data, i.e., the southern Quebec-Ontario region in Canada and Bangladesh. Description of the predictors and predictands and details of each step of the MMSD procedures are provided in the following subsections.

3.2 Description of predictors and predictands

This section provides the description of predictors (large-scale climate variables) and predictands (local scale climate variables) used in this study.

3.2.1 Large-scale climatic variables (Predictors)

NCEP reanalysis data (Kistler et al., 2001; Kalnay et al., 1996) has been used as observed large-scale climate variables (i.e., predictors) in this study. NCEP provides a set of 26 atmospheric predictor variables, which are given in Table 3.1. The NCEP predictors are available for the period of around 1961 to 2001 and are normalized with respect to the period 1961 to 1990 to avoid systematic biases contained within the variables.

Table 3.1 List of atmospheric variables of NCEP re-analysis data.

Variable		Level of measurement	
Mean sea level	Surface		
Geopotential height		500 hPa	850 hPa
Airflow strength	Surface	500 hPa	850 hPa
Zonal velocity	Surface	500 hPa	850 hPa
Meridional velocity	Surface	500 hPa	850 hPa
Vorticity	Surface	500 hPa	850 hPa
Wind direction	Surface	500 hPa	850 hPa
Divergence	Surface	500 hPa	850 hPa
Specific humidity*	Near surface	500 hPa	850 hPa
Relative humidity*	Near surface	500 hPa	850 hPa
Precipitation*			
Air temperature	2m above surface		

*Specific humidity at levels of 500 hPa and 850 hPa and precipitation are available only for the NCEP interpolated on CGCM grid. Relative humidity is available only for the NCEP interpolated on HadCM grid.

CGCM and HadCM models are credible GCMs recognized in model intercomparison studies, such as the Coupled Model Intercomparison Project (CMIP), due to their ability to

simulate current climate behavior and project future climate change. Both CGCM and HadCM models are widely used in the climate science community. In present study two independent GCMs, namely: CGCM3.1 (Canadian Centre for Climate Modelling and Analysis (CCCma) Coupled Global Climate Model, version 3.1) and HadCM3 (UK Hadley Centre Coupled Model, version 3) have been used. As mentioned before the downscaling model was calibrated with NCEP reanalysis data before generating climate scenarios with GCM simulations. In this regard, variables of the NCEP reanalysis data need to conform to the grid size of corresponding GCM simulations. Hence, NCEP daily predictors have been re-gridded, i.e., interpolated on the two respective GCMs (CGCM and HadCM) grids. The sizes of grid boxes are defined as 3.75° lat. $\times$ 3.75° lon. and as 2.5° lat. $\times$ 3.75° lon. respectively for CGCM and HadCM (DAI CGCM3 Predictors 2008). Overlays of the grid cells of two GCMs are shown in Figures 3.2 and 3.3 for the southern Quebec-Ontario region and Bangladesh respectively.

In this study, temperature scenarios were generated under four SRES scenarios (Special Report on Emission Scenarios) of IPCC (Nakic'enovic' et al., 2000). Details about the emission scenarios are given in IPCC and a very short description of those is as follows: There are four qualitative storylines yielding four sets of scenarios called "families": A1, A2, B1, and B2. The A1 storyline and scenario family represents a converging future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter with a substantial reduction in regional differences in per capita income. The CO² emission is highest compared to other storylines resulting in a rapid global warming. The A1 scenario family develops into three groups distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B), which means, not relying too heavily on one particular energy source. The A2 storyline and scenario family describes a very heterogeneous world where economic development is primarily regionally oriented. Here per capita economic growth and the technological changes are more fragmented and slower than in other storylines causing high to medium degree of CO² emission. The B1 storyline and scenario family describes a convergent world with the same global population as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy with the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability without additional climate initiatives. The CO² emission is low compared to other storylines with a slower rate of global warming. The B2 storyline and scenario

family describes a world with continuously increasing global population at a rate lower than A2. It represents intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines emphasizing on local solutions to economic, social, and environmental sustainability. The CO₂ emission is low to medium in this storyline.

3.2.2 Local scale observed variables (Predictands)

The feasibility and effectiveness of the proposed MMSD procedures have been evaluated using two sets of daily temperature data obtained from two networks of weather stations located in two completely different climatic regions. One region is southern Quebec-Ontario in Canada representing cold climate, whereas the other region is Bangladesh representing tropical to subtropical climate. Daily extreme temperature series, that means, daily *T_{max}* and *T_{min}* from seven and four weather stations located respectively in the southern Quebec-Ontario region and Bangladesh have been used as predictands. It should be mentioned that Bangladesh is one of the most vulnerable countries to climate change and global warming. Being geographically located at the confluence of the GBM basins and in a low-latitude region, the coastal regions of Bangladesh, prone to natural disasters, are especially susceptible to climate change-induced impacts. The monsoon of Bangladesh is heavily influenced by the monsoon circulation pattern and the southwest monsoon accounts for most of the country's annual precipitation from June to September contributing to widespread flooding. In the context of downscaling, a model that performs well in one region might not be feasible for another region due to inherent differences in the climatic conditions of different regions. Hence, the proposed MMSD models were applied to temperature data from two climatic regions to assess the robustness of the downscaling techniques and their consistency in providing accurate results in different climate regions.

Figure 3.2 and Table 3.2 represent the name and geographical information of the selected seven weather stations located in the southern Quebec-Ontario region of Canada. It can be observed from Table 3.2 that seven stations are located on a varying altitude ranging from 21 to 188.6 meters above mean sea level. Daily series of *T_{max}* and *T_{min}* for the period of 1961 to 1990 of those seven weather stations were selected as predictands. Daily temperature data for the period 1961-1975 was used for calibration while the period 1976-1990 was used for validation purposes. The observed temperature data were collected by Environment and Climate Change Canada

(ECCC), which is the responsible organization for archiving the historic weather records in Canada and were available through Data Access Integration (DAI) portal.

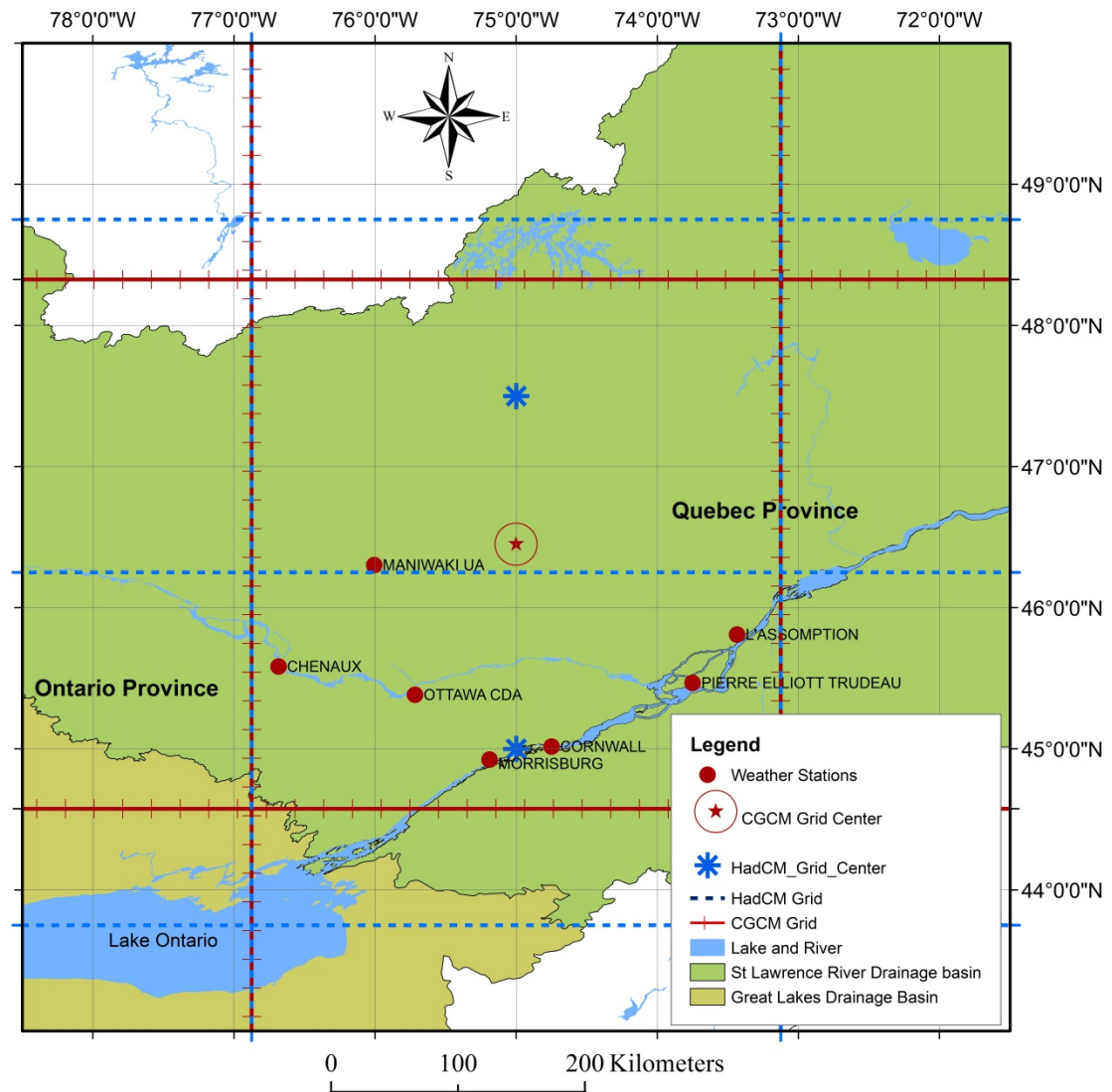


Figure 3.2: Study area with the location of selected seven weather stations in the southern Quebec-Ontario region in Canada and GCM grids.

Table 3.2 Name and coordinates of selected seven stations in the southern Quebec-Ontario region in Canada.

Station No	Station name	Province	Latitude	Longitude	Altitude (meters above sea level)
Station 1	L'Assomption	Quebec	45.81 ⁰ N	73.43 ⁰ W	21
Station 2	Montreal Pierre Elliotte Trudeau Intl A (Dorval)	Quebec	45.47 ⁰ N	73.75 ⁰ W	36
Station 3	Chenau	Ontario	45.58 ⁰ N	76.68 ⁰ W	84.1
Station 4	Maniwaki UA	Quebec	46.30 ⁰ N	76.0 ⁰ W	188.6
Station 5	Cornwall	Ontario	45.02 ⁰ N	74.75 ⁰ W	64
Station 6	Ottawa CDA	Ontario	45.38 ⁰ N	75.72 ⁰ W	79.2
Station 7	Morrisburg	Ontario	44.92 ⁰ N	75.19 ⁰ W	81.7

Source: ECCC

Name and geographical information of selected four stations in Bangladesh are presented in Figure 3.3 and Table 3.3. As indicated in Table 3.3, all of four stations are located on the low and flat land in Bangladesh. Twenty year (1981-2000) temperature data from these four weather stations archived by Bangladesh Meteorological Department (BMD) in Bangladesh were used as predictands. The period from 1981 to 1990 was used for model calibration and 1991 to 2000 was used for model validation purposes. Generally, in Bangladesh it is difficult to obtain consistent long-term homogeneous temperature datasets for all the BMD stations due to large number of missing data and/or other reasons. Hence, the number of meteorological stations having long records of historic data with very few missing data and acceptable accuracy was limited for performing an accurate spatiotemporal analysis. As this present study considers downscaling of temperature at many sites simultaneously, it requires temperature records over a concurrent time period for all the stations to be downscaled. The period from 1981 to 2000 was selected because there are fewer missing data in this period for all four stations considered in this study.

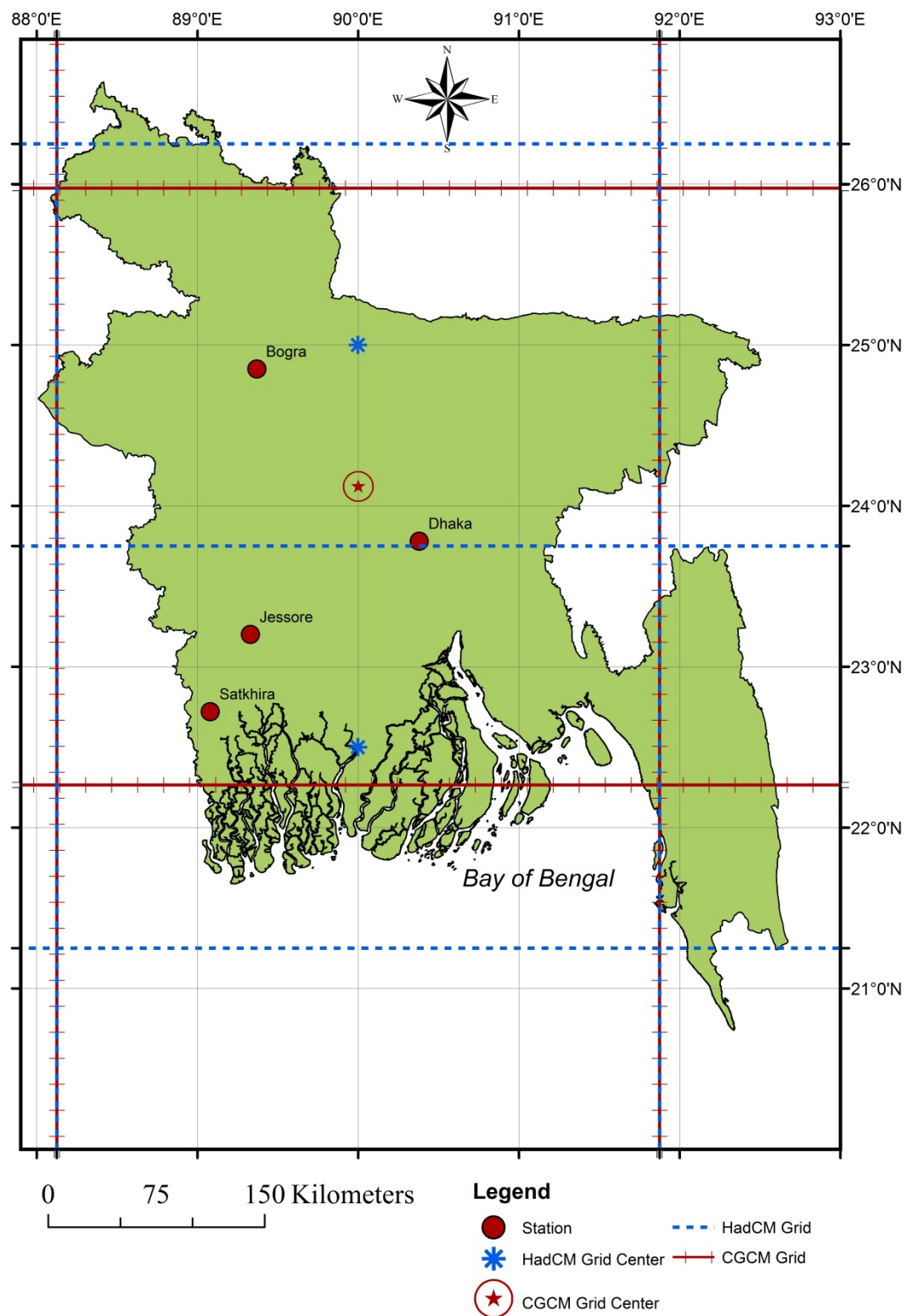


Figure 3.3: Study area with the location of selected four weather stations in Bangladesh and GCM grids.

Table 3.3 Names and coordinates of selected four weather stations in Bangladesh.

Station No	Station Name	Latitude	Longitude	Altitude (meters above sea level)
Station 1	Bogra	24.85 ⁰ N	89.37 ⁰ E	17.9
Station 2	Jessore	23.2 ⁰ N	89.33 ⁰ E	6
Station 3	Dhaka	23.78 ⁰ N	90.38 ⁰ E	6.5
Station 4	Satkhira	22.72 ⁰ N	89.08 ⁰ E	4

Source: Islam, 2009a

3.3 Selection of predictors

The predictor-predictand relationship is central to any statistical downscaling model. Hence, selection of the large-scale atmospheric predictors is an important step in order to obtain accurate estimation of climate change signals. It is one of the most challenging stages since the characteristics of the downscaled climate scenarios are largely determined by the selection of predictors (Winkler et al., 1997; Charles et al.; 1999b, Huth, 2004). However, there are no hard and fast rules for the selection of predictors. Selection of predictors is an iterative process, partly based on the user's subjective judgment and statistically judicious concern (Wilby et al., 2002). However, some studies (e.g., Hessami et al., 2008) used stepwise regression for the selection of significant predictors. The stepwise procedure is basically a sequence of tests for significance of explanatory variables at a predefined statistical significance level (McCuen, 2003). Partial correlation coefficient (discussed below) is another method for choosing the appropriate set of predictors (e.g., Wilby, 2002; Hessami et al., 2008). Other methods for selecting the predictors include Principal Component Analysis (PCA) with or without stepwise screening (e.g., Huth, 2002); Variable Importance in the Projection (VIP) scores obtained from Partial Least Square (PLS) regression (PLS-VIP method) (e.g., Ju Eun, 2012); N-way partial least squares regression (N-PLS) (e.g., Bergant and Kajfež-Bogataj, 2005) etc.

In the present study, predictors have been selected mainly based on partial correlation coefficient. However, subjective selections have been made in many cases. Partial correlation is the correlation between two variables after removing the linear effect of the third or more other variables. For any three variables denoted as i , j and k , the partial correlation between variable i and j while controlling for variable k is computed using Eq.3.1 (Afifi and Clark, 1996):

$$\rho_{ij,k} = \frac{\rho_{ij} - \rho_{ik}\rho_{jk}}{\sqrt{(1 - \rho_{ik}^2)(1 - \rho_{jk}^2)}} \quad \text{Eq.3.1}$$

Here, ρ_{ij} , ρ_{ik} and ρ_{jk} denote the correlation coefficient between i^{th} and j^{th} ; i^{th} and k^{th} ; j^{th} and k^{th} variables respectively; In partial correlation method, the significance of a predictor is determined through t-statistic having $N - Q - 2$ degrees of freedom, where N is the number of observations and Q is the number of variables adjusted for. The probability of the t-statistic, computed by Eq.3.2, indicates whether the observed correlation occurred by chance if the true correlation is zero. In this study, the partial correlation was computed by SPSS (Statistical Package for the Social Sciences) software package.

$$t = \frac{\rho (N-Q-2)^{1/2}}{\sqrt{(1-\rho^2)}} \quad \text{Eq.3.2}$$

A common problem in selecting the predictors is that some of the atmospheric predictors of NCEP re-analysis as well as GCM simulations have a high degree of correlations between them having the risk of confounding multicollinearity. Multicollinearity is a statistical phenomenon in which two or more explanatory variables in a multiple regression model are highly correlated, meaning that they are linearly dependent. In linear regression models, the estimated regression coefficients and variances could be unstable due to the presence of multicollinearity. Variance inflation factor (VIF) is one of the ways to detect multicollinearity in the predictor variables which is expressed as follows (Eq.3.3):

$$VIF_k = \frac{1}{1 - R_k^2} \quad \text{Eq.3.3}$$

Where, R_k^2 is the R^2 value obtained by regressing the k^{th} predictor on the remaining predictors. A VIF is 1, when $R_k^2 = 0$, which means that there is no correlation among the k^{th} predictor and the remaining predictor variables. On the other hand, VIF tends to ∞ , when $R_k^2 = 1$, meaning that the k^{th} variable is perfectly linearly related to the other predictor variables. The critical value of VIF_k is considered 10. VIF_k above 10 is an indication that the multicollinearity may be unduly influencing the least squares estimates (Neter et al., 1985).

The pattern of predictor-predictand relationship varies with different stations as well as different seasons. Moreover, this relationship is assumed to be valid under future climate conditions lying beyond the range of the calibration period. In this study, the predictors were selected for each of stations and for each month separately for T_{max} and T_{min} for better representation of site specific physiographic and temporal characteristics and thereby making predictor-predictand relationship more stable. After selecting a set of few significant predictors depending on the value of partial correlation for each station for each of the months, the VIF score was checked for each predictor if it was within the critical value. If any predictor was found with VIF score above 10, then the most inter-correlated variable(s) were removed from that set of predictors. Then again a new set of predictors were selected and the VIF scores were checked again.

Prior to selection of the predictors, two predictors variables such as near surface specific humidity and mean temperature at 2 m have been removed from NCEP predictors interpolated on CGCM grid. In case of NCEP interpolated on HadCM grid, three predictors such as near surface relative humidity, near surface specific humidity and mean temperature at 2 m were removed before selecting the predictors. This was done because these predictors are believed not to be properly represented by GCM simulations (Hessami et al., 2008).

3.4 Multisite multivariate statistical downscaling (MMSD) models

Both of MMSD methods presented in the study are basically based on multiple linear regression models. The concept of the first method is based on multiple linear regressions with the combination of singular value decomposition technique and multivariate autoregressive (SVD-MAR) model. The second method is combination of multiple linear regression and multivariate stochastic model (MSM). In fact, multiple linear regression models were used to build the direct quantitative linkage between global climate predictors and local T_{max} and T_{min} series. And, the SVD-MAR and MSM techniques have been applied to describe the observed statistical properties of the stochastic components of the downscaling model.

3.4.1 Regression model

Eq.3.4 represents the multiple linear regression model for daily $Tmax$.

$$\begin{pmatrix} Tmax_{i,m,1} \\ Tmax_{i,m,2} \\ \vdots \\ Tmax_{i,m,s} \end{pmatrix} = \begin{pmatrix} \alpha_{Tmax_{0,m,1}} \\ \alpha_{Tmax_{0,m,2}} \\ \vdots \\ \alpha_{Tmax_{0,m,s}} \end{pmatrix} + \begin{pmatrix} \sum_{j=1}^q \alpha_{Tmax_{j,m,1}} p_{Tmax_{ij,m,1}} \\ \sum_{j=1}^q \alpha_{Tmax_{j,m,2}} p_{Tmax_{ij,m,2}} \\ \vdots \\ \sum_{j=1}^q \alpha_{Tmax_{j,m,s}} p_{Tmax_{ij,m,s}} \end{pmatrix} + \begin{pmatrix} E_{Tmax_{i,m,1}} \\ E_{Tmax_{i,m,2}} \\ \vdots \\ E_{Tmax_{i,m,s}} \end{pmatrix} \quad \text{Eq. 3.4}$$

where, $Tmax_{i,m,k}$ is the maximum temperature on day i in month m and at station k from a network of s stations; $\alpha_{Tmax_{j,m,k}}$ is the j^{th} regression parameter for month m and at station k ; $p_{Tmax_{ij,m,k}}$ is the value of the j^{th} predictor, from a total of q monthly significant predictors, on day i in month m and at station k ; $E_{Tmax_{i,m,k}}$ is the residual value on day i in month m and at station k . Eq.3.4 is only for $Tmax$ but the similar representation is applicable for $Tmin$ as well.

Residual values in Eq.3.4 are the differences between the observed values at each station and the estimated ones obtained by the regression equation. After estimating the parameters during calibration period, the residuals were simulated by SVD-MAR and MSM, which are described in section 3.4.2. As the proposed methodology considers the simultaneous downscaling of $Tmax$ and $Tmin$, the general matrix of the residual values E is obtained by the concatenation of the matrices E_{Tmax} and E_{Tmin} as described in Eq.3.5 (Khalili and Nguyen, 2018). The elements of E_{Tmax} and E_{Tmin} are the residuals obtained for daily $Tmax$ and $Tmin$, respectively.

$$E = [E_{Tmax} \ E_{Tmin}] \quad \text{Eq.3.5}$$

3.4.2 Generating residual matrix

The residuals in the regression model in Eq.3.4 are the stochastic components of downscaling models. Usually only the deterministic components are not capable to account for all the predictand variance in downscaled series due to unexplained sub-grid scale or some other phenomena (Cannon, 2008). Therefore, in order to restore the level of observed variance in simulated series additional measures are needed. Some methods which have been used in previous studies for increasing the variance of predictand series include: inflation (e.g., Karl et al., 1990), randomization (e.g., Von Storch, 1999) and expansion (e.g., (Bürger, 1996, 2002) etc.

It can be noticed, that the deterministic parts of the proposed MMSD is simply multiple linear regression which has been performed independently for each of the stations and separately for the daily T_{max} and T_{min} . Thus this portion of the model does not differ from the single-site and univariate (i.e., downscaling either T_{max} or T_{min} at a time) downscaling models. In fact, local spatial and temporal variability are only partially captured by the large-scale variables. Rest of the spatio-temporal attributes inherent in daily temperature series at different locations are incorporated by reproducing the observed statistical properties in simulated stochastic components of the model. Hence, generating the stochastic elements independently for each station cannot adequately represent the spatial coherency among the stations. Therefore, while multivariate uncorrelated random variables can be generated independently by repeated application of the univariate generation techniques, the correlated multivariate random variables need to be generated simultaneously in order to preserve the correlation among them (Chandler, 2020, Haan, 2002). In this context, SVD-MAR technique and MSM are capable to generate the correlated residuals preserving the observed statistical properties in simulated series. Details description and steps for these two techniques are given in subsections 3.4.2.1 and 3.4.2.2.

3.4.2.1 Singular value decomposition and multivariate autoregressive model (SVD-MAR)

SVD is a useful statistical technique, which transform a large matrix into smaller matrices preserving some basic statistical properties of the original matrix. It is a generalization of the eigenvalue decomposition and has the advantages of decomposing any rectangular $m \times n$ matrix A into three matrices, such that (Green, 1978):

$$A = S_A D_A V_A^T \quad \text{Eq.3.6}$$

Where, S_A is an $m \times m$ orthogonal matrix whose columns, called left singular vectors, are the eigenvectors of the matrix AA^T . V_A is an $n \times n$ orthogonal matrix whose columns, called right singular vectors, are the eigenvectors of the matrix $A^T A$. D_A is an $m \times n$ diagonal matrix of non-zero ordered singular values of A . The non-zero singular values of A are the square roots of the non-zero eigenvalues of $A^T A$ or AA^T .

SVD technique has been used in many hydrological applications and climate research. For example, Cavadias (1985) developed a multivariate seasonal model for stream flow generation to preserve the correlations of stream flow between the periods and among the stations. Following the similar approach by Cavadias, Chaleeraktragoon (1995) proposed a multivariate seasonal streamflow model based on the SVD technique combined with a multivariate autoregressive process to generate streamflow at a single location as well as at many locations concurrently. Qinglan (2006) used SVD technique for generating daily temperature series at a single site. Example of application of SVD technique in statistical downscaling includes the study by Khalili and Nguyen (2018), in which SVD technique was used for downscaling daily temperature extremes.

So far, no reasearch has been conducted using SVD-MAR technique for downscaling of daily tamperature series. In this context, the present study involves the combined use of SVD technique and the MAR model for the downscaling of daily extreme temperature series.

Description of SVD-MAR

Detail description of SVD-MAR technique is provided below (Chaleeraktragoon, 1995):

Let Y be an $m \times n$ data matrix and Ys is the $m \times n$ matrix of the standardized values of Y by its columns (Eq.3.7), such as:

$$Ys_{ij} = \frac{y_{ij} - \bar{y}_j}{s_j} \quad \text{Eq.3.7}$$

where Y_{ij} is the value of Y at the i^{th} row and j^{th} column. $\bar{Y}_j$ and S_j are respectively the mean and the standard deviation of the j^{th} column.

Let $M_{Y_{s0}}$ be the $n \times n$ correlation matrix of Y_s , which can be computed as follows (Eq.3.8):

$$M_{Y_{s0}} = \frac{1}{m-1} \times Y_s^T \times Y_s \quad \text{Eq.3.8}$$

The correlation matrix $M_{Y_{s0}}$ can be decomposed by following way (Eq.3.9):

$$M_{Y_{s0}} = \Psi_{Y_s} \times \Omega_{Y_s} \times \Psi_{Y_s}^T \quad \text{Eq.3.9}$$

where, Ω_{Y_s} is thus the $r \times r$ diagonal matrix of the ordered r non-zero eigenvalues of $M_{Y_{s0}}$, and Ψ_{Y_s} is the $n \times r$ matrix of the corresponding r eigenvectors of $M_{Y_{s0}}$. Here, r is the rank of Y_s .

SVD technique can compute the standardized principal components of Y_s using the given matrices, by Eq.3.10:

$$W_{Y_s} = Y_s \times \Psi_{Y_s} \times \Omega_{Y_s}^{-\frac{1}{2}} \quad \text{Eq.3.10}$$

where W_{Y_s} is the $m \times r$ matrix of the r standardized principal components of Y_s .

Here, it can be shown that SVD technique is capable to preserve the lag-zero correlation matrix $M_{Y_{s0}}$ of Y_s exactly using Ψ_{Y_s} and Ω_{Y_s} (Eq.3.11).

$$\begin{aligned} M_{Y_{s0}} &= \frac{1}{m-1} \times Y_s^T \times Y_s \\ &= \frac{1}{m-1} \times \Psi_{Y_s} \times \Omega_{Y_s}^{\frac{1}{2}} \times W_{Y_s}^T \times W_{Y_s} \times \Omega_{Y_s}^{\frac{1}{2}} \times \Psi_{Y_s}^T \\ &= \frac{1}{m-1} \times \Psi_{Y_s} \times \Omega_{Y_s}^{\frac{1}{2}} \times (m-1) \times I_{Y_{sr}} \times \Omega_{Y_s}^{\frac{1}{2}} \times \Psi_{Y_s}^T \\ &= \Psi_{Y_s} \times \Omega_{Y_s} \times \Psi_{Y_s}^T \end{aligned} \quad \text{Eq.3.11}$$

If the column size is greater than row size of Y_s (that is, $n > m$) the SVD technique can compute $m \times m$ matrix $N_{Y_{s0}}$ (Eq.3.12) instead of $M_{Y_{s0}}$.

$$N_{Y_{S0}} = \frac{1}{m-1} \times Y_S \times Y_S^T \quad \text{Eq.3.12}$$

The matrix $N_{Y_{S0}}$ can be decomposed by SVD technique producing same diagonal matrix of eigenvalues Ω_{Y_S} , but different matrices of corresponding eigenvectors Γ_{Y_S} of size $m \times r$. However, SVD technique can estimate the Ψ_{Y_S} matrix of the eigenvectors of $M_{Y_{S0}}$, using the Γ_{Y_S} matrix of the eigenvectors of $N_{Y_{S0}}$ following Eq.3.13.

$$\Psi_{Y_S} = \frac{1}{\sqrt{m-1}} \times Y_S^T \times \Gamma_{Y_S} \times \Omega_{Y_S}^{-\frac{1}{2}} \quad \text{Eq.3.13}$$

In the case of decomposing the $N_{Y_{S0}}$ matrix, the $m \times r$ matrix W_{Y_S} of the r standardized principal components of Y_S , can be expressed by Eq.3.14.

$$W_{Y_S} = \sqrt{m-1} \times \Gamma_{Y_S} \quad \text{Eq.3.14}$$

In SVD-MAR process, multivariate autoregressive model with one time lag, denoted as, MAR(1) model is fitted to the principal component matrix W as expressed in Eq.3.15.

$$W_{Y_{Sv}} = W_{Y_{Sv-1}} \phi_{Y_{S1}} + U_{Y_{Sv}} \quad \text{Eq.3.15}$$

where, $W_{Y_{Sv}}$ is the $1 \times r$ row vector of W_{Y_S} , $\phi_{Y_{S1}}$ is the $r \times r$ parameter matrix of the MAR(1) model, and $U_{Y_{Sv}}$ is the $1 \times r$ residual row vector of U_{Y_S} with zero mean and Σ_{Y_S} variance-covariance residual properties of size $r \times r$. The parameter matrix $\phi_{Y_{S1}}$, and the variance-covariance matrix of residuals Σ_{Y_S} are expressed as follows:

$$\begin{aligned} \phi_{Y_{S1}} &= R_{Y_{S0}}^{-1} R_{Y_{S1}} \\ &= R_{Y_{S1}} \end{aligned} \quad \text{Eq.3.16}$$

And

$$\begin{aligned} \Sigma_{Y_S} &= R_{Y_{S0}} - \phi_{Y_{S1}}^T R_{Y_{S0}} \phi_{Y_{S1}} \\ &= I_r - \phi_{Y_{S1}}^T \phi_{Y_{S1}} \end{aligned} \quad \text{Eq.3.17}$$

where, $R_{Y_{S0}}$ and $R_{Y_{S1}}$ are the $r \times r$ lag-zero and lag-one correlation matrices of W_{Y_S} . It signifies that the lag-one correlation matrix $R_{Y_{S1}}$ is reproduced through the parameter matrix $\phi_{Y_{S1}}$.

It can be noted that, since the columns of the principal component matrix is perfectly uncorrelated, the lag-zero correlation matrix $R_{Y_{S0}} = I_r$ (Eqs.3.16 & 3.17). Therefore, the inverse matrix $R_{Y_{S0}}^{-1}$, which is sometimes cumbersome to compute and arise numerical errors, is not necessary to calculate.

It can be also noted that the lag-one correlation matrix $M_{Y_{S1}}$ of Y_S can be reproduced through the preservation of $R_{Y_{S1}}$ which is lag-one correlation matrices of W . Because these two matrices are linearly correlated (Eq.3.18):

$$M_{Y_{S1}} = \Psi_{Y_S} \times \Omega_{Y_S}^{\frac{1}{2}} \times R_{Y_{S1}} \times \Omega_{Y_S}^{\frac{1}{2}} \times \Psi_{Y_S}^T \quad \text{Eq.3.18}$$

Therefore, by generating MAR(1)-residual matrix $\hat{U}_{ES}$ following the normal distribution $(0, \Sigma_{Y_S}^{1/2})$ in Eq.3.15, simulated matrix of standardized principal components $\hat{W}_{Y_S}$ can be computed following the Eqs.3.15-3.17.

Using simulated matrix of principal components $\hat{W}_{Y_S}$, the simulated matrix $\hat{Y}_S$ can be obtained using the SVD theorem (Eq.3.19):

$$\hat{Y}_S = \hat{W}_{Y_S} \times \Omega_{Y_S}^{\frac{1}{2}} \times \Psi_{Y_S}^T \quad \text{Eq.3.19}$$

Then, the non-standardized elements of the matrix $\hat{Y}$ can be obtained as follows:

$$\hat{Y}_{ij} = \hat{Y}_{Sij} \times S_j + \bar{Y}_j \quad \text{Eq.3.20}$$

If the number of row vectors in a data matrix is not sufficiently greater than that of column vectors, then modeling all the correlation elements of lag-zero and lag-one correlation matrices of W_{ES} is not permissible as the number of records are limited. In that case, it is not possible to describe lag-zero and lag-one correlation matrices jointly because the residual variance-covariance properties Σ_{Y_S} in Eq.3.17 will have zero degree of freedom left and hence, it cannot be estimated

(Chaleeraktragoon, 1995). One of the possible solutions proposed by Chaleeraktragoon (1995) is to partition the matrix W_{Y_S} of standardized principal components into smaller matrices. Here, it can be noticed that the resulting matrix W_{Y_S} of the standardized principal components have independent column vectors. Thus, it is possible to divide this matrix into smaller partition matrices, and then to describe the lag-one correlation matrices of each of the partitioned matrices using MAR(1) models.

In this study, the matrix W_{Y_S} is partitioned into three sub-matrices (namely, $W_{Y_S}^1$, $W_{Y_S}^2$, $W_{Y_S}^3$) of successive principal components. In this case, MAR(1) model is fitted to $W_{Y_S}^z$ (Eqs. 3.15 - 3.17) for $z = 1, 2, 3$. By generating MAR(1)-residual matrix $\hat{U}_{Y_S}^z$ following the normal distribution $N\left(0, \left(\Sigma_{Y_S,j,j}^z\right)^{\frac{1}{2}}\right)$, simulated matrix of standardized principal components $\hat{W}_{Y_S}^z$ are computed. After computing the matrices $\hat{W}_{Y_S}^z$, for $z = 1, 2, 3$, the $\hat{W}_{Y_S}$ can be concatenated by as follows:

$$\hat{W}_{Y_S} = \left[\hat{W}_{Y_S}^1 \quad \hat{W}_{Y_S}^2 \quad \hat{W}_{Y_S}^3 \right] \quad \text{Eq.3.21}$$

Detail description of all the steps for the application of above mentioned has been provided in Appendix A.

3.4.2.2 Multivariate stochastic model (MSM)

MSM is the multivariate generation model that generates multivariate correlated random variables. Matalas (1967) has proposed a multisite normal generation model that preserves the means, variances, lag1 serial correlation, lag0 and lag1 cross-correlations among the variables at many sites. The model suggested by Matalas was applied in various studies conducted for studying multivariate stochastic hydrological processes. For example, Richardson (1981) proposed a multivariate weather model to generated daily precipitation, maximum temperature and minimum temperature, and solar radiation. In that study, Matalas model was used to generate maximum temperature and minimum temperature and solar radiation simultaneously. This approach was further followed by Wilks (1999) to generate of daily precipitation, maximum temperature, minimum temperature and solar radiation, simultaneously at a collection of stations in a complex terrain.

In this present study, Matalas model was used to simulate the residuals of T_{max} and T_{min} at all of the stations concurrently. Description of Matalas model and the steps describing how this model has been used for generating residuals are given below.

Description of MSM

Let $x^{(p)}$, where $p = 1, 2, \dots, m$, denotes the random variable at p^{th} station over an area and is assumed to follow a normal distribution at each of the stations. $\mu_x^{(p)}$ and $\sigma_x^{(p)}$ are the mean and standard deviation for $x^{(p)}$, which can be obtained from the observed data. The lag0 cross correlation between the p^{th} and q^{th} stations (where, $p, q = 1, 2, \dots, m$) is denoted by $\rho_x^{(p)(q)}(0)$ and, $\rho_x^{(p)}(1)$ denotes lag1 autocorrelation at p^{th} station. Then multivariate stochastic model is defined as Eq.3.22 (Matalas, 1967).

$$x_{i+1} = A_x x_i + B_x \epsilon_{x_{i+1}} \quad \text{Eq.3.22}$$

Here, x_{i+1} and x_i are $m \times 1$ matrices whose p^{th} elements are $x_{i+1}^{(p)} - \mu_x^{(p)}$ and $x_i^{(p)} - \mu_x^{(p)}$, respectively, where, $x_{i+1}^{(p)}$ and $x_i^{(p)}$ represent the variable $x^{(p)}$ at the times $i + 1$ and i respectively. The random components $\epsilon_{x_{i+1}}$ is an $m \times 1$ matrix of random numbers, which are independent of the elements of x_i . A_x and B_x are $m \times m$ matrices whose elements are defined in such a way that the observed statistical properties like $\mu_x^{(p)}$, $\sigma_x^{(p)}$, $\rho_x^{(p)(q)}(0)$ and $\rho_x^{(p)}(1)$ are preserved in the simulated series.

Here, since $[x_{i+1}] = E[x_i] = 0$, $E[\epsilon_{i+1}]$ is zero, where E denotes the mathematical expectation of the arguments. By post-multiplying Eq.3.22 by transpose of x_i and taking its expectation, Eq.3.22 converts to Eq.3.23, such as:

$$\begin{aligned} E[x_{i+1} \times x_i^T] &= A_x \times E[x_i \times x_i^T] + B_x \times E[\epsilon_{x_{i+1}} \times x_i^T] \\ M_{x_1} &= A_x M_{x_0} + 0 \quad (\text{since, } \epsilon_{i+1} \text{ and } x_i \text{ are independent}) \\ M_{x_1} &= A_x M_{x_0} \\ A_x &= M_{x_1} M_{x_0}^{-1} \end{aligned} \quad \text{Eq.3.23}$$

Here, M_{x_0} is the lag-zero variance-covariance matrix of size of $m \times m$ for a network of m number stations. The main diagonal elements of the matrix M_{x_0} represents the variance, $\sigma_x^{2(p)}$, of p^{th} station, where, $p = 1, 2, \dots, m$. The off-diagonal elements represent the covariance, $\rho_x^{(p)(q)}(0)\sigma_x^{(p)}\sigma_x^{(q)}$, where, $p, q = 1, 2, \dots, m$ and $p \neq q$. M_{x_1} is the lag-one variance-covariance matrix and its diagonal elements are lag-one auto variance, $\rho_x^{(p)}(1)\sigma_x^{2(p)}$, where, $p = 1, 2, \dots, m$. The off-diagonal elements of M_{x_1} are $\rho_x^{(p)(q)}(1)\sigma_x^{(p)}\sigma_x^{(q)}$, where, $p, q = 1, 2, \dots, m$ and $p \neq q$. Therefore, the matrix M_{x_0} is symmetric but M_{x_1} is not. Here, it can be mentioned that, if $x^{(p)}$ is of unit variance for all the stations, then in effect the matrices M_{x_0} and M_1 are lag-zero and lag-one cross correlation matrices respectively. Because, $\sigma_x^{(p)} = \sigma_x^{(q)} = 1$, where, $p, q = 1, 2, \dots, m$.

Again, post-multiplying Eq.3.22 is by transpose of x_{i+1} , then taking the expectation:

$$E[x_{i+1} \times x_{i+1}^T] = A_x \times E[x_i \times x_{i+1}^T] + B_x \times E[\epsilon_{x_{i+1}} \times x_{i+1}^T]$$

$$M_{x_0} = A_x \times E[x_i \times x_{i+1}^T] + B_x \times E[\epsilon_{x_{i+1}} \times x_{i+1}^T] \quad \text{Eq.3.24}$$

The term $E[x_i \times x_{i+1}^T]$ in Eq.3.24 can be expressed in terms of $M_{x_1}^T$. The explanation is given below:

$$M_{x_1} = E[x_i \times x_{i-1}^T]$$

$$M_{x_1}^T = \{E[x_i \times x_{i-1}^T]\}^T$$

$$= E[\{x_i \times x_{i-1}^T\}^T]$$

$$= E[x_{i-1} \times x_i^T]$$

$$\text{Or, } M_{x_1}^T = E[x_i \times x_{i+1}^T] \quad \text{Eq.3.25}$$

It should be noted that although $\epsilon_{x_{i+1}}$ and x_i are independent, but $\epsilon_{x_{i+1}}$ and x_{i+1} are not necessarily independent. Therefore, the term $E[\epsilon_{x_{i+1}} \times x_{i+1}^T]$ is not guaranteed to be zero. The term $E[\epsilon_{x_{i+1}} \times x_{i+1}^T]$ can be expressed in the following way (Eq.3.26).

$$\begin{aligned}
\epsilon_{x_{i+1}} \times x_{i+1}^T &= \epsilon_{x_{i+1}} \times \{A_x x_i + B_x \epsilon_{x_{i+1}}\}^T \text{ (substituting the value from Eq.3.22)} \\
&= \epsilon_{x_{i+1}} \times x_i^T \times A_x^T + \epsilon_{x_{i+1}} \times \epsilon_{x_{i+1}}^T \times B_x^T
\end{aligned}$$

Taking expectation on both sides,

$$\begin{aligned}
E[\epsilon_{x_{i+1}} \times x_{i+1}^T] &= E[\epsilon_{x_{i+1}} \times x_i^T \times A_x^T + \epsilon_{x_{i+1}} \times \epsilon_{x_{i+1}}^T \times B_x^T] \\
&= E[\epsilon_{x_{i+1}} \times x_i^T \times A_x^T] + E[\epsilon_{x_{i+1}} \times \epsilon_{x_{i+1}}^T \times B_x^T] \\
&= A_x^T \times E[\epsilon_{x_{i+1}} \times x_i^T] + B_x^T \times E[\epsilon_{x_{i+1}} \times \epsilon_{x_{i+1}}^T] \\
&= A_x^T \times 0 + I \times B_x^T \quad (\text{since } \epsilon_{x_{i+1}} \text{ has unit variance}) \\
&= B_x^T \tag{q.3.26}
\end{aligned}$$

Substituting the values of Eqs 3.25 and 3.26 in Eq.3.24, the following relationship can be obtained:

$$\begin{aligned}
M_{x_0} &= A_x M_{x_1}^T + B_x B_x^T \\
&= M_{x_1} M_{x_0}^{-1} M_{x_1}^T + B_x B_x^T \text{ (since } A_x = M_{x_1} M_{x_0}^{-1} \text{)} \\
B_x B_x^T &= M_{x_0} - M_{x_1} M_{x_0}^{-1} M_{x_1}^T \tag{Eq.3.27}
\end{aligned}$$

There are several alternate solutions for obtaining the values of B_x that can satisfy the expression of Eq.3.27. The way to obtain the values of B_x is discussed by Matalas(1967). One of the possible ways is to assume a particular structure for the matrix B_x . In this study, B_x is assumed to be a lower triangular matrix and B_x^T is an upper triangular matrix and both of them are of size $m \times m$. If the matrix C_x is defined by Eq.3.28,

$$C_x = B_x B_x^T \tag{Eq.3.28}$$

$$\text{then, } C_x = M_{x_0} - M_{x_1} M_{x_0}^{-1} M_{x_1}^T \quad \text{Eq.3.29}$$

The matrices B_x and B_x^T can be obtained by factorizing of the matrix C_x . One of the possible limitations is that the matrix C_x has to be a positive definite matrix, which may not be the case always. However, one way to solve the problem is to make some small changes in the matrix C_x in order to make it positive definite, if needed. The process has been well described by Rebonato and Jäckel (1999).

Here, it is notable that the coefficient matrices A_x and B_x are determined through M_{x_0} and M_{x_1} . Since the matrices M_{x_0} and M_{x_1} are determined from the observed data, the lag0 cross correlation and lag1 autocorrelation are preserved in the simulated series. Once the matrices A_x and B_x are determined, the simulated series can be generated by the following equation:

$$\hat{x}_{i+1} = A_x \hat{x}_i + B_x \epsilon_{x_{i+1}} \quad \text{Eq.3.30}$$

Here, ϵ_x are independent random components, which are normally distributed with zero mean and unit variance. Description of all the steps are given in Appendix A.

As described, both of the proposed MMSD methods in the present study are basically based on the multiple linear regression models. In fact, the main differences of these models are in modeling of the stochastic components of the downscaling models. In the first method, the modeling of stochastic components was generated by SVD-MAR technique. In fact, SVD can efficiently reduce the dimensionality of a large matrix by transforming it into independent principal components. SVD is considered as a powerful tool for dimensionality reduction and has the advantages of computational efficiency. The second method is a combination of multiple linear regression and MSM. MSM is the multivariate generation model that generates multivariate correlated random variables. As mentioned earlier, one of the limitations of proposed MSM is associated with infeasibility of matrix factorizing, especially when large number of stations needs to be considered. Hence, compared to MSM model, SVD-MAR model is capable to provide a more stable and efficient way of computation where downscaling at many stations is necessary.

3.5 Generating scenarios with GCM simulations

The calibration process involves developing the relationship with NECP predictors. This established relationship during calibration period is used to generate the synthetic series of daily T_{max} and T_{min} using the GCMs outputs for current and future periods. In this case, atmospheric

predictor variables of the NCEP reanalysis data were replaced by the predictors of the GCMs, but with the same regression parameters obtained using NCEP reanalysis data. It is to be noted that the downscaling models needed to be calibrated separately with two series of NCEP predictors as those are interpolated distinctly on the two different grids of CGCM and HadCM. After calibration with NCEP predictors, the synthetic series of daily T_{max} and T_{min} for current and future period was generated under four SRES scenarios from two CGMs (A1B and A2 scenarios from CGCM and A2 and B2 scenarios from HadCM). Here it should be mentioned that different GCMs have different year length. For example, CGCM ignores the 29th February in leap years and thus has 365 days in all years. HadCM considers 30 days each month and has a year length of 360 days.

When NCEP data was used for downscaling the temperatures, both the observed mean and standard deviation were reproduced accurately in the simulated series. But when GCM simulations were used for downscaling, the observed mean was accurately simulated but there was a bias in the standard deviation of simulated series. Therefore, a correction method for the standard deviation was required. In order to correct the standard deviation, the simulated series were multiplied by a factor Δ_{STD} . The factor Δ_{STD} was obtained by (Eq.3.32):

$$\Delta_{STD} = \frac{STD_{Obs}}{STD_{Sim}} \quad \text{Eq.3.32}$$

where, STD_{Obs} and STD_{Sim} stand for standard deviation of the observed and simulated series respectively. As mentioned earlier, the mean was simulated accurately, correction of the mean in the simulated series was not necessary. Therefore, the correction for standard deviation was made after subtraction of the mean. Otherwise, it would affect the mean also. After making the correction for standard deviation the mean was added again to the simulated series.

3.6 Evaluation of model performance

Both numerical and graphical analysis were performed to evaluate the effectiveness and accuracy of the proposed model. The feasibility of the models was evaluated for both regions (i.e., southern Quebec-Ontario region and Bangladesh) during calibration as well as validation periods. A set of indices was used to evaluate the models' capability to reproduce the observed statistical properties in the downscaled temperature series. The basic temperature indices that were investigated for model evaluation are mean and standard deviation of T_{max} and T_{min} , the 90th

percentile of daily T_{max} , and the 10th percentile of daily T_{min} , freeze-thaw cycle, diurnal temperature range etc.

The effectiveness of the models to capture the temporal dependencies was evaluated through the reproducibility of serial autocorrelation coefficients up to lag3 at each station. Along with autocorrelation coefficients, interannual anomalies of different standardized seasonal indices were also evaluated. The spatial variability was evaluated in terms of interstation correlations of daily T_{max} and T_{min} between the stations. The interstation correlations were calculated by commonly used Pearson's correlation coefficient method. In addition, the results were compared with those obtained by the using one of the most popular existing single-site downscaling tool called Statistical DownScaling Model (SDSM). The first public version of SDSM was released in 2001 and since then there have been more than 170 documented studies worldwide in which the use of SDSM has been identified (Wilby and Dawson, 2013). The examples of the use of SDSM for downscaling of different climate variable(s) include the studies conducted by Gachon and Dibike, 2007; Chu et al., 2010; Huang et al., 2011; Mahmood and Babel, 2013, 2014; Wang et al., 2012; Charleeraktrakoon and Punlum, 2010; Nury and Alam, 2013; Rahman et al., 2015; Shahriar et al., 2021 etc. Detailed methodology of SDSM can be in found in Wilby and Dawson, 2002, 2007.

The numerical evaluations were performed through coefficient of determination (R^2), Mean Absolute Error (MAE) or Mean absolute Differences (MAD), and Root Mean Square Error (RMSE) or Root Mean Square Differences (RMSD). The expressions of R^2 , MAE or MAD, and RMSE or RMSD are given by the equation Eqs.3.33, 3.34 and 3.35 respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^t (X_{Obs,i} - X_{Sim,i})^2}{\sum_{i=1}^t (X_{Obs,i} - \bar{X}_{Obs})^2} \quad \text{Eq.3.33}$$

$$MAE \text{ or } MAD = \frac{1}{t} \sum_{t=1}^t |X_{Obs,i} - X_{Sim,i}| \quad \text{Eq.3.34}$$

$$RMSE \text{ or } RMSD = \sqrt{\frac{1}{t} \sum_{i=1}^t (X_{Obs,i} - X_{Sim,i})^2} \quad \text{Eq.3.35}$$

where, t , $\bar{X}_{Obs}$, $X_{Obs,i}$ and $X_{Sim,i}$ denote the length of series, average of observed values, observed and simulated values for i^{th} observation respectively.

3.7 Evaluation the effectiveness of multisite over single-site downscaling

In reality, weather data at different sites over an area are not independent of each other and show some degree of correlations among them since the neighbouring sites over a given area experience similar weather on the same day due to common exposure to a single weather system (Yang, et al., 2005). For example, on a given day, if the temperature is observed high at one station, then temperature at another nearby station is also observed high. Moreover, daily $Tmax$ and $Tmin$ exhibit specific relationship between them. If $Tmax$ is high one day, $Tmin$ is also observed usually high on the same day at the same location.

If an area is considered, on a given day the average temperature of that area is calculated by averaging temperature at all the stations located over that area. So, on given day if the temperature is very high, it is reflected at almost all the stations over that area. That means, all the stations over that area usually exhibit relatively high $Tmax$ and $Tmin$ and thus, the average temperature of that area is observed high on that particular day. Similarly, on a very cold day, almost all the stations over that area usually show relatively low $Tmax$ and $Tmin$, resulting in a low temperature over that area. This feature of correlation inherent in daily $Tmax$ and $Tmin$ must be preserved in downscaled series. Downscaling of temperature at several stations over a given area individually (i.e., single-site and univariate downscaling) is not capable to preserve these properties; leaving the scope of simulating very high temperature at one station while very low temperature at another nearby station on the same day. As a result the simulated average temperature of that area may not represent actual temperature on that day. Again, if the $Tmax$ and $Tmin$ are downscaled separately, the correlation between $Tmax$ and $Tmin$ at a given station is not preserved. Therefore, there remains a scope of simulating the $Tmax$ very high at one station, while simulating very low $Tmin$ at the same station on the same day, producing a misrepresentative average temperature on that day. Moreover, sometimes it may produce the unrealistic data, like, $Tmin$ higher than $Tmax$. These problems associated with single-site and univariate downscaling have triggered the necessity of multisite multivariate downscaling techniques in order to incorporate the correlation structure of daily $Tmax$ and $Tmin$ in simulated series. The comparison of single and multisite downscaling is conceptually depicted in Figure 3.4.

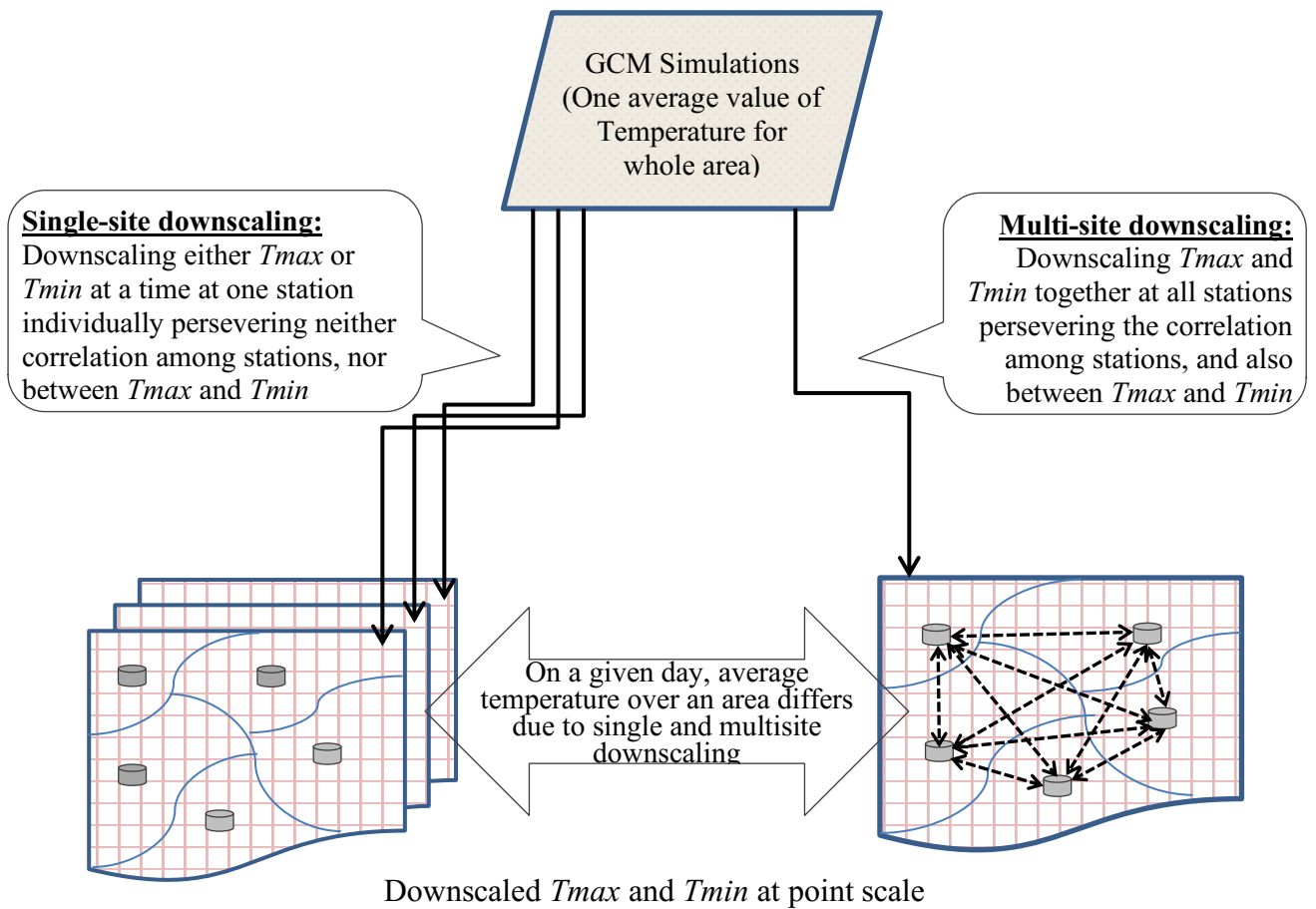


Figure 3.4: Comparison of the single and multisite downscaling to represent average temperature over a given area.

In fact, downscaling of weather variables, in most cases, does not end in itself but provides a product in the form of data or information to impact assessment studies (Maraun et al., 2010). Hence, one of the fundamental necessities of downscaling procedures stems from the need of climate scenarios at finer resolution for using in different hydrologic and climate change impact models. Therefore, the downscaled series are required to be a true representative of the weather variables over a given area for an accurate assessment of climate change impacts. For most of the water resources studies weather parameters are required to be known at several locations over a given area rather than at a single individual point. Thus, if weather data having strong correlations are downscaled individually without accounting for the spatial dependence among them, will fail to adequately represent the actual weather condition over a given area and thereby would adversely affect the end users.

Although several studies suggested different methods for multisite downscaling, but the number of studies about evaluating the efficacy of multisite versus single-site downscaling at application level is very limited. In other words, most studies related to multisite downscaling were focused on the accuracy of these procedures in capturing the observed spatio-temporal characteristics of the selected weather series; but these studies did not demonstrate the significant impact of multisite downscaling on the application results as compared to those given by single-site downscaling approaches. In this context, the present study provides a detailed comparison of the performance of both multisite and single-site downscaling methods in the computation of snowmelt using the degree-day approach. It should be noted that an accurate estimation of snowmelt is crucial for planning, design, and management of various hydraulic and flood control infrastructures in regions where snowfall is a significant contributor of streamflow generation and runoff. For instance, lack of accurate information on snowmelt may result in failure of dam and reservoir's spillway imposing potential threats to public safety and economic loss (Henn et al., 2020). In addition, in the climate change context a warmer climate can lead to significant changes in snowmelt pattern, amount, timing, and thereby runoff characteristics. Hence, an accurate prediction of timing and magnitude of snowmelt is essential for the design or upgrading of drainage infrastructures adaptive to the climate change (Arisz and Burrell, 2006).

In this study, the snowmelt was computed using the degree-day method which has been commonly used in practice (NRCS 2004, He et al, 2014). The degree-day method is a temperature index approach that equates the total daily snowmelt to a coefficient times the temperature difference between the mean daily temperature and a base temperature. The Degree-day method for calculating snowmelt is represented by the following equation (Eq.3.36) :

$$h = CM(T_{avg} - T_b) \quad \text{Eq.3.36}$$

where, h is snowmelt in in/d, CM is the degree-day coefficient in in/degree-day F, T_{avg} is daily average air temperature in °F and T_b is base temperature in °F. The value of degree-day coefficient varies depending on several factors, including the characteristics of the snowpack, location, seasonality, and other weather parameters. Typical values of CM range from 0.035 to 0.13 inches per degree-day Fahrenheit and in general 0.06 in/degree-day °F is often used (NRCS

2004). Hence, in this study, the value of the CM coefficient was chosen as 0.06 in/degree-day °F (NRCS, 2004; Anctil et al., 2012).

Degree-day method was used to calculate the snowmelt using three sets of data: observed daily temperature, downscaled daily temperature obtained by applying SVD-MAR (as a representation of multisite multivariate downscaling method) and SDSM (as a representation of single-site univariate downscaling method). The average of daily T_{max} and T_{min} of the mentioned seven weather stations in the southern Quebec-Ontario region has been used as T_{avg} in Eq.3.36. After computing the snowmelt with three aforementioned sets of data, the results were computed through some indices which have been discussed in chapter 5.

Chapter 4

ANALYSIS OF DAILY EXTREME TEMPERATURE SERIES

In this study, the feasibility and accuracy of the proposed MMSD models have been assessed using two sets of daily extreme temperature data obtained from two different climatic regions: the southern Quebec-Ontario region in Canada, representing a cold climate, and Bangladesh, representing a tropical climate. In this context, this chapter provides detailed statistical analysis of the variability of daily maximum and minimum temperature for the selected stations in the southern Quebec and Ontario region and Bangladesh. Daily extreme temperature series at seven weather stations located in the southern Quebec-Ontario region in Canada and four stations in Bangladesh have been used as predictands in this study. Here, at first the descriptions of the temperature indices and computational methodology have been explained. Then the statistical analysis of the temperature variability in each of the two regions are given.

4.1 Temperature indices and computational methodology

The variability of daily T_{max} and T_{min} has been analyzed through some temperature related indices, which are presented in Table 4.1.

Table 4.1 Temperature indices and description.

Name of the indices	Description	Unit
TmaxMean	Annual Mean of daily maximum temp	°C
TminMean	Annual Mean of daily minimum temp	°C
TavgMean	Annual Mean of daily average temp	°C
Diurnal temperature	Mean of diurnal temperature range	°C
Cool nights (TN10p)	Percentage of days when daily minimum temp<10th percentile	Days
Cool days (TX10p)	Percentage of days when daily maximum temp<10th percentile	Days
Warm nights (TN90p)	Percentage of days when daily minimum temp>90th percentile	Days
Warm days (TX90p)	Percentage of days when daily maximum temp>90th percentile	Days
MaxTmax (TXx)	Annual maximum value of daily maximum temp	°C
MaxTmin (TNx)	Annual maximum value of daily minimum temp	°C
MinTmax (TXn)	Annual minimum value of daily maximum temp	°C
MinTmin (TNn)	Annual minimum value of daily minimum temp	°C
Frost days (FD0)	Annual count when daily minimum temp<0°C	Days
Summer days (SU25)	Annual count when daily maximum temp>25°C	Days
Ice days (ID0)	Annual count when daily maximum temp<0°C	Days
Tropical nights (TR20)	Annual count when daily minimum temp>20°C	Days

Growing season Length (GSL)	Annual (1st Jan to 31 st Dec in NH, 1 st July to 30 th June in SH) count between first span of at least 6 days with average temp > 5°C and first span after July 1 (January 1 in SH) of 6 days with average temp < 5°C	Days
Freeze and thaw cycle (Fr-Th)	Days with freeze and thaw cycle (daily maximum temp > 0°C and daily minimum temp < 0°C)	Days
Warm spell duration indicator (WSDI)	Annual count of days with at least 6 consecutive days when daily maximum temp > 90th percentile	Days
Cold spell duration indicator (CSDI)	Annual count of days with at least 6 consecutive days when daily minimum temp < 10th percentile	Days

The indices have been selected from the indicators recommended by the Canadian Climate Change Scenarios Network (CCCSN) and the Expert Team on Climate Change Detection and Indices (ETCCDI). Definition and detailed description of these indices can be found at http://etccdi.pacificclimate.org/list_27_indices.shtml website.

RClimdex software was used for computing the temperature indices and also for quality control of the data. This software is based on R software and was developed by Zhang and Yang (2004) at the Canadian Meteorological Service to analyse the climatic extremes indices. RClimdex has been used in various previous studies for the analysis of climate indices in different regions; for example: South America (e.g., Vincent et al., 2005; Haylock et al. 2006b), Africa (e.g. Easterling et al., 2003), Utha in North America (Santos, 2011), Iran (e.g. Sohrabi et al. 2013; Molanejad et al., 2014), and also on a global scale (Alexander et al., 2006). Usually RClimdex computes 27 indices both for temperature and precipitation. However, in this study only temperature related indices were chosen to compute by RClimdex. After calculating the indices, slopes of the annual trends of those indices were computed using the least squares fitting. The statistical significances of the trends were evaluated by the non-parametric Mann-Kendall trend test (Mann, 1945; Kendall, 1975). This test has proven to be useful in detecting the possible existence of statistically significant trends in hydro-meteorological time series such as water quality, streamflow, temperature and precipitation (Yue et al., 2002).

Mann-Kendall trend test depends on the relative ranking of a time series and their time order, not on their actual values. The products of the test are the statistics S and Z . A positive value of S indicates upward trend while a negative value indicates a downward trend. Z determines the acceptance or rejection of the null hypothesis, H_0 , which states that there is no trend in the time series, at a predefined significance level. The statistics S and Z are calculated in the following way (Kamal and Pachauri, 2018):

For performing Mann-Kendall test, at first the time series $X(t)$ for $t = 1, 2, \dots, N$, is ordered sequentially. Then each value in the series is given a score +1, 0 or -1 depending on the following equation (Eq. 4.1).

$$\text{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if } x_j - x_i > 0 \\ 0 & \text{if } x_j - x_i = 0 \\ -1 & \text{if } x_j - x_i < 0 \end{cases} \quad \text{Eq. 4.1}$$

where x_i and x_j are the sequential data values on order i and j respectively ($j > i$), and N is length of the record. Then the Mann Kendall statistic S is defined as Eq.4.2.

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{sgn}(x_j - x_i) \quad \text{Eq. 4.2}$$

For $N \geq 10$, the Mann-Kendall trend test statistics Z is estimated as Eq. 4.3.

$$Z = \begin{cases} \frac{S - 1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S + 1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad \text{Eq. 4.3}$$

Where, $\text{Var}(S)$ is given by Eq. 4.4:

$$\text{Var}(S) = \frac{1}{18} N(N-1)(2N+5) - \frac{1}{18} \sum_{i=1}^q t_i(t_i-1)(2t_i+5) \quad \text{Eq. 4.4}$$

where q is the number of tied groups and t_i is the number of data values in i^{th} the group. If there are no ties in ranking, the last term of Eq. 4.4 becomes zero.

The Z value evaluates the rejection or acceptance of H_0 , that means, whether the trend is statistically significant or not. H_0 is rejected if $|Z| > Z_{1-\alpha/2}$, where, $Z_{1-\alpha/2}$ is the $1 - \alpha/2$ quantile of the standard normal distribution and α is the significance level. The rejection of H_0 at a given significance level, α , indicates a significant trend in the data series.

4.2 Analysis of temperature indices in the southern Quebec-Ontario region in Canada

Several studies were carried out to analyze the trends in temperatures in Canada over different time scale. For example, a comprehensive study by Zhang et al. (2000) investigated the temperature trends in Canada using four temperature indices: maximum, minimum, mean temperatures, and diurnal temperature range (DTR). In that study, seasonal and annual temperature trends were studied for the period from 1900 to 1998 for southern Canada (south of 60°N) and for the period from 1950 to 1998 for the entire country. The study revealed that the annual mean temperature had increased between 0.5 and 1.58°C in southern Canada during the period from 1900 to 1998. Minimum temperature increased more compared to maximum temperature especially over the first half of the century, resulting in a decrease of the DTR. This study showed a distinct pattern of temperature change across Canada during 1950–1998: warming in the south and west and cooling in the northeast, with similar magnitudes in maximum and minimum temperatures. This pattern was mostly evident for winter and spring seasons. Bonsal (2000) examined the trends and variations in daily and extreme temperature related variables over Canada during the twentieth century. This study showed that low and high percentiles of daily minimum and maximum temperature from 1900 to 1998 had significant trends toward fewer days with extreme low temperature in winter, spring and summer and less pronounced trends toward more days with extreme high temperature in winter and spring over most of southern Canada. Analyses of extreme temperature related trends for the period 1950 to 1998 showed stronger regional differences specially during winter and spring including significant increases to low and high percentiles of daily minimum and maximum temperature over the west, while significant decreases over the east. Trends in Canadian temperature at 20 stations in eastern Canada between 1941 and 2000 were analyzed by Gachon et al. (2005). This study showed that temperatures (minimum and maximum) had become even warmer in most of the seasons except for fall. There was a significant increase in minimum temperature during summer at many stations, whereas other seasons were rarely affected by such a trend.

In this present study, statistical analysis of different indices of daily temperatures have been provided for seven weather stations located in the southern Quebec-Ontario region in Canada for the period from 1961 to 1990, which have been used as predictands in this study. Name of these stations are L'Assomption, Dorval, Chenaux, Maniwaki UA, Cornwall, Ottawa CDA and

Morrisburg. Geographical information of these seven stations is given in Figure 3.2 and Table 3.2. The following subsections (4.2.1 and 4.2.2) describe the interannual variability and the spatial distribution of trends of the indices during the period 1961 to 1990.

4.2.1 Temperature indices at L'Assomption station

This section provides detailed trend analysis of each of the temperature indices for L'Assomption station as an example to illustrate the application of the data analysis procedure. Same graphical representations of the trend analysis for rest of the stations are given in Appendix B.

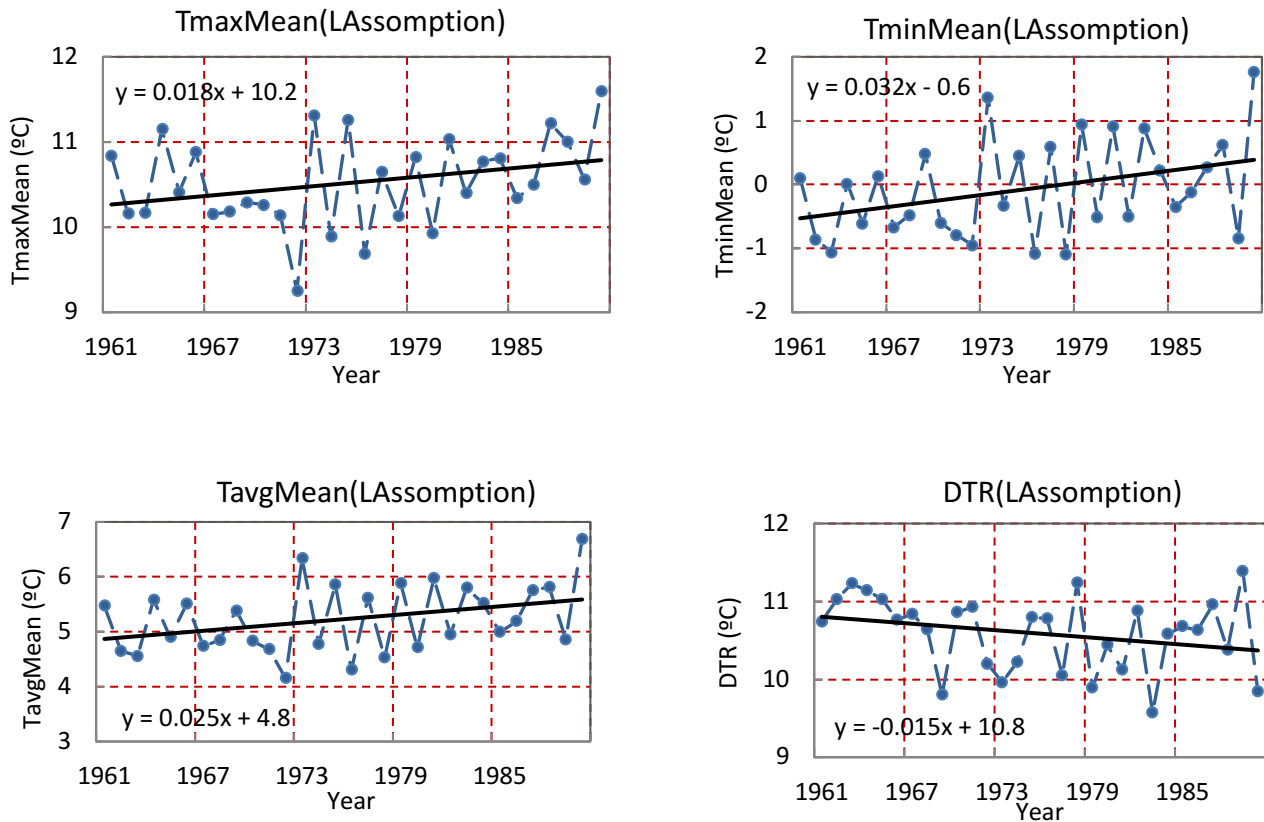


Figure 4.1: Trends in TmaxMean (upper left), TminMean (upper right), TavgMean (lower left), and DTR (lower right) at L'Assomption station during the period 1961-1990.

The L'Assomption station is located in the south-western Quebec at latitude 45.81° N and longitude 73.43° W. The temporal variation of temperature extremes indices at L'Assomption station is shown in Figures 4.1 to 4.5. Figure 4.1 represents the annual variation in means of daily *Tmax* (TmaxMean), daily *Tmin* (TminMean), daily *Tmean* (TavgMean) and diurnal temperature

range (DTR) at this station during the period of 1961-1990. The positive trends were observed in $T_{max}Mean$ ($0.018^{\circ}C$ per year), $T_{min}Mean$ ($0.032^{\circ}C$ per year) and $T_{avg}Mean$ ($0.025^{\circ}C$ per year) during the mentioned period. Rising of T_{min} at a higher rate than that of T_{max} has resulted in decreasing trend in DTR ($-0.015^{\circ}C$ per year). However, according to Mann-Kendall test, all the trends were insignificant at the 95% confidence level corresponding to $\alpha = 0.05$.

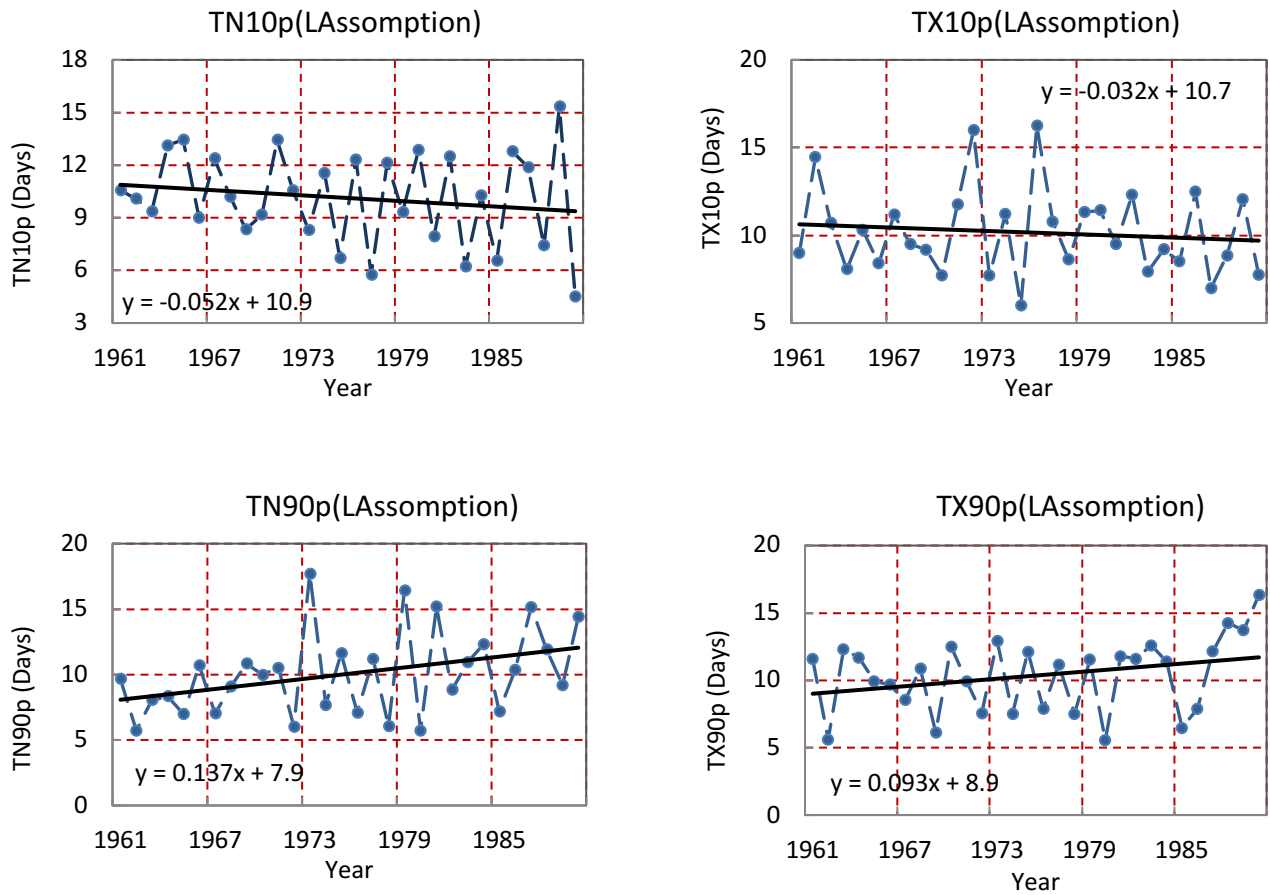


Figure 4.2: Trends in cool nights (TN10p) (upper left), cool days (TX10p) (upper right), warm nights (TN90p) (lower left), and warm days (TX90p) (lower right) at L'Assomption station during the period 1961-1990.

Interannual variability in cool nights (TN10p), cool days (TX10p), warm nights (TN90p) and warm days (TX90p) at L'Assomption station are delineated in Figure 4.2. Cool nights (days) are defined as the percentage of days when T_{min} (T_{max}) is below 10th percentile of the climatology during the period 1961-1990. Warm nights (days) are defined as the percentage of days when T_{min} (T_{max}) is above 90th percentile of the climatology during the same period. Decreasing trends were detected in both cool nights and cool days indices having the slopes -0.052

and -0.032 days per year respectively. Based on Mann-Kendall test trends in both indices were found insignificant. A positive trend (0.137 days per year) was observed in warm nights and the trend was statistically significant. Although warm days showed a positive trend (0.093 days per year), it was insignificant at the 95% confidence level.

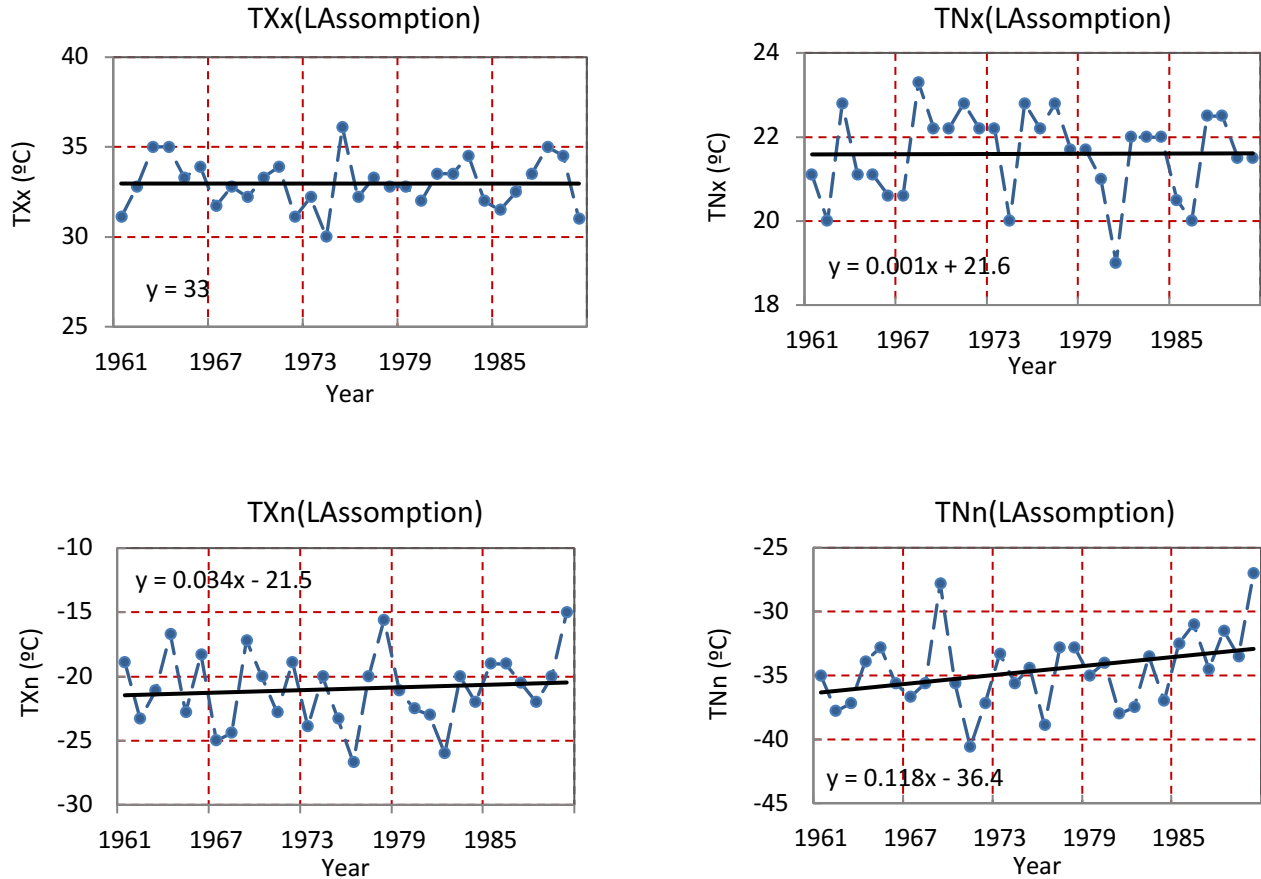


Figure 4.3: Trends in MaxTmax (TXx) (upper left), MaxTmin (TNx) (upper right), MinTmax (TXn) (lower left) and MinTmin (TNn) (lower right) at L'Assomption station during the period 1961-1990.

Temporal variability in MaxTmax (TXx), MaxTmin (TNx), MinTmax (TXn) and MinTmin (TNn) at L'Assomption station is presented in Figure 4.3. In this present study, MaxTmax and MaxTmin are described as annual maximum value of daily *Tmax* and *Tmin* respectively, whereas MinTmax and MinTmin are defined as annual minimum value of daily *Tmax* and *Tmin* respectively. A steady MaxTmax is observed at L'Assomption station showing no trend in this index over the period 1961-1990. Very slight increasing trend (0.001°C per year) was observed in MaxTmin index showing no significance at the 95% confidence level. Although both

MinTmax and MinTmin indices showed positive trends (0.034°C and 0.118°C per year) during this period, only the trend in MinTmin index was found significant.

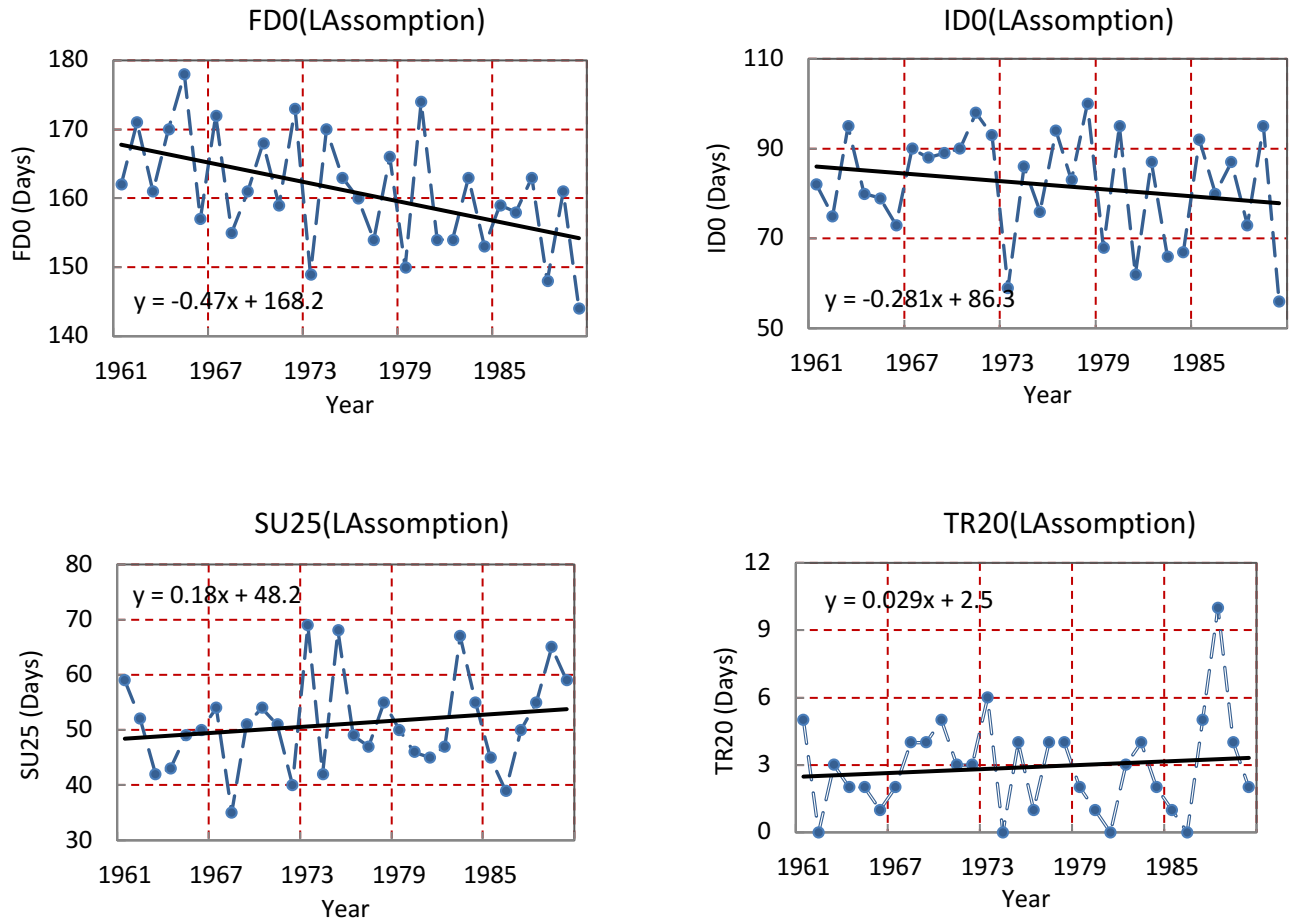


Figure 4.4: Trends in frost days (FD0) (upper left), ice days (ID0) (upper right), summer days (SU25) (lower left), and tropical nights (TR20) (lower right) at L'Assomption station during the period 1961-1990.

Figure 4.4 presents the trends in frost days (FD0), ice days (ID0), summer days (SU25), tropical nights (TR20). In this study, the index frost days is defined as annual counting of days with daily T_{min} below 0°C , whereas ice days index is represented as the annual counting of days with daily T_{max} below 0°C . Summer days represents the annual counting of days with daily T_{max} above 25°C and tropical nights is defined as the annual counting of days with daily T_{min} above 20°C . A significant decreasing trend (-0.467 days per year) was found in frost days at this station indicating that the number of days having T_{min} above 0°C has been increased during this period. The index ice days also showed a decreasing trend (-0.281 days per year) during the period although it was not statistically significant. A positive trend (0.184 days per year) was detected in summer

days and the trend was slightly increasing (0.029 days per year) in tropical nights. However, none of these two trends was significant at the 95% confidence level.

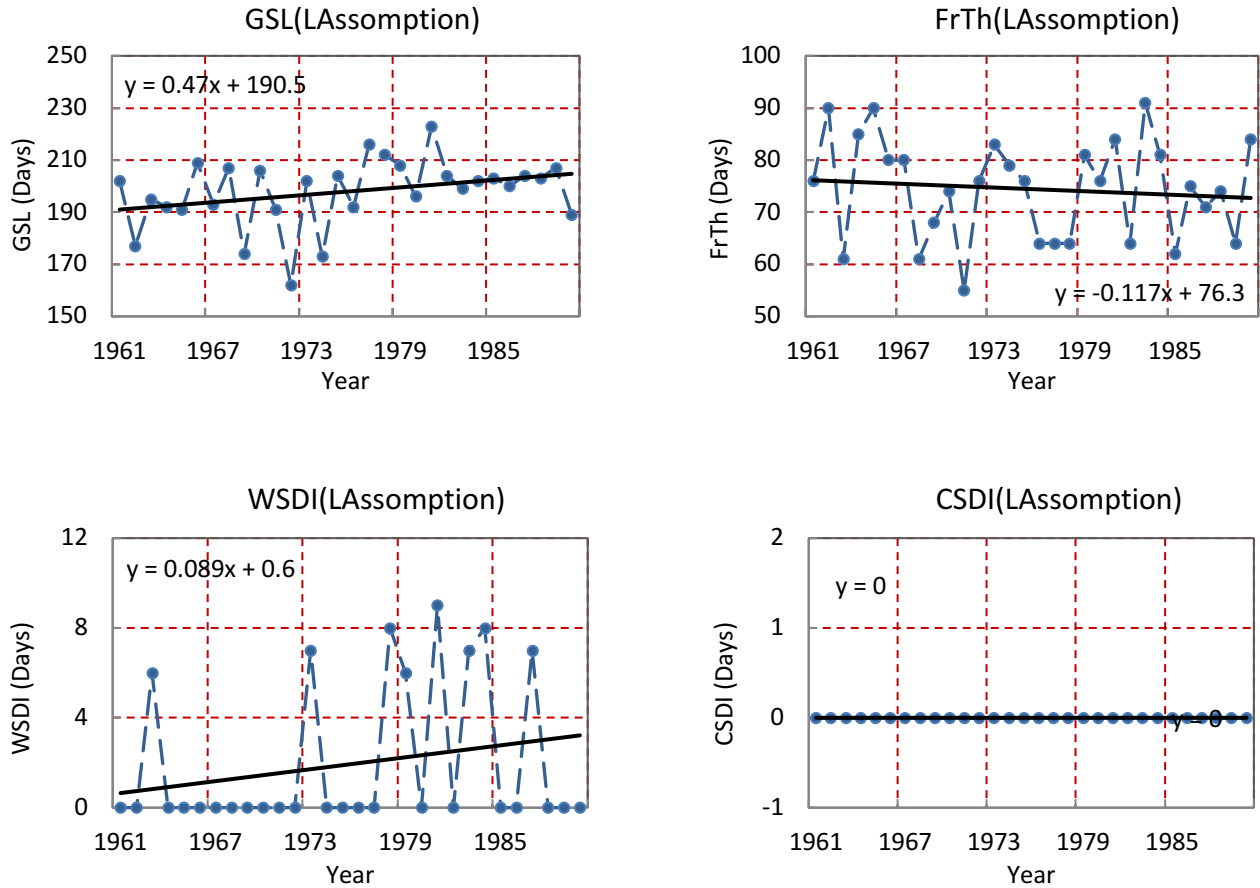


Figure 4.5: Trends in growing season length (GSL) (upper left), freeze and thaw cycle (Fr-Th) (upper right), warm spell duration indicator (WSDI) (lower left), and cold spell duration indicator (CSDI) (lower right) at L'Assomption station during the period 1961-1990.

Trends in growing season length (GSL), freeze and thaw cycle (Fr-Th), warm spell duration indicator (WSDI) and cold spell duration indicator (CSDI) at L'Assomption are given in Figure 4.5. Growing season begins when there are more than six consecutive days with daily T_{mean} above 5°C and ends when there are more than six consecutive days with daily T_{mean} below 5°C . In this study, freeze and thaw (Fr-Th) cycle is defined as the annual counting of days with T_{max} above 0°C and T_{min} below 0°C . Warm spell duration is defined as the annual counting of days with at least 6 consecutive days when T_{max} exceeds 90th percentile of the climatology during the period 1961-1990. Similarly, cold spell duration is defined as annual counting of days with a least 6 consecutive days when T_{min} below 10th percentile of the climatology during the same period.

Positive trends were found in both GSL and WSDI and the slopes were 0.473 and 0.089 days per year respectively for those two indices. As found earlier, the number of days having *T_{min}* above 0°C has been increased during the period 1961-1990, it has caused a negative trend in Fr-Th cycle (-0.117 days per year) at this station during this period. However, all the trends were found insignificant at the 95% confidence level according to Mann-Kendall test. It is noticeable in Figure 4.5 (lower right) that there was never any cold spell at L'Assomption station during the period 1961-1990 and hence, no trend in this index.

The analysis suggests that the trends in almost all the indices have indicated the warming of temperature at L'Assomption station during the period 1961-1990, although for many of the indices the trends were statistically insignificant. In addition, the findings indicates that *T_{min}* had increased comparatively at a higher rate than *T_{max}* resulting in decreasing trends in some indices like DTR, frost days, freeze and thaw cycle etc.

4.2.2 Spatial distribution of temperature indices in the southern Quebec-Ontario region

Spatial variability of the temperature indices for the selected seven stations in the southern Quebec and Ontario region is illustrated through the following maps (Figures 4.6 to 4.10). Here the positive and negative trends are indicated by triangles and circles respectively. The sizes of the symbols represent magnitudes of the trends. The rectangle symbol represents no trend. Red and blue colours represent the insignificant and significant trends respectively at the 95% confidence level according to Mann-Kendall test.

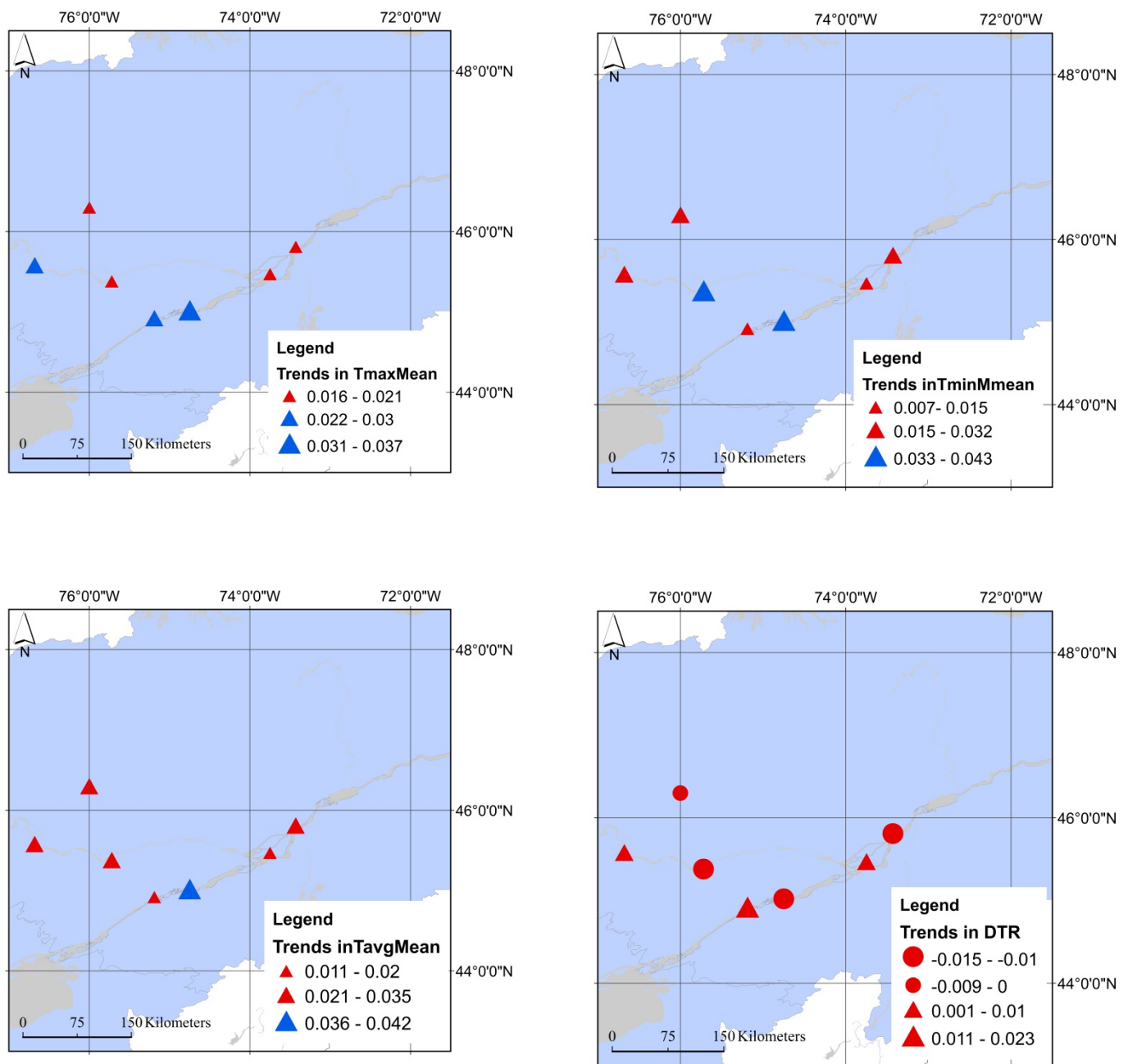


Figure 4.6: Spatial distribution of the trends in TmaxMean (upper left), TminMean (upper right), TavgMean (lower left) and DTR (lower right) during the period of 1961-1990 in the southern Quebec-Ontario region.

The spatial distributions of the trends in TmaxMean, TminMean, TavgMean and DTR during the period of 1961-1990 at seven stations located over southern Quebec and Ontario region are shown in Figure 4.6. Positive trends were observed at all of the seven stations both for TmaxMean and TminMean. In case of TmaxMean, the slopes ranged between 0.016 - 0.037°C per

year for all of the station, whereas, for $T_{min}Mean$ the slopes were between $0.007 - 0.043^{\circ}C$ per year. The positive trends in $T_{max}Mean$ were significant for three stations (Chenau, Cornwall and Morrisburg, the slopes were $0.028^{\circ}C$, $0.037^{\circ}C$ and $0.029^{\circ}C$ per year respectively) at the 95% confidence level. Two stations (Cornwall and Ottawa CDA, the slopes were $0.043^{\circ}C$ and $0.034^{\circ}C$ per year respectively) showed significant positive trends in $T_{min}Mean$ at the 95% confidence level. The highest slopes both in $T_{max}Mean$ and $T_{min}Mean$ were found in Cornwall station. Like $T_{max}Mean$ and $T_{min}Mean$, all of the seven stations showed positive trends ($0.011 - 0.042^{\circ}C$ per year) in $T_{avg}Mean$ during this period. The highest slope was found in Cornwall being significant at the 95% confidence level. Changes in DTR, which is an important indicator for climate change and variability, are often associated with relatively larger increases in T_{min} than in T_{max} (Karl et al., 1991; Karl et al., 1993; Braganza et al., 2004). The decreasing trend in DTR over some parts in Canada has been reported in some studies (e.g., Karl et al., 1984; Zhang et al. 2000). In parallel with these findings, this study also shows decreasing trends at four stations: Cornwall, L'Assomption, Maniwaki and Ottawa CDA (the slopes were -0.01 , -0.015 , -0.008 and $-0.013^{\circ}C$ per year respectively). The trend in DTR approximately was equal to the difference in trends between T_{max} and T_{min} over time. The stations that showed positive trends in DTR are: Chenau, Dorval and Morrisburg (the slopes are 0.008 , 0.008 and $0.023^{\circ}C$ per year respectively). However, none of seven stations showed significant trend in DTR at the 95% confidence level.

The trends in monthly means of daily T_{max} and T_{min} for each of the months at seven stations have been presented in Table 4.2 and 4.3 respectively. It could be noticed that all stations followed a particular pattern for increasing or decreasing trends in monthly means of daily T_{max} and T_{min} . For example, in the months of June, September and October all the stations showed negative trends in daily T_{max} . On the other hand, almost all the stations showed increasing trends in daily T_{max} in rest nine months except those three (i.e., except June, September and October). The significant positive trends were found in the month of July at four stations (Table 4.2). The negative trend was significant in the month of June at only Dorval station for daily T_{max} . In case of daily T_{min} , almost all stations showed positive trends during the months from January to September. The trends were significant in April and May for few stations (Table 4.3) and in July only for Cornwall. Decreasing trends were found in daily T_{min} at all the stations in October, November, and December, although none was significant at the 95% confidence level. It is

observed from Tables 4.2 and 4.3 that both T_{max} and T_{min} showed increasing trends in most of the months, which has resulted in positive trends in annual means.

Table 4.2: Trends in monthly means of daily T_{max} at seven stations in the southern Quebec-Ontario region.

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
L'Assomption	0.060	0.083	0.017	0.070	0.033	-0.034	0.024	0.052	-0.034	-0.062	-0.009	0.022
Dorval	0.050	0.060	0.032	0.062	0.030	-0.046	0.032	0.031	-0.027	-0.064	0.005	0.026
Maniwaki UA	0.053	0.062	0.017	0.084	0.029	-0.029	0.046	0.029	-0.021	-0.067	0.000	0.004
Chenauux	0.05	0.084	0.035	0.089	0.054	-0.005	0.079	0.057	-0.014	-0.077	0.001	0.017
Cornwall	0.078	0.07	0.065	0.068	0.033	-0.024	0.056	0.030	-0.026	-0.067	0.017	0.051
Ottawa CDA	0.058	0.088	0.034	0.069	0.025	-0.031	0.055	0.036	-0.026	-0.081	0.004	0.033
Morrisburg	0.046	0.064	0.046	0.071	0.048	0.002	0.065	0.052	-0.027	-0.067	0.005	0.044

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 4.3: Trends in monthly means of daily T_{min} at seven stations in the southern Quebec-Ontario region.

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
L'Assomption	0.066	0.118	0.017	0.081	0.086	0.021	0.027	0.033	0.011	-0.028	-0.009	-0.027
Dorval	0.058	0.110	0.009	0.040	0.036	-0.037	0.005	0.008	-0.018	-0.058	-0.030	-0.032
Maniwaki UA	0.069	0.133	0.037	0.069	0.056	0.009	0.027	0.035	0.005	-0.030	-0.029	-0.070
Chenauux	0.055	0.116	0.015	0.056	0.09	0.005	0.028	0.040	0.000	-0.041	-0.031	-0.019
Cornwall	0.091	0.106	0.034	0.084	0.066	0.011	0.045	0.049	0.021	-0.026	-0.003	0.026
Ottawa CDA	0.079	0.122	0.013	0.073	0.072	0.021	0.037	0.035	0.006	-0.029	-0.012	0.003
Morrisburg	0.056	0.078	-0.008	0.039	0.031	-0.020	0.003	0.009	0.016	-0.051	-0.022	-0.014

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

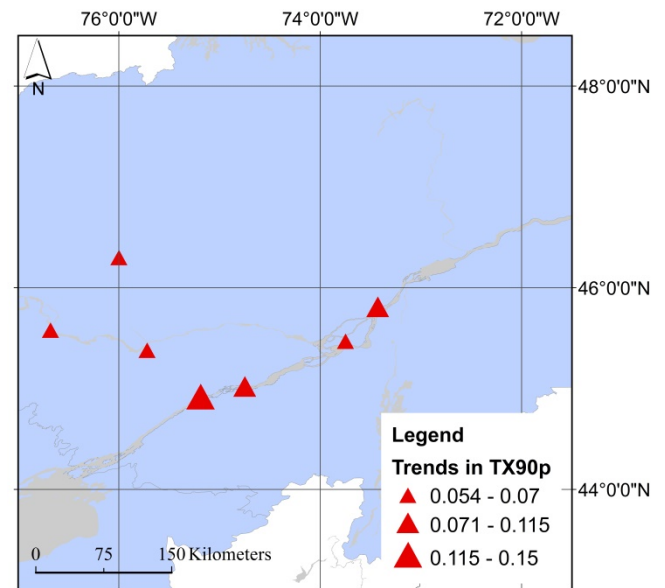
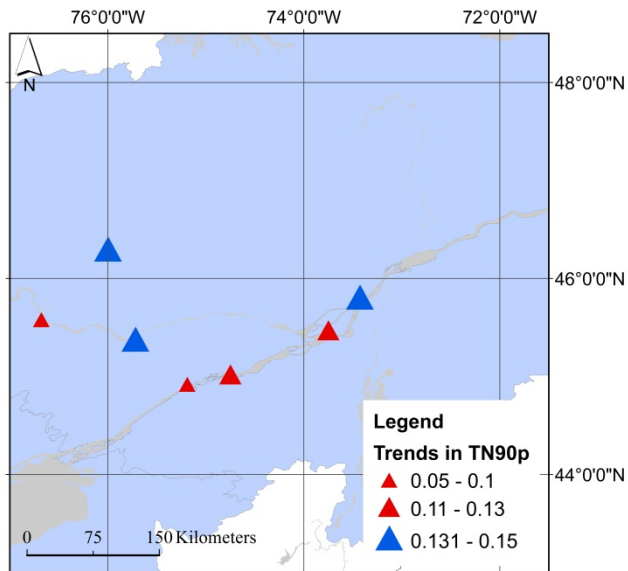
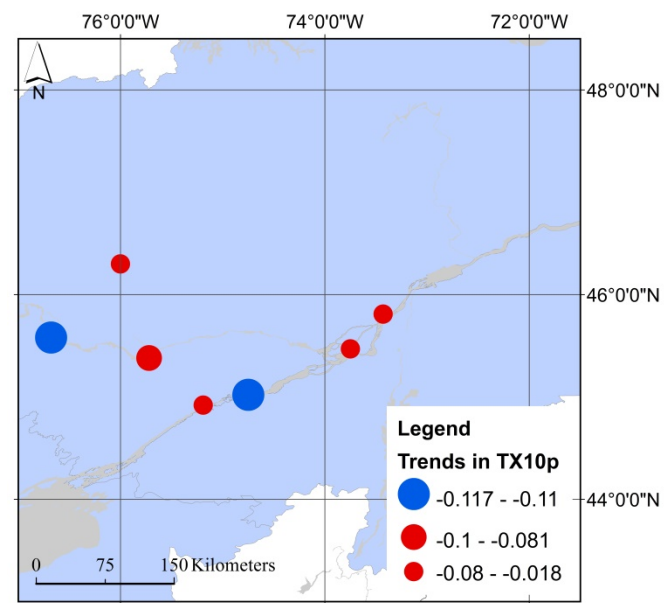
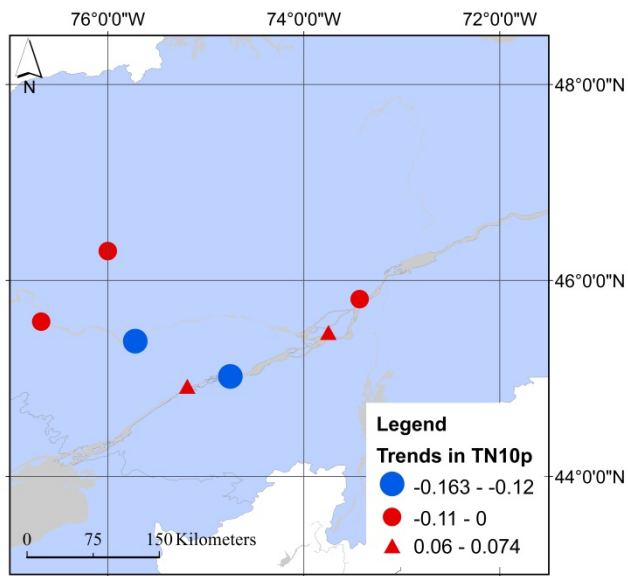
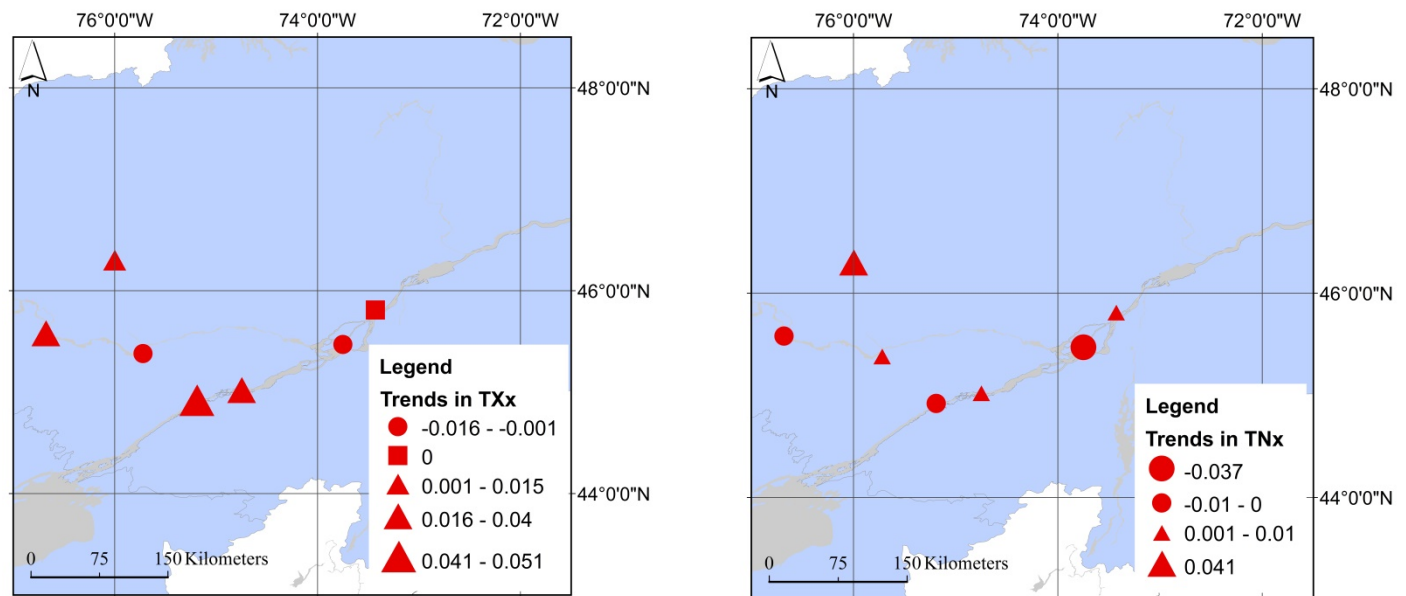


Figure 4.7: Spatial distribution of the trends in cool nights (TN10p) (upper left), cool days (TX10p) (upper right), warm nights (TN90p) (lower left), and warm days (TX90p) (lower right) during the period of 1961-1990 in the southern Quebec-Ontario region.

The asymmetric warming of T_{max} and T_{min} is associated with the changes in extremes of weather and climate, e.g., reduced frost days, increased warm nights, reduced cold nights,

lengthened heat wave duration etc. (IPCC, 2007). According to the AR5, the number of cold days and nights has decreased, while the number of warm days and nights has increased on global scale (IPCC, 2013). Complying with IPCC findings this fact is reflected in the trends of cool nights, cool days, warm nights, and warm days over study area (Figure 4.7). All the stations showed negative trends in cool days (-0.018 - -0.117 days per year) during the period of 1961-1990. In cool nights also almost all the stations (except Morrisburg and Dorval) showed negative trends (-0.163 - 0.074 days per year). Stations indicating significant negative trends are Cornwall and Ottawa CDA (-0.163 and -0.118 days per year) in cool nights and Cornwall and Chenaux (-0.117 and -0.114 days per year) in cool days. All of seven stations showed positive trends in the indices of warm nights (0.05 - 0.148 days per year) and warm days (0.054 - 0.147 days per year) during this period. Significant increasing trends in warm nights were detected in three stations: L'Assomption, Maniwaki and Ottawa CDA (The slopes were respectively 0.137, 0.134 and 0.148 days per year). None of the trends was found significant in warm days during this period.



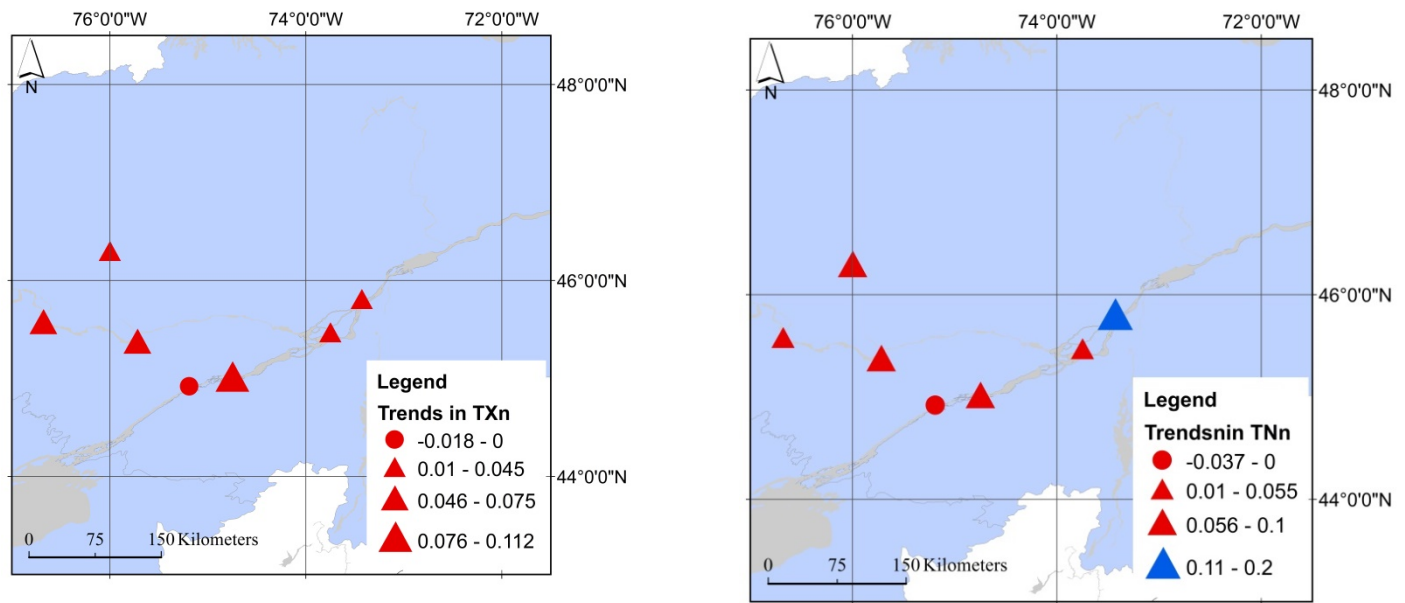


Figure 4.8: Spatial distribution of the trends in MaxTmax (TXx) (upper left), MaxTmin (TNx) (upper right), MinTmax (TXn) (lower left) and MinTmin (TNn) (lower right) during the period of 1961-1990 in the southern Quebec-Ontario region.

Figure 4.8 represents the trends in the indices of MaxTmax, MaxTmin, MinTmax and MinTmin. Some stations showed increasing trends while some showed decreasing trends in MaxTmax index showing a non-homogeneous pattern over study area. Four stations namely Chenaux, Cornwall, Maniwaki and Morrisburg showed positive trends (the slopes were 0.038, 0.034, 0.013 and 0.051 °C per year respectively) in MaxTmax during this period. Dorval and Ottawa CDA exhibited negative trends (-0.016 and -0.002 °C per year respectively) while L'Assomption showed no trend in this index. The MaxTmin index showed a similar behaviour like MaxTmax showing both increasing and decreasing trends. Stations exhibiting positive trends in MaxTmin are: Cornwall, L'Assomption, Maniwaki and Ottawa CDA (0.005, 0.001, 0.041 and 0.009 °C per year respectively). Stations showing negative trends in this index are Chenaux, Dorval and Morrisburg (-0.01, -0.037, -0.005 °C per year respectively). Except Morrisburg, rest of the stations showed positive trends in MinTmax (-0.018-0.112 °C per year) as well as MinTmin (-0.037-0.118 °C per year) evidencing that the minimums of both *Tmax* and *Tmin* have been increased over this area during this period. However, only L'Assomption showed significant positive trend in MinTmin. No significant trend was found for rest of the indices at any of seven stations.

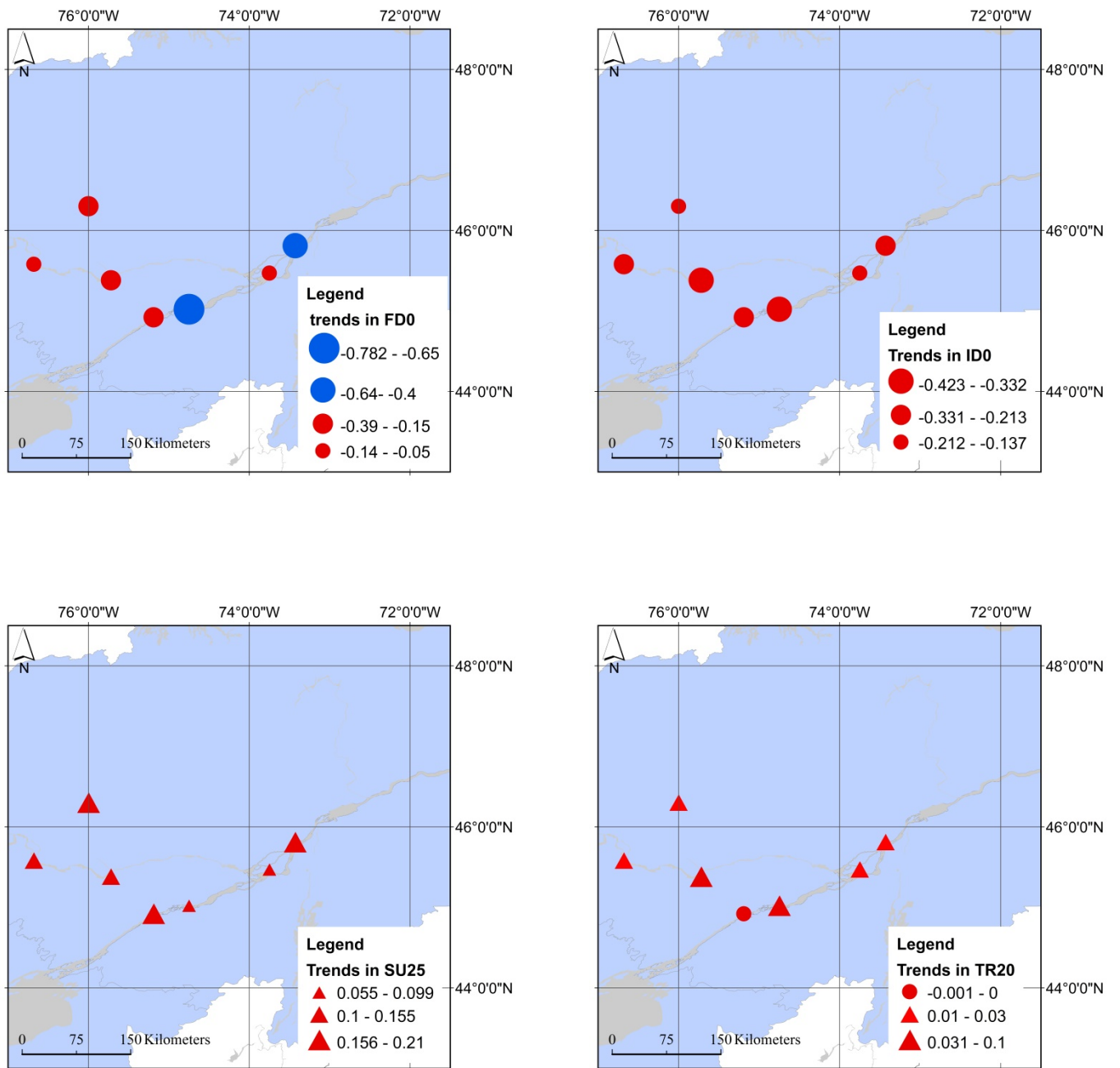
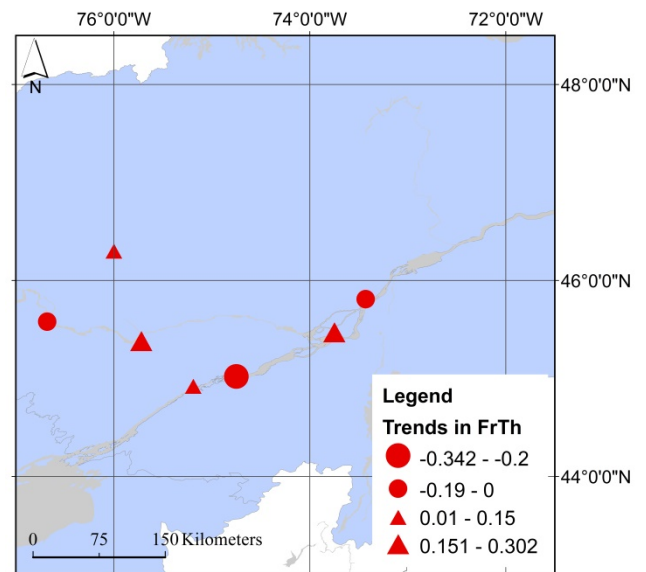
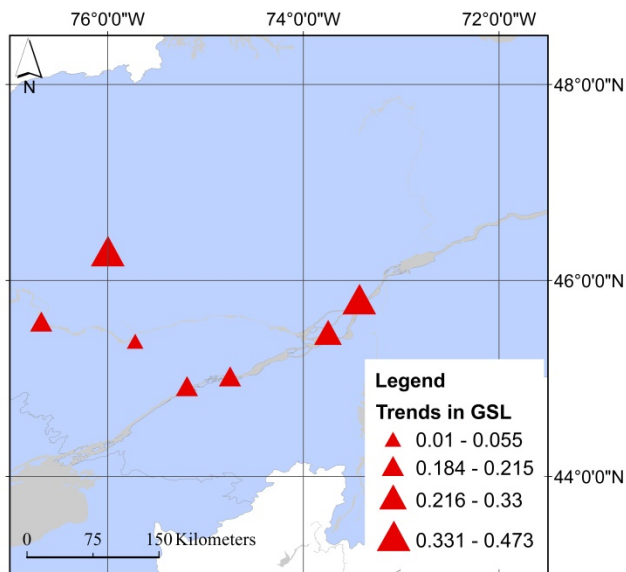


Figure 4.9: Spatial distribution of the trends in frost days (FD0) (upper left), ice days (ID0) (upper right), summer days (SU25) (lower left), and tropical nights (TR20) (lower right) during the period of 1961-1990 in the southern Quebec-Ontario region.

The trends in frost days, ice days, summer days and tropical nights are delineated in Figure 4.9. Negative trends (-0.061 - -0.782 days per year) were found in frost days whereas positive trends (0.055 - 0.21 days per year) were found in summer days at all of seven stations, evidencing

warming of temperature over the study area. Negative trends in frost days were found significant at Cornwall and L'Assomption stations. None of the trends was found significant in summer days at the 95% confidence level. Highest slopes in frost (-0.782 days per year) and summer days (0.21 days per year) during this period were detected at Cornwall and Morrisburg respectively. Like frost days, in case of ice days also all of seven stations showed decreasing trends (-0.137 - -0.423 days per year). Except Morrisburg, rest of the stations showed positive trends in tropical nights (-0.001 - 0.1 days per year). However, none of the stations showed significant trend in the indices of ice days and tropical nights at the 95% confidence level during this period. Largest slopes were observed at Cornwall in both ice days and tropical nights, which are -0.423 and 1 days per year respectively. It could be noticed that the station Morrisburg had experienced an increasing variability of temperature during the mentioned period. This station showed the highest positive slopes in summer days and MaxTmax at one end, while negative slopes in tropical nights and MinTmin on the other hand. The highest positive slope in DTR also evidenced the increased variability of temperature at this station.



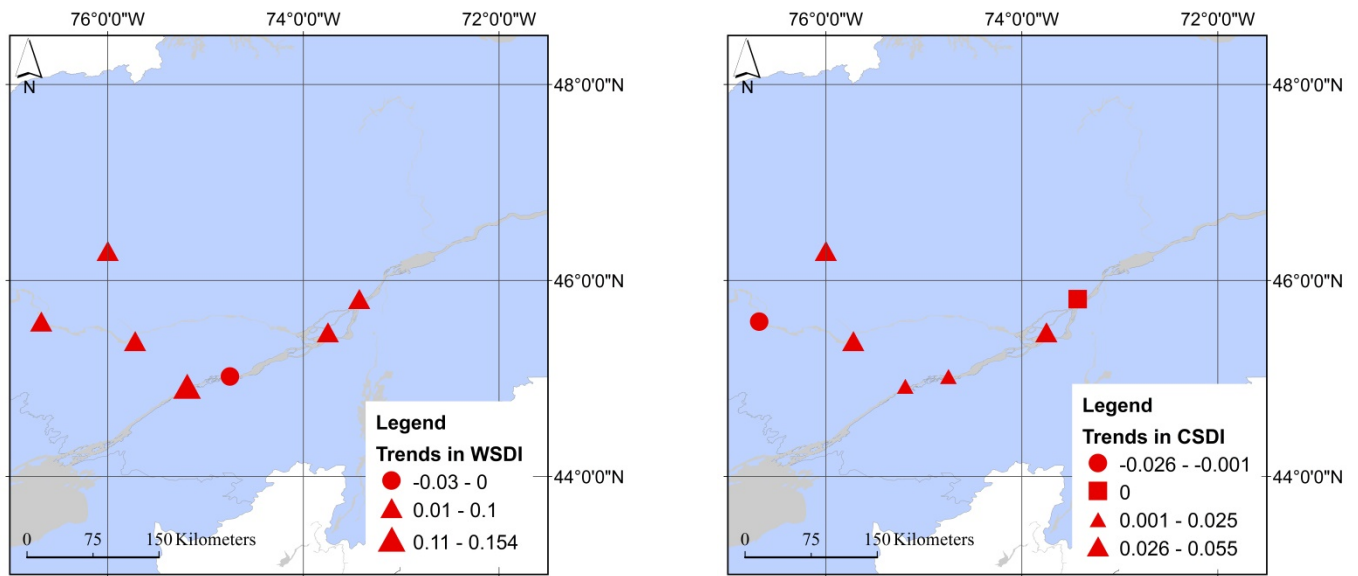


Figure 4.10: Spatial distribution of the trends in growing season length (GSL) (upper left), freeze and thaw cycle (Fr-Th) (upper right), warm spell duration indicator (WSDI) (lower left), and cold spell duration indicator (CSDI) (lower right) during the period of 1961-1990 in the southern Quebec-Ontario region.

Spatial distribution of the trends in the indices of GSL, Fr-Th cycle, WSDI and CSDI are presented in Figure 4.10. Positive trends (0.053 - 0.473 days per year) were found in GSL at all seven stations over the study area with L'Assomption showing the highest slope. For Fr-Th cycle, Chenaux, L'Assomption and Cornwall showed negative trends (-0.018, -0.117 and -0.342 days per year respectively) while rest of the stations exhibited positive trends (0.078 - 0.302 days per year) over the area. Both WSDI and CSDI showed positive trends at most of the stations indicating the increased variability of temperature over the area. Six stations out of seven exhibited positive trend (0.045 - 0.154 days per year) in WSDI. Like WSDI, in case of CSDI positive trends (0.012 - 0.055 days per year) were observed in most of the stations (five stations) over the study area. The stations that experienced decreasing trends in WSDI (-0.03 days per year) and CSDI (-0.026 days per year) are Cornwall and Chenaux respectively. L'Assomption showed no trend, meaning no change in CSDI over the period. It is to be noted that although both indices showed positive trends at most of the stations, the slopes are higher in WSDI than in CSDI. However none of the stations showed significant trend in these indices at the 95% confidence level.

4.3 Analysis of temperature indices in Bangladesh

Bangladesh experiences a humid, warm and tropical climate, which is influenced primarily by monsoon and partly by pre-monsoon and post-monsoon circulations (Huq et al., 1999). From hydro meteorological point of view, there are four prominent seasons in Bangladesh (Agrawala et al., 2003): Winter (December to February), Pre-monsoon (March to May), Monsoon (June to September/early-October), Post-monsoon (October to November). Winter is relatively cooler and drier compared to other seasons. The average temperature in winter ranges from a minimum of 7.2 to 12.8°C to a maximum of 23.9 to 31.1°C. In the north the minimum temperature occasionally falls below 5°C and frost is extremely rare (Agrawala et al., 2003). Pre monsoon is hot with high rate of evaporation. The average maximum temperature is 36.7°C, but occasionally rises up to 40.6°C or more in some places (Agrawala et al., 2003). Monsoon is hot and humid and brings torrential rainfall. The south-west monsoon originated over the Indian Ocean carries warm, moist, and unstable air. About two-thirds of the mean annual rainfall occurs in this season (Huq et al., 1999). Post monsoon is a short living season and is characterized by withdrawal of rainfall along with gradual lowering of nighttime temperature. The peak of the maximum temperatures in Bangladesh is observed in April, the beginning of pre-monsoon season and minimum temperature is experienced in December-January.

Geographically Bangladesh is situated at the interface of two distinct environments, with the Himalayas to the north and the Bay of Bengal (which mingles with the Indian Ocean) to the south. The funnel shaped exposure to the ocean allows plenty of rain laden wind to propagate over the country causing heavy rainfall in monsoon (Bhowmik, 2013). Many studies conducted for analyzing the trends in climate variables pointed out that temperature has been changed over time in Bangladesh. For example, using the data provided by Climate Research Unit (CRU), University of East Anglia, Warrick et al. (1996) showed that Bangladesh has experienced more warm years especially after 1930s and shown an overall average warming of about 0.5°C from the latter part of the last century. Islam (2009a) investigated long term trends of maximum and minimum daily temperature over the period 1948-2007. The 60 years trends show that daily maximum temperature had increased at a rate of $0.621 \pm 0.491^{\circ}\text{C}$ per 100 year, whereas daily minimum temperature showed a more significant increasing trend at a rate of $1.536 \pm 0.461^{\circ}\text{C}$ per 100 year. The study showed that temperature has increased predominantly over the recent 30 years (1978-2007) than

the period 1948-2007. Trends in daily maximum and minimum temperature during the 30 years period (1978-2007) are 2.05°C and 1.2°C per 100 years respectively. A study conducted by Mondal et al. (2013) showed that, over recent years, the temperature in the Khulna region located in South-Western part of Bangladesh has been increased at a significant rate. The number of extremely cold nights has decreased, while the heat index has increased in this region during the recent period.

In this present study trend analysis of various temperature related indices have been performed for eight stations for the period 1976-2000. The stations are Barisal, Bogra, Dhaka, Jessore, Khulna, Rajshahi, Satkhira and Sylhet. The geographical information of these eight stations are presented in Table 4.4. It should be mentioned that temperature data from four out of these eight stations namely Bogra, Dhaka, Jessore, and Satkhira have been used as predictands in this study. The subsection 4.3.1 provides detailed trend analysis of the temperature indices at Dhaka station (similar analysis for rest seven stations are given in Appendix C) and subsection 4.3.2 describes the spatial distribution of the trends over the area.

Table 4.4 Names and coordinates of eight weather stations in Bangladesh.

Station Name	Latitude	Longitude	Altitude (meters above sea level)
Barisal	22.72°N	90.37°E	2.1
Bogra	24.85°N	89.37°E	17.9
Dhaka	23.78°N	90.38°E	6.5
Jessore	23.2°N	89.33°E	6
Khulna	22.78°N	89.53°E	2.1
Rajshahi	24.37°N	88.7°E	19.5
Satkhira	22.72°N	89.08°E	4
Sylhet	24.9°N	91.88°E	33.5

Source: (Islam, 2009a)

4.3.1 Temperature indices at Dhaka station

The interannual variation of temperature indices during the period 1976-2000 at Dhaka station in Bangladesh is discussed in this section and shown in Figures 4.11 to 4.14. The Dhaka station is located in central Bangladesh at latitude 23.78°N and longitude 90.38°E .

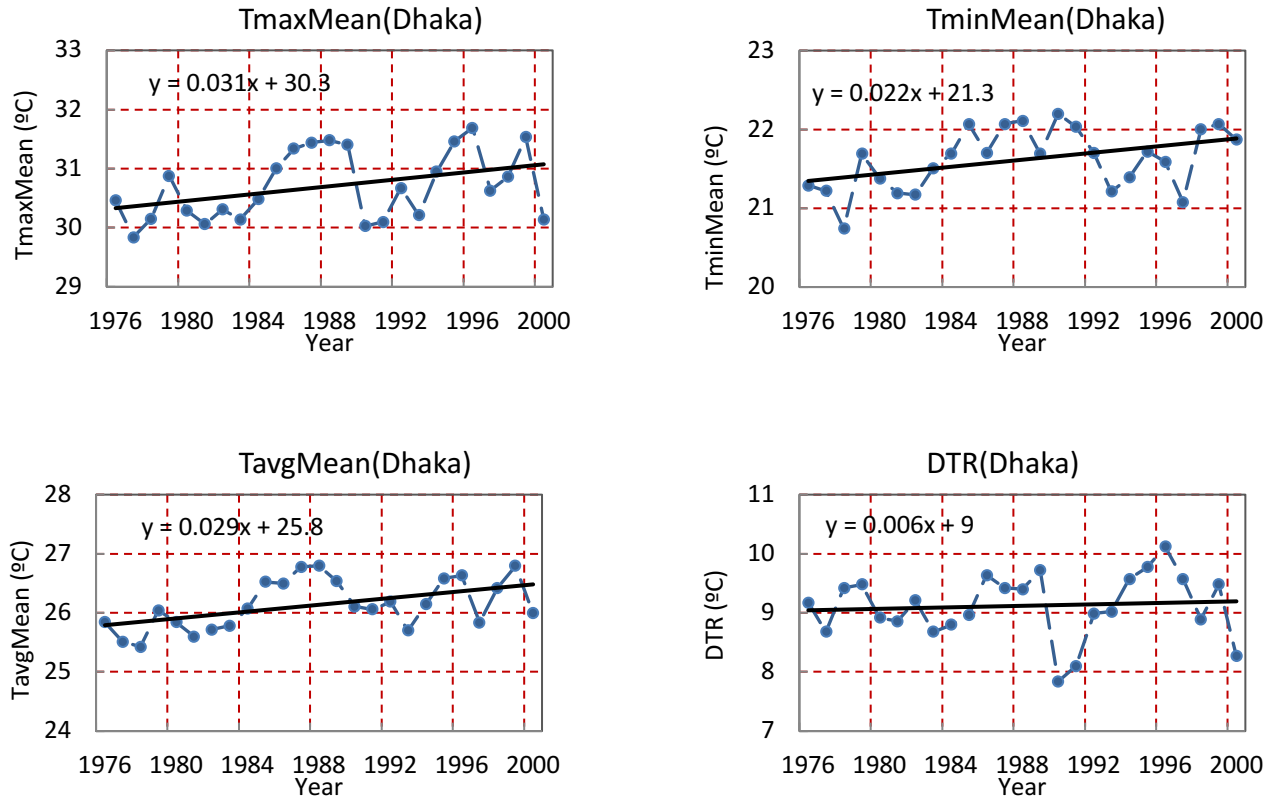


Figure 4.11: Trends in TmaxMean (upper left), TminMean (upper right), TavgMean (lower left), and DTR (lower right) at Dhaka station during the period 1976-2000.

Temporal variation in TmaxMean, TminMean, TavgMean and DTR at Dhaka station during the period 1976-2000 is shown in Figure 4.11. Positive trends were observed in TmaxMean as well as TminMean. The slopes were 0.031 and 0.022°C per year respectively and found significant at the 95% confidence level according to Mann-Kendall test. As both TmaxMean and TminMean were increasing, TavgMean also showed a positive trend (0.029°C per year) showing significance at the 95% confidence level. The figure shows that increasing of *Tmax* at a higher rate than *Tmin* has resulted in a slightly increasing trend in DTR (0.006°C per year) at this station, which was not statistically significant.

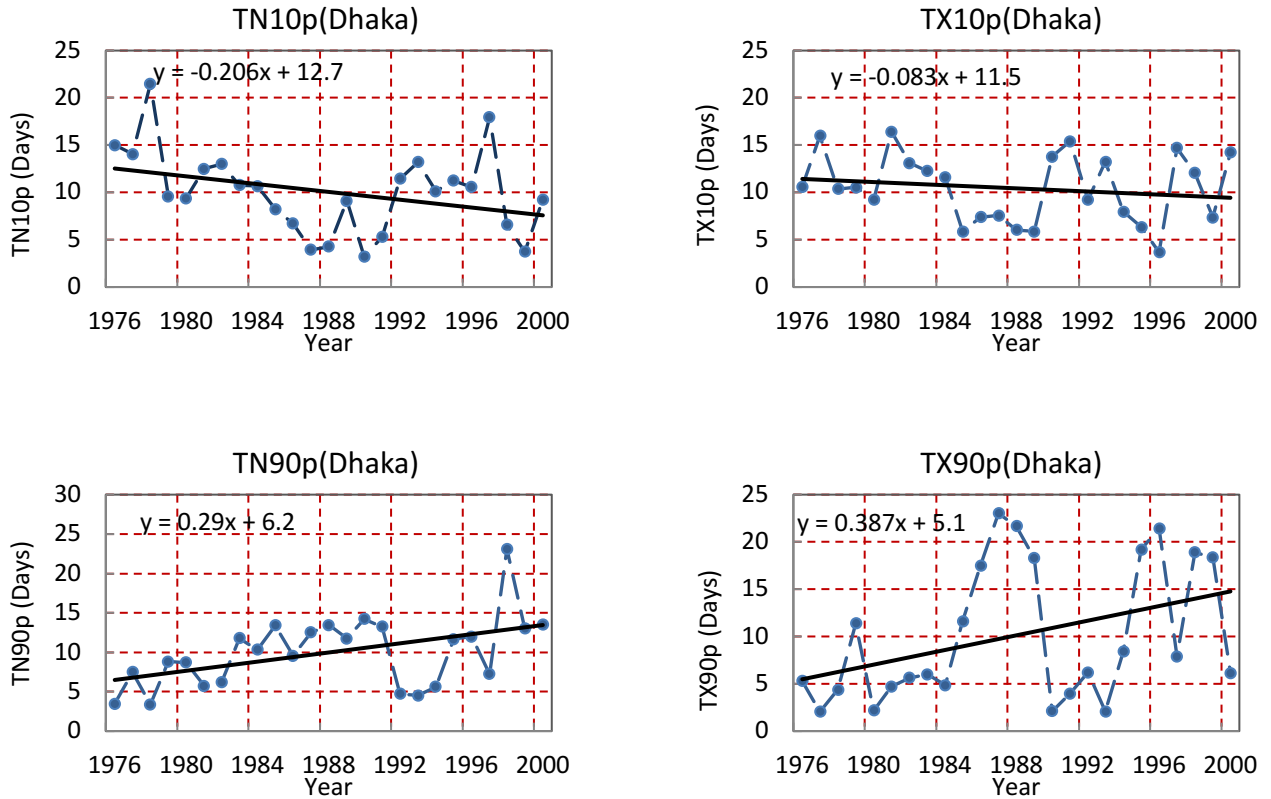


Figure 4.12: Trends in cool nights (TN10p) (upper left), cool days (TX10p) (upper right), warm nights (TN90p) (lower left), and warm days (TX90p) (lower right) at Dhaka station during the period 1976-2000.

Figure 4.12 presents the trends in cool nights, cool days, warm nights and warm days at Dhaka station. The indices cool nights and cool days showed decreasing trends (-0.206 and -0.083 days per year respectively) during the 1976-2000. However, the trends in these two indices were insignificant at the 95% confidence level. On the other hand, significant increasing trends were detected in warm nights and warm days (0.29 and 0.387 days per year respectively) indicating the warming of temperature at Dhaka station during the period.

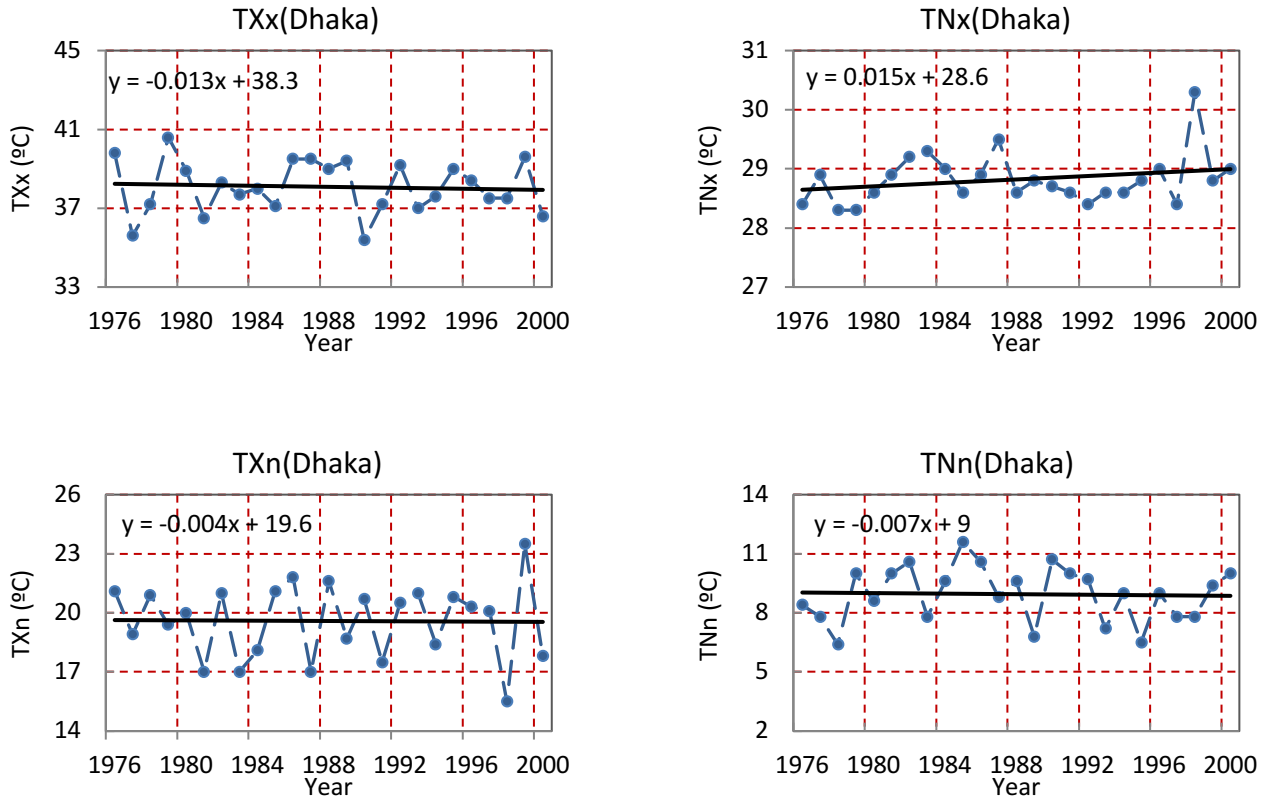


Figure 4.13: Trends in MaxTmax (TXx) (upper left), MaxTmin (TNx) (upper right), MinTmax (TXn) (lower left) and MinTmin (TNn) (lower right) at Dhaka station during the period 1976-2000.

Annual variability in MaxTmax, MaxTmin, MinTmax and MinTmin at Dhaka station is given in Figure 4.13. A negative trend was detected in MaxTmax (-0.013°C per year), whereas a positive trend was found in MaxTmin (0.015°C per year). Both MinTmax and MinTmin indices showed slightly negative trends (-0.004 and -0.007°C per year) at this station. However, according to Mann-Kendall test, the trends in these four indices were found insignificant at the 95% confidence level.

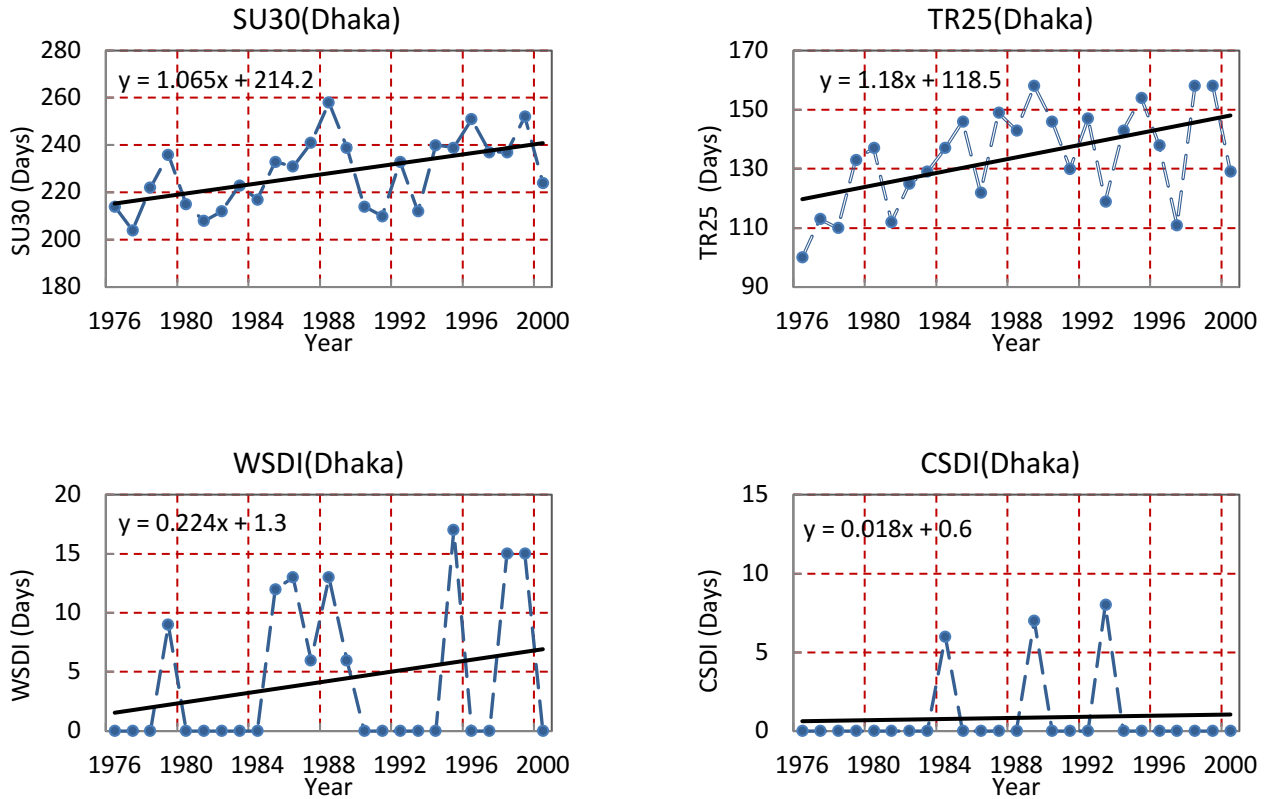


Figure 4.14: Trends in summer days (SU30) (upper left), tropical nights (TR25) (upper right), warm spell duration indicator (WSDI) (lower left), and cold spell duration indicator (CSDI) (lower right) at Dhaka station during the period 1976-2000.

Interannual variability in summer days, tropical nights, WSDI and CSDI are given in Figure 4.14. In a tropical country like Bangladesh, daily T_{max} usually goes above 25°C on most of the days of the year (about more than 275 days out of 365 days). In this regard computing SU30 (annual counting of days with daily T_{max} above 30°C) instead of SU25 is more meaningful to represent the summer days index. Likewise, in case of tropical nights, computing TR25 (annual counting of days with daily T_{min} above 25°C) instead of TR20 has been considered to represent the tropical nights index in Bangladesh. Hence the summer days and tropical nights indices in Bangladesh have been represented respectively by SU30 and TR25. At Dhaka station a significant positive trend (1.065 days per year) was detected in summer days (SU30) during the period 1976-2000. For tropical nights (TR25) also, the trend was found positive (1.18 days per year) and significant at the 95% confidence level. Like SU30 and TR25, in the indices WSDI and CSDI also showed positive trends at this station during the mentioned period. The slopes were 0.224 and

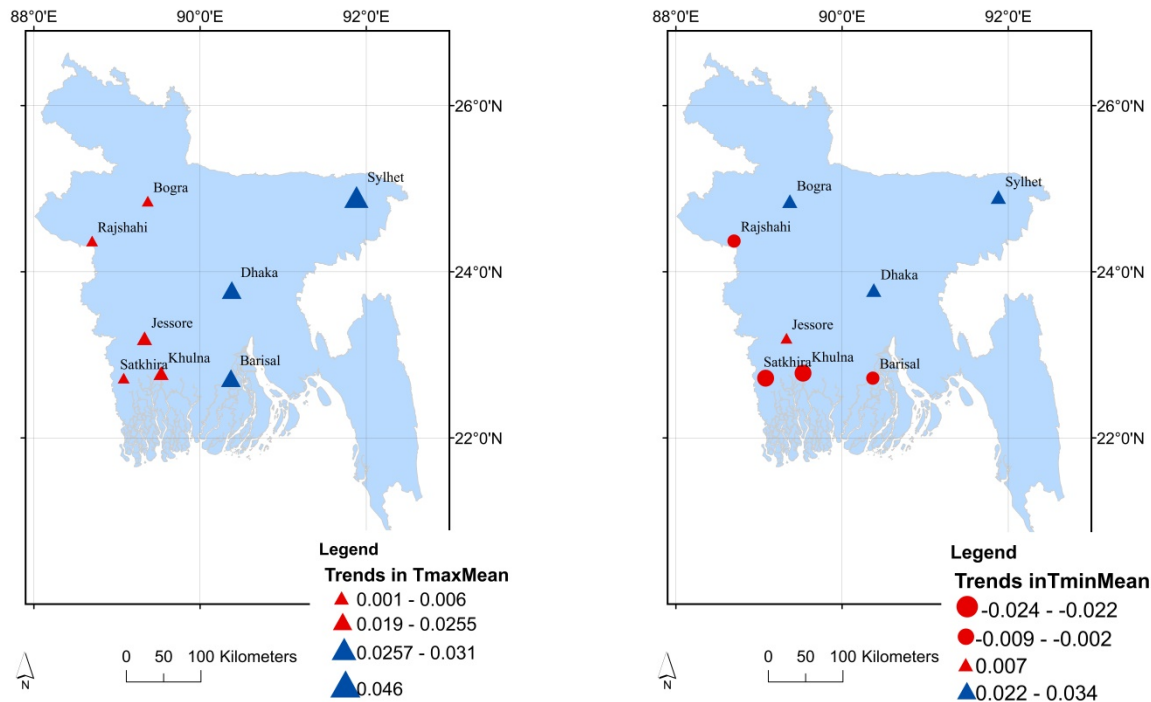
0.018 days per year respectively. However, both trends were insignificant at the 95% confidence level.

The aforementioned trend analysis delineates that a number of indices such as TmaxMean, TminMean, TavgMean, warm nights, warm days, summer days and tropical nights have significantly increased at Dhaka station during the period of twenty five years ranging from 1976 to 2000. This finding gives a clear indication of increasing of temperature at this station during the mentioned period.

Since the daily temperature in Bangladesh usually does not go below 0° C, the indices like Fr-Th cycle, frost days and ice days for Bangladesh have not been analysed in this study.

4.3.2 Spatial distribution of temperature indices in Bangladesh

Spatial distributions of the trends of temperature indices for selected eight stations (Table 4.4) located in Bangladesh have been provided in this section and illustrated through the following Figures from 4.15 to 4.18.



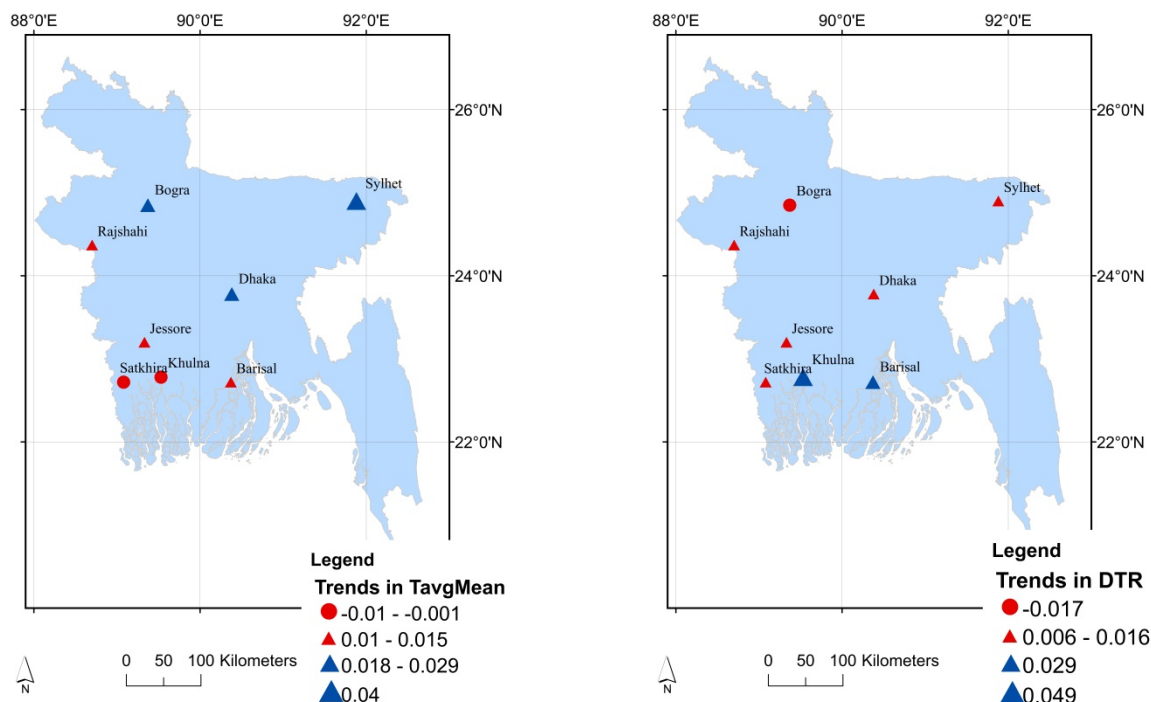


Figure 4.15: Spatial distribution of the trends in TmaxMean (upper left), TminMean (upper right), TavvMean (lower left) and DTR (lower right) during the period of 1976-2000 in Bangladesh.

Figure 4.15 delineates the spatial distributions of the trends in TmaxMean, TminMean, TavvMean and DTR. Positive trends were observed in TmaxMean for all of the eight stations. The slopes ranged between 0.001 - 0.046°C per year, where the highest slope was observed at Sylhet station and the lowest trend at Satkhira. Only three stations out of eight namely Barisal, Dhaka and Sylhet showed significant trends at the 95% confidence level. In case of TminMean four stations showed positive trends, while the rest four stations showed the negative trends. The stations showed positive trends were Bogra, Dhaka, Jessore and Sylhet (0.007 - 0.034°C per year) and the stations showed negative trends were Barisal, Khulna, Rajshahi and Satkhira (-0.002 - -0.024°C per year). The largest positive and negative trends were found respectively at Khulna and Sylhet. Only three stations namely Bogra, Dhaka and Sylhet showed significant trends in this index. Except Khulna and Satkhira, rest six stations showed positive trends (0.01 - 0.04°C per year) in TavvMean, of which Bogra, Dhaka and Sylhet showed the significant trends, with Sylhet showing the highest one. The stations Khulna and Satkhira showed negative trends (respectively -0.001 and -0.01°C per year) in this index. The trend in DTR showed positive trends at seven stations and the slopes ranged between 0.006 - 0.049°C per year at those seven stations, with Khulna showing the

highest slope. Only Bogra showed a negative trend (-0.017°C per year) in this index. However, the trends in DTR were significant only at Barisal and Khulna at the 95% confidence level.

The trends in monthly means of daily T_{max} and T_{min} for each of the months at eight stations have been presented in Table 4.5 and 4.6 respectively. Monthly means of daily T_{max} demonstrated increasing trends at most of the stations in most of the months except January (Table 4.5). Relatively higher and significant increasing trends were observed in the months of June, July, August and December. In case of T_{min} , a heterogeneous pattern was observed for the trends of monthly means. For instance, Dhaka and Sylhet showed increasing trends in all of twelve months (Table 4.6). Except January, Bogra showed increasing trends for rest of the months. On the other hand, Khulna and Satkhira exhibited decreasing trends for most of the months. The rest three stations were found to show increasing trend in some of the months while decreasing trends in the rests. It can be observed that the monthly means of both daily T_{max} and T_{min} showed decreasing trends in January at most of the stations, which indicates that the coldest month in Bangladesh approached toward a more extreme end during 1976-2000.

Table 4.5: Trends in monthly means of daily T_{max} at eight stations in Bangladesh.

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barisal	-0.006	0.018	0.012	0.015	0.023	0.057	0.029	0.032	0.028	0.028	0.013	0.054
Bogra	-0.048	-0.009	-0.069	-0.074	0.043	0.049	0.035	0.029	0.003	0.063	0.04	0.057
Dhaka	-0.018	0.02	0.009	0.026	0.046	0.075	0.041	0.038	0.035	0.041	0.023	0.038
Jessore	-0.048	-0.002	0.002	0.009	0.046	0.053	0.029	0.039	0.007	0.033	0.021	0.048
Khulna	-0.002	0.037	0.004	0.004	0.028	0.034	0.041	0.046	0.036	0.031	0.023	0.061
Rajshahi	-0.043	0.001	-0.032	0.008	0.066	0.055	0.023	0.038	-0.017	0.027	-0.002	0.01
Satkhira	-0.041	-0.009	-0.028	-0.017	-0.006	0.012	0.028	0.028	0.013	0.01	-0.022	0.008
Sylhet	0.05	0.02	0.006	0.056	0.055	0.056	0.057	0.022	0.04	0.053	0.038	0.053

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 4.6: Trends in monthly means of daily T_{min} at eight stations in Bangladesh.

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barisal	0.004	0.041	0.004	-0.013	0.011	-0.008	-0.014	-0.026	-0.034	0.012	0.002	0.012
Bogra	-0.005	0.041	0.035	0.011	0.047	0.02	0.014	0.01	0.004	0.043	0.034	0.029
Dhaka	0.024	0.043	0.004	0.028	0.051	0.035	0.014	0.011	0.003	0.018	0.007	0.038
Jessore	-0.027	0.027	-0.027	0.001	0.054	0.019	0.016	0.019	-0.007	0.021	0.003	0.006
Khulna	-0.089	-0.026	-0.034	-0.011	0.012	-0.01	-0.002	-0.012	-0.02	-0.017	-0.035	-0.044
Rajshahi	-0.076	-0.028	-0.034	0.004	0.052	0.027	0	0.005	-0.022	0.009	-0.02	-0.006
Satkhira	-0.066	0.004	-0.03	-0.033	0.013	-0.001	-0.005	-0.008	-0.033	-0.009	-0.063	-0.041
Sylhet	0.045	0.047	0.015	0.016	0.041	0.004	0.014	0.008	0.016	0.067	0.049	0.059

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

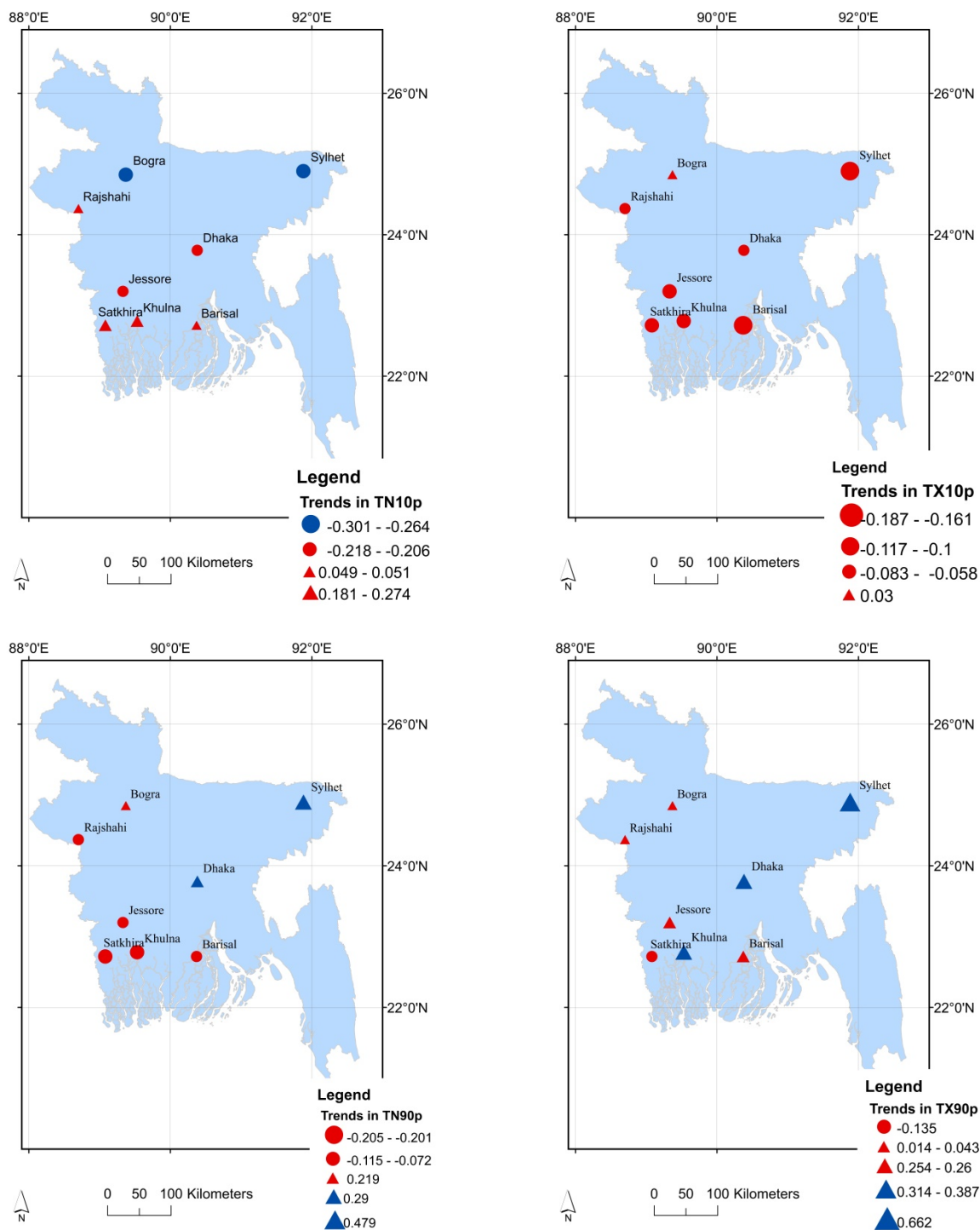


Figure 4.16: Spatial distribution of the trends in cool nights (TN10p) (upper left), cool days (TX10p) (upper right), warm nights (TN90p) (lower left), and warm days (TX90p) (lower right) during the period of 1976-2000 in Bangladesh.

The spatial distributions of the trends in cool nights, cool days, warm nights and warm days are given in Figure 4.16. The figure shows that the stations showing positive trends in cool nights (Satkhira, Khulna, Barisal and Rajshahi) mostly (except Rajshahi) located in the south-western part of Bangladesh. Conversely, the stations located in the south-western part of the country showed negative trends in warm nights. The positive trends in cool nights ranged between 0.049 - 0.274 days per year with Satkhira showing the highest slope. The stations showed negative trends were Bogra, Dhaka, Jessore and Sylhet (-0.206 - -0.301 days per year) and the largest negative trend was observed at Sylhet station. The trends in cool nights are statistically significant only at Bogra and Sylhet. The stations showing negative trends in warm nights are Barisal, Jessore, Khulna, Rajshahi and Satkhira. The positive trends were observed at Bogra, Dhaka and Sylhet. The slopes in warm nights ranged between -0.205 - 0.479 days per year and the largest positive and negative slopes were observed respectively at Sylhet and Khulna stations. Only Dhaka and Sylhet were found to show significant trends in this index. Seven out of eight stations (except Bogra) showed decreasing trends in cool days, whereas the same number of stations (except Satkhira) showed increasing trends in warm days indicating the warming of temperature over the area. The slopes in cool and warm days ranged respectively between -0.187 - 0.03 days and -0.135 - 0.662 days per year. In both cases the highest slopes were observed at Sylhet station. However, none of the stations showed significant trend in cool days. The trends in warm days were statistically significant for Dhaka, Khulna, and Sylhet.

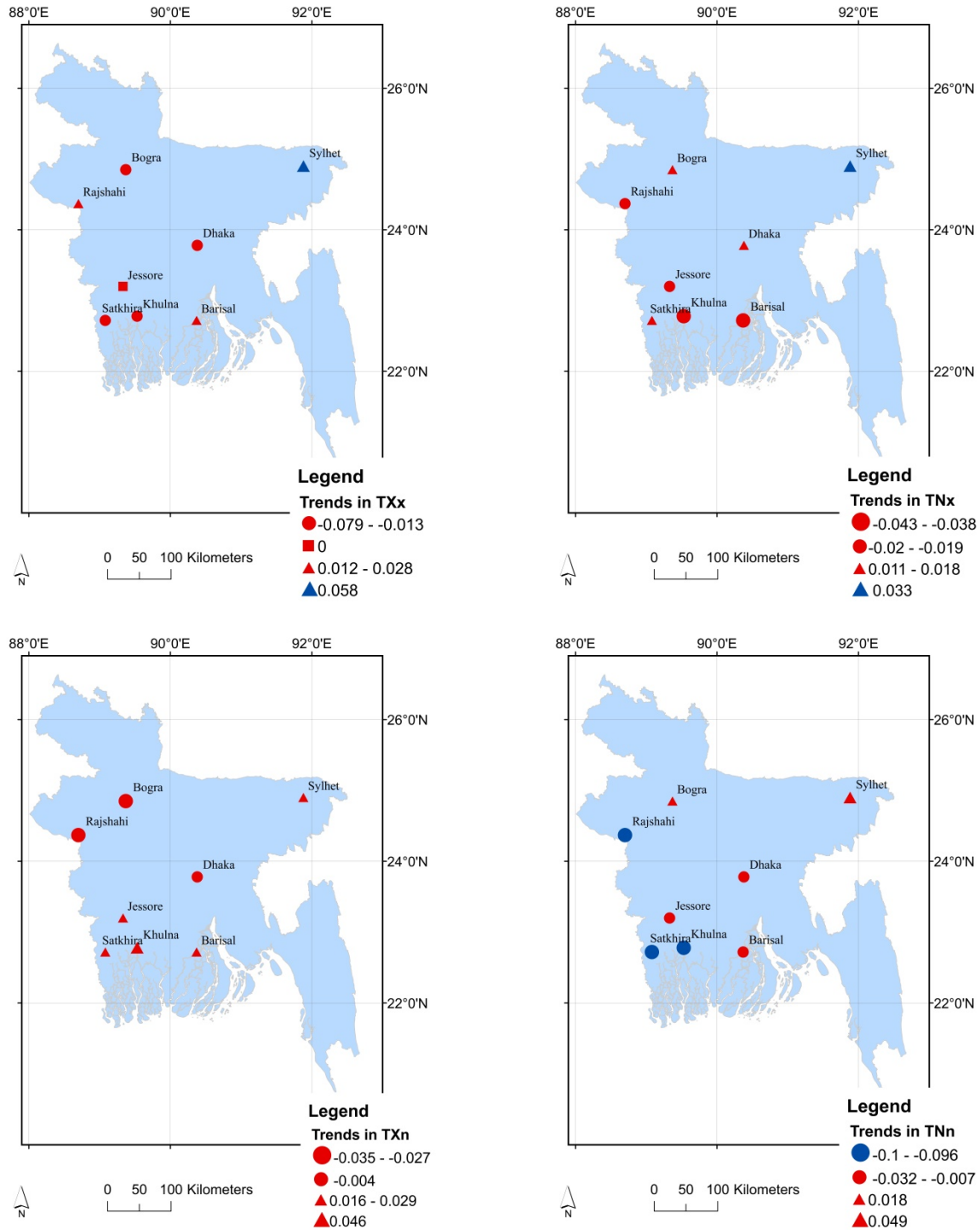
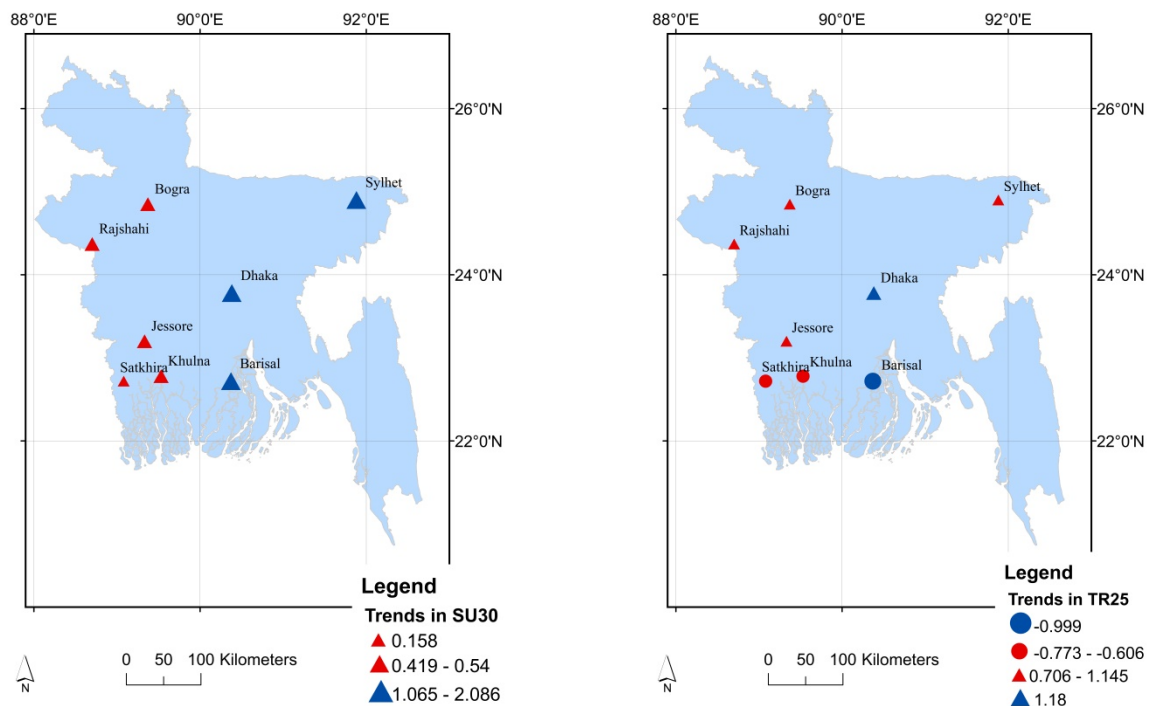


Figure 4.17: Spatial distribution of the trends in MaxTmax (TXx) (upper left), MaxTmin (TNx) (upper right), MinTmax (TXn) (lower left) and MinTmin (TNn) (lower right) during the period of 1976-2000 in Bangladesh.

Figure 4.17 presents the trends in the indices of MaxTmax, MaxTmin, MinTmax and MinTmin. A heterogeneous pattern was observed in MaxTmax index. Three stations (Barisal,

Rajshahi and Sylhet) showed increasing trends, four stations (Bogra, Dhaka, Khulna and Satkhira) showed decreasing trends, whereas one station (Jessore) exhibited no trend in this index. The slopes ranged between $-0.079 - 0.058^{\circ}\text{C}$ per year in this index. In MaxTmin, some stations (Bogra, Dhaka, Satkhira and Sylhet) showed increasing trends, whereas some (Barisal, Jessore, Khulna and Rajshahi) showed decreasing trends. The slopes in this index were between $-0.043 - 0.033^{\circ}\text{C}$ per year. In both cases, the largest positive and negative slopes were detected respectively at Sylhet and Khulna. Among eight stations only Sylhet was found to show significant trend in both indices. In case of MinTmax, Barisal, Jessore, Khulna, Satkhira and Sylhet showed increasing trends, while Bogra, Dhaka and Rajshahi showed decreasing trends. The slopes ranged between $-0.035 - 0.046^{\circ}\text{C}$ per year showing no significance at the 95% confidence level. The highest positive slope was detected at Khulna and the negative slope was detected at Bogra. Except Bogra and Sylhet, rest six stations exhibited negative trend in MinTmin and the slopes in this index at all stations ranged between $-0.1 - 0.049^{\circ}\text{C}$ per year. The largest positive and negative slopes in MinTmin were found respectively at Sylhet and Rajshahi. Significant trends in MinTmin were found at Khulna, Rajshahi and Satkhira stations.



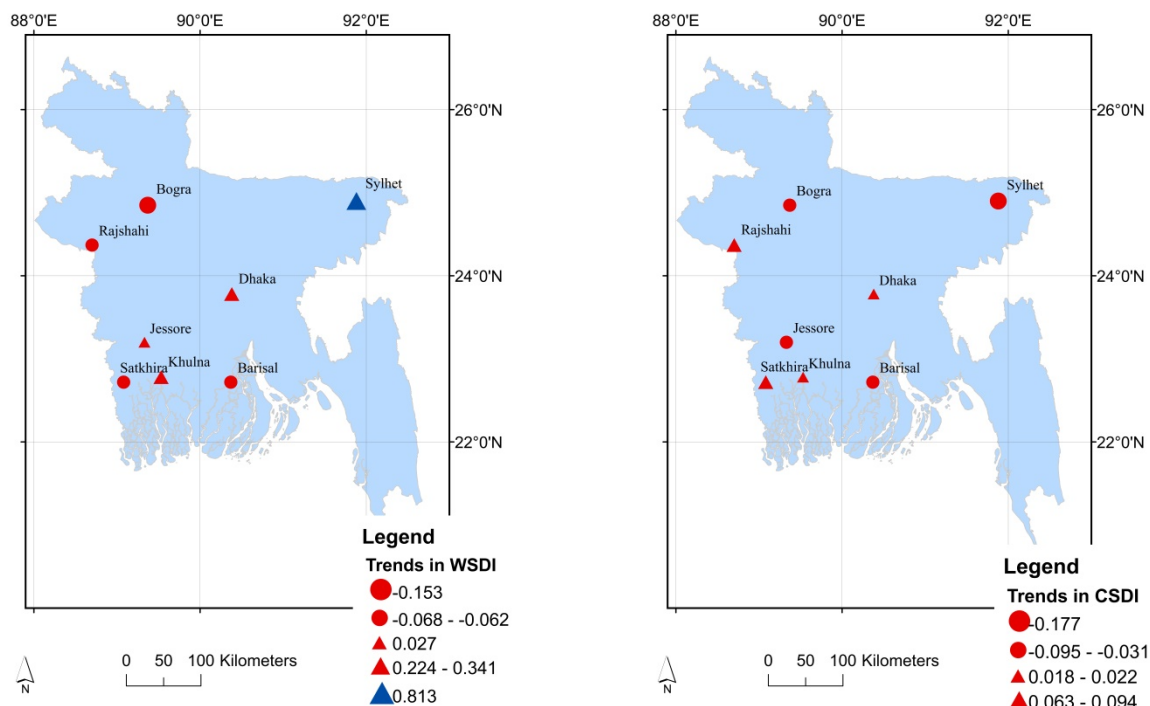


Figure 4.18: Spatial distribution of the trends in summer days (SU30) (upper left), tropical nights (TR25) (upper right), warm spell duration indicator (WSDI) (lower left) and cold spell duration indicator (CSDI) (lower right) during the period of 1976-2000 in Bangladesh.

As mentioned earlier, in case of Bangladesh the indices of summer days and tropical nights were represented respectively by SU30 and TR25 instead of SU25 and TR20. The trends in summer days (SU30), tropical nights (TR25), WSDI and CSDI are given in Figure 4.18. Increasing trends were found at all of eight stations in summer days (0.158 - 2.086 days per year). The highest and lowest slopes were observed respectively at Sylhet and Satkhira stations. Three stations such as Barisal, Dhaka and Sylhet stations showed significant trends in summer days. In case of tropical nights the increasing trends were detected at Bogra, Dhaka, Jessore, Rajshahi and Sylhet, while the rest three stations (Barisal, Khulna and Satkhira) showed decreasing trends. It is observed that the stations showing decreasing trends are located in south-western part of Bangladesh. The slopes in this index ranged between -0.999 - 1.18 days per year. The largest negative and positive trends were found respectively at Barisal and Dhaka stations and these two stations showed significant trends in tropical nights. For WSDI, the stations showing increasing trends were Dhaka, Jessore, Khulna and Sylhet (0.027 - 0.813 days per year). The highest positive slope was detected at Sylhet station showing significance at the 95% confidence level. The rest four stations namely Bogra,

Barisal, Rajshahi and Satkhira showed decreasing trends in WSDI (-0.062 - -0.153 days per year) and the largest negative slope was found at Bogra. In case of CSDI, increasing trends were observed in Dhaka, Khulna, Rajshahi and Satkhira (0.018 - 0.094 days per year) and decreasing trends were detected at Barisal, Bogra, Jessore and Sylhet (-0.031 - -0.177 days per year). The largest positive and negative slopes were detected respectively at Satkhira and Sylhet stations. None of the stations showed significant trend in CSDI index.

Positive trends in the indices like TmaxMean, Tmin Mean, warm days, summer days, tropical nights etc. at majority of the selected stations in Bangladesh evidence the warming of temperature over the area during the period 1976-2000. The above discussion manifests that among eight selected stations Sylhet was found to exhibit the highest increase of temperature during the mentioned period showing the highest positive trends in TmaxMean, TminMean and TavgMean. For some other indices also, the largest and significant trends were detected at this station.

Chapter 5

APPLICATIONS OF MULTISITE MULTIVARIATE DOWNSCALING MODELS TO DAILY EXTREME TEMPERATURE SERIES IN SOUTHERN QUEBEC-ONTARIO REGION

This chapter presents the applications of the proposed MMSD procedures to daily extreme temperature series of seven weather stations located in the southern Quebec-Ontario region in Canada. The chapter starts with presenting the results obtained using NCEP reanalysis data and then it provides the results regarding GCM simulations. In the subsequent section, the comparison of the effectiveness of multisite multivariate downscaling versus single-site downscaling of daily extreme temperature series is given. At last, predictions of daily T_{max} and T_{min} for future periods have been provided.

5.1 Results and evaluation of MMSD models for NCEP reanalysis data

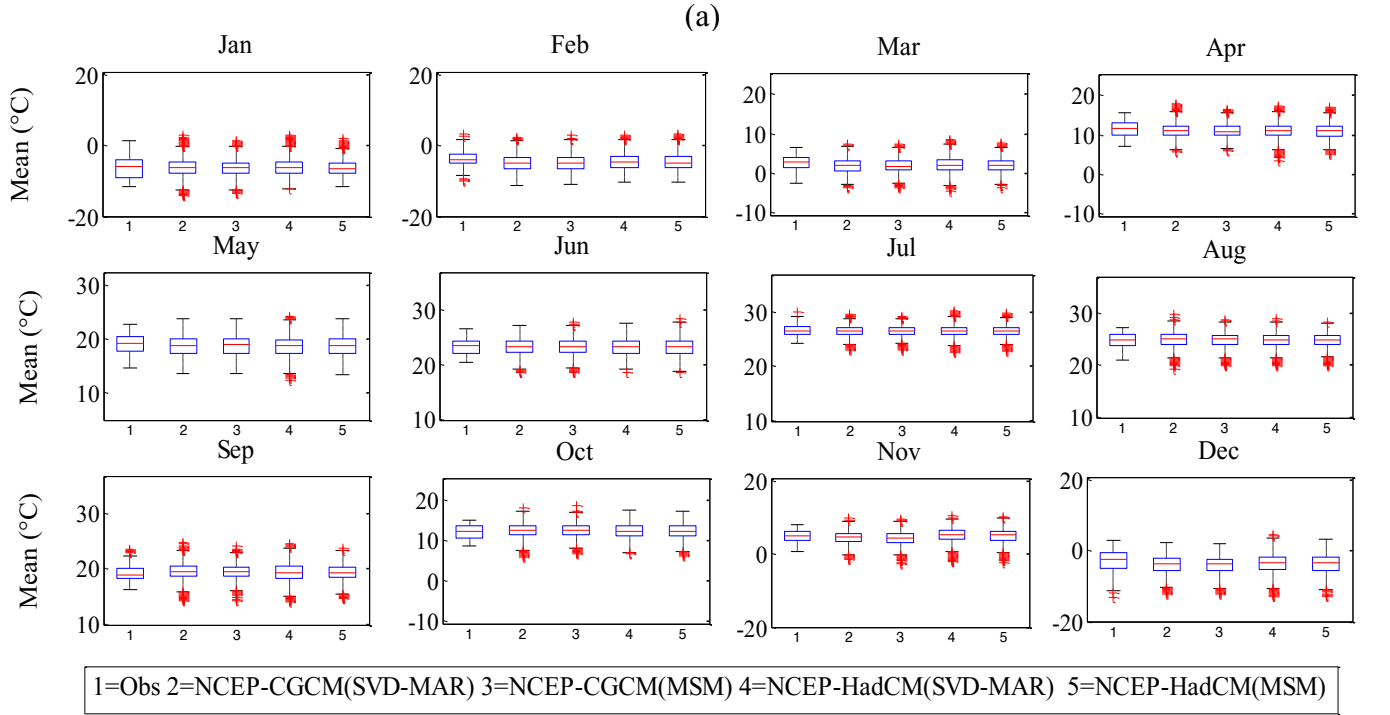
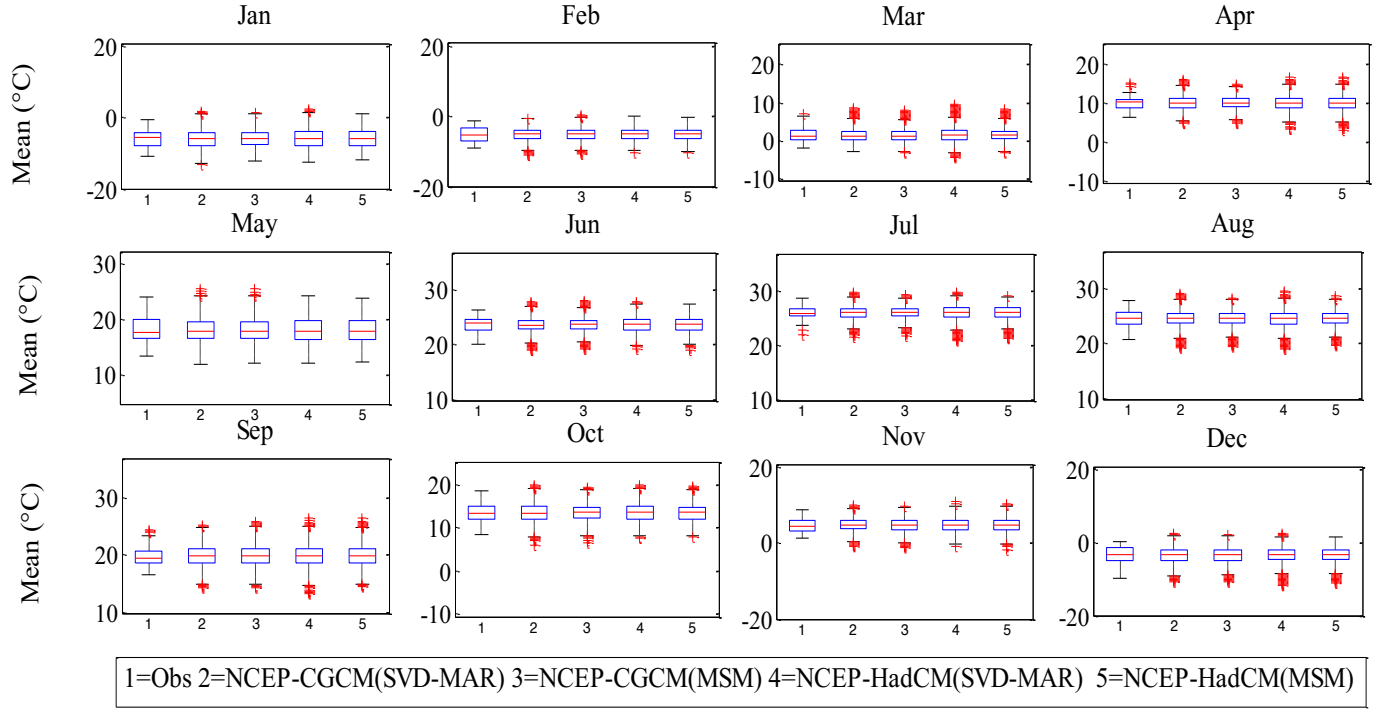
In statistical downscaling processes the standard procedure is to calibrate the downscaling model with the variables of large-scale atmospheric predictors (i.e., NCEP reanalysis data in this study) before generating climate scenarios with GCM simulations. As mentioned before, in this study two GCMs such as, CGCM and HadCM have been used as large-scale predictors. In this regard, the NCEP daily predictors need to be interpolated on the respective GCM grid in order to conform to the grid size of the corresponding GCM. Hence, the proposed models have been applied separately to both of the NCEP interpolated on CGCM and HadCM before generating climate scenarios with CGCM and HadCM simulations. The results obtained by applying both models (e.g., SVD-MAR and MSM) during calibration (1961-1975) and validation (1976-1990) periods are presented in the following subsections.

5.1.1 Goodness of fit

The performance of the proposed models has been evaluated through graphical representations as well as numerical analysis. Four temperature indices, such as, mean, standard deviations (STD) of T_{max} and T_{min} , 90th percentile of daily T_{max} (T_{max90p}) and 10th percentile of daily T_{min} (T_{min10p}) were computed for each of the months for both of the NCEP interpolated on CGCM and HadCM. Their boxplot representations are given in Figures 5.1 through 5.6. Each

boxplot represents the monthly indices aggregated at seven stations in the southern Quebec-Ontario region. It is observed that SVD-MAR and MSM produced similar results and are capable of reproducing the monthly means of T_{max} accurately for all the months during calibration and validation periods (Figure 5.1). In case of T_{min} also, monthly means were simulated well by both models for both NCEP (Figures 5.2). The monthly STD of T_{max} as well as T_{min} were reproduced well in almost all the months by both models (Figures 5.3 and 5.4 respectively). Figure 5.5 shows that the index monthly T_{max90p} was simulated accurately by both models in almost all the months during calibration and validation periods for both NCEP. For T_{min10p} also, very good agreements were found between the observed and simulated values in all the months during calibration and validation periods (Figure 5.6).

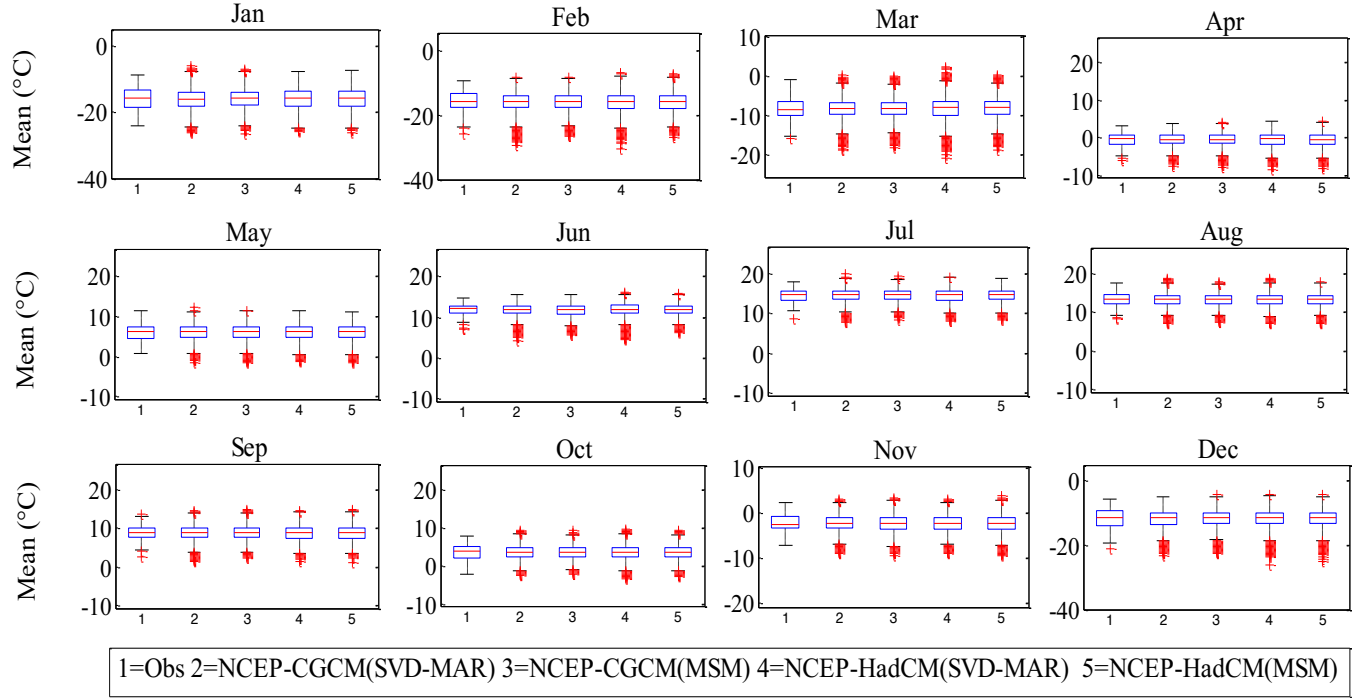
The values of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of monthly averages based on 100 simulations of daily T_{max} and T_{min} series at each of seven stations are presented in Table 5.1. Low values of MAE and RMSE for T_{max} and T_{min} evidence the accuracy of the proposed models. The values of MAE (RMSE) produced by SVD-MAR and MSM ranged between 0.01-0.04 (0.01-0.06) and 0.02-0.1 (0.02-0.13) respectively for T_{max} and T_{min} during the calibration period for both NCEP interpolated on CGCM and HadCM. During validation period the values of MAE (RMSE) ranged between 0.22-0.54 (0.27-0.69) and 0.28-0.59 (0.42-0.79) respectively for T_{max} and T_{min} . Table 5.1 indicates that the values of MAE and RMSE were produced better for the NCEP interpolated on HadCM than on CGCM at most of the stations by both models for T_{max} as well as T_{min} .



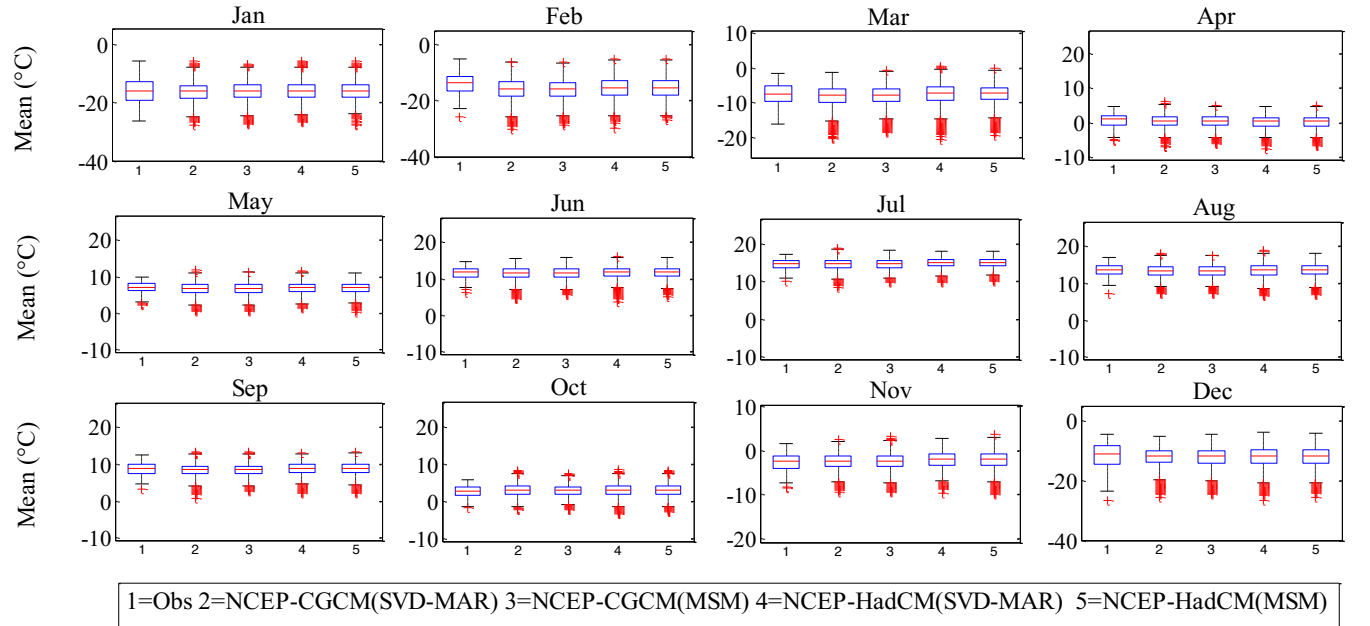
(b)

Figure 5.1: Boxplots of the mean of daily T_{max} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods. Each boxplot represents the values obtained at seven stations in Quebec-Ontario region aggregated over each period of 15 years. The band in the middle of each

box represents the median value, the boxes and whiskers represent the inter-quartile range (IQR) and $1.5 \times IQR$ respectively. Crosses beyond the whiskers represent outliers.

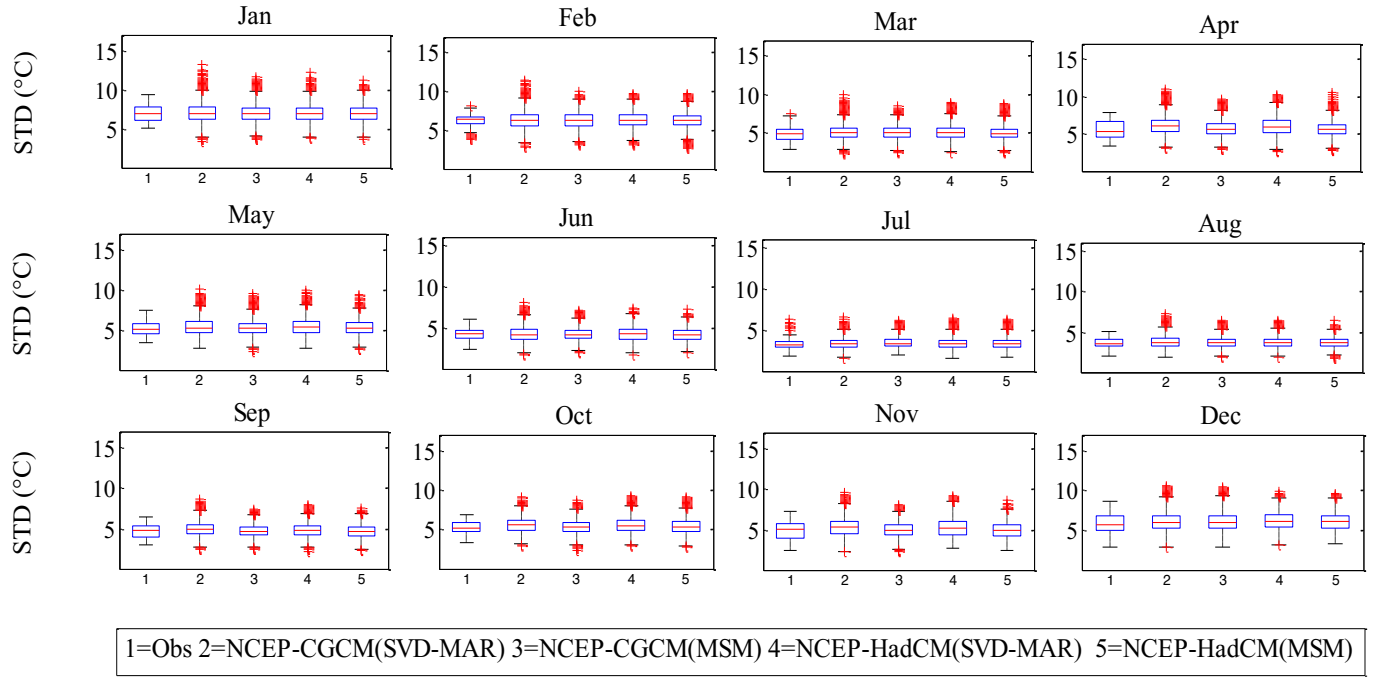


(a)

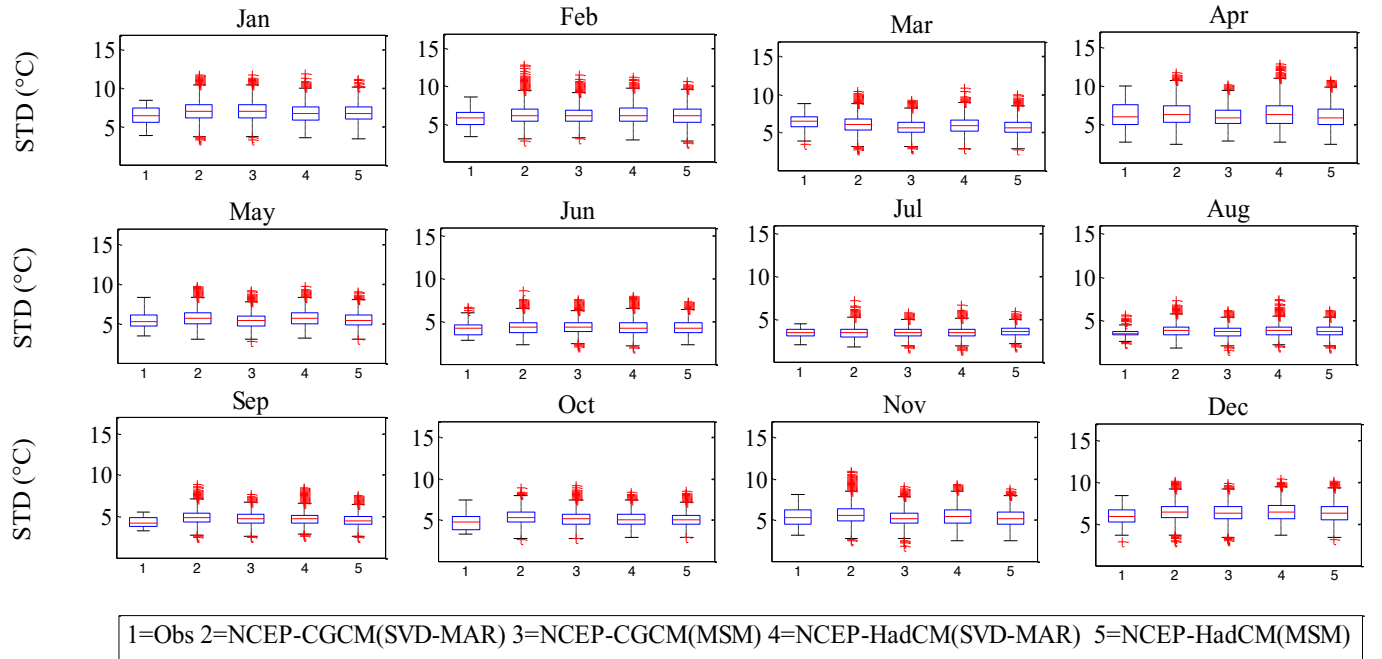


(b)

Figure 5.2: Boxplots of the mean of daily T_{min} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

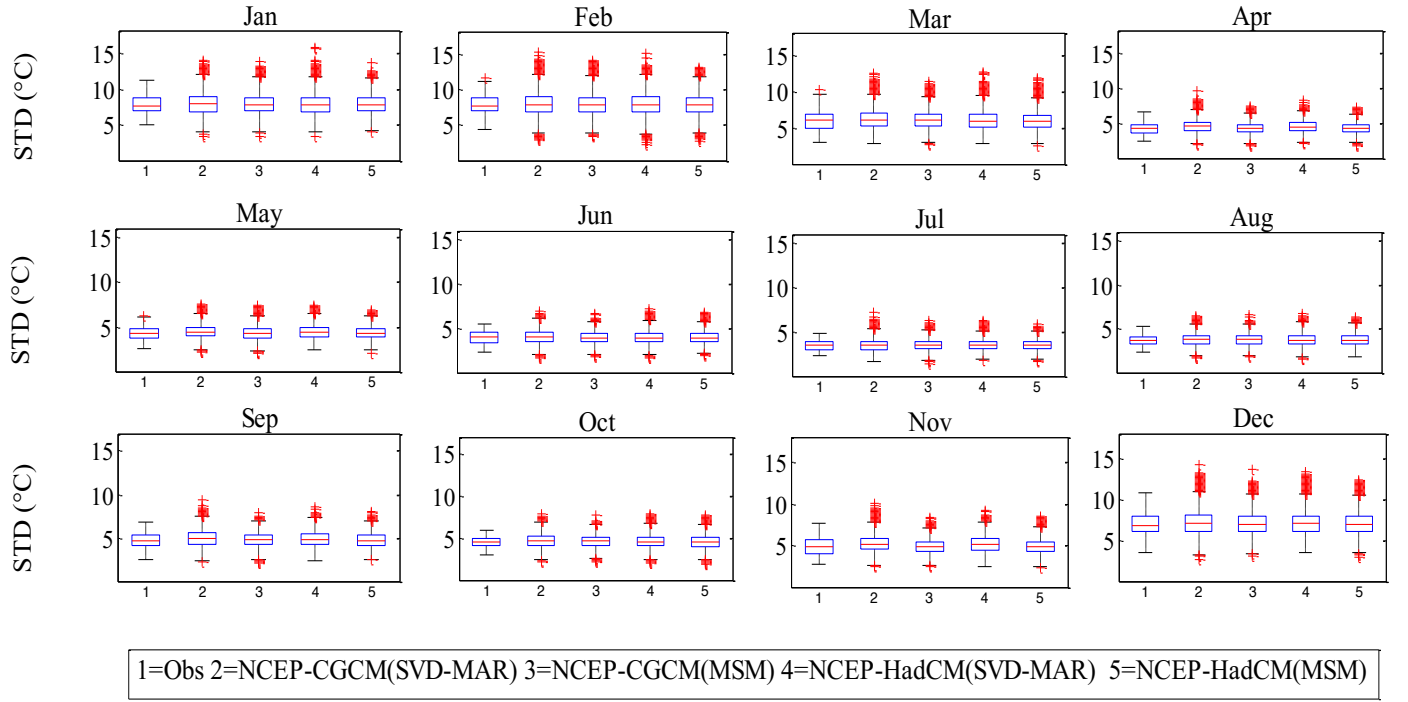


(a)

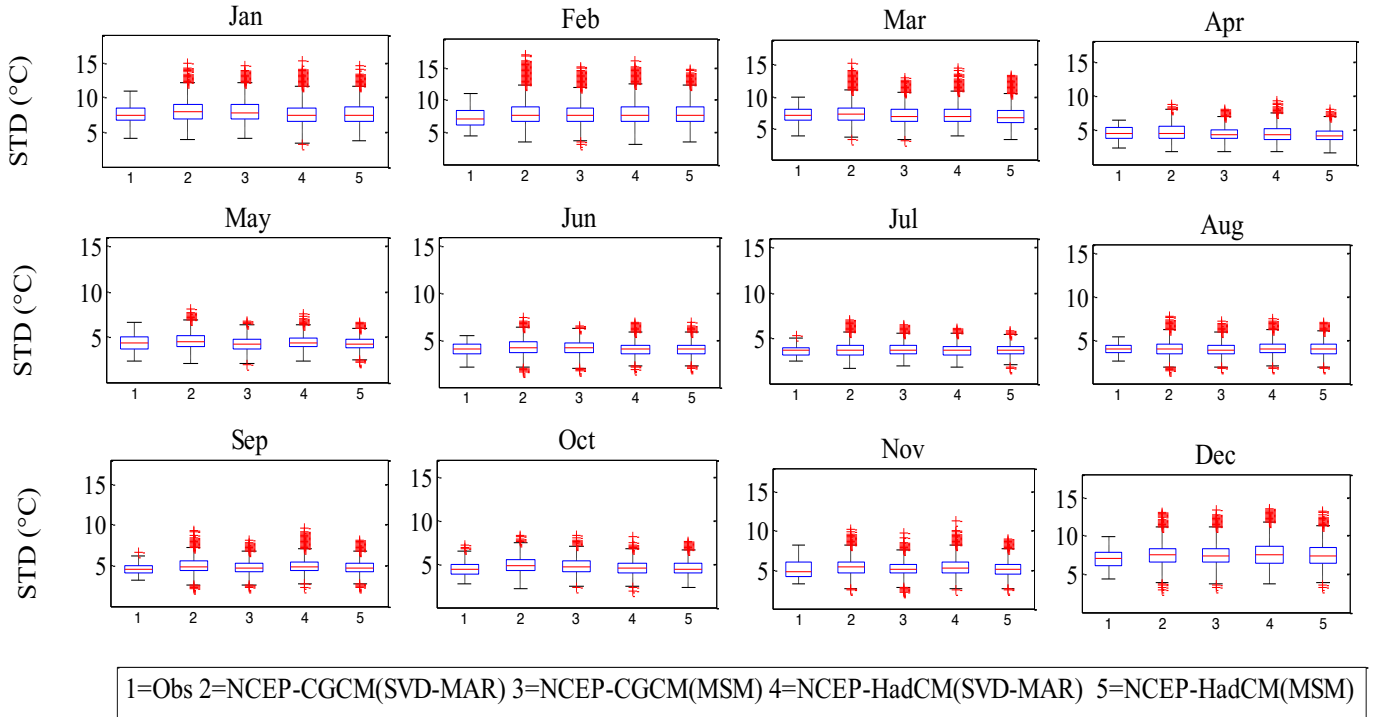


(b)

Figure 5.3: Boxplots of the STD of daily T_{max} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

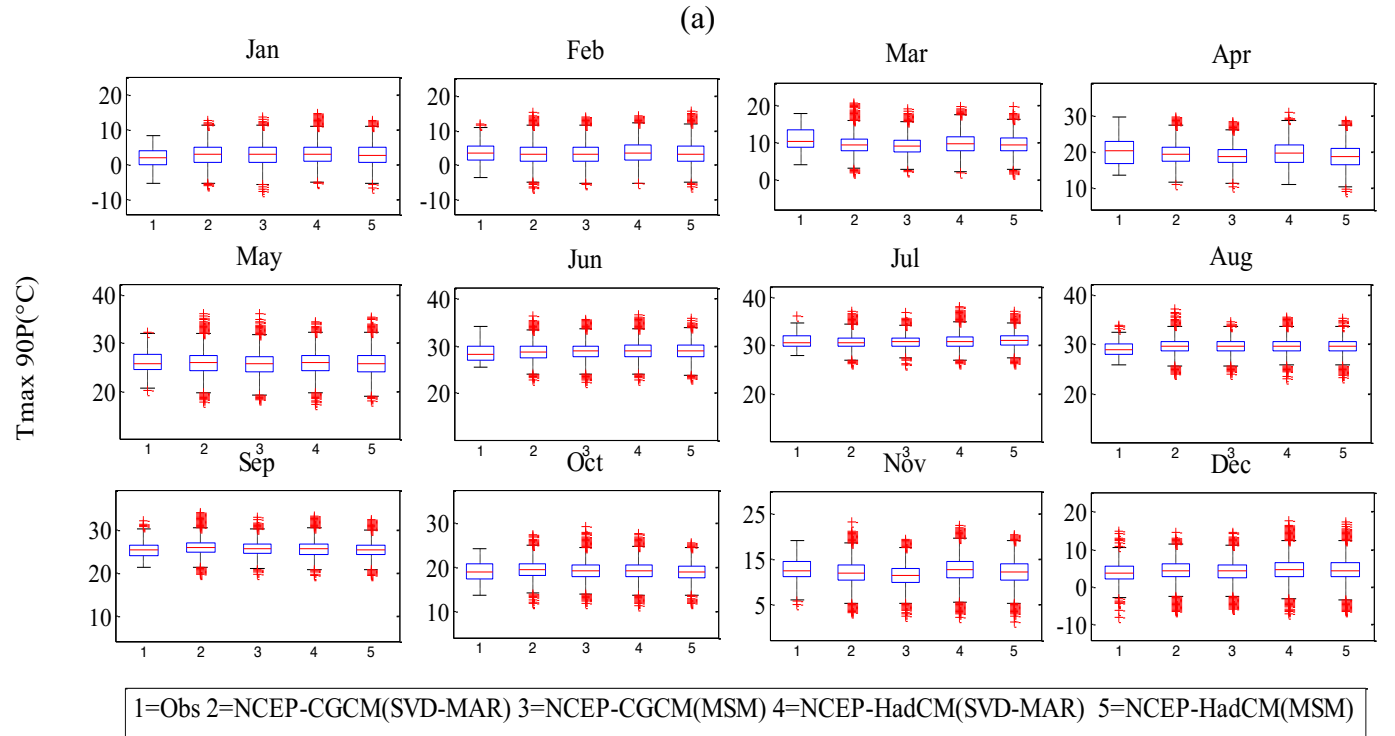
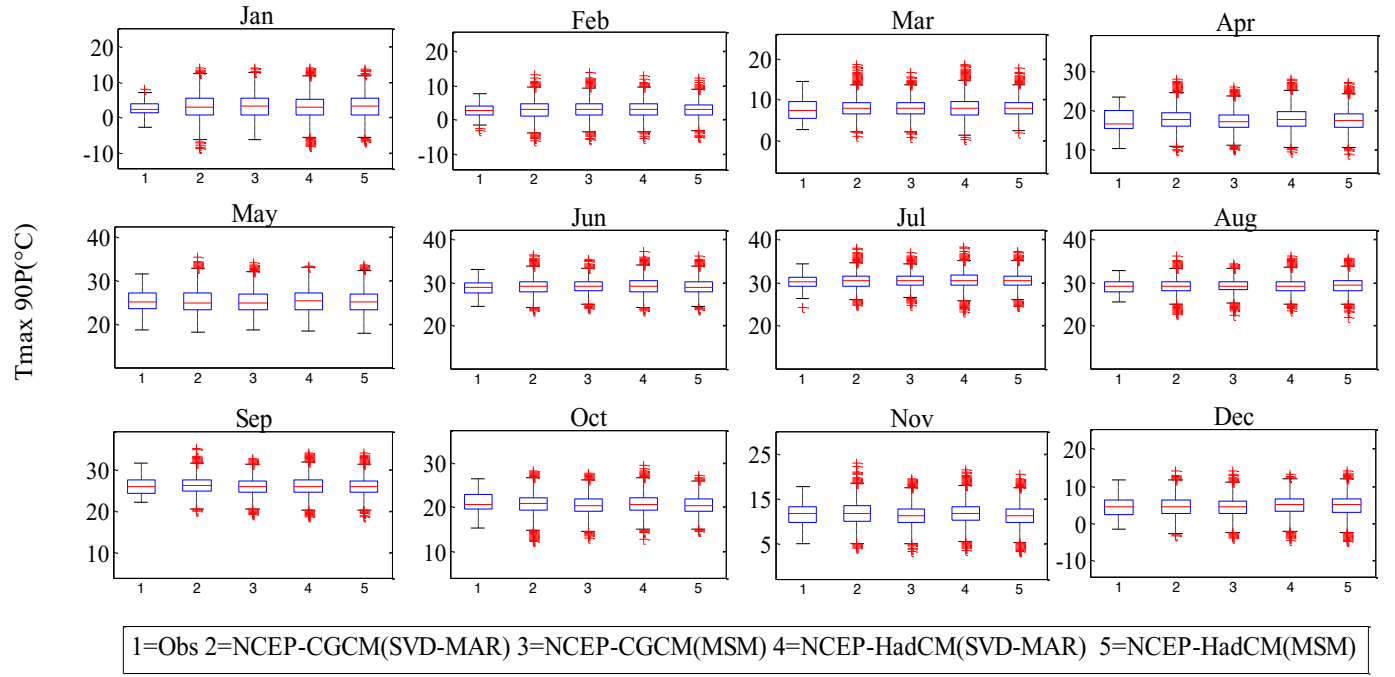


(a)



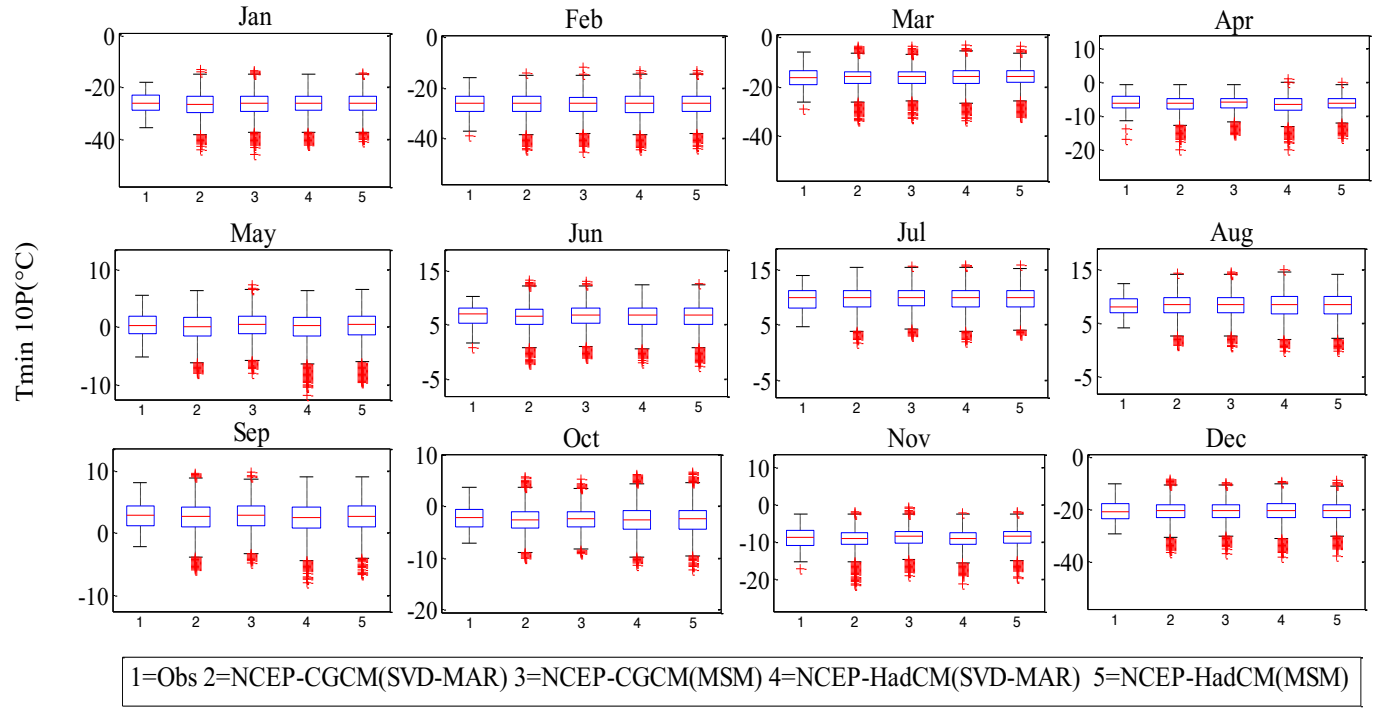
(b)

Figure 5.4: Boxplots of the STD of daily T_{min} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

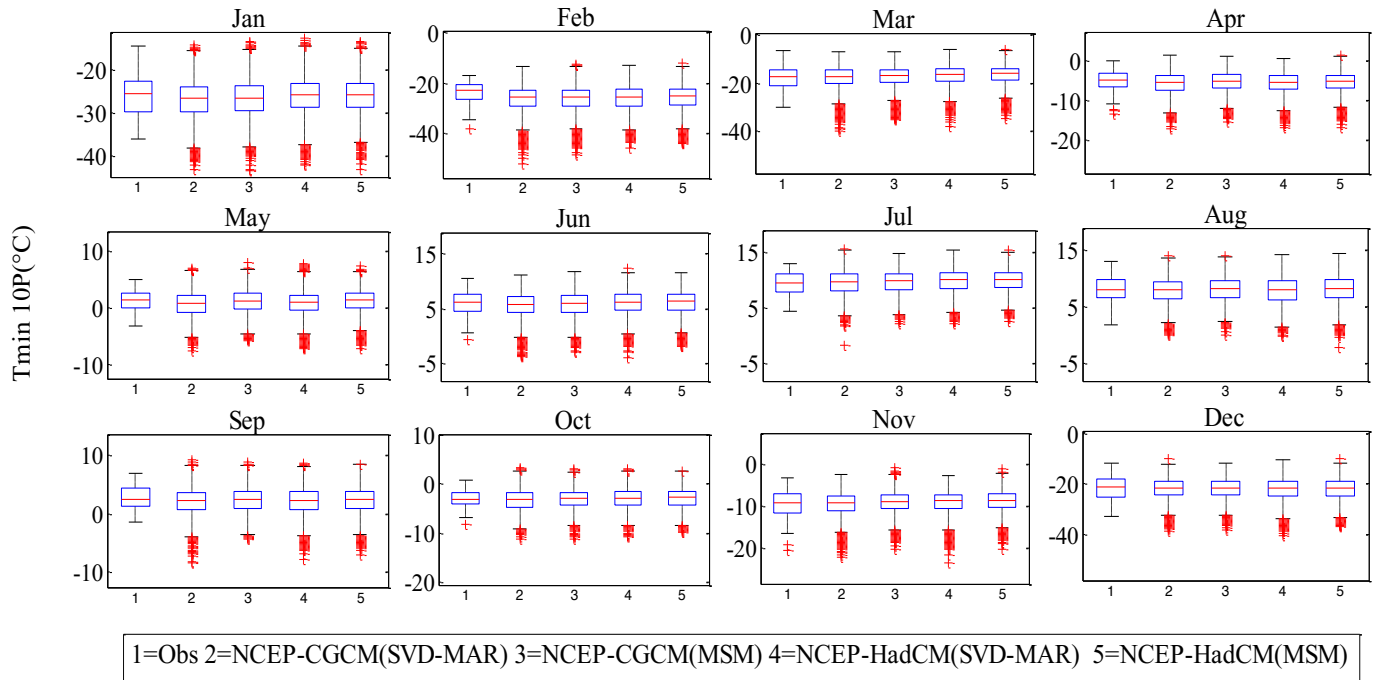


(b)

Figure 5.5: Boxplots of the Tmax90p for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.



(a)



(b)

Figure 5.6: Boxplots of the Tmin10p for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

Table 5.1: MAE and RMSE values of T_{max} and T_{min} for NCEP at seven stations in Quebec-Ontario region.

NCEP-CGCM									
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.03	0.03	0.01	0.02	0.44	0.54	0.44	0.54
	Station 2	0.02	0.03	0.01	0.01	0.41	0.5	0.41	0.49
	Station 3	0.03	0.03	0.02	0.02	0.44	0.55	0.44	0.55
	Station 4	0.02	0.03	0.01	0.02	0.27	0.34	0.26	0.34
	Station 5	0.04	0.06	0.03	0.04	0.54	0.69	0.52	0.67
	Station 6	0.03	0.03	0.01	0.01	0.38	0.54	0.39	0.54
	Station 7	0.03	0.03	0.01	0.01	0.54	0.63	0.53	0.62
T_{min}	Station 1	0.07	0.09	0.05	0.06	0.54	0.77	0.52	0.76
	Station 2	0.05	0.06	0.02	0.03	0.35	0.55	0.34	0.55
	Station 3	0.10	0.12	0.09	0.1	0.5	0.78	0.5	0.78
	Station 4	0.05	0.06	0.04	0.05	0.43	0.73	0.44	0.72
	Station 5	0.08	0.1	0.06	0.08	0.59	0.79	0.57	0.77
	Station 6	0.08	0.1	0.06	0.08	0.5	0.73	0.49	0.71
	Station 7	0.1	0.13	0.08	0.1	0.29	0.47	0.28	0.47
NCEP-HadCM									
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.02	0.03	0.01	0.02	0.34	0.42	0.35	0.44
	Station 2	0.02	0.03	0.01	0.02	0.29	0.35	0.3	0.36
	Station 3	0.02	0.02	0.01	0.02	0.39	0.47	0.39	0.47
	Station 4	0.02	0.02	0.01	0.01	0.22	0.27	0.23	0.29
	Station 5	0.04	0.05	0.03	0.04	0.4	0.51	0.41	0.53
	Station 6	0.02	0.03	0.01	0.02	0.29	0.39	0.29	0.4
	Station 7	0.02	0.03	0.02	0.02	0.45	0.51	0.46	0.52
T_{min}	Station 1	0.06	0.08	0.06	0.09	0.36	0.58	0.38	0.59
	Station 2	0.02	0.02	0.03	0.03	0.38	0.53	0.39	0.54
	Station 3	0.09	0.11	0.09	0.11	0.41	0.64	0.42	0.64
	Station 4	0.05	0.06	0.05	0.06	0.4	0.58	0.41	0.6
	Station 5	0.06	0.07	0.05	0.07	0.4	0.58	0.4	0.58
	Station 6	0.06	0.08	0.06	0.08	0.35	0.52	0.36	0.52
	Station 7	0.06	0.08	0.07	0.09	0.36	0.42	0.37	0.42

5.1.2 Spatial variability

Daily temperature series are not independent of each other; rather show some sorts of spatio-temporal relationships. The variability of temperature with respect to distance can be shown through interstation correlations of daily T_{max} and T_{min} among the stations. Although variability of interstation correlation of daily temperature does not depend solely on geographical distance, generally on a flat terrain it tends to decrease with the increase of distance. The variability of interstation correlations of T_{max} and T_{min} with respect to distance are presented in Figures 5.7 and 5.8. One of the main criteria of multisite downscaling is to incorporate this observed space-variant interstation correlation structure in the simulated series of temperature. Figures 5.7 and 5.8 delineate the observed and simulated values of average of monthly cross-site correlations of daily T_{max} and T_{min} between each pair of stations versus distance between the stations. The black solid line represents the best fit linear line for the observed interstation correlations. These figures evince the decline of interstation correlations of observed T_{max} and T_{min} with distance. The decrease of interstation correlations with distance is more prominent for T_{max} than T_{min} . The figures show that the interstation correlations of simulated temperature also decrease in accordance with the observed ones, evidencing the capability of the proposed models (SVD-MAR and MSM) to capture the observed spatial variability of T_{max} and T_{min} in simulated series.

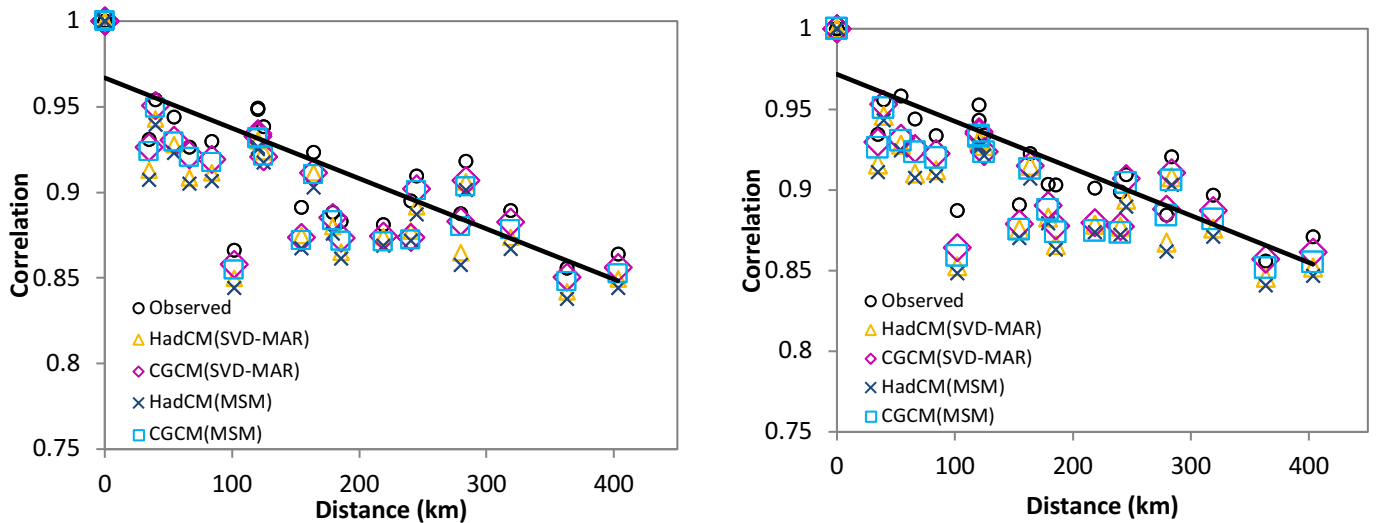


Figure 5.7: Relationship between spatial distance and interstation correlation of T_{max} during (a) calibration period and (b) validation periods for the stations in Quebec-Ontario region.

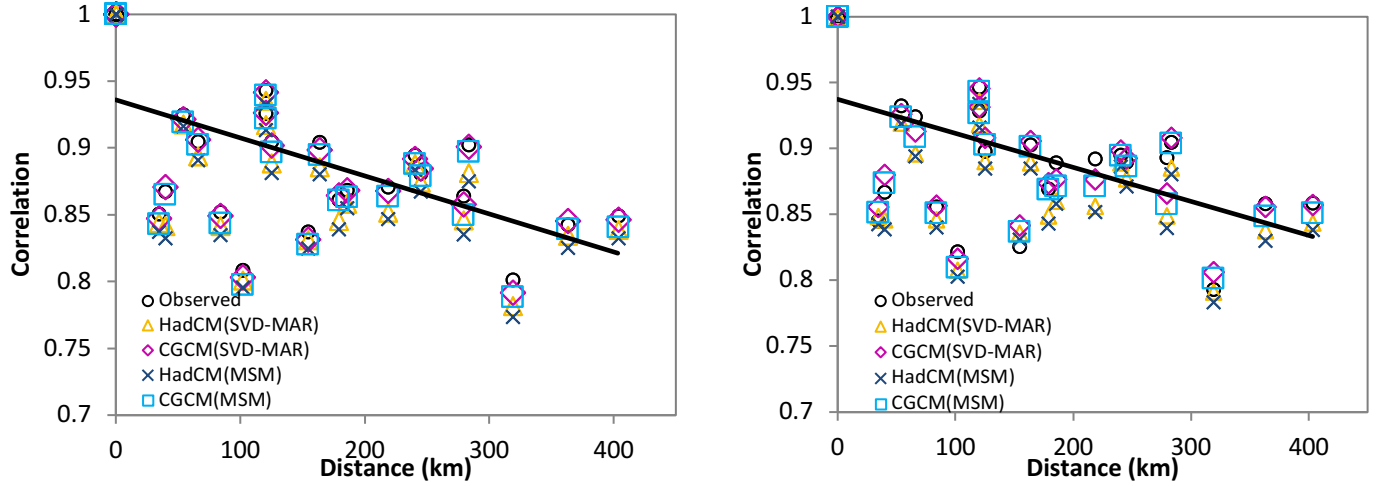


Figure 5.8: Relationship between spatial distance and interstation correlation of T_{min} during (a) calibration period and (b) validation periods for the stations in Quebec-Ontario region.

The capability of the proposed models to capture the spatial variability inherent in daily temperature series has been evaluated through the models' reproducibility of observed inter-station correlations of daily T_{max} and T_{min} in each of the months for all combinations of station pairs. In addition, the results have been compared with those obtained from one of the most widely used single-site downscaling software called SDSM. Figures 5.9 to 5.12 show the graphical presentation of lag0 interstation correlations of daily T_{max} and T_{min} for all combinations of station pairs in each of the months. Here, the interstation correlations were calculated by commonly used Pearson's correlation coefficient method. The observed correlations are presented on ordinate and the simulated results are presented on abscissa. The diagonal line represents the one to one ratio line. It means that, if the simulated correlations are similar to the observed ones, then the data points lie on or closer to the diagonal line. All of the three models (SVD-MAR, MSM and SDSM) were applied separately to both of the NCEP data interpolated on CGCM and HadCM grids. The left panels of the figures show the results obtained by SVD-MAR and SDSM while the right panels show the results obtained by MSM. The figures demonstrate that the interstation correlations produced by SVD-MAR and MSM lie close to the diagonal line for both daily T_{max} and T_{min} during calibration as well as validation periods. Whereas, for SDSM the interstation correlations lie far apart from the diagonal line. It articulates that SVD-MAR and MSM are quite capable to capture the spatial variability of temperature by preserving interstation correlations for both T_{max}

and T_{min} for both NCEP interpolated on CGCM and HadCM. But, the single-site downscaling model SDSM fails to encounter the observed interstation correlations of daily T_{max} and T_{min} in simulated series.

Along with the graphical representations, numerical analysis were performed to evaluate the accuracy of the proposed models. Table 5.2 shows the values of MAD, RMSD and R^2 for the lag0 interstation correlations of T_{max} and T_{min} . Here, MAD (RMSD) denotes the mean of absolute differences (root of the mean of squared differences) between the observed and simulated values of correlations for each of the pairs in each of the months. It is observed that the values of R^2 (RMSD and MAD) for SVD-MAR and MSM are very high (low) compared to those of SDSM. For example, during calibration period the values of MAD (RMSD) produced by SVD-MAR and MSM ranged between 0.01-0.02 (0.02-0.03) and 0.01-0.02 (0.01-0.03) respectively for T_{max} and T_{min} interstation correlations for both of the NCEP. Whereas, the values of MAD (RMSD) produced by SDSM were between 0.21-0.28 (0.24-0.31) and 0.19-0.27 (0.21-0.3) respectively for T_{max} and T_{min} during the same period. The R^2 values ranged between 0.76-0.85 and 0.85-0.94 respectively for T_{max} and T_{min} for both of the models during calibration period. For SDSM, the R^2 values were as low as 0.08-0.16 for T_{max} and 0.02 for T_{min} . During validation period the values of MAD (RMSD) were 0.02 (0.03) and 0.01-0.02 (0.02-0.03) respectively for T_{max} and T_{min} for SVD-MAR and MSM. For SDSM, these values were between 0.21-0.27 (0.23-0.29) and 0.18-0.25 (0.2-0.28) respectively for T_{max} and T_{min} . The R^2 values ranged between 0.7-0.73 and 0.76-0.84 respectively for T_{max} and T_{min} for the models SVD-MAR and MSM during validation period. For SDSM, the R^2 value ranged between 0.11-0.15 for T_{max} and 0.02-0.03 for T_{min} . Therefore, like graphical analysis, the numerical evaluation also evidences the better accuracy of the proposed multisite downscaling models (i.e., SVD-MAR and MSM) than single-site downscaling model (i.e., SDSM) in capturing the spatial variability of daily T_{max} and T_{min} .

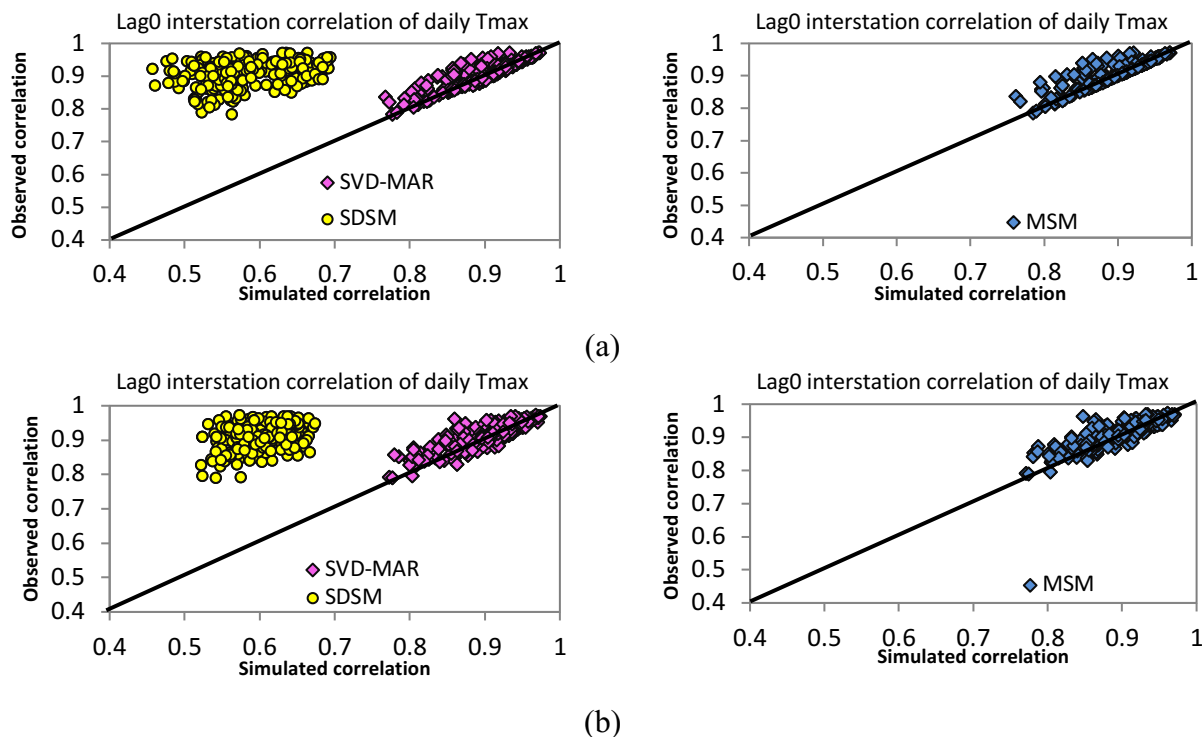


Figure 5.9: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Quebec-Ontario region.

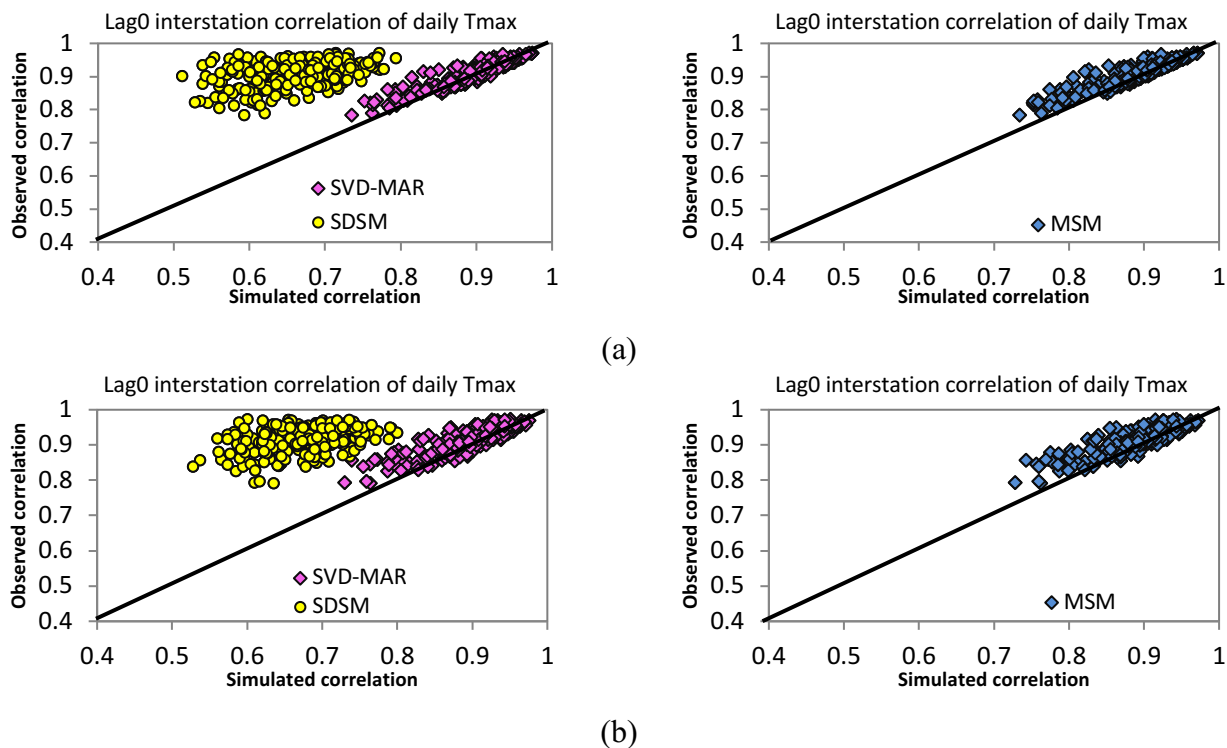
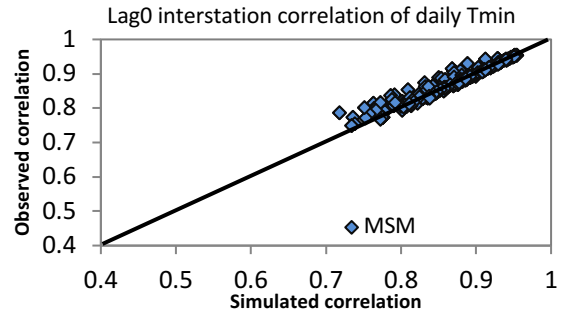
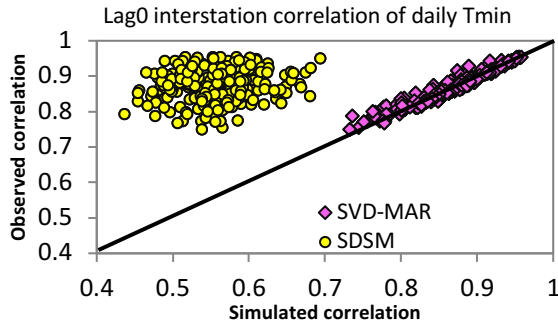
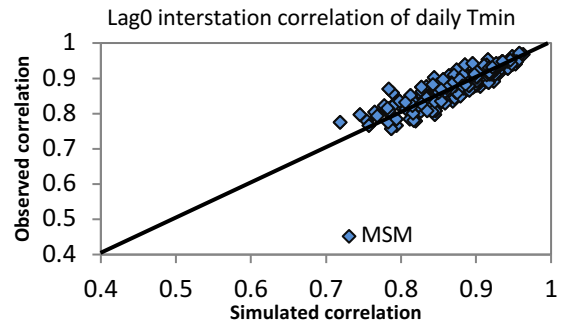
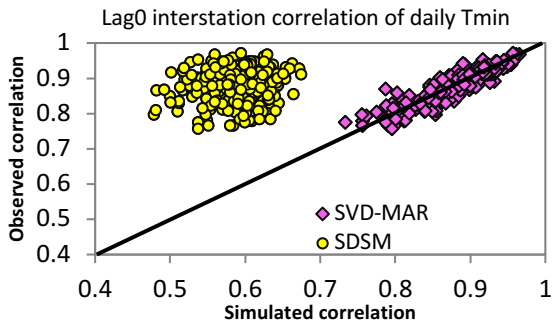


Figure 5.10: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Quebec-Ontario region.

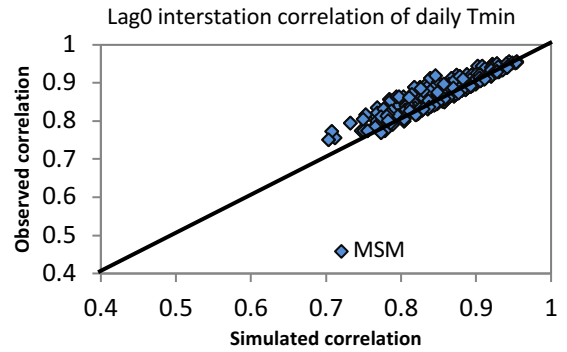
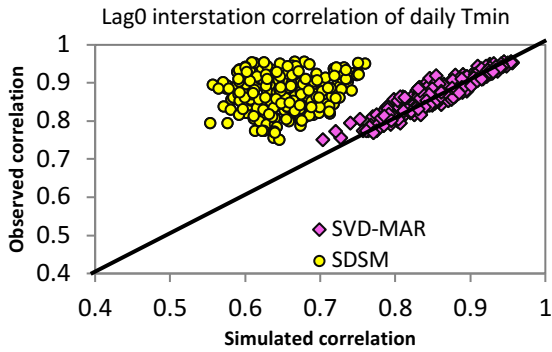


(a)

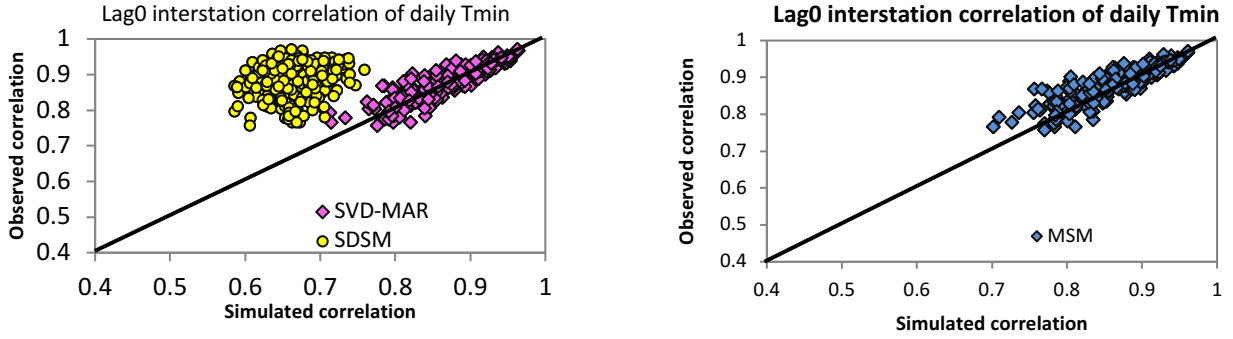


(b)

Figure 5.11: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Quebec-Ontario region.



(a)



(b)

Figure 5.12: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Quebec-Ontario region.

Table 5.2: Numerical analysis for lag0 interstation correlations of daily *Tmax* and *Tmin* at seven stations in Quebec-Ontario region for NCEP.

NCEP-CGCM										
		SVD-MAR			MSM			SDSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag0 correlation	0.01	0.02	0.78	0.01	0.02	0.76	0.28	0.31	0.08
	<i>Tmin</i> lag0 correlation	0.01	0.01	0.94	0.01	0.01	0.94	0.27	0.3	0.02
Validation	<i>Tmax</i> lag0 correlation	0.02	0.03	0.7	0.02	0.03	0.72	0.27	0.29	0.11
	<i>Tmin</i> lag0 correlation	0.01	0.02	0.84	0.01	0.02	0.82	0.25	0.28	0.02
NCEP-HadCM										
		SVD-MAR			MSM			SDSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag0 correlation	0.02	0.02	0.85	0.02	0.03	0.83	0.21	0.24	0.16
	<i>Tmin</i> lag0 correlation	0.01	0.02	0.88	0.02	0.03	0.85	0.19	0.21	0.02
Validation	<i>Tmax</i> lag0 correlation	0.02	0.03	0.73	0.02	0.03	0.73	0.21	0.23	0.15
	<i>Tmin</i> lag0 correlation	0.02	0.03	0.77	0.02	0.03	0.76	0.18	0.2	0.03

The ability to capture the observed spatio-temporal attributes in simulated series by SVD-MAR and MSM was further investigated through lag1 interstation correlations of daily *Tmax* and *Tmin*. Lag1 interstation correlations of daily *Tmax* and *Tmin* are presented in Figures 5.13 to 5.16. In general, for the NCEP interpolated on HadCM both methods produced acceptable results. However, it is observed that both models underestimated the lag1 interstation correlations of *Tmax* especially for the NCEP interpolated on CGCM. In case of *Tmin* also, lag1 interstation correlation was underestimated during both calibration and validation periods by both of the models especially in the areas where the observed correlations are relatively high. Figures 5.15 and 5.16 show that

the variability of simulated correlations is comparatively higher for the NCEP interpolated on CGCM than that on HadCM during validation period.

Table 5.3 shows the MAD, RMSD and R^2 values for lag1 interstation correlations of T_{max} and T_{min} . During calibration period the values of MAD (RMSD) for lag1 interstation correlations ranged between 0.06-0.1 (0.07-0.11) and 0.06-0.12 (0.07-0.13) respectively for T_{max} and T_{min} by SVD-MAR and MSM models for both of the NCEP. The R^2 values ranged between 0.63-0.67 and 0.62-0.72 respectively for T_{max} and T_{min} . During validation period the values of MAD (RMSD) were between 0.08-0.12 (0.1-0.13) and 0.07-0.15 (0.09-0.16) respectively for T_{max} and T_{min} . The R^2 values ranged between 0.51-0.62 and 0.52-0.65 respectively for T_{max} and T_{min} for both models.

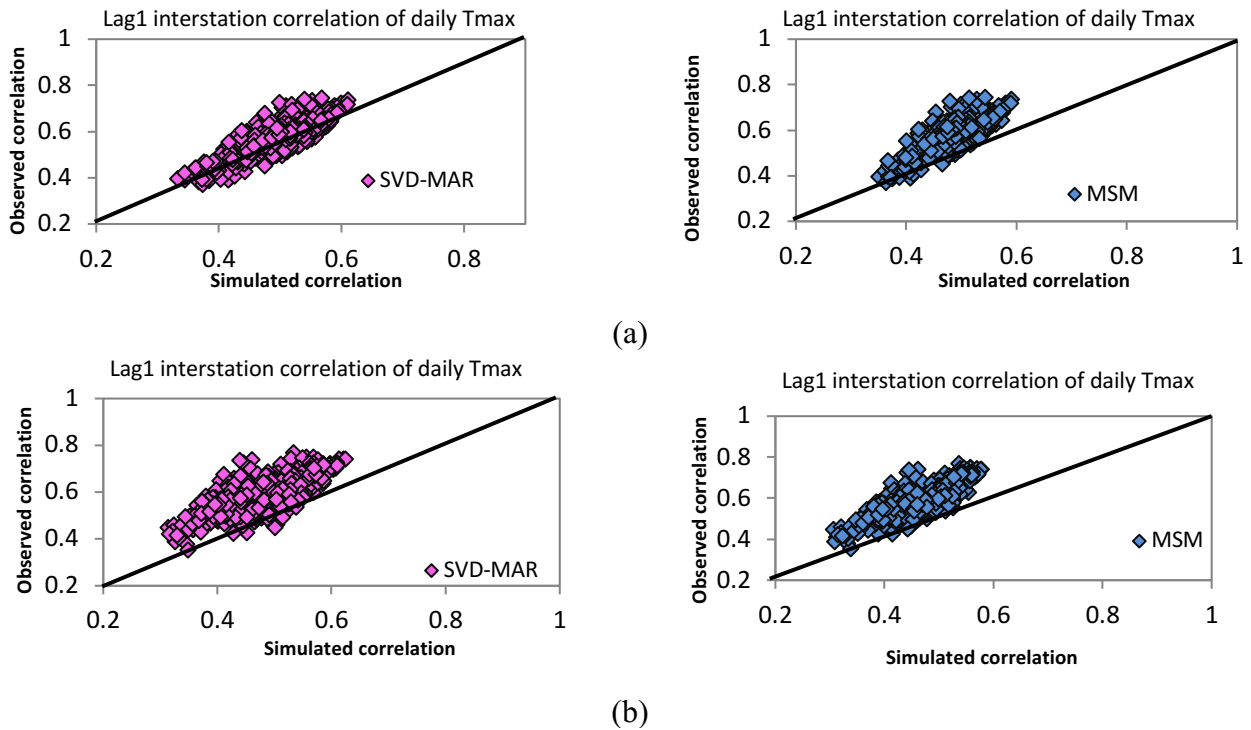


Figure 5.13: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Quebec-Ontario region.

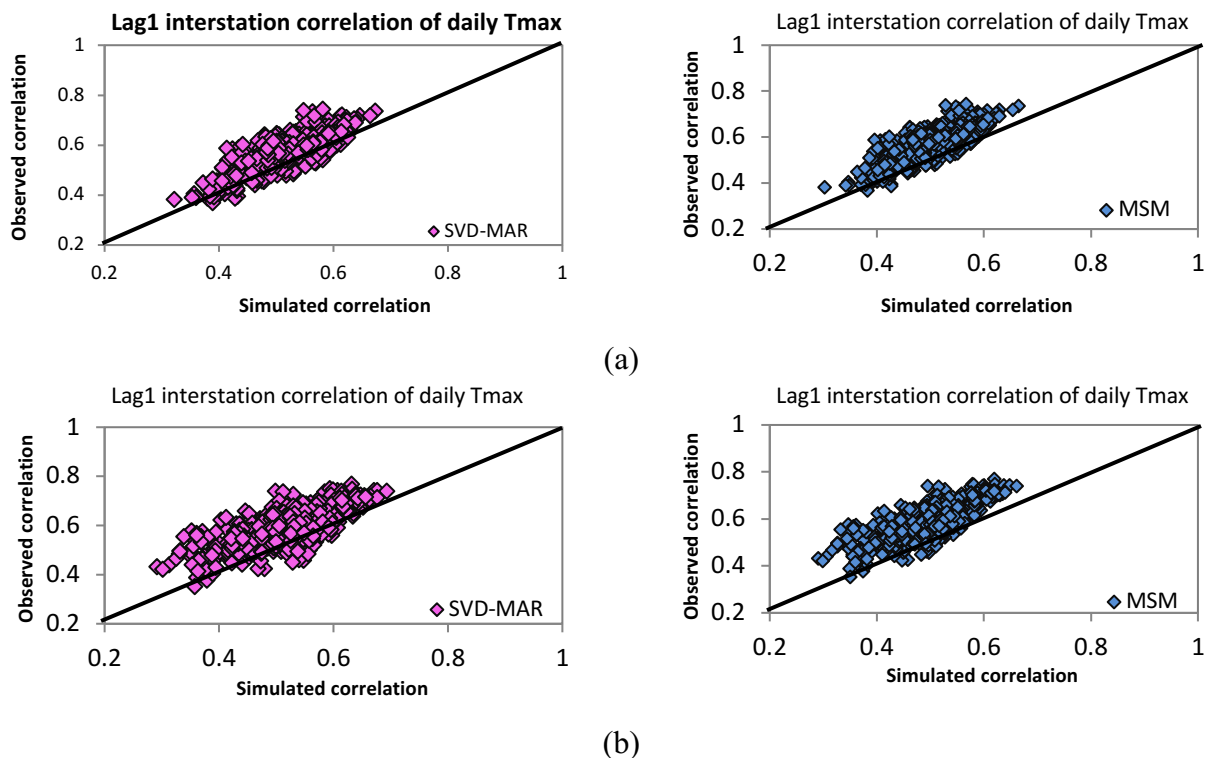


Figure 5.14: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Quebec-Ontario region.

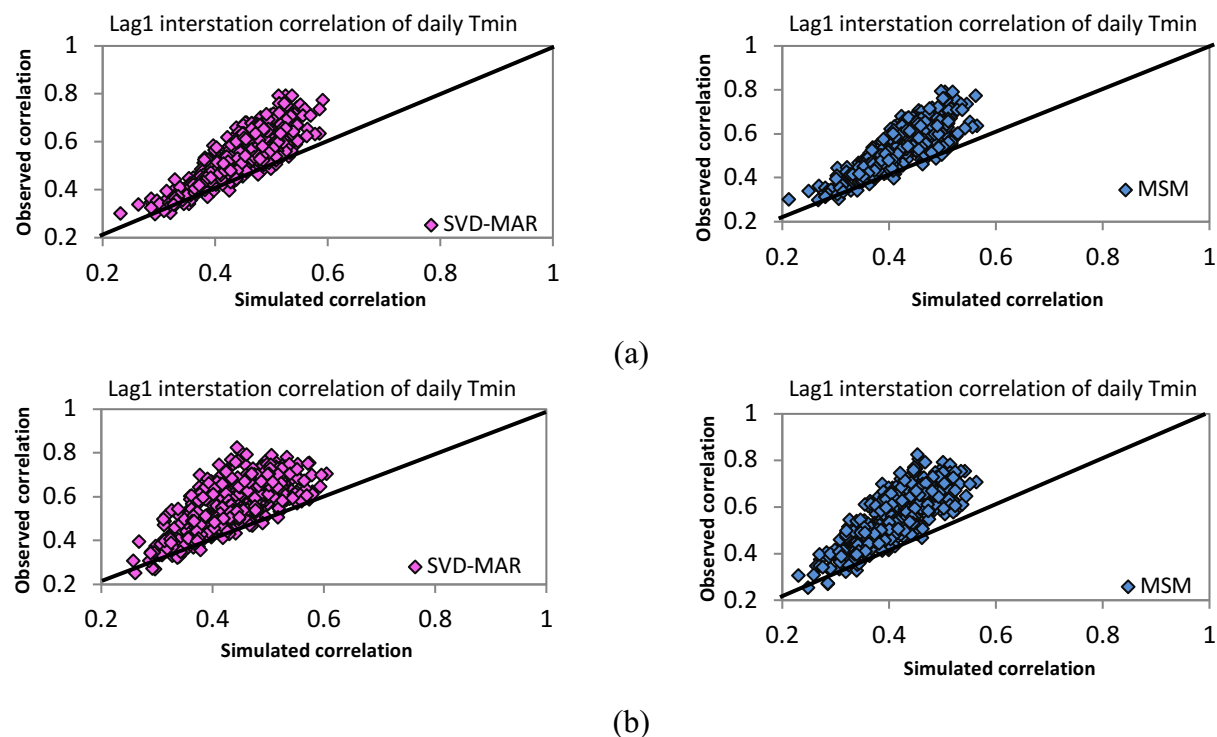


Figure 5.15: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Quebec-Ontario region.

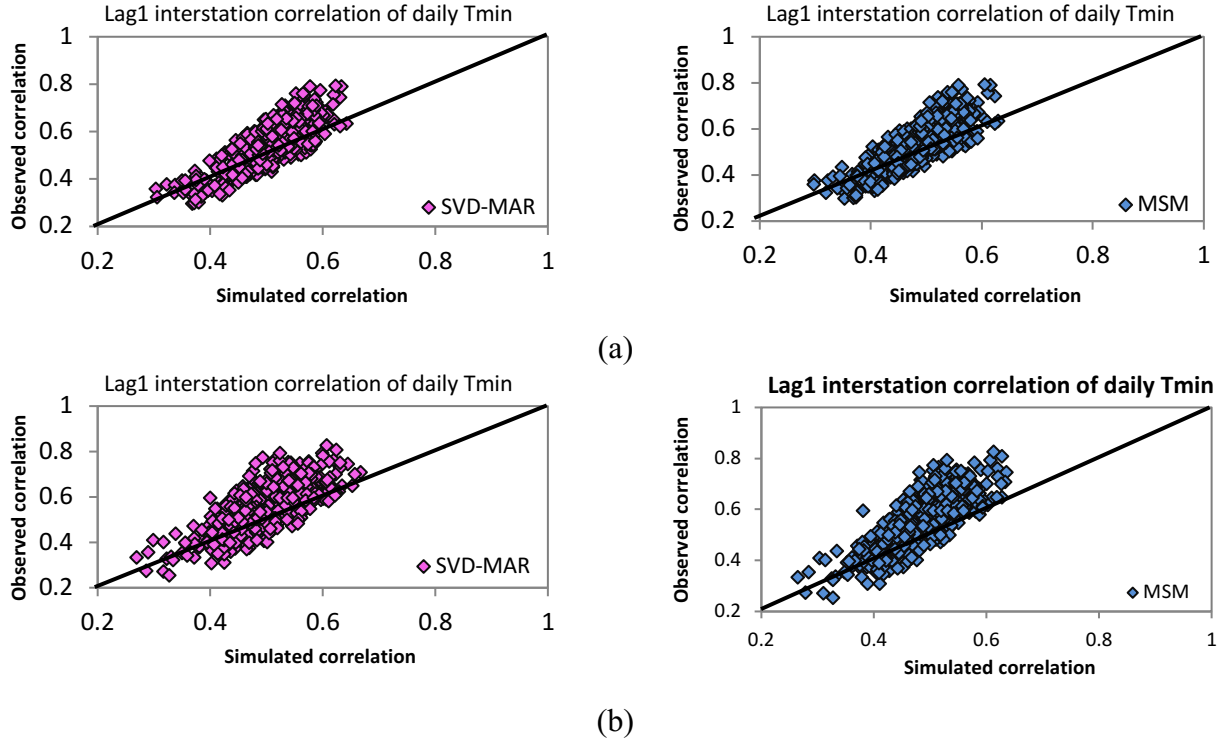


Figure 5.16: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Quebec-Ontario region.

Table 5.3: Numerical analysis for lag1 interstation correlations of daily T_{max} and T_{min} at seven stations in Quebec-Ontario region for NCEP.

NCEP-CGCM							
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag1 correlation	0.08	0.09	0.67	0.1	0.11	0.66
	T_{min} lag1 correlation	0.09	0.11	0.71	0.12	0.13	0.72
Validation	T_{max} lag1 correlation	0.1	0.12	0.51	0.12	0.13	0.62
	T_{min} lag1 correlation	0.12	0.14	0.52	0.15	0.16	0.65
NCEP-HadCM							
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag1 correlation	0.06	0.07	0.64	0.07	0.08	0.63
	T_{min} lag1 correlation	0.06	0.07	0.65	0.06	0.08	0.62
Validation	T_{max} lag1 correlation	0.08	0.1	0.53	0.09	0.1	0.58
	T_{min} lag1 correlation	0.07	0.09	0.55	0.08	0.1	0.61

5.1.3 Temporal dependency

The capability of the proposed models to preserve the temporal dependencies has been evaluated in terms of reproducing the observed serial autocorrelation coefficients in the downscaled temperature series at each station. The observed versus simulated serial autocorrelations of lags from one to three at Dorval station are presented in Figures 5.17 and 5.18 respectively for T_{max} and T_{min} as the examples for illustration. These figures suggest that SVD-MAR and MSM produced similar results and both of the models are capable to reproduce the observed autocorrelation very accurately for T_{max} as well as T_{min} during calibration and validation periods for both of the NCEP interpolated on CGCM and HadCM. Similar results were obtained for rest of the stations. Results of rest of the stations are given in Appendix D.

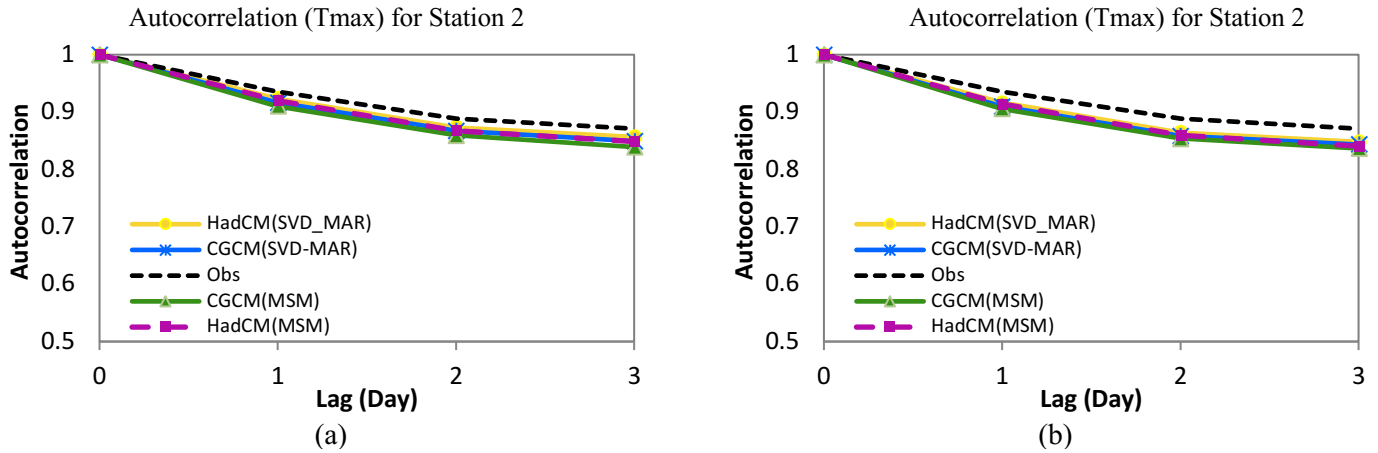


Figure 5.17: Observed and downscaled autocorrelation coefficients of T_{max} at Dorval station during (a) calibration and (b) validation periods for NCEP.

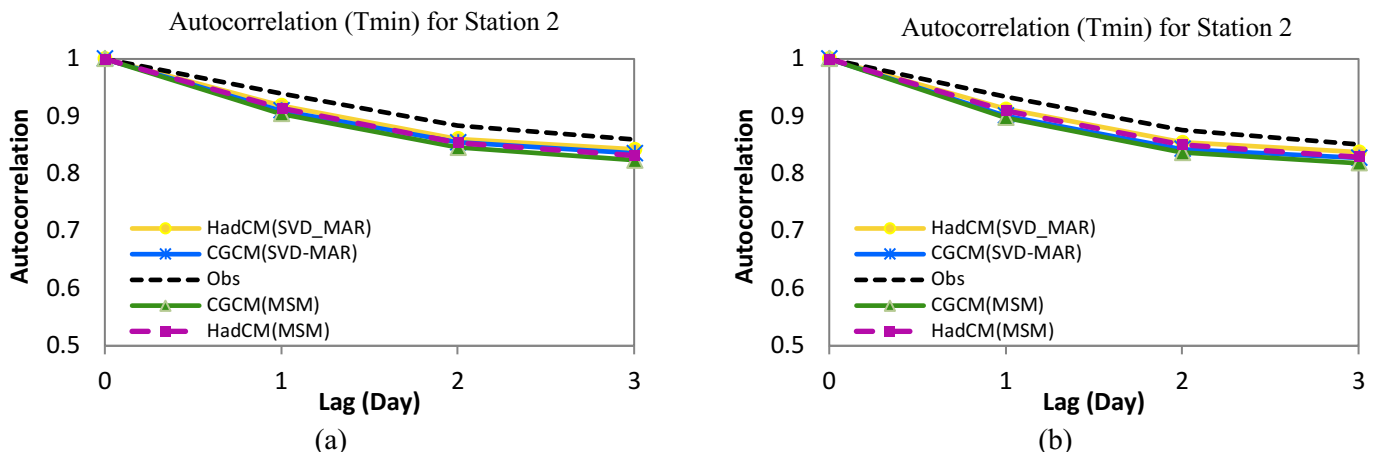


Figure 5.18: Observed and downscaled autocorrelation coefficients of T_{min} at Dorval station during (a) calibration and (b) validation periods for NCEP.

5.1.4 Correlation between daily T_{max} and T_{min} and DTR

As the proposed MMSD procedures consider the simultaneous downscaling of T_{max} and T_{min} , along with preserving the cross site correlations of temperature, these models also aim to preserve at-site correlation between daily T_{max} and T_{min} (Figures 5.19 and 5.20). The figures show that during calibration period both SVD-MAR and MSM were found capable to preserve the correlation between daily T_{max} and T_{min} very accurately for both NCEP. During validation period also, the correlations between daily T_{max} and T_{min} were accurately reproduced by both of the models.

During calibration period the R^2 values produced by SVD-MAR and MSM ranged between 0.94-0.96 for both of the NCEP interpolated on CGCM and HadCM. During validation period the R^2 values were between 0.9-0.92 for both of the NCEP (Figures 5.19 and 5.20). Table 5.4 shows that the values of MAD (RMSD) for the correlation between daily T_{max} and T_{min} produced by SVD-MAR and MSM ranged between 0.01-0.03 (0.01-0.04) during calibration period. During validation period those values ranged between 0.02-0.04 (0.02-0.05) for both of the NCEP.

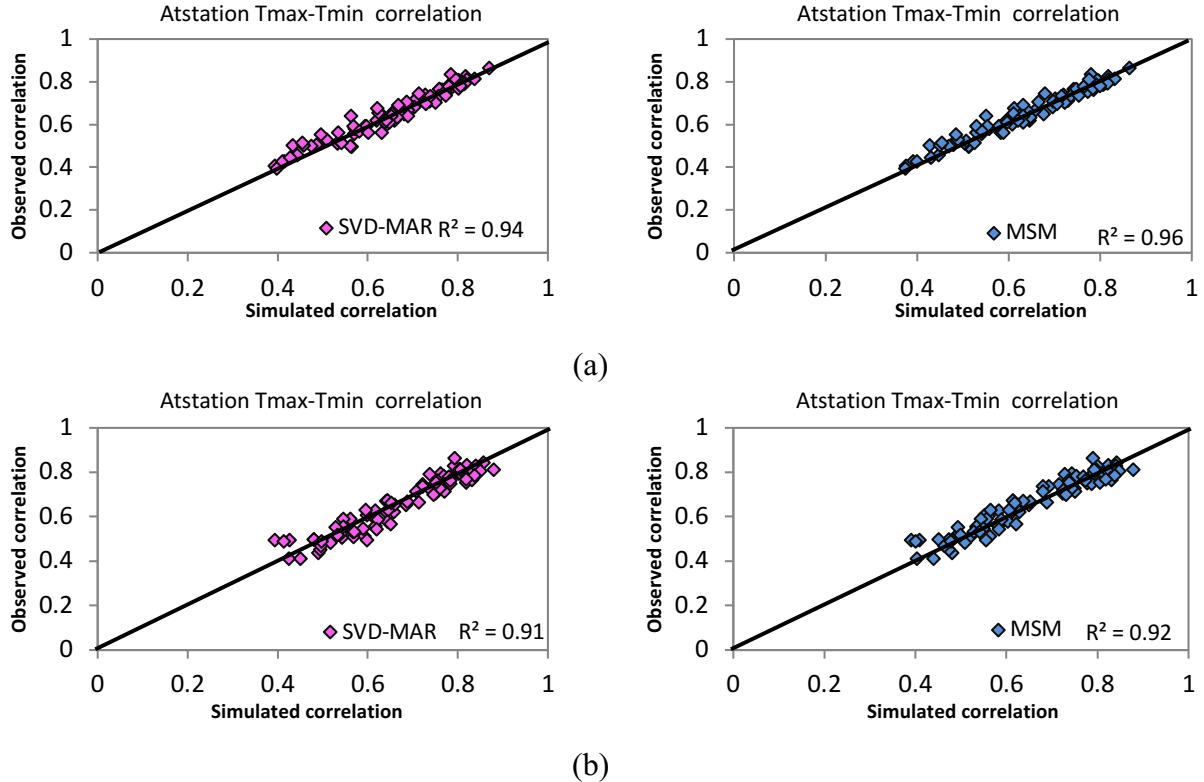


Figure 5.19: Correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM.

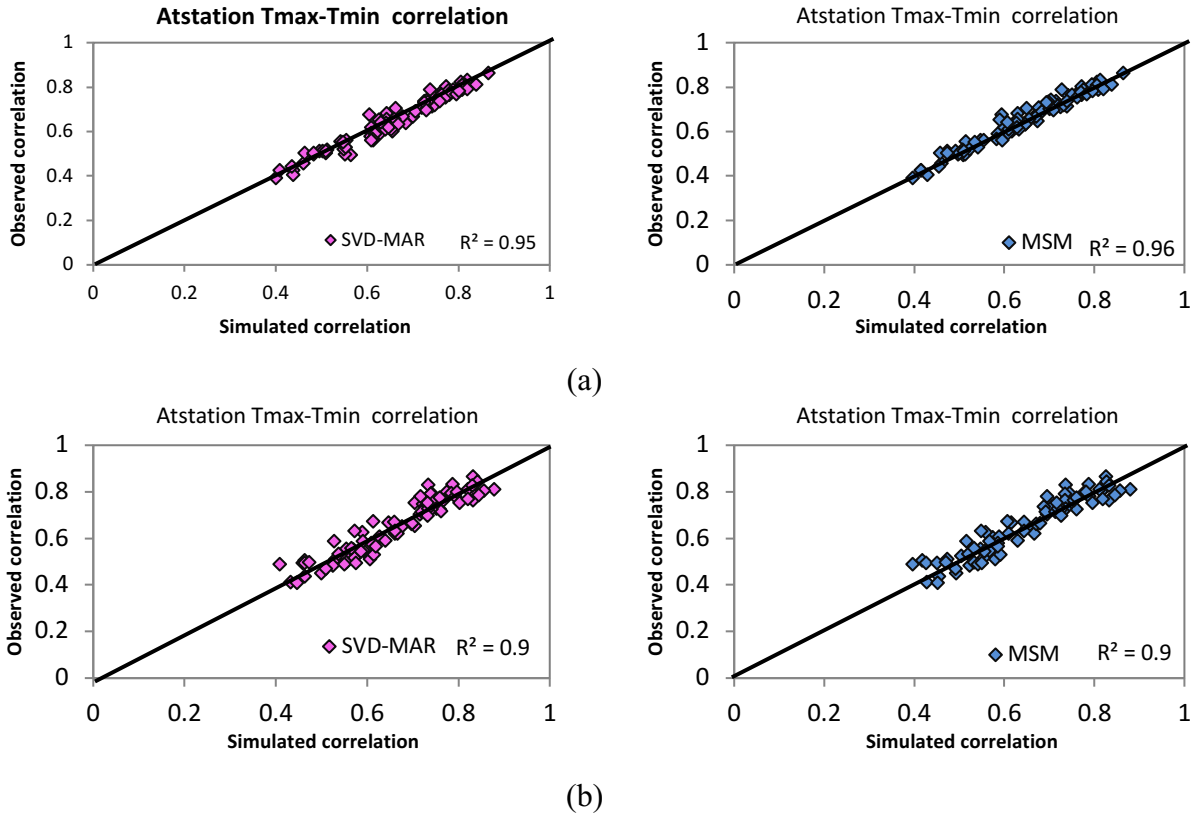


Figure 5.20: Correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM.

Table 5.4: Numerical analysis for the correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region for NCEP.

	NCEP-CGCM							
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.03	0.03	0.02	0.03	0.04	0.05	0.04	0.04
Station 2	0.02	0.03	0.03	0.04	0.03	0.04	0.03	0.04
Station 3	0.03	0.03	0.02	0.03	0.04	0.05	0.03	0.04
Station 4	0.02	0.02	0.02	0.02	0.03	0.04	0.04	0.05
Station 5	0.02	0.03	0.03	0.04	0.03	0.03	0.03	0.04
Station 6	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03
Station 7	0.02	0.03	0.02	0.03	0.04	0.04	0.03	0.03

NCEP-HadCM								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.02	0.03	0.02	0.03	0.04	0.04	0.04	0.05
Station 2	0.02	0.03	0.03	0.04	0.03	0.04	0.03	0.04
Station 3	0.03	0.03	0.02	0.02	0.03	0.04	0.03	0.04
Station 4	0.02	0.03	0.02	0.03	0.04	0.05	0.04	0.05
Station 5	0.02	0.02	0.01	0.01	0.03	0.03	0.02	0.02
Station 6	0.02	0.02	0.01	0.01	0.03	0.04	0.04	0.04
Station 7	0.02	0.03	0.01	0.01	0.04	0.05	0.03	0.03

Observed and downscaled values of average diurnal temperature range (DTR) in each of the months at all of seven stations are presented in Figures 5.21 and 5.22. These figures show that both SVD-MAR and MSM produced the average DTR almost perfectly during calibration period for both NCEP interpolated on CGCM and HadCM. During validation period also, both models were found capable to reproduce the average DTR very accurately for both NCEP.

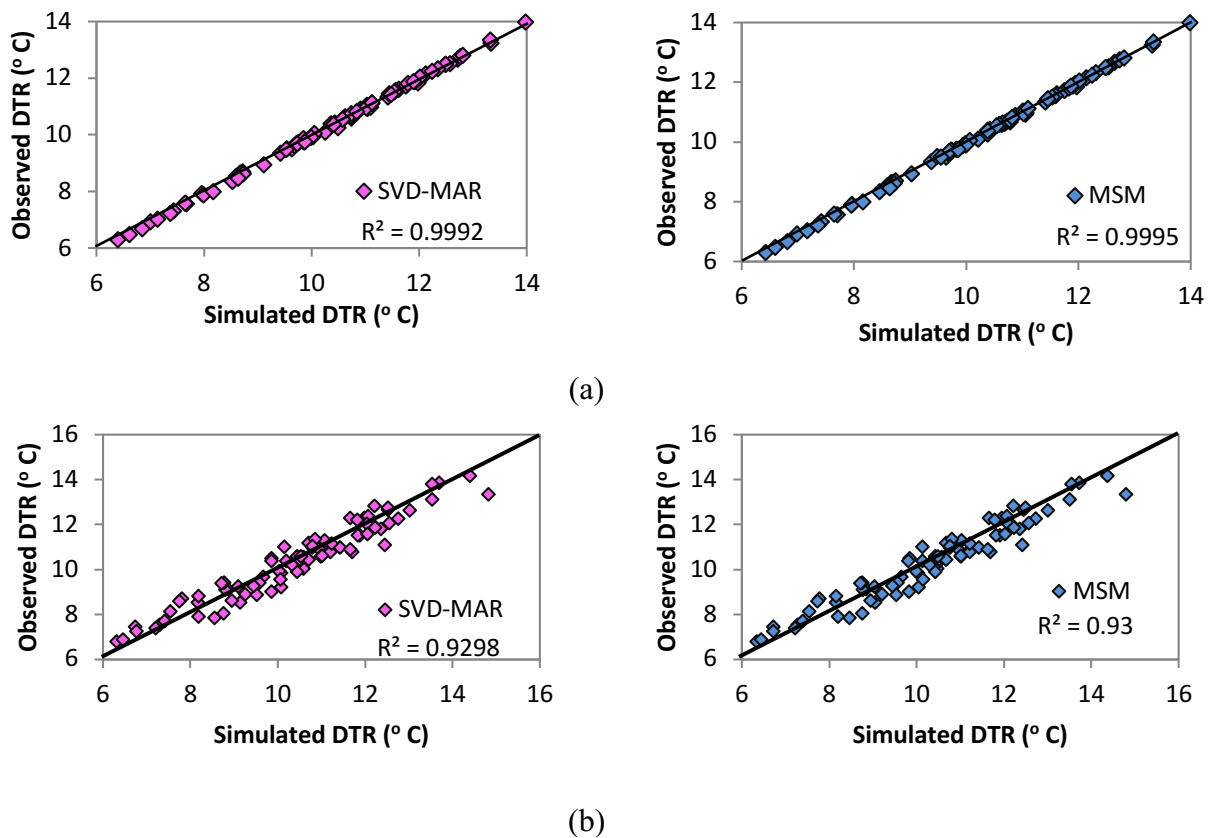
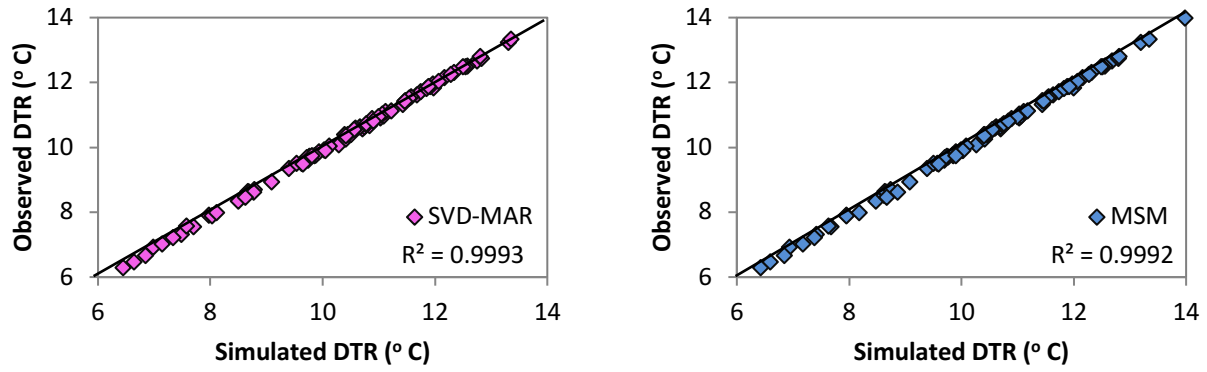
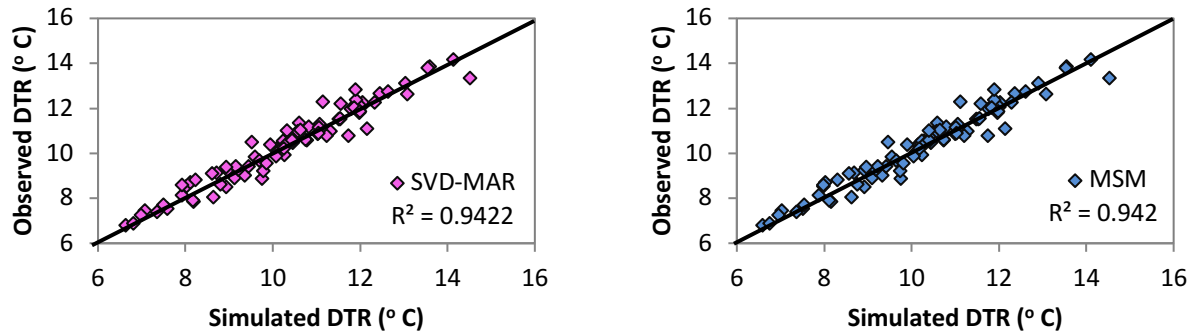


Figure 5.21: Average DTR in each month at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM.



(a)

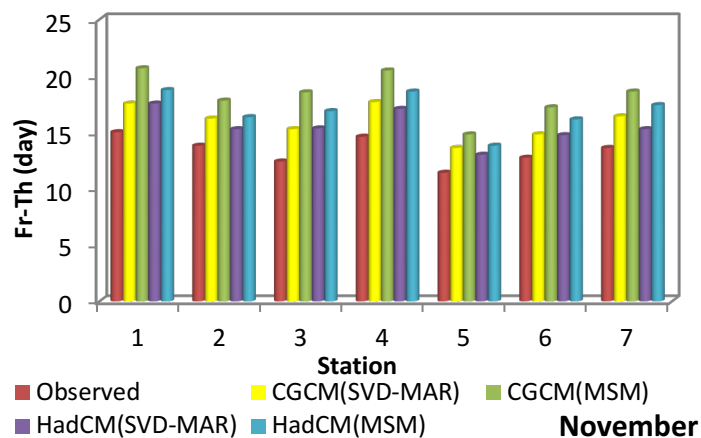
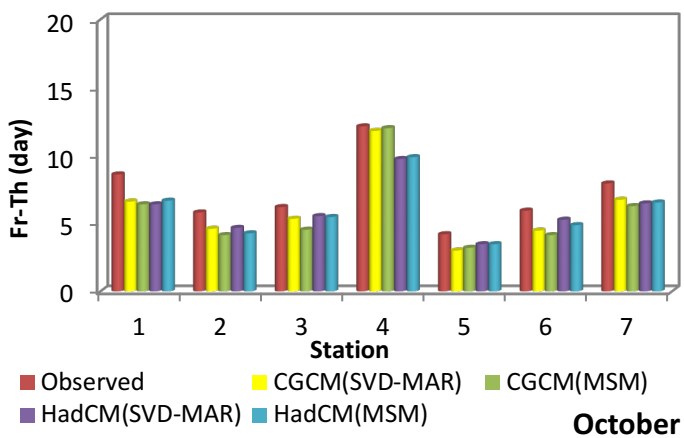
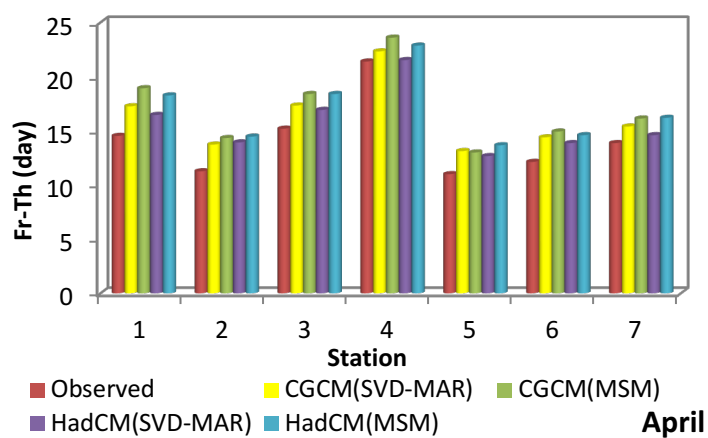
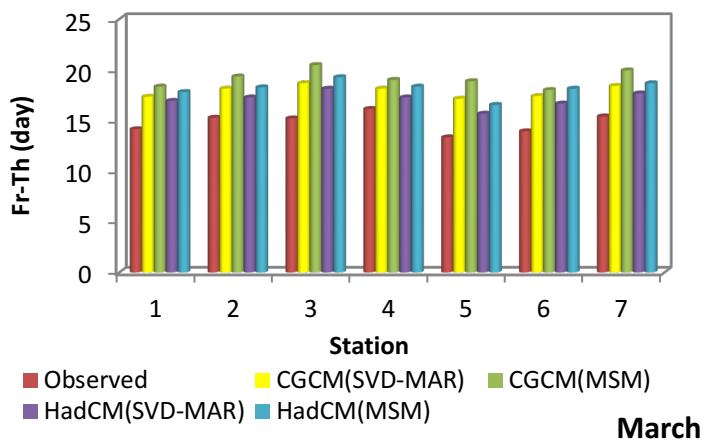


(b)

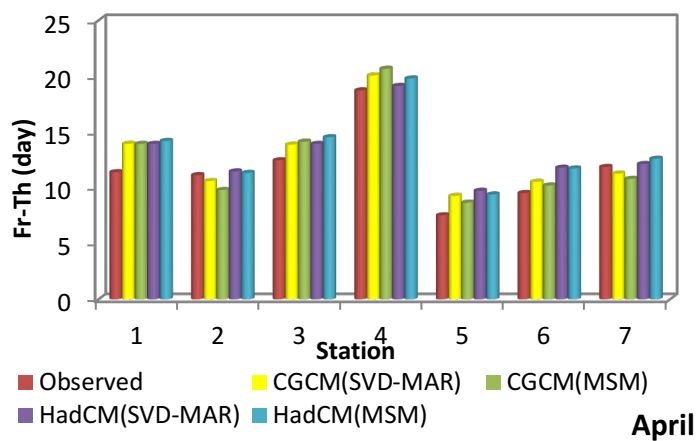
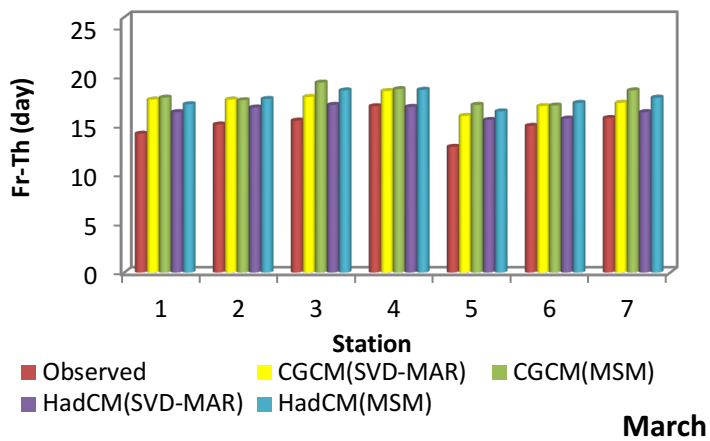
Figure 5.22: Average DTR in each month at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM.

5.1.5 Freeze-Thaw cycle

Figure 5.23 shows the days with freeze-thaw (Fr-Th) cycle (i.e., days with T_{max} above 0°C and T_{min} below 0°C) for selected months. During calibration period both of two models were able to produce Fr-Th cycle acceptably in April and October at most of the stations. In March and November MSM could not encounter Fr-Th cycle accurately. However, SVD-MAR produced better results compared to MSM in later two months, although the results were not very accurate. Likewise, during validation period both of the models were able to simulate Fr-Th cycle acceptably at most of the stations in April and October for both of the NCEP. Although none of the models was able to produce very accurate results in November, SVD-MAR model produced fairly better results than MSM at all of the stations.



(a)



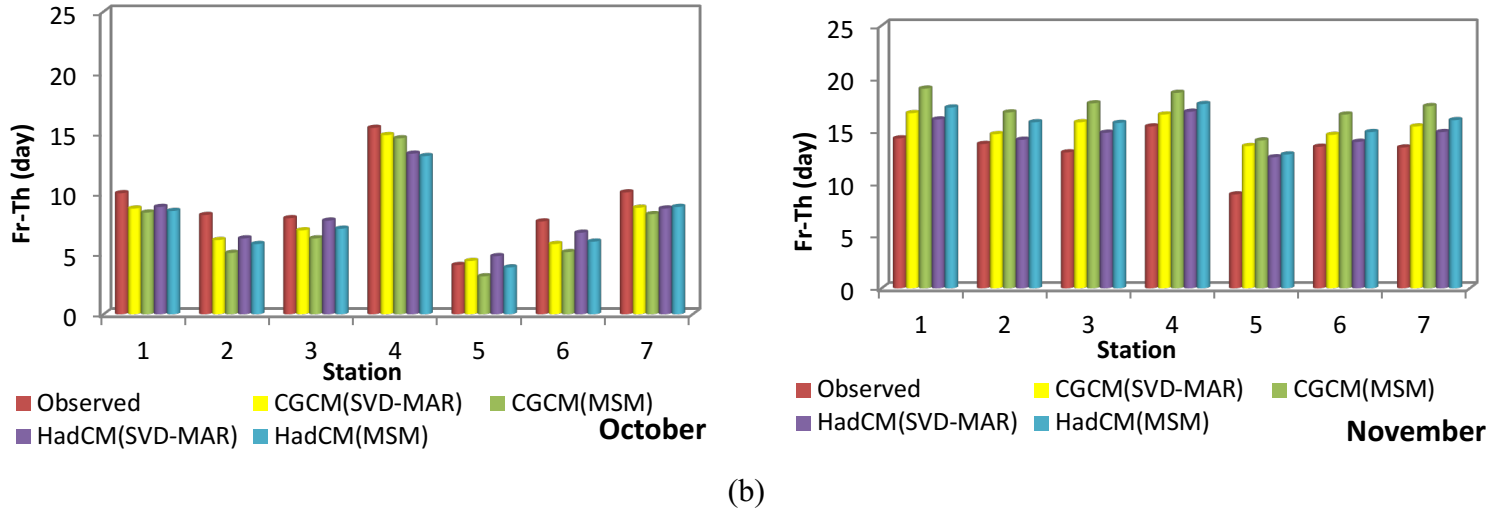


Figure 5.23: Freeze-thaw cycle at the stations in Quebec-Ontario region during (a) calibration and (b) validation periods for NCEP.

5.1.6 Interannual anomalies of the standardized indices

In addition to above mentioned analysis, the effectiveness of the proposed models to capture the temporal variability was investigated through interannual anomalies of the standardized seasonal mean and STD of T_{max} and T_{min} and standardized seasonal T_{max90p} and T_{min10p} indices. The standardized seasonal indices were calculated for each season over 15 years during calibration and validation periods. Graphical representations of these results are given in the Figures 5.24 to 5.29. Good agreements were found between the observed and simulated values of Interannual variability in standardized mean of T_{max} for both of the NCEP in most of the years during calibration period. For validation period also, this index was reproduced well in all of four seasons by both of the models (Figure 5.24). The standardized STD of T_{max} was produced well during calibration and validation periods, although very few deviations were observed in winter and summer especially during calibration period (Figure 5.25). The figure shows that although similar results were produced for both of the NCEP, slightly better fit was observed for the NCEP interpolated on HadCM than CGCM. Standardized T_{max90p} was simulated acceptably for almost all the years in all seasons during both calibration and validation periods (Figure 5.26). In case of T_{min} , the interannual variability of standardized mean was well captured for both of NCEP by both of the models (Figure 5.27). Although simulated trends followed the observed ones for the index standardized STD of T_{min} , some deviations were observed specially in winter and summer

during calibration period and in summer and autumn during validation period (Figure 5.28). Like T_{max} , in this index also the results were simulated better for the NCEP interpolated on HadCM in some of the years. Figure 5.29 shows that standardized T_{min10p} was reproduced well by both of the models in almost all of the years during both calibration and validation periods.

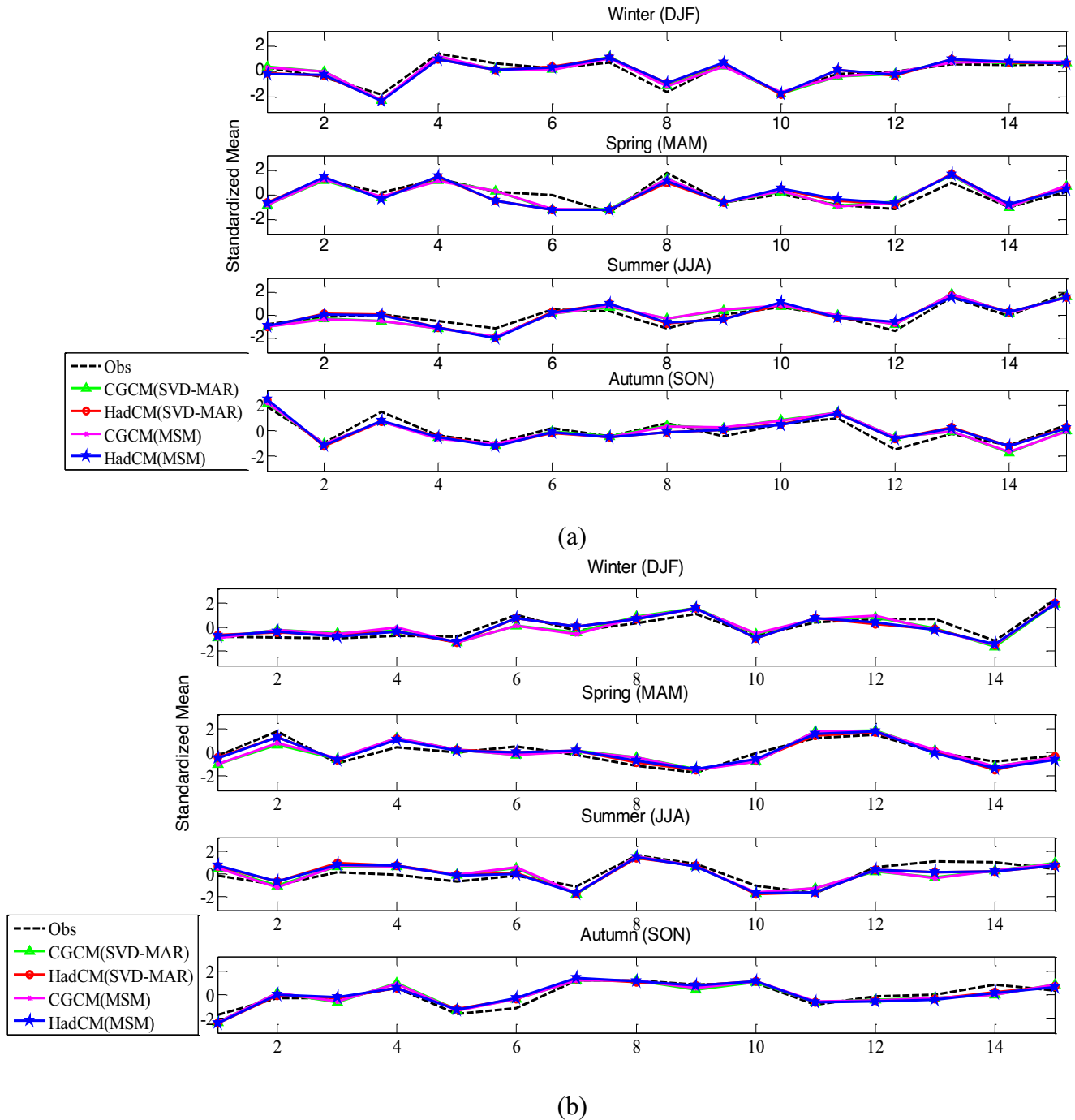
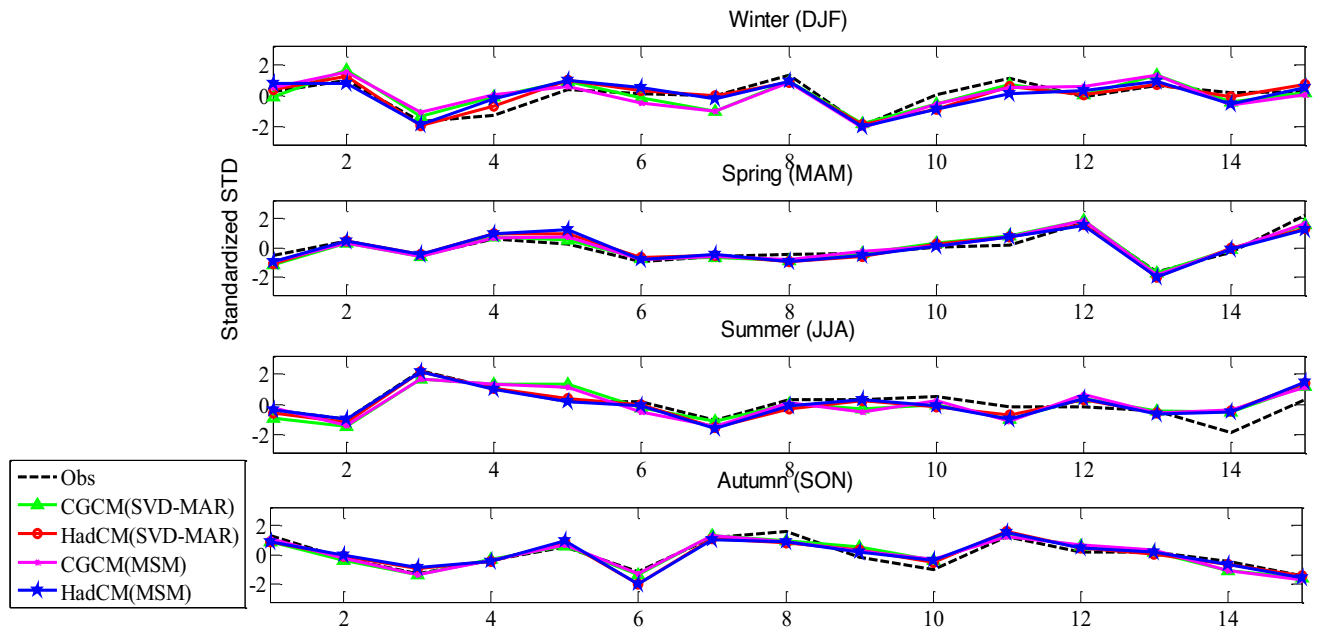
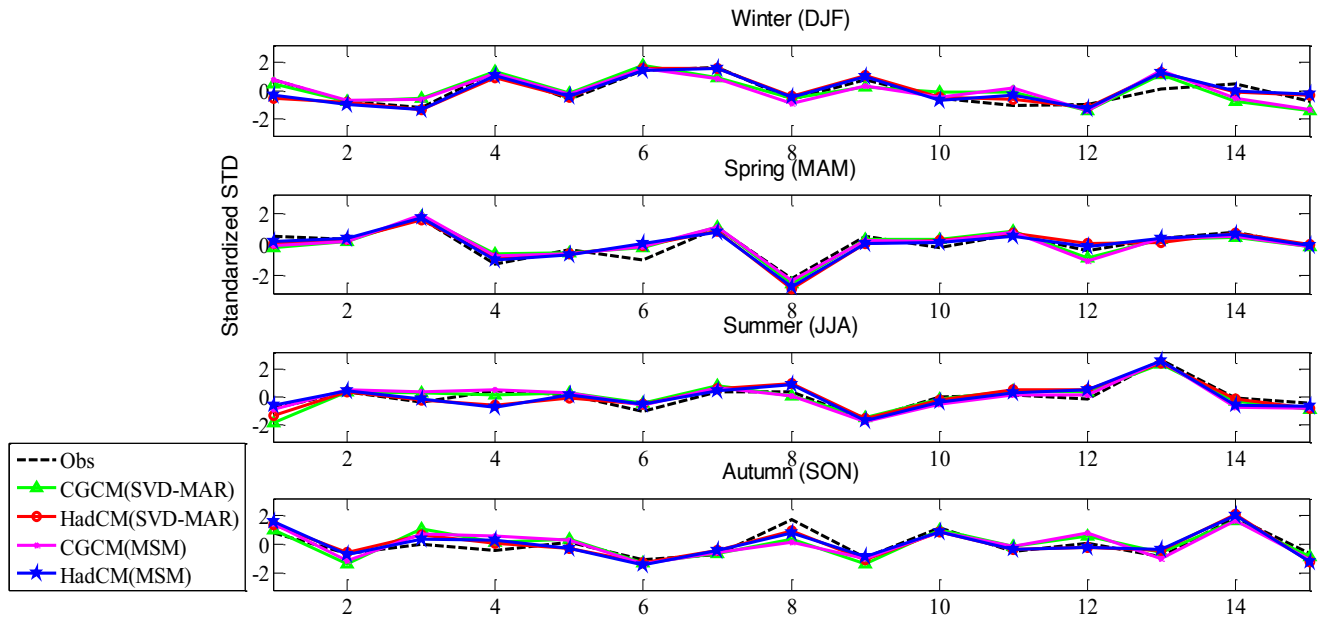


Figure 5.24: Interannual anomalies of standardized seasonal mean of T_{max} during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

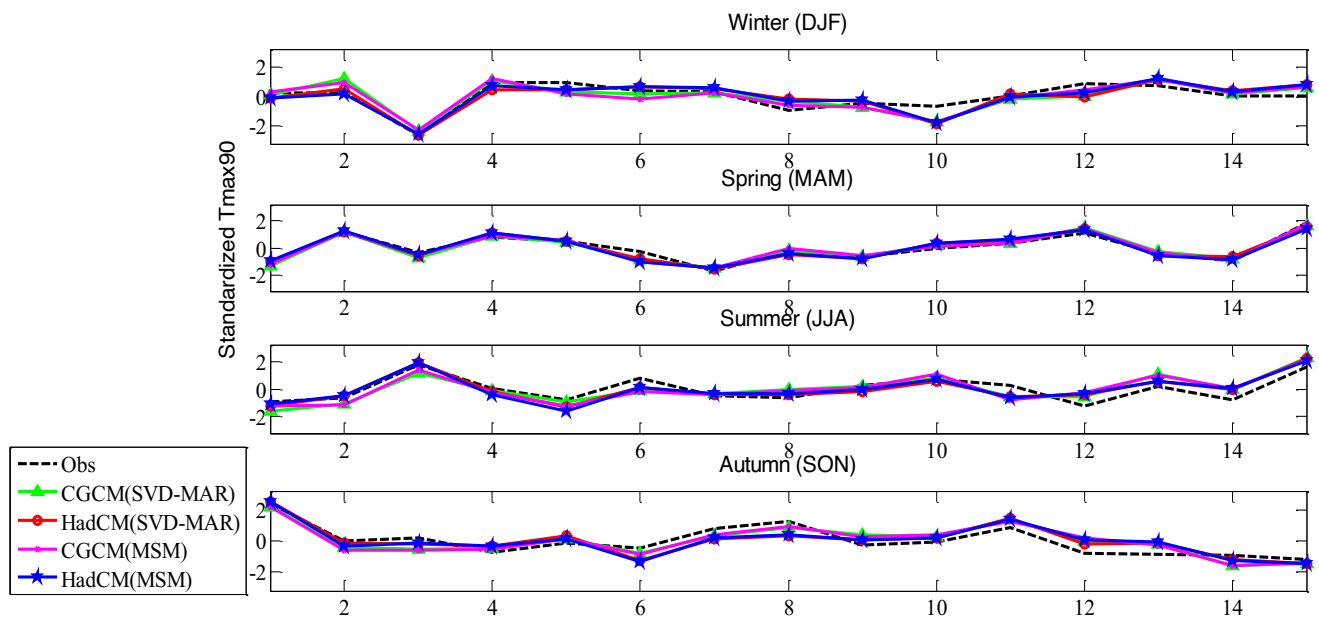


(a)

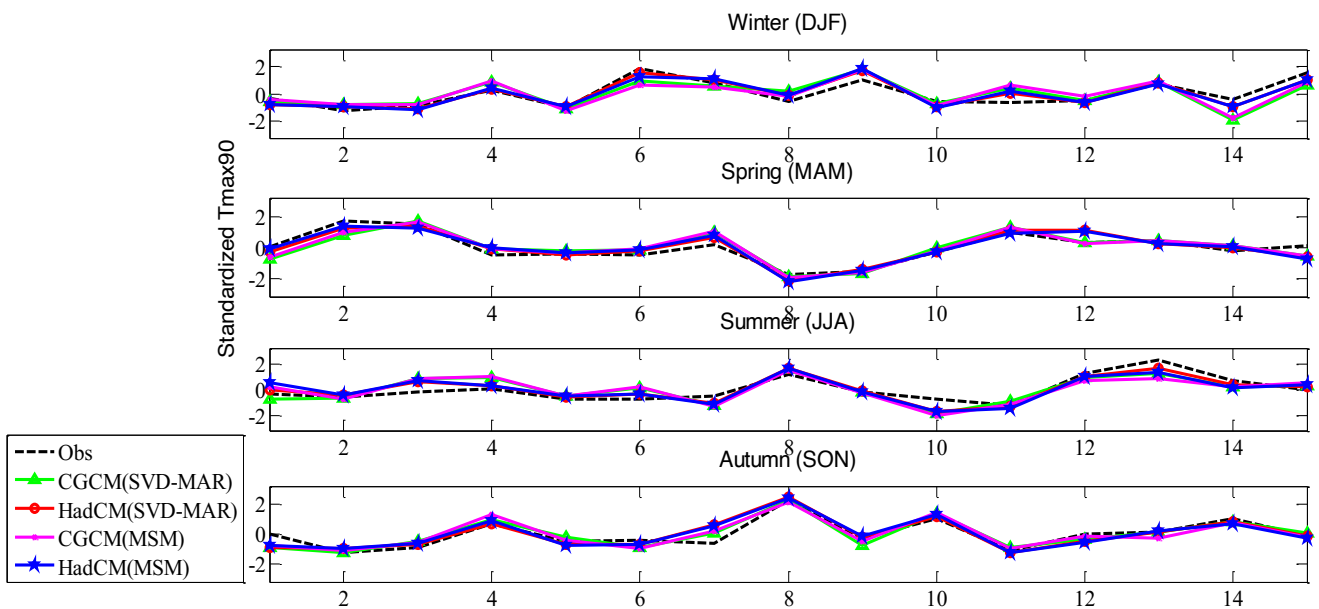


(b)

Figure 5.25: Interannual anomalies of standardized seasonal STD of T_{max} during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

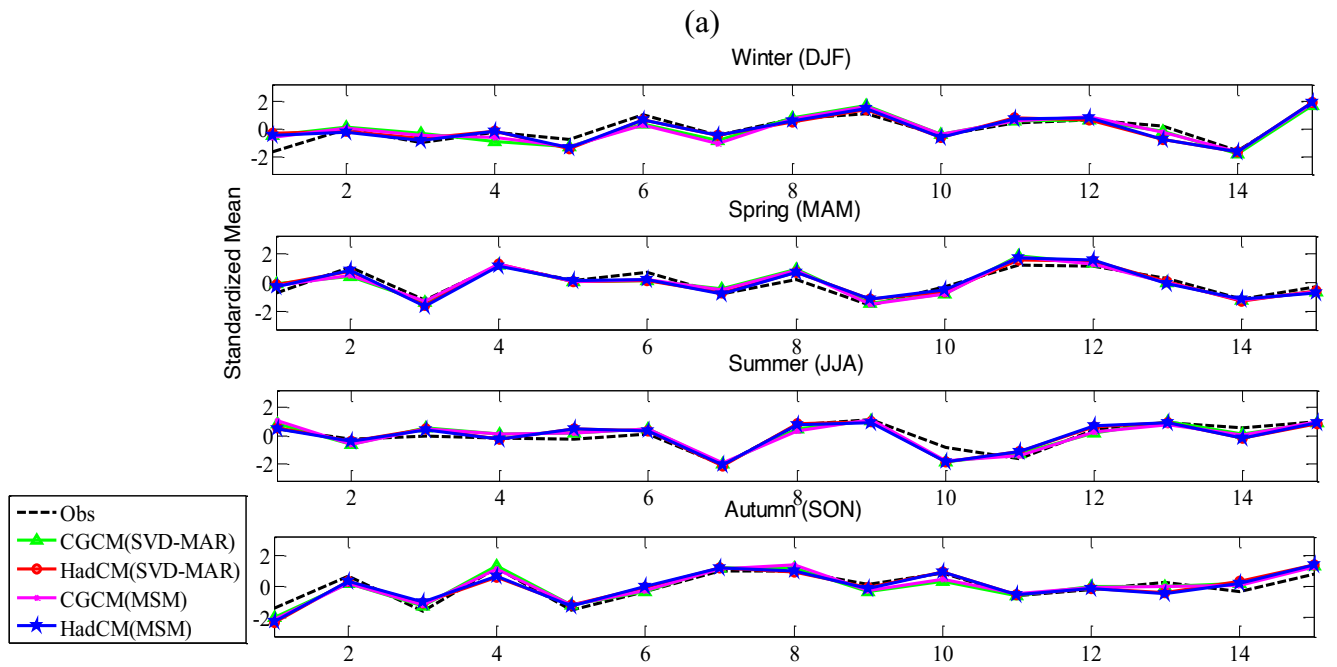
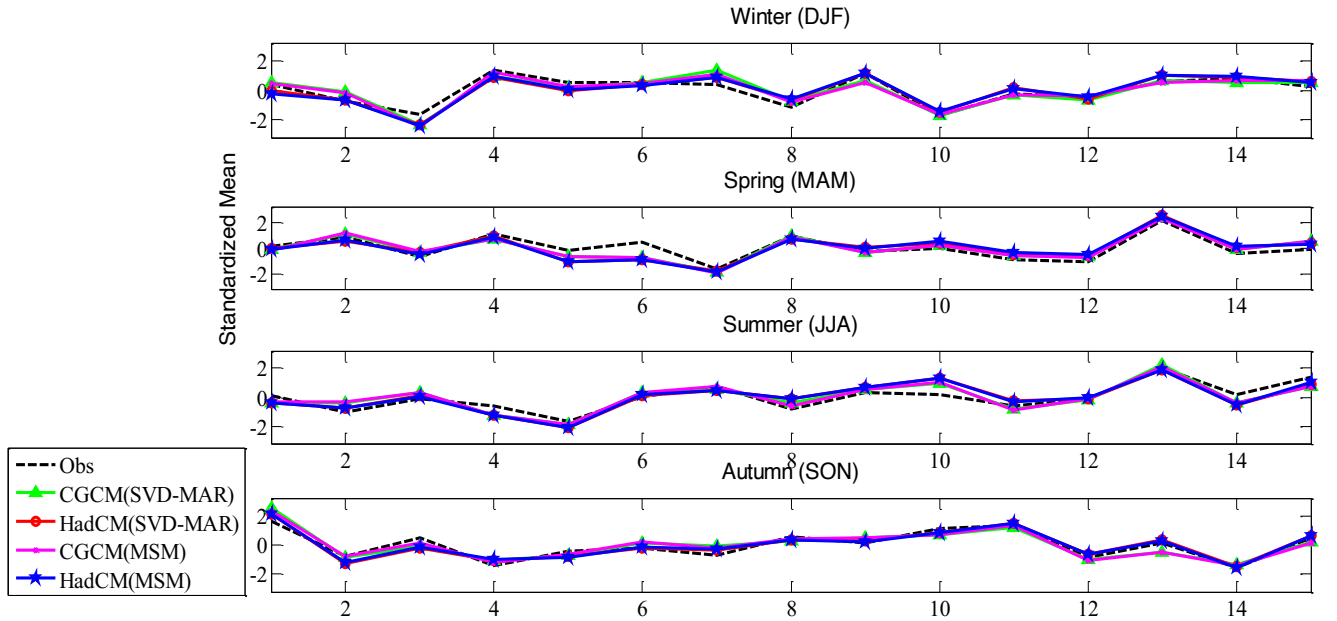


(a)



(b)

Figure 5.26: Interannual anomalies of standardized seasonal Tmax90p during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.



(b)

Figure 5.27: Interannual anomalies of standardized seasonal mean of T_{min} during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

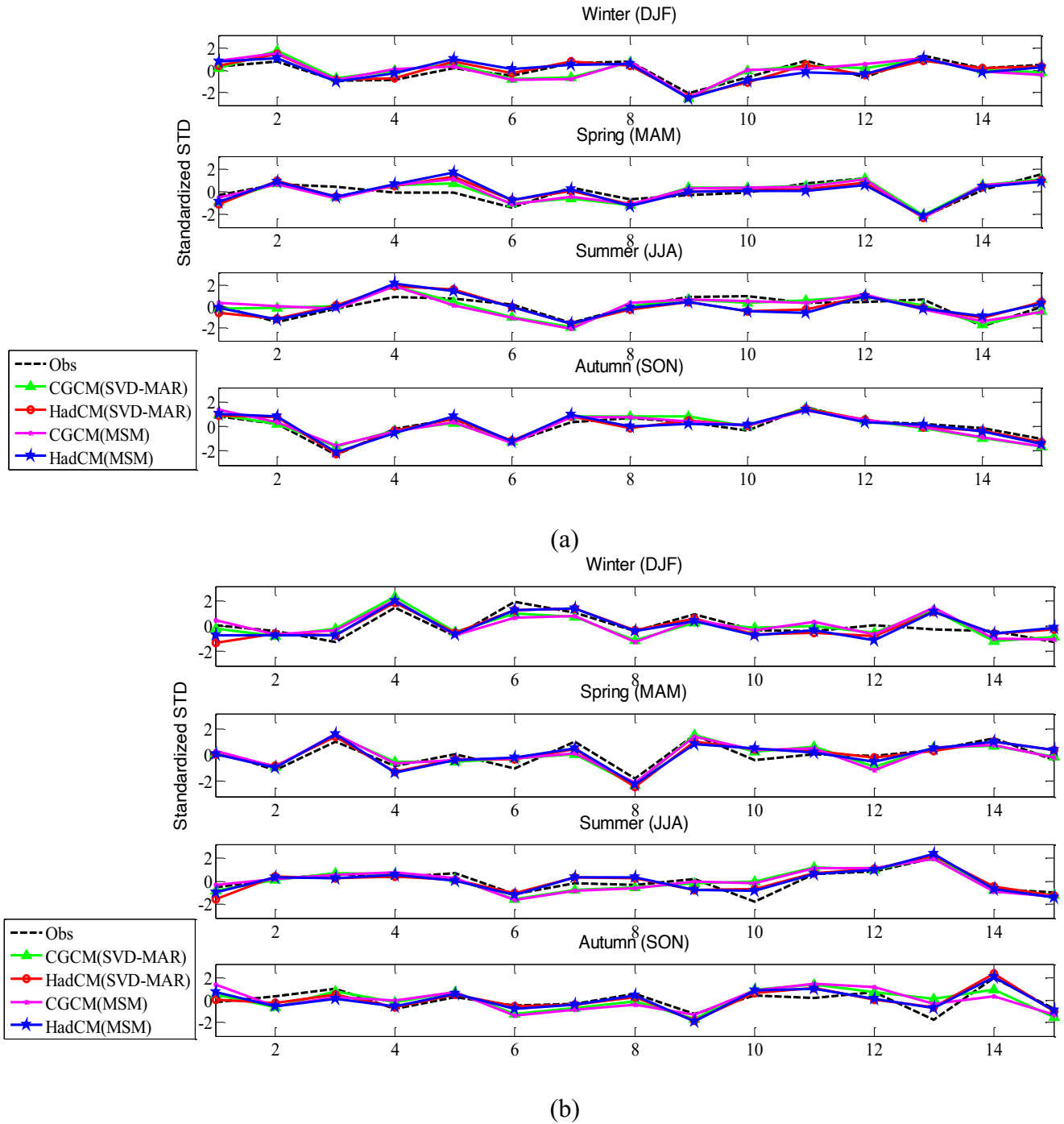
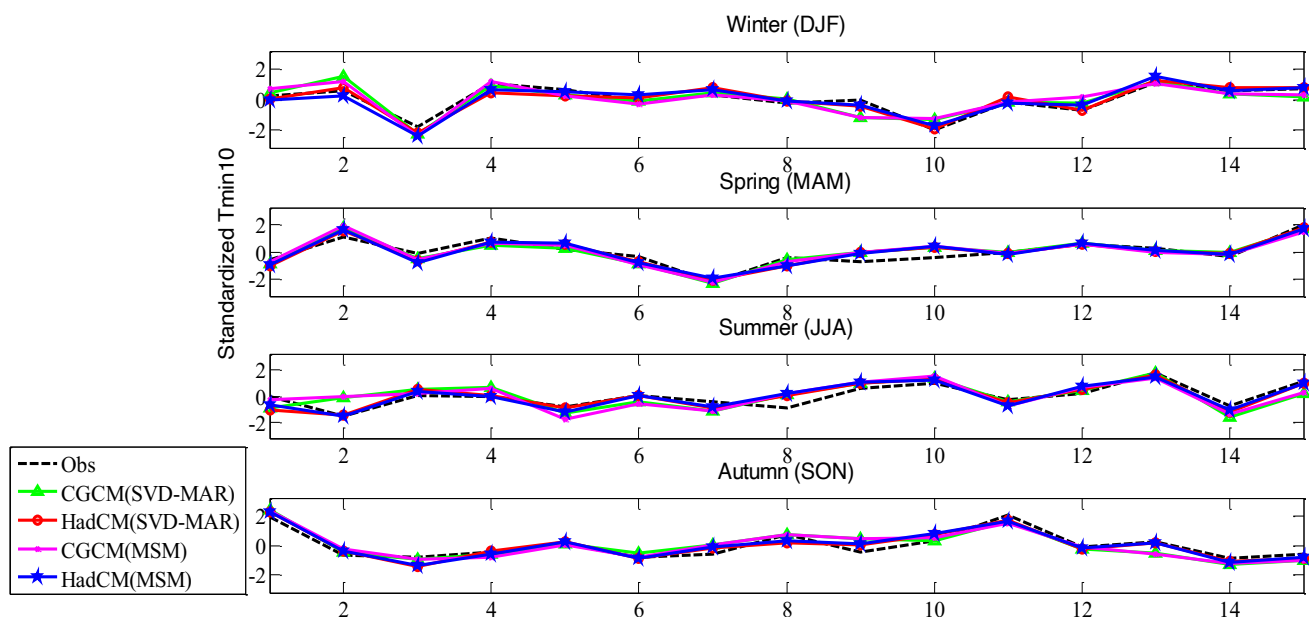
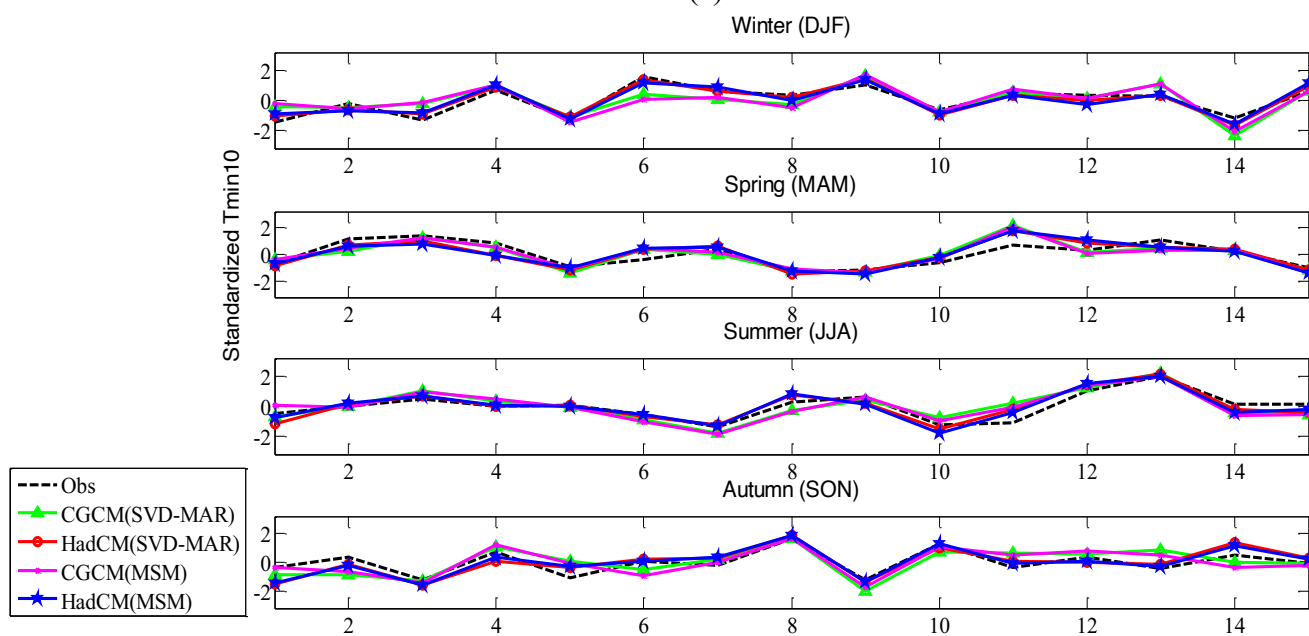


Figure 5.28: Interannual anomalies of standardized seasonal STD of T_{min} during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.



(a)



(b)

Figure 5.29: Interannual anomalies of standardized seasonal T_{min10p} during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

5.2 Results and evaluation of MMSD models for GCM simulations

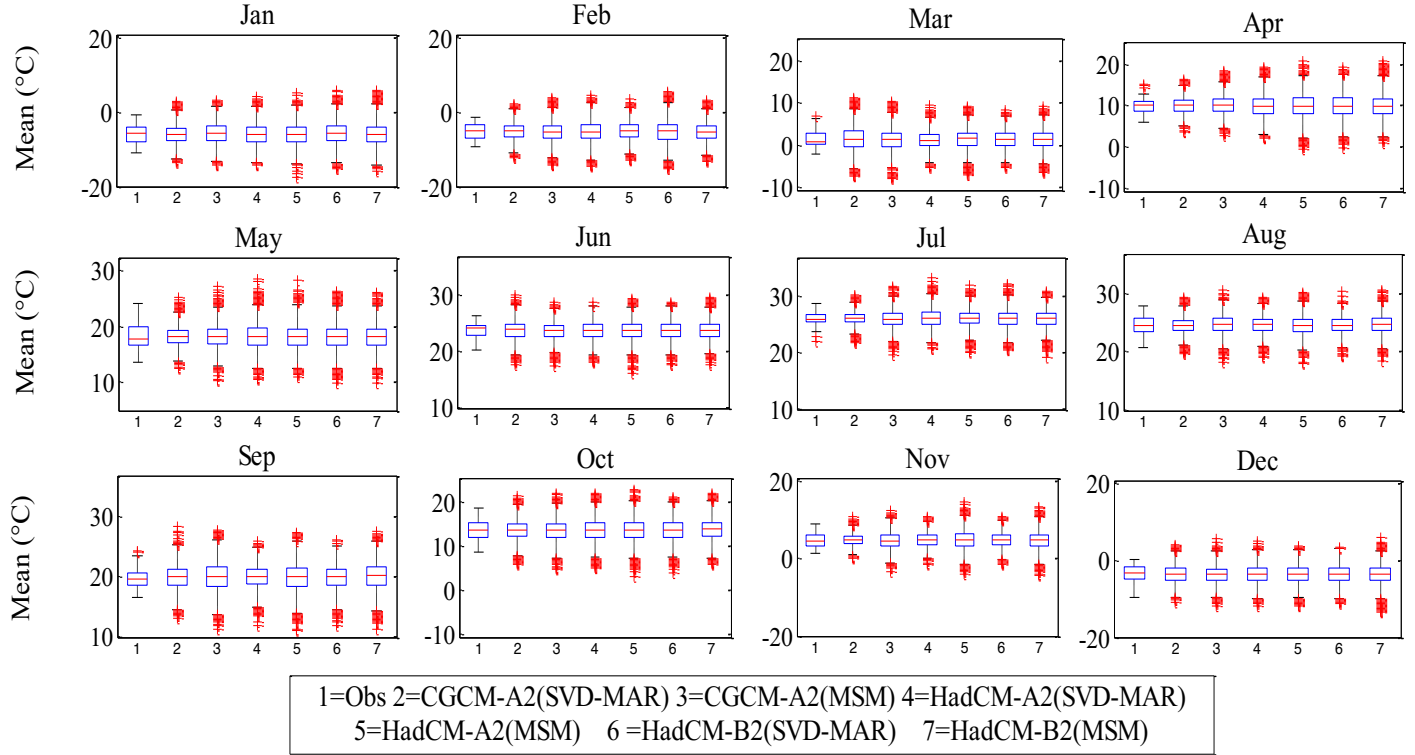
This section provides the results obtained by using GCM outputs for three climate scenarios namely CGCM-A2, HadCM-A2 and HadCM-B2 during the current period. Here, current period is denoted by the period 1961-1990, of which, 1961-1975 represents the calibration period and 1976-1990 represents the validation period.

5.2.1 Goodness of fit

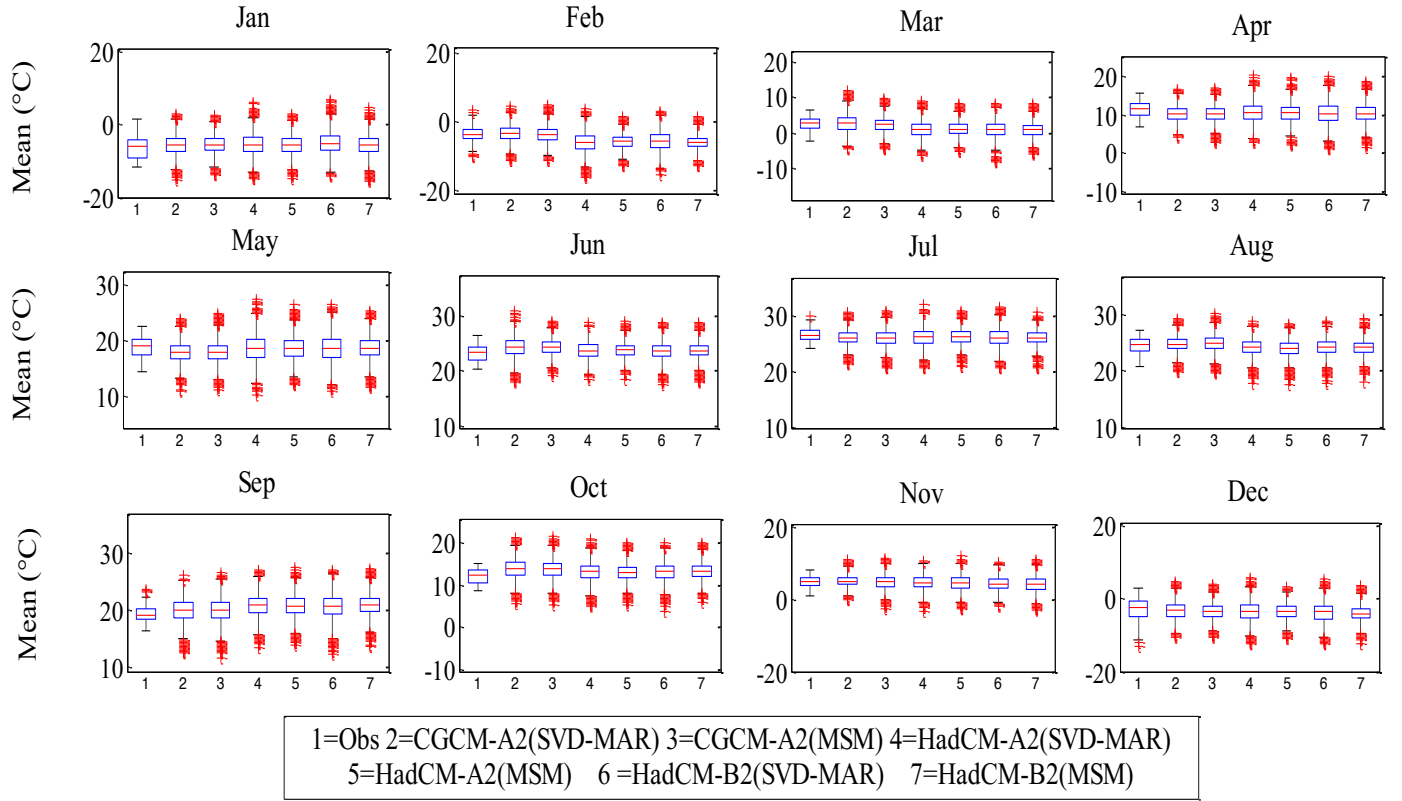
Like NCEP reanalysis data, for GCM outputs also, four temperature indices, such as mean, STD, T_{max90p} and T_{min10p} were computed and compared with the observed ones during current period for three scenarios (e.g., CGCM-A2, HadCM-A2 and HadCM-B2). Figures 5.30 through 5.35 present the boxplots of those indices. It is observed that both of the models reproduced monthly means of T_{max} accurately in almost all the months for all the scenarios during calibration period (Figure 5.30). During validation period although this index was reproduced adequately, some biases were observed in few months. For monthly means of T_{min} also, good agreements were observed between simulated and observed values during calibration period for all of three scenarios by both of the models (Figure 5.31). During validation period this index was reproduced accurately in almost all the months. Monthly STD of T_{max} was simulated well by both of the models for all the scenarios during calibration period. During validation also, STD of T_{max} were acceptably reproduced with few biases (Figure 5.32). It can be observed that during validation period SVD-MAR model produced better fit than MSM in March, April and November specially for HadCM scenarios, whereas, in February and October MSM produced better results than SVD-MAR. However, for rest of the months both models produced almost similar results in this index. In case of T_{min} , good agreements were found between the observed ones and simulated monthly STD during calibration period. For validation period also, this index was reproduced well, although few biases were observed in March and November (Figure 5.33). Monthly T_{max90p} was reproduced accurately by both of the models for all scenarios during calibration period and in most of the months during validation period (Figures 5.34). The index T_{min10p} was also reproduced well by both of the models during calibration and validation periods (Figure 5.35).

The values of MAE (RMSE) produced by SVD-MAR and MSM for three scenarios ranged between 0.03-0.13 (0.04-0.16) and 0.03-0.15 (0.04-0.2) at all of seven stations respectively for

T_{max} and T_{min} during calibration period (Table 5.5). The values of MAE and RMSE in table 5.5 suggest that SVD-MAR produced better results than MSM during calibration period especially for CGCM-A2 scenario. During validation period those values ranged between 0.6-1.08 (0.8-1.27) and 0.43 -1.06 (0.57-1.38) respectively for T_{max} and T_{min} for all of three scenarios. Table 5.5 shows that both of the models produced relatively lower values of MAE and RMSE for CGCM-A2 scenario than those of HadCM-2 and HadCM-B2 scenarios especially during validation period.

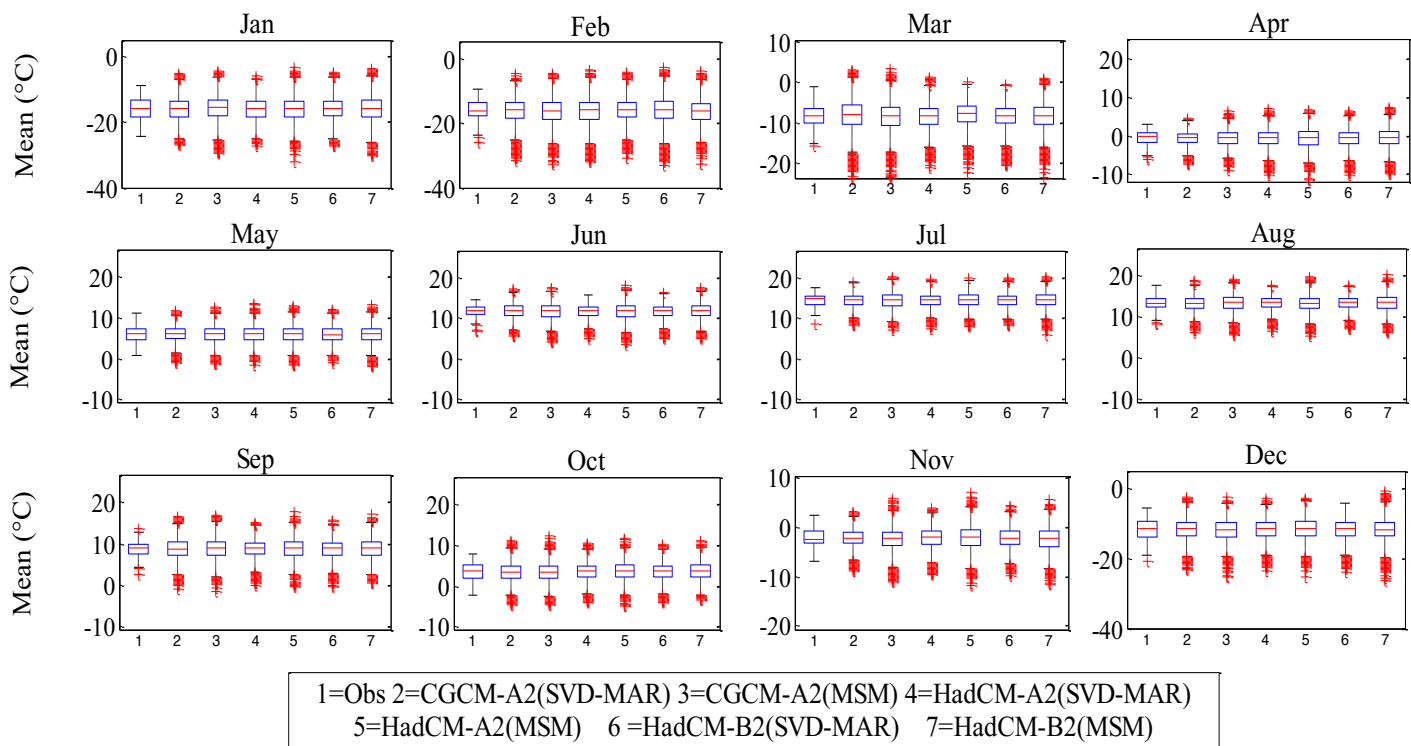


(a)

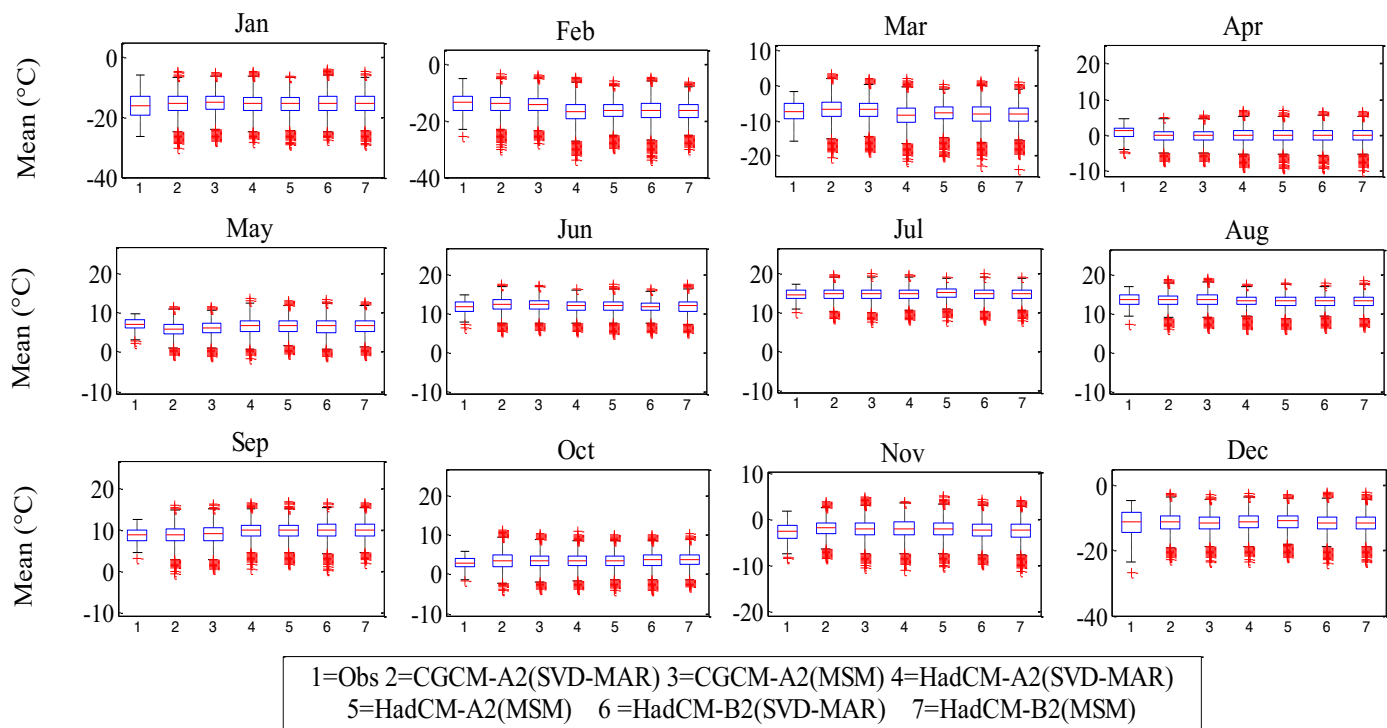


(b)

Figure 5.30: Boxplots of the mean of daily T_{max} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

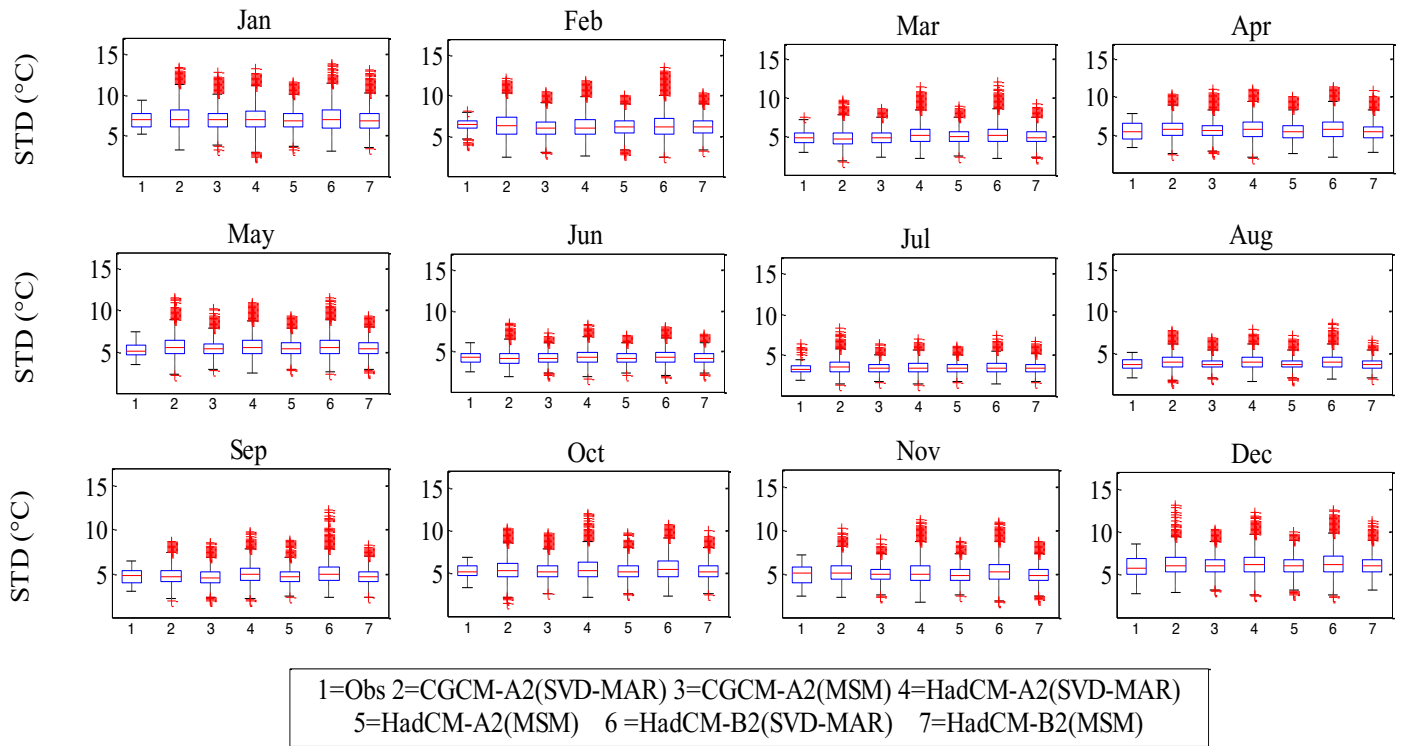


(a)

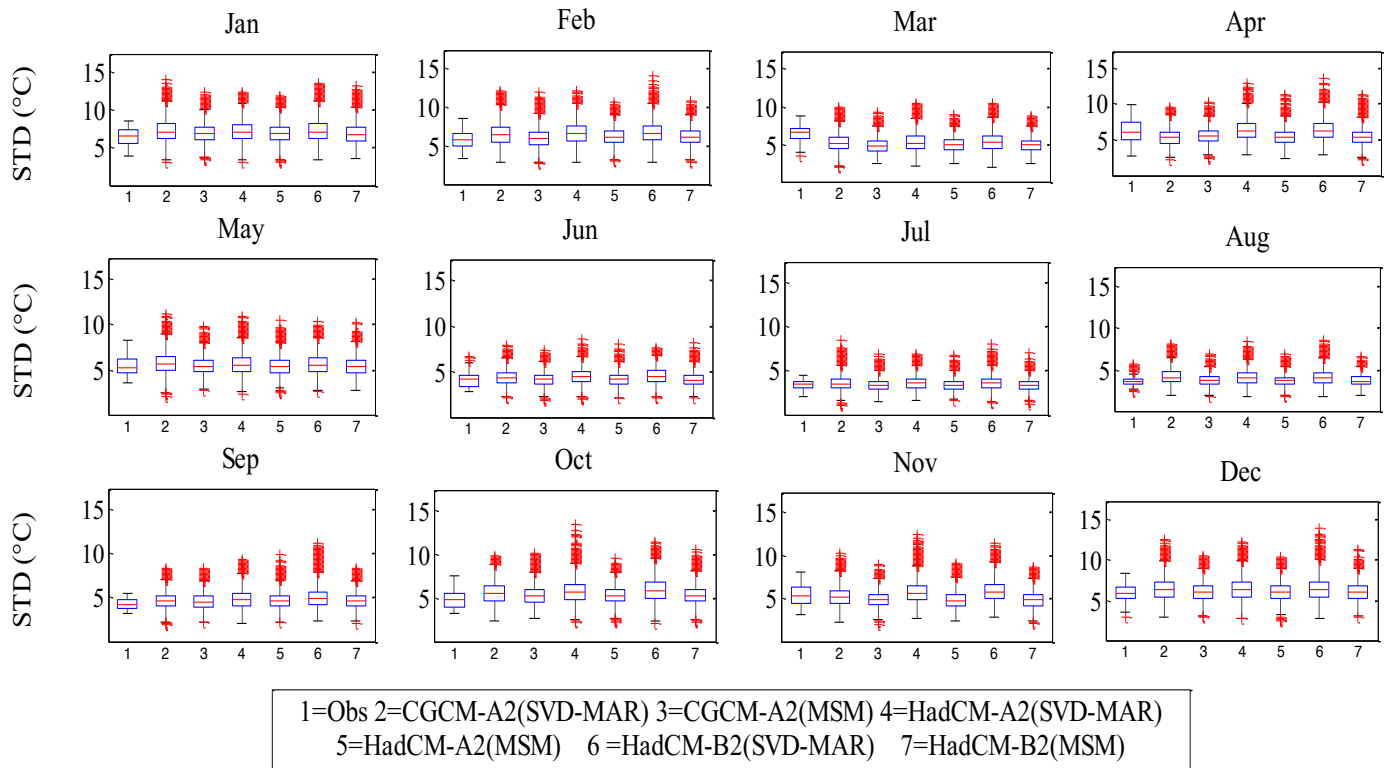


(b)

Figure 5.31: Boxplots of the mean of daily T_{min} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

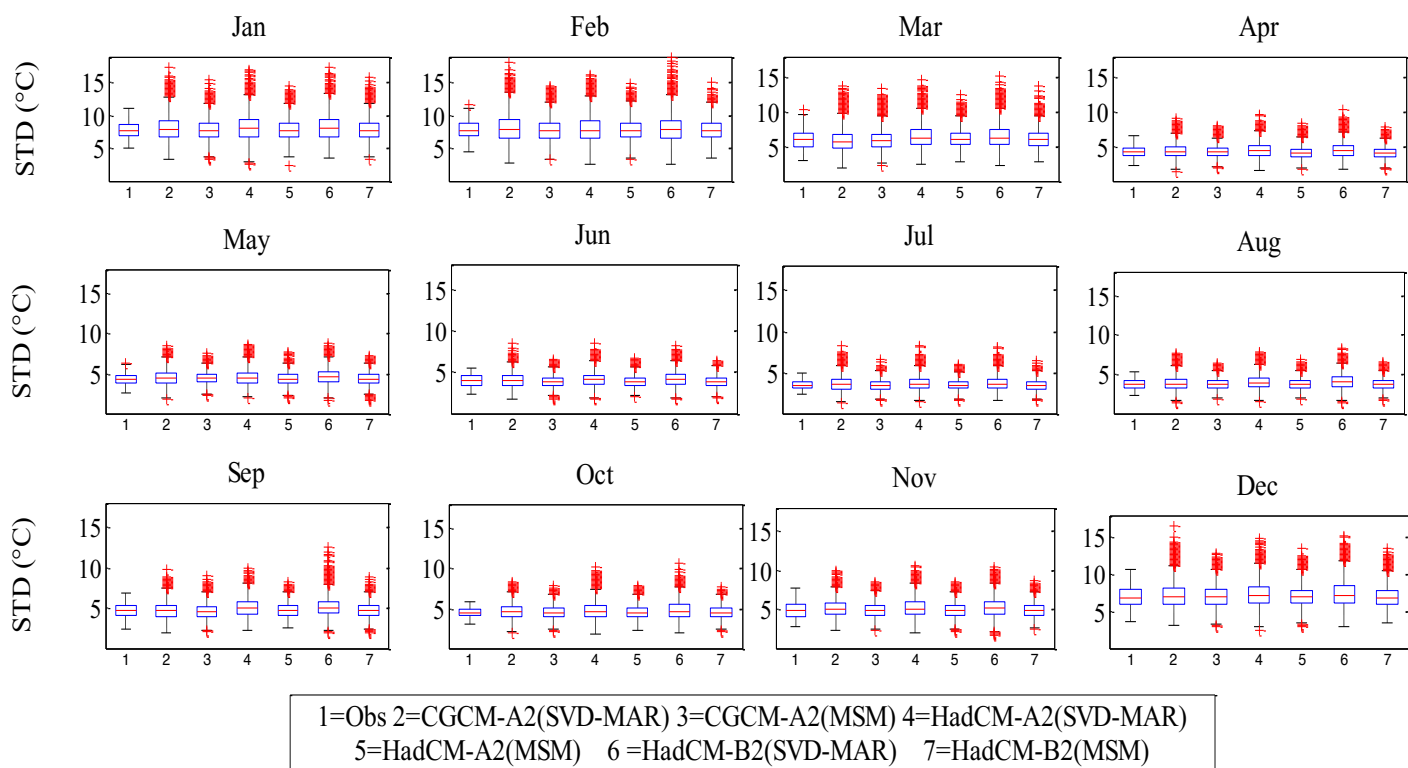


(a)

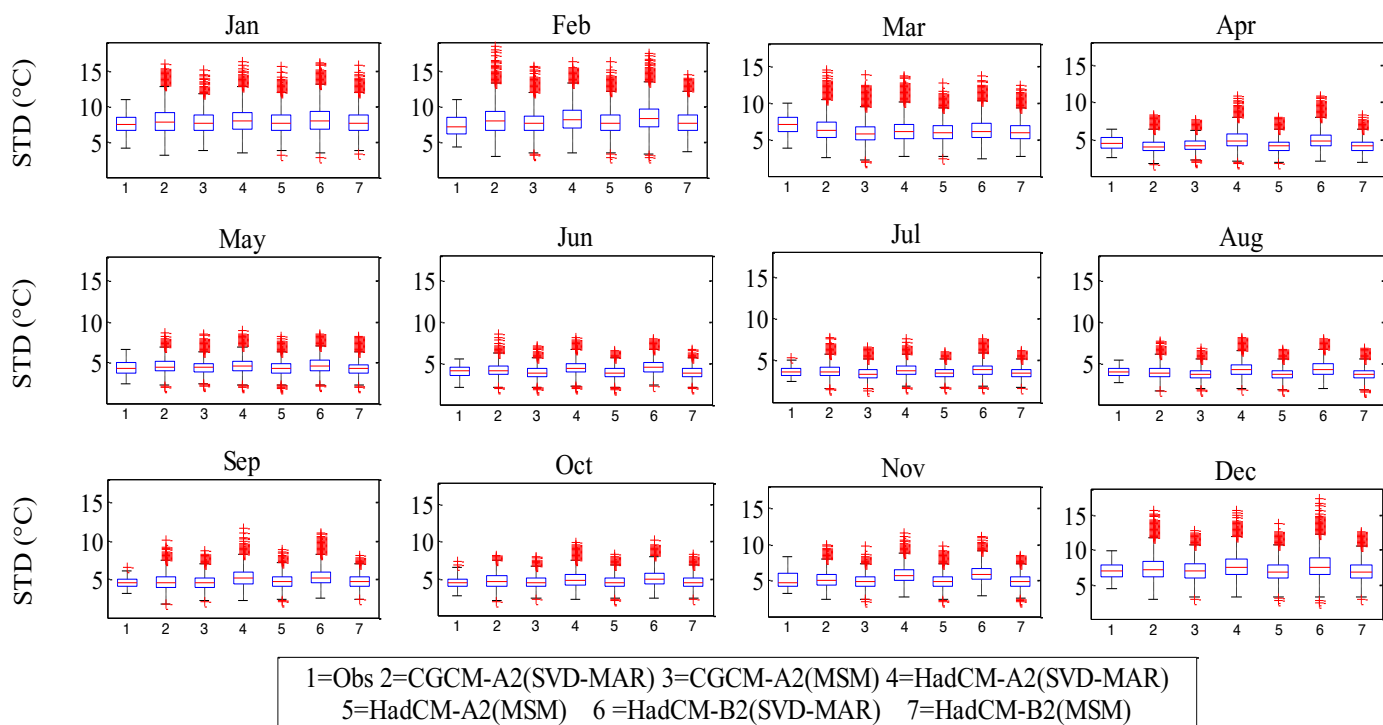


(b)

Figure 5.32: Boxplots of the STD of daily T_{max} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

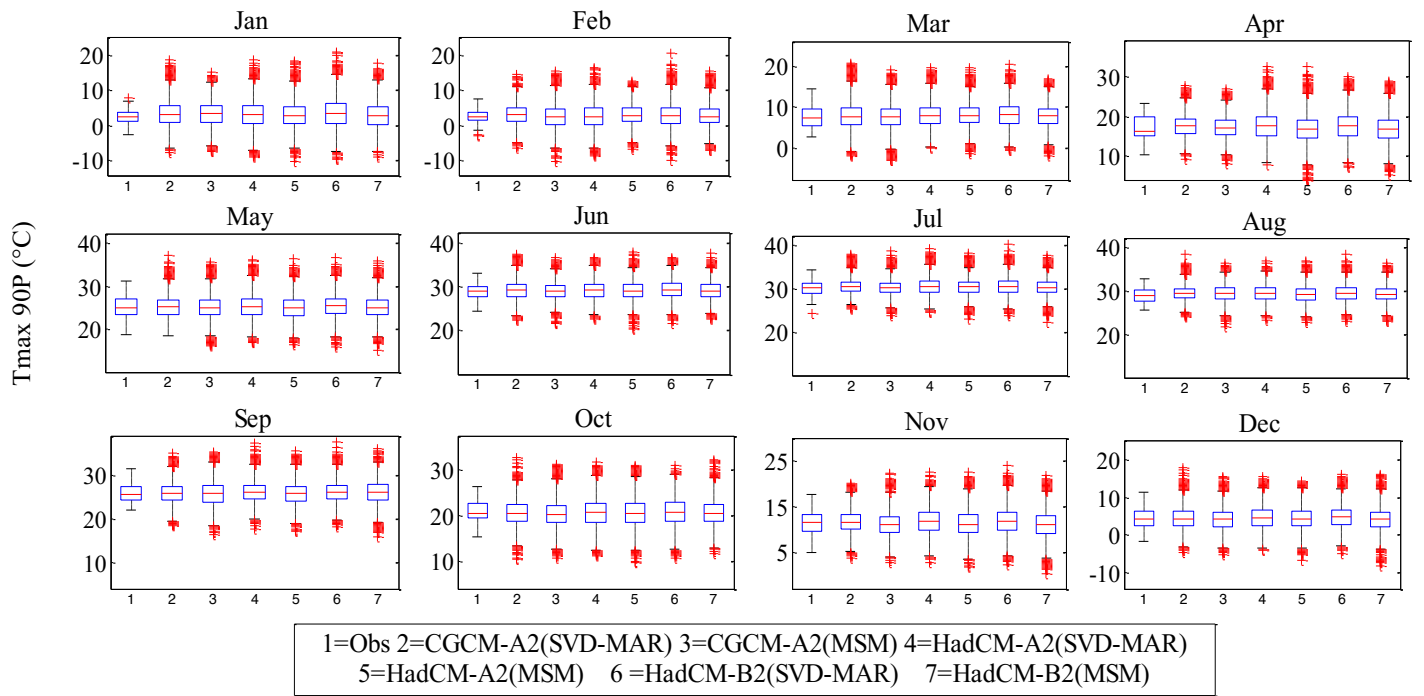


(a)

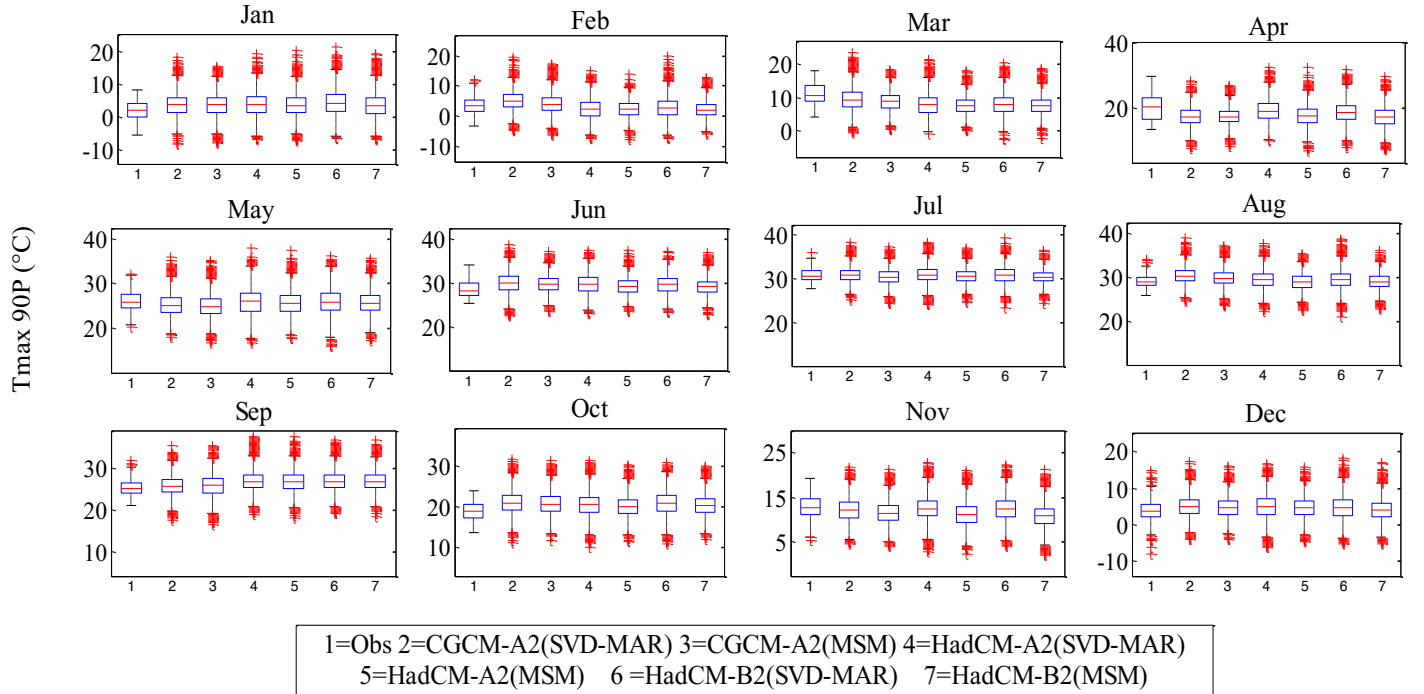


(b)

Figure 5.33: Boxplots of the STD of daily T_{min} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.



(a)



(b)

Figure 5.34: Boxplots of the Tmax90p for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

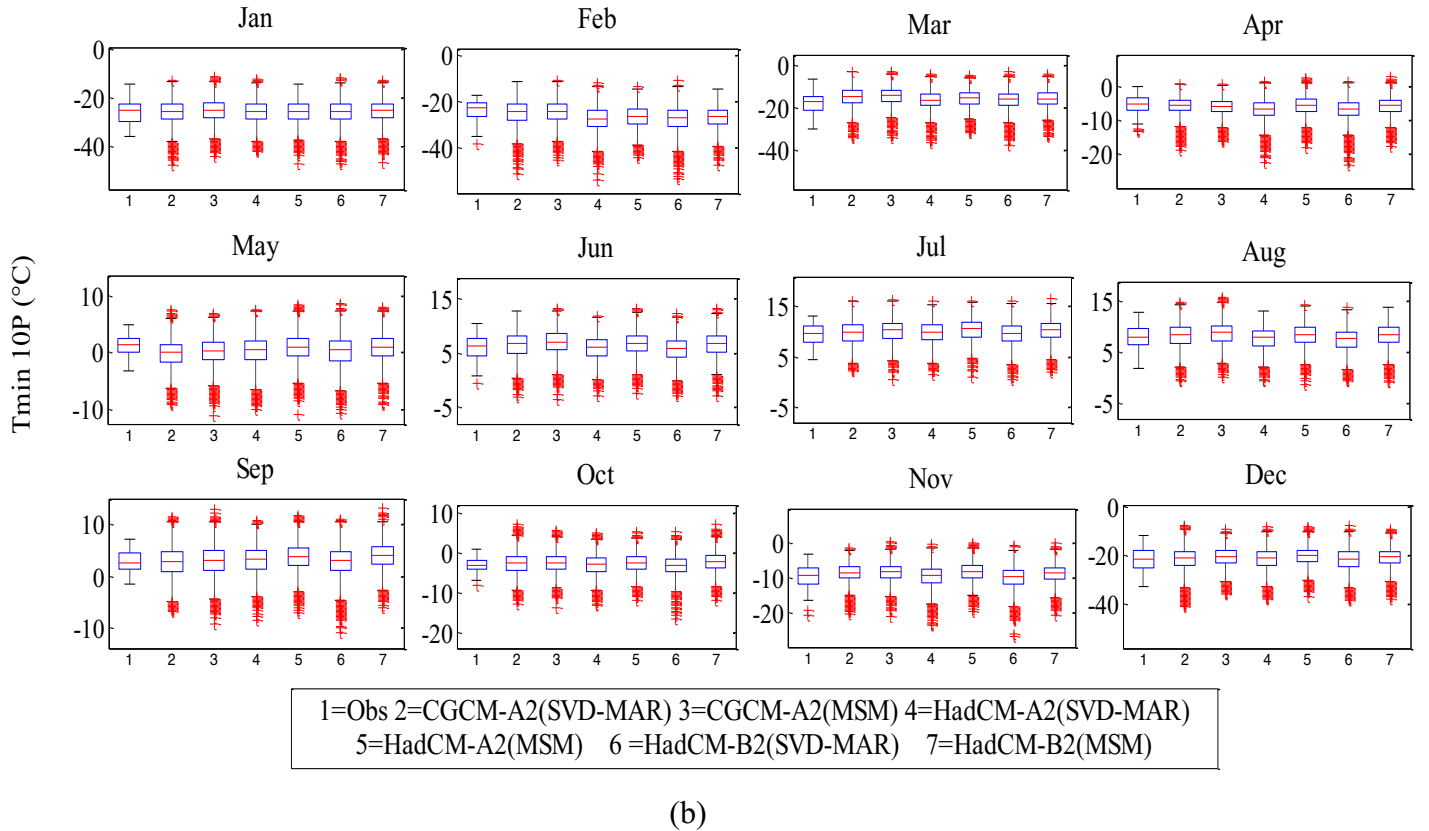
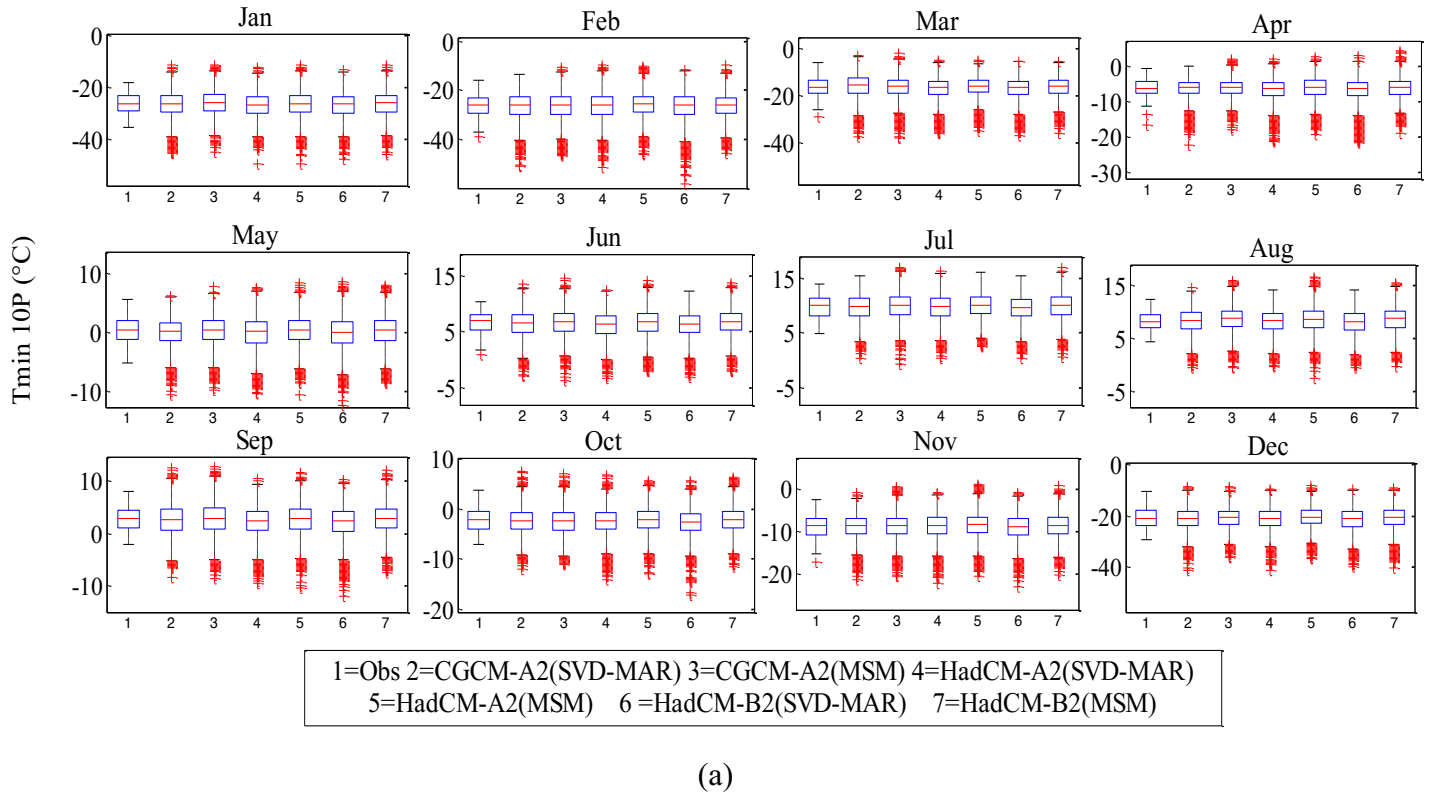


Figure 5.35: Boxplots of the Tmin10p for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at seven stations in Quebec-Ontario region.

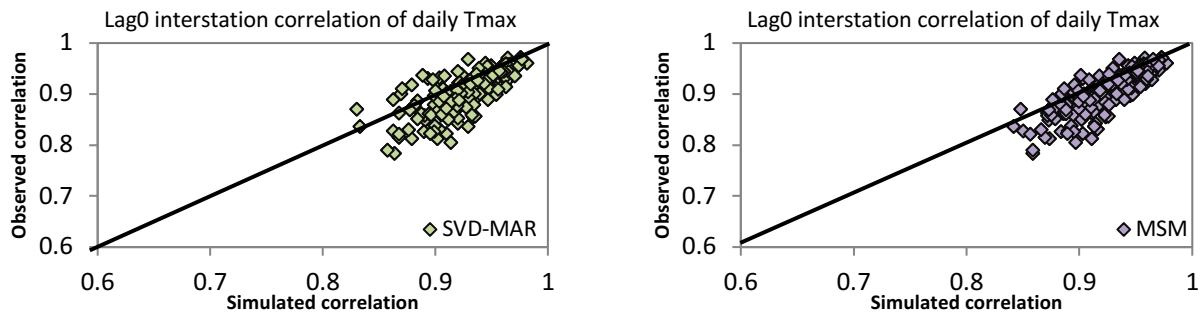
Table 5.5: MAE and RMSE values of T_{max} and T_{min} for different climate scenarios at seven stations in Quebec-Ontario region.

CGCM-A2									
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.03	0.04	0.11	0.14	0.62	0.82	0.6	0.8
	Station 2	0.03	0.04	0.12	0.14	0.65	0.82	0.64	0.82
	Station 3	0.03	0.04	0.13	0.16	0.67	0.85	0.66	0.86
	Station 4	0.03	0.04	0.12	0.14	0.73	0.84	0.68	0.82
	Station 5	0.04	0.06	0.13	0.16	0.66	0.83	0.75	0.86
	Station 6	0.03	0.04	0.12	0.14	0.63	0.83	0.67	0.84
	Station 7	0.03	0.04	0.13	0.16	0.7	0.86	0.75	0.89
T_{min}	Station 1	0.05	0.06	0.12	0.16	0.58	0.72	0.54	0.71
	Station 2	0.03	0.04	0.13	0.16	0.65	0.72	0.63	0.67
	Station 3	0.06	0.08	0.15	0.2	0.61	0.73	0.59	0.74
	Station 4	0.03	0.04	0.14	0.17	0.76	0.91	0.77	0.88
	Station 5	0.06	0.08	0.13	0.18	0.43	0.57	0.43	0.59
	Station 6	0.06	0.07	0.13	0.17	0.5	0.63	0.47	0.62
	Station 7	0.06	0.09	0.15	0.2	0.61	0.66	0.55	0.61
HadCM-A2									
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.07	0.08	0.07	0.08	0.79	1	0.77	0.96
	Station 2	0.07	0.09	0.06	0.07	0.78	0.94	0.76	0.9
	Station 3	0.07	0.08	0.07	0.08	0.88	1.1	0.88	1.06
	Station 4	0.07	0.08	0.07	0.08	0.78	0.98	0.77	0.93
	Station 5	0.08	0.11	0.08	0.09	0.95	1.19	0.93	1.14
	Station 6	0.07	0.09	0.08	0.08	0.83	1.09	0.8	1.03
	Station 7	0.07	0.1	0.06	0.07	0.94	1.14	0.92	1.09
T_{min}	Station 1	0.08	0.1	0.07	0.09	0.82	1.03	0.77	0.99
	Station 2	0.07	0.09	0.06	0.08	0.74	0.99	0.72	0.95
	Station 3	0.09	0.12	0.06	0.08	0.9	1.2	0.86	1.1
	Station 4	0.08	0.11	0.1	0.14	1.06	1.38	0.98	1.25
	Station 5	0.08	0.11	0.06	0.08	0.66	1	0.61	0.92
	Station 6	0.08	0.1	0.07	0.1	0.74	1.06	0.69	0.96
	Station 7	0.09	0.13	0.08	0.1	0.7	0.91	0.68	0.87
HadCM-B2									
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.06	0.07	0.09	0.12	0.84	1	0.88	1.06
	Station 2	0.06	0.08	0.1	0.12	0.86	0.96	0.89	1.01
	Station 3	0.06	0.07	0.1	0.12	0.98	1.13	1.02	1.19
	Station 4	0.06	0.07	0.09	0.12	0.84	1	0.89	1.05
	Station 5	0.07	0.08	0.1	0.12	1.04	1.21	1.08	1.27
	Station 6	0.06	0.07	0.1	0.12	0.91	1.1	0.97	1.17
	Station 7	0.06	0.08	0.09	0.11	1.03	1.18	1.06	1.21
T_{min}	Station 1	0.06	0.08	0.13	0.15	0.78	0.99	0.8	1.05
	Station 2	0.06	0.07	0.1	0.12	0.7	0.93	0.7	0.99
	Station 3	0.08	0.1	0.12	0.15	0.85	1.14	0.86	1.18
	Station 4	0.06	0.08	0.1	0.13	0.99	1.28	1	1.33
	Station 5	0.06	0.07	0.12	0.15	0.68	0.95	0.71	1.02
	Station 6	0.05	0.07	0.11	0.14	0.72	1.02	0.72	1.07
	Station 7	0.09	0.08	0.13	0.17	0.64	0.85	0.66	0.92

5.2.2 Spatial variability

The capability of the proposed models to capture the spatial variability of daily T_{max} and T_{min} for the scenarios of CGCM and HadCM during current period is graphically presented in the Figures 5.36 through 5.41. It is observed that both SVD-MAR and MSM produced similar results for lag0 interstation correlations of daily T_{max} for HadCM-A2 and B2 scenarios (Figures 5.37 and 5.38). Both of the models were found well capable to capture the lag0 interstation correlations of daily T_{max} accurately during calibration and validation periods. For CGCM-A2 scenario also, it was preserved well by both of the models. However, for this scenario MSM produced better results compared to SVD-MAR. Figures 5.39 to 5.41 show that in general lag0 interstation correlations of daily T_{min} were well reproduced by both of the models for all the scenarios. However, the interstation correlations of T_{min} were slightly overestimated by both of the models for HadCM-A2 and B2 scenarios especially for the areas where the observed correlations are relatively low. For CGCM-A2 scenario also, very few isolated points are observed which lie apart from the diagonal line.

Numerical analysis (Table 5.6) shows that the values of MAD (RMSD) of lag0 interstation correlations produced by both of the models were 0.02 (0.03) and 0.02-0.04 (0.03-0.05) for all of three scenarios respectively for T_{max} and T_{min} during calibration period. The R^2 values ranged between 0.61-0.78 and 0.65-0.79 respectively for T_{max} and T_{min} lag0 interstation correlations. During validation period the values of MAD (RMSD) ranged between 0.02 (0.02-0.03) and 0.02-0.04 (0.02-0.05) respectively for T_{max} and T_{min} . The R^2 values were between 0.55-0.68 and 0.54-0.77 respectively for T_{max} and T_{min} lag0 interstation correlations for three scenarios.



(a)

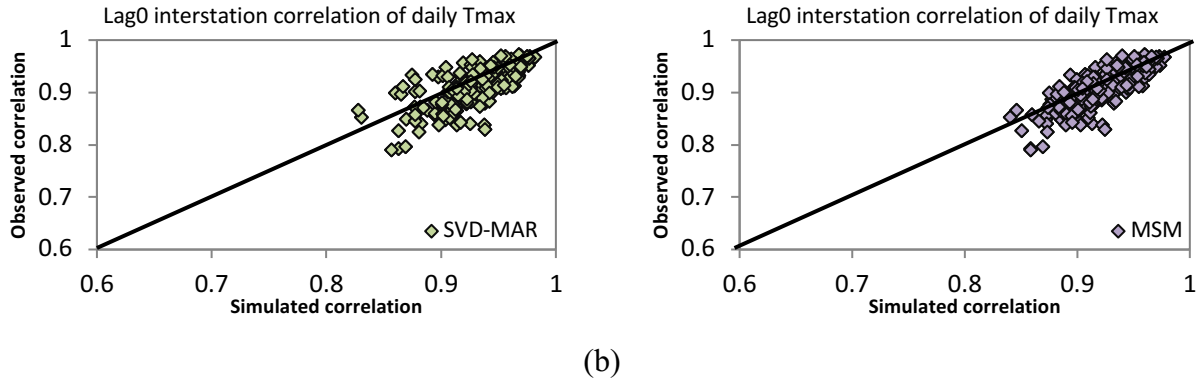


Figure 5.36: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Quebec-Ontario region.

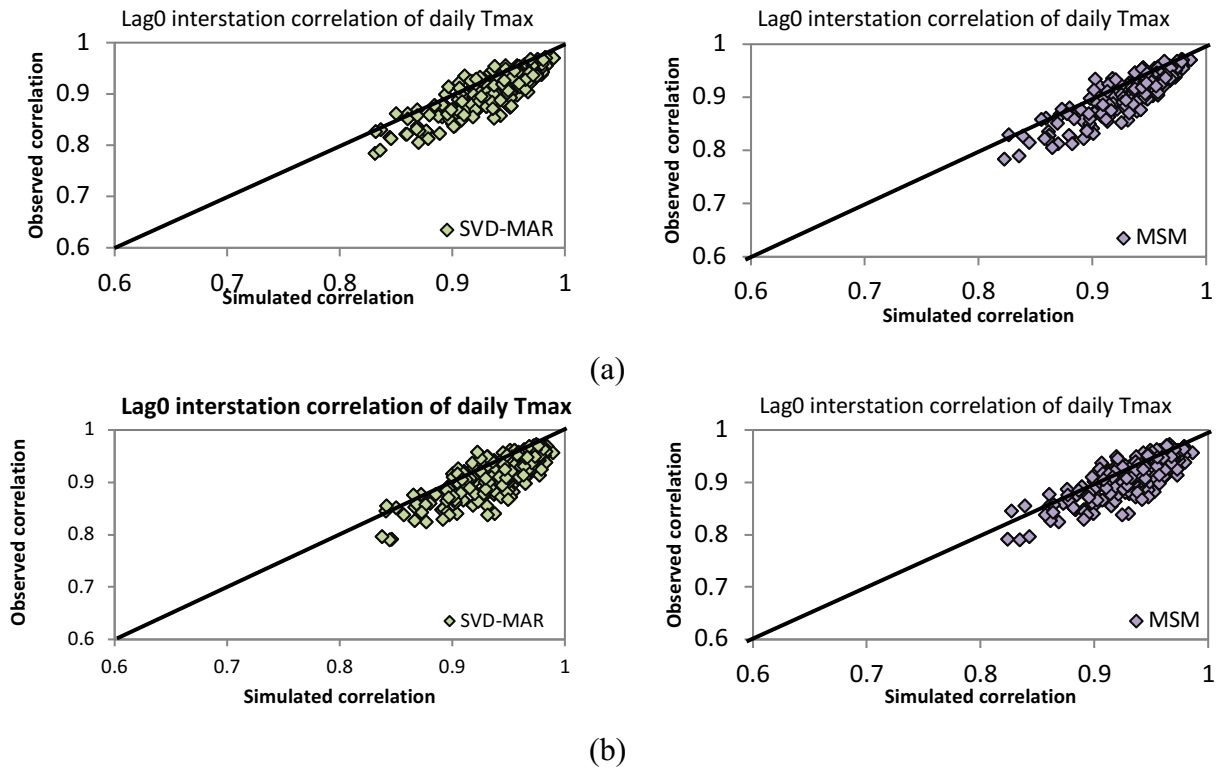


Figure 5.37: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Quebec-Ontario region.

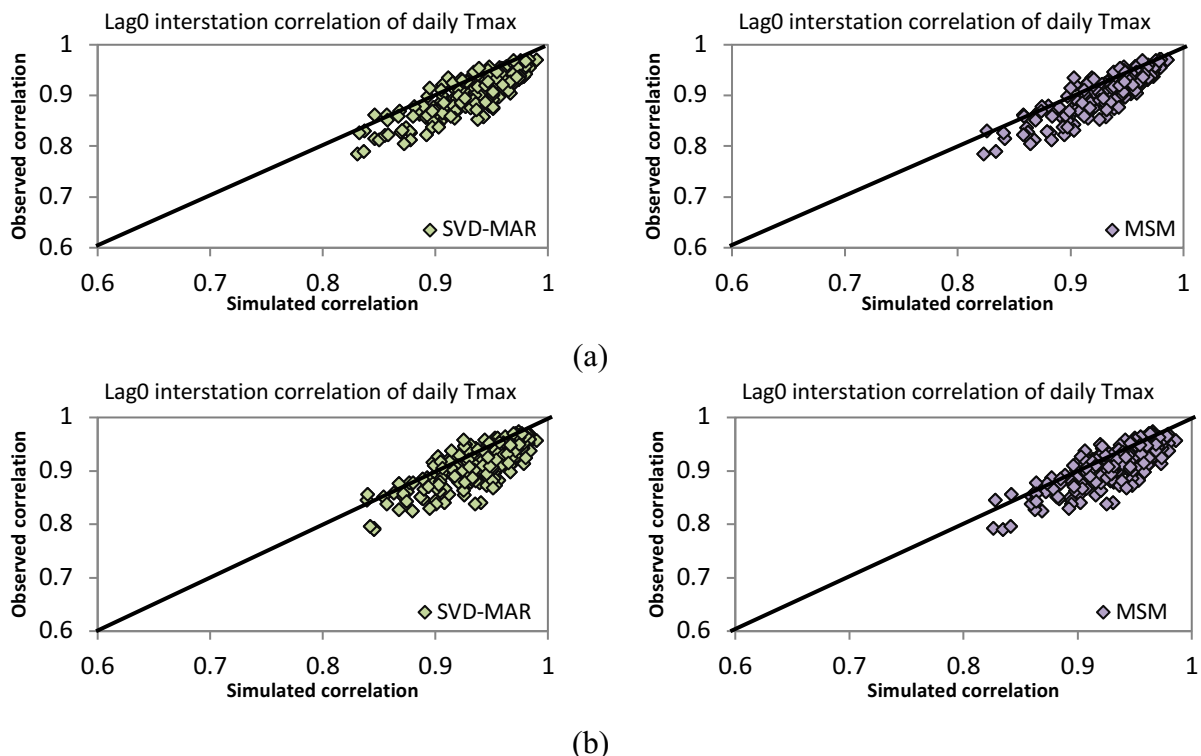


Figure 5.38: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Quebec-Ontario region.

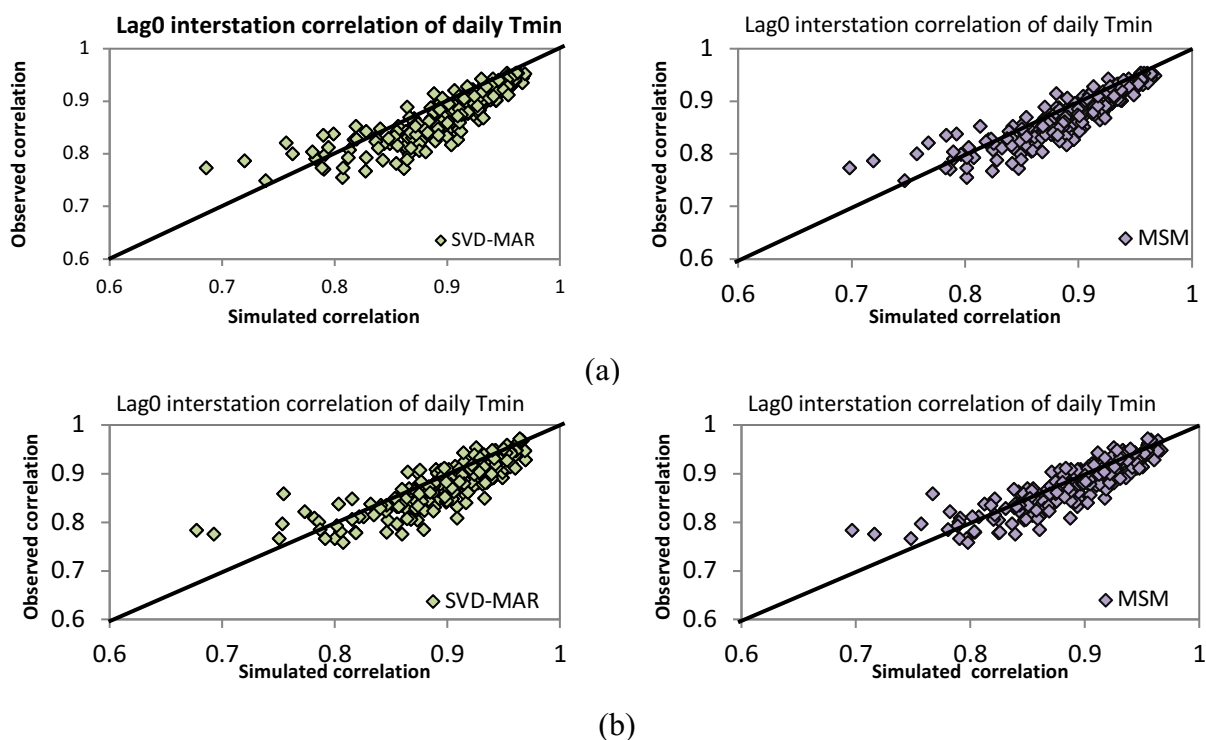


Figure 5.39: Lag0 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Quebec-Ontario region.

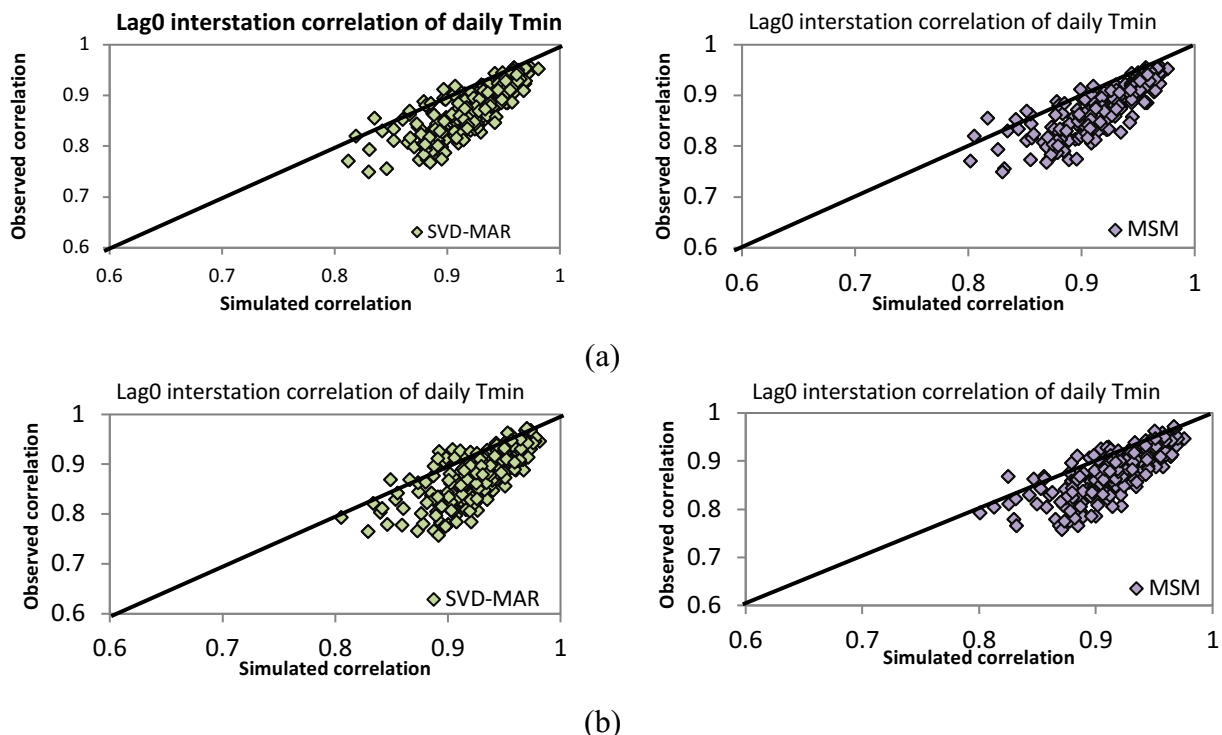


Figure 5.40: Lag0 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Quebec-Ontario region.

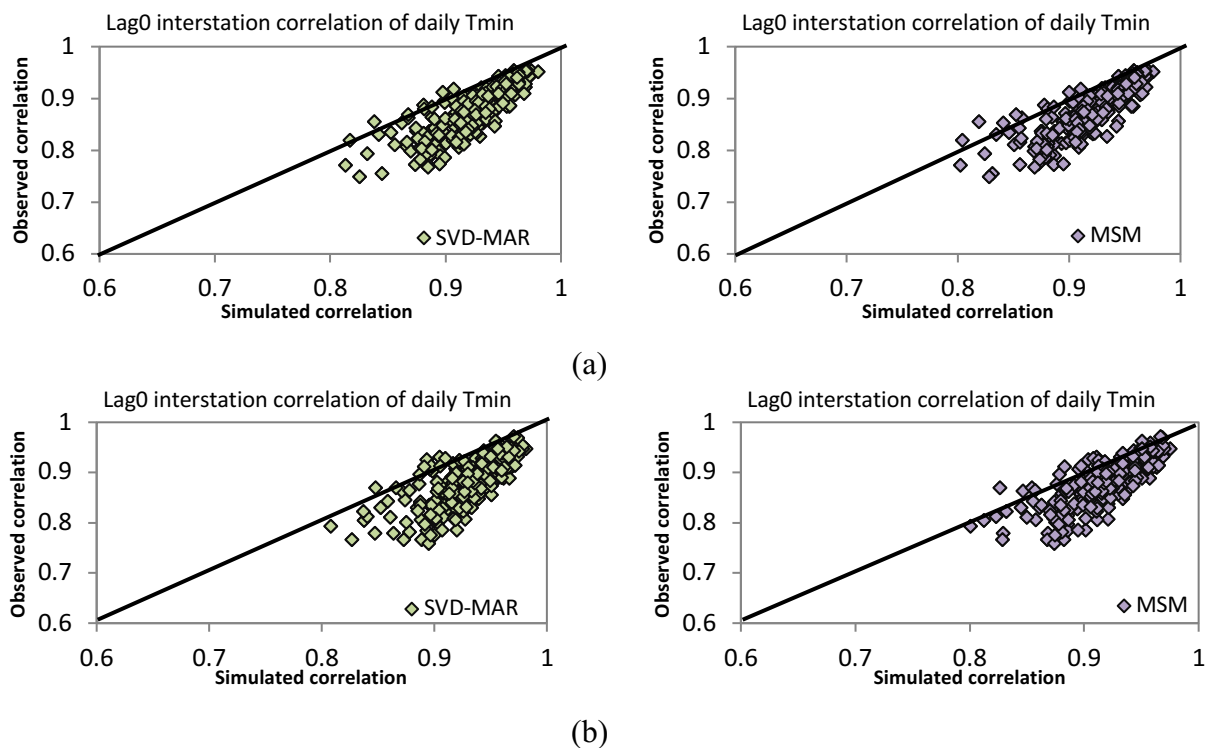


Figure 5.41: Lag0 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Quebec-Ontario region.

Table 5.6: Numerical analysis for lag0 interstation correlations of daily T_{max} and T_{min} at seven stations in Quebec-Ontario region for different climate scenarios.

CGCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag0 correlation	0.02	0.03	0.61	0.02	0.03	0.68
	T_{min} lag0 correlation	0.02	0.03	0.74	0.02	0.03	0.79
Validation	T_{max} lag0 correlation	0.02	0.03	0.55	0.02	0.02	0.66
	T_{min} lag0 correlation	0.02	0.03	0.7	0.02	0.02	0.77
HadCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag0 correlation	0.02	0.03	0.74	0.02	0.03	0.78
	T_{min} lag0 correlation	0.04	0.05	0.65	0.04	0.05	0.66
Validation	T_{max} lag0 correlation	0.02	0.03	0.63	0.02	0.03	0.68
	T_{min} lag0 correlation	0.04	0.05	0.54	0.03	0.04	0.61
HadCM-B2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag0 correlation	0.02	0.03	0.74	0.02	0.03	0.78
	T_{min} lag0 correlation	0.04	0.05	0.66	0.04	0.05	0.66
Validation	T_{max} lag0 correlation	0.02	0.03	0.62	0.02	0.03	0.67
	T_{min} lag0 correlation	0.04	0.05	0.54	0.03	0.04	0.61

Lag1 interstation correlations of daily T_{max} and T_{min} are graphically presented in Figures 5.42 through 5.47. It is observed that both SVD-MAR and MSM were able to reproduce the lag1 interstation correlations very well for daily T_{max} as well as T_{min} during calibration period for all the scenarios. During validation period also, the lag1 interstation correlations were reproduced acceptably for daily T_{max} and T_{min} by both of the models. However, the variability of the simulated correlations is relatively high during the validation period especially for CGCM-A2 scenario.

The values of MAD (RMSD) of lag1 interstation correlations respectively for T_{max} and T_{min} ranged between 0.03-0.05 (0.03-0.06) and 0.04-0.06 (0.05-0.07) for both of the models for all of three scenarios during calibration period (Table 5.7). The R² values ranged between 0.44-

0.78 and 0.56-0.73 respectively for T_{max} and T_{min} lag1 interstation correlations. During validation period the values of MAD (RMSD) ranged between 0.04-0.05 (0.05-0.06) and 0.04-0.07 (0.06-0.08) respectively for T_{max} and T_{min} . The R^2 values ranged between 0.4-0.51 and 0.37-0.74 respectively for T_{max} and T_{min} lag1 interstation correlations. Like graphical representations, numeric analysis also indicate that both models produced better results for HadCM scenarios compared to those for CGCM-A2 scenario.

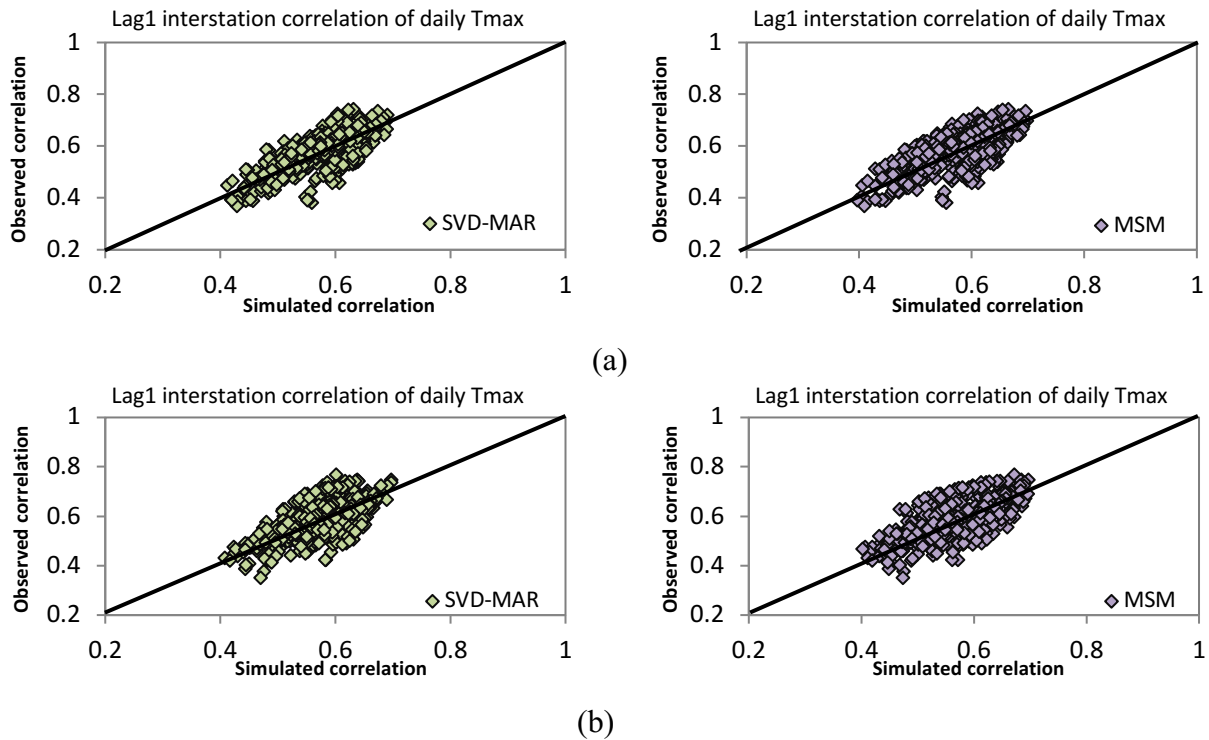
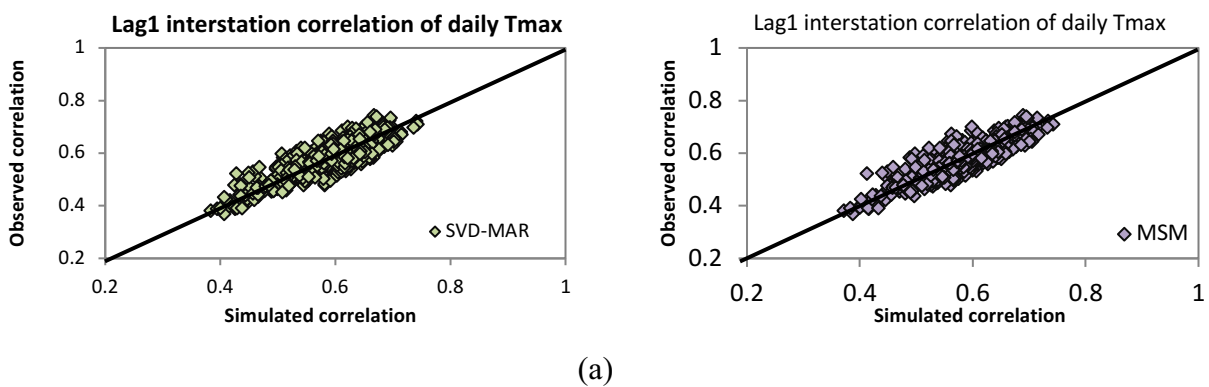
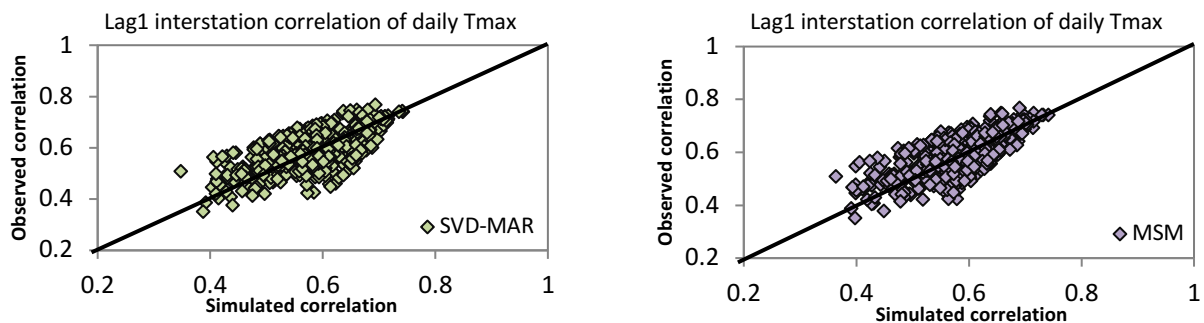


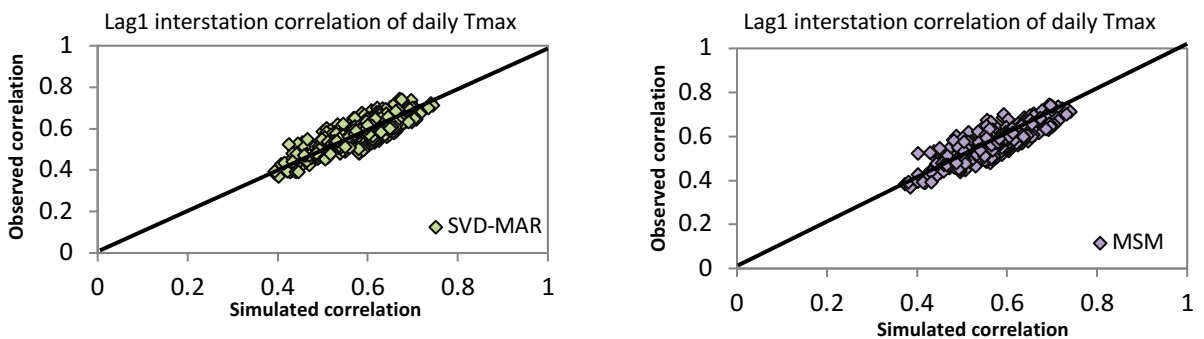
Figure 5.42: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Quebec-Ontario region.



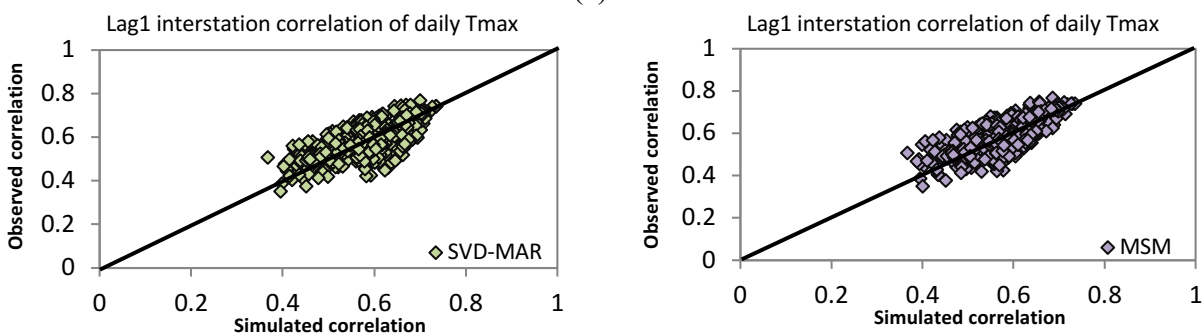


(b)

Figure 5.43: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Quebec-Ontario region.

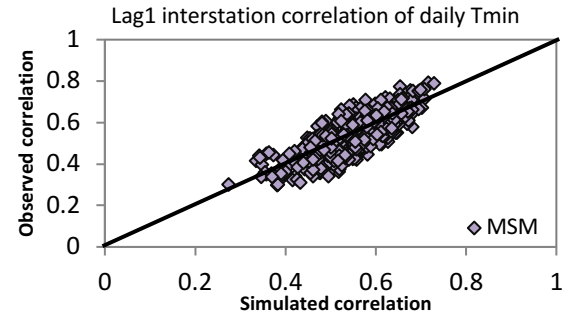
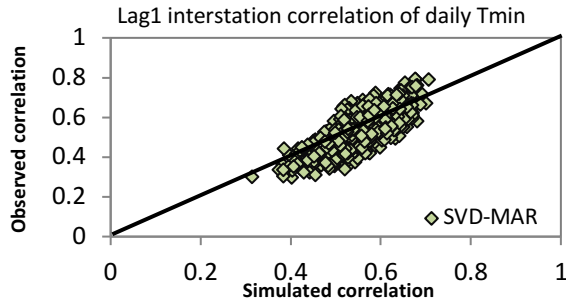


(a)

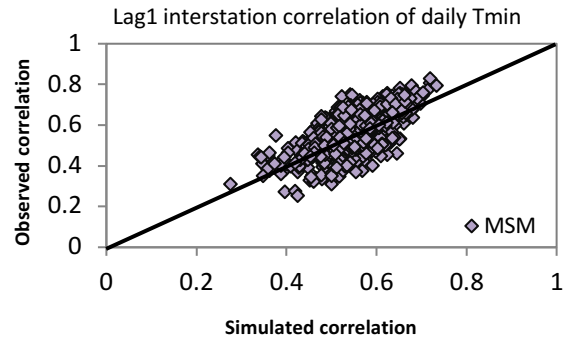
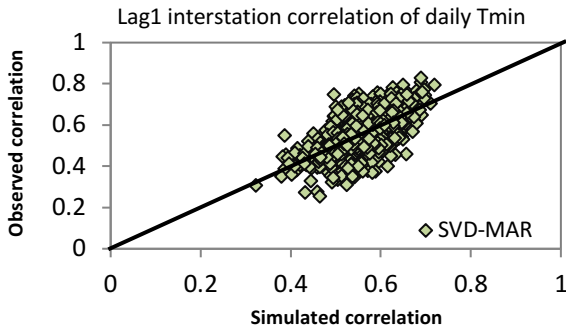


(b)

Figure 5.44: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Quebec-Ontario region.

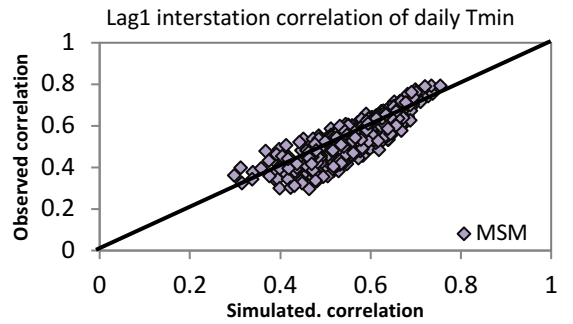
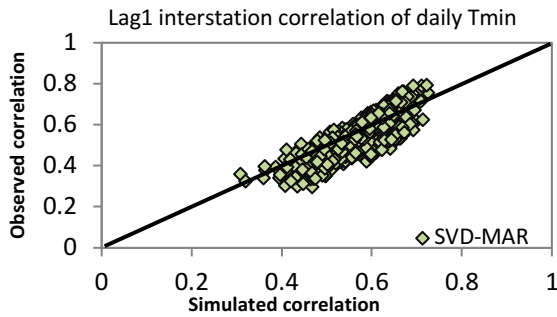


(a)

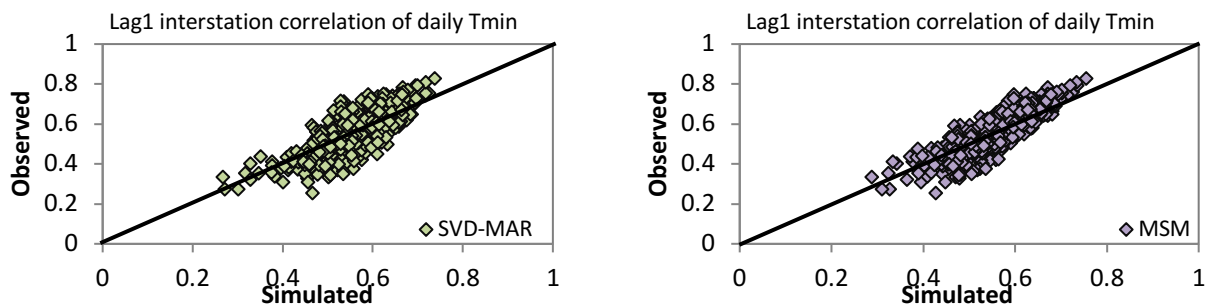


(b)

Figure 5.45: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Quebec-Ontario region.

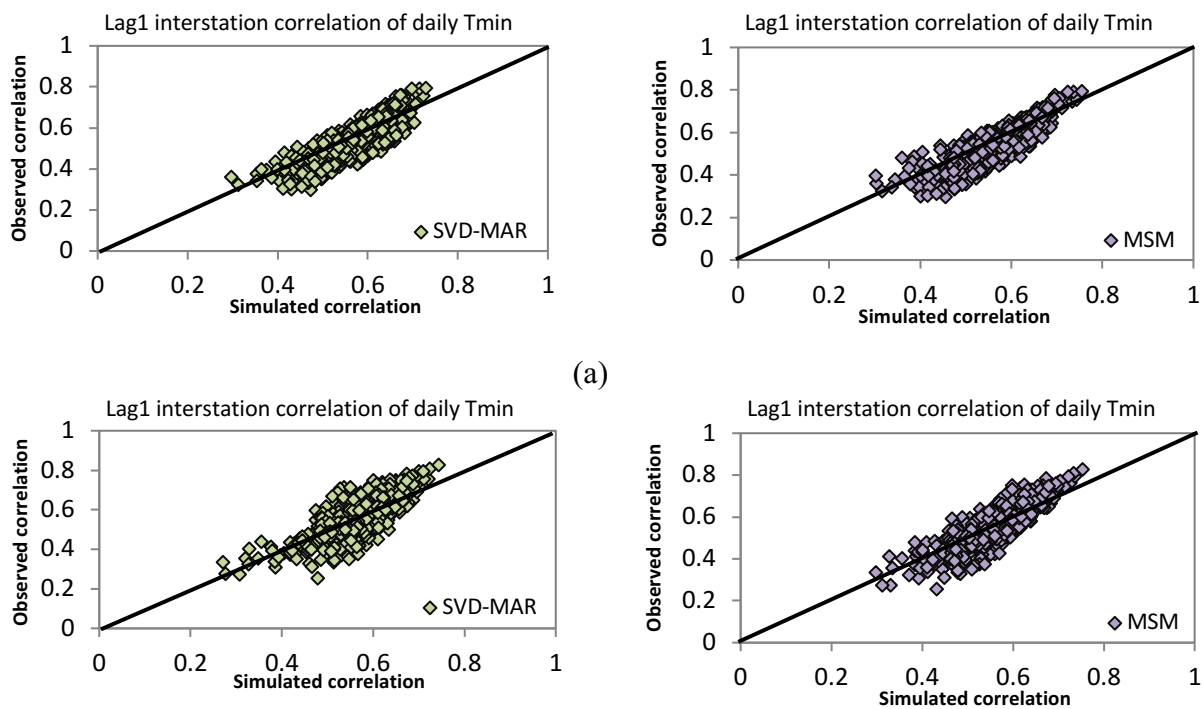


(a)



(b)

Figure 5.46: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Quebec-Ontario region.



(b)

Figure 5.47: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Quebec-Ontario region.

Table 5.7: Numerical analysis for lag1 interstation correlations of daily T_{max} and T_{min} at seven stations in Quebec-Ontario region for different climate scenarios.

CGCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag1 correlation	0.04	0.05	0.49	0.05	0.06	0.44
	T_{min} lag1 correlation	0.06	0.07	0.56	0.05	0.06	0.63
Validation	T_{max} lag1 correlation	0.05	0.06	0.4	0.05	0.06	0.41
	T_{min} lag1 correlation	0.07	0.08	0.37	0.06	0.08	0.46
HadCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag1 correlation	0.03	0.04	0.74	0.03	0.03	0.78
	T_{min} lag1 correlation	0.05	0.06	0.68	0.04	0.05	0.73
Validation	T_{max} lag1 correlation	0.05	0.06	0.45	0.04	0.05	0.51
	T_{min} lag1 correlation	0.05	0.06	0.63	0.04	0.06	0.74
HadCM-B2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	T_{max} lag1 correlation	0.03	0.04	0.74	0.03	0.04	0.76
	T_{min} lag1 correlation	0.05	0.06	0.69	0.04	0.05	0.73
Validation	T_{max} lag1 correlation	0.05	0.06	0.43	0.05	0.06	0.49
	T_{min} lag1 correlation	0.05	0.06	0.64	0.04	0.06	0.74

5.2.3 Temporal dependency

Figures 5.48 and 5.49 delineate the autocorrelation coefficients up to lag3 respectively for T_{max} and T_{min} for CGCM-A2, HadCM-A2 and HadCM-B2 scenarios during current period at Dorval station. A very good agreement was found between the observed and simulated autocorrelation coefficients of daily T_{max} for both SVD-MAR and MSM for all scenarios during calibration period. During validation period also, the autocorrelation coefficients were reproduced accurately for all scenarios by both of the models. For T_{min} also, the autocorrelation coefficients were well simulated by both of the models for all scenarios. Like Dorval station, at rest of the stations the autocorrelation coefficients were reproduced accurately by both of the models for T_{max} as well as T_{min} for all of three scenarios. Results for rest of the stations are given in Appendix D.

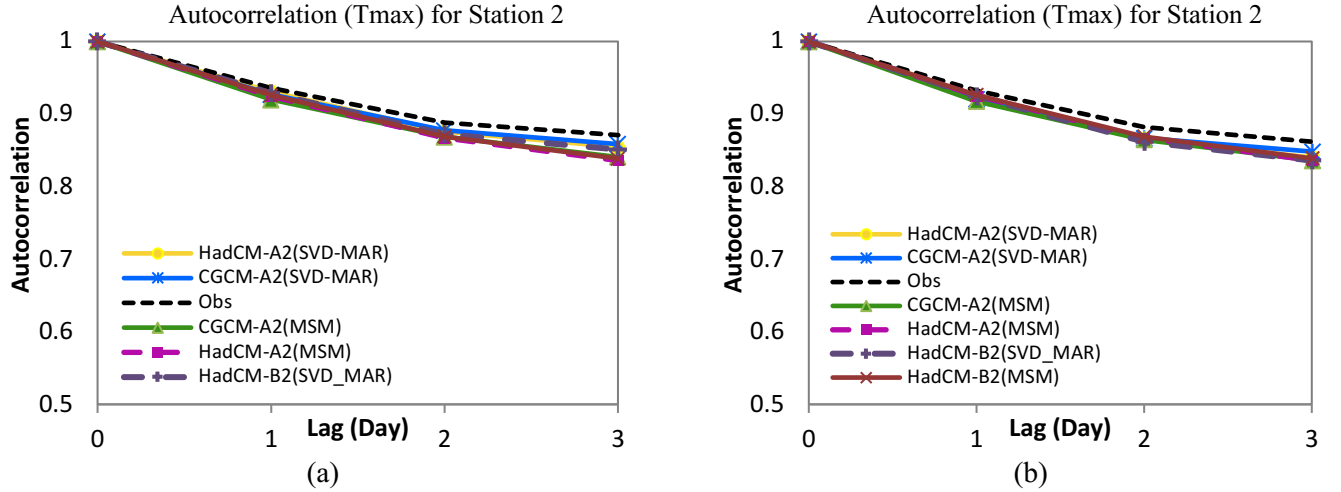


Figure 5.48: Observed and downscaled autocorrelation coefficients of T_{max} at Dorval station for different climate scenarios during (a) calibration and (b) validation periods.

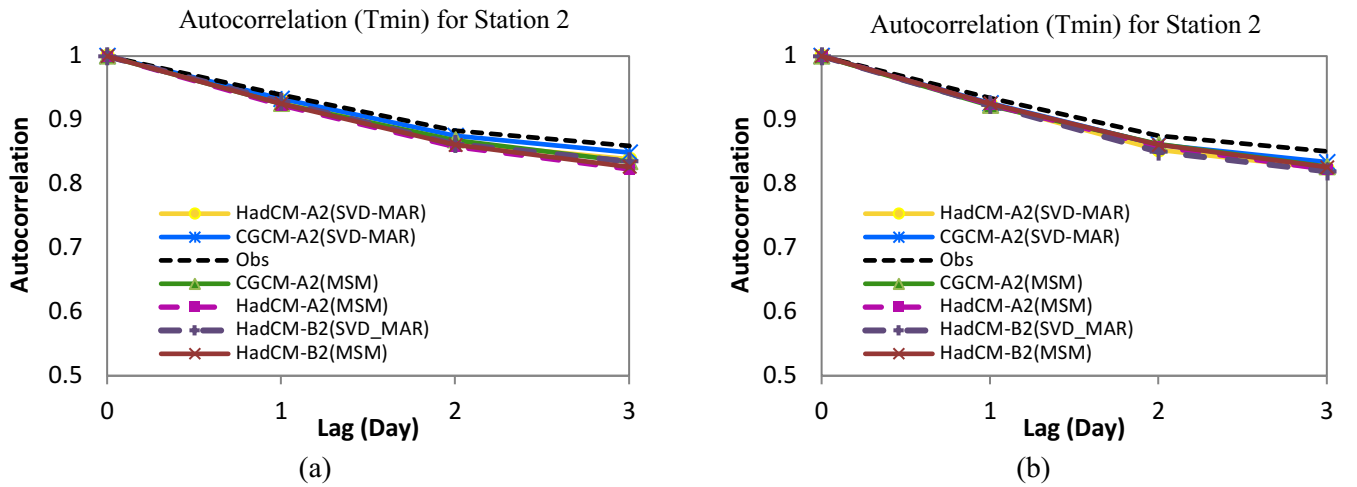


Figure 5.49: Observed and downscaled autocorrelation coefficients of T_{min} at Dorval station for different climate scenarios during (a) calibration and (b) validation periods.

5.2.4 Correlation between daily T_{max} and T_{min} and DTR

The correlations between daily T_{max} and T_{min} at each station for three scenarios are shown in Figures 5.50 to 5.52. High R^2 values suggest that the correlation between daily T_{max} and T_{min} was reproduced well by SVD-MAR and MSM for all the scenarios. However, the figures show that the correlations were slightly overestimated by both of the models during both calibration and validation periods. Graphically it is observed that MSM produced slightly better results than SVD-MAR especially for HadCM scenarios during both calibration and validation periods.

During calibration period the R^2 values produced by SVD-MAR and MSM ranged between 0.82- 0.88 for all of CGCM-A2, HadCM-A2 and HadCM-B2 scenarios (Figures 5.50 to 5.52). During validation period these values were between 0.77-0.8. The values of MAD (RMSD) for the correlations between daily T_{max} and T_{min} at all the stations are presented in Table 5.8. During calibration period the values of MAD (RMSD) produced by SVD-MAR and MSM ranged between 0.04-0.1 (0.05-0.12) for all the stations for CGCM-A2, HadCM-A2 and HadCM-B2 scenarios. During validation period these values ranged between 0.05-0.12 (0.05-0.13) for those three scenarios.

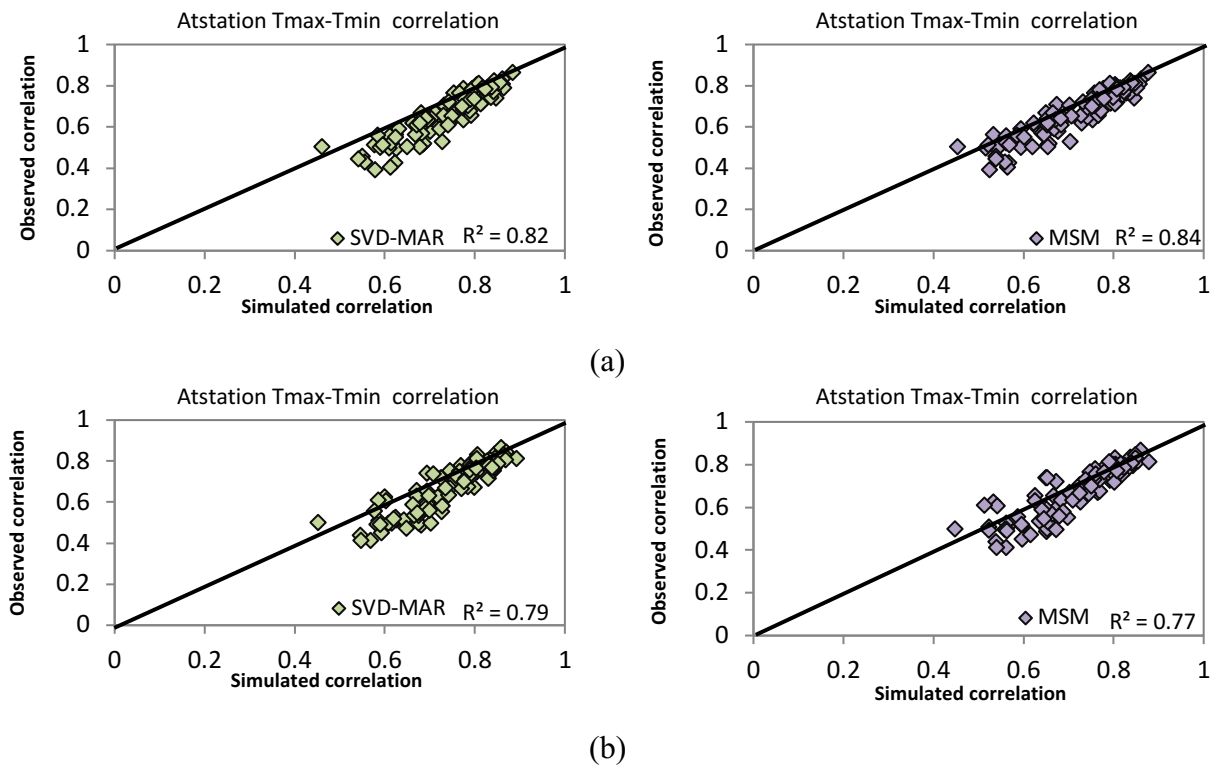


Figure 5.50: Correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for CGCM-A2 scenario.

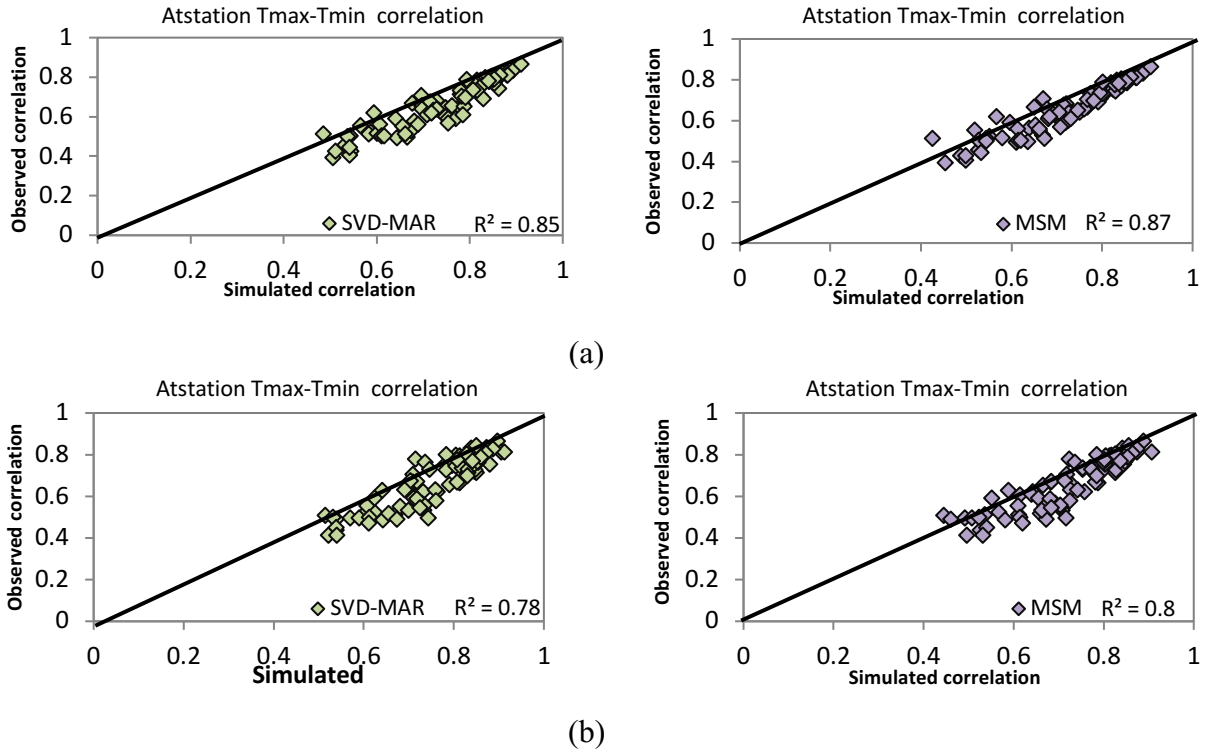


Figure 5.51: Correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for HadCM-A2 scenario.

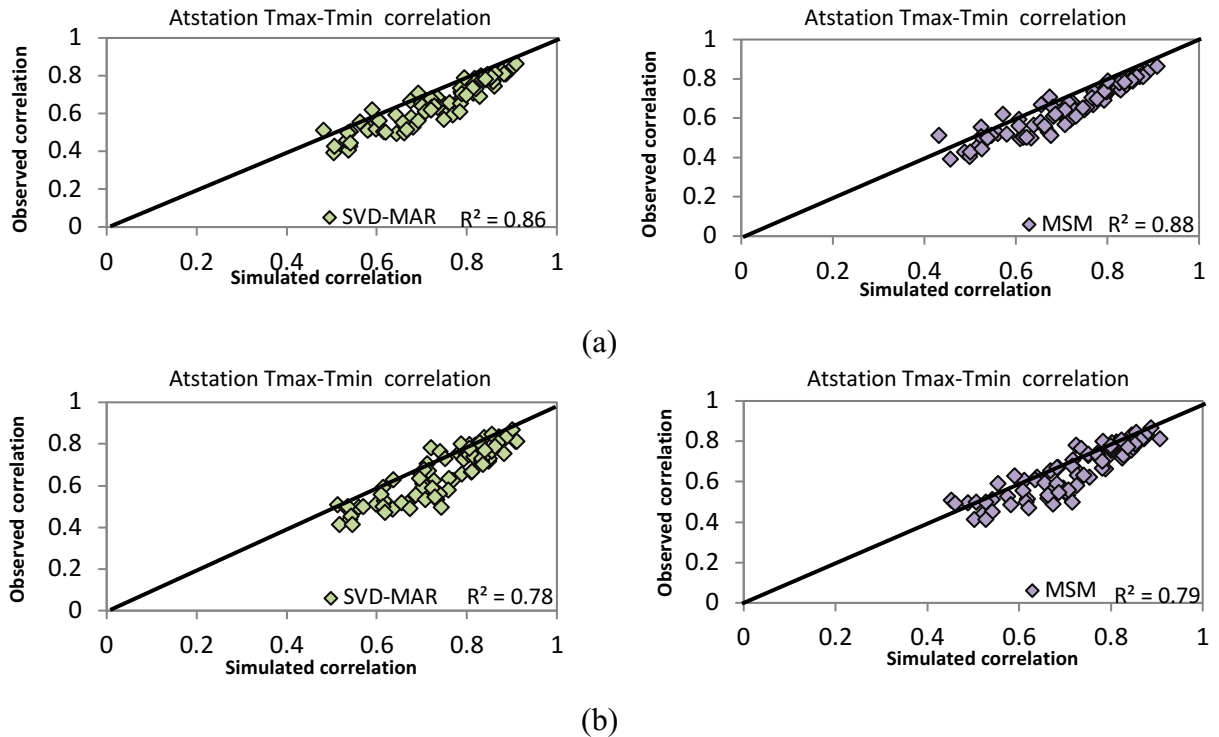
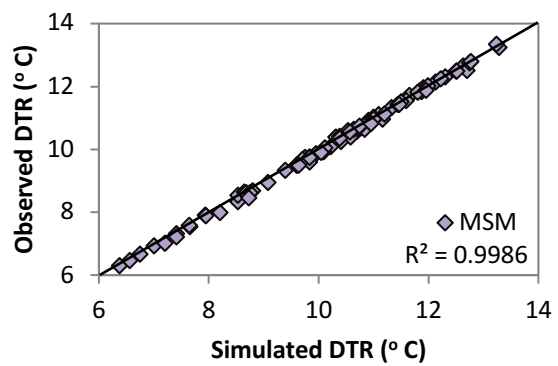
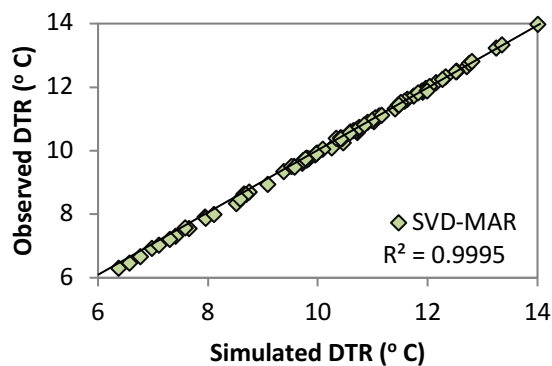


Figure 5.52: Correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for HadCM-B2 scenario.

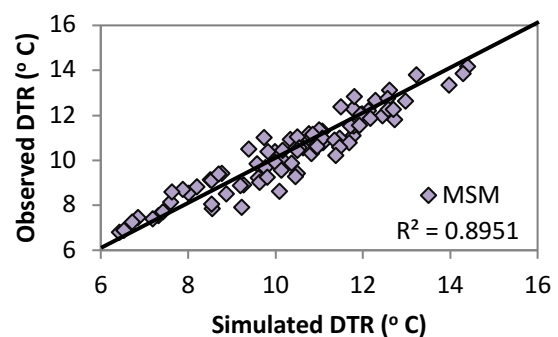
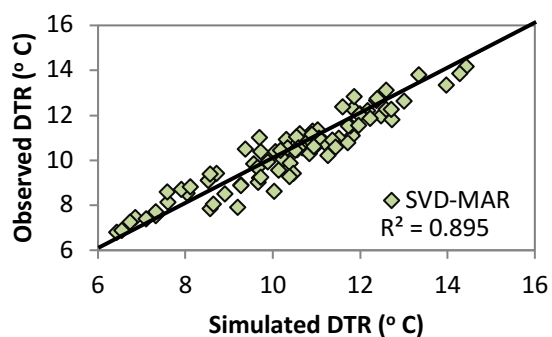
Table 5.8: Numerical analysis for the correlations between daily T_{max} and T_{min} at seven stations in Quebec-Ontario region for different climate scenarios.

CGCM-A2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.07	0.08	0.05	0.06	0.07	0.08	0.05	0.07
Station 2	0.05	0.07	0.04	0.06	0.06	0.07	0.05	0.06
Station 3	0.1	0.11	0.08	0.09	0.09	0.11	0.08	0.09
Station 4	0.1	0.12	0.08	0.09	0.08	0.1	0.06	0.08
Station 5	0.05	0.06	0.04	0.05	0.05	0.06	0.05	0.05
Station 6	0.08	0.09	0.06	0.07	0.07	0.08	0.05	0.07
Station 7	0.08	0.09	0.06	0.07	0.09	0.1	0.07	0.08
HadCM-A2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.07	0.09	0.06	0.07	0.09	0.1	0.07	0.08
Station 2	0.07	0.07	0.06	0.06	0.07	0.09	0.06	0.07
Station 3	0.09	0.1	0.08	0.09	0.1	0.12	0.07	0.09
Station 4	0.09	0.1	0.07	0.08	0.07	0.09	0.05	0.07
Station 5	0.07	0.08	0.06	0.07	0.08	0.09	0.06	0.07
Station 6	0.08	0.09	0.07	0.07	0.07	0.09	0.06	0.08
Station 7	0.1	0.11	0.08	0.09	0.12	0.13	0.09	0.1
HadCM-B2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.07	0.09	0.06	0.07	0.08	0.1	0.06	0.08
Station 2	0.07	0.07	0.06	0.06	0.07	0.09	0.06	0.07
Station 3	0.09	0.11	0.08	0.09	0.1	0.12	0.07	0.09
Station 4	0.09	0.1	0.08	0.08	0.07	0.09	0.05	0.07
Station 5	0.07	0.08	0.06	0.07	0.08	0.09	0.06	0.07
Station 6	0.08	0.09	0.07	0.07	0.07	0.09	0.06	0.08
Station 7	0.1	0.11	0.08	0.09	0.12	0.13	0.09	0.1

Figures 5.53 through 5.55 present the average values of DTR in each of the months for all the stations for CGCM-A2, HadCM-A2 and HadCM-B2 scenarios. It is observed that both SVD-MAR and MSM produced the average DTR almost perfectly at all the stations during calibration period for all the scenarios. During validation period also, both of the models reproduced the average DTR very accurately for all of three scenarios.

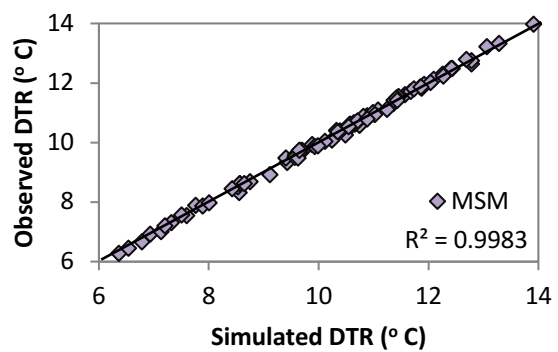
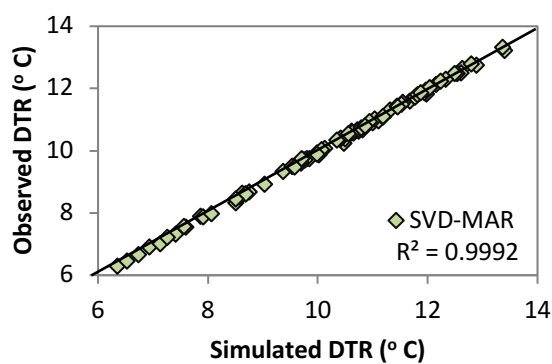


(a)

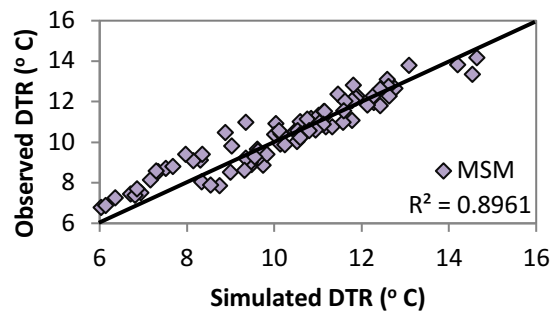
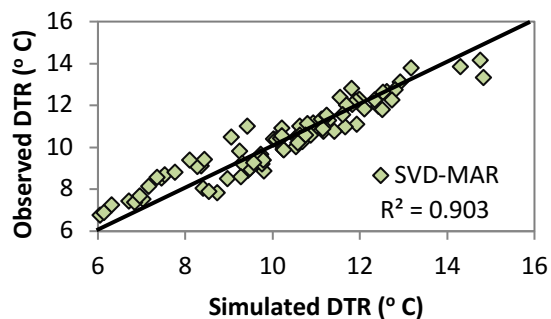


(b)

Figure 5.53: Average DTR in each month at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for CGCM-A2 scenario.

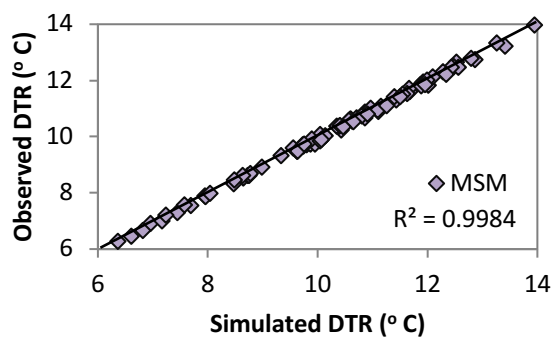
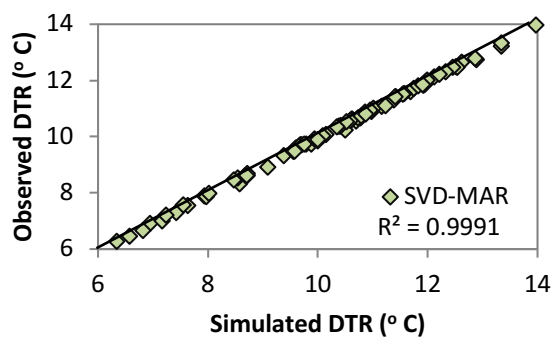


(a)

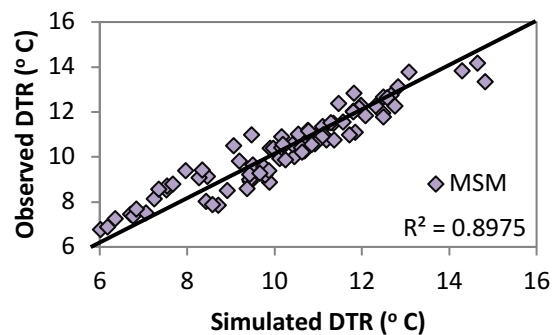
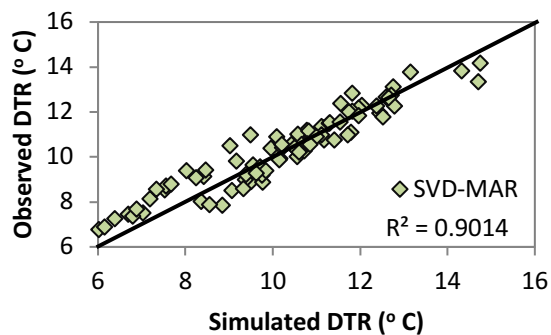


(b)

Figure 5.54: Average DTR in each month at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for HadCM-A2 scenario.



(a)



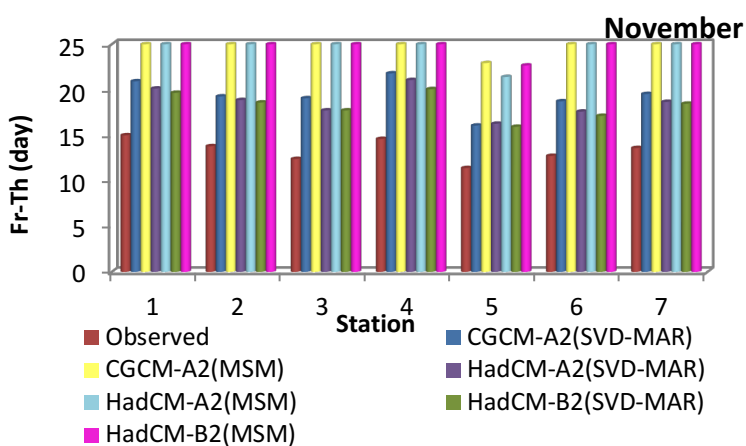
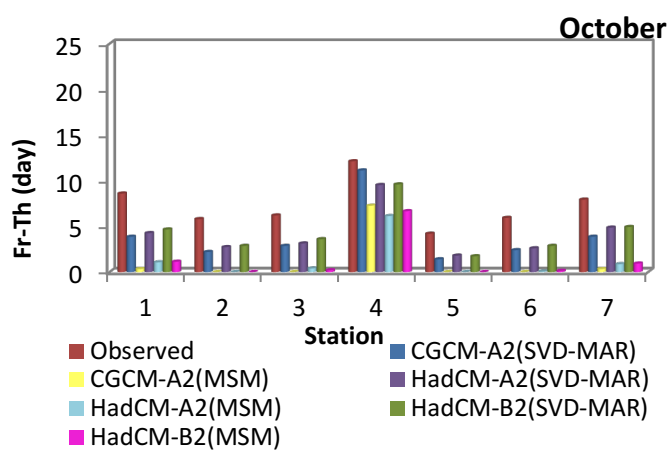
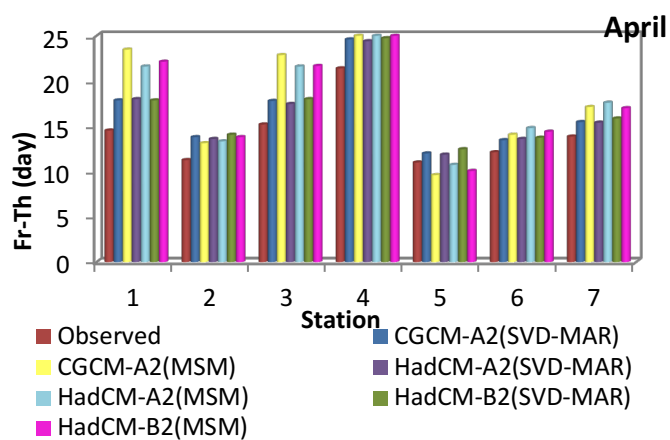
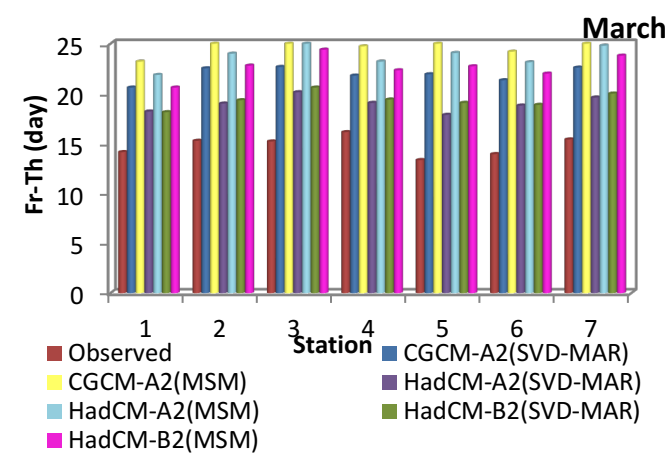
(b)

Figure 5.55: Average DTR in each month at seven stations in Quebec-Ontario region during (a) calibration and (b) validation periods for HadCM-B2 scenario.

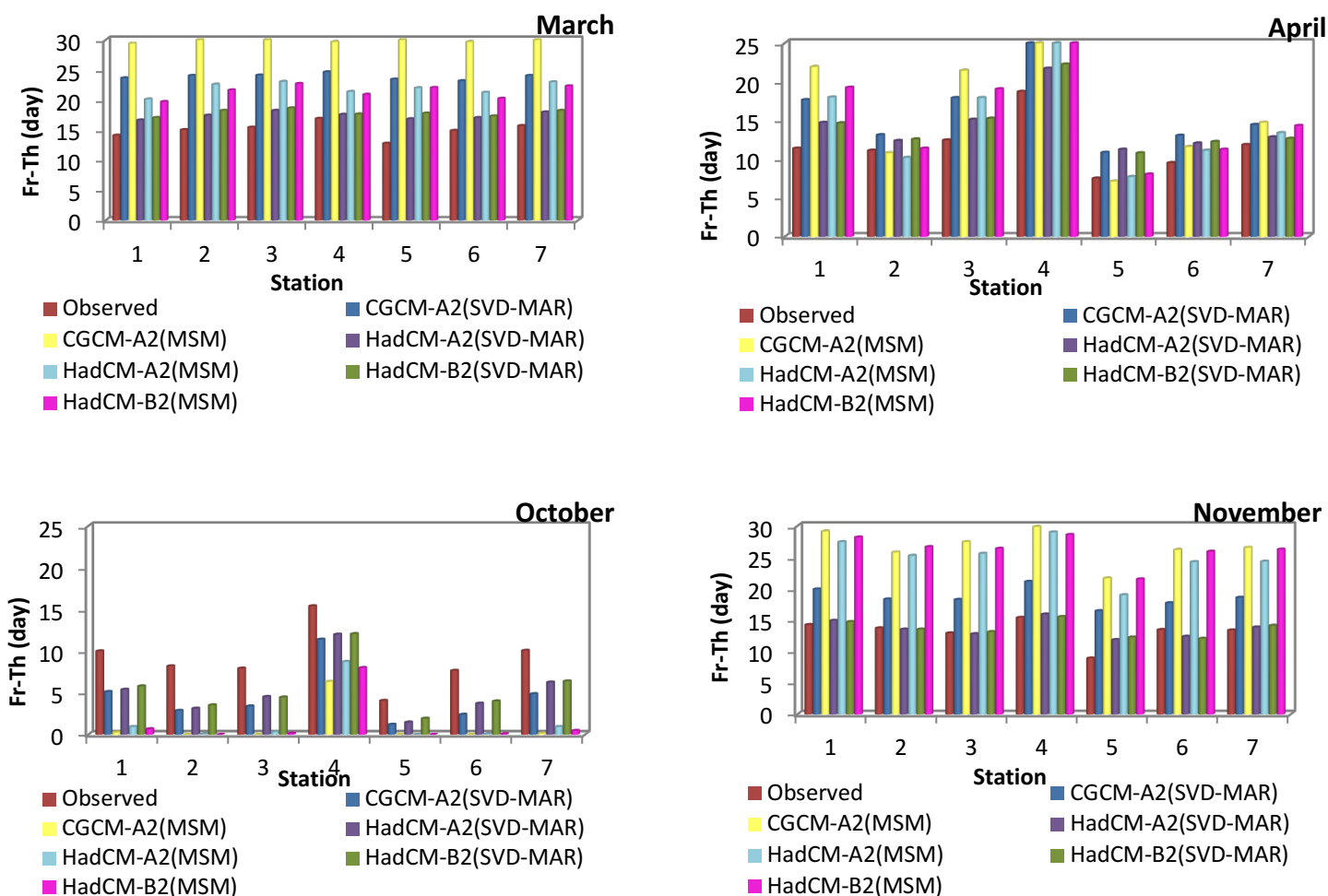
5.2.5 Freeze-Thaw cycle

Figure 5.56 shows the observed and simulated days with Fr-Th cycle for selected months. Fr-Th cycle was well reproduced by SVD-MAR in April for all the scenarios during calibration as well as validation periods. However, in March and November, the number of days having Fr-Th cycle was simulated greater than the observed values by SVD-MAR during calibration period. During validation period, in November, although the freeze-thaw cycle was simulated accurately for the NCEP interpolated on HadCM, it was over estimated for the NCEP interpolated on CGCM. In October, the number of days having Fr-Th cycle was underestimated for both of the NCEP. On the other hand, although MSM was able to produce Fr-Th cycle close to the observed ones at some stations in April, this model could not encounter this index at any of the stations in March, October and November during calibration and validation periods. In March and November (October), MSM produced the number of days having Fr-Th cycle much greater (less) than the observed ones during both calibration and validation periods and for both of the NCEP. Figure 5.56 clearly depicts that although SVD-MAR model could not simulate this index properly, it produced fairly better results than MSM for both of the NCEP.

It is noticeable that both of the models were efficient to produce monthly mean of daily T_{max} and T_{min} , DTR and some other indices very accurately. However, the index Fr-Th cycle was not well captured in some of the months. Actually, computing of this index depends on very precise value of daily T_{max} or T_{min} . Hence, a very small fraction of difference between simulated and observed daily T_{max} (or T_{min}) sometimes results in two different values in simulating Fr-Th index for simulated and observed ones. For example, on a given day, even though both observed and simulated values of T_{max} (or T_{min}) are very close to 0°C , the observed and simulated Fr-Th index may be different on that same day. Because, the observed T_{max} (or T_{min}) might be marginally greater than 0°C by having very small values after decimal point (for example: 0.05), while the simulated value might be marginally lower than 0°C (for example: -0.01) on the same day, or vice versa. This phenomenon leads to two different results for the observed Fr-Th index and the simulated one, although both observed and simulated temperature lie close to zero. This may explain the reasons for not capturing the observed Fr-Th values very well in the simulated results.



(a)



(b)

Figure 5.56: Freeze-thaw cycle at the stations in Quebec-Ontario region during (a) calibration and (b) validation periods for different climate scenarios.

Overall analysis suggests that both of the models (i.e., SVD-MAR and MSM) showed almost similar abilities to reproduce the observed basic statistical properties and spatio-temporal attributes (e.g., mean, standard deviation, cross-site correlations, at-site serial correlation etc.) of daily extreme temperature series at a single site as well as for different locations. However, the above analysis shows that SVD-MAR was found capable to provide comparatively better results than MSM in simulating the number of days with freeze-thaw cycle.

5.3 Comparison of the accuracy of multisite multivariate and single-site downscaling in snowmelt computations

The previous two sections investigated the effectiveness and capability of the proposed models to capture the observed spatio-temporal attributes of temperature in the simulated series using NCEP and GCM outputs. This section presents the usefulness of multisite downscaling over single-site downscaling at the application level. In this regard, a comparison has been made to show the effectiveness of multisite multivariate downscaling versus single-site and univariate downscaling of daily extreme temperature series in snowmelt estimation at mentioned seven stations. The snowmelt was computed using the degree-day method which has been described in Methodology chapter. Degree-day method was used to compute the snowmelt using three sets of data: observed daily average temperature, downscaled daily average temperature obtained by applying SVD-MAR (as a representation of multisite multivariate downscaling method, which is denoted as MMSD in this section) and SDSM (as a representation of single-site and univariate downscaling method). The comparison has been performed for the NCEP reanalysis data interpolated on CGCM. The results have been evaluated through some indices which are described below.

Table 5.9 shows the monthly total of daily snowmelt for selected months averaged over fifteen years during calibration and validation periods. It is found that snowmelt calculated from downscaled temperature series both by multisite and multivariate downscaling model (MMSD) and SDSM techniques were underestimated compared to those of observed temperature during both calibration and validation periods. However, MMSD technique provided better results than SDSM in each of the selected months.

Table 5.9: Monthly total of daily snowmelt in inches.

	Calibration period			Validation period		
	MMSD	Obs	SDSM	MMSD	Obs	SDSM
January	2.29	2.36	1.43	1.92	2.26	1.36
February	1.72	1.89	1.20	2.57	3.29	1.76
March	8.82	9.08	7.49	11.58	12.84	9.49
April	29.59	29.66	29.55	33.10	34.26	32.22
November	19.29	19.40	19.01	19.14	19.37	19.04
December	4.11	4.47	3.12	3.95	4.83	3.08

* Here, in this study, “Obs” does not mean observed snowmelt; it means the calculated snowmelt following Degree-day method using observed temperature.

Figure 5.57 shows the Interannual variability in total amounts of snowmelt in each of fifteen years during calibration and validation periods (total snowmelt in a year over the months of January, February, March, April, November and December, because other months were not considered). The total amounts of snowmelt given by both MMSD and SDSM techniques were distinctly underestimated than the observed ones in most of the years. However, the figures suggest that both the amounts and annual variability of snowmelt calculated by MMSD technique fairly resemble better result than those of SDSM in almost every year during calibration and validation period as well.

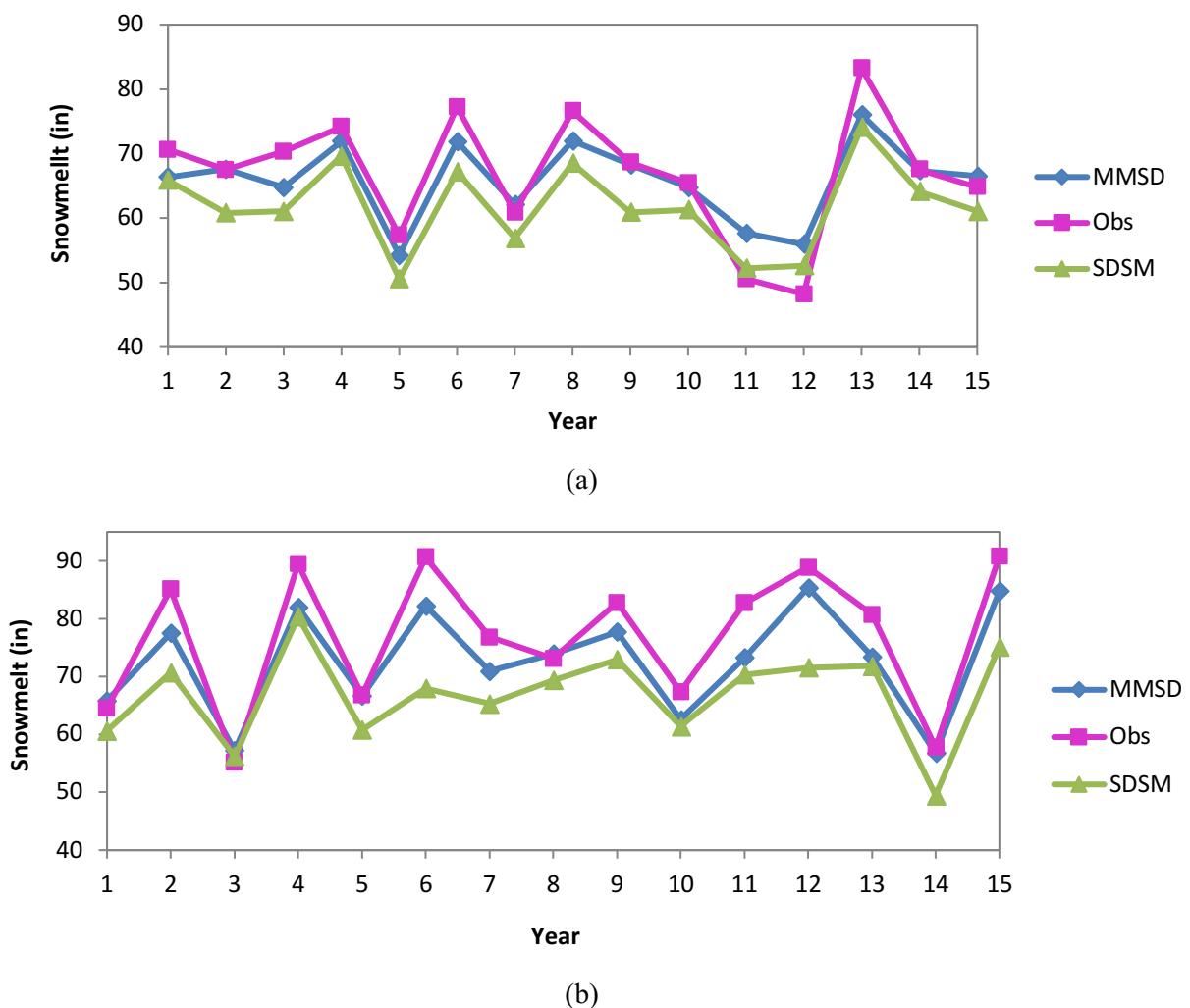


Figure 5.57: Interannual variability in total annual snowmelt during (a) calibration and (b) validation periods.

In snowmelt-dominated basins the variability of runoff is much more strongly controlled by daily variations in temperature rather than precipitation (Hay and Clark, 2003). In those regions snowmelt has significant contributions to annual peak flow of floods. So analysis regarding maximum snowmelt is important for design flood analysis. Hence failure in simulating the maximum snowmelt may result in erroneous estimation of an extreme event. In this regard, an attempt has been made to compare the capability of SDSM and MMSD techniques to capture the extreme snowmelt, which has been evaluated through daily maximum snowmelt amounts (both year wise and month wise). Figure 5.58 shows the interannual variability of the maximum daily snowmelt amounts over fifteen years during calibration and validation periods. It is found that SDSM was not capable to capture the maximum snowmelt amounts and always underestimated it in almost all the years. On the contrary, MMSD was well capable to reproduce the maximum snowmelt amounts in most of the years and captured the annual variability better than SDSM.

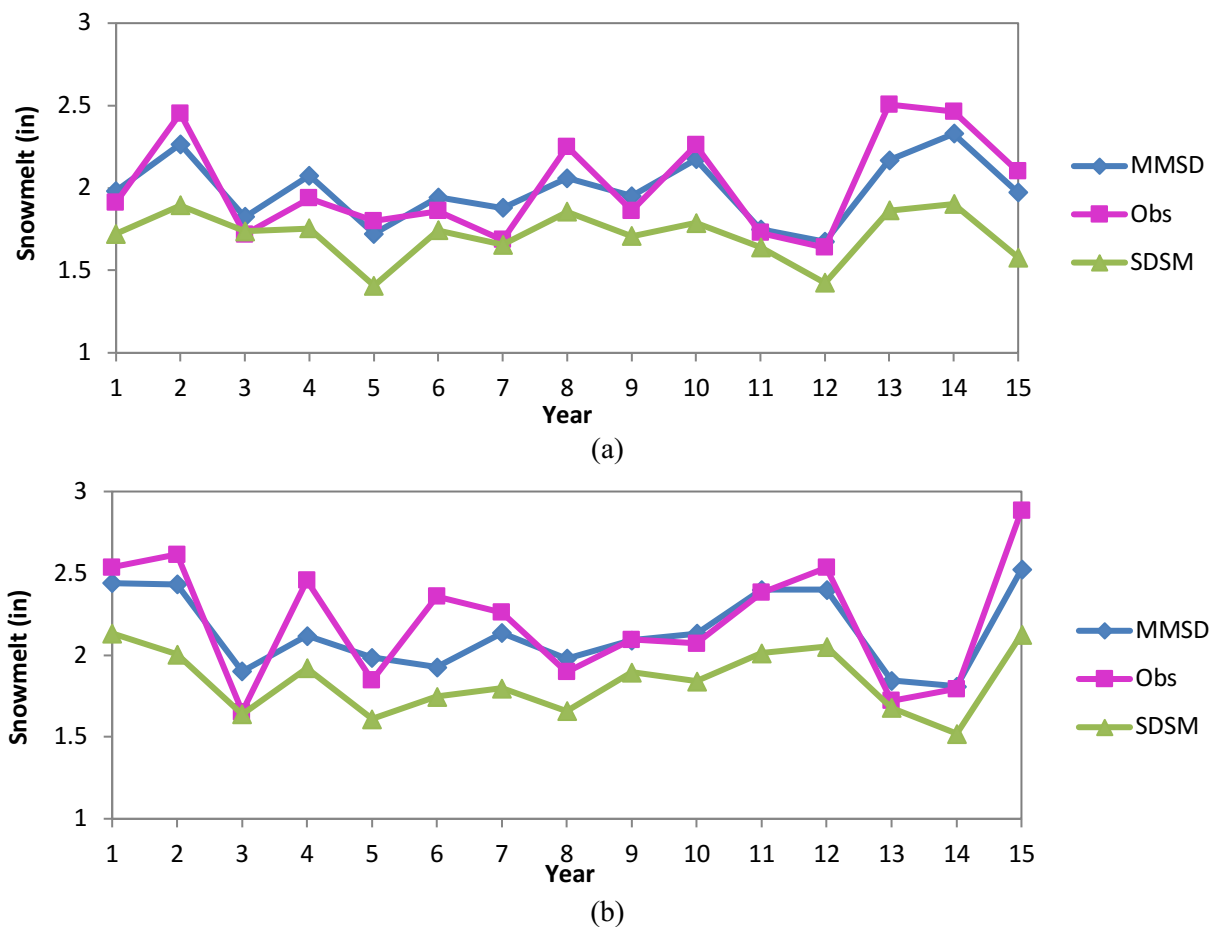


Figure 5.58: Interannual variability in maximum of daily snowmelt during (a) calibration and (b) validation periods.

Figure 5.59 shows the monthly average of maximum daily snowmelt in each of the selected months (The calculation procedure includes taking the maximum daily snowmelt in each of the months in every year. So fifteen maximum values are obtained for fifteen years for each month. Then the values were averaged for each month). MMSD technique was found capable to simulate average of maximum daily snowmelt very accurately for all the months except January during calibration period. However, SDSM was never capable to reproduce this index accurately and underestimated it for most of the months during both calibration and validation periods.

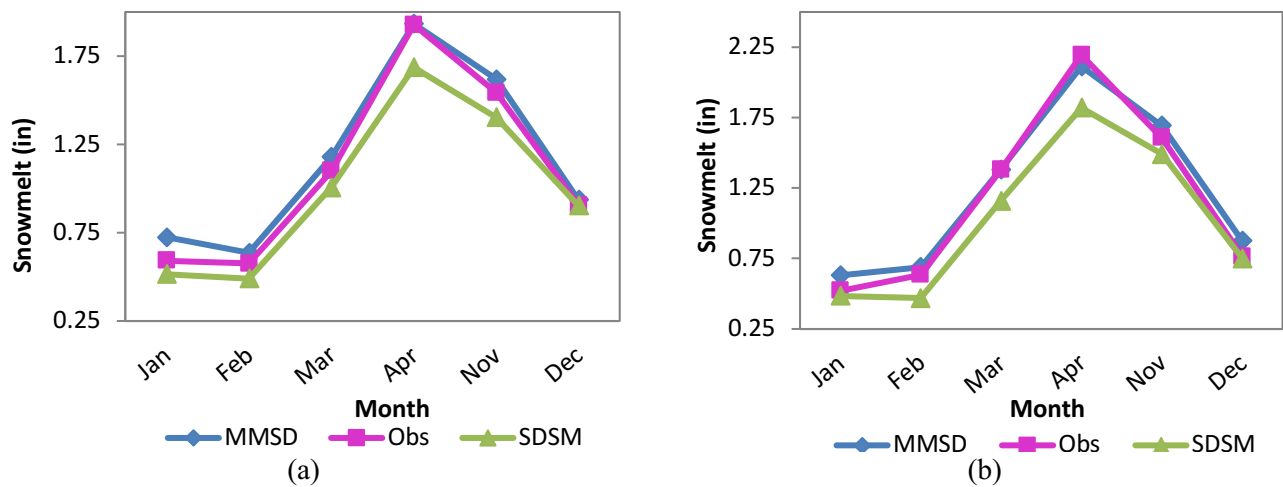
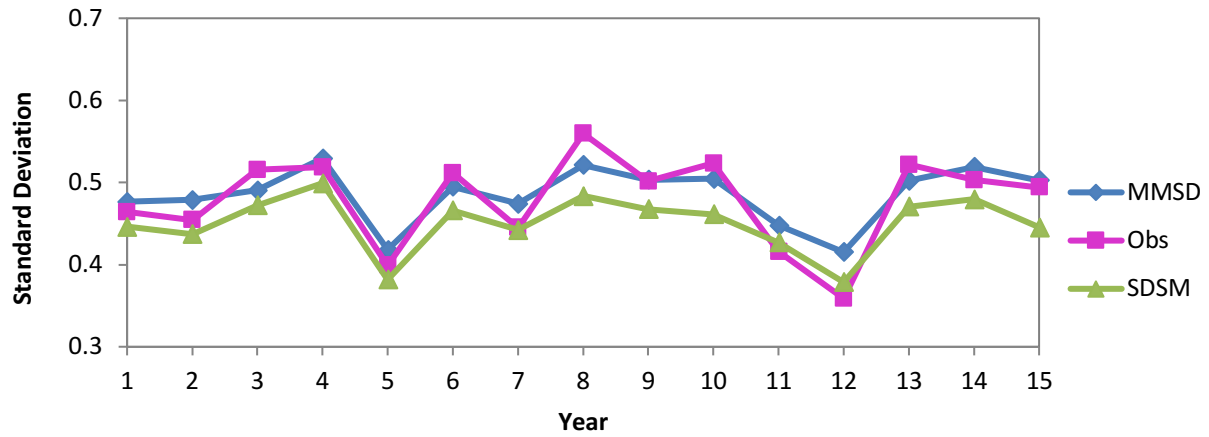
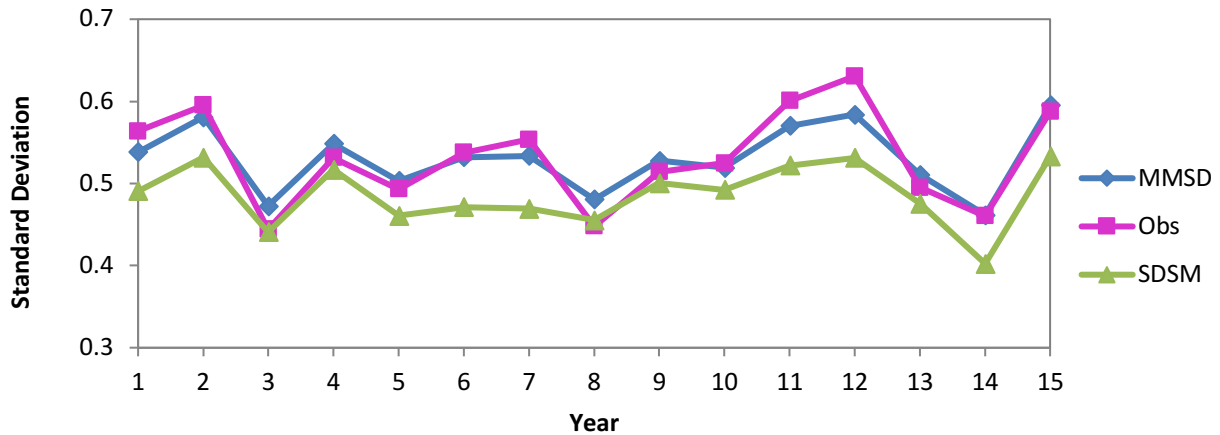


Figure 5.59: Monthly average of the daily maximum snowmelt in each month during (a) calibration and (b) validation periods.

The effectiveness to capture the variability of snowmelt by SDSM and MMSD techniques is evaluated in terms of standard deviation of the total annual snowmelt (Figure 5.60) and interannual variability of standard deviations of monthly snowmelt amounts for selected months (Figure 5.61). Figure 5.60 shows that the yearly standard deviation given by SDSM was not well captured and underestimated during both calibration and validation periods. Whereas MMSD was able to produce better results than SDSM and provided comparatively accurate estimation of standard deviation for most of the years.



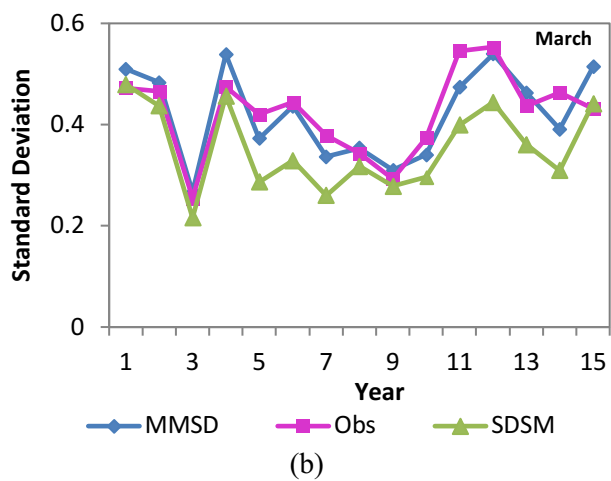
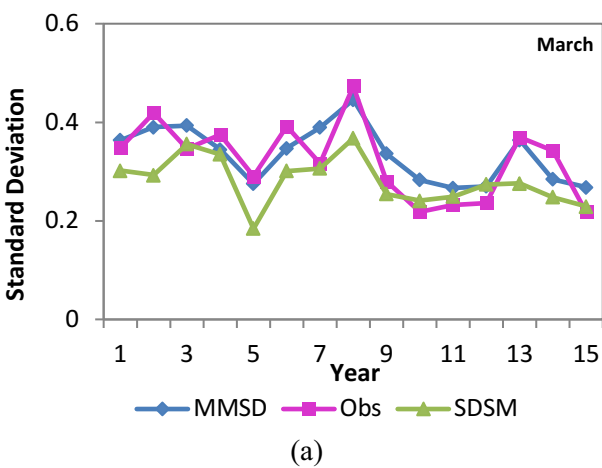
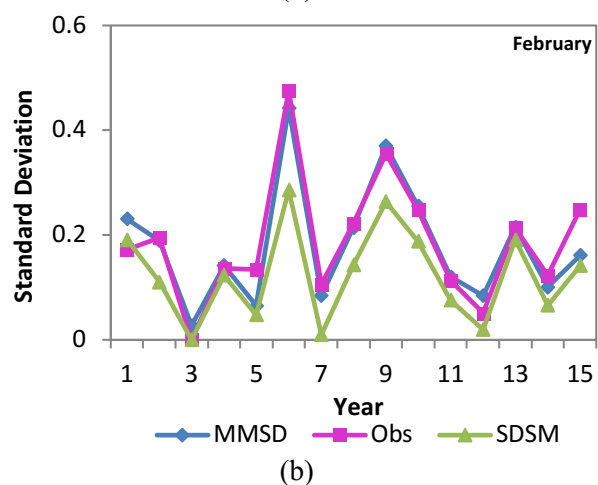
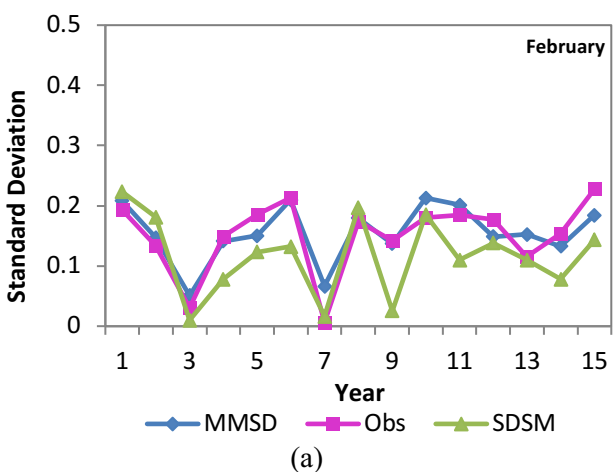
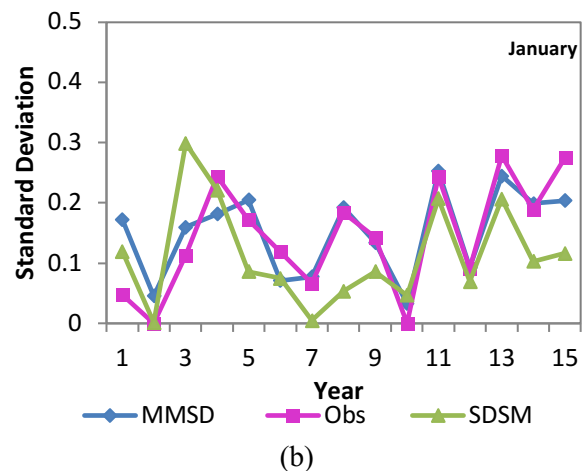
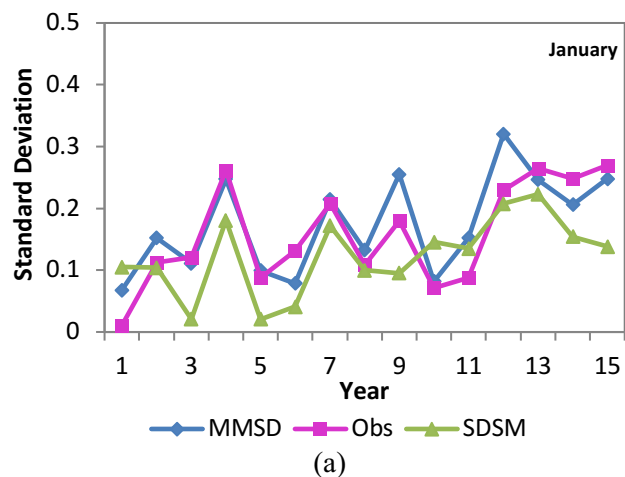
(a)



(b)

Figure 5.60: Standard deviations of total annual snowmelt during (a) calibration and (b) validation periods.

Figure 5.61 represents the interannual variability of standard deviation of monthly snowmelt amounts. During calibration period MMSD technique was able to capture the interannual variability in standard deviation very well, whereas, SDSM underestimated it for most of the cases. However, MMSD overestimated the standard deviation for few years especially in the months of January, March and April during calibration period. During validation period also, MMSD was found capable to reproduce the interannual variability accurately for most of the years and produced better results than those of SDSM.



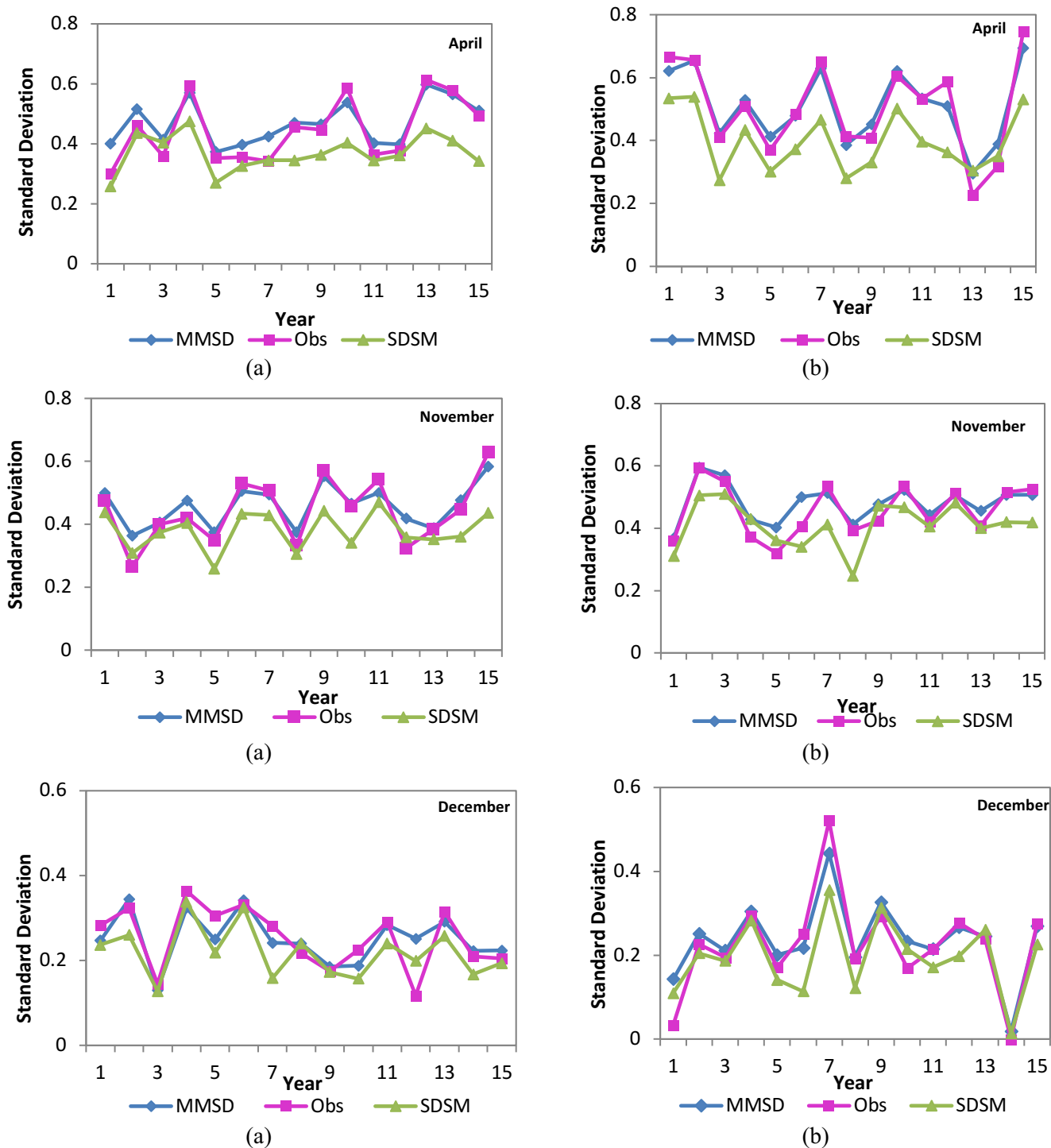


Figure 5.61: Standard deviations of montly snowmelt amounts during (a) calibration and (b) validation periods.

Therefore, it is evident that the indices given by SDSM were mostly underestimated compared to the observed ones. In addition, the above results indicate that snowmelt indices were better captured by MMSD technique compared to SDSM.

5.4 Prediction of future extreme temperature series in the southern Quebec-Ontario region

This section provides the prediction of T_{max} and T_{min} for the future periods at seven stations in the southern Quebec-Ontario region. The temperature was projected under four SRES climate scenarios of IPCC. Those are A1B and A2 emission scenarios of CGCM and A2 and B2 emission scenarios of HadCM. The analysis in previous sections showed that both models (i.e., SVD-MAR and MSM) produced almost similar skills to reproduce the observed basic statistical properties, and spatial and temporal relationship, although SVD-MAR simulated the number of days with freeze-thaw cycle better than MSM. Thus, the predictions of temperature for future periods using the SVD-MAR method are presented in this section.

5.4.1 Prediction of future changes in annual average

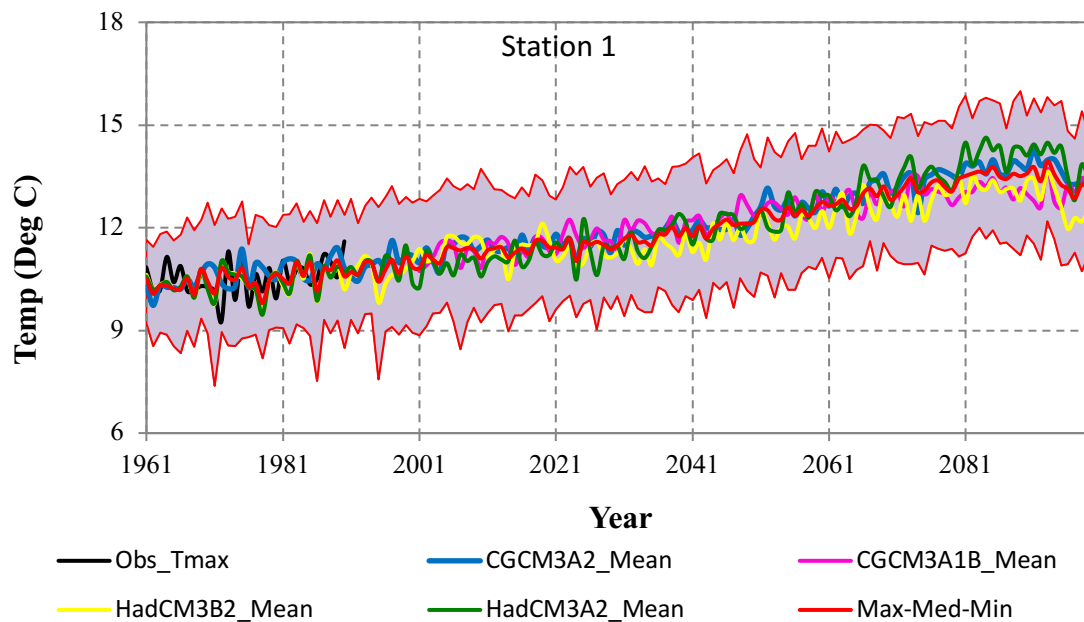
This section provides the predicted annual average of the daily T_{max} and T_{min} for the period 1961-2100 under CGCM-A2 scenario, 2001-2100 period under CGCM-A1B scenario and 1961-2099 period under HadCM-A2 and B2 scenarios depending on the available length of predictors of the respective GCMs. The solid lines represent the annual average of daily T_{max} and T_{min} (different colours represent different scenarios as described by the legends) and the grey shaded area in the figures shows the total uncertainty for all the ensembles of four scenarios of CGCM and HadCM.

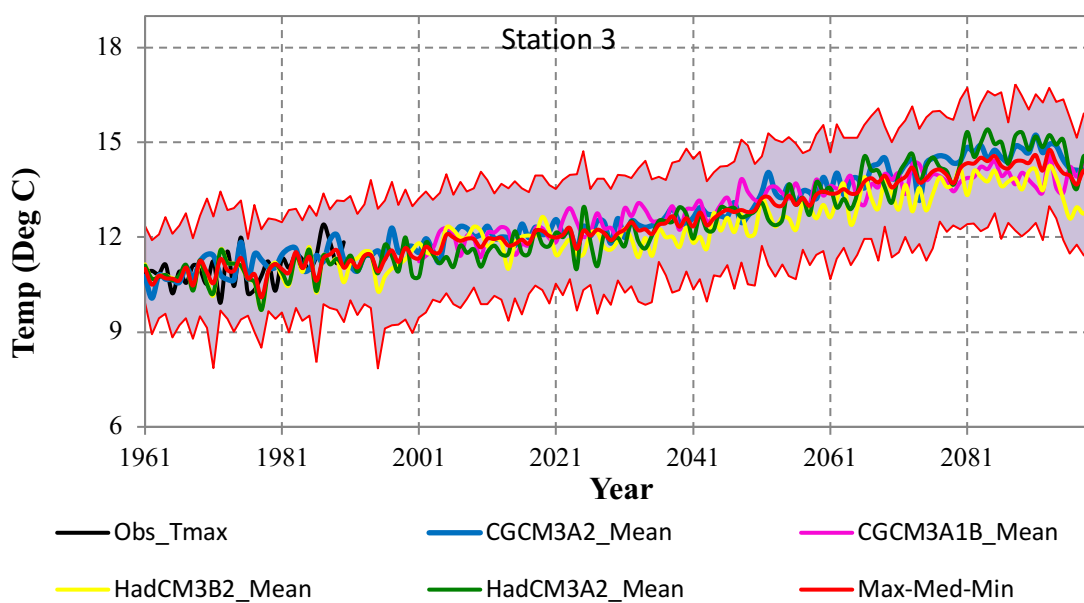
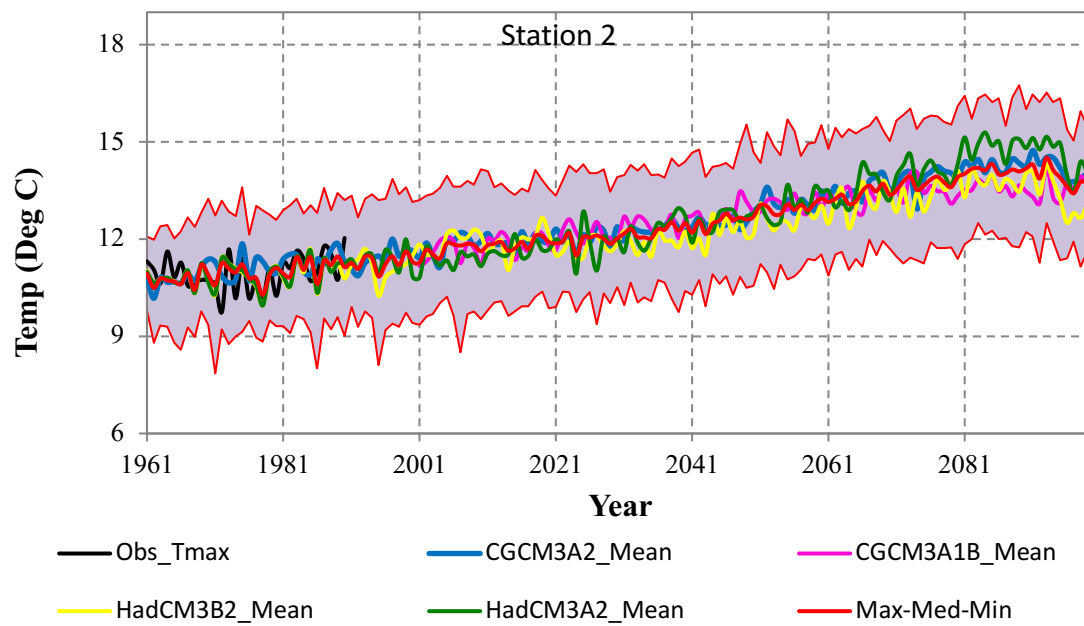
Figure 5.62 shows very good agreements between the observed and simulated values of annual average of the daily T_{max} during the current period (1961-1990) under all scenarios at all the stations. The observed Interannual variability in annual average of daily T_{max} was captured very well by the simulated series. For annual average of the daily T_{min} also, a good fit was observed between the simulated values and the observed ones during the current period (Figure 5.63).

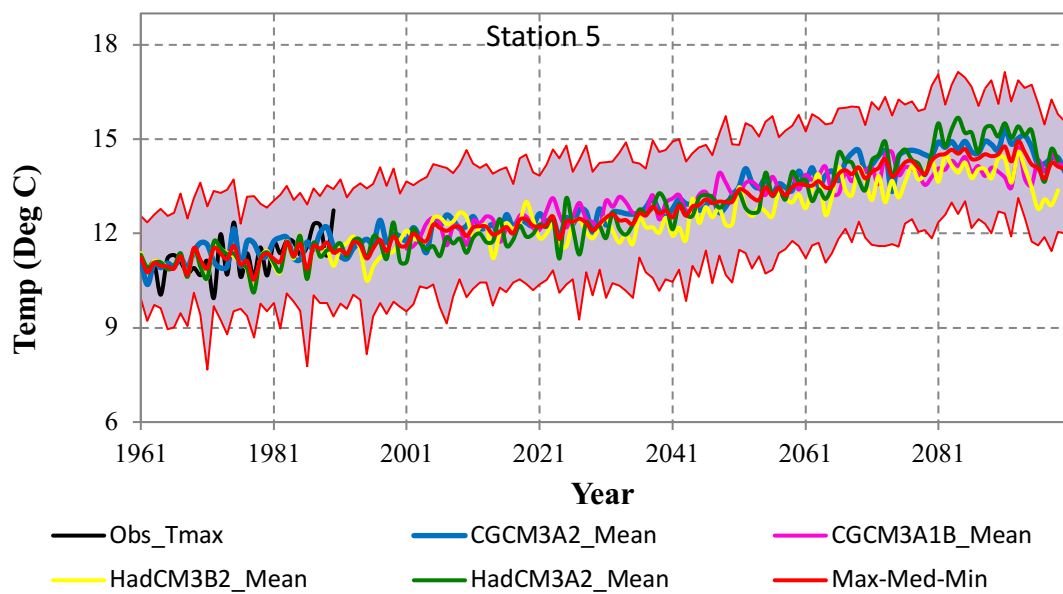
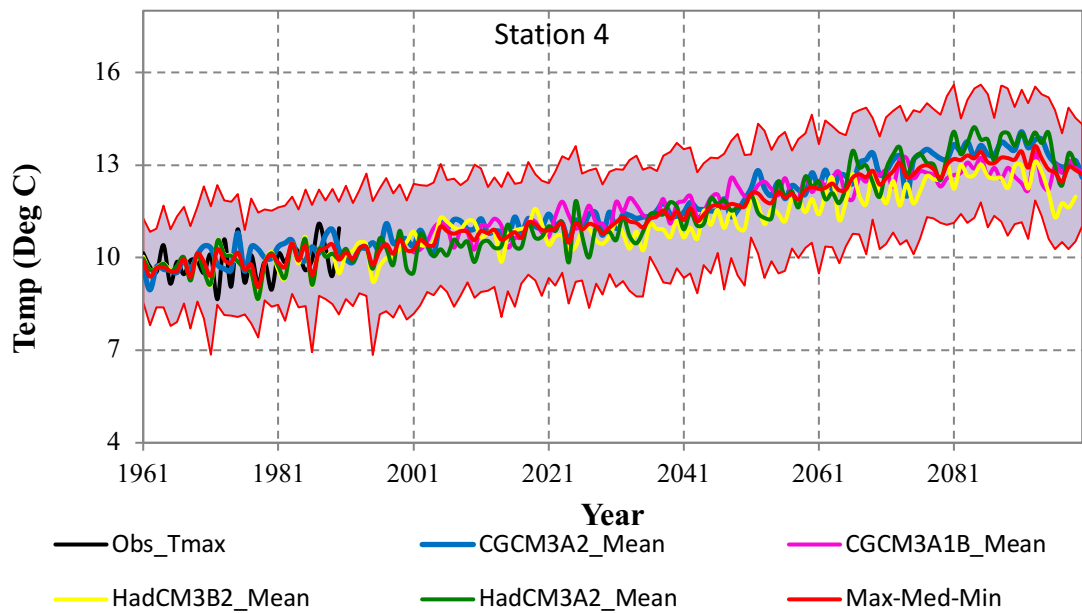
Each of the four scenarios shows distinct upward trends in annual average of the daily T_{max} during future period at all seven stations; but the rate of increase is not same under all

scenarios (Figure 5.62). However, the rate of increase in annual average of T_{max} is similar under all scenarios until around 2050s and the differences manifest beyond 2060s. Figure 5.62 shows that HadCM-A2 and CGCM-A2 exhibit similar rates of increase in annual average of T_{max} , nevertheless, among all the scenarios HadCM-A2 exhibits the highest trends especially beyond 2080s. The lowest trend is simulated under HadCM-B2 scenario at all the stations.

Like T_{max} , annual average of the daily T_{min} also exhibits distinct increasing trends under all the scenarios at all the stations (Figure 5.63). Different scenarios show different rates of increase and in general, HadCM scenarios exhibit higher trends than CGCM scenarios. The highest trend is predicted under HadCM-A2 scenario at all the stations. However, all the scenarios exhibit almost similar rates of increase until around 2050s at most of the stations and the differences in annual average of the daily T_{min} under different scenarios predominantly tend to be higher after 2060s. The lowest trend is predicted under CGCM-A1B scenario, although HadCM-B2 and CGCM-A1B show similar rates of increase until around 2080s.







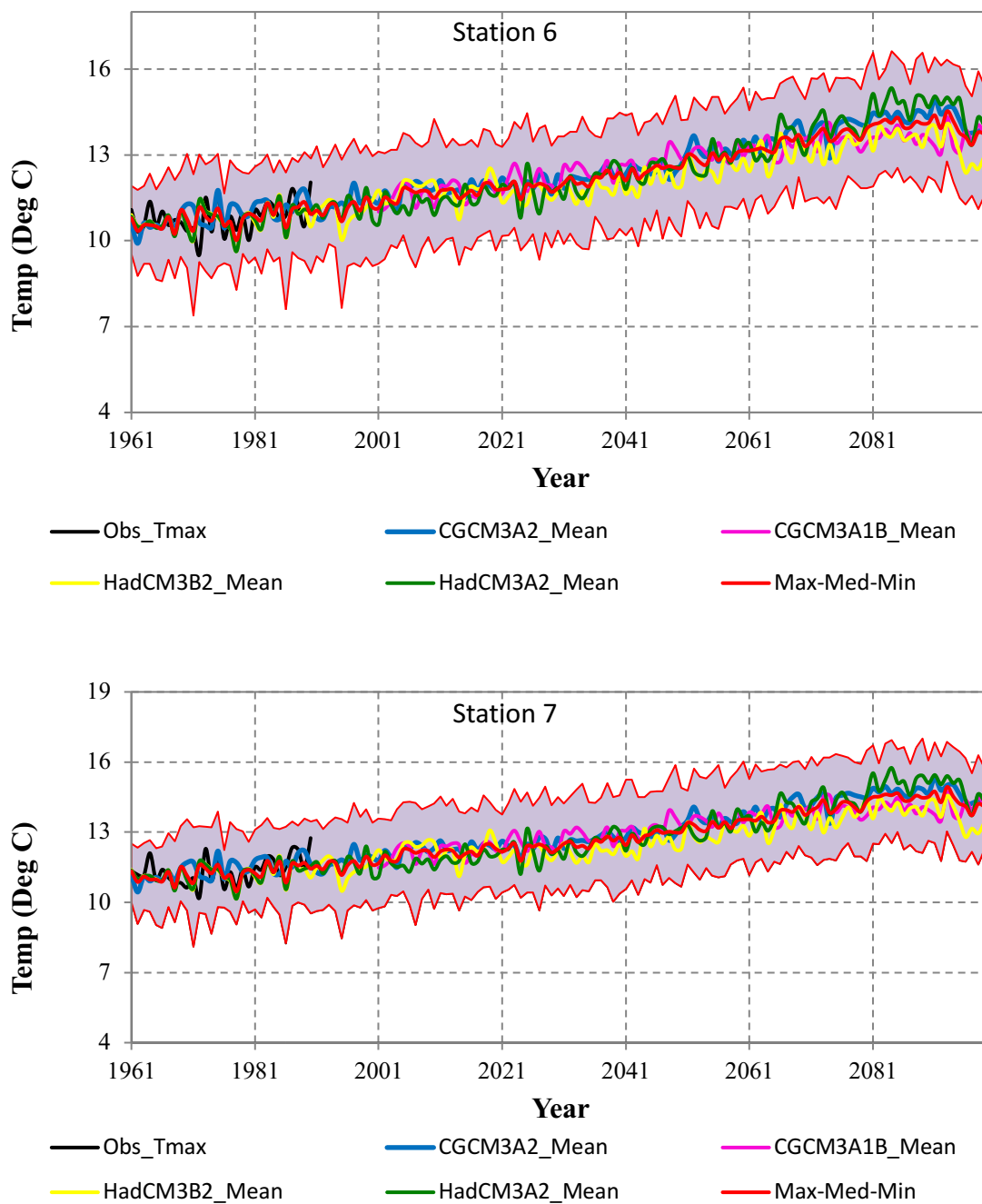
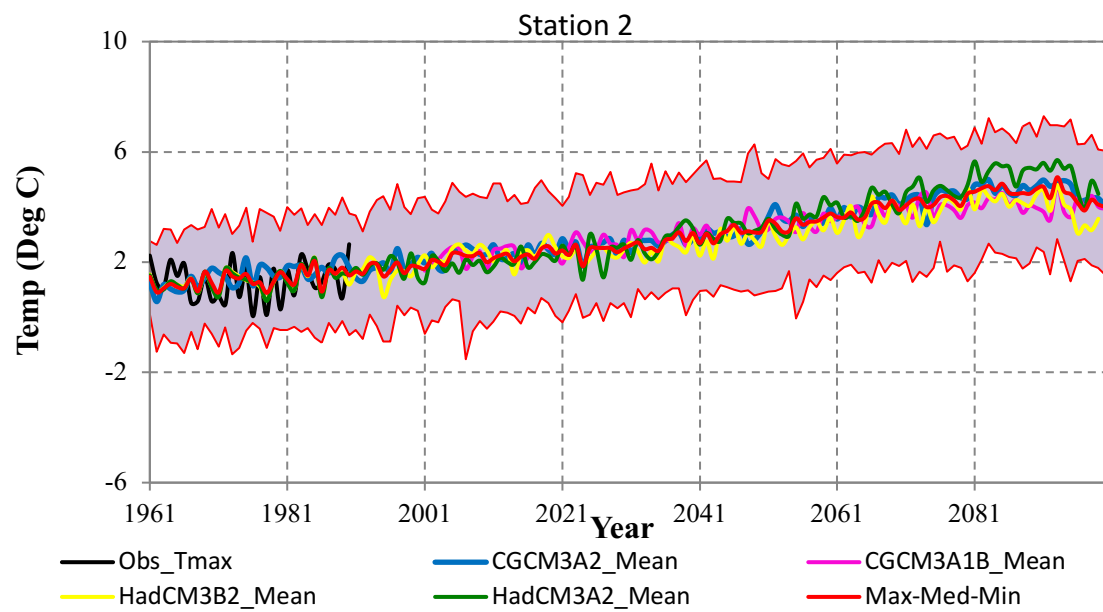
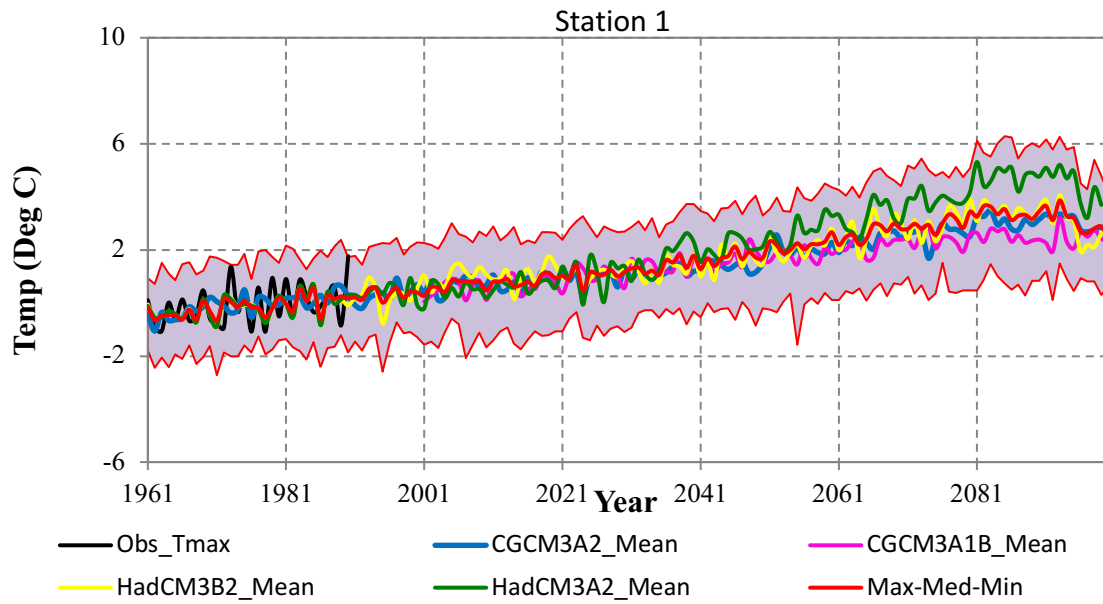
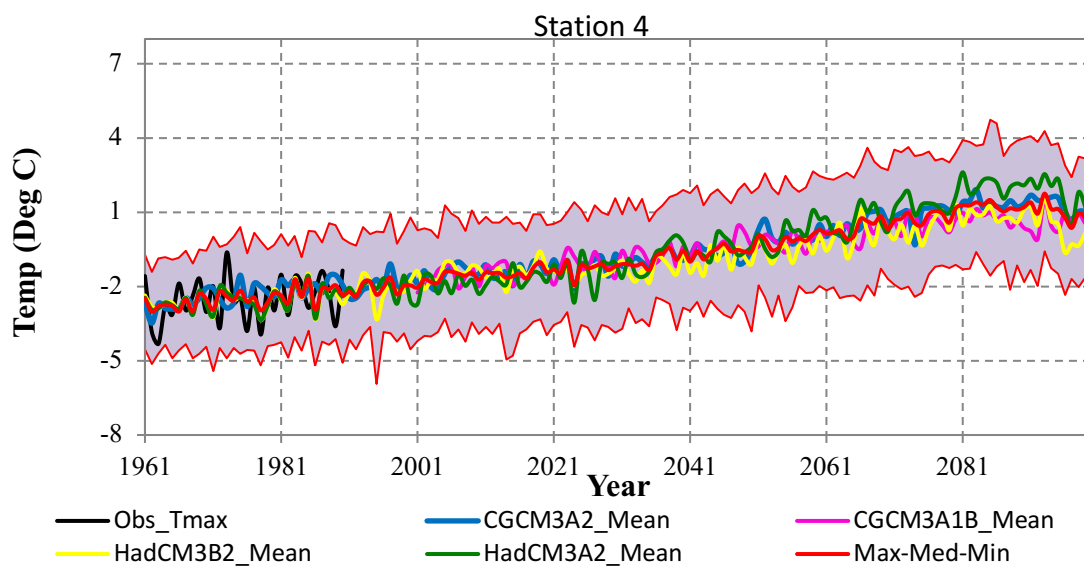
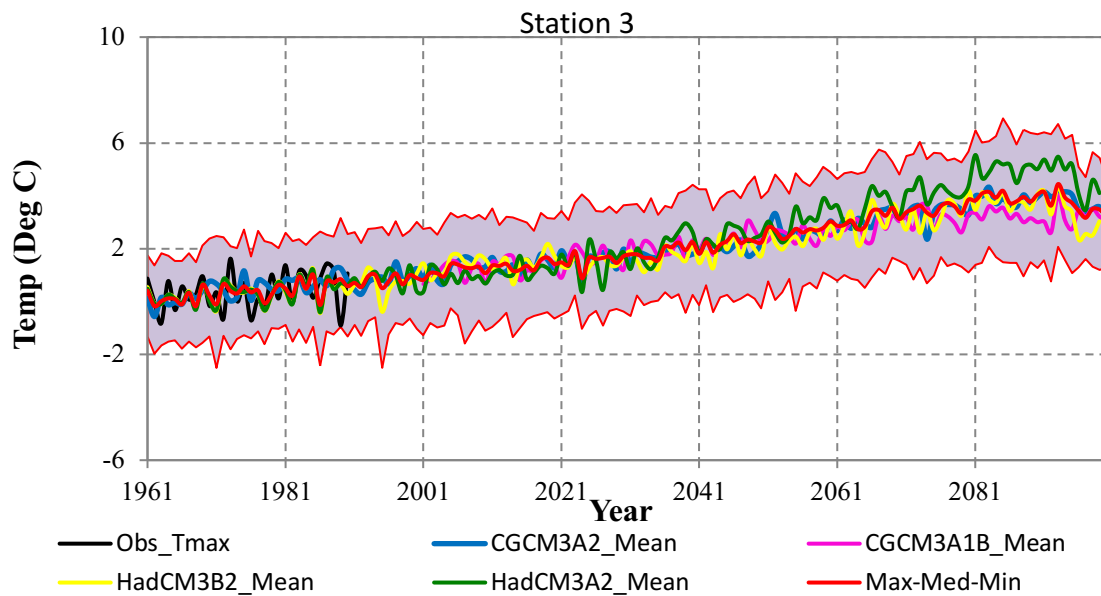
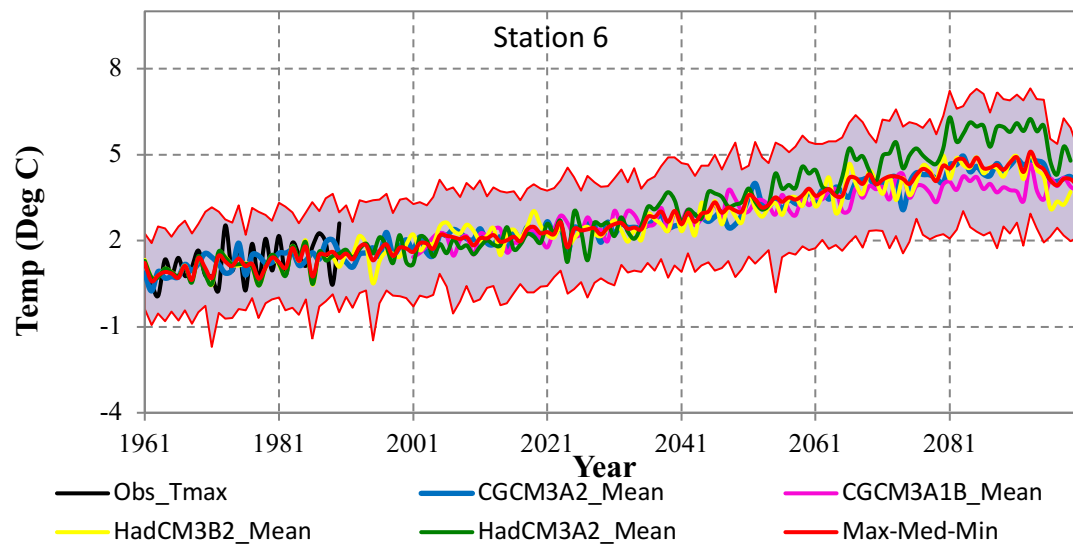
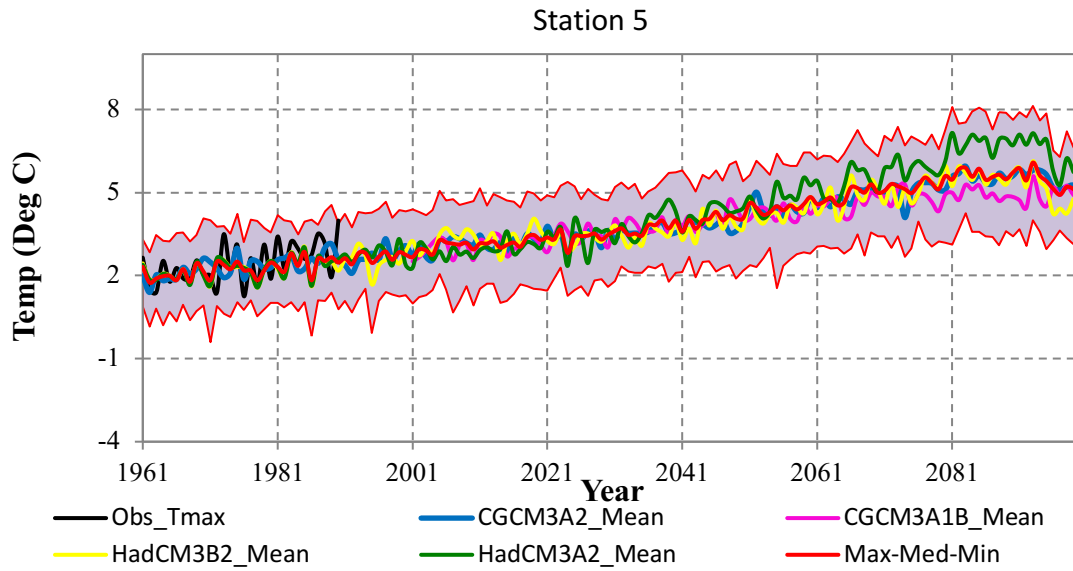


Figure 5.62: Projection of annual average of daily T_{max} under different emission scenarios at seven stations in Quebec-Ontario region.







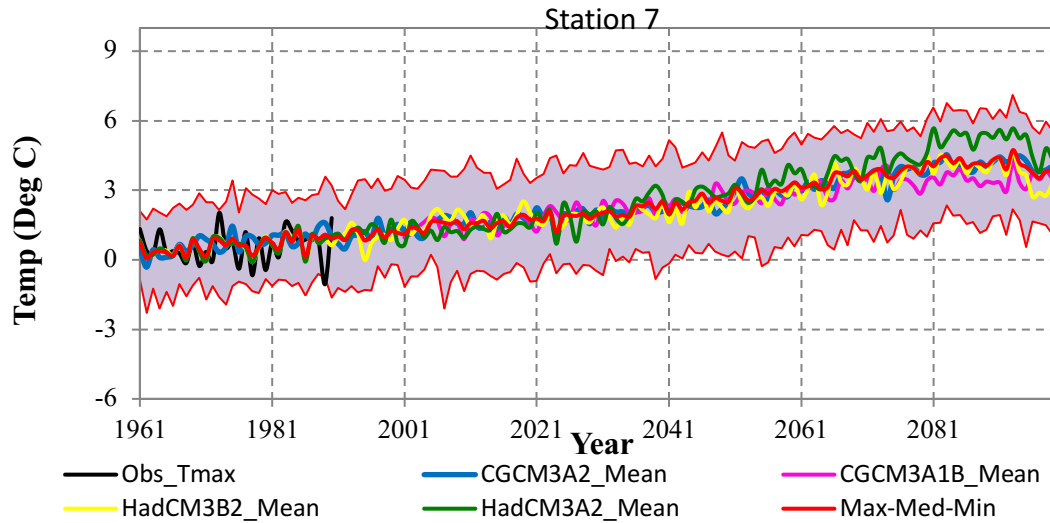


Figure 5.63: Projection of annual average of daily T_{min} under different emission scenarios at seven stations in Quebec-Ontario region.

5.4.2 Prediction of future changes in monthly means

Figures 5.64 and 5.65 present the boxplots of increase in monthly means of daily T_{max} and T_{min} respectively in four months: January, April, July and October, representing the four seasons (e.g., winter, spring, summer and autumn) during current period, 2040s, 2070s and 2090s under all scenarios. Here, current period represents simulated temperatures from respective GCMs for the period 1981-1990. Each boxplot represents monthly means of T_{max} and T_{min} aggregated at seven stations.

Like the trends in annual average, the monthly means of daily T_{max} show distinct consecutive increases during the decades of 2040s, 2070s and 2090s (Figure 5.64). However, the rate of increase differs under different scenarios and in different months. In general, HadCM-A2 scenario shows the highest increase in monthly means for all the selected four months. However, like annual average of daily T_{max} , the rate of increase in monthly mean is similar under all the scenarios till the decades of 2040s, and even 2070s in most cases. The higher increase under the scenario of HadCM-A2 compared to other scenarios is mainly evident during 2090s. Like T_{max} , for T_{min} also, consecutive increase in monthly means is indicated in 2040s, 2070s and 2090s (Figure 5.65). The rate of increase differs in different months under different scenarios. In line

with annual average, the highest increase in monthly mean of daily T_{min} is detected under HadCM-A2 scenario, which is manifested during 2070s and 2090s.

Although in general, the figures show distinct increase in monthly means of daily T_{max} and T_{min} during consecutive decades, CGCM-A1B scenario shows some exceptions. Under this scenario the monthly means do not increase during 2090s compared to 2070s in the months of January and July for both T_{max} and T_{min} . Again, under HadCM-B2 scenarios, although the monthly means of T_{max} and T_{min} during 2090s increased noticeably compared to current period and 2040s, the increases are not prominent compared to 2070s.

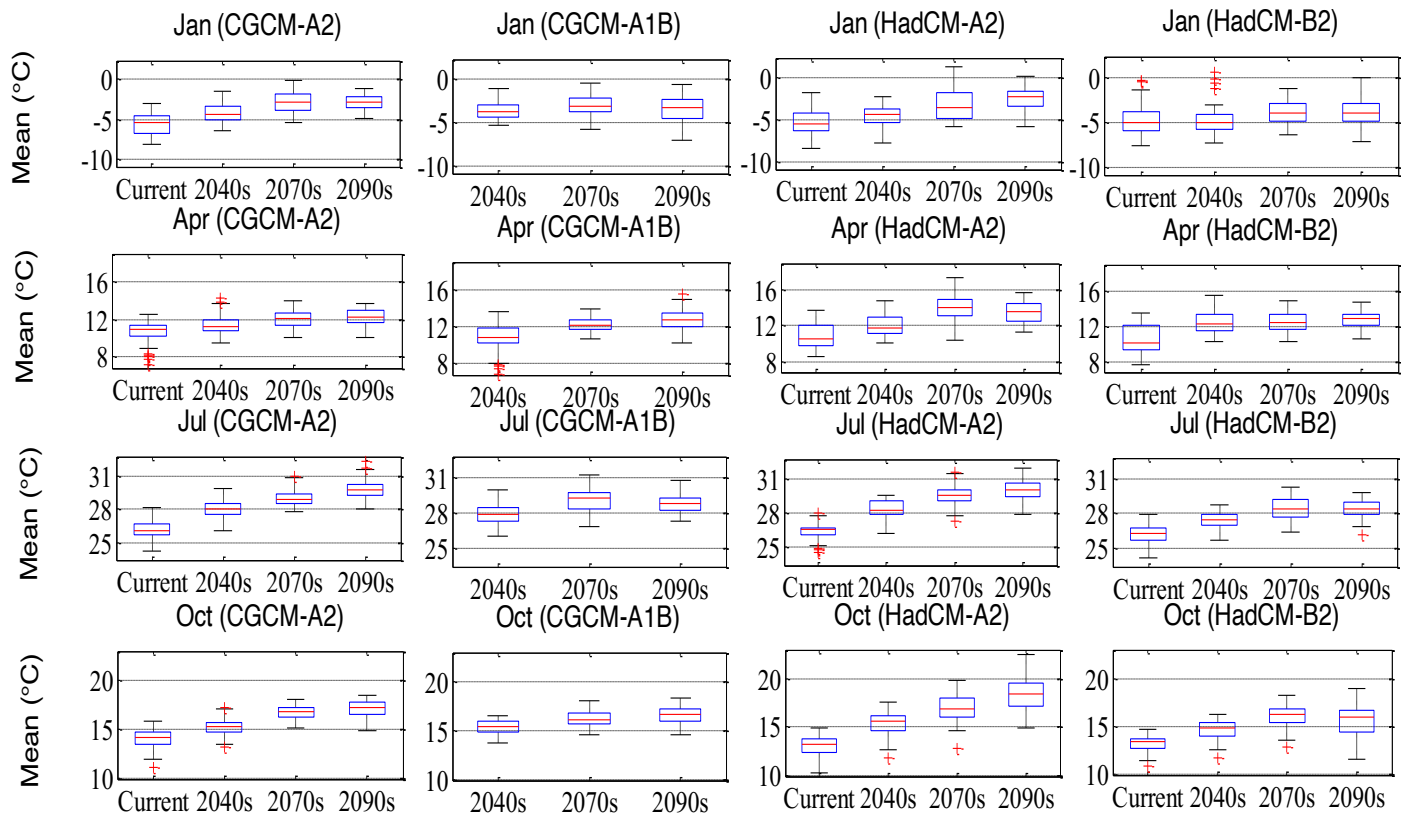


Figure 5.64: Prediction of monthly means of T_{max} in 2040s, 2070s and 2090s aggregated at seven stations in Quebec-Ontario region.

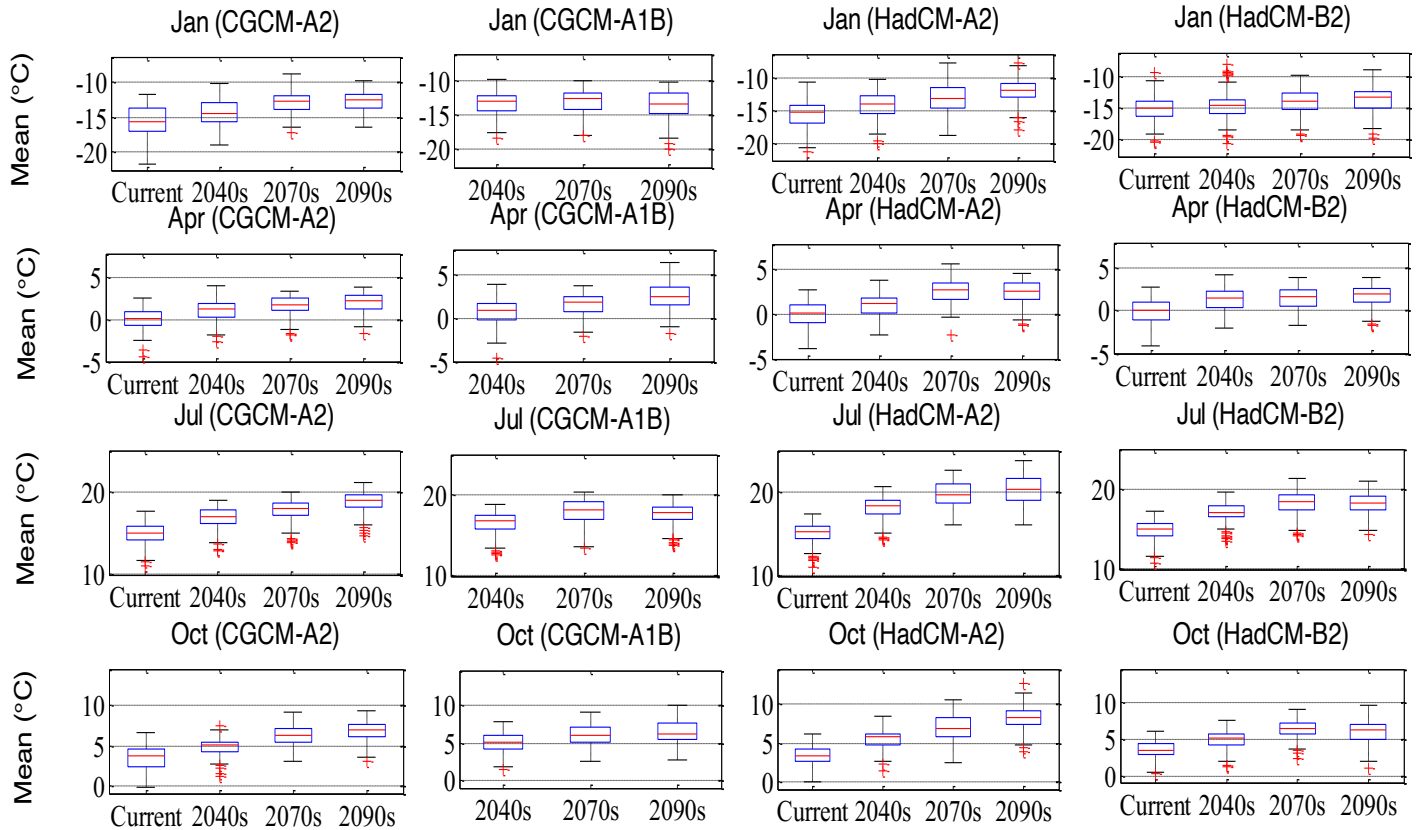


Figure 5.65: Prediction of monthly means of T_{min} in 2040s, 2070s and 2090s aggregated at seven stations in Quebec-Ontario region.

5.4.3 Future trends in temperature indices

This section describes the trends in some temperature related indices of simulated temperature during future periods and compares with the observed ones during current period (Table 5.10). Here, current and future periods represent the periods 1961-1990 and 2041-2070 respectively.

Trend analysis of simulated temperature shows increasing trends in $T_{maxMean}$ at all seven stations during future periods under all scenarios of CGCM and HadCM. According to Mann-Kendall test, all the trends are significant at the 95% confidence level. Whereas, during current period the significant trends were detected at only three stations, although positive trends were observed at all of seven stations in $T_{maxMean}$. The magnitudes of slopes in this index during future period under all scenarios range between 0.025-0.054°C per year and the highest slope is found at station 3 under CGCM-A2 scenario. Like $T_{maxMean}$, all the stations show significant

positive trends in TminMean under all scenarios during future periods. The range of the magnitudes of the slopes during future periods under all scenarios lies between 0.027 to 0.059°C per year and relatively higher slopes are detected under HadCM-A2 scenario. The highest slope in this index is detected at stations 4 and 6 under HadCM-A2 scenario. During current period although all of seven stations showed positive trends, significant trends were observed at only two stations. The index DTR shows heterogeneous pattern of trends during future periods, which means, some stations show positive trends, some show negative trends while some show no trend in this index. Under HadCM-A2 and HadCM-B2 scenarios, almost all the stations show negative trends whereas, under CGCM-A2 scenario most of the stations show positive trends in this index. However, significant trends are mostly detected under HadCM-A2 scenario and the highest negative trend is detected at station 1 under HadCM-B2 scenario. During current period the trends in DTR were observed negative at all the stations although none was significant at the 95% confidence level. It could be seen that during same period of time (i.e., 30 years) future simulated temperature shows significant trends at more stations compared to the observed trends during current period in TmaxMean and TminMean indices. Moreover, the slopes are also higher during future periods compared to current ones at all the stations especially under CGCM-A2, HadCM-A2 and HadCM-B2 scenarios.

In cool days and cool nights all the stations show significant negative trends under all four scenarios during future periods. The slopes lie between -0.141 - -0.361 days per year and -0.163 - -0.415 days per year respectively in cool days and nights under all scenarios. CGCM-A2 and HadCM-A2 scenarios show relatively larger slopes in cool days and cool nights respectively. Station 4 under CGCM-A2 and station 6 under HadCM-A2 scenario show the highest slopes respectively in cool days and cool nights during future periods. During current period also, negative trends were observed at all of the stations in these two indices, where, three and two out of seven stations showed significant trends respectively in cool days and cool nights. On the contrary to cool days and nights, the indices warm days and nights show significant positive trends at all the stations under all scenarios, which gives a clear indication of rising of temperature during future periods. The slopes range between 0.163 -0.344 days per year and 0.186 - -0.321 days per year in warm days and nights respectively and relatively larger slopes are detected under CGCM-A2 scenario for both of the indices. The highest slope in warm days is detected at station 5 under CGCM-A2 scenario, whereas both stations 1 and 2 show highest slopes in warm night under the

same scenario. During current period all the stations showed increasing trends in these two indices. Significant trends were observed at three stations in warm nights and none in warm days. Table 5.10 shows that the slopes in these four indices are much higher than the observed ones under all four scenarios at all the stations.

Except station 5 under CGCM-A2 scenario, rest of the scenarios exhibit positive trends in WSDI at all the stations during future periods. The slopes lie between -0.017 - 0.12 days per year under all scenarios. However, none of the trends is significant in WSDI. In the index CSDI, majority of the stations show decreasing trends under all scenarios and the slopes range between -0.098 - 0.023 day per year. Like WSDI, none of the stations show significant trends in CSDI. During current period six out of seven stations showed negative trends in WSDI as well as CSDI indices and none of those was significant. Both frost days and ice days show decreasing trends at all of seven stations under all scenarios during future periods. The slopes are comparatively higher and significant in ice days (-0.021 - -0.582 days per year) than in frost days (-0.115 - -0.482 days per year). The highest slopes are detected at station 4 under CGCM-A2 and at station 7 under HadCM-B2 scenario respectively in frost and ice days. During current period also, decreasing trends were observed at all the stations in both of the indices. However, none of the trends was found significant in ice days and two stations exhibited significant trends in frost days.

The index summer days shows increasing trends at all the stations under all of four scenarios during future period. The significant trends in this index are detected under CGCM-A2, HadCM-A2 and B2 scenarios at all the stations. The magnitudes of the slopes range between 0.012-1.045 days per year and relatively larger slopes are detected under HadCM-A2 scenario with station 4 showing the highest slope. The observed trends during current period were positive at all the stations. However, none of those was significant at the 95% confidence level. All the stations show increasing trends in tropical nights and the slopes range between 0.009-1.107 days per year. Except station 4 under CGCM-A2 and A1B scenarios, rest of the stations show significant trend in this index. Relatively higher slopes are detected under HadCM-A2 and the largest slope is detected at station 5 under the same scenario. During current period although most of the stations showed positive trends in tropical nights, none of those was significant. Comparison with the observed trends shows that these two indices show much higher slopes under CGCM-A2 and HadCM-A2 and B2 scenarios during future periods.

The above stated analysis suggest the increasing of temperature relatively at a higher rate during future period (2041-2070) compared to the current (1961-1990) period at seven stations in the southern Quebec-Ontario region. Almost all of the stations show significant trends in most of the indices during future periods especially under CGCM-A2 and HadCM-A2 and HadCM-B2 scenarios and the magnitudes of the trends are simulated higher than the observed ones in most cases. Among all the selected indices relatively higher increases are detected in the indices of summer days and tropical nights under A2 scenarios of CGCM and HadCM in terms of the magnitudes of future slopes with respect to observed ones.

In this chapter, the performance of two proposed MMSD models was evaluated for daily *Tmax* and *Tmin* series at selected seven stations in the southern Quebec-Ontario region in Canada. It was found that both SVD-MAR and MSM models were capable to reproduce the monthly means, STD of *Tmax* and *Tmin*, *Tmax*90p, *Tmin*10p etc. accurately for almost all the months during calibration and validation periods for both NCEP data. In addition, both SVD-MAR and MSM models were able to capture the observed spatial variability of daily *Tmax* and *Tmin* in the simulated series and produced lag0 interstation correlations better than those from widely used single-site downscaling software, SDSM, for both *Tmax* and *Tmin*. Furthermore, both models were able to preserve the at-site correlation between daily *Tmax* and *Tmin* and observed autocorrelation coefficients of lags from one to three at each station very accurately for both NCEP. In general, SVD-MAR and MSM were found to produce similar results, however, SVD-MAR produced comparatively better results than MSM for the index Fr-Th cycle. Predictions for the future period indicates upward trends in annual average of the daily *Tmax* and *Tmin* at all selected stations, however, the rate of increase is not equal under all scenarios. Trend analysis of temperature related indices suggests significant trends in most of the indices during future period (2041-2070) compared to the current period (1961-1990) particularly under CGCM-A2 and HadCM-A2 and HadCM-B2 scenarios.

In addition to assessing the feasibility and accuracy of the proposed MMSD techniques in capturing the spatial and temporal statistical properties of daily extreme temperature series, the present study also compared the accuracy of SVD-MAR model and single-site downscaling procedure (SDSM) in snowmelt computations. It was found that the SVD-MAR was able to provide more accurate estimates of the snowmelt than the SDSM.

Table 5.10: Observed and future trends in temperature indices at seven stations in Quebec-Ontario region.

Station No.	TmaxMean					TminMean					DTR				
	Current		Future (2041-2070)			Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	0.018	0.025	0.047	0.048	0.044	0.032	0.027	0.047	0.059	0.057	-0.015	-0.002	0.001	-0.011	-0.012
2	0.016	0.026	0.047	0.049	0.049	0.007	0.027	0.047	0.049	0.046	0.008	-0.001	0.001	0	0.003
3	0.028	0.027	0.054	0.05	0.049	0.019	0.027	0.048	0.058	0.054	0.008	-0.001	0.005	-0.008	-0.005
4	0.017	0.027	0.053	0.05	0.048	0.025	0.03	0.054	0.059	0.052	-0.008	-0.002	-0.001	-0.009	-0.004
5	0.037	0.028	0.052	0.045	0.051	0.043	0.028	0.046	0.056	0.052	-0.01	0	0.006	-0.01	-0.001
6	0.021	0.027	0.052	0.051	0.049	0.034	0.028	0.047	0.059	0.051	-0.013	0	0.005	-0.009	-0.003
7	0.029	0.028	0.049	0.044	0.05	0.008	0.03	0.048	0.056	0.054	0.023	-0.003	0.001	-0.011	-0.004

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 5.10 (Continued)

Station No.	Tx10p (Cool days)					Tx90p (Warm days)					Tn10p (Cool nights)					Tn90p (Warm nights)				
	Current		Future			Current		Future			Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	-0.032	-0.168	-0.36	-0.351	-0.258	0.093	0.182	0.309	0.241	0.231	-0.052	-0.194	-0.376	-0.385	-0.283	0.137	0.186	0.321	0.273	0.238
2	-0.028	-0.148	-0.36	-0.345	-0.287	0.054	0.163	0.309	0.262	0.253	0.063	-0.21	-0.376	-0.371	-0.284	0.11	0.242	0.321	0.272	0.229
3	-0.114	-0.141	-0.35	-0.33	-0.27	0.063	0.184	0.303	0.247	0.237	-0.088	-0.179	-0.319	-0.396	-0.305	0.092	0.202	0.294	0.272	0.266
4	-0.018	-0.143	-0.361	-0.328	-0.273	0.068	0.192	0.341	0.236	0.227	-0.062	-0.163	-0.349	-0.361	-0.232	0.134	0.192	0.314	0.275	0.247
5	-0.117	-0.165	-0.347	-0.325	-0.295	0.114	0.22	0.344	0.249	0.22	-0.163	-0.167	-0.332	-0.399	-0.307	0.125	0.201	0.29	0.249	0.27
6	-0.081	-0.157	-0.332	-0.343	-0.27	0.068	0.189	0.295	0.245	0.235	-0.118	-0.197	-0.332	-0.415	-0.302	0.148	0.192	0.293	0.307	0.251
7	-0.043	-0.149	-0.349	-0.297	-0.265	0.147	0.208	0.327	0.271	0.221	0.074	-0.184	-0.324	-0.373	-0.277	0.05	0.232	0.28	0.245	0.208

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 5.10 (Continued)

Station No.	WSDI					CSDI					FD0 (Frost days)					ID0 (Ice days)				
	Current		Future			Current		Future			Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	0.089	0.023	0.036	0.062	0.004	0	0.007	-0.098	0.001	-0.063	-0.467	-0.156	-0.255	-0.229	-0.285	-0.281	-0.387	-0.371	-0.185	-0.292
2	0.045	0.026	0.036	0.089	0.023	0.032	-0.007	-0.098	0.051	0.017	-0.061	-0.115	-0.255	-0.198	-0.262	-0.185	-0.43	-0.371	-0.038	-0.458
3	0.09	0.023	0	0.088	0.003	-0.026	-0.078	-0.032	-0.046	-0.018	-0.074	-0.294	-0.258	-0.23	-0.288	-0.241	-0.383	-0.417	-0.173	-0.42
4	0.1	0.026	0.038	0.065	0.04	0.055	-0.076	-0.049	0.023	0.02	-0.285	-0.317	-0.482	-0.303	-0.289	-0.137	-0.435	-0.455	-0.287	-0.422
5	-0.03	0.026	-0.017	0.12	0.028	0.012	-0.047	-0.06	-0.034	-0.018	-0.782	-0.233	-0.245	-0.249	-0.279	-0.423	-0.426	-0.392	-0.021	-0.495
6	0.056	0.023	0.042	0.12	0.004	0.033	-0.05	-0.069	-0.019	0.006	-0.227	-0.179	-0.209	-0.26	-0.284	-0.332	-0.409	-0.467	-0.147	-0.378
7	0.154	0.026	0.023	0.033	0.064	0.021	-0.084	-0.004	-0.034	0.006	-0.172	-0.273	-0.187	-0.294	-0.271	-0.213	-0.427	-0.425	-0.032	-0.582

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 5.10 (Continued)

Station No.	SU25(Summer days)					TR20(Tropical nights)				
	Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	0.184	0.012	0.629	0.889	0.551	0.029	0.128	0.552	0.834	0.249
2	0.055	0.099	0.629	0.992	0.64	0.02	0.247	0.552	0.678	0.296
3	0.153	0.027	0.568	0.992	0.683	0.028	0.147	0.321	0.894	0.289
4	0.199	0.246	0.751	1.045	0.664	0.012	0.02	0.009	0.237	0.077
5	0.099	0.111	0.735	0.946	0.548	0.1	0.394	0.663	1.107	0.5
6	0.139	0.032	0.673	1.028	0.68	0.075	0.206	0.396	0.939	0.349
7	0.21	0.145	0.618	1.038	0.611	-0.001	0.12	0.225	0.765	0.203

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Chapter 6

APPLICATIONS OF MULTISITE MULTIVARIATE DOWNSCALING MODELS TO DAILY EXTREME TEMPERATURE SERIES IN BANGLADESH

This chapter provides the applications of proposed MMSD procedures to daily extreme temperature series of four weather stations located in Bangladesh. Like the previous chapter, at first the results obtained by using NCEP reanalysis data are presented. Then the results regarding GCM simulations are provided. At last predictions of daily T_{max} and T_{min} for future periods under different climate scenarios are given.

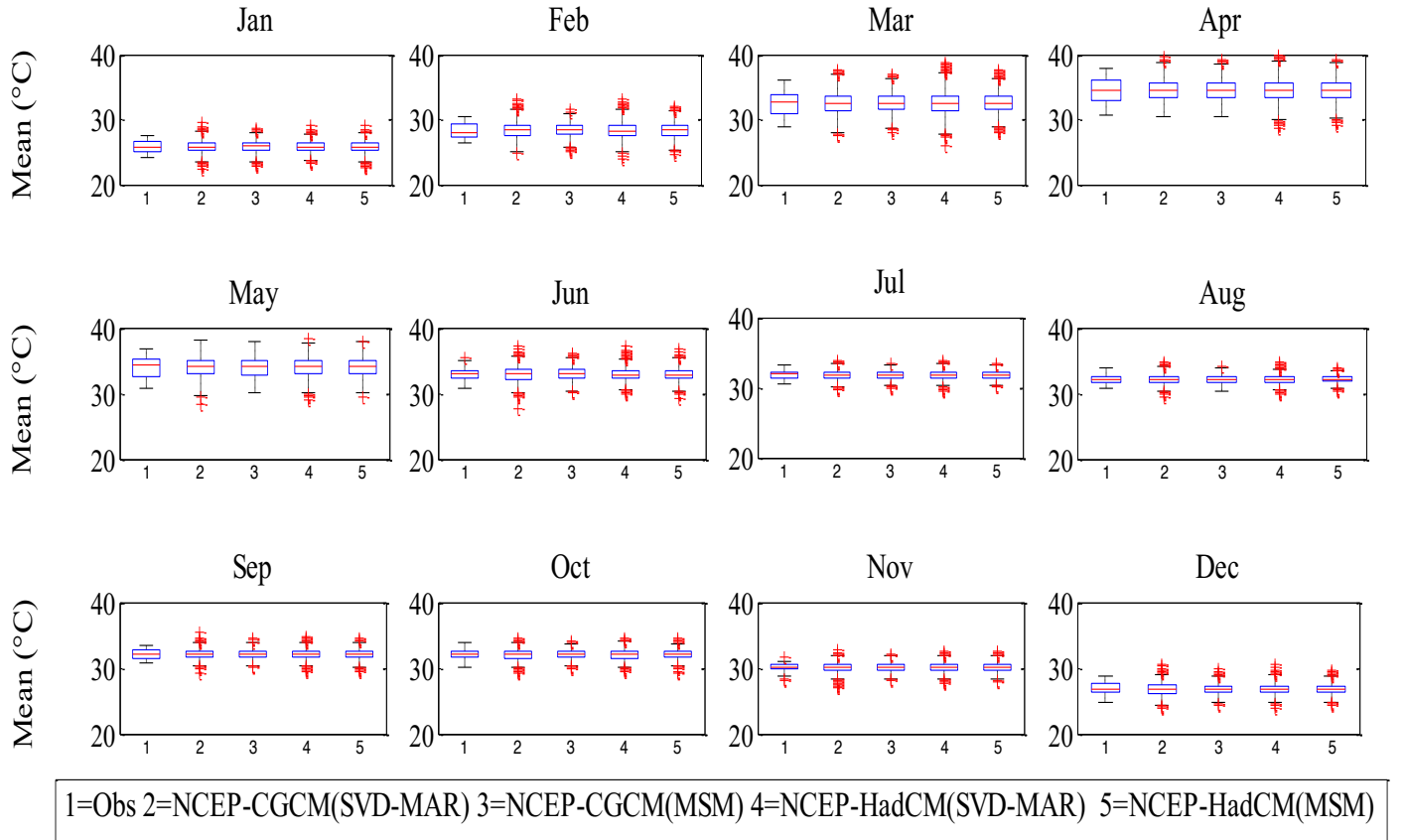
6.1 Results and evaluation of MMSD models for NCEP reanalysis data

This section describes the results obtained by applying SVD-MAR and MSM models to both of the NCEP data interpolated on CGCM and HadCM. Here, the period 1981-1990 represents the calibration period, while 1991-2000 represents the validation period.

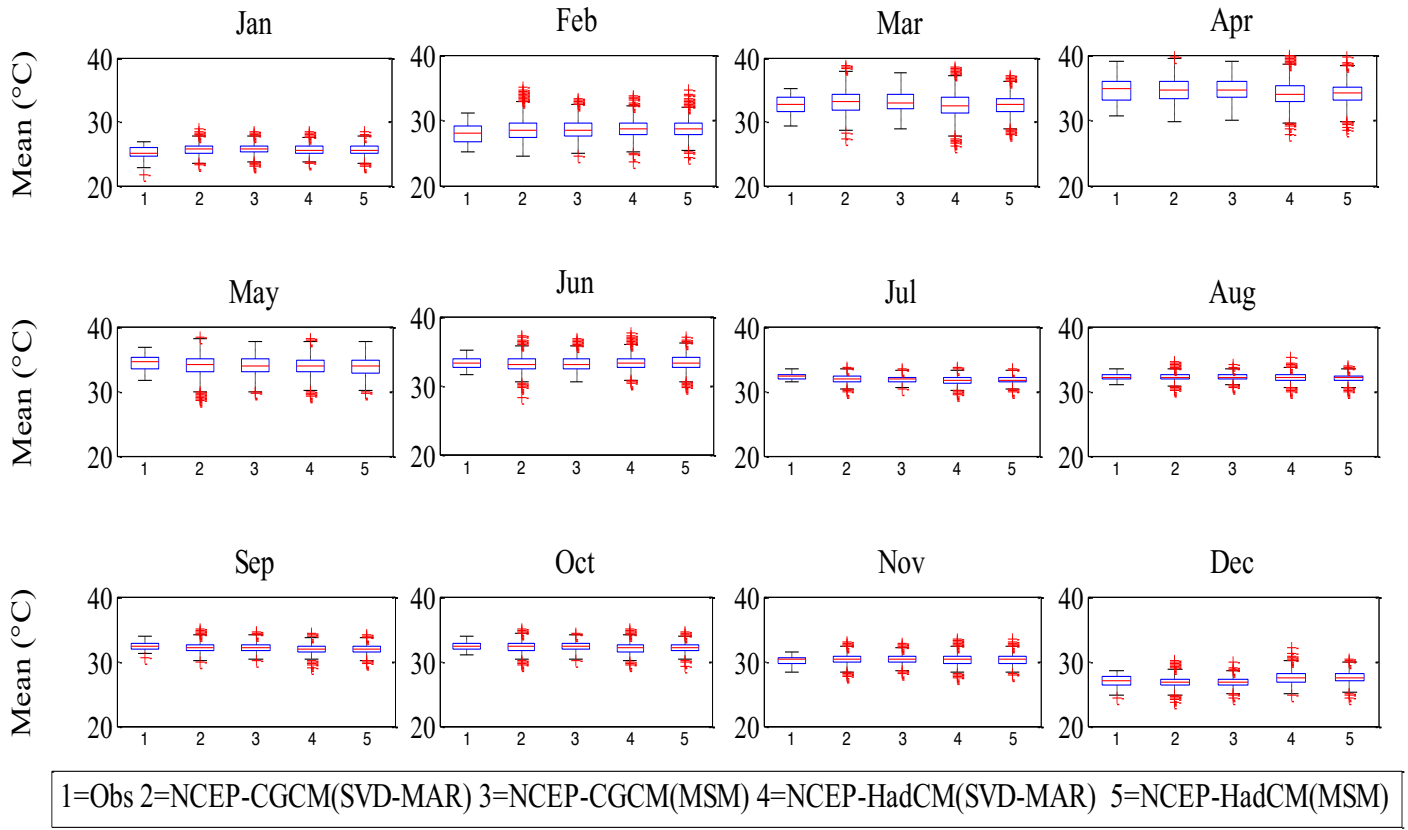
6.1.1 Goodness of fit

The performance of the proposed MMSD models has been evaluated through graphical representations and numerical analysis. The boxplot representations of four temperature indices like mean and STD of T_{max} and T_{min} , the 90th percentile of daily T_{max} and the 10th percentile of daily T_{min} for both of NCEP interpolated on CGCM and HadCM are given in Figures 6.1 to 6.6. Each boxplot represents monthly indices aggregated at four stations during calibration as well as validation periods. The figures show that both of the suggested downscaling models, SVD-MAR and MSM, produced similar results and are capable to produce the monthly means of T_{max} and T_{min} accurately during calibration and validation periods for both of the NCEP (Figures 6.1 and 6.2). Monthly STD of T_{max} and T_{min} were simulated well by both of the models in almost all the months (Figures 6.3 and 6.4). For monthly T_{max90p} , very good agreements were found between the observed and downscaled values during calibration as well as validation periods for both of the models (Figure 6.5). The index T_{min10p} also was accurately reproduced by both of the models for both of the NCEP interpolated on CGCM and HadCM (Figure 6.6).

Table 6.1 shows the values of MAE and RMSE of monthly averages based on 100 simulations of daily T_{max} and T_{min} series at each of four stations. Very accurate results were obtained as indicated by very low values of MAE and RMSE for both T_{max} and T_{min} during calibration period for both of the models. The values of MAE (RMSE) produced by SVD-MAR and MSM ranged between 0.01-0.02 (0.01-0.03) and 0.03-0.07 (0.04-0.1) respectively for T_{max} and T_{min} during calibration period for both of the NCEP for all of four stations. During validation period MAE (RMSE) values were between 0.27-0.48 (0.35-0.54) and 0.16-0.4 (0.19-0.45) respectively for T_{max} and T_{min} for both of the NCEP. Numerical evaluation indicates that both of the models produced comparatively better results for the NCEP interpolated on CGCM than that on HadCM during validation period for T_{max} and T_{min} as well.

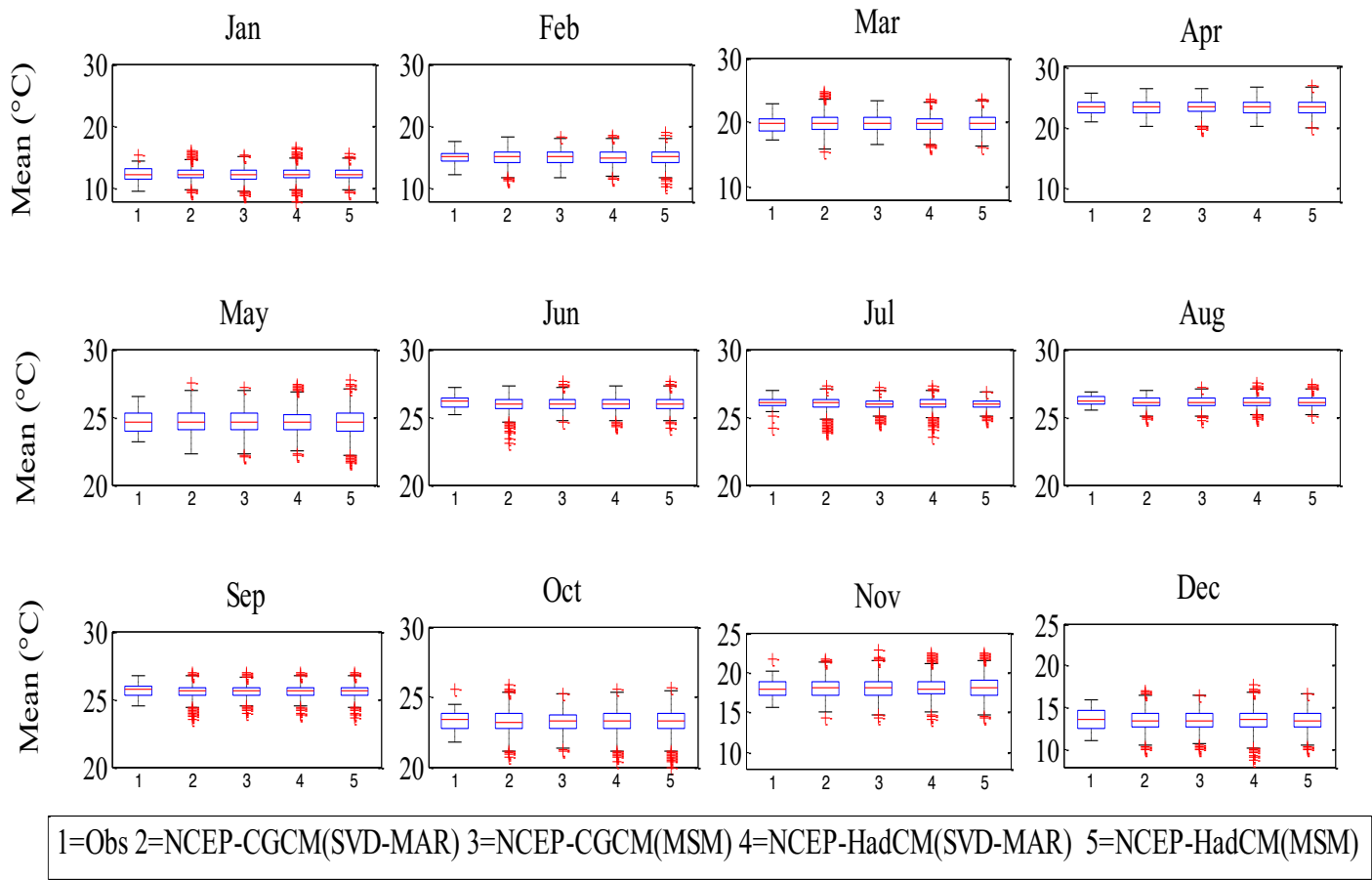


(a)

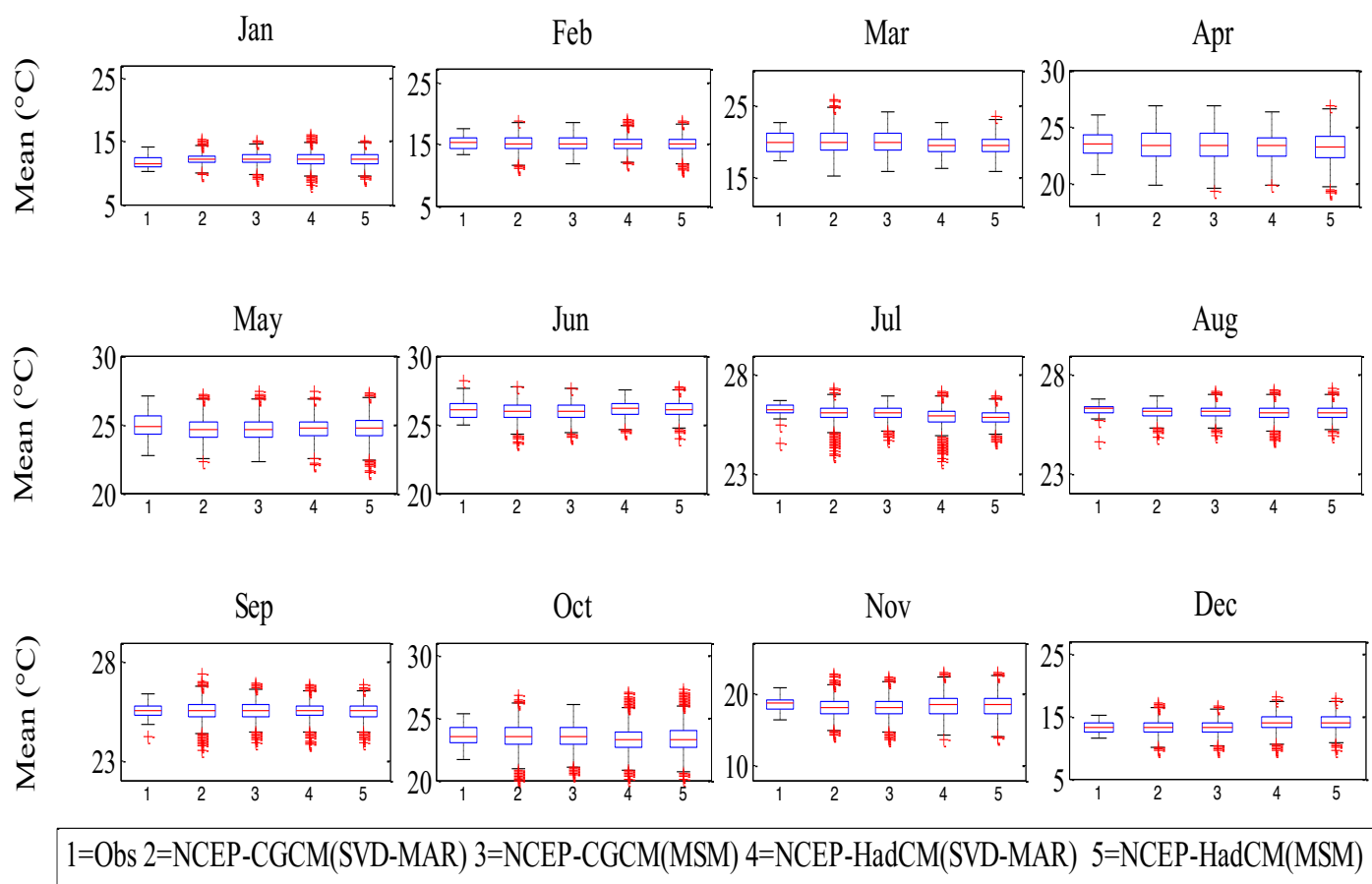


(b)

Figure 6.1: Boxplots of the mean of daily T_{max} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods. Each boxplot represents the values obtained at four stations in Bangladesh aggregated over each period of 10 years.

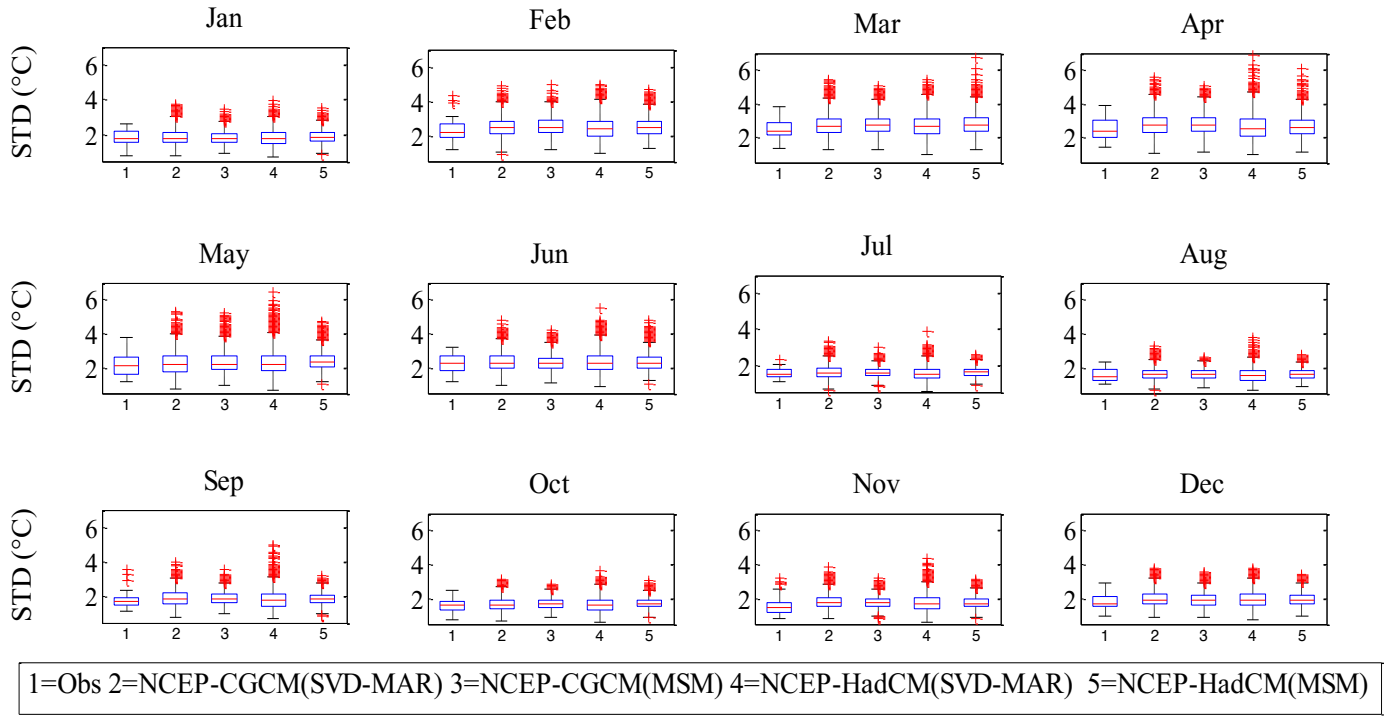


(a)

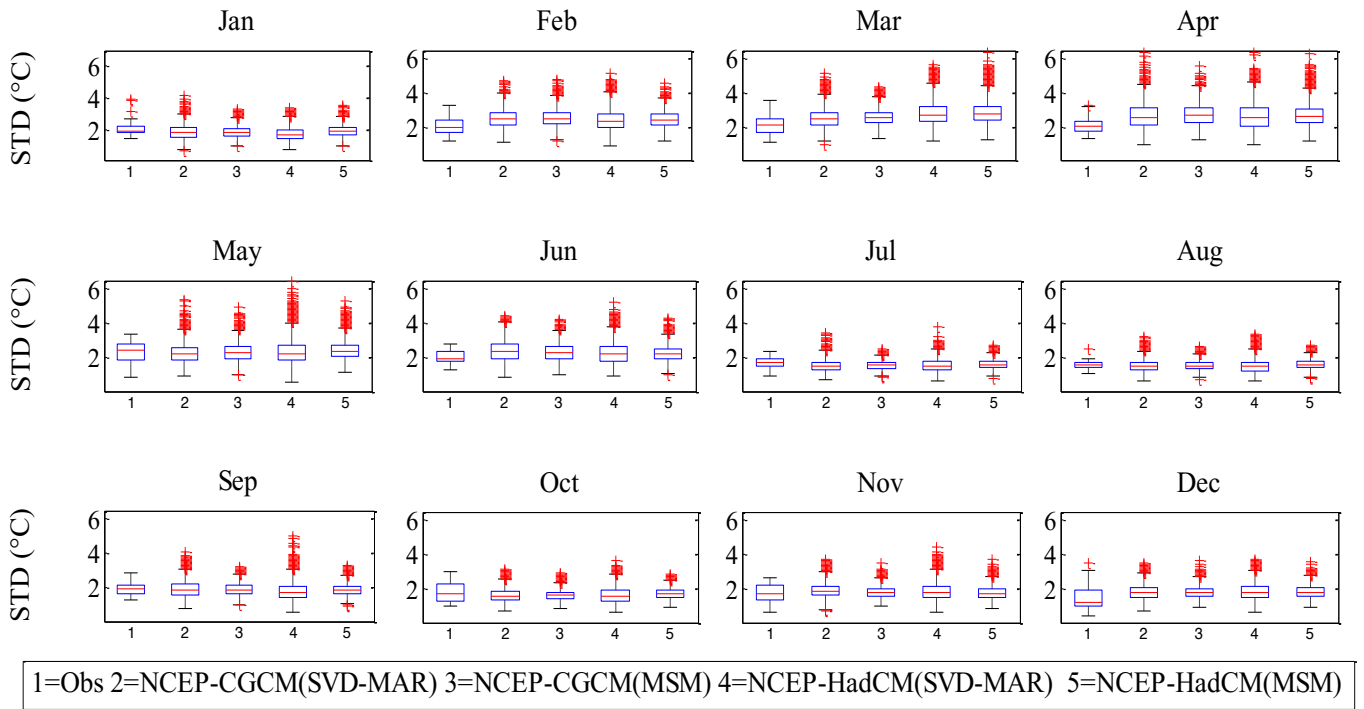


(b)

Figure 6.2: Boxplots of the mean of daily T_{min} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at four stations in Bangladesh.

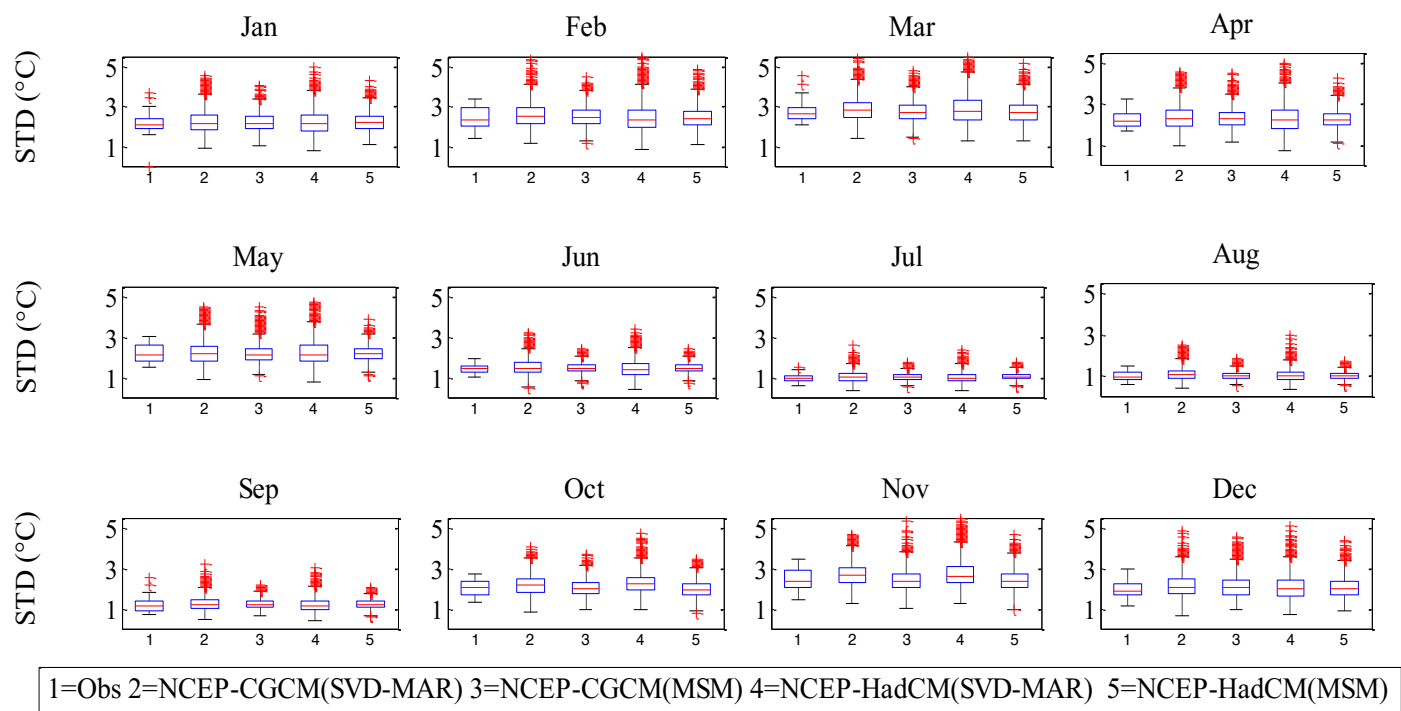


(a)

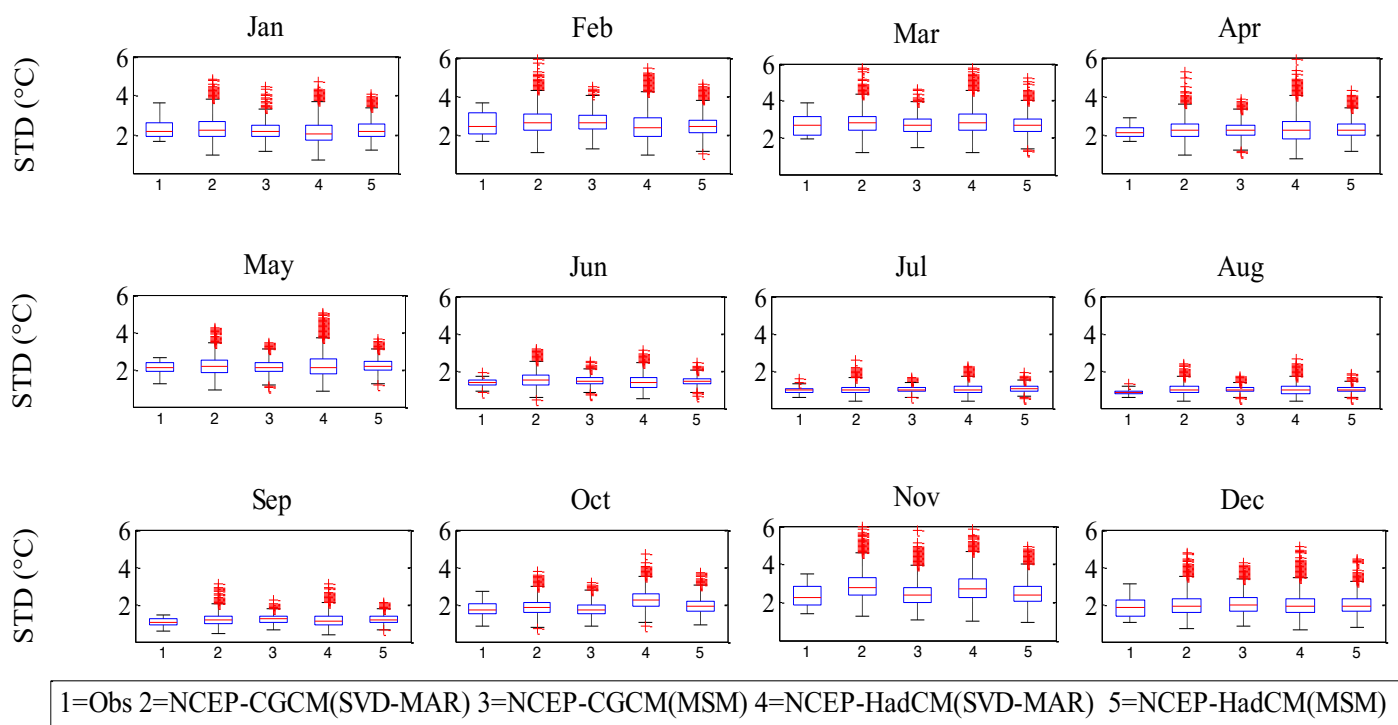


(b)

Figure 6.3: Boxplots of the STD of daily T_{max} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at four stations in Bangladesh.

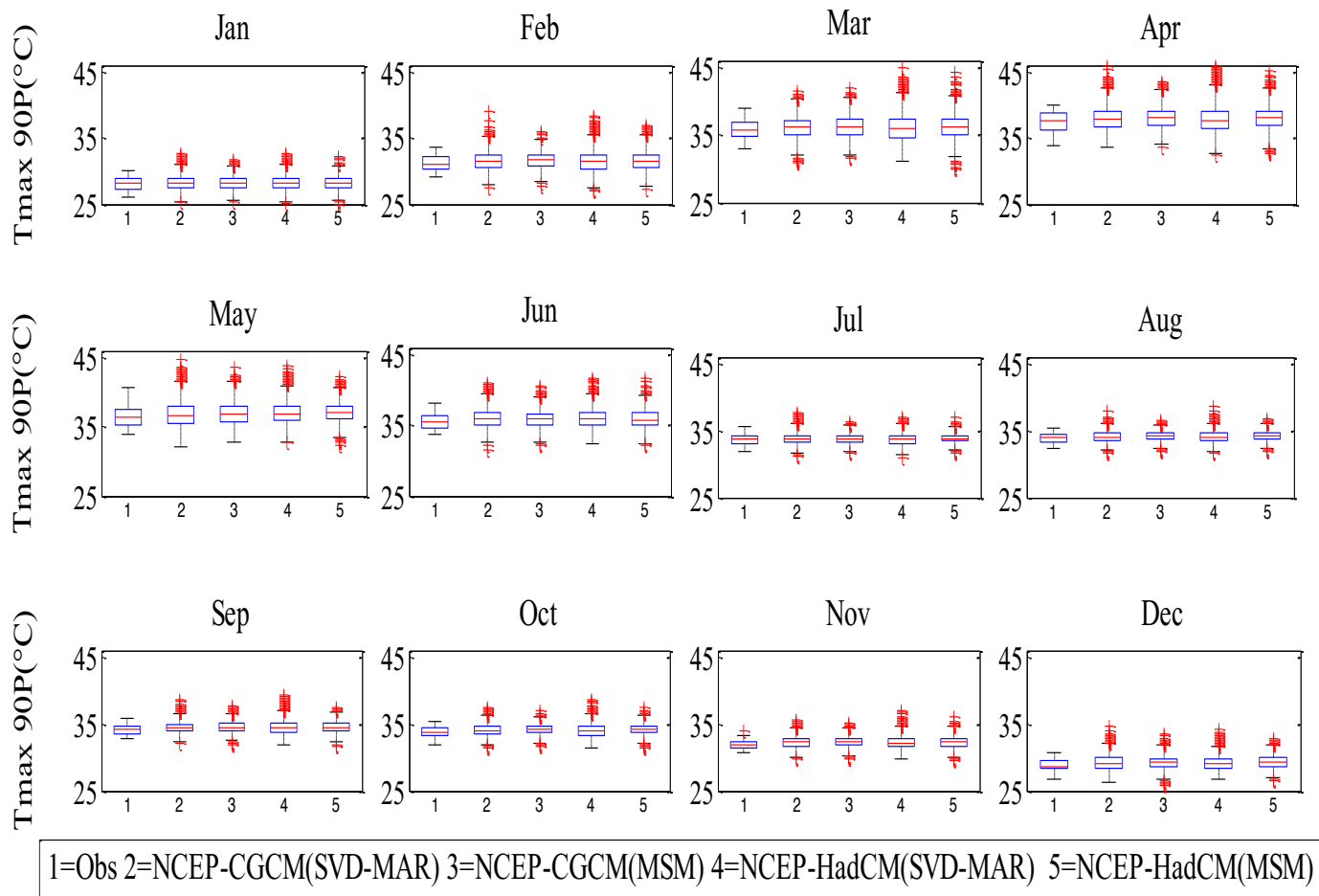


(a)

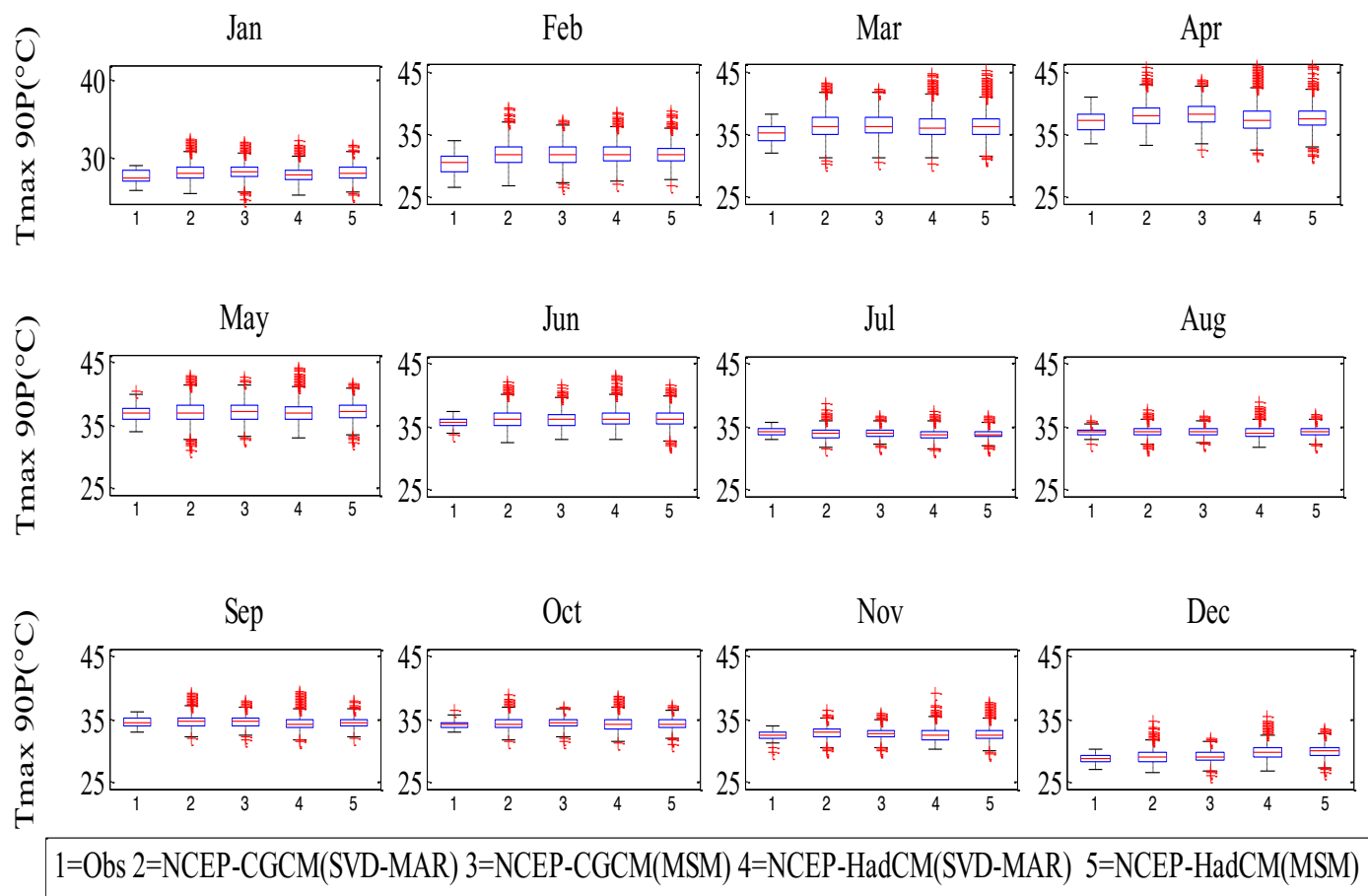


(b)

Figure 6.4: Boxplots of the STD of daily T_{min} for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at four stations in Bangladesh.

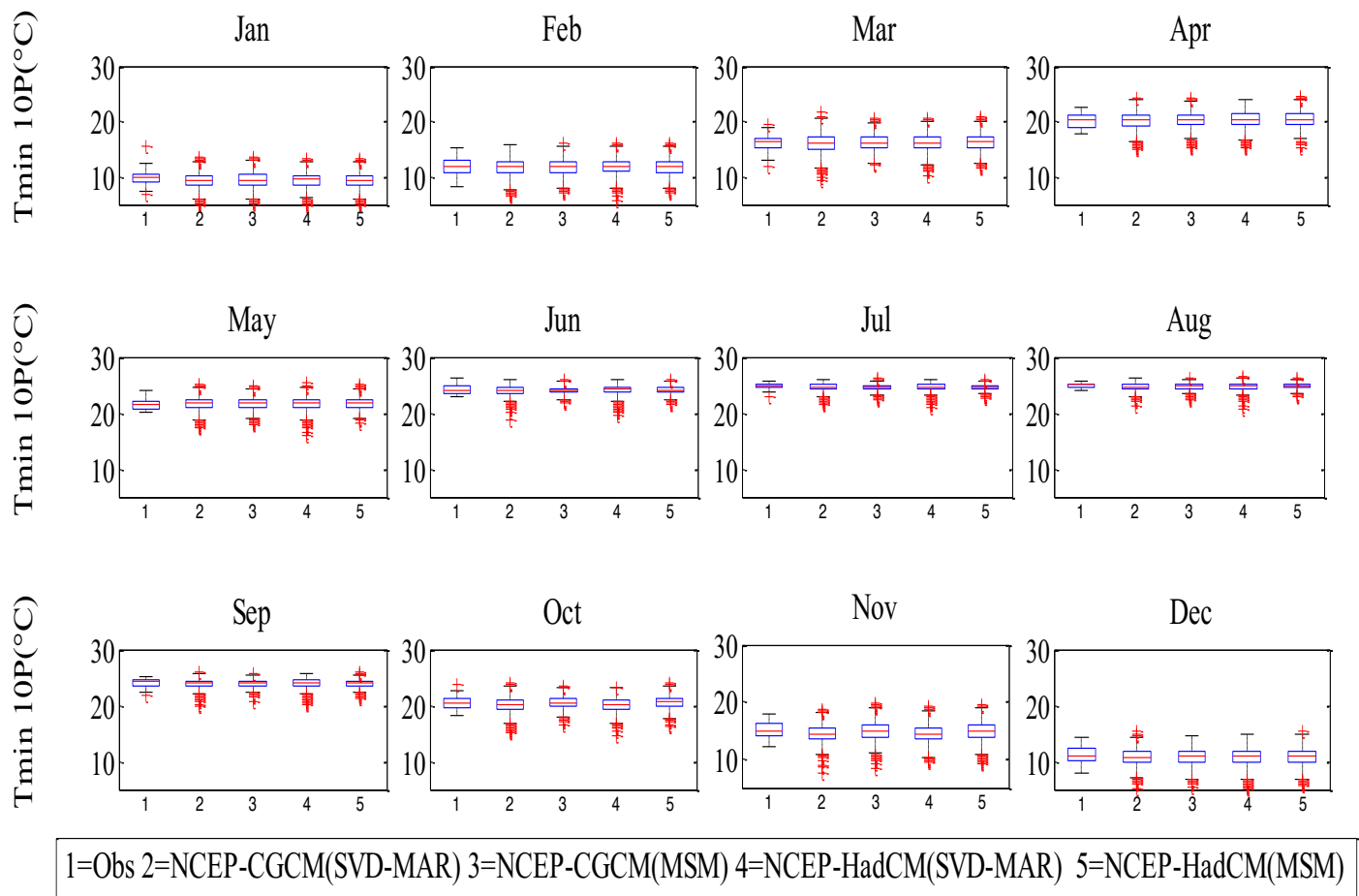


(a)

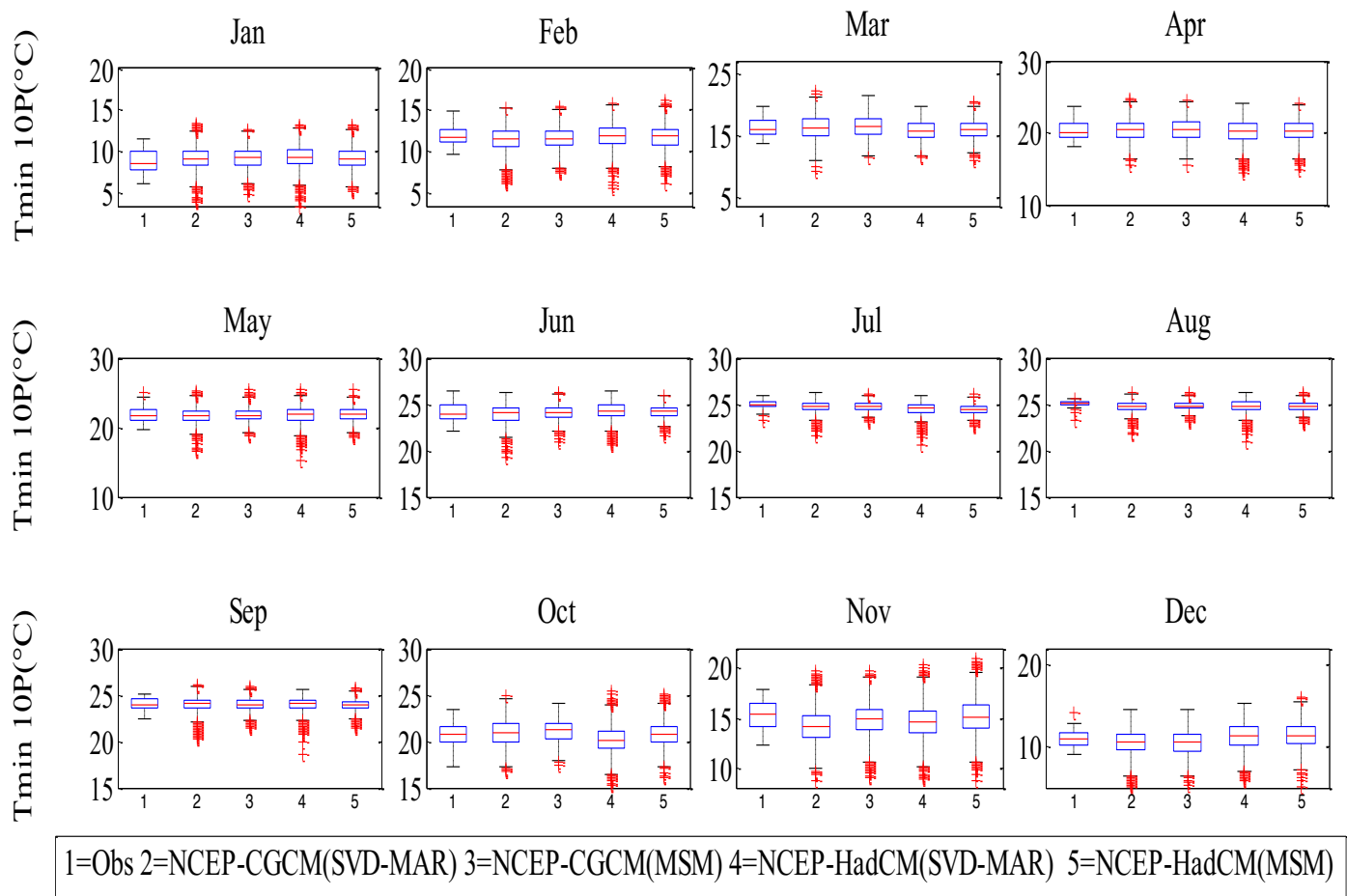


(b)

Figure 6.5: Boxplots of the Tmax90p for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at four stations in Bangladesh.



(a)



(b)

Figure 6.6: Boxplots of the $Tmin_{10p}$ for the observed and downscaled series for NCEP during (a) calibration and (b) validation periods at four stations in Bangladesh.

Table 6.1: MAE and RMSE values of $Tmax$ and $Tmin$ for NCEP at four stations in Bangladesh.

		NCEP-CGCM							
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
$Tmax$	Station 1	0.01	0.02	0.02	0.02	0.38	0.46	0.4	0.47
	Station 2	0.01	0.02	0.02	0.02	0.34	0.4	0.35	0.4
	Station 3	0.01	0.02	0.02	0.02	0.27	0.35	0.28	0.37
	Station 4	0.01	0.01	0.02	0.02	0.28	0.36	0.28	0.37
$Tmin$	Station 1	0.05	0.07	0.05	0.06	0.38	0.44	0.38	0.44
	Station 2	0.04	0.05	0.04	0.05	0.23	0.28	0.23	0.29
	Station 3	0.07	0.1	0.07	0.1	0.16	0.19	0.16	0.19
	Station 4	0.04	0.06	0.05	0.06	0.2	0.28	0.21	0.28

NCEP-HadCM									
Calibration Period					Validation Period				
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.01	0.02	0.01	0.02	0.45	0.49	0.46	0.5
	Station 2	0.01	0.01	0.02	0.03	0.48	0.54	0.48	0.54
	Station 3	0.02	0.02	0.02	0.03	0.36	0.44	0.35	0.44
	Station 4	0.02	0.02	0.02	0.03	0.37	0.46	0.36	0.46
T_{min}	Station 1	0.04	0.06	0.05	0.06	0.4	0.45	0.4	0.45
	Station 2	0.03	0.04	0.04	0.05	0.26	0.35	0.26	0.35
	Station 3	0.06	0.09	0.07	0.1	0.25	0.39	0.25	0.39
	Station 4	0.04	0.06	0.05	0.07	0.31	0.38	0.3	0.37

6.1.2 Spatial variability

This section presents the variability of the interstation correlations of daily T_{max} and T_{min} with respect to distance. Observed and simulated values of the average of monthly interstation correlations between each pair of stations versus distance between the stations are shown in Figures 6.7 and 6.8 respectively for daily T_{max} and T_{min} . The black solid line in the figures represents the best fit linear line for the observed interstation correlations. It is observed that the interstation correlations of daily T_{max} and T_{min} decrease with the increase of spatial distance. In addition, the figures show that both of the proposed models (SVD-MAR and MSM) were capable to capture the observed spatial variability of daily T_{max} and T_{min} in the simulated series quite acceptably during calibration as well as validation periods.

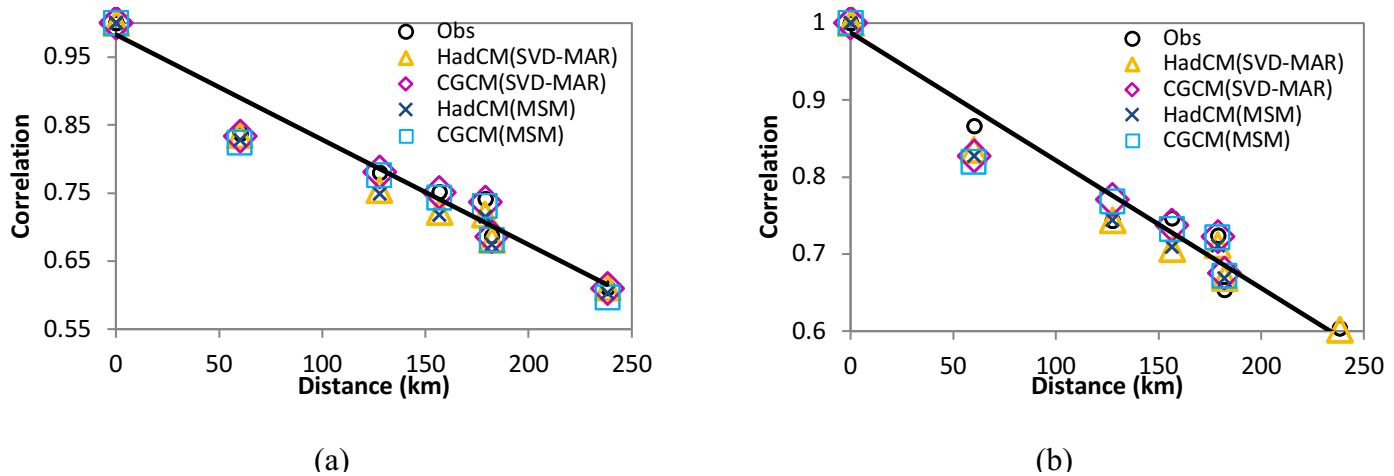


Figure 6.7: Relationship between spatial distance and interstation correlation of T_{max} during (a) calibration and (b) validation periods for the stations in Bangladesh.

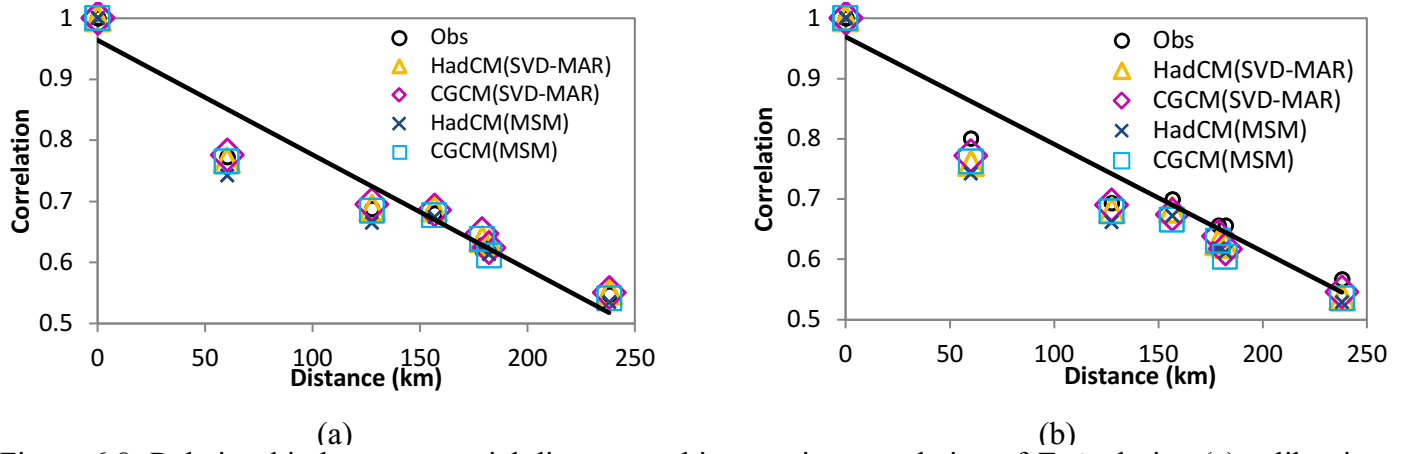


Figure 6.8: Relationship between spatial distance and interstation correlation of T_{min} during (a) calibration and (b) validation periods for the stations in Bangladesh.

Figures 6.9 to 6.12 show the graphical presentations of observed and simulated lag0 interstation correlations of daily T_{max} and T_{min} in each of the months for all combinations of station pairs. The simulated interstation correlations produced by SDM-MAR and MSM are compared with those of SDSM. Left panels of the figures show the results obtained by SVD-MAR and SDSM and the right panels show those of MSM. It is observed that both models, SVD-MAR and MSM are quite capable to capture the observed interstation correlations very accurately in the simulated series for both T_{max} and T_{min} , and for both NCEP (i.e., interpolated on CGCM and HadCM) during calibration period. During validation period also, both of the models efficiently reproduced the lag0 interstation correlations of daily T_{max} for both of the NCEP. The interstation correlations of daily T_{min} also were produced very well by both of the models during validation period. The figures depict that SDSM fairly underestimated the interstation correlations both for T_{max} and T_{min} during calibration as well as validation periods manifesting its inefficiency to capture the spatial dependency in the simulated T_{max} and T_{min} series.

Along with the graphical representations, the numerical evaluations also indicate the models' reproducibility of the observed interstation correlations in the simulated series. Table 6.2 presents the MAD, RMSD and R^2 values for lag0 interstation correlations of daily T_{max} and T_{min} for both of the NCEP interpolated on CGCM and HadCM. The values of MAD and RMSD produced by SVD-MAR and MSM are very low compared to those of SDSM. In case of SVD-MAR and MSM, during calibration period the values of MAD (RMSD) ranged between 0.01-0.02 (0.02-0.03) and 0.02 (0.02-0.04) for lag0 interstation correlations of T_{max} and T_{min} respectively. For SDSM the values of MAD (RMSD) were between 0.32-0.38 (0.39-0.45) and 0.29-0.30 (0.36-

0.38) respectively for T_{max} and T_{min} during the same period. The R^2 values produced by SVD-MAR and MSM ranged between 0.96-0.98 and 0.95-0.98 respectively for T_{max} and T_{min} interstation correlations for both of the NCEP, whereas, for SDSM those values were between 0.03-0.04 for T_{max} and 0.23-0.45 for T_{min} . During validation period the values of MAD (RMSD) produced by SVD-MAR and MSM were 0.04 (0.06) and 0.03-0.04 (0.05-0.06) respectively for T_{max} and T_{min} interstation correlations. In case of SDSM, these values ranged between 0.32-0.38 (0.39-0.46) and 0.31-0.32 (0.38-0.39) respectively. The R^2 values ranged between 0.73-0.76 and 0.89-0.91 respectively for T_{max} and T_{min} for both of the models SVD-MAR and MSM during validation period. For SDSM, these values ranged between 0.05-0.06 and 0.31-0.45 for T_{max} and T_{min} respectively.

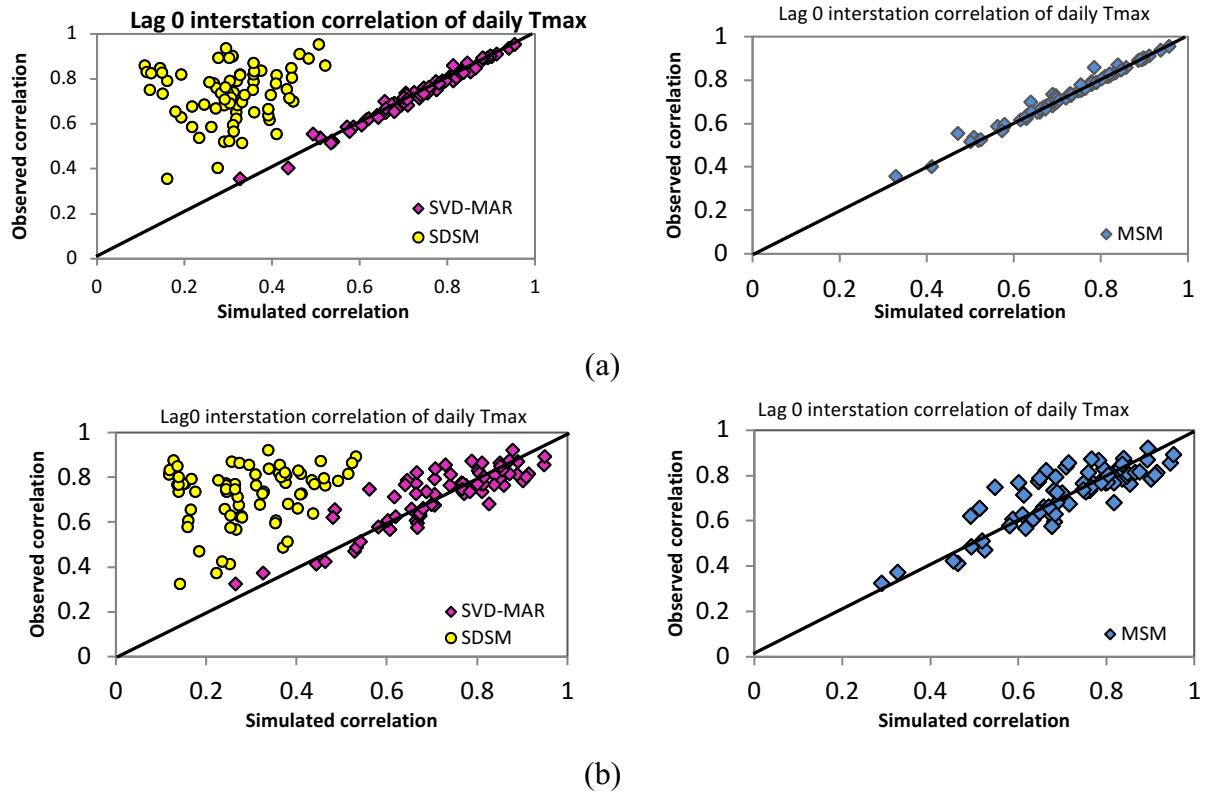
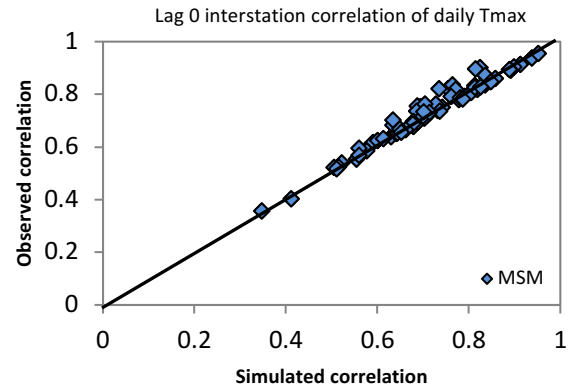
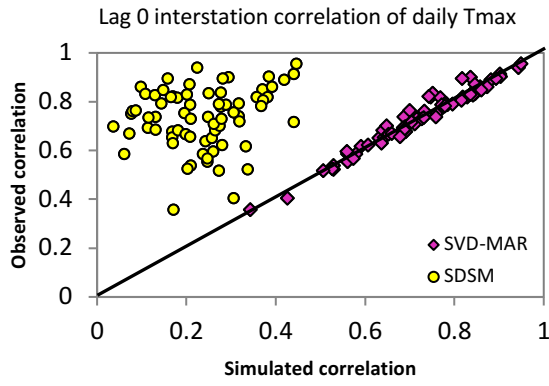
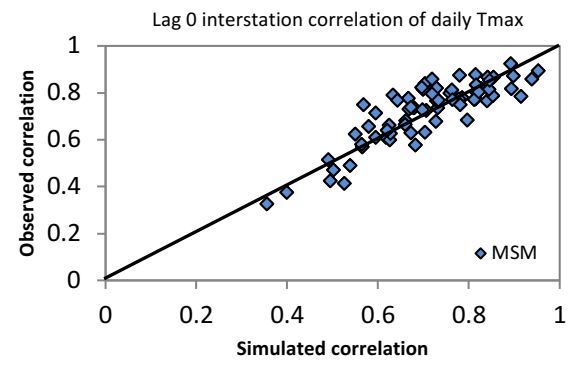
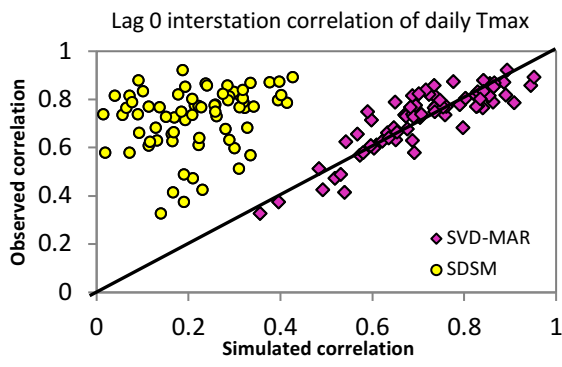


Figure 6.9: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Bangladesh.

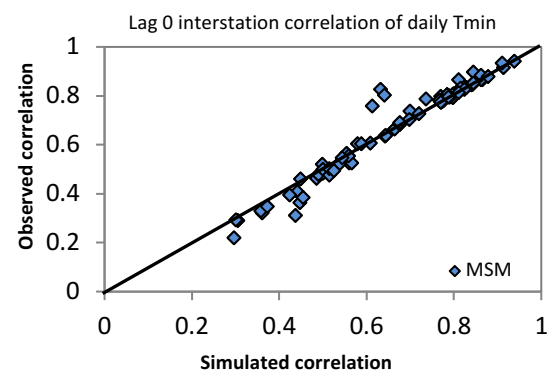
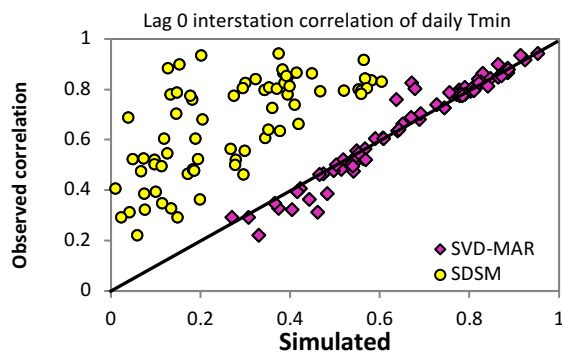


(a)

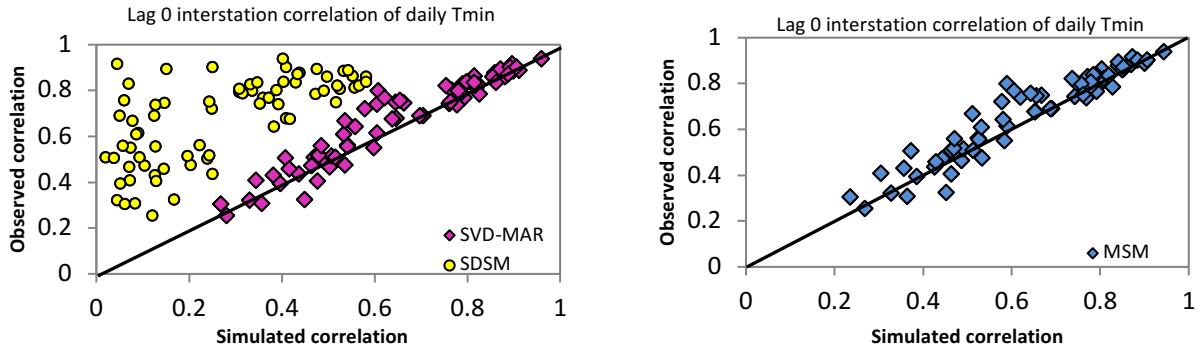


(b)

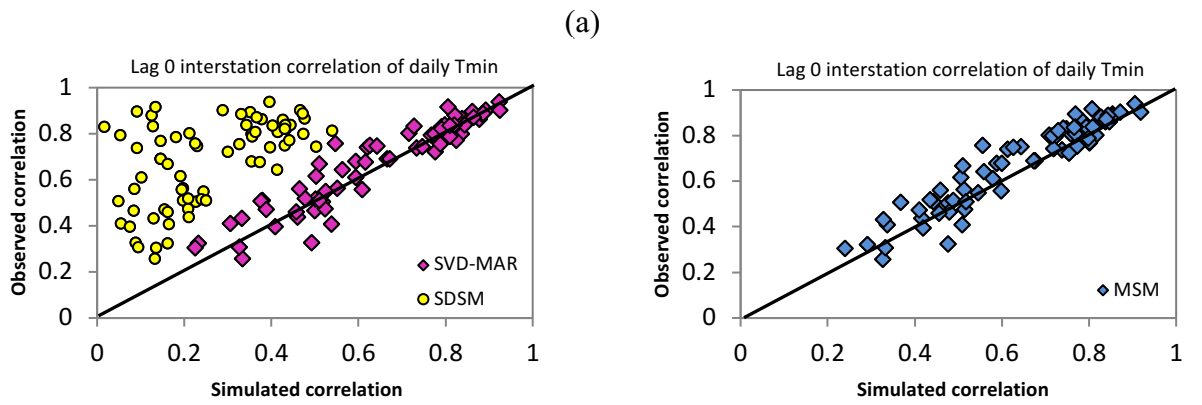
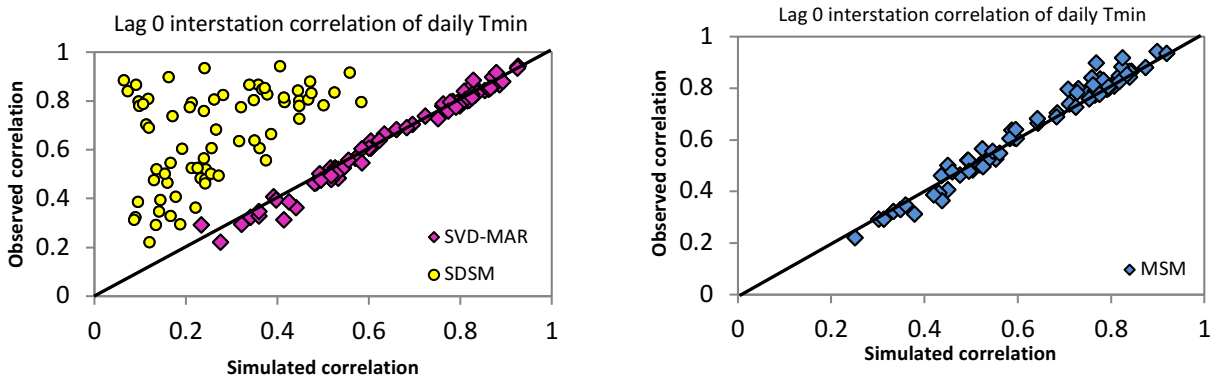
Figure 6.10: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Bangladesh.



(a)



(b)
Figure 6.11: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Bangladesh.



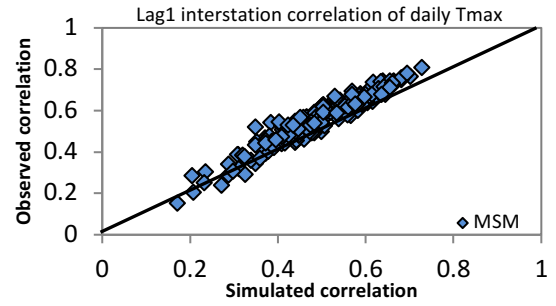
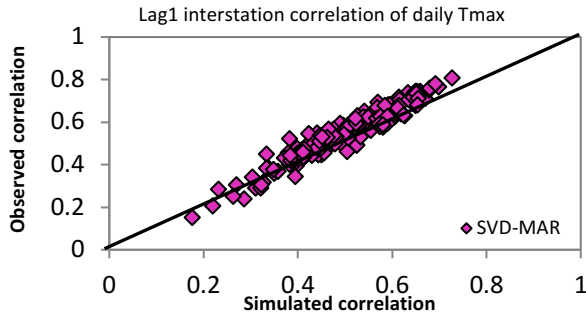
(b)
Figure 6.12: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Bangladesh.

Table 6.2: Numerical analysis for lag0 interstation correlations of daily *Tmax* and *Tmin* at four stations in Bangladesh for NCEP.

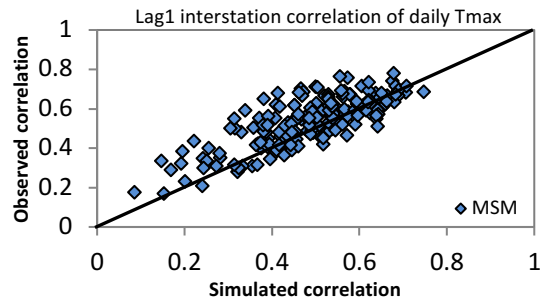
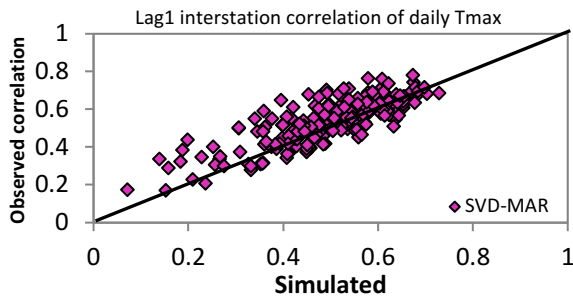
NCEP-CGCM										
		SVD-MAR			MSM			SDSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag0 correlation	0.01	0.02	0.98	0.01	0.02	0.98	0.32	0.39	0.03
	<i>Tmin</i> lag0 correlation	0.02	0.04	0.96	0.02	0.04	0.95	0.29	0.36	0.45
Validation	<i>Tmax</i> lag0 correlation	0.04	0.06	0.73	0.04	0.06	0.73	0.32	0.39	0.05
	<i>Tmin</i> lag0 correlation	0.03	0.05	0.91	0.04	0.06	0.91	0.31	0.38	0.45
NCEP-HadCM										
		SVD-MAR			MSM			SDSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag0 correlation	0.01	0.03	0.96	0.02	0.03	0.97	0.38	0.45	0.04
	<i>Tmin</i> lag0 correlation	0.02	0.02	0.98	0.02	0.03	0.98	0.3	0.38	0.23
Validation	<i>Tmax</i> lag0 correlation	0.04	0.06	0.76	0.04	0.06	0.74	0.38	0.46	0.06
	<i>Tmin</i> lag0 correlation	0.04	0.06	0.89	0.04	0.06	0.9	0.32	0.39	0.31

Lag1 interstation correlations of daily *Tmax* and *Tmin* are presented in Figures 6.13 to 6.16. These figures indicate that both SVD-MAR and MSM accurately reproduced the lag1 interstation correlations of daily *Tmax* for both of the NCEP during calibration as well as validation periods. For *Tmin* also, the lag1 interstation correlations were well reproduced by both of the models for both NCEP during calibration period. However, both models slightly underestimated the lag1 interstation correlations of daily *Tmin* during validation period especially for those areas where the observed correlations are relatively high.

Numerical analysis (Table 6.3) shows that MAD and RMSD values for lag1 inter station correlations are very low for both of the NCEP especially during calibration period. The values of MAD (RMSD) during calibration period ranged between 0.05-0.07 (0.06-0.07) and 0.03-0.05 (0.04-0.07) respectively for *Tmax* and *Tmin* lag1 inter station correlations for both SVD-MAR and MSM models. The R² values were between 0.93-0.96 and 0.95-0.97 respectively for *Tmax* and *Tmin*. During validation period the values of MAD (RMSD) ranged between 0.06-0.07 (0.08-0.1) and 0.09-0.1 (0.1-0.12) respectively for *Tmax* and *Tmin* and the R² values were between 0.62-0.72 and 0.83-0.86 respectively.

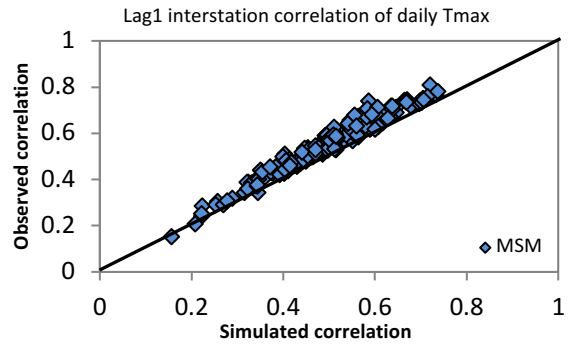
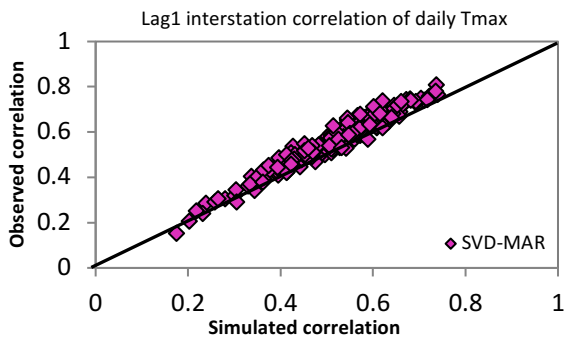


(a)

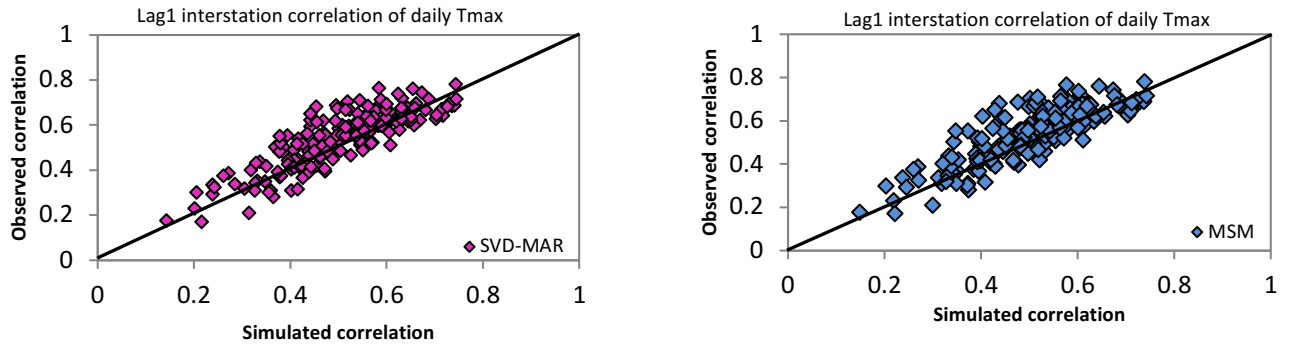


(b)

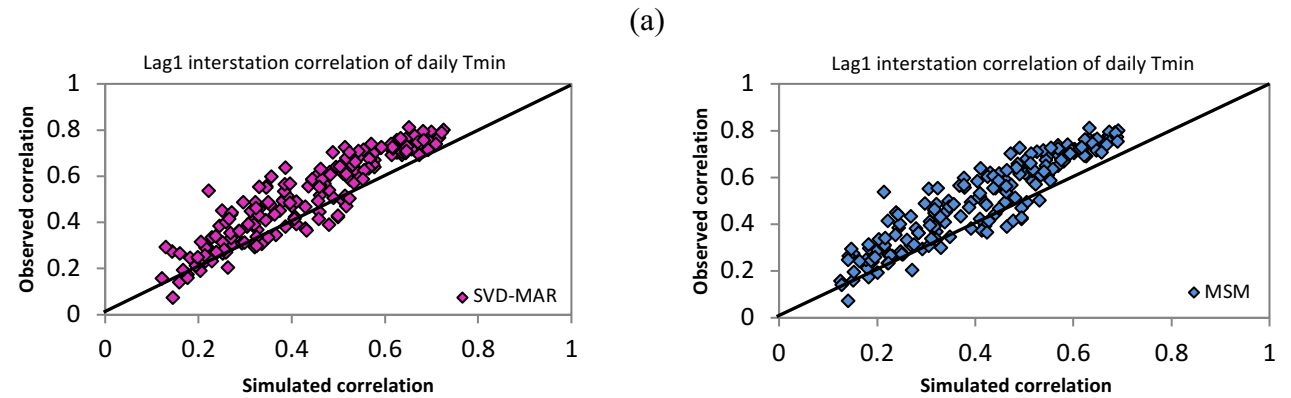
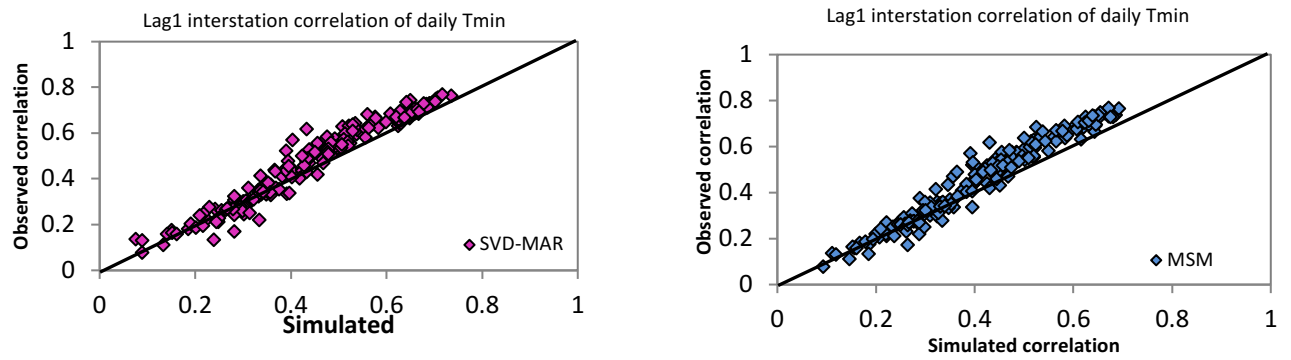
Figure 6.13: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Bangladesh.



(a)



(b)
Figure 6.14: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Bangladesh.



(b)
Figure 6.15: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM for the stations in Bangladesh.

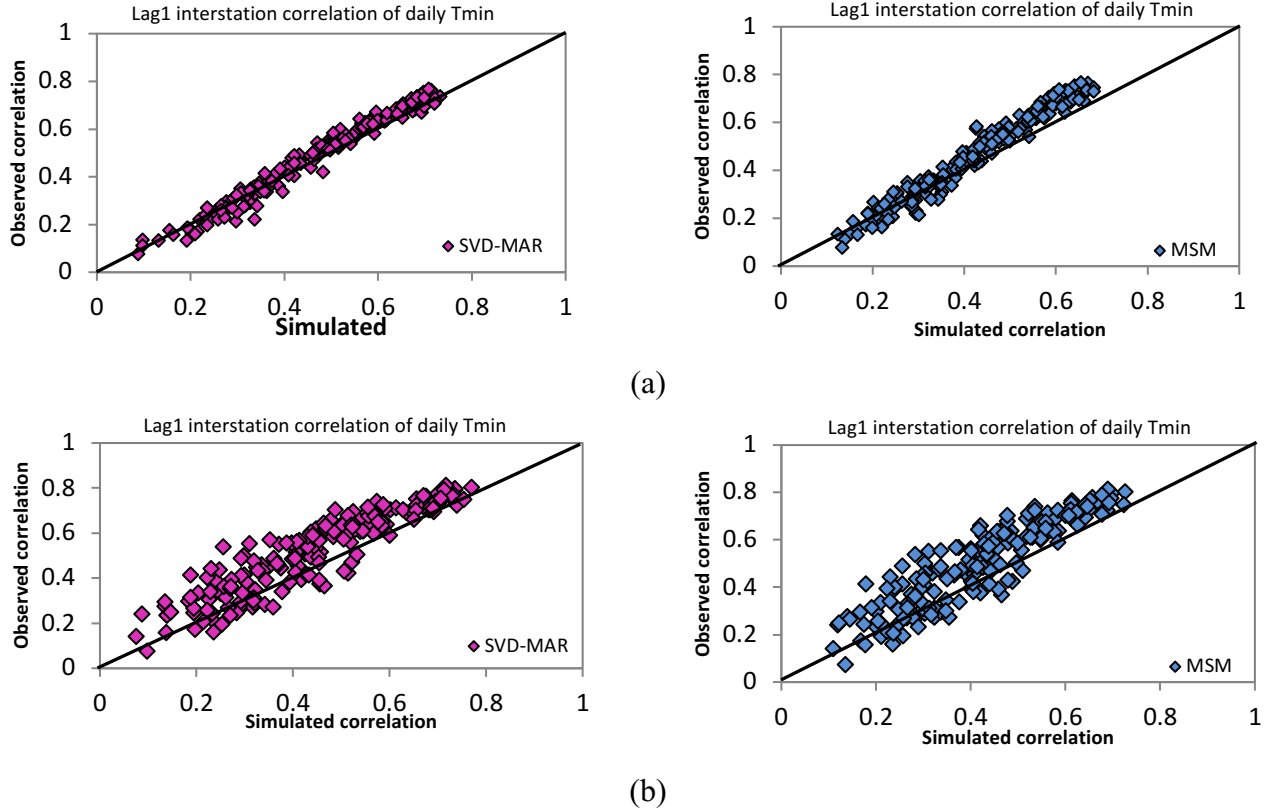


Figure 6.16: Lag1 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM for the stations in Bangladesh.

Table 6.3: Numerical analysis for lag1 interstation correlations of daily T_{max} and T_{min} at four stations in Bangladesh for NCEP.

		NCEP-CGCM					
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag1 correlation	0.06	0.06	0.93	0.07	0.07	0.93
	T_{min} lag1 correlation	0.04	0.05	0.95	0.05	0.07	0.96
Validation	T_{max} lag1 correlation	0.07	0.09	0.66	0.07	0.1	0.62
	T_{min} lag1 correlation	0.09	0.11	0.86	0.1	0.12	0.86
		NCEP-HadCM					
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag1 correlation	0.05	0.06	0.95	0.06	0.06	0.96
	T_{min} lag1 correlation	0.03	0.04	0.97	0.05	0.06	0.96
Validation	T_{max} lag1 correlation	0.06	0.08	0.72	0.06	0.08	0.7
	T_{min} lag1 correlation	0.09	0.1	0.84	0.1	0.11	0.83

6.1.3 Temporal dependency

Like previous chapter, the reproducibility of temporal dependencies is evaluated in terms of reproducing the observed autocorrelation coefficients in simulated series at each station. The observed versus simulated serial autocorrelations of lags from one to three at Jessore station are presented in Figures 6.17 and 6.18 for T_{max} and T_{min} respectively. Results for rest of the stations are given in Appendix D. These figures demonstrate that both of the proposed models are efficient to reproduce the observed autocorrelation almost accurately for T_{max} and T_{min} during the calibration as well as validation periods for both of the NCEP interpolated on CGCM and HadCM. It is observed that, although SVD-MAR and MSM reproduced similar autocorrelations, SVD-MAR was able to produce better results than those of MSM especially for lag2 and lag3 autocorrelations of daily T_{max} .

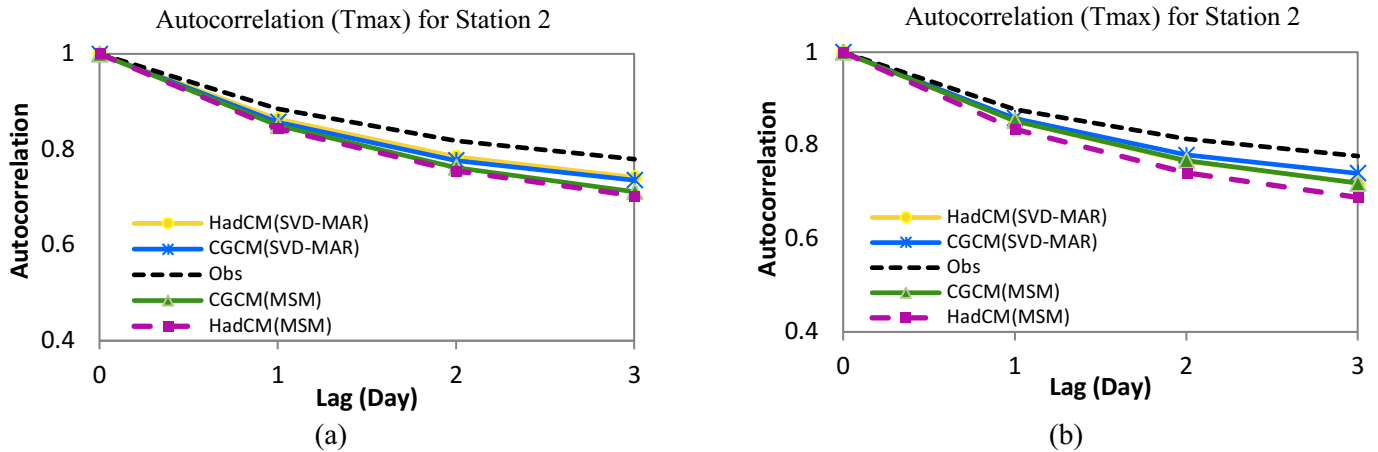


Figure 6.17: Observed and downscaled autocorrelation coefficients of T_{max} at Jessore station during (a) calibration and (b) validation periods for NCEP.

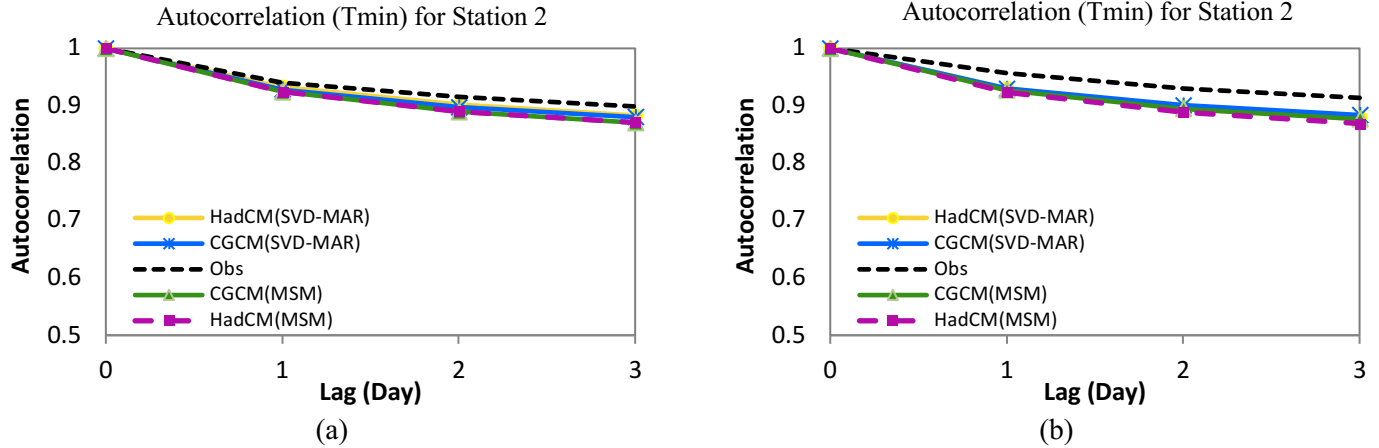
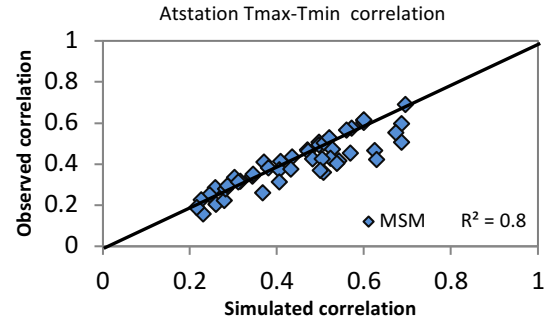
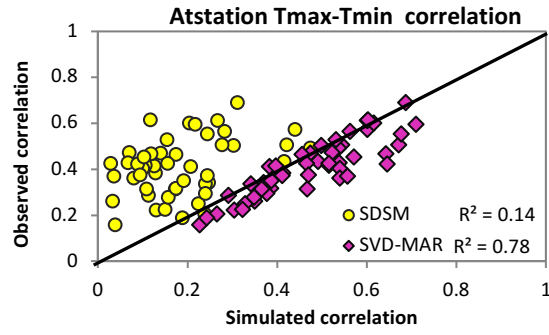


Figure 6.18: Observed and downscaled autocorrelation coefficients of T_{min} at Jessore station during (a) calibration and (b) validation periods for NCEP.

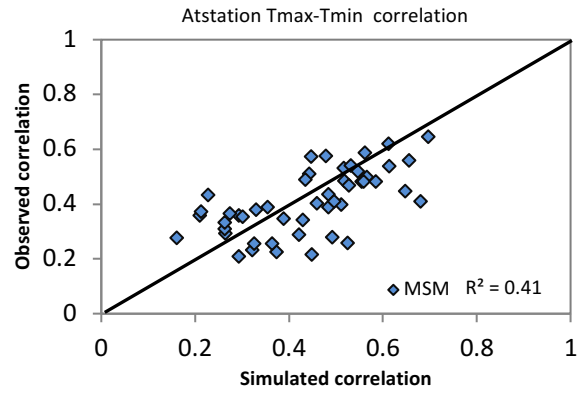
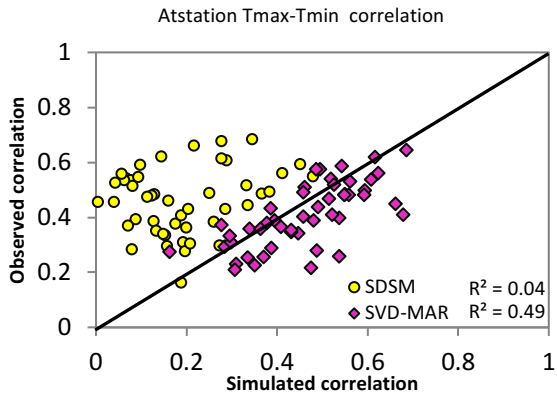
6.1.4 Correlation between daily T_{max} and T_{min} and DTR

At-site correlations between daily T_{max} and T_{min} produced by SVD-MAR, MSM and SDSM are presented in Figures 6.19 and 6.20. It is observed that during calibration period SVD-MAR and MSM reproduced the correlations between daily T_{max} and T_{min} quite well and better than SDSM for both of the NCEP. During calibration period the values of R^2 for SVD-MAR and MSM were between 0.78-0.8 for both of the NCEP interpolated on CGCM and HadCM, whereas for SDSM the values ranged between 0.05-0.14 (Figures 6.19 and 6.20). Although the results during validation period are not as good as during calibration period, those are better than SDSM. The R^2 values during validation period produced by SVD-MAR and MSM were between 0.41-0.56, and 0.04 for SDSM for both of the NCEP.

Table 6.4 shows that during calibration period the values of MAD (RMSD) produced by SVD-MAR and MSM ranged between 0.04-0.08 (0.05-0.1) for all the stations for both of the NCEP, whereas, those values for SDSM ranged between 0.17-0.25 (0.21-0.29). During validation period the values of MAD (RMSD) for SVD-MAR and MSM ranged between 0.06-0.11 (0.07-0.13) for both of the NCEP. For SDSM those values ranged between 0.13-0.29 (0.16-0.31).

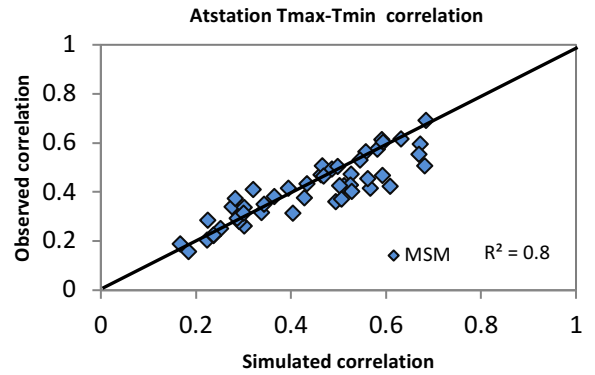
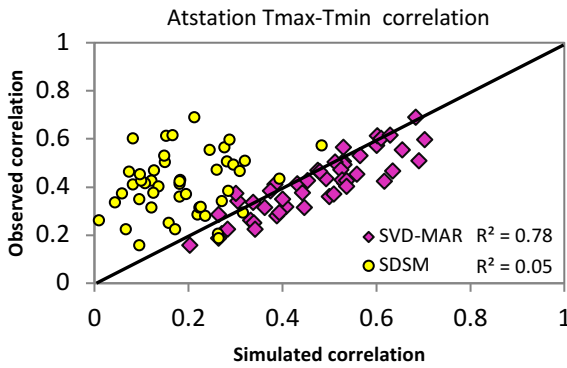


(a)



(b)

Figure 6.19: Correlations between daily T_{max} and T_{min} at four stations in Bangladesh during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM.



(a)

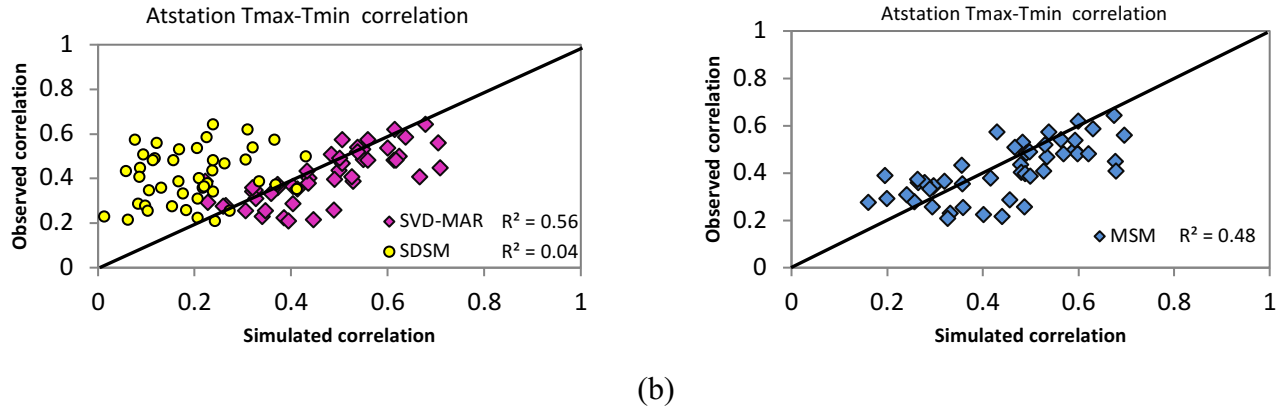


Figure 6.20: Correlations between daily T_{max} and T_{min} at four stations in Bangladesh during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM.

Table 6.4: Numerical analysis for the correlations between daily T_{max} and T_{min} at four stations in Bangladesh for NCEP.

NCEP-CGCM												
Calibration Period							Validation Period					
	SVD-MAR		MSM		SDSM		MSM		SVD-MAR		SDSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.06	0.08	0.04	0.07	0.25	0.29	0.07	0.09	0.09	0.11	0.25	0.28
Station 2	0.06	0.07	0.04	0.05	0.17	0.21	0.09	0.13	0.1	0.13	0.13	0.16
Station 3	0.08	0.1	0.07	0.1	0.25	0.26	0.1	0.12	0.11	0.12	0.23	0.27
Station 4	0.08	0.1	0.05	0.08	0.24	0.26	0.06	0.07	0.07	0.08	0.29	0.31
NCEP-HadCM												
Calibration Period							Validation Period					
	SVD-MAR		MSM		SDSM		SVD-MAR		MSM		SDSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.06	0.08	0.05	0.06	0.22	0.26	0.06	0.1	0.09	0.11	0.26	0.28
Station 2	0.06	0.07	0.04	0.05	0.23	0.26	0.08	0.11	0.09	0.11	0.19	0.2
Station 3	0.08	0.1	0.07	0.1	0.25	0.28	0.09	0.12	0.09	0.11	0.24	0.29
Station 4	0.07	0.08	0.05	0.07	0.21	0.25	0.07	0.09	0.08	0.1	0.25	0.3

In fact, the characteristics of statistically downscaled temperature series are influenced partly by the deterministic components which are directly dependent on the large-scale predictors, and partly by stochastic components. Actually the stochastic components of the models are simulated based on the characteristic which are inherited during the calibration period. As a result, the simulated series of stochastic components during validation period follow the similar pattern to those of the calibration period. Therefore, if the observed data during validation period differ much from those of calibration period, the simulated series also differ from the observed ones during the validation period. In this study, the observed correlation coefficients between daily

T_{max} and T_{min} at some of the stations differ much during validation period from those of calibration period. The observed at-site correlation coefficients between daily T_{max} and T_{min} during calibration and validation periods for selected months are shown in Figure 6.21. The figures show that the observed correlation coefficients during validation period differ substantially from those of calibration period at each of four stations in the month of January and at station 2 in the month of June. In October also, the differences are noticeable at some of the stations. The correlations between daily T_{max} and T_{min} for the months of January, June and October are presented as examples for illustration, but similar types of differences exist in other months also. The differences in observed correlations between calibration and validation periods are the reasons for not capturing observed correlations between daily T_{max} and T_{min} very well in simulated series during validation period.

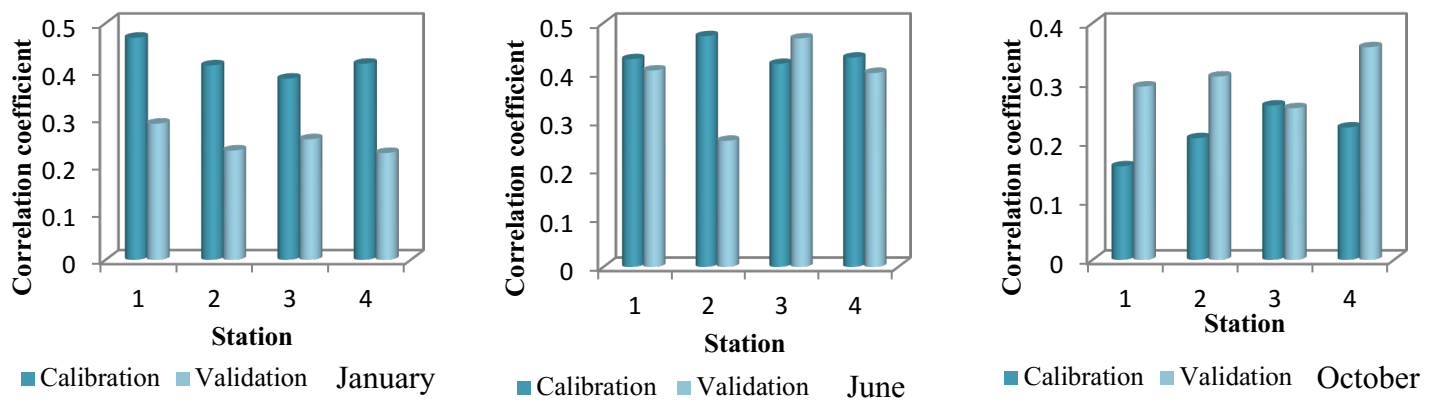
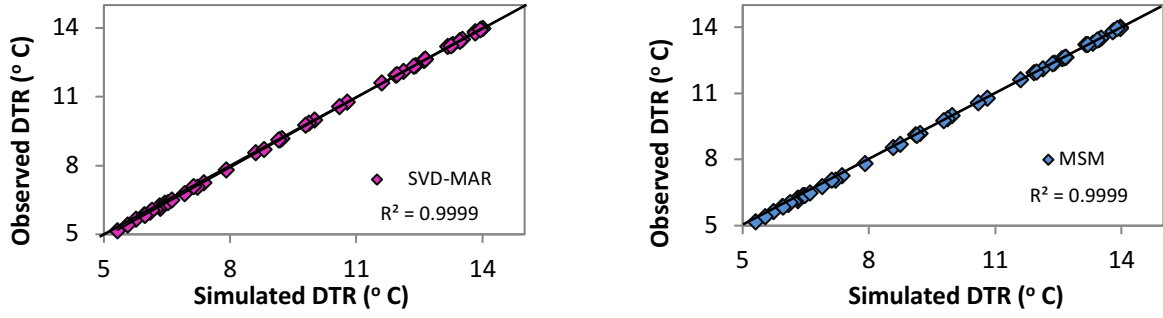
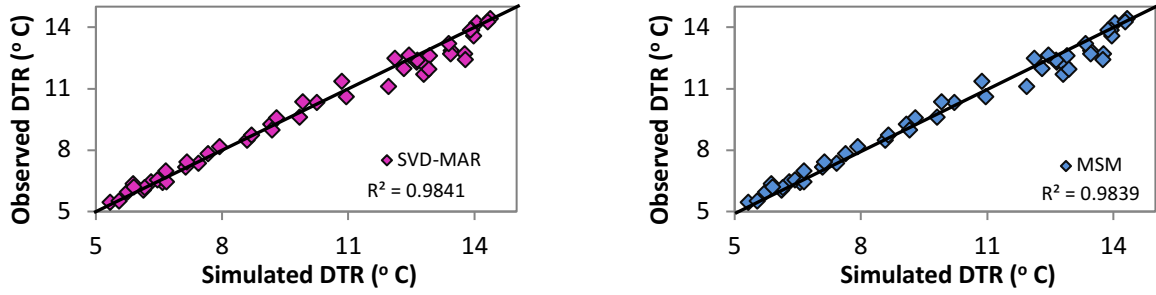


Figure 6.21: Observed at-site correlation coefficients between daily T_{max} and T_{min} during calibration and validation periods.

The figures 6.22 and 6.23 show the observed versus downscaled average DTR in each month at all of four stations for both of the NCEP interpolated on CGCM and HadCM. These figures show that both SVD-MAR and MSM produced DTR perfectly during calibration period for both of the NCEP. During validation period also, both models were found very efficient to produce DTR accurately in simulated series.

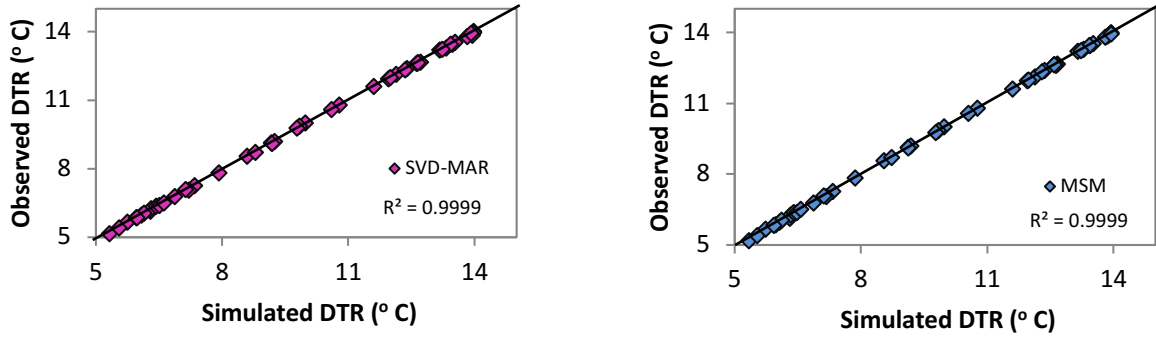


(a)

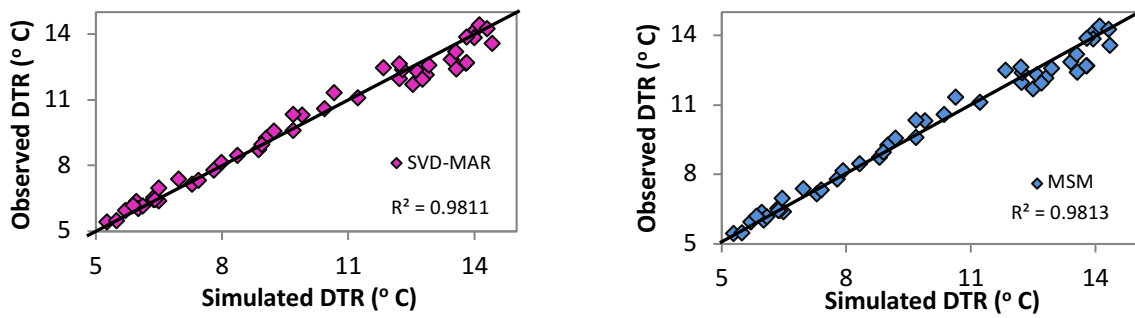


(b)

Figure 6.22: Average DTR in each month at four stations in Bangladesh during (a) calibration and (b) validation periods for the NCEP interpolated on CGCM.



(a)

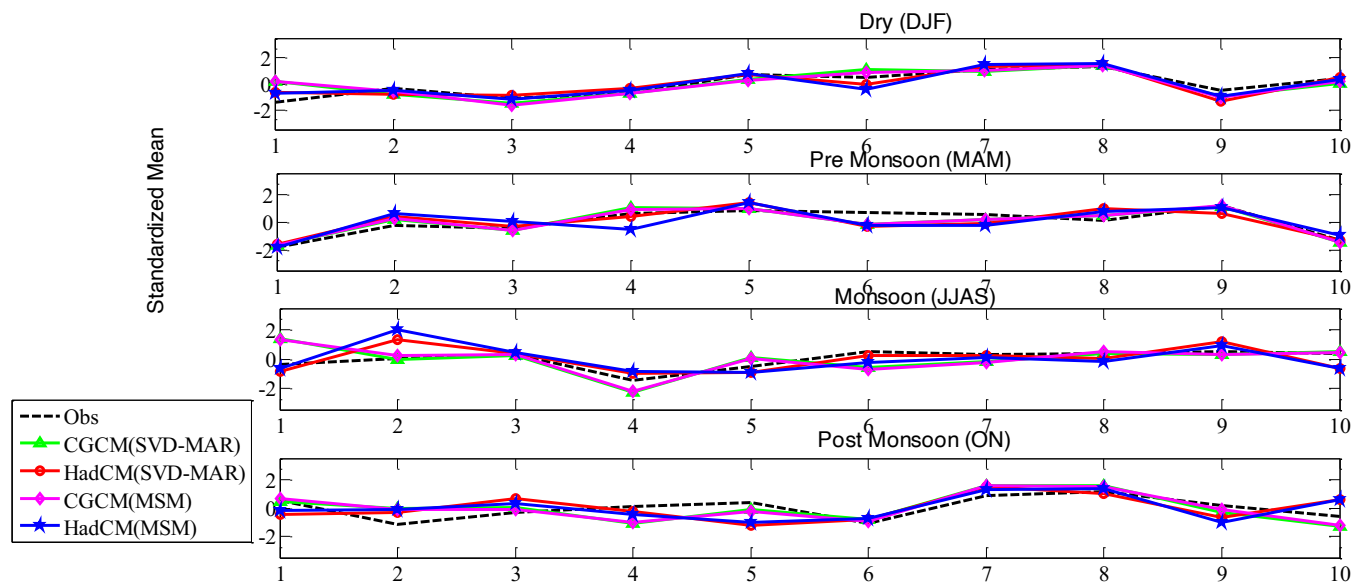


(b)

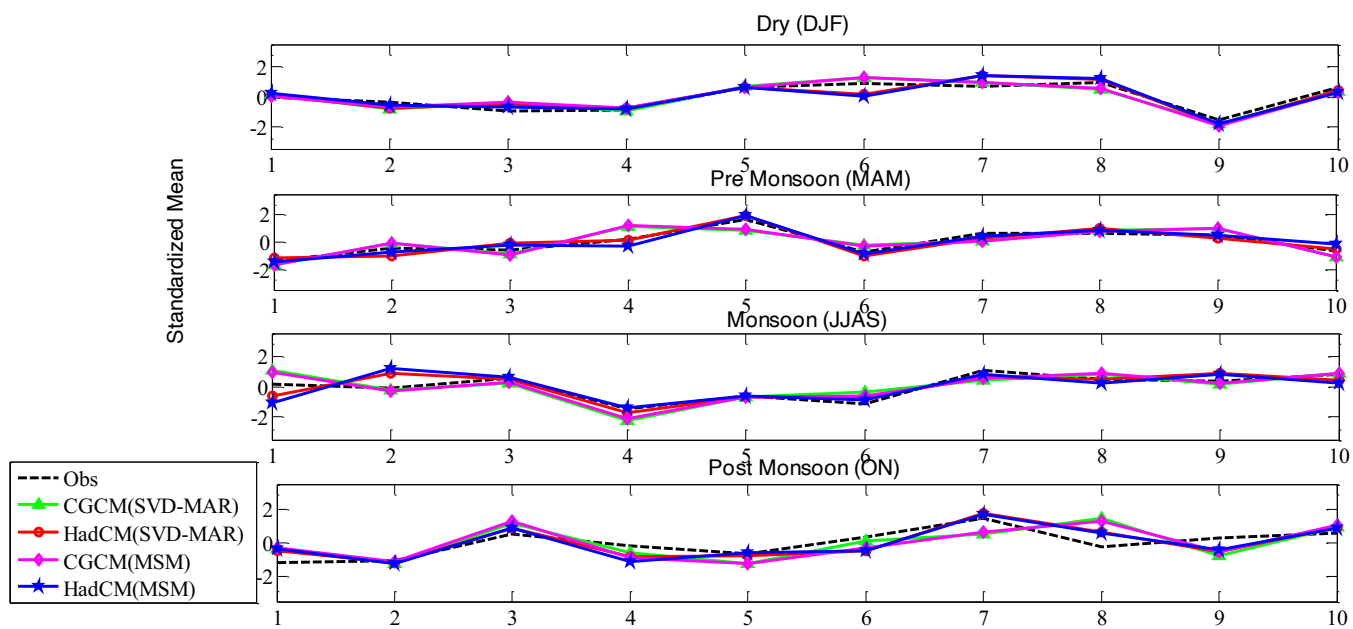
Figure 6.23: Average DTR in each month at four stations in Bangladesh during (a) calibration and (b) validation periods for the NCEP interpolated on HadCM.

6.1.5 Interannual anomalies of the standardized indices

The interannual anomalies of the standardized seasonal means and STD of T_{max} and T_{min} and standardized seasonal T_{max90p} and T_{min10p} indices are presented in Figures 6.24 to 6.29. The standardized seasonal indices are calculated for each season over 10 years during calibration and validation periods. It should be mentioned that the seasonal classification in Bangladesh (from hydro-meteorological point of view) is as follows: December-January-February belong to dry; March-April-May belong to pre-monsoon; June-July-August-September belong to monsoon; and October-November to post-monsoon season. Graphical representations show that, in general the annual variability in the simulated series follow those of the observed ones for these standardized seasonal indices. In case of standardized seasonal means of T_{max} both models were able to capture the observed Interannual variability during calibration and validation periods. However, some exceptions were observed in very few years for the NCEP interpolated on CGCM (Figure 6.24). For STD of T_{max} also, some deviations were observed by both of the models during calibration and validation periods (Figure 6.25). The standardized seasonal T_{max90p} index was reproduced acceptably by both of the models during calibration period. However, during validation period few deviations were observed for the NCEP interpolated on HadCM (Figure 6.26). Figure 6.27 shows that Interannual variability in standardized means of T_{min} were captured well for both of the NCEP during calibration period and also for validation period with few exceptions. STD of T_{min} were reproduced well in most of the years except for post monsoon season during validation period (Figures 6.28). Standardized T_{min10p} was simulated well by both of the models for during calibration period. During validation period also, this index was produced acceptably for most of the years (Figure 6.29).

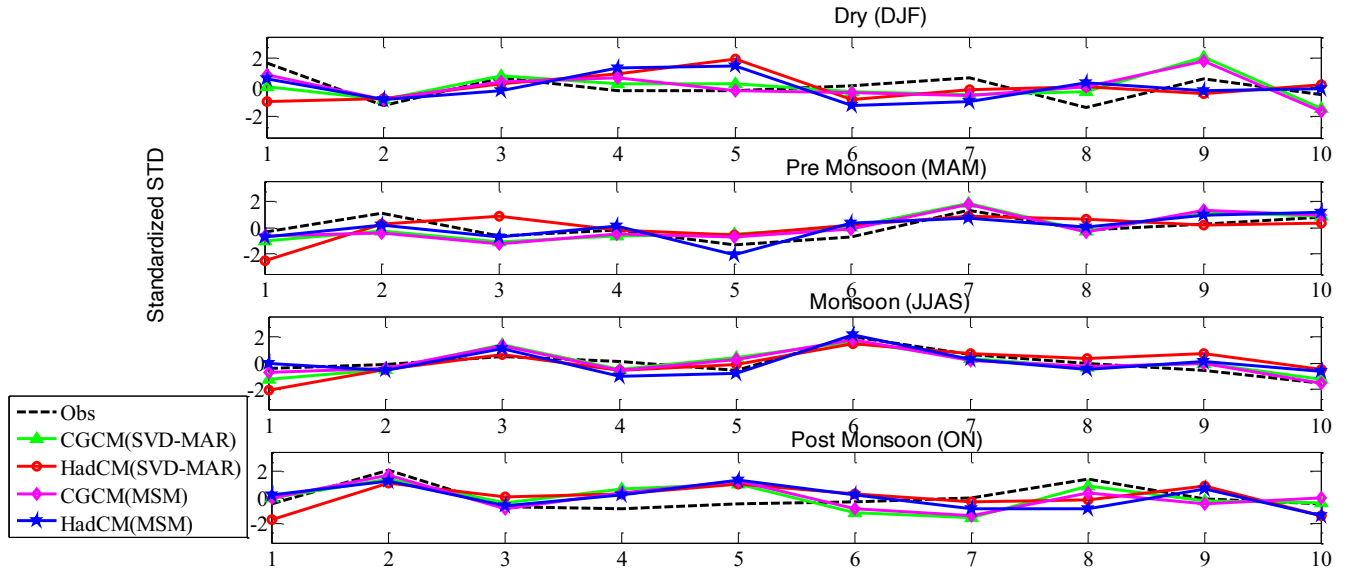


(a)

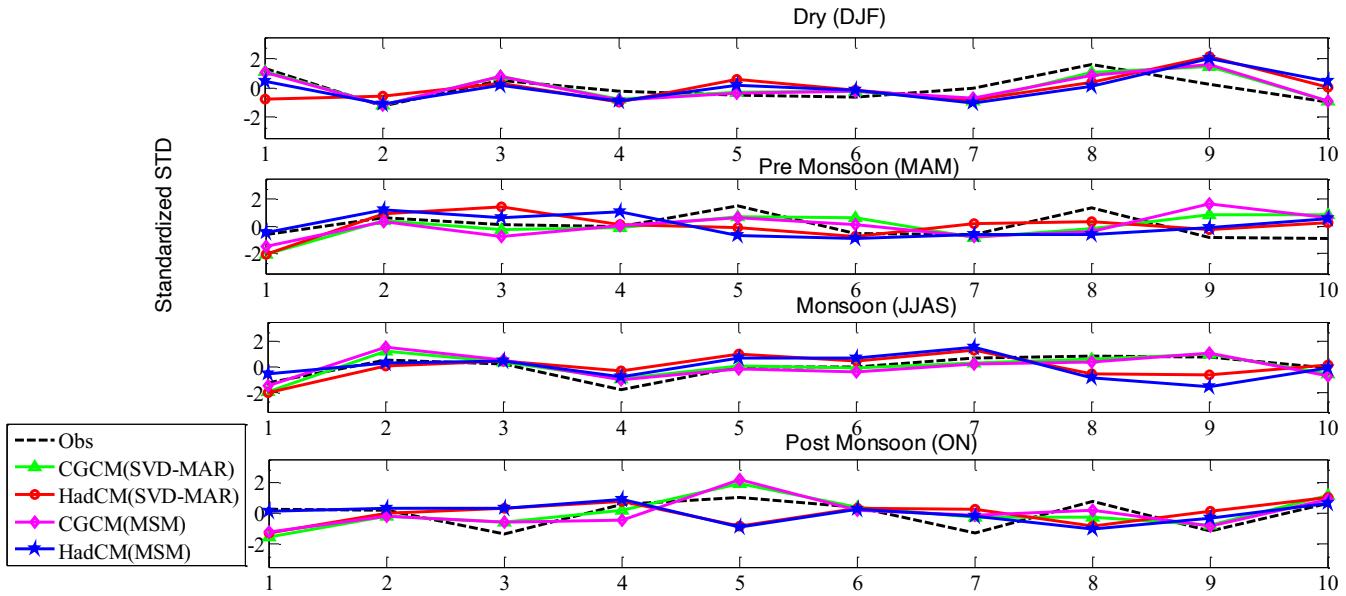


(b)

Figure 6.24: Interannual anomalies of standardized seasonal mean of T_{max} during (a) calibration and (b) validation periods at four stations in Bangladesh.

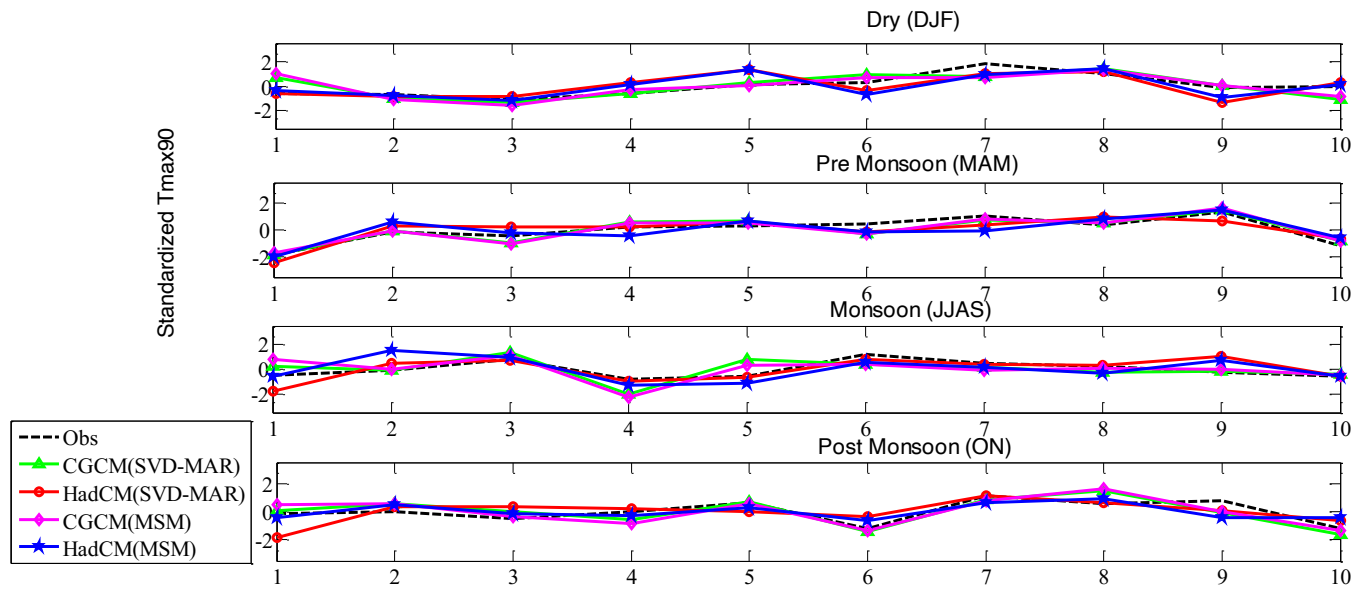


(a)

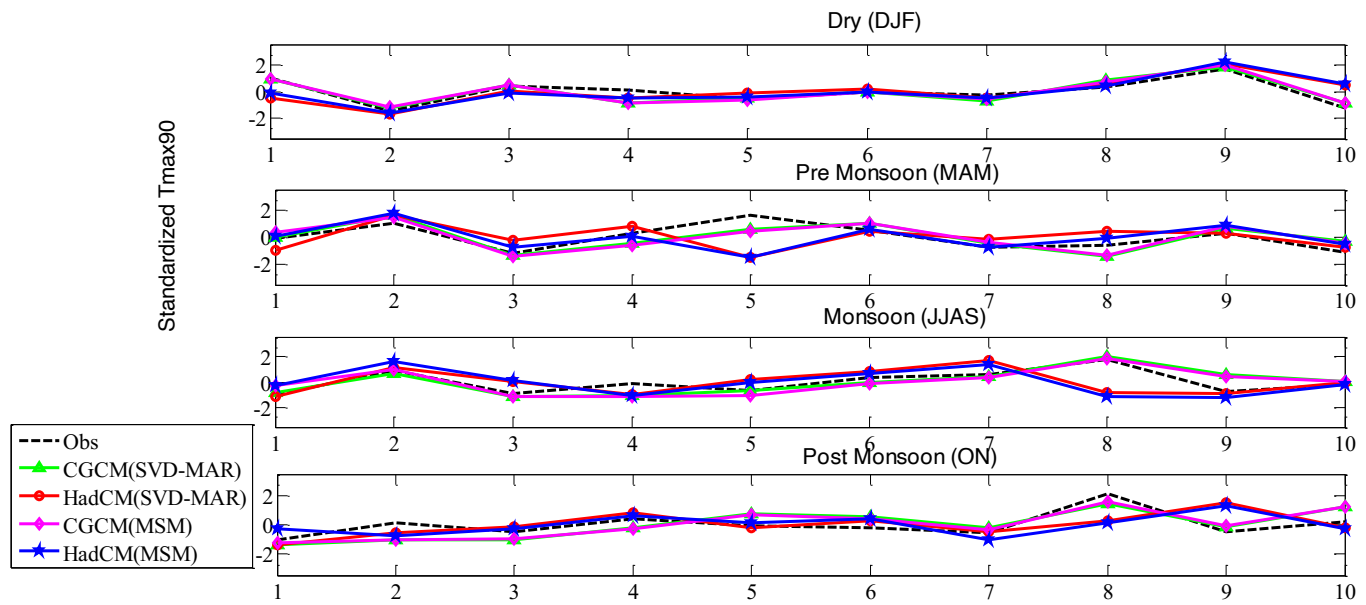


(b)

Figure 6.25: Interannual anomalies of standardized seasonal STD of T_{max} during (a) calibration and (b) validation periods at four stations in Bangladesh.

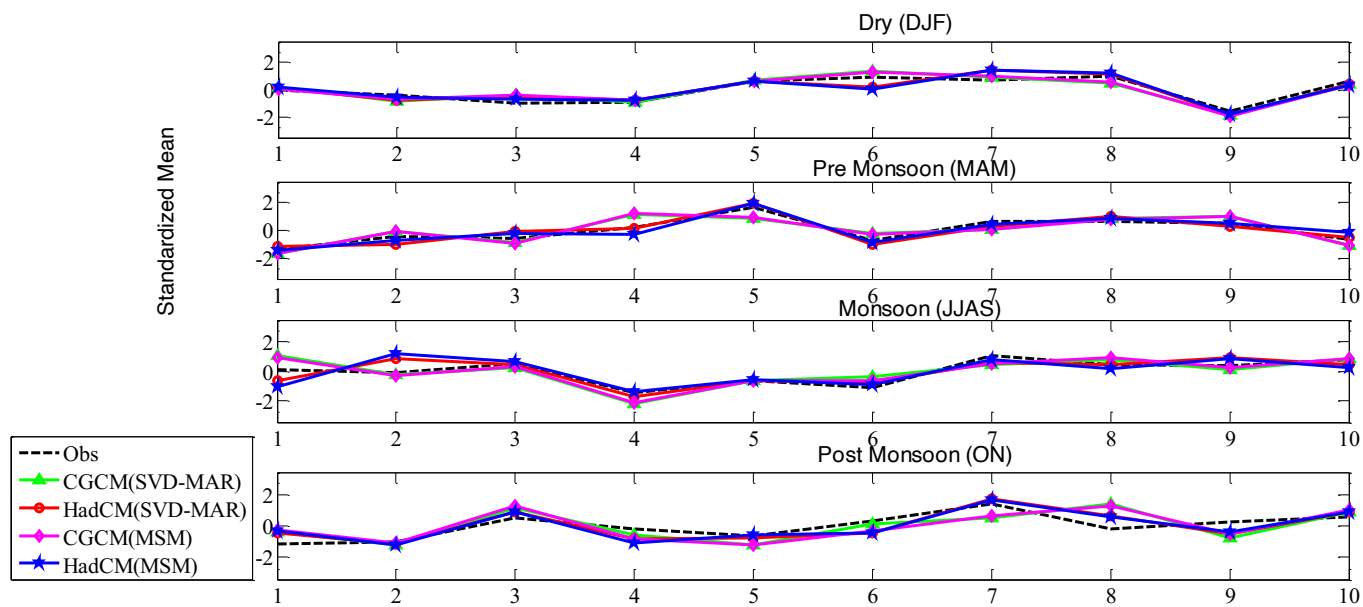


(a)

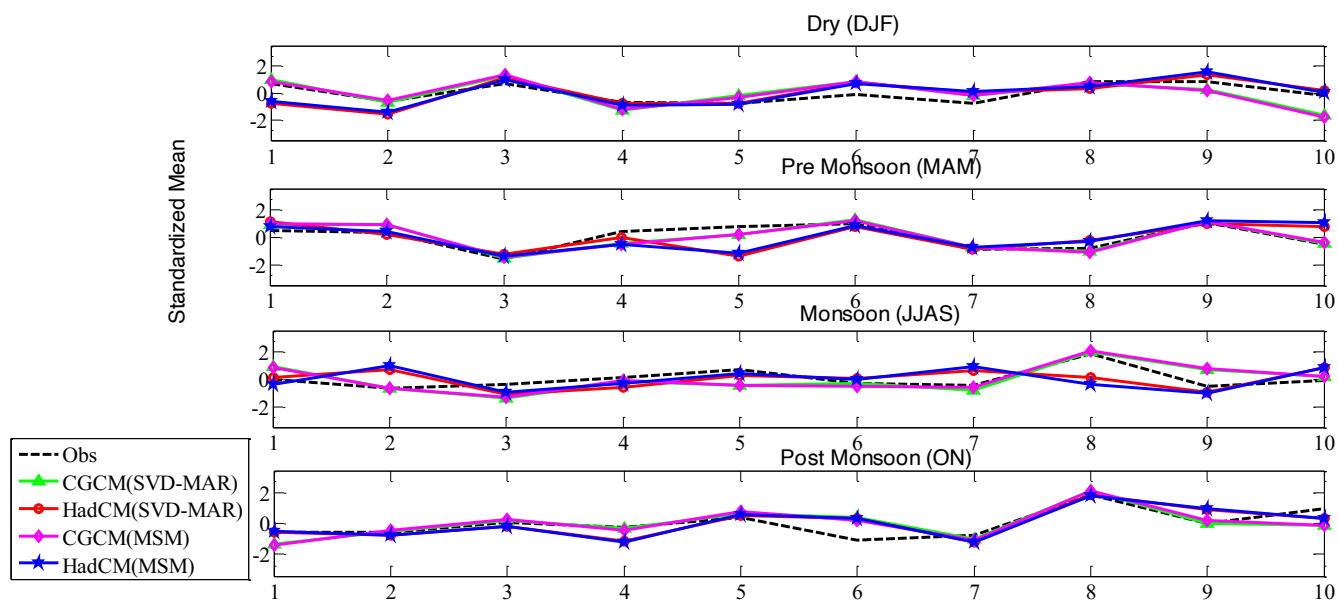


(b)

Figure 6.26: Interannual anomalies of standardized seasonal Tmax90p during (a) calibration and (b) validation periods at four stations in Bangladesh.



(a)



(b)

Figure 6.27: Interannual anomalies of standardized seasonal mean of T_{min} during (a) calibration and (b) validation periods at four stations in Bangladesh.

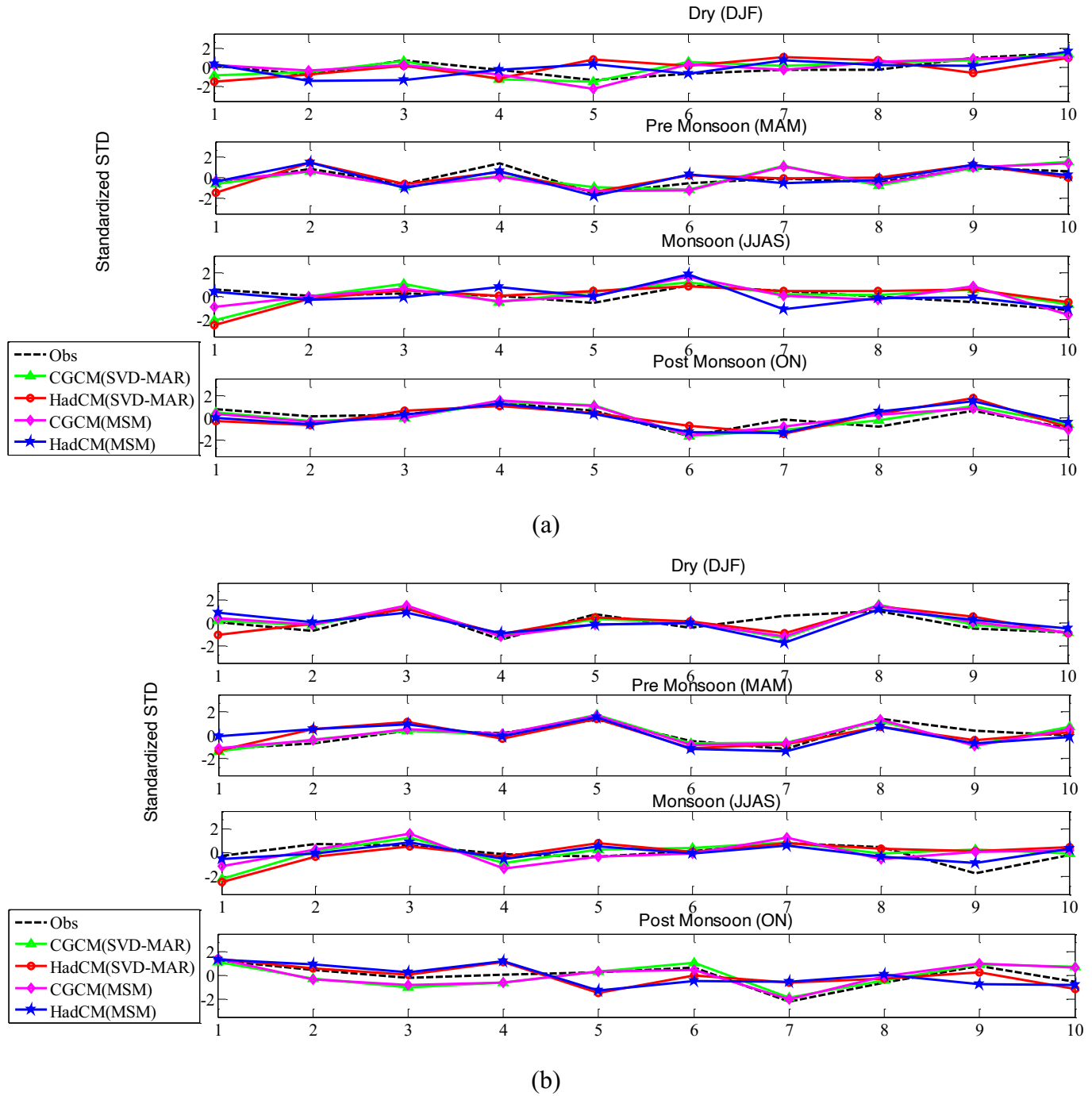
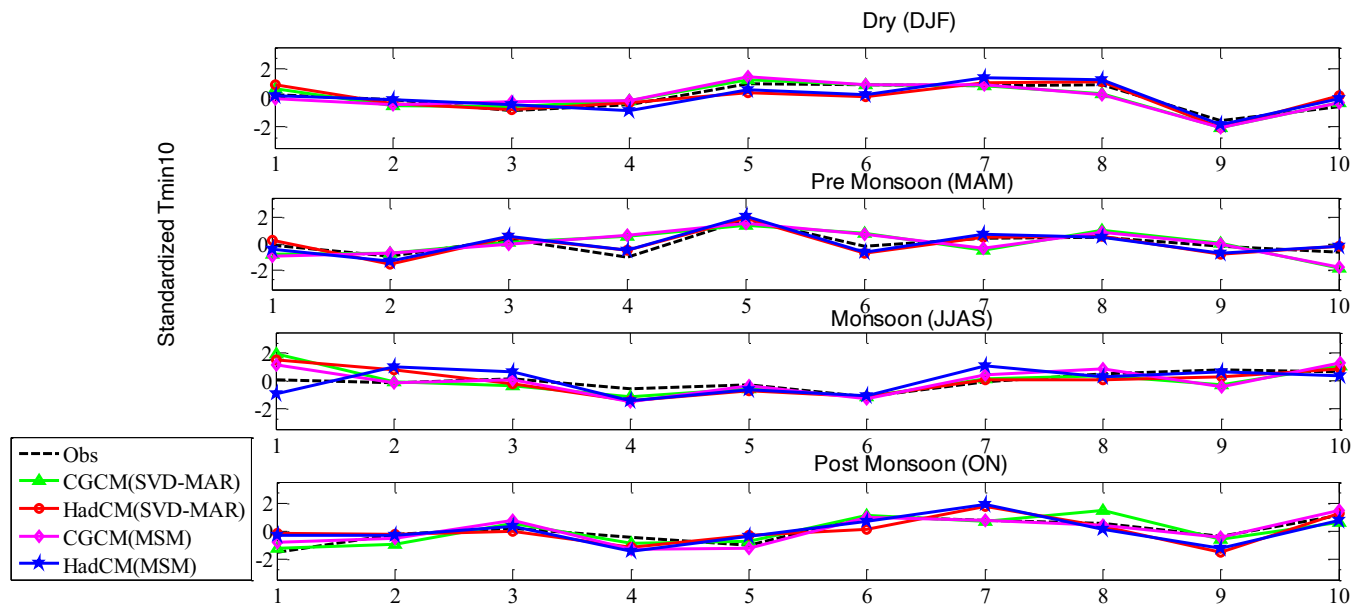
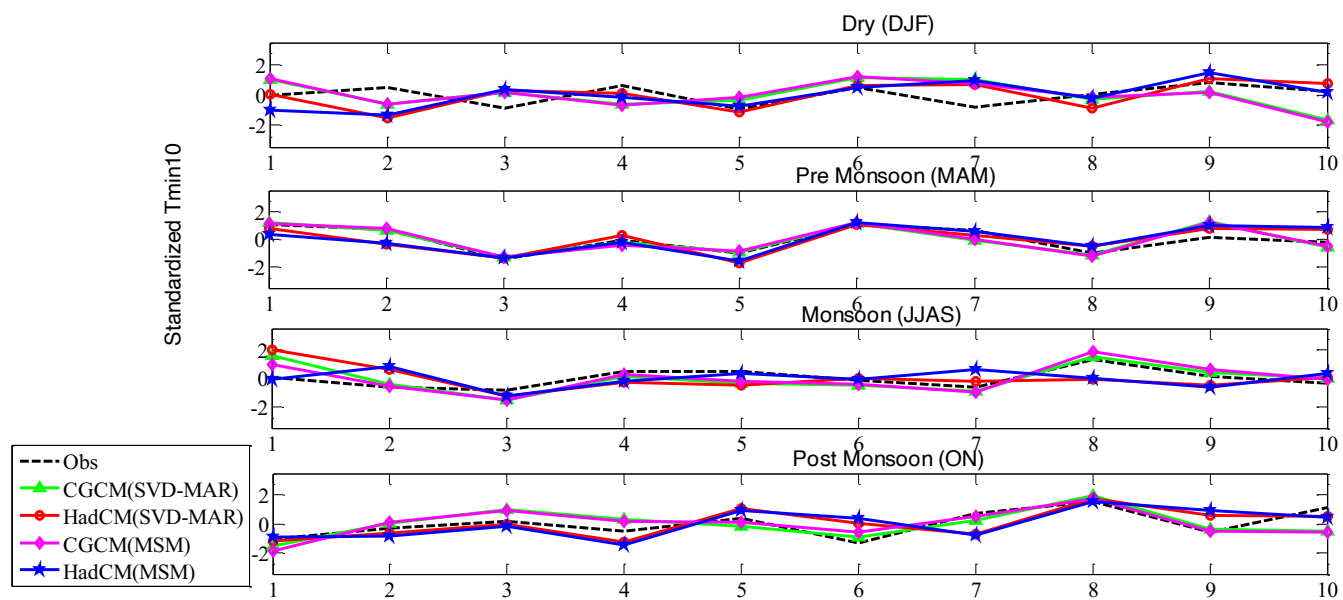


Figure 6.28: Interannual anomalies of standardized seasonal STD of T_{min} during (a) calibration and (b) validation periods at four stations in Bangladesh.



(a)



(b)

Figure 6.29: Interannual anomalies of standardized seasonal Tmin10p during (a) calibration and (b) validation periods at four stations in Bangladesh.

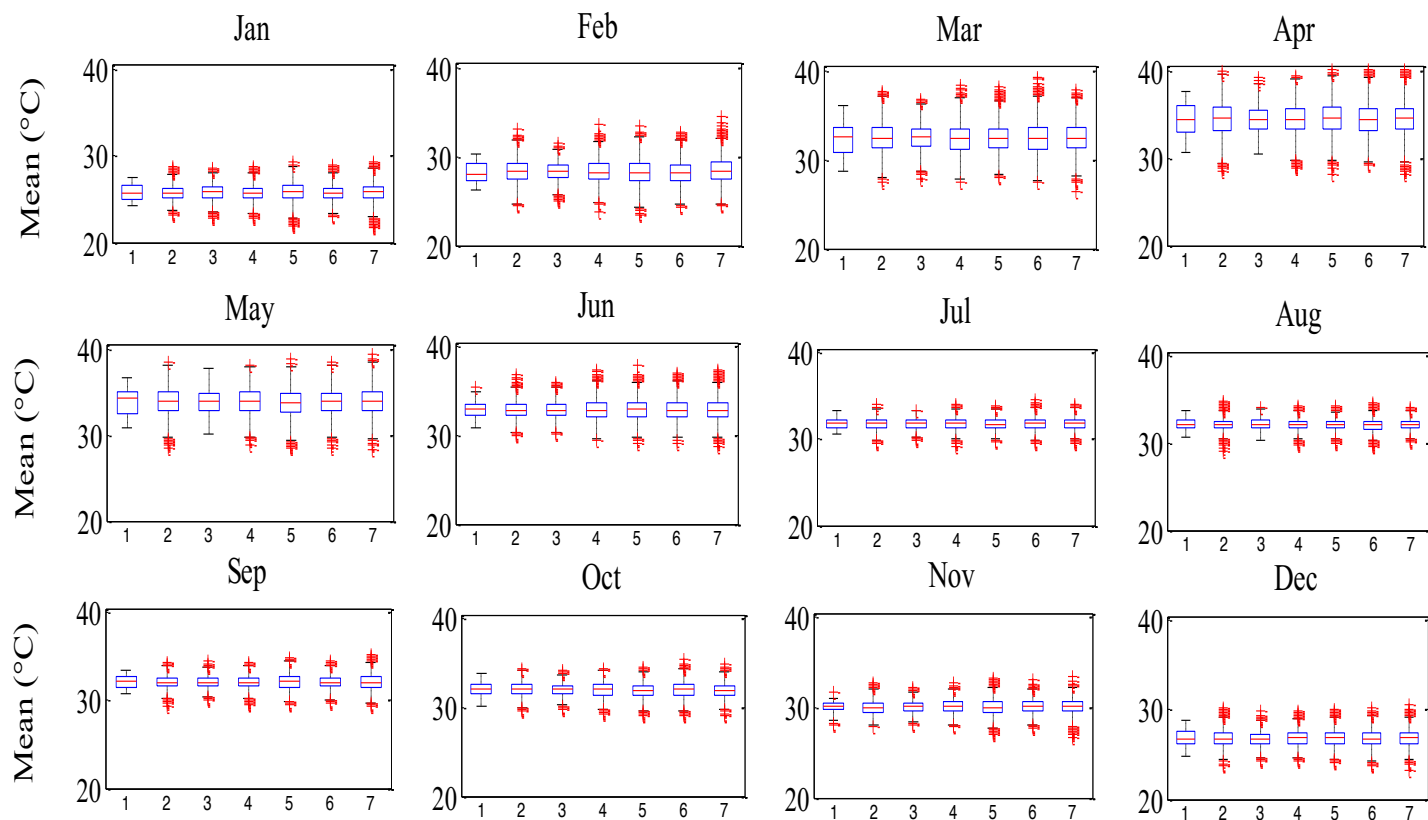
6.2 Results and evaluation of MMSD models for GCM simulations

This section presents the results regarding GCM outputs for three emission scenarios, e.g., CGCM-A2, HadCM-A2 and HadCM-B2 for current period. Here, the current period is represented as 1981-2000. The period 1981-1990 represents the calibration period while the period 1991-2000 represents the validation period.

6.2.1 Goodness of fit

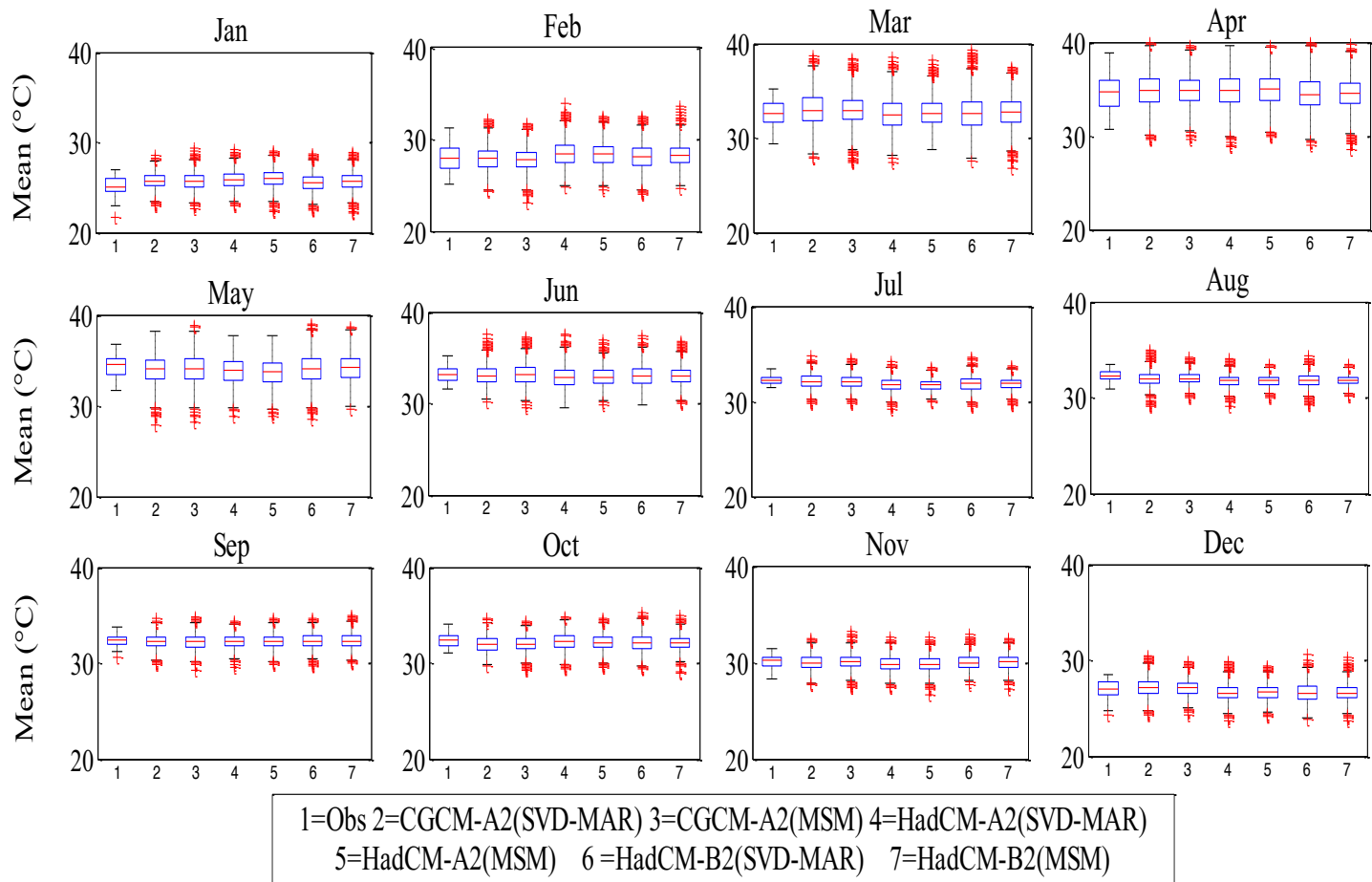
Graphical representations of four temperature indices: mean, STD, T_{max90p} and T_{min10p} for three climate scenarios during current period are presented in Figures 6.30 through 6.35. Good agreements were found between the observed ones and simulated values of monthly means of T_{max} during calibration as well as validation periods for all of three scenarios (Figure 6.30). For monthly means of T_{min} also, accurate results were produced by both of the models in all the months during calibration period and in almost all the months during validation period (Figure 6.31). Monthly STD of T_{max} and T_{min} were reproduced well by both of the models during calibration period (Figures 6.32 and 6.33). During validation period although monthly STD were produced well for T_{max} , slight biases were observed in the months of February, March and April. For T_{min} , although both of the models simulated similar results in most of the months, MSM was found to produce slightly better results in the months of April and November during validation period. Both of two indices, monthly T_{max90p} and T_{min10p} were captured well by both of the models for all scenarios during calibration period and in most of the months during validation period (Figures 6.34 and 6.35).

Table 6.5 shows that the values of MAE (RMSE) produced by SVD-MAR and MSM for all of three scenarios during calibration period ranged between 0.02-0.07 (0.03-0.08) and 0.05-0.11 (0.06-0.13) respectively for T_{max} and T_{min} for all of four stations. During validation period MAE (RMSE) values for T_{max} and T_{min} ranged respectively between 0.19-0.55 (0.25-0.6) and 0.22-0.36 (0.27-0.43) for all of the stations. The values of MAE and RMSE in Table 6.5 show that SVD-MAR produced comparatively better results than MSM for T_{max} as well as T_{min} . Lower values of MAE and RMSE indicate that the results were produced better for CGCM-A2 and HadCM-B2 scenarios than for HadCM-A2 scenario especially for T_{max} by both of the models.



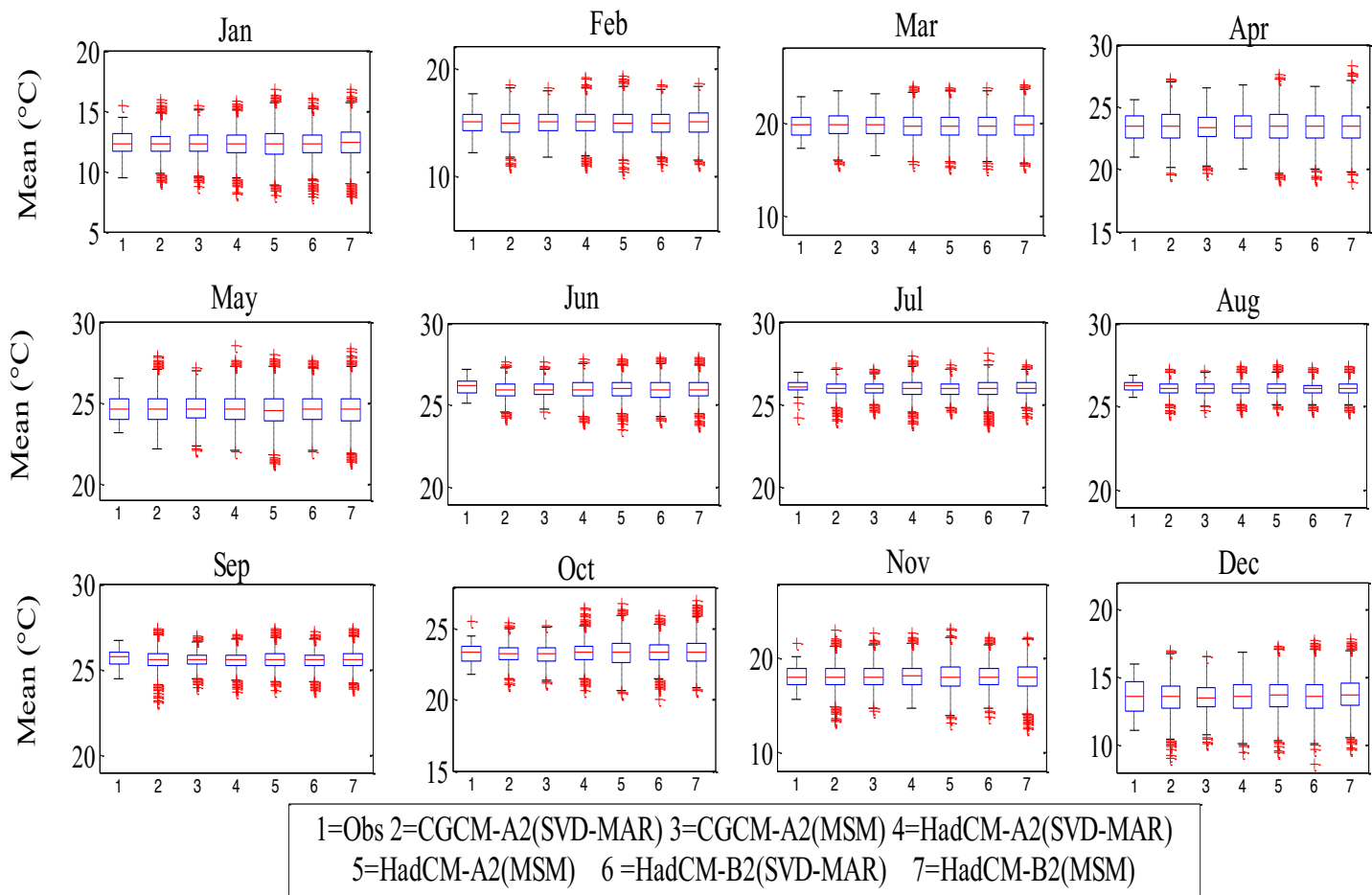
1=Obs 2=CGCM-A2(SVD-MAR) 3=CGCM-A2(MSM) 4=HadCM-A2(SVD-MAR)
 5=HadCM-A2(MSM) 6=HadCM-B2(SVD-MAR) 7=HadCM-B2(MSM)

(a)

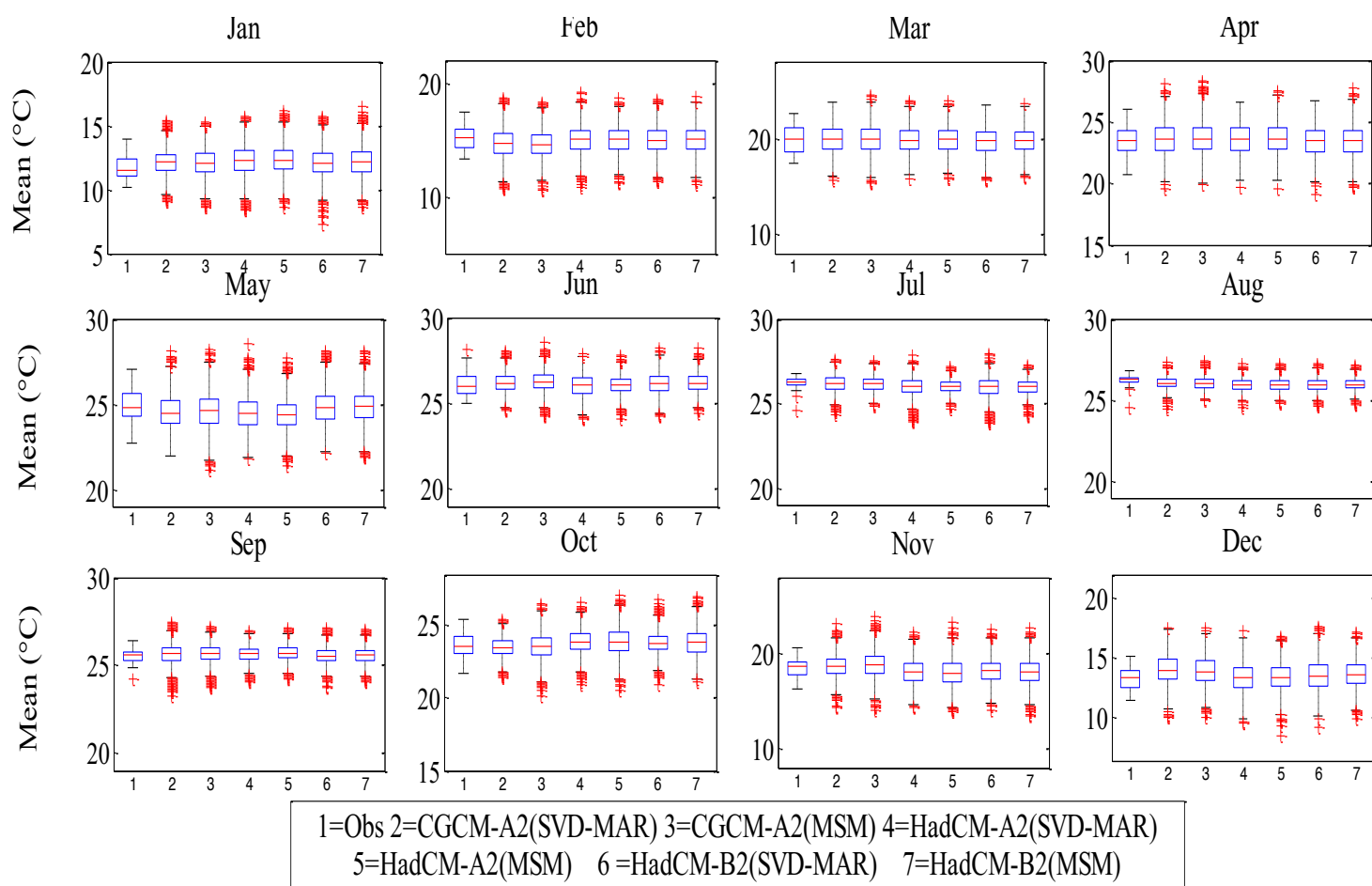


(b)

Figure 6.30: Boxplots of the mean of daily T_{max} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.

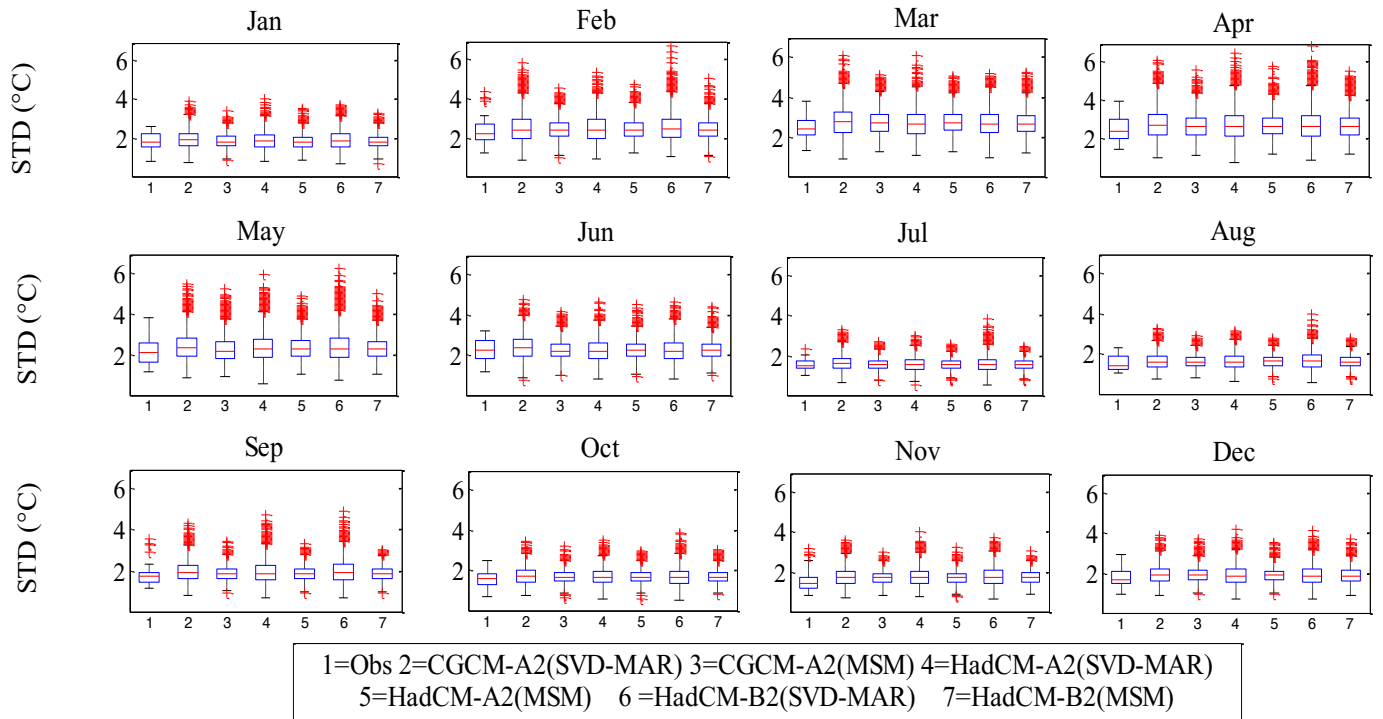


(a)

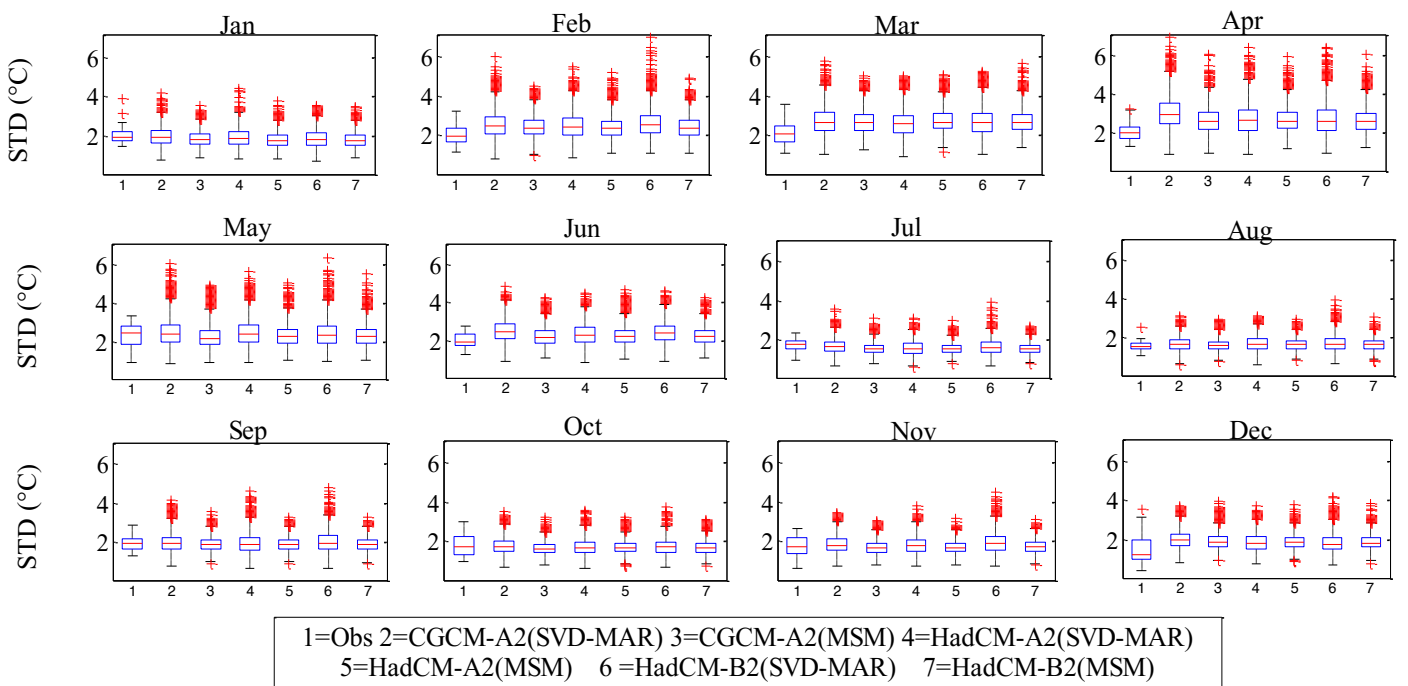


(b)

Figure 6.31: Boxplots of the mean of daily *Tmin* for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.

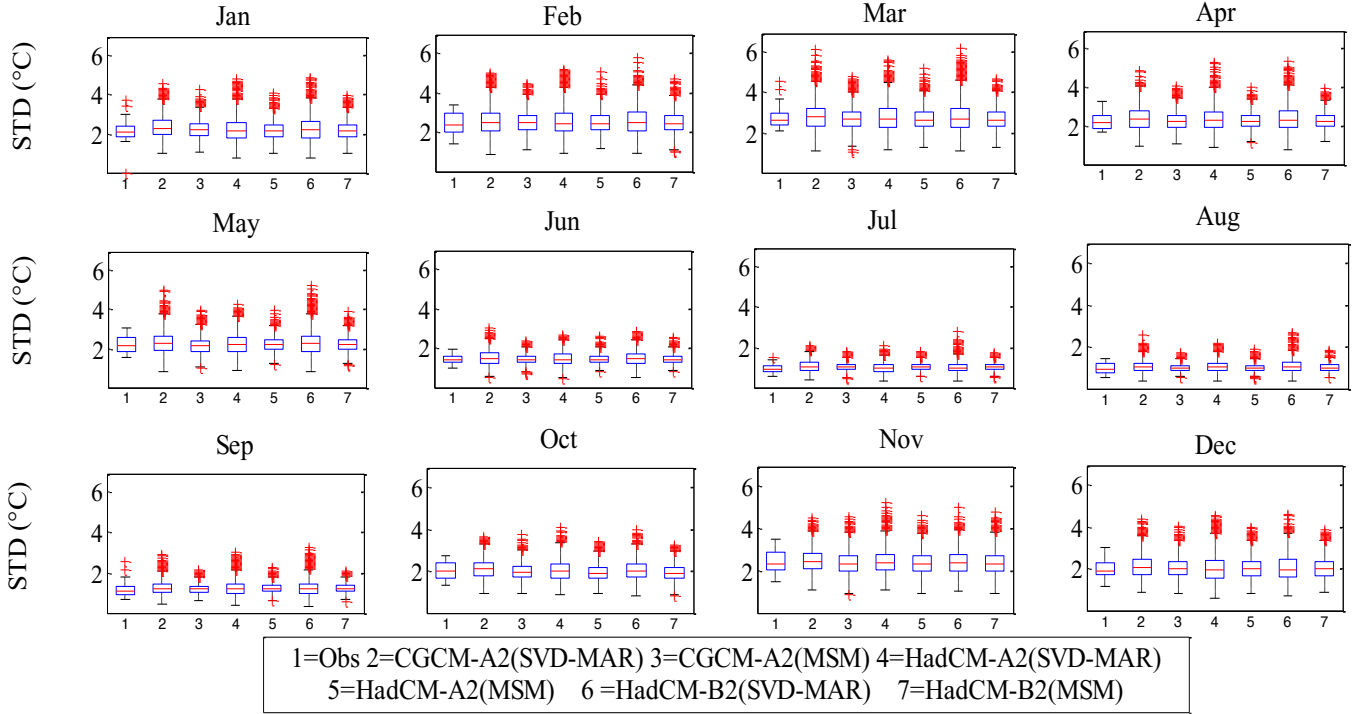


(a)

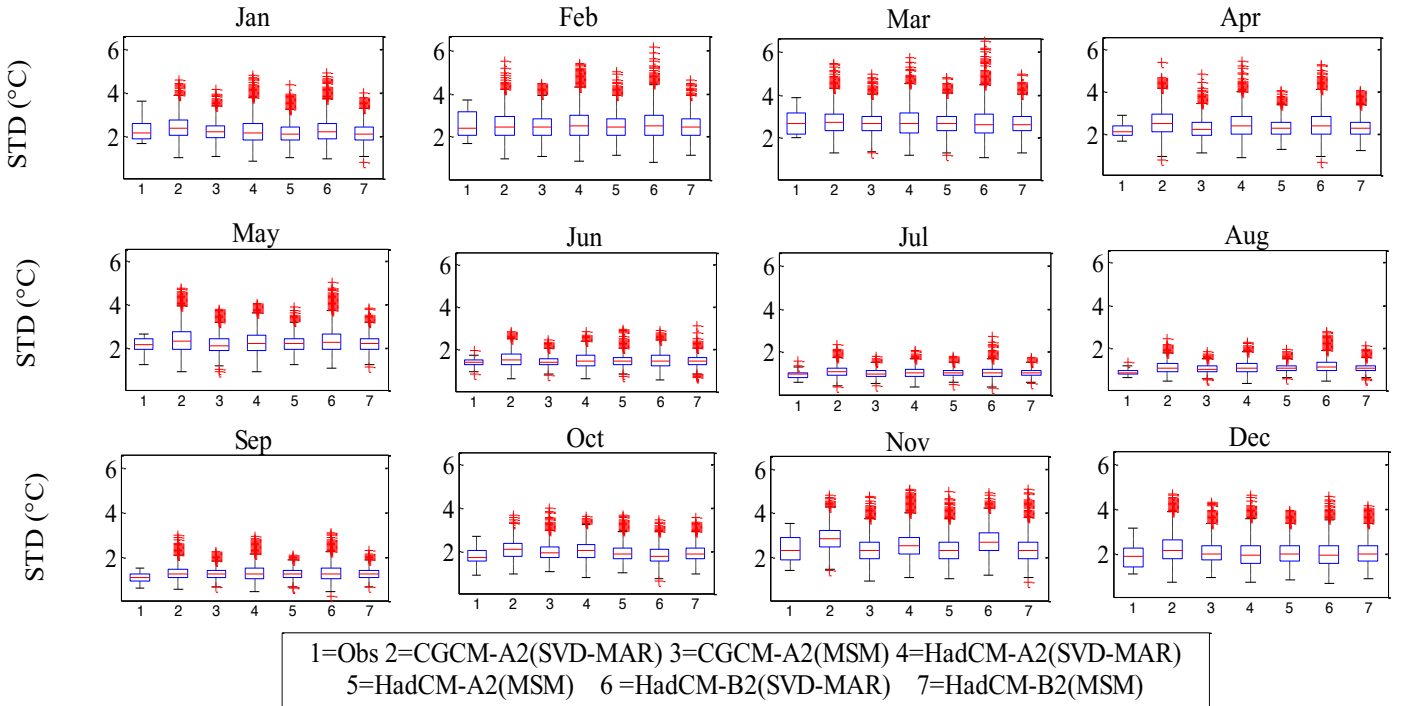


(b)

Figure 6.32: Boxplots of the STD of daily T_{max} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.

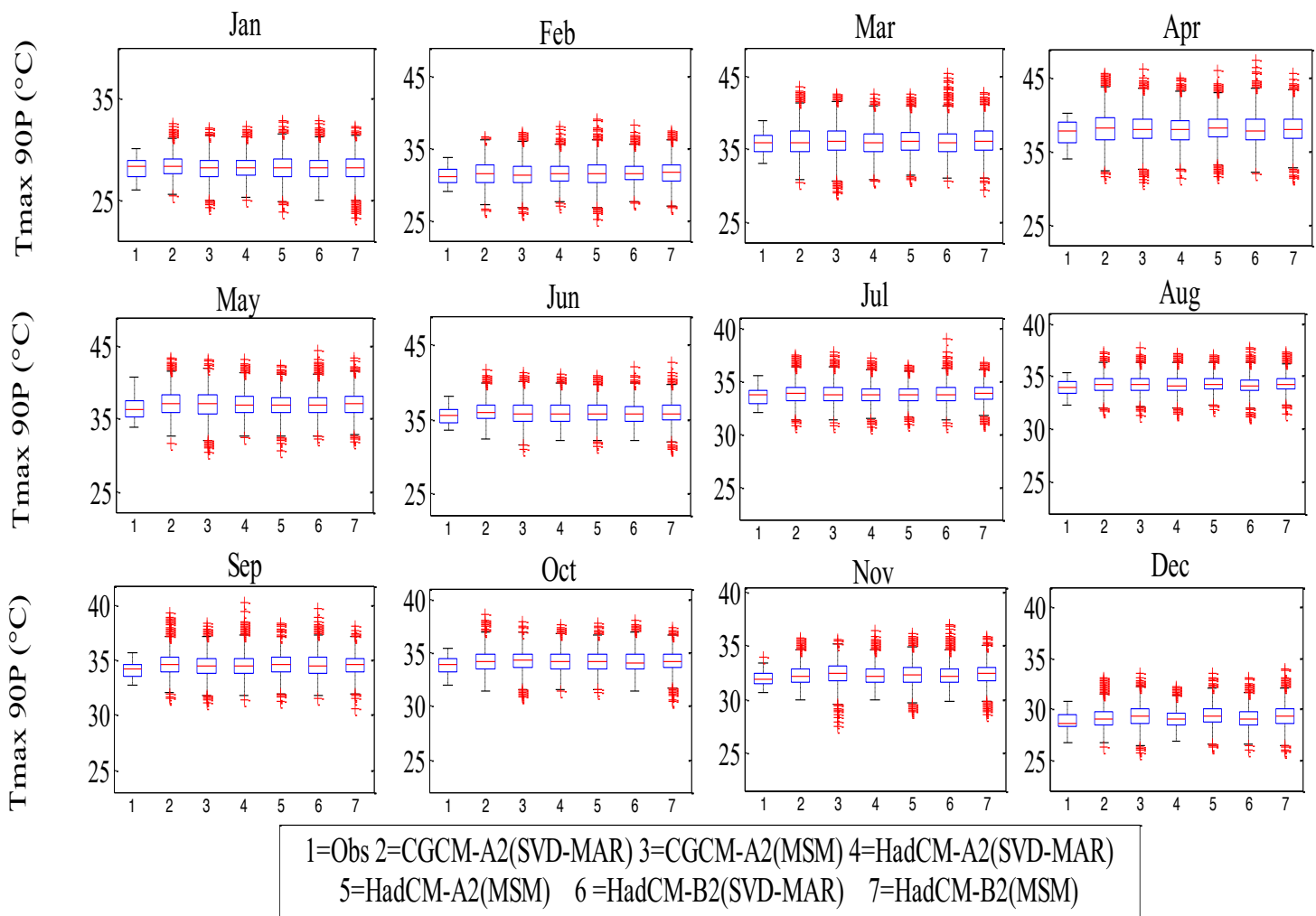


(a)

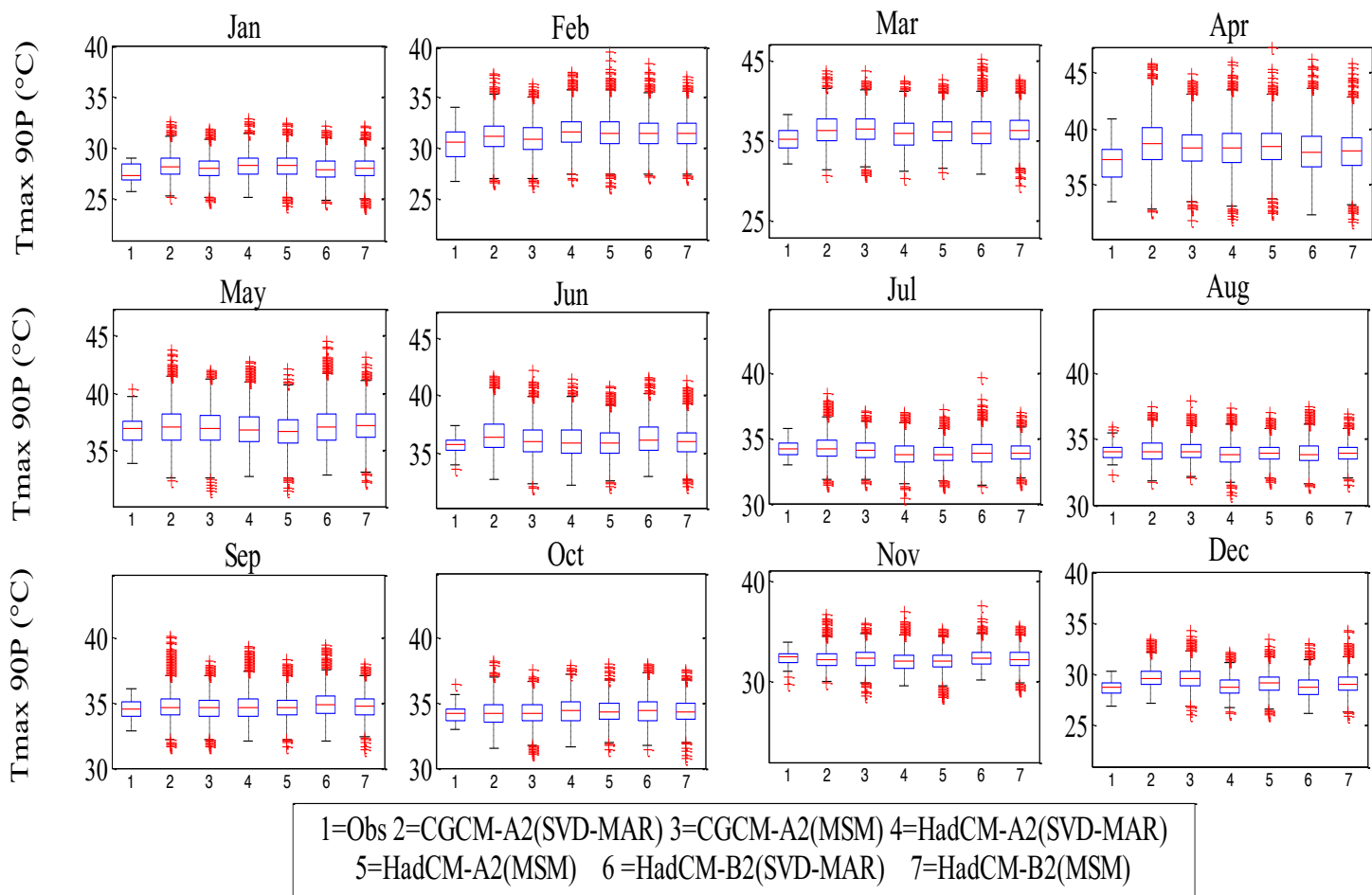


(b)

Figure 6.33: Boxplots of the STD of daily T_{min} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.

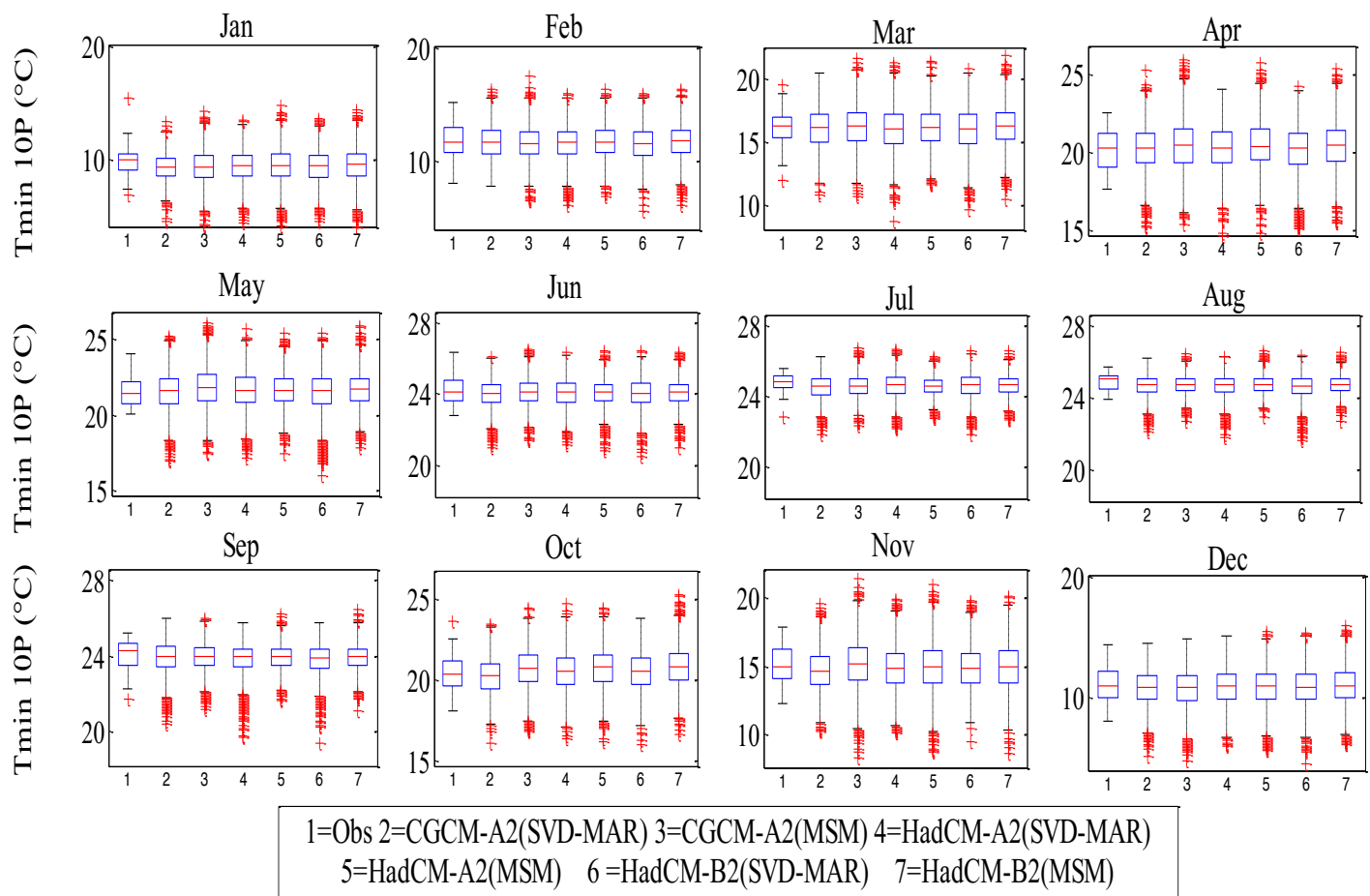


(a)

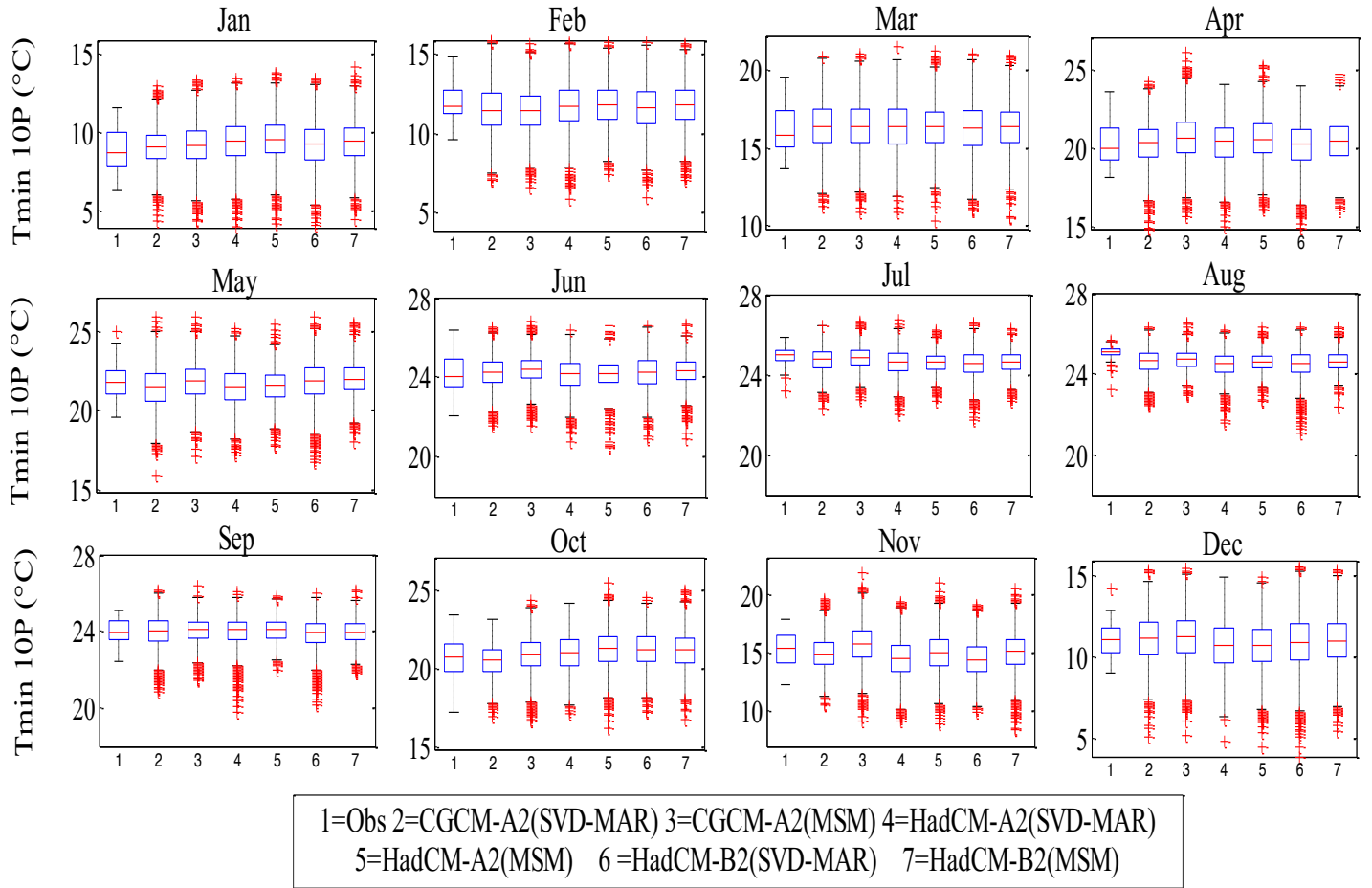


(b)

Figure 6.34: Boxplots of the Tmax90p for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.



(a)



(b)

Figure 6.35: Boxplots of the T_{min10p} for the observed and downscaled series for different climate scenarios during (a) calibration and (b) validation periods at four stations in Bangladesh.

Table 6.5: MAE and RMSE values of T_{max} and T_{min} for different climate scenarios at four stations in Bangladesh.

		CGCM-A2							
		Calibration Period				Validation Period			
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
T_{max}	Station 1	0.03	0.03	0.05	0.07	0.39	0.46	0.38	0.44
	Station 2	0.02	0.03	0.05	0.06	0.33	0.42	0.31	0.39
	Station 3	0.03	0.04	0.04	0.05	0.23	0.33	0.23	0.3
	Station 4	0.02	0.03	0.05	0.06	0.23	0.32	0.24	0.29
T_{min}	Station 1	0.05	0.07	0.08	0.09	0.27	0.33	0.28	0.35
	Station 2	0.05	0.06	0.06	0.08	0.3	0.39	0.31	0.38
	Station 3	0.08	0.1	0.09	0.1	0.28	0.43	0.29	0.43
	Station 4	0.05	0.07	0.08	0.09	0.3	0.43	0.31	0.42

HadCM-A2									
Calibration Period					Validation Period				
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
<i>T_{max}</i>	Station 1	0.03	0.05	0.07	0.08	0.49	0.53	0.55	0.6
	Station 2	0.02	0.03	0.07	0.08	0.52	0.57	0.53	0.6
	Station 3	0.02	0.03	0.06	0.07	0.31	0.38	0.32	0.4
	Station 4	0.02	0.03	0.07	0.07	0.27	0.34	0.28	0.37
<i>T_{min}</i>	Station 1	0.07	0.08	0.07	0.08	0.35	0.41	0.36	0.43
	Station 2	0.06	0.07	0.06	0.07	0.3	0.37	0.32	0.4
	Station 3	0.09	0.11	0.11	0.13	0.23	0.29	0.25	0.32
	Station 4	0.07	0.09	0.09	0.1	0.29	0.36	0.32	0.4
HadCM-B2									
Calibration Period					Validation Period				
		SVD-MAR		MSM		SVD-MAR		MSM	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
<i>T_{max}</i>	Station 1	0.03	0.04	0.04	0.05	0.39	0.43	0.41	0.45
	Station 2	0.03	0.04	0.04	0.05	0.38	0.43	0.39	0.43
	Station 3	0.04	0.05	0.04	0.06	0.22	0.29	0.24	0.32
	Station 4	0.04	0.05	0.04	0.05	0.19	0.25	0.22	0.28
<i>T_{min}</i>	Station 1	0.08	0.09	0.07	0.08	0.33	0.38	0.31	0.36
	Station 2	0.07	0.08	0.06	0.07	0.22	0.27	0.25	0.31
	Station 3	0.1	0.12	0.08	0.11	0.22	0.3	0.21	0.31
	Station 4	0.09	0.1	0.07	0.09	0.27	0.3	0.28	0.34

6.2.2 Spatial variability

Effectiveness of the proposed models to reproduce the spatial variability of daily *T_{max}* and *T_{min}* during current period for three scenarios of CGCM-A2, HadCM-A2 and HadCM-B2 are presented in the Figures 6.36 through 6.41. The graphical representations show that the lag0 interstation correlations of daily *T_{max}* were reproduced well for all of three scenarios by both of the models during calibration period and also for validation period. For lag0 interstation correlations of daily *T_{min}* also, both models were found capable to preserve the observed lag0 interstation correlations in simulated series for all the scenarios. However, the interstation correlations of daily *T_{min}* were slightly overestimated by both of the models for CGCM-A2 scenario during calibration period especially for those where the observed correlations are relatively low.

Numerical analysis regarding lag0 interstation correlations of daily *T_{max}* and *T_{min}* are given in Table 6.6. The values of MAD (RMSD) for SVD-MAR and MSM models ranged between 0.03-0.04 (0.04-0.06) and 0.03-0.05 (0.04-0.08) respectively for *T_{max}* and *T_{min}* lag0 interstation correlations during calibration period for all of three scenarios. During validation period those

values were between 0.05-0.06 (0.07-0.09) and 0.04-0.05 (0.06-0.08) respectively for T_{max} and T_{min} . The R^2 values for lag0 interstation correlations produced by both of the models ranged between 0.82-0.9 and 0.89-0.95 respectively for T_{max} and T_{min} for three scenarios during calibration period. During validation period the R^2 values were between 0.58-0.74 and 0.8-0.86 respectively for T_{max} and T_{min} .

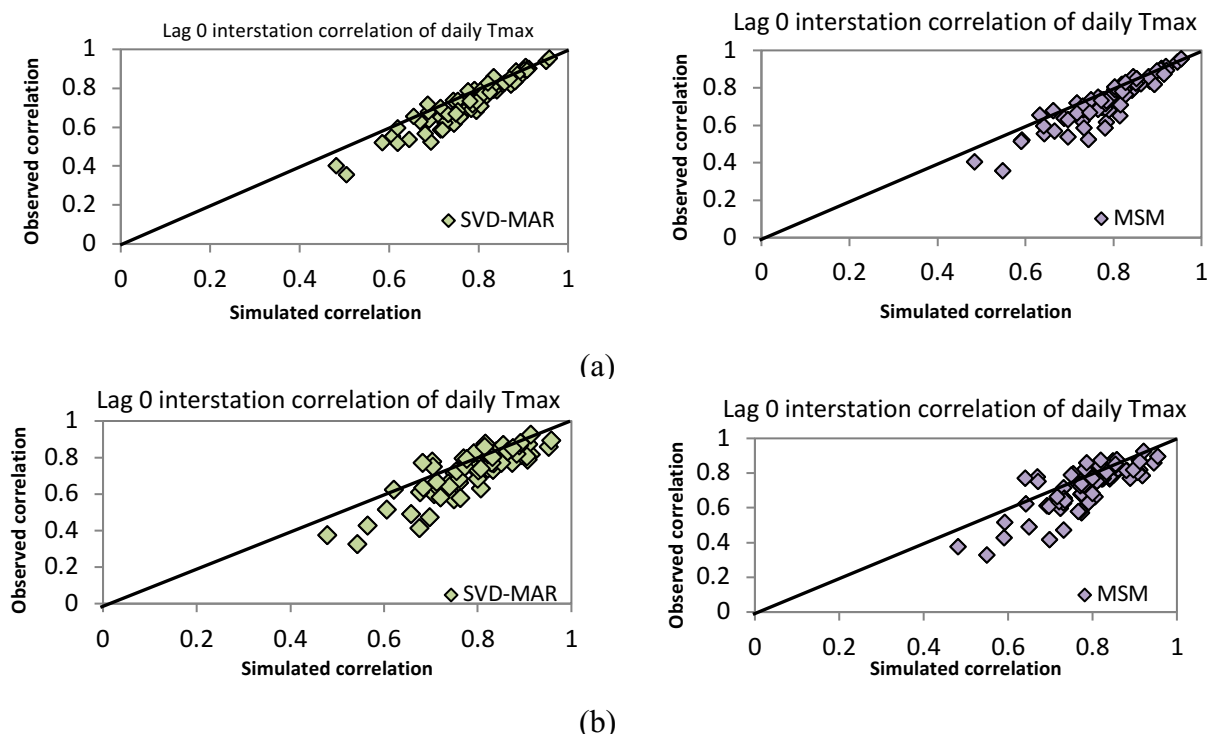
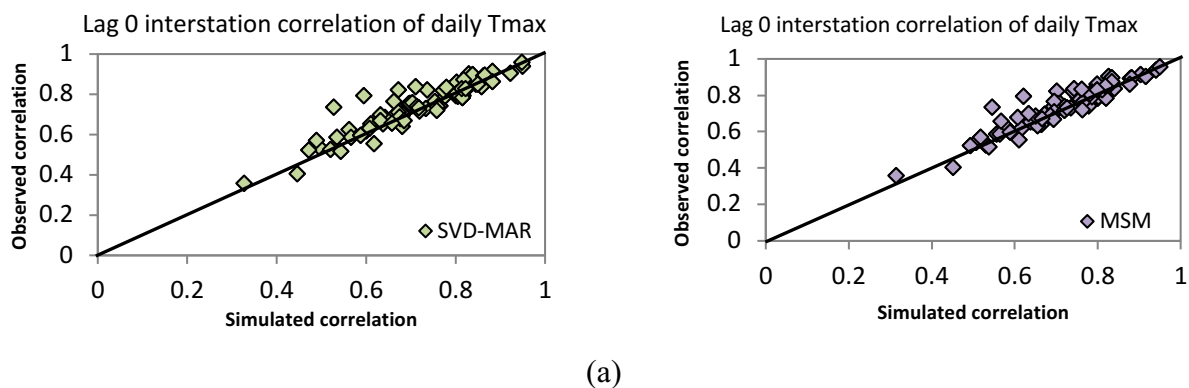
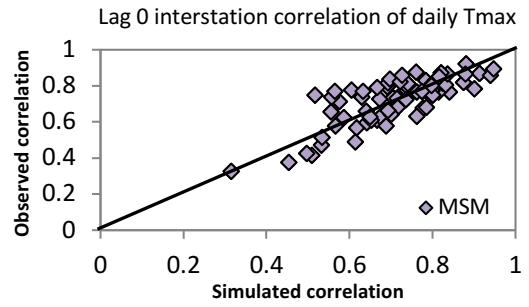
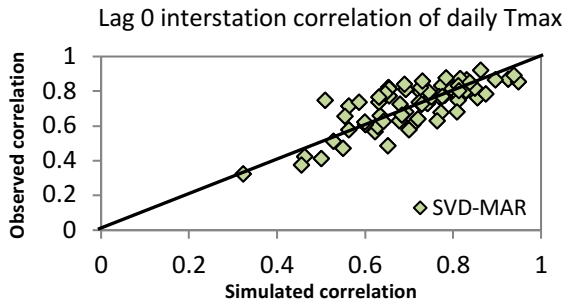


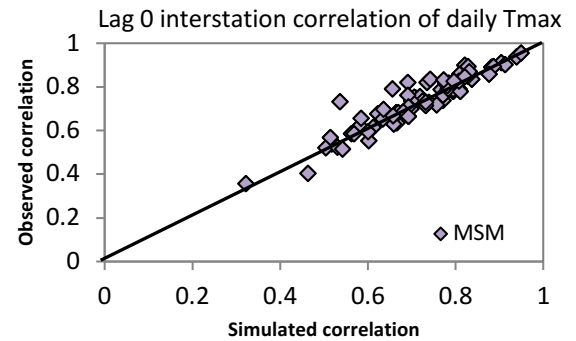
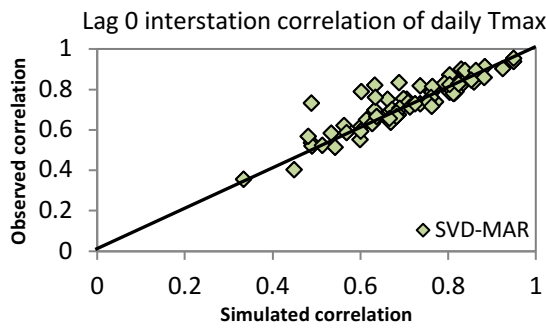
Figure 6.36: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Bangladesh.



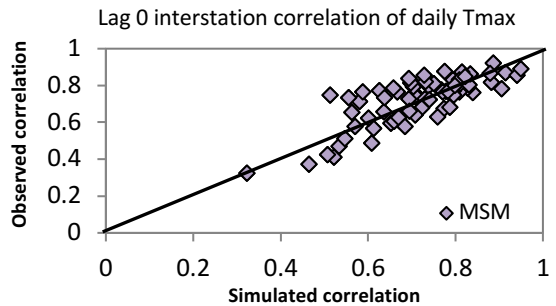
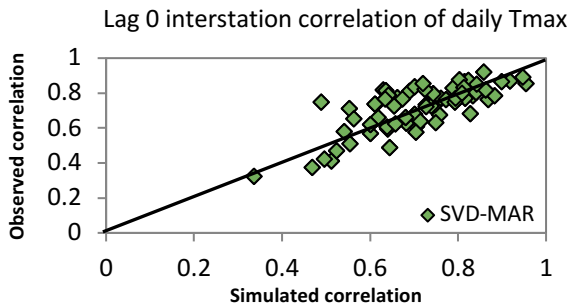


(b)

Figure 6.37: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Bangladesh.

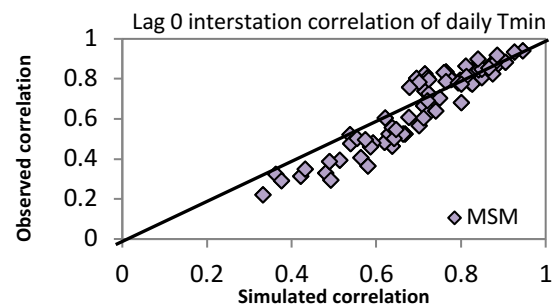
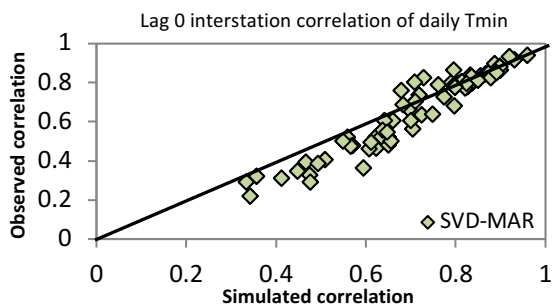


(a)

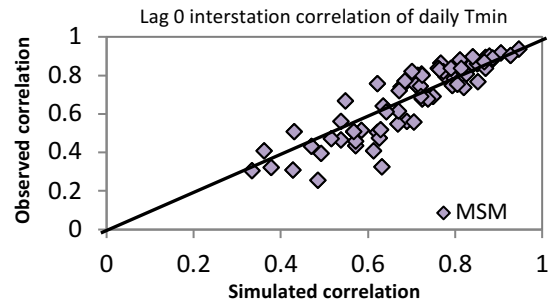
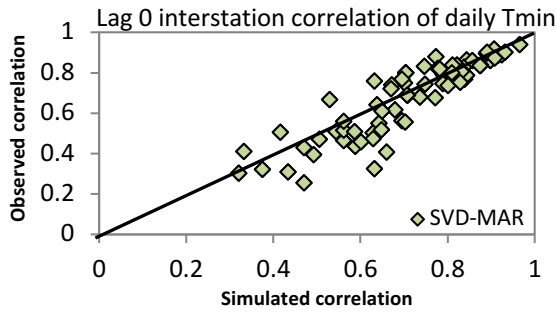


(b)

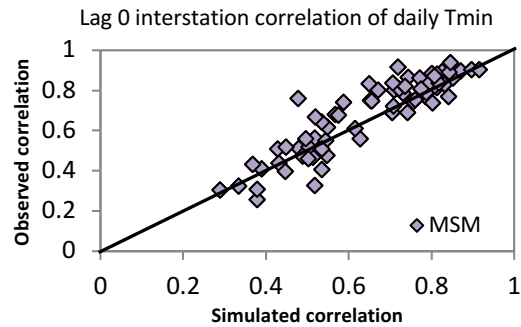
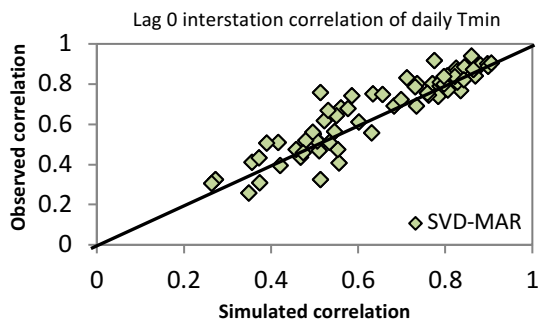
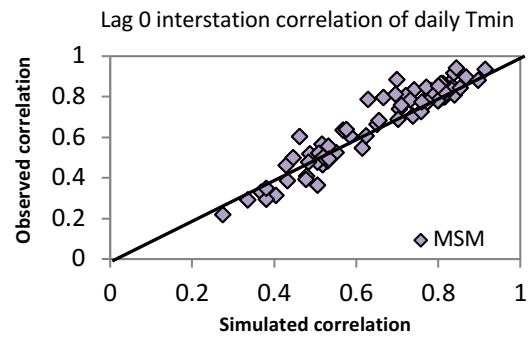
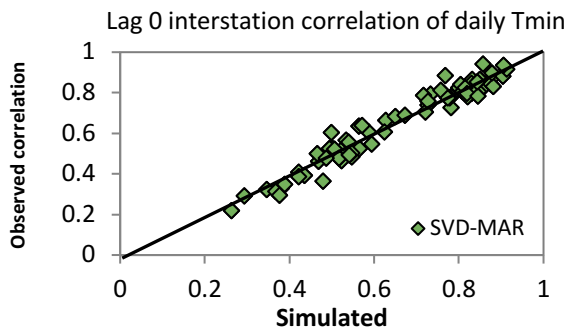
Figure 6.38: Lag0 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Bangladesh.



(a)



(b)
Figure 6.39: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Bangladesh.



(b)
Figure 6.40: Lag0 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Bangladesh.

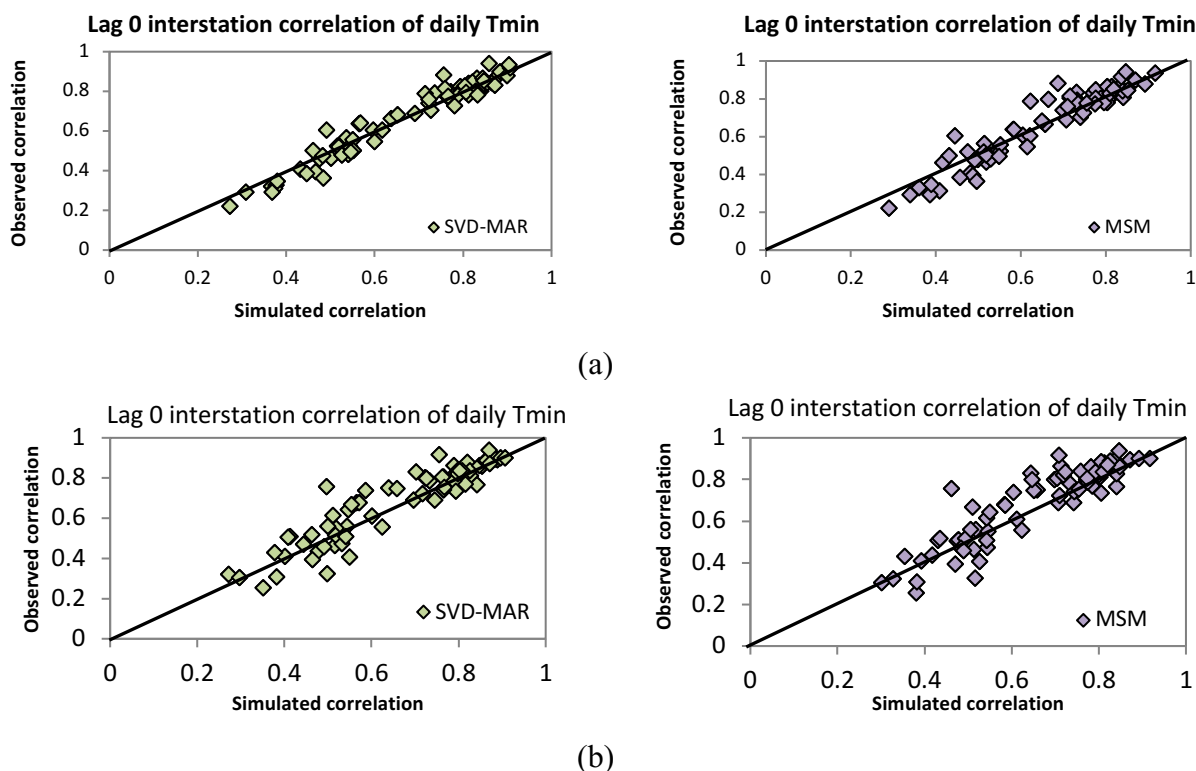


Figure 6.41: Lag0 interstation correlations of daily T_{min} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Bangladesh.

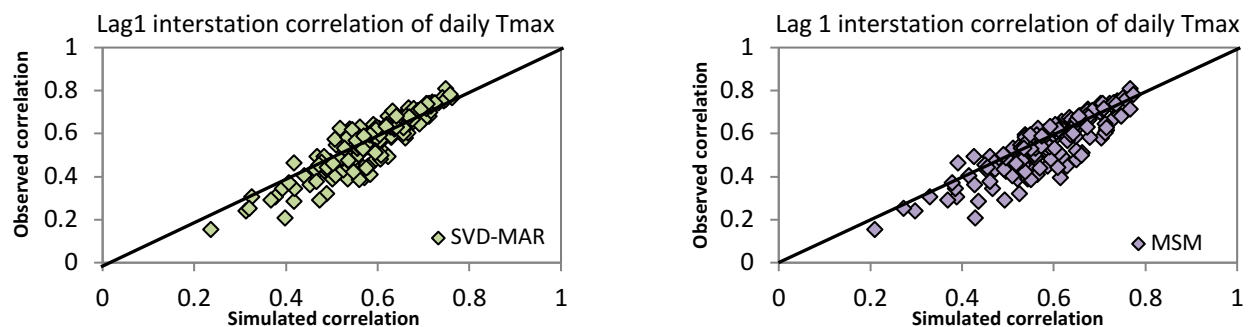
Table 6.6: Numerical analysis for lag0 interstation correlations of daily T_{max} and T_{min} at four stations in Bangladesh for different climate scenarios.

CGCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag0 correlation	0.04	0.05	0.9	0.04	0.06	0.85
	T_{min} lag0 correlation	0.05	0.07	0.92	0.05	0.08	0.89
Validation	T_{max} lag0 correlation	0.06	0.08	0.74	0.06	0.09	0.64
	T_{min} lag0 correlation	0.05	0.08	0.8	0.05	0.08	0.8
HadCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R^2	MAD	RMSD	R^2
Calibration	T_{max} lag0 correlation	0.03	0.05	0.85	0.03	0.04	0.88
	T_{min} lag0 correlation	0.03	0.04	0.95	0.04	0.05	0.91
Validation	T_{max} lag0 correlation	0.05	0.07	0.6	0.05	0.07	0.61
	T_{min} lag0 correlation	0.04	0.06	0.86	0.05	0.07	0.82

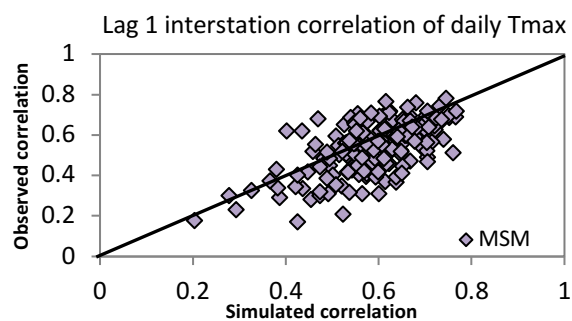
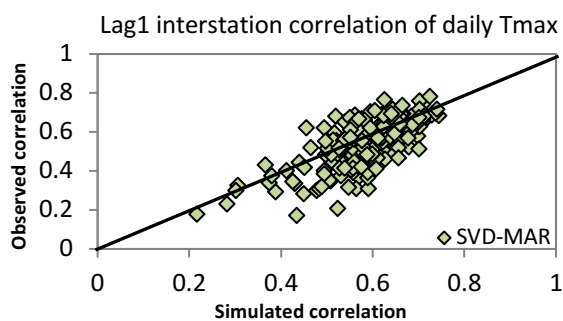
HadCM-B2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	Tmax lag0 correlation	0.03	0.05	0.82	0.03	0.04	0.88
	Tmin lag0 correlation	0.03	0.04	0.95	0.04	0.06	0.91
Validation	Tmax lag0 correlation	0.05	0.08	0.58	0.05	0.07	0.62
	Tmin lag0 correlation	0.04	0.06	0.86	0.05	0.07	0.82

Figures 6.42 to 6.47 depict the lag1 interstation correlations of daily *Tmax* and *Tmin*. It is observed that both SVD-MAR and MSM were able to preserve the observed lag1 interstation correlations in simulated series for daily *Tmax* as well as *Tmin* very well during calibration period for all the scenarios. During validation period also, the lag1 interstation correlations were reproduced well for daily *Tmax* and *Tmin* by both of the models. However, the variability of the simulated correlations is relatively high during the validation period especially for CGCM-A2 scenario.

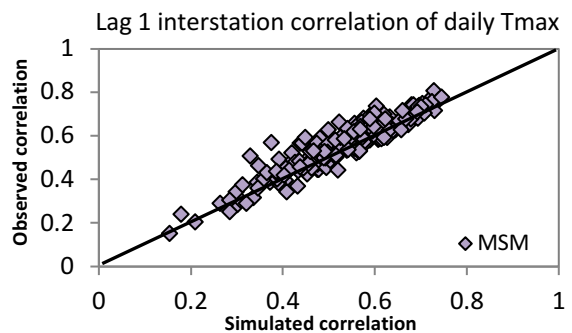
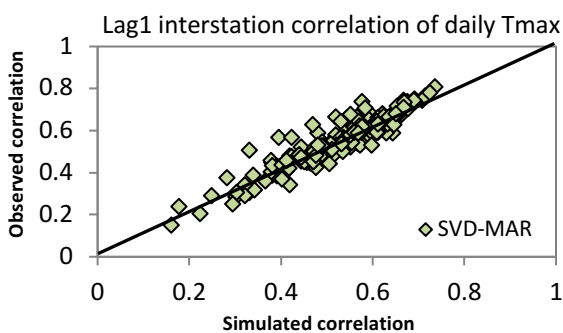
Numerical evaluation (Table 6.7) shows that the values of MAD (RMSD) ranged between 0.04-0.05 (0.05-0.07) and 0.04-0.08 (0.05-0.1) respectively for *Tmax* and *Tmin* lag1 interstation correlations during calibration period for SVD-MAR and MSM for all of three scenarios. During validation period those values ranged between 0.07-0.08 (0.08-0.11) and 0.08-0.1 (0.09-0.12) respectively for *Tmax* and *Tmin*. The R² values for lag1 interstation correlations of daily *Tmax* and *Tmin* ranged respectively between 0.77-0.89 and 0.78-0.93 for both of the models during calibration period for three scenarios. Those values ranged between 0.4-0.56 and 0.63-0.81 respectively for *Tmax* and *Tmin* during validation period.



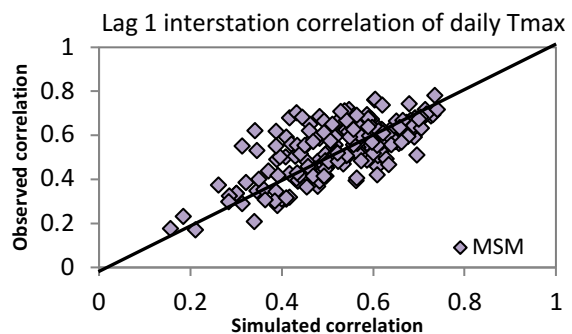
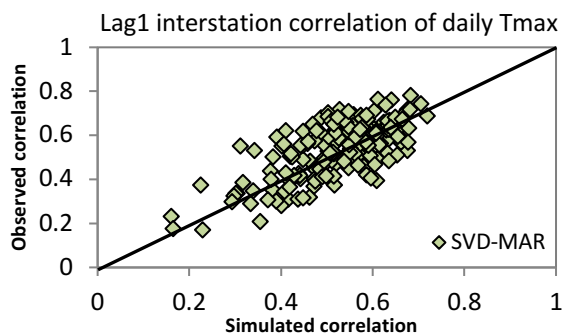
(a)



(b)
Figure 6.42: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Bangladesh.

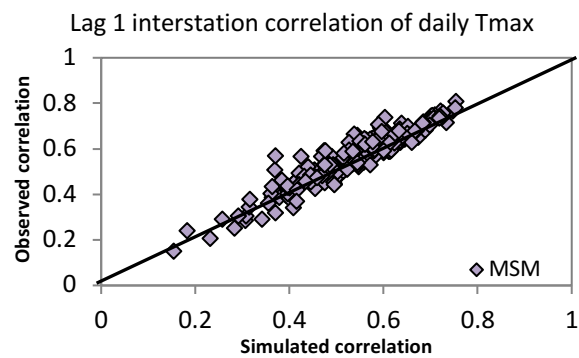
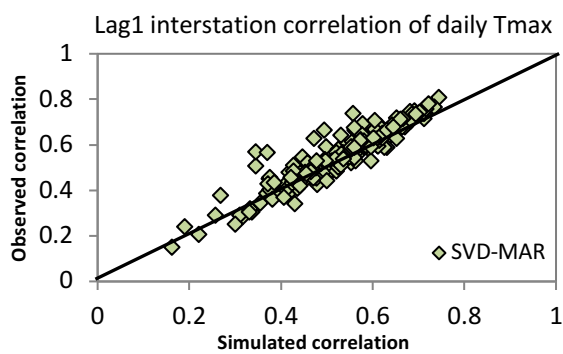


(a)

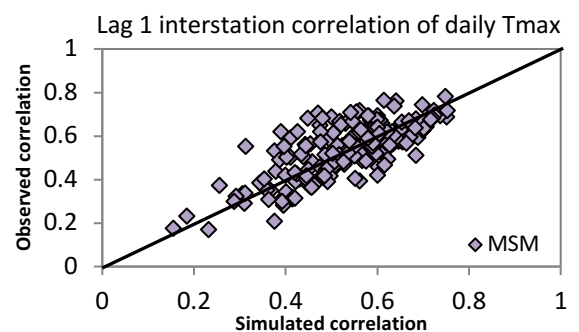
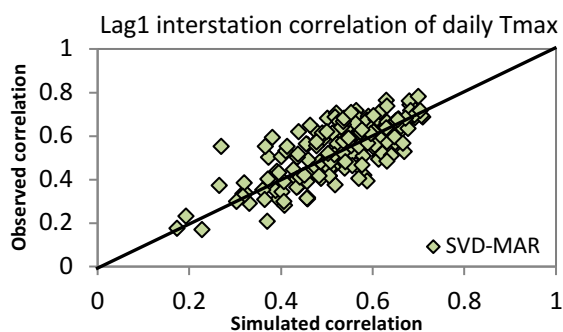


(b)

Figure 6.43: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Bangladesh.

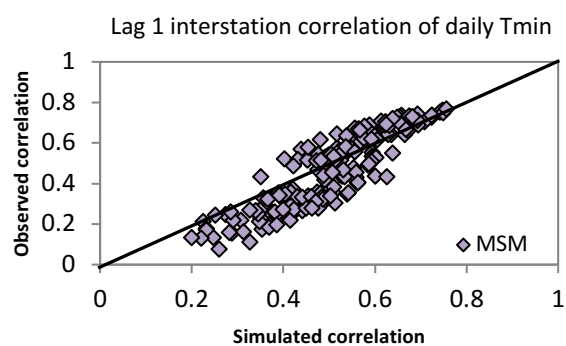
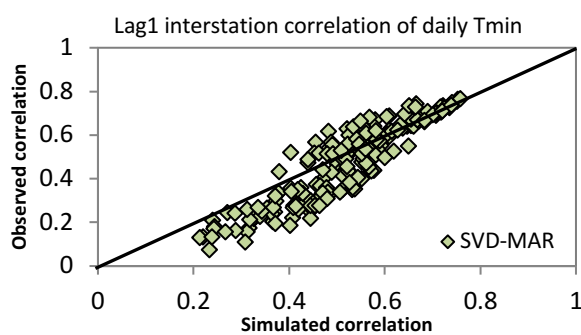


(a)

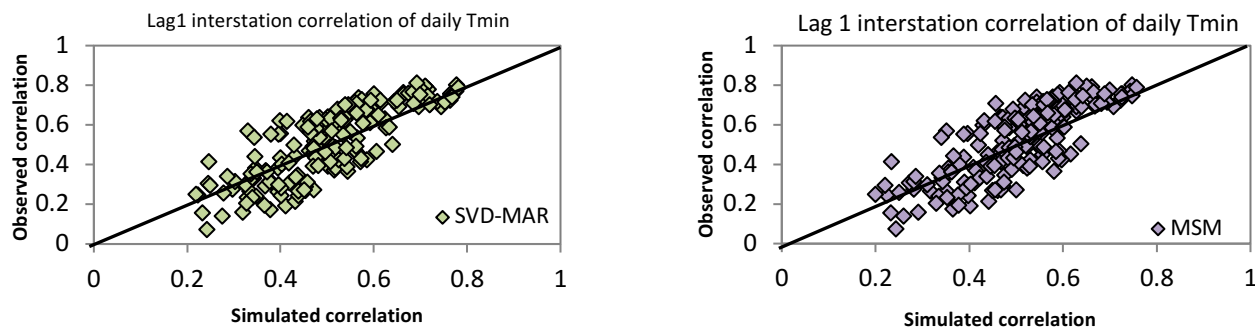


(b)

Figure 6.44: Lag1 interstation correlations of daily T_{max} during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Bangladesh.

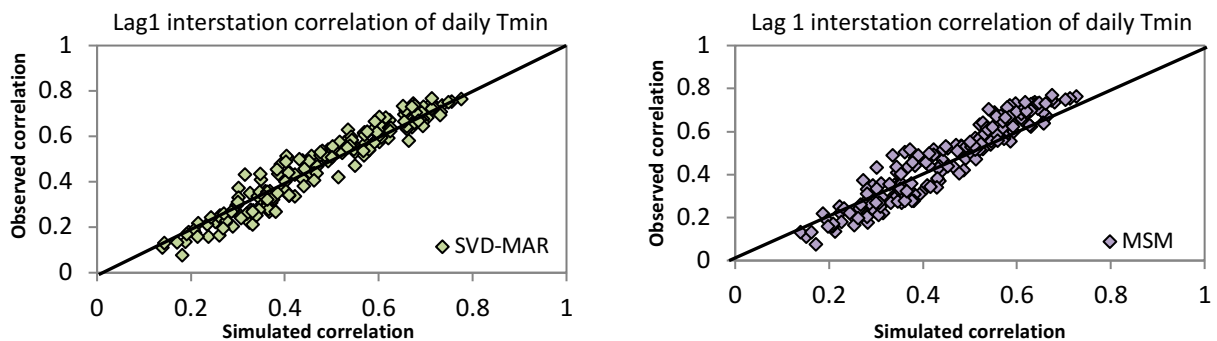


(a)

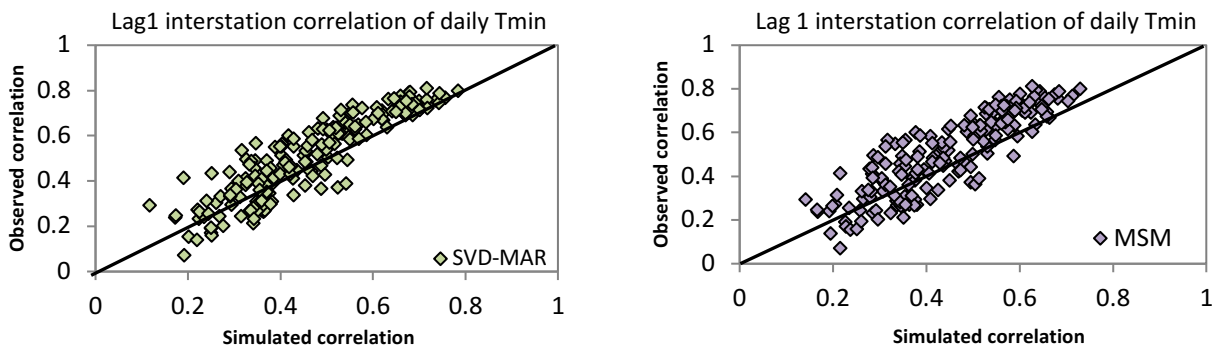


(b)

Figure 6.45: Lag1 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for CGCM-A2 scenario for the stations in Bangladesh.



(a)



(b)

Figure 6.46: Lag1 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for HadCM-A2 scenario for the stations in Bangladesh.

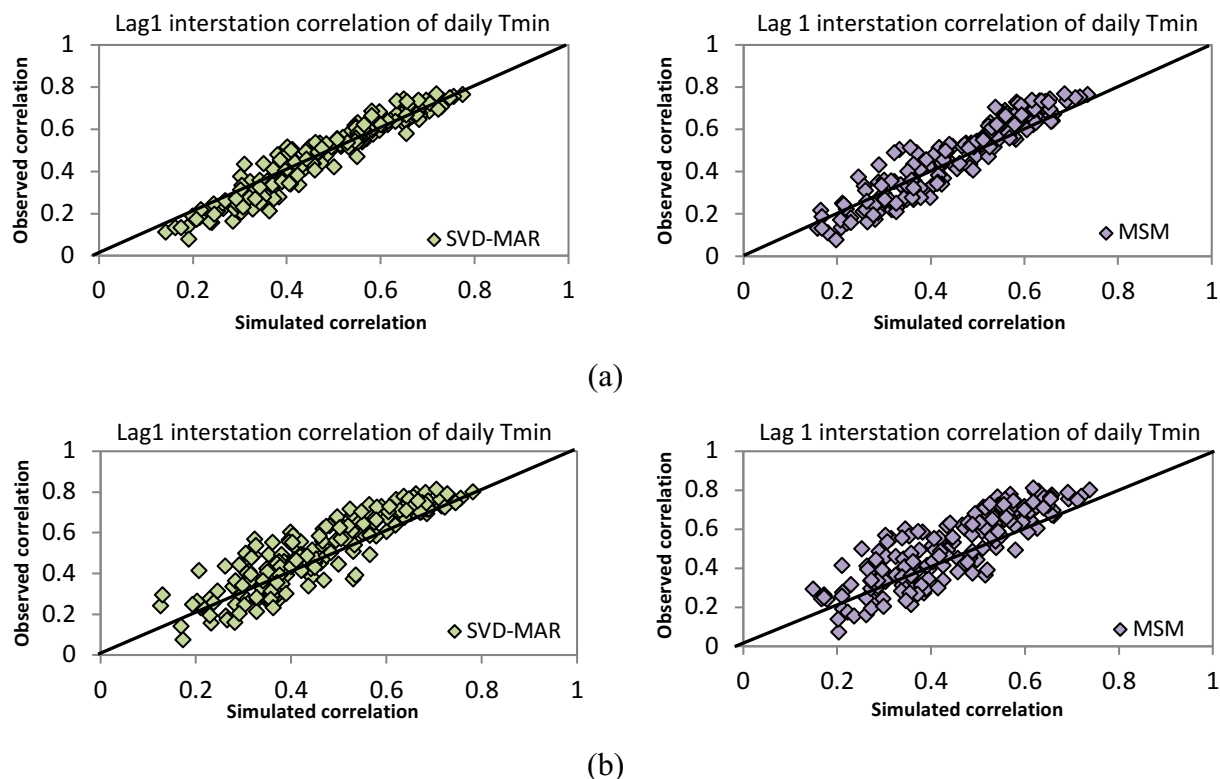


Figure 6.47: Lag1 interstation correlations of daily *Tmin* during (a) calibration and (b) validation periods for HadCM-B2 scenario for the stations in Bangladesh.

Table 6.7: Numerical analysis for lag1 interstation correlations of daily *Tmax* and *Tmin* at four stations in Bangladesh for different climate scenarios.

CGCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag1 correlation	0.04	0.06	0.82	0.05	0.07	0.77
	<i>Tmin</i> lag1 correlation	0.07	0.09	0.83	0.08	0.1	0.78
Validation	<i>Tmax</i> lag1 correlation	0.07	0.1	0.5	0.08	0.11	0.4
	<i>Tmin</i> lag1 correlation	0.09	0.11	0.66	0.09	0.11	0.63
HadCM-A2							
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag1 correlation	0.04	0.05	0.88	0.04	0.05	0.87
	<i>Tmin</i> lag1 correlation	0.04	0.05	0.93	0.05	0.07	0.91
Validation	<i>Tmax</i> lag1 correlation	0.07	0.09	0.5	0.07	0.09	0.5
	<i>Tmin</i> lag1 correlation	0.08	0.09	0.81	0.1	0.11	0.77

		HadCM-B2					
		SVD-MAR			MSM		
		MAD	RMSD	R ²	MAD	RMSD	R ²
Calibration	<i>Tmax</i> lag1 correlation	0.04	0.05	0.86	0.04	0.05	0.89
	<i>Tmin</i> lag1 correlation	0.04	0.05	0.93	0.06	0.07	0.89
Validation	<i>Tmax</i> lag1 correlation	0.07	0.08	0.55	0.07	0.09	0.56
	<i>Tmin</i> lag1 correlation	0.08	0.1	0.81	0.1	0.12	0.73

6.2.3 Temporal dependency

Figures 6.48 and 6.49 show the observed and simulated autocorrelation coefficients of lags from one to three at Jessore station in Bangladesh. Results for rest of the stations are given in Appendix D. The figures suggest that both of the models efficiently reproduced the observed autocorrelation in the simulated series for *Tmax* during calibration as well as validation periods (Figure 6.48). For *Tmin* also the autocorrelation coefficients were produced well by both of the models (Figure 6.49). However, the results were better during calibration period than validation period for *Tmin* especially for those produced by SVD-MAR. At most of the stations, the autocorrelations were better simulated for the scenario of CGCM than those of HadCM. Although both of the models simulated similar autocorrelations up to lag1, SVD-MAR produced better results than those of MSM for the autocorrelations of lag2 and 3 at most of the stations.

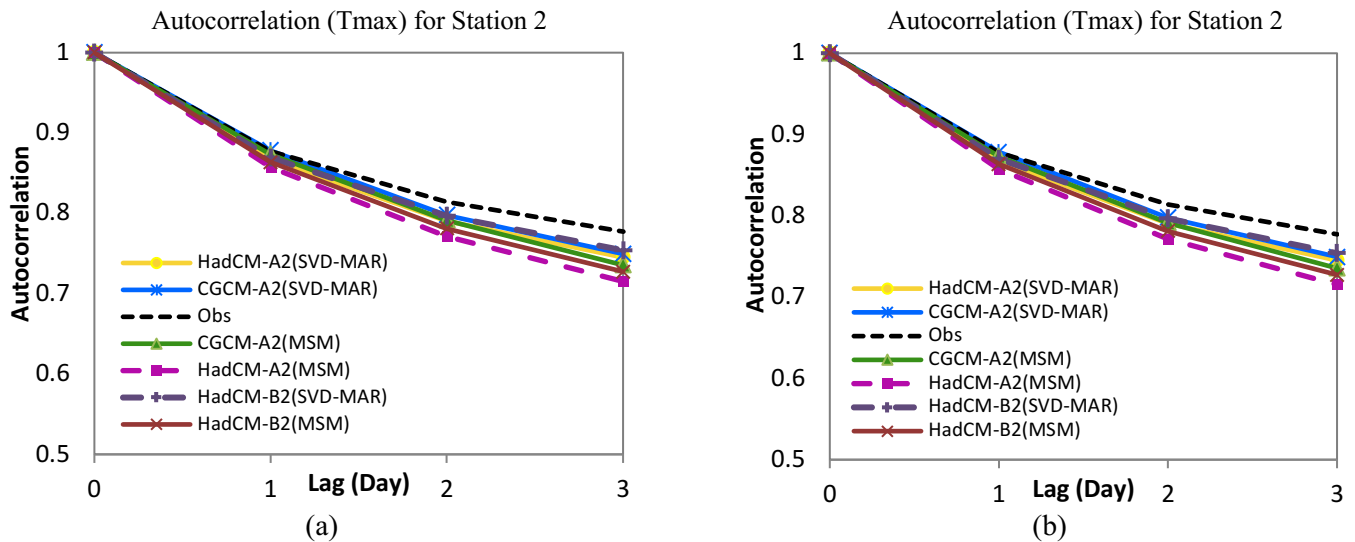


Figure 6.48: Observed and downscaled autocorrelation coefficients of *Tmax* at Jessore station for different climate scenarios during (a) calibration and (b) validation periods.

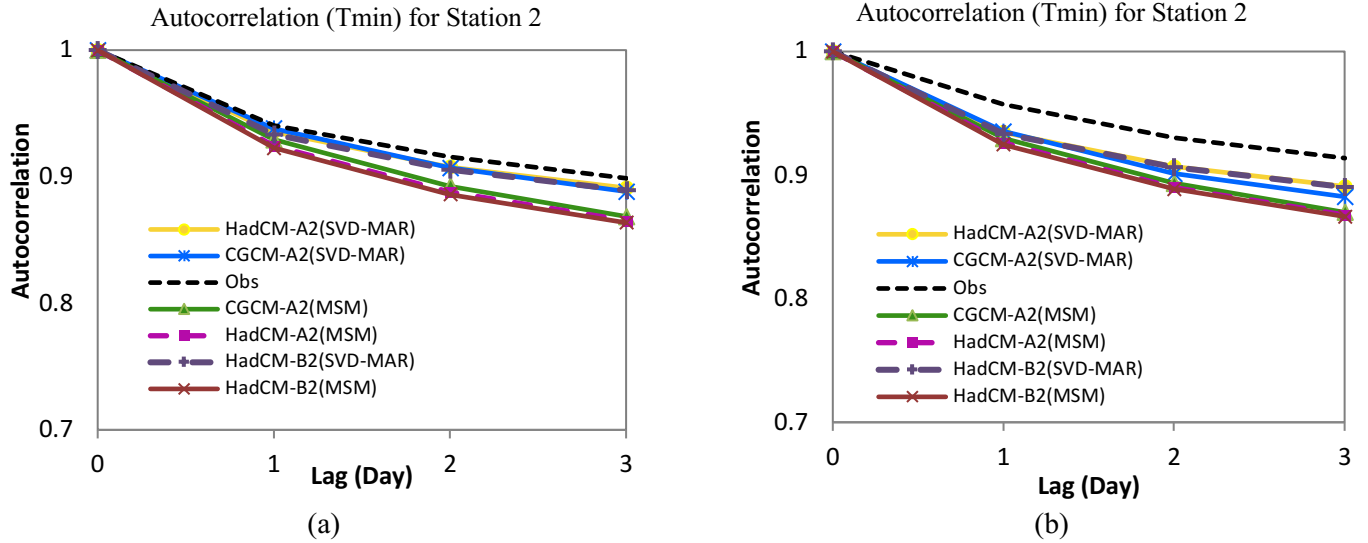


Figure 6.49: Observed and downscaled autocorrelation coefficients of T_{min} at Jessore station for different climate scenarios during (a) calibration and (b) validation periods.

6.2.4 Correlation between daily T_{max} and T_{min} and DTR

At-site correlations between daily T_{max} and T_{min} for CGCM-A2, HadCM-A2 and HadCM-B2 scenarios are presented in Figures 6.50 to 6.52. Graphically it is observed that both of the models overestimated the daily T_{max} - T_{min} correlations during calibration period, especially for those cases where the observed correlations are relatively high. However, for CGCM-A2 scenario SVD-MAR produced slightly better results than MSM, whereas, for HadCM-A2 and HadCM-B2 scenarios both models produced similar results during calibration period. The R^2 values produced by SVD-MAR and MSM model ranged between 0.66 - 0.77 during calibration period for all of CGCM-A2, HadCM-A2 and HadCM-B2 scenarios (Figures 6.50 to 6.52). During validation period none of the models could reproduce the observed correlations very well specially for HadCM scenarios. For CGCM-A2 scenario also, both models overestimated the daily T_{max} - T_{min} correlations in most of the cases. Moreover, the variability of the simulated correlations is high for both of the models for all of three scenarios. During validation period the R^2 values ranged between 0.3 - 0.45 for both of the models for all three scenarios.

Table 6.8 shows that the values of MAD (RMSD) for all the stations produced by SVD-MAR and MSM ranged between 0.06-0.12 (0.07-0.14) for CGCM-A2, HadCM-A2 and HadCM-

B2 scenarios during calibration period. During validation period those values were between 0.1-0.17 (0.13-0.19) for three scenarios for both of the models.

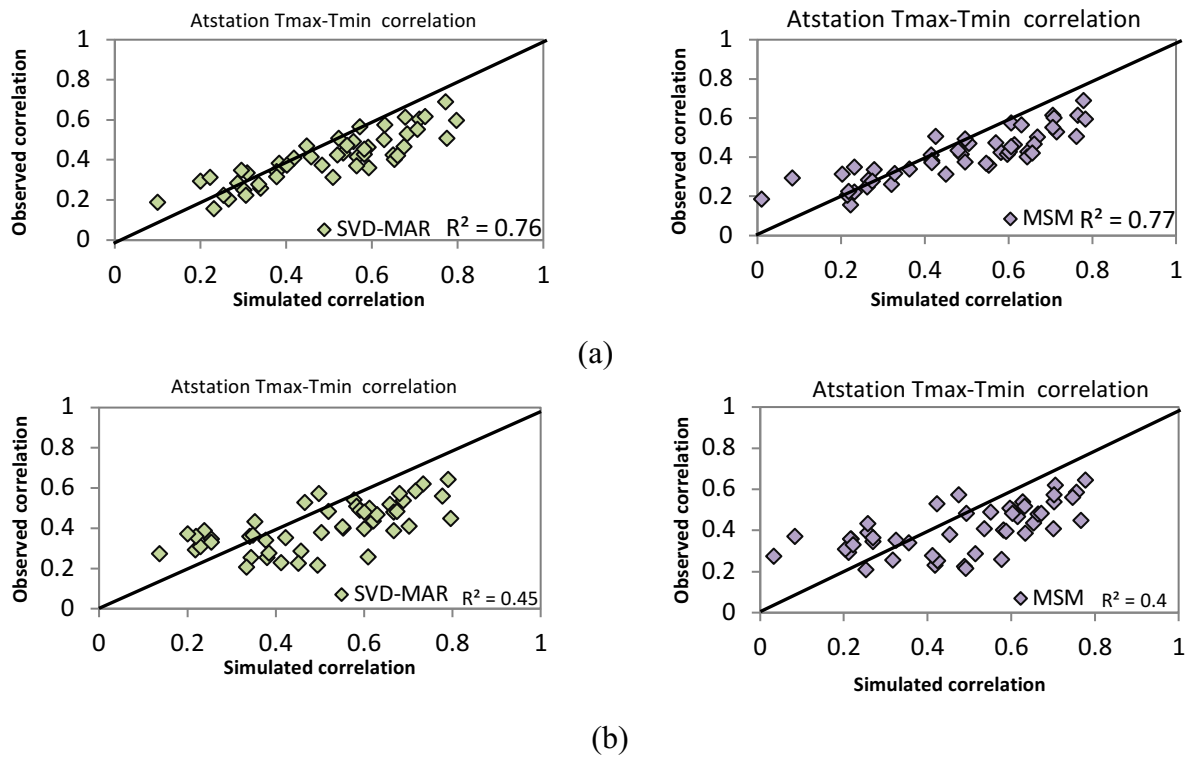
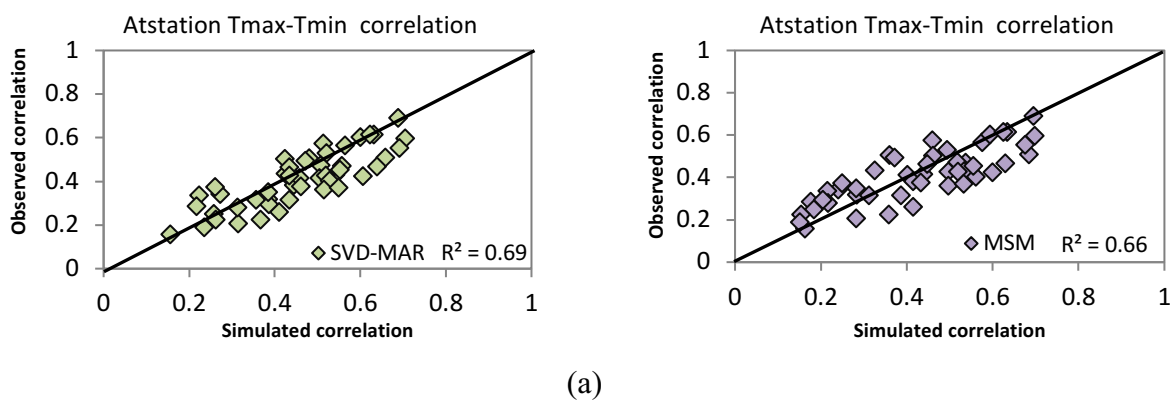
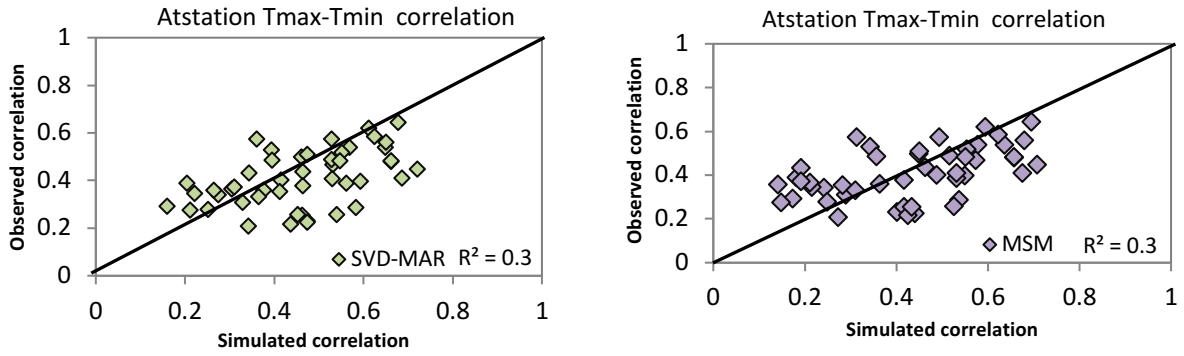


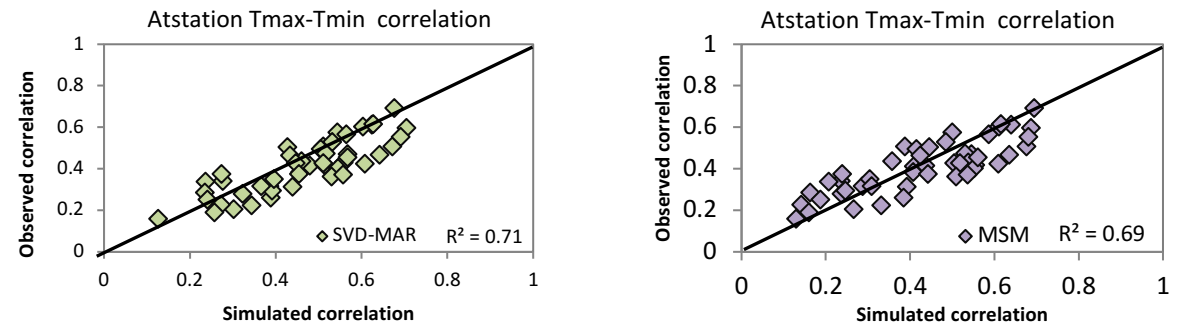
Figure 6.50: Correlations between daily T_{max} and T_{min} at four stations in Bangladesh during (a) calibration and (b) validation periods for CGCM-A2 scenario.



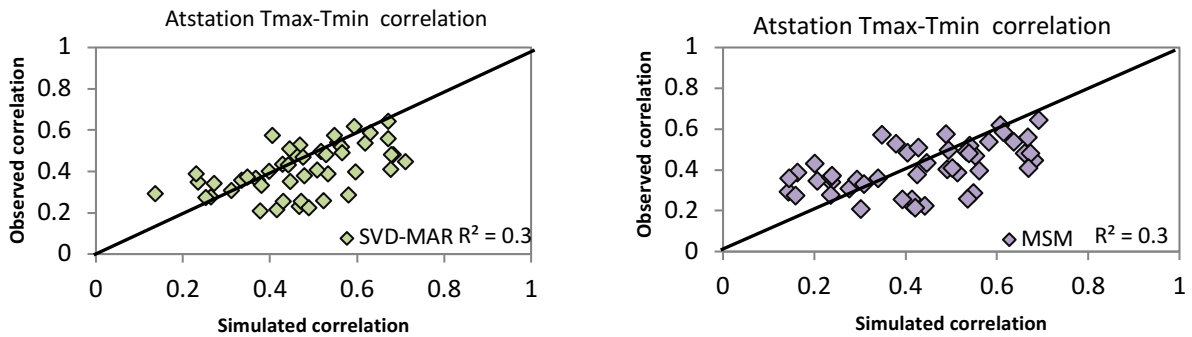


(b)

Figure 6.51: Correlations between daily T_{max} and T_{min} at four stations in Bangladesh during (a) calibration and (b) validation periods for HadCM-A2 scenario.



(a)



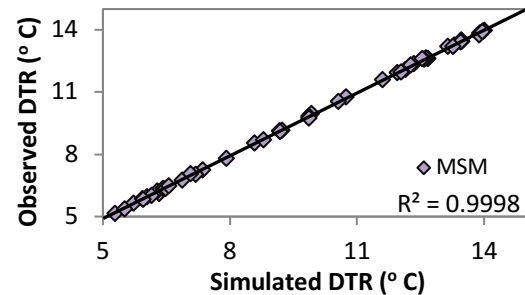
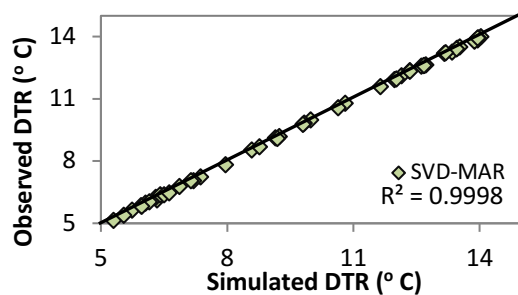
(b)

Figure 6.52: Correlations between daily T_{max} and T_{min} at four stations in Bangladesh during (a) calibration and (b) validation periods for HadCM-B2 scenario.

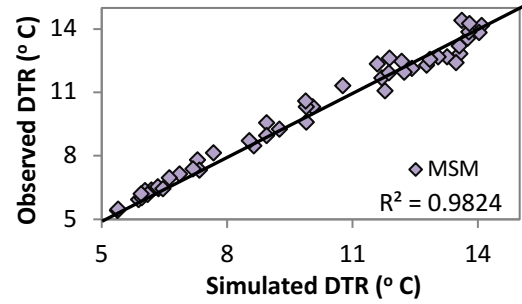
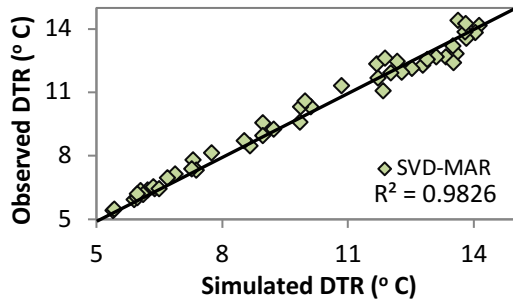
Table 6.8: Numerical analysis for the correlations between daily T_{max} and T_{min} at four stations in Bangladesh for different climate scenarios.

CGCM-A2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.09	0.11	0.11	0.13	0.13	0.15	0.16	0.18
Station 2	0.09	0.11	0.09	0.12	0.16	0.19	0.17	0.19
Station 3	0.11	0.13	0.12	0.14	0.14	0.16	0.14	0.15
Station 4	0.11	0.14	0.11	0.13	0.13	0.13	0.12	0.13
HadCM-A2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.06	0.08	0.08	0.09	0.11	0.15	0.14	0.16
Station 2	0.07	0.07	0.06	0.07	0.13	0.15	0.13	0.15
Station 3	0.09	0.1	0.1	0.12	0.11	0.14	0.12	0.14
Station 4	0.08	0.1	0.08	0.1	0.1	0.13	0.1	0.13
HadCM-B2								
	Calibration Period				Validation Period			
	SVD-MAR		MSM		SVD-MAR		MSM	
	MAD	RMSD	MAD	RMSD	MAD	RMSD	MAD	RMSD
Station 1	0.06	0.08	0.08	0.09	0.1	0.14	0.14	0.16
Station 2	0.07	0.07	0.06	0.07	0.1	0.13	0.13	0.15
Station 3	0.08	0.1	0.09	0.11	0.1	0.14	0.11	0.13
Station 4	0.09	0.1	0.08	0.1	0.1	0.13	0.1	0.13

Figures 6.53 to 6.55 delineate the average values of DTR in each month for CGCM-A2, HadCM-A2 and HadCM-B2 scenarios at all of four stations. The figures show that both SVD-MAR and MSM reproduced the observed DTR perfectly in simulated series for all of three scenarios during calibration period. During validation period as well, both models reproduced the observed DTR very accurately for all the scenarios.

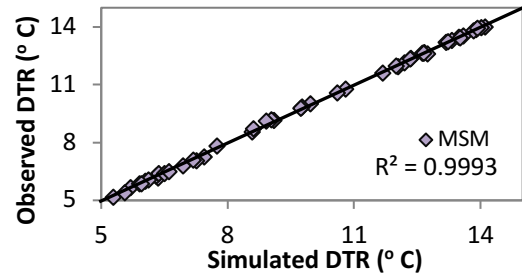
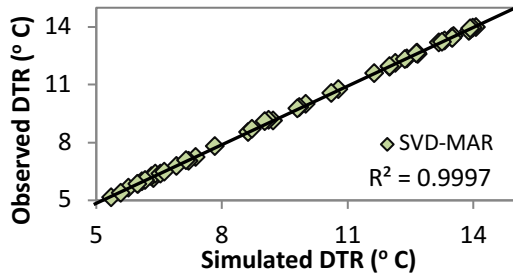


(a)

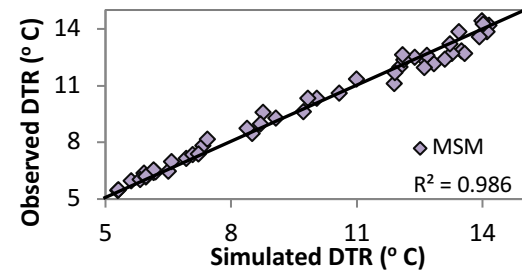
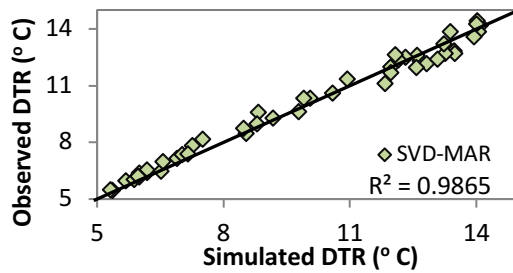


(b)

Figure 6.53: Average DTR in each month at four stations in Bangladesh during (a) calibration and (b) validation periods for CGCM-A2 scenario.

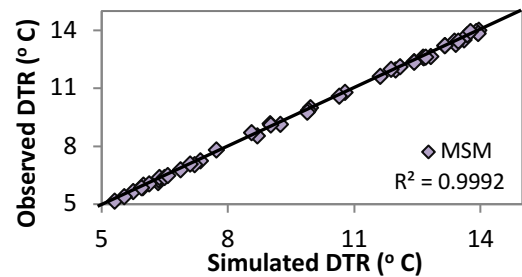
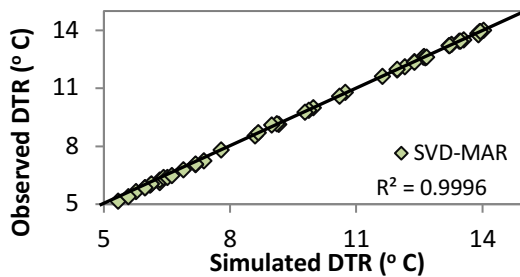


(a)

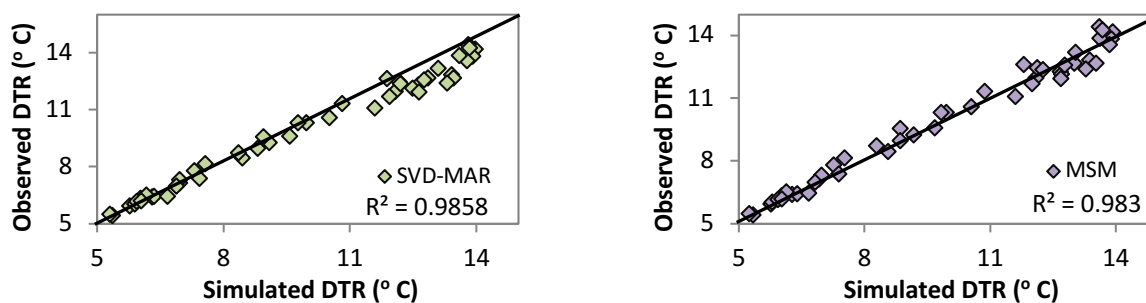


(b)

Figure 6.54: Average DTR in each month at four stations in Bangladesh during (a) calibration and (b) validation periods for HadCM-A2 scenario.



(a)



(b)

Figure 6.55: Average DTR in each month at four stations in Bangladesh during (a) calibration and (b) validation periods for HadCM-B2 scenario.

6.3 Prediction of future extreme temperature series in Bangladesh

This section provides the predictions of daily T_{max} and T_{min} for future period at four stations in Bangladesh using the SVD-MAR model under the A1B and A2 emission scenarios of CGCM and A2 and B2 emission scenarios of the HadCM.

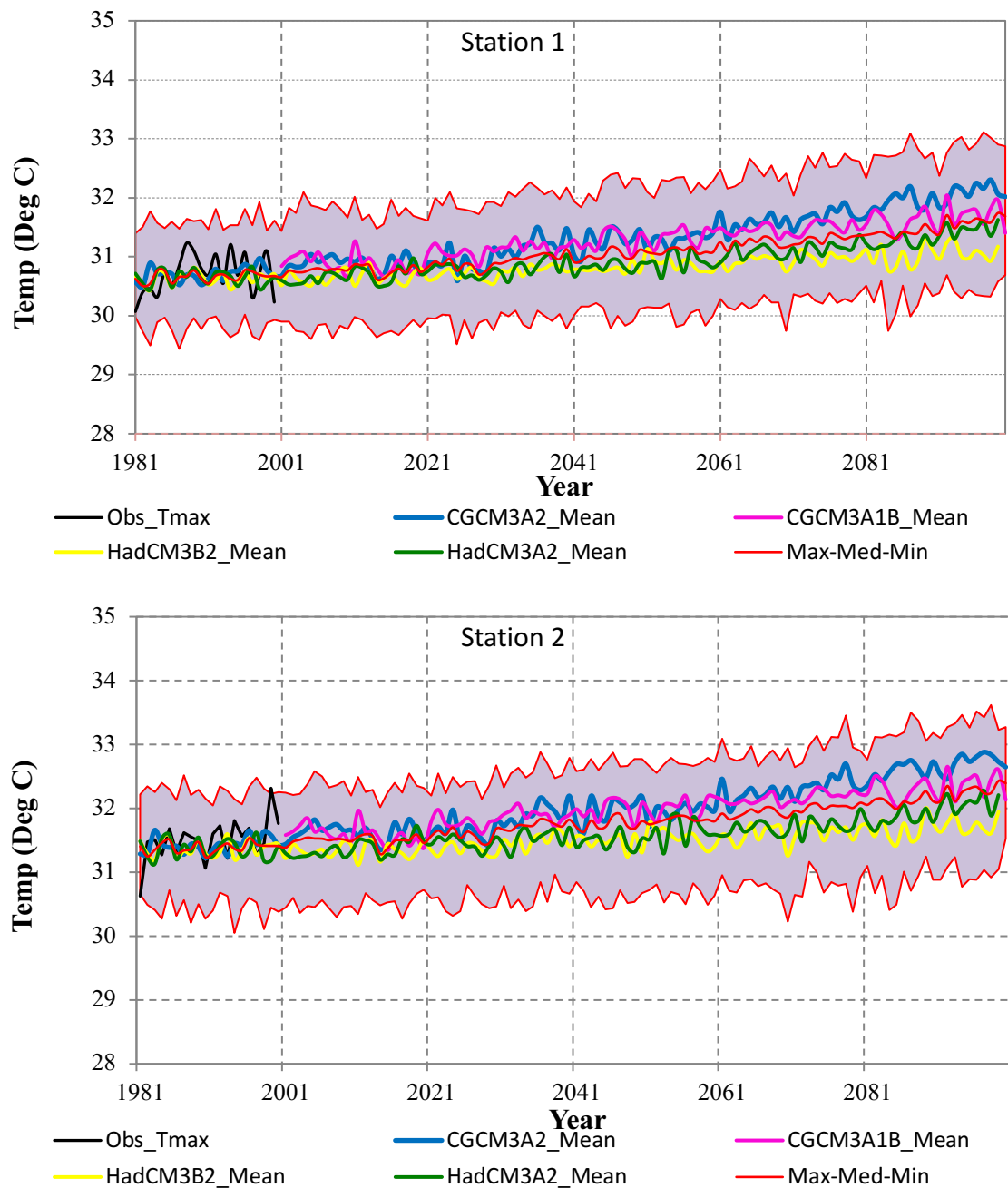
6.3.1 Prediction of future changes in annual average

Figures 6.56 and 6.57 show the annual averages of the daily T_{max} and T_{min} respectively for the period 1981-2100 under CGCM-A2 scenario, 2001-2100 period under CGCM-A1B and 1981-2099 period under HadCM-A2 and B2 scenarios depending on the available length of predictors of the respective GCMs. The solid lines represent the annual average of daily T_{max} and T_{min} in respective figures at each station (different colours represent different scenarios as described by the legends) and the grey shaded area in the figures show the total uncertainty of all the ensembles of four scenarios of CGCM and HadCM.

Figure 6.56 figures shows upward trends in annual average of daily T_{max} during future period especially for stations 1 and 2. However, at station 3 the trend is not so obvious especially under A2 and B2 scenarios of HadCM. At all the stations the scenarios of CGCM exhibit relatively higher increase in annual average of daily T_{max} than the scenarios of HadCM, including CGCM-A2 showing the highest trend and HadCM-B2 showing the lowest.

For T_{min} , upward trends were identified at each of the stations under all climate scenarios during future period (Figure 6.57). The scenarios of CGCM exhibit higher trends than the scenarios

of HadCM in annual average of daily *Tmin*, including CGCM-A2 showing the highest increase and HadCM-B2 showing the lowest at all the stations. The figures show that the total range of uncertainty of all the ensembles under four scenarios and differences in annual average of daily *Tmin* under different scenarios are relatively less than those of *Tmax*.



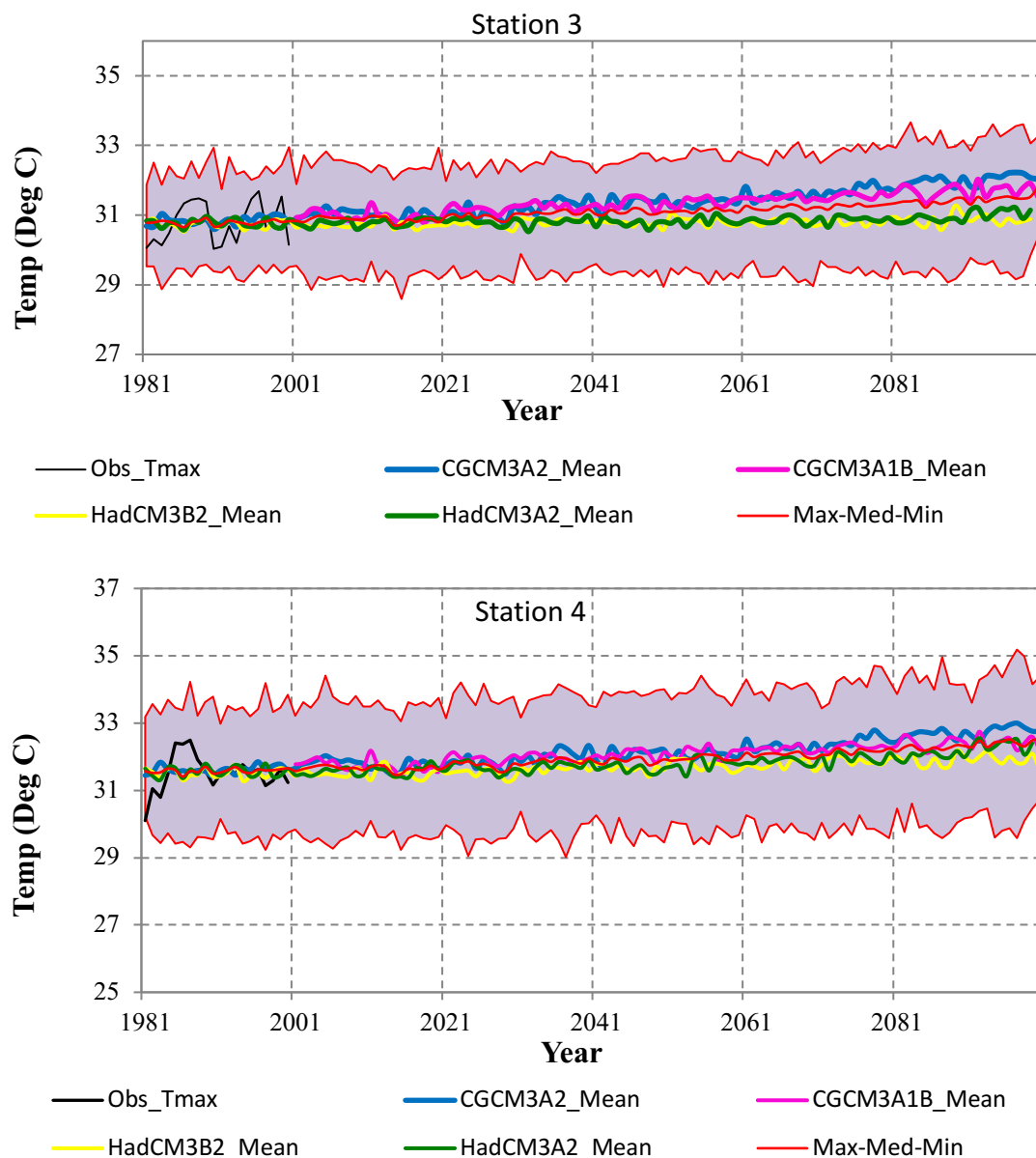
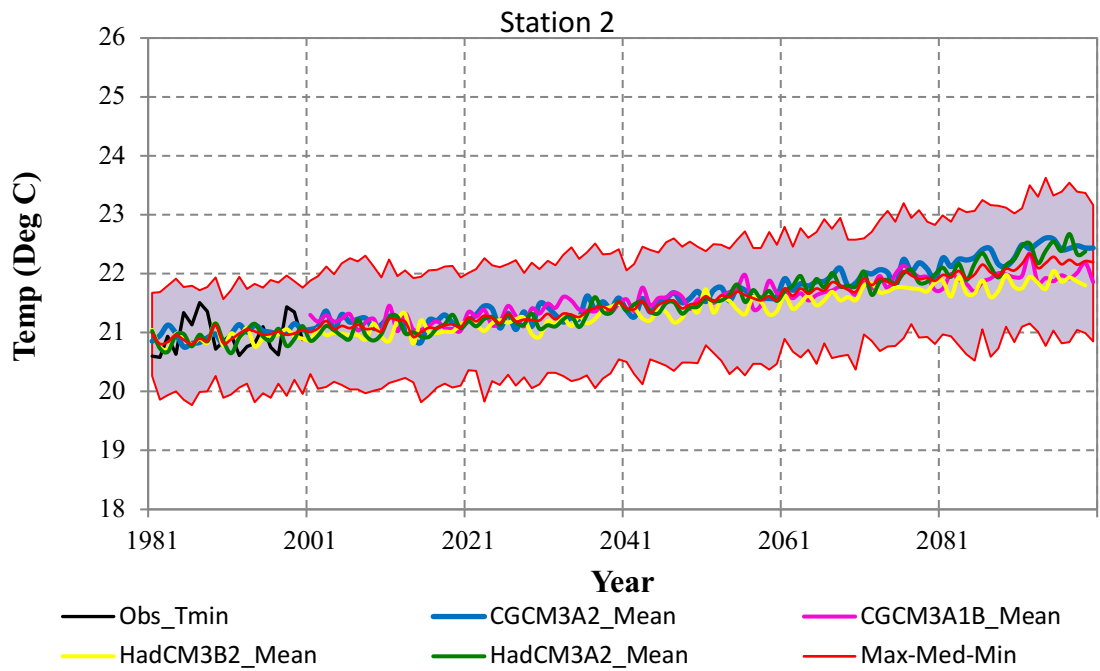
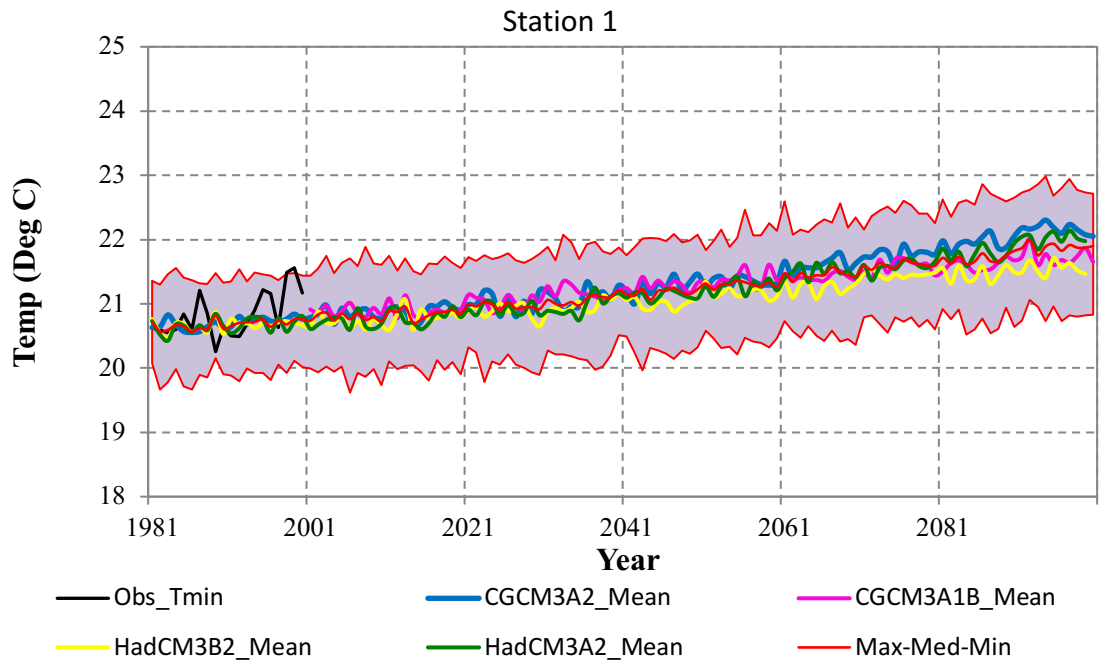


Figure 6.56: Projection of annual average of daily T_{max} under different emission scenarios at four stations in Bangladesh.



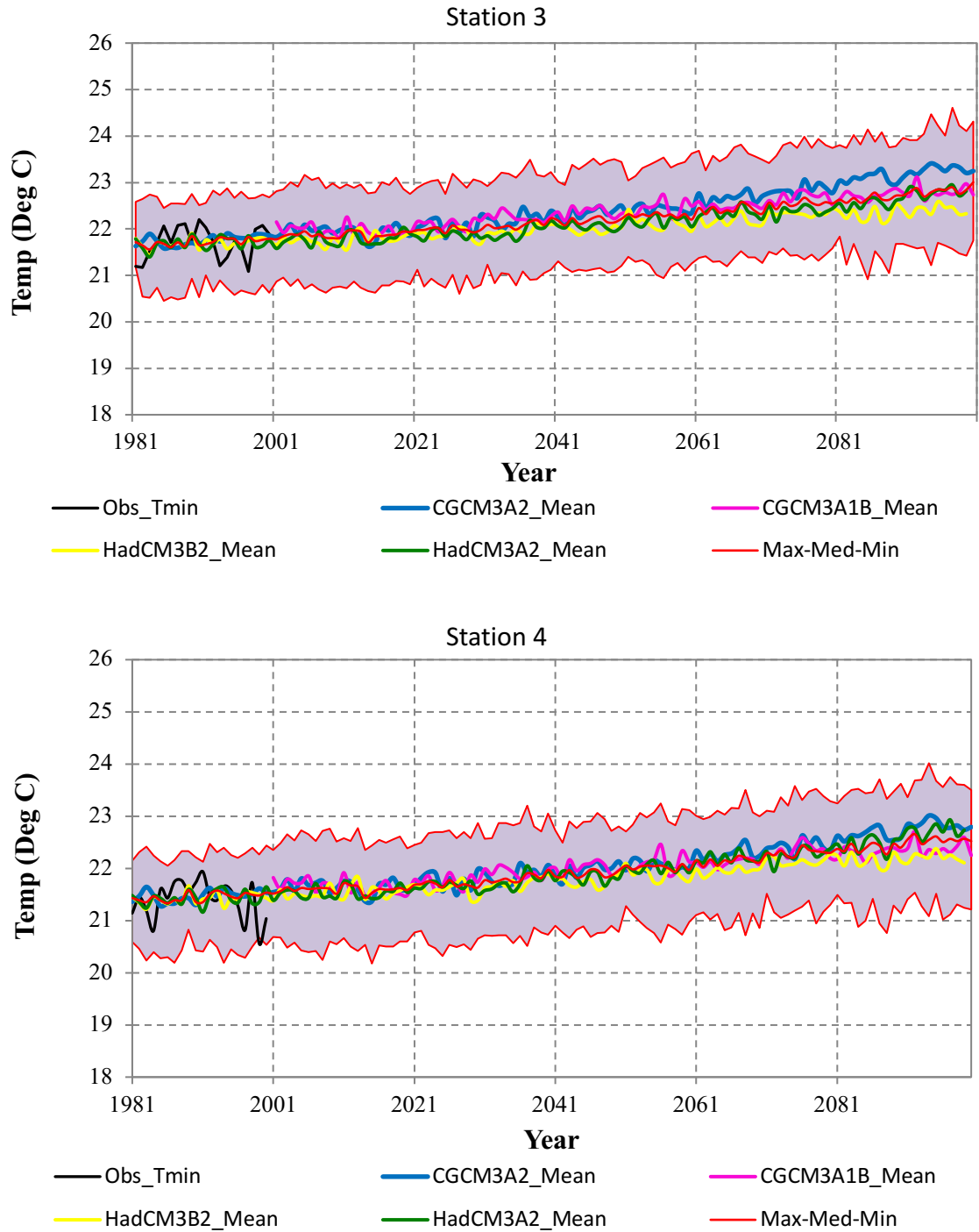


Figure 6.57: Projection of annual average of daily *Tmin* under different emission scenarios at four stations in Bangladesh.

6.3.2 Prediction of future changes in monthly means

Figures 6.58 and 6.59 present the boxplots of monthly means of daily T_{max} and T_{min} respectively in four months: January, March, September, and November, representing the four seasons (e.g., dry, pre-monsoon, monsoon and post-monsoon) for current period, 2040s, 2070s and 2090s under all scenarios. Here, current period represents simulated temperatures from respective GCMs for the period 1981-1990. Each boxplot represents monthly means of T_{max} and T_{min} aggregated at four stations.

Figure 6.58 shows the consecutive increase in monthly means of daily T_{max} during the decades of 2040s, 2070s and 2090s in each of the selected months under all the scenarios. However, the rate of increase differs under different scenarios and in different months. For example, in January the increase in monthly mean is relatively higher under HadCM scenarios than those of CGCM especially during 2070s and 2090s. On the contrary, in September the increase in monthly mean is higher under CGCM scenarios than those of HadCM over the same period. Like T_{max} , for monthly means of T_{min} also, positive trends are obvious in most of the months under all scenarios and the rate of increase is not equal under all the scenarios and for all months (Figure 6.59). Relatively higher increase is simulated under A2 scenarios of HadCM than that of CGCM except for September.

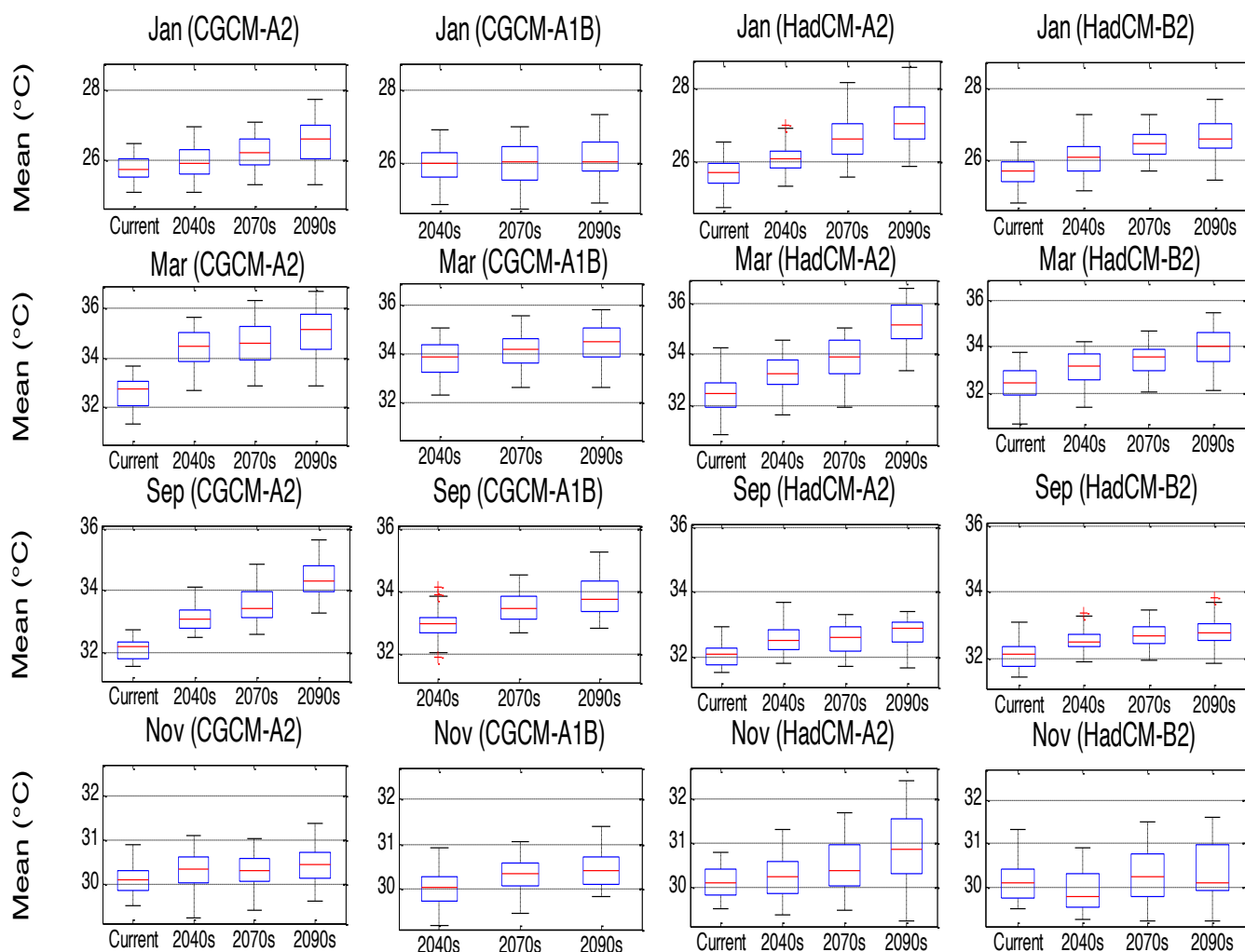


Figure 6.58: Prediction of monthly means of T_{max} in 2040s, 2070s and 2090s aggregated at four stations in Bangladesh.

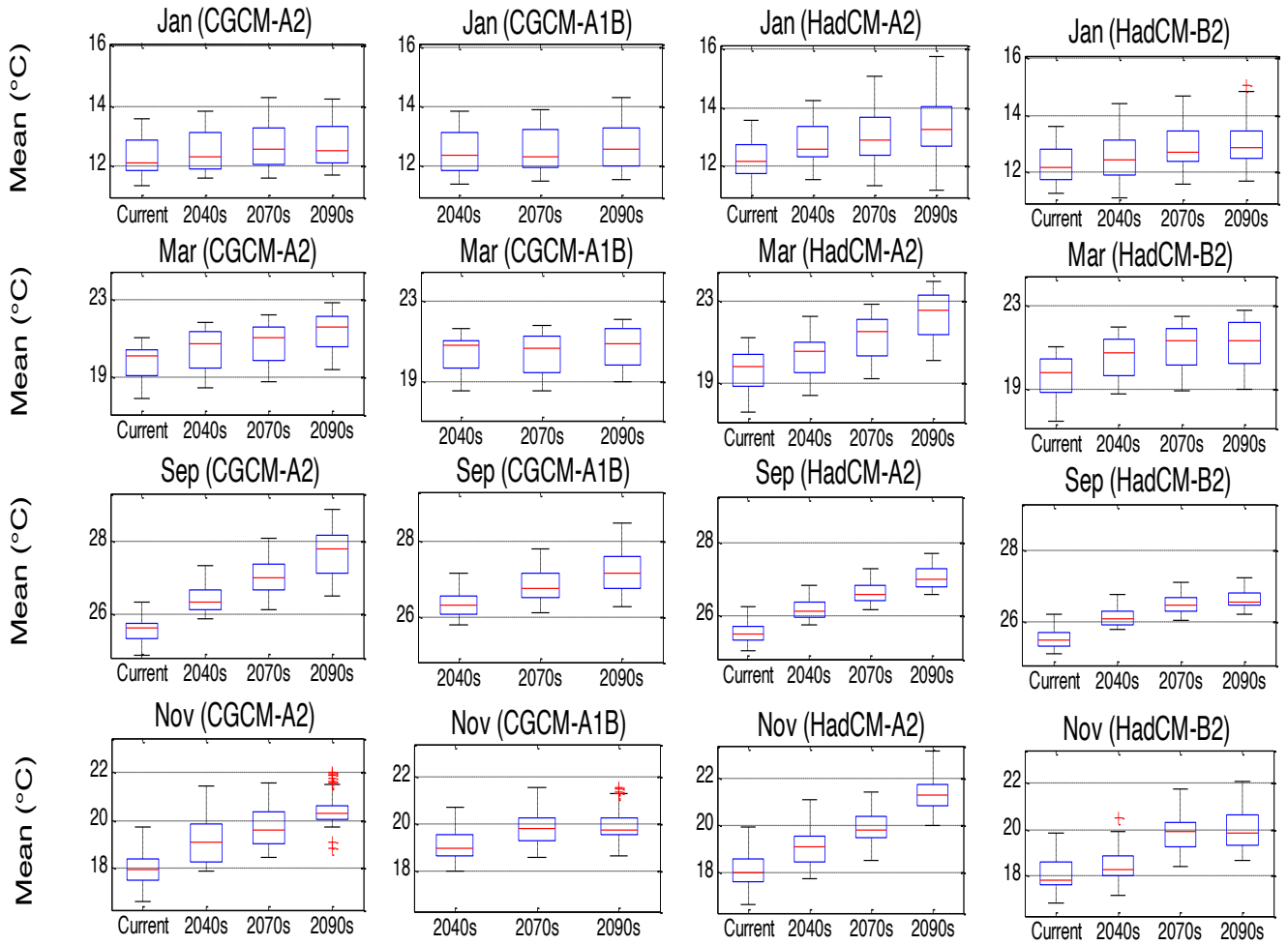


Figure 6.59: Prediction of monthly means of T_{min} in 2040s, 2070s and 2090s aggregated at four stations in Bangladesh.

6.3.3 Future trends in temperature indices

Table 6.9 presents the trends in selected indices of simulated temperature during future periods and compares with the observed ones during current period. Here, future and current periods represent 1981-2000 and 2041-2070 respectively.

All of four stations show positive trends in $T_{max}Mean$ during current as well as future periods under all scenarios. Although the magnitudes of the slopes during future period are less than the observed ones during current period, according to Mann-Kendall test the trends are significant at the 95% confidence level at most of the stations under A2 and A1B scenarios of CGCM and A2 scenario of HadCM. The slopes are highest under CGCM-A2 scenario at all the

stations whereas the lowest slopes are detected under HadCM-B2 scenario. The slopes in this index range between 0.001 - 0.016°C per year at all the stations under all scenarios during future period. Like $T_{max}Mean$, in case of $T_{min}Mean$, all the stations show positive trends under all the scenarios during future period and the trends are significant at the 95% confidence level at all of the stations. The slopes are relatively higher under A2 scenarios of CGCM and HadCM and lowest under CGCM-A1B scenario. The ranges of the slopes are between 0.005 - 0.018°C per year under all scenarios during future period for all the stations. Increasing trends in $T_{min}Mean$ than in $T_{max}Mean$ result in negative trends in DTR during future period under all the scenarios except CGCM-A1B, whereas positive trends were observed at most of the stations during current period. The slopes in this index ranges between -0.009 - 0.002°C per year during future period and relatively higher and significant trends are detected under A2 and B2 scenarios of HadCM.

Table 6.9 shows that both cool days and nights are decreasing at all the four stations under all scenarios and the slopes are higher for cool nights than in cool days indicating higher increase in T_{min} than in T_{max} . For cool days, the slopes are relatively higher under CGCM-A2 scenario and significant at all of the stations. Almost all the stations show significant trends in cool nights under CGCM-A2, CGCM-A1B and HadCM-A2 scenarios and the slopes are higher under A2 scenarios of CGCM and HadCM. The ranges of the slopes for cool days and nights are between -0.004 - -0.265 days per year and -0.065 - -0.381 days per year respectively. The slopes in both indices are larger during future period especially under CGCM-A2 and HadCM-A2 scenarios than the observed ones during current period at almost all the stations. All the stations show positive trends in the indices warm days and nights under all the scenarios, which is a clear anticipation of rapid warming of temperature during the period 2041-2070. The slopes in warm days are relatively higher and significant at all the stations under A1B and A2 scenarios of CGCM. In case of warm nights, the slopes are higher under A2 scenarios of CGCM and HadCM and significant at all the stations. The slopes in warm days and nights range respectively between 0.067 - 0.238 days per year and 0.115 - 0.348 days per year at all the stations under all the scenarios. The magnitudes of the slopes suggest that warm nights will be increasing at a higher rate than that of warm days during future period.

WSDI shows increasing trends at most of stations under all the scenarios during future period. On the other hand, CSDI exhibits decreasing trends under all the scenarios at almost all the

stations contrary to the observed increasing trends in this index at most of the stations during current period. The ranges of the slopes lie between -0.016 - 0.138 days per year and -0.214 - 0.055 days per year respectively for WSDI and CSDI during future period. However, none of four stations shows significant trend in these two indices under any scenario at the 95% confidence level.

The trend analysis indicate significant trends in most of the aforementioned temperature indices during the period 2041-2070 compared to 1981-2000 especially under A2 scenarios of CGCM and HadCM, signifying rapid warming of temperature at these four stations located in Bangladesh. Furthermore, the findings suggest that warming of T_{min} will be comparatively at a higher rate than T_{max} at most of the stations.

In this chapter proposed MMSD procedures were applied to daily T_{max} and T_{min} of selected four weather stations in Bangladesh. Both SVD-MAR and MSM models were found to reproduce monthly means and standard deviations of daily T_{max} and T_{min} , T_{max90p} , T_{min10p} etc. accurately for both NCEP. In addition, both MMSD methods were able to capture accurately the observed interstation correlations in the simulated series for T_{max} as well as T_{min} , and produced more accurate lag0 interstation correlations compared to singlesite downscaling SDSM procedure. Predictions of extreme temperature series for future period using the SVD-MAR model indicated upward trends in annual averages of T_{max} and T_{min} at the majority of the selected stations especially under CGCM scenarios. Most of the temperature related indices showed significant trends during future period (2041-2070) compared to current period (1981-2000) especially under A2 scenarios of CGCM and HadCM. In general, it was observed that SVD-MAR and MSM produced almost similar results in most cases.

In this study, only four stations were considered in Bangladesh and seven stations in the southern Quebec-Ontario region in Canada. However, SVD-MAR would be more computationally efficient and effective way of dimensionality reduction compared to MSM model, particularly where large number of stations needs to be considered.

Table 6.9: Observed and future trends in temperature indices at four stations in Bangladesh.

Station No.	TmaxMean					TminMean					DTR				
	Current		Future (2041-2070)			Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	0.017	0.008	0.016	0.011	0.005	0.037	0.006	0.016	0.017	0.01	-0.021	0.002	0	-0.006	-0.006
2	0.029	0.007	0.014	0.008	0.002	0.009	0.006	0.017	0.018	0.01	0.021	0.001	-0.003	-0.009	-0.007
3	0.024	0.008	0.011	0.003	0.001	0.01	0.006	0.016	0.013	0.007	0.013	0.002	-0.005	-0.009	-0.006
4	0.008	0.007	0.011	0.009	0.003	-0.01	0.005	0.015	0.016	0.009	0.019	0.002	-0.004	-0.006	-0.005

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 6.9 (Continued)

Station No.	Tx10p (Cool days)					Tx90p (Warm days)					Tn10p (Cool nights)					Tn90p (Warm nights)				
	Current		Future			Current		Future			Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	-0.072	-0.099	-0.265	-0.143	-0.081	0.154	0.168	0.227	0.148	0.105	-0.387	-0.135	-0.372	-0.331	-0.218	0.376	0.18	0.348	0.343	0.209
2	-0.201	-0.046	-0.242	-0.06	-0.004	0.335	0.156	0.238	0.145	0.07	-0.183	-0.113	-0.358	-0.232	-0.158	-0.044	0.143	0.339	0.286	0.188
3	-0.073	-0.108	-0.225	-0.01	0.008	0.22	0.164	0.192	0.097	0.067	0.004	-0.139	-0.381	-0.233	-0.113	0.215	0.18	0.293	0.186	0.115
4	-0.199	-0.065	-0.244	-0.133	-0.036	-0.236	0.136	0.184	0.196	0.155	0.274	-0.067	-0.271	-0.193	-0.065	-0.104	0.126	0.253	0.253	0.149

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Table 6.9 (Continued)

Station No.	WSDI					CSDI				
	Current		Future			Current		Future		
	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2	Obs	CGCM A1B	CGCM A2	HadCM A2	HadCM B2
1	0.043	0.09	0.115	0.13	0.023	-0.257	-0.019	-0.169	-0.122	-0.102
2	0.195	-0.001	0.027	0.085	0.127	0.074	-0.094	-0.214	-0.098	-0.138
3	0.259	0.061	0.063	0.066	-0.016	0.092	0.055	-0.129	-0.129	-0.132
4	-0.477	0.087	0.138	0.092	0.058	0.346	-0.051	-0.115	-0.11	0.007

*Bold value denotes statistically significant (significance level $\alpha = 0.05$)

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The following conclusions are drawn from the present study:

1. In this study, two multisite multivariate statistical downscaling (MMSD) techniques have been proposed for downscaling daily extreme temperature series at many sites concurrently. Both of these methods are basically based on the multiple linear regression model. The basic concept of the first method is based on a combination of the modeling of the linkages between local daily extreme temperature series and global climate predictors by multiple linear regression models; and the modeling of its stochastic components by the combined singular value decomposition and multivariate autoregressive (SVD-MAR) model to represent effectively and accurately the space-time variabilities of extreme daily temperature series. The second method is a combination of multiple linear regression models and a multivariate stochastic model (MSM). In fact, for these MMSD methods the main difference is in the description of the stochastic components of the downscaling model either by the SVD-MAR model or the MSM model.
2. The feasibility and accuracy of these proposed MMSD methods have been assessed using two sets of daily maximum (T_{max}) and minimum (T_{min}) temperature data from two networks of weather stations located in two completely different climatic regions: the cold-climate southern Quebec-Ontario region in Canada and tropical-climate region in Bangladesh. Moreover, NCEP reanalysis data for two different GCMs (Canadian CGCM and UK HadCM) were used as large-scale climate predictors in this study.
3. Based on different graphical and numerical performance, it was found that both SVD-MAR and MSM procedures were capable to reproduce accurately the basic statistical properties of daily extreme temperature series, such as monthly mean and standard deviation of daily T_{max} and T_{min} , the 90th percentile of daily T_{max} (T_{max90p}) and the 10th percentile of daily T_{min} (T_{min10p}) for both data sets in the southern Quebec-Ontario region and Bangladesh for both NCEP data. Additionally, in general, interannual anomalies of the standardized seasonal means and standard deviations of T_{max} and T_{min} and standardized

seasonal T_{max90p} and T_{min10p} indices were acceptably reproduced by these MMSD models.

4. The ability of the suggested models to capture the spatial variability in daily extreme temperature series at different locations has been evaluated through the reproducibility of the observed interstation correlations of T_{max} and T_{min} in the simulated series. Both MMSD methods were capable to capture accurately the observed interstation correlations in the simulated series for T_{max} as well as T_{min} series in both study regions for NCEP data for both CGCM and HadCM. In addition, it has been demonstrated that both suggested MMSD methods were capable of producing more accurate results than those given by the popular single-site downscaling procedure, SDSM, in terms of reproducing lag0 interstation correlations for daily T_{max} and T_{min} among different stations. For the stations in the southern Quebec-Ontario region, the R^2 values ranged between 0.76-0.85 and 0.85-0.94 respectively for T_{max} and T_{min} for SVD-MAR and MSM during calibration period, whereas for SDSM the R^2 values were as low as 0.08-0.16 for T_{max} and 0.02 for T_{min} . During validation period the R^2 values ranged between 0.7-0.73 and 0.76-0.84 respectively for T_{max} and T_{min} for SVD-MAR and MSM, and for SDSM those values were between 0.11-0.15 for T_{max} and 0.02-0.03 for T_{min} . For the stations in Bangladesh, during calibration period the R^2 values for SVD-MAR and MSM ranged between 0.96-0.98 and 0.95-0.98 respectively for T_{max} and T_{min} , and for SDSM those values were between 0.03-0.04 and 0.23-0.45 for T_{max} and T_{min} . For validation period R^2 values were between 0.73-0.76 and 0.89-0.91 respectively for T_{max} and T_{min} for SVD-MAR and MSM, and for SDSM these values ranged between 0.05-0.06 and 0.31-0.45 for T_{max} and T_{min} respectively.
5. The observed at-site correlations between daily T_{max} and T_{min} were reproduced accurately for the southern Quebec-Ontario region and acceptably for Bangladesh by both MMSD methods for both NCEP data sets. Along with preserving the correlations between daily T_{max} and T_{min} , both MMSD methods were found capable of producing the diurnal temperature range DTR very accurately for both NCEP data and for both regions. Furthermore, the effectiveness of the proposed methods to preserve the temporal dependencies was evaluated in terms of capturing the observed autocorrelation coefficients up to lag3 at each of the stations in the southern Quebec-Ontario region and Bangladesh.

Both of the proposed MMSD methods were capable to reproduce accurately the observed autocorrelation for T_{max} and T_{min} during calibration as well as validation periods for both CGCM and HadCM.

6. In addition to assessing the feasibility and accuracy of MMSD techniques in capturing the spatial and temporal statistical properties of daily extreme temperature series at different locations, the present study also demonstrated how multisite downscaling procedures can provide a significant improvement in the accuracy of impact assessment results as compared to single-site downscaling techniques. Hence, this study compared the accuracy of snowmelt computations given by the SVD-MAR method and widely used single-site downscaling SDSM procedure. The snowmelt was calculated by the degree-day approach using three sets of data: observed daily temperature series, downscaled daily temperature series given by the SVD-MAR and SDSM. It was found that SVD-MAR model was able to provide more accurate estimates of the snowmelt computations than SDSM (e.g., the total annual and monthly snowmelt amounts, the maximum daily snowmelt, standard deviation etc.). Therefore, MMSD should be used in practice to obtain more accurate impact assessment results especially for the areas where an accurate description of the spatial and temporal variations of weather variables is required.
7. The temperature scenarios for future periods were generated under A1B and A2 emission scenarios of CGCM (CGCM-A1B and CGCM-A2) and A2 and B2 emission scenarios of HadCM (HadCM-A2 and HadCM-B2). Predictions of extreme temperature series for the future periods indicated upward trends in the annual averages of both T_{max} and T_{min} at all seven stations in the southern Quebec-Ontario region under all scenarios. However, the rates of increase are not equal under all the scenarios, and HadCM-A2 showed the highest trends especially beyond 2080s. Furthermore, almost all of the selected stations in this region showed significant trends in most of the temperature related indices during future periods, especially under CGCM-A2, HadCM-A2 and HadCM-B2 scenarios compared to the current period. In Bangladesh, upward trends in annual averages of T_{max} and T_{min} were observed at the majority of the selected stations especially under CGCM scenarios, with CGCM-A2 scenario showing the highest increase. Trend analysis indicated significant trends in most of the temperature related indices, especially under A2 scenarios of CGCM and HadCM during future periods.

8. In the present study CGCM3.1 and HadCM3 versions have been used. However, since climate models are continually updated, it is recommended to use the latest model versions, as they integrate the most recent understanding of climate systems, represent advancements in resolution and incorporate improvements in accuracy and reliability for current climate research and projections. Furthermore, temperature projections for future periods should be made under different Representative Concentration Pathways (RCPs), as they provide plausible future scenarios.

7.2 Recommendations for future research

The following recommendations are suggested for further studies:

1. The MMSD models have been developed for downscaling daily extreme temperature processes in this study. The proposed models could be extended to downscale the precipitation processes at many sites concurrently in order to describe the spatio-temporal variability of the precipitation more accurately. Multisite downscaling of precipitation could provide a more accurate estimation of the runoff properties over a given watershed for various impact and adaptation studies.
2. In reality, temperature and precipitation are not entirely independent processes, but they could be interrelated. Hence, further studies could be carried out to downscale these two processes concurrently considering that daily temperature extremes could be conditioned on the wet or dry state of the day. This could lead to a more complete and more accurate description of climate conditions at a given location for climate change impact assessment studies.
3. In the present study, scenarios from two GCMs (CGCM and HadCM) have been used as an illustration to predict extreme temperature series for future periods under different climate change scenarios. But, to apply in the real world for hydrologic design and planning purposes, impact assessments, etc. predictions of future extreme temperature series must be generated using the climate scenarios given by other GCMs to assess the possible ranges of uncertainty and to obtain more reliable predictions.
4. The application of machine learning techniques in downscaling procedures is becoming increasingly important; therefore, further research could be conducted to compare their effectiveness in multisite, multivariate downscaling with traditional statistical downscaling

methods. Moreover, comparison of the performance of regional climate models (RCMs) and statistical downscaling methods can be useful especially where climate projections are required at a regional level.

5. The predictor-predictand relationship is central to any statistical downscaling model and choosing the significant large-scale atmospheric predictors is an important step to obtain accurate estimation of climate change impacts. However, there is no hard and fast rule for the selection of these predictors. Hence, predictor selection process remains as one of the most challenging tasks in practice. Therefore, there is the necessity to develop better screening methods for selecting the most significant predictors that could be able to describe the predictand characteristics more accurately at local study sites.

Chapter 8

STATEMENTS OF ORIGINALITY

To the best of the author's knowledge, the following are the original contributions of the present study to the hydrological science and engineering communities:

1. An original statistical modeling has been proposed for multisite multivariate downscaling (MMSD) of daily extreme temperature series at many locations concurrently. The proposed approach consists of a combination of multiple regression models to represent the linkage between global climate predictors and local T_{max} and T_{min} series, and singular value decomposition and multivariate autoregressive model (SVD-MAR) to describe the observed statistical properties of the regression model stochastic components. The proposed MMSD procedure has been proved to be able to capture accurately the spatial-temporal statistical properties of daily extreme temperature series at many sites concurrently in the climate change context. Therefore, this MMSD procedure can be used as an essential tool for accurate climate change impact assessment studies in engineering practice.
2. Another MMSD technique has been suggested, which is a combination of a multiple linear regression model and a multivariate stochastic model (MSM). This method was also found capable to preserve accurately the observed statistical properties (mean, standard deviation, correlations etc.) of the historical daily extreme temperature records at a single site as well as for different locations. Thereby, reproducibility of these important characteristics inherent in daily temperature series signifies the necessity and suitability of this model to provide fine resolute temperature data for hydrologic models as well as climate change impact assessment studies in any climatic region. Moreover, as two downscaling techniques have been proposed, it could assist to compare the results from two methods and to comprehend (estimate) the range of uncertainty that may originate due to different downscaling procedures.
3. The present study compared the effectiveness of multisite versus single-site downscaling techniques in preserving the spatial dependency of daily T_{max} and T_{min} among different locations. In addition, this study provided an evaluation of the

usefulness of multisite downscaling over single-site downscaling for impact assessment studies. This comparative assessment could lead to selecting the best downscaling method for providing more accurate assessment of the climate change impacts in engineering practice.

4. This is one of very few studies conducted for statistical modeling for multivariate downscaling of daily extreme temperature series concurrently at many sites in Bangladesh. Due to the geographical location and geomorphological conditions Bangladesh is one of the most vulnerable countries in the world to climate change. Many important sectors in Bangladesh, such as agriculture and food security, hydrology and water resources, surface and groundwater quantity and quality, coastal resources and wetland, natural ecosystems and biodiversity, human health, socio-economic condition are very much susceptible to climate change. This research, therefore, could be very helpful by providing valuable information regarding the future changes of climate variables in Bangladesh.

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Appendix A

DESCRIPTION OF THE STEPS FOR SIMULATING RESIDUALS OF EXTREME TEMPERATURE SERIES

Description of the steps for generating the residuals of daily T_{max} and T_{min} following SDV-MAR and MSM techniques described in Methodology chapter is provided in this section.

A-1 Generating residual matrix for seven stations in the southern Quebec-Ontario region

The following subsections provide detailed description of the steps for SVD-MAR (A-1-1) and MSM (A-1-2) for simulating the residual matrix of daily temperature series at seven stations in the southern Quebec-Ontario region.

A-1-1 SVD-MAR

Description of SVD-MAR method is provided in section 3.4.2.1 in chapter 3. The residual matrix E contains both the residual matrices $E_{T_{max}}$ and $E_{T_{min}}$ (Eq.3.5). Therefore, for the 15-year calibration period (1961-1975), for the seven used stations, and for both T_{max} and T_{min} , the residual matrix E will be of size 15×5110 . The rows are the records in years and the columns are the residuals of 2555 daily T_{max} at the seven stations followed by the residuals of 2555 daily T_{min} at these stations. The computational steps of the SVD-MAR procedures are described in the following:

Step 1: Compute the 15×5110 matrix E_s of standardized values of E (Eq.3.7).

Step 2: Compute the 15×15 matrix N_{ES_0} (Eq.3.12) instead of matrix M_{ES_0} . Because the size 15×15 of N_{ES_0} is smaller than the size 5110×5110 of M_{ES_0} matrix.

Step 3: Decompose N_{ES_0} matrix (by using Eq.3.9 but applied to the matrix N_{ES_0}) to obtain the 14×14 diagonal matrix Ω_{ES} of the ordered 14 non-zero eigenvalues of N_{ES_0} and the 15×14 matrix Γ_{ES} of the corresponding 14 eigenvectors. Here, 14 is the rank r of N_{ES_0} .

Step 4: Compute the matrix Ψ_{ES} of the eigenvectors of M_{ES_0} using the matrix Γ_{ES} of the eigenvectors of N_{ES_0} (Eq.3.13).

Step 5: Compute 15×14 sized standardized principal components matrix W_{Es} of Es by Eq.3.14.

Step 6: Partition the matrix W_{Es} into three sub matrices like: W_{Es}^1 , W_{Es}^2 , W_{Es}^3 . Their sizes are 15×5 , 15×4 and 15×5 respectively.

Step 7: Compute the lag-one correlation matrices $R_{Es_1}^1$ of W_{Es}^1 of size 5×5 . Note that, since the columns of the principal component matrix are perfectly uncorrelated, the lag-zero correlation matrix $R_{Es_0}^1$ is equal to I_5 (Identity matrix of size 5×5).

Step 8: Calculate $\phi_{Es_1}^1$ and Σ_{Es}^1 matrices (Eq.3.16 and Eq.3.17) of size 5×5 .

Step 9: Generate 15×5 MAR(1)-residual matrix $\hat{U}_{Es}^1$ following the normal distribution $N\left(0, \left(\Sigma_{Es,j,j}^1\right)^{\frac{1}{2}}\right)$.

Step 10: Compute the matrices $\hat{W}_{Es}^1$ using Eq.3.15 of size 15×5 .

Step 11: Repeat the steps 7-10 for $z = 2, 3$ and obtain the matrices $\hat{W}_{Es}^2$ and $\hat{W}_{Es}^3$ of size 15×4 and 15×5 respectively.

Step 12: Concatenate the 15×14 matrix $\hat{W}_{Es}$ using Eq.3.21.

Step 13: Compute the simulated matrix $\hat{E}s$ following Eq.3.19.

Step 14: Compute the non-standardize values of the matrix $\hat{E}$ using the Eq.3.20.

Finally, when the non-standardized simulated matrix $\hat{E}$ is computed, it is used in the Eq.3.4 to obtain the downscaled daily $Tmax$ and $Tmin$ values over the calibration period. The generation procedure was repeated hundred times to obtain enough series of the simulated data for an efficient statistical analyzes.

A-1-2 MSM

Description of MSM method is provided in section 3.4.2.2 in chapter 3. In this method the residuals are generated separately for each month. Then it was concatenated to obtain the daily synthetic series for required length. The steps for generating the residuals for seven stations located in the southern Quebec-Ontario region are described below.

Step 1: Obtain the residual values, which are the differences between the observed daily temperature and the estimated ones, for each month at each of the stations. Construct the residual matrix E by concatenating the elements of E_{Tmax} and E_{Tmin} , which are the residuals obtained for daily $Tmax$ and $Tmin$, respectively. For 15-year calibration period (1961-1975) and for seven used stations, and for both $Tmax$ and $Tmin$, the size of the residual matrix E for each month is: 465×14 , for the months Jan, Mar, May, Jul, Aug, Oct and Dec; 450×14 , for the months Apr, Jun, Sep and Nov; 420×14 , for the month Feb (without considering the leap years). Here, each row of matrix E represents a day for a given month and the columns represent the stations for E_{Tmax} and then followed by E_{Tmin} .

Step 2: Compute the matrix Es of standardized values of E . The size of the matrix Es is same as that of the matrix E . The standardized element, $Es_{i,j}$, of the matrix Es is computed as:.

$$Es_{i,j} = \frac{E_{i,j} - \bar{E}_j}{S_j}$$

$$= \frac{E_{i,j}}{S_j} \text{ (since, } \bar{E}_j \text{ is zero for all } j \text{, as, mean of the residuals is zero)}$$

where, $E_{i,j}$ is the value of E of i^{th} row and j^{th} column. $\bar{E}_j$ and S_j are the mean and the standard deviation of the column respectively.

Here, it can be noticed that, each of the columns has zero mean. Because it is one of the conditions of regression model that mean of the residuals is zero. But each of the columns has their specified (their own distinct) standard deviation for each month for each of the stations both for $Tmax$ and $Tmin$. Therefore, the matrix Es of the standardized values of E is computed by dividing each element by the standard deviation of their respective column.

The steps onward 3 to 9 are given here to explain the procedures for generating residual matrix for a particular month. The same steps are to be followed for each of the months separately.

Step 3: Compute the 14×14 lag-zero correlation matrix M_{Es0} and lag-one correlation matrix M_{Es1} of Es .

Step 4: Compute the matrix A_{Es} of size 14×14 using Eq.3.23.

Step 5: Compute 14×14 matrix C_{ES} using Eq.3.29.

Step 6: Factorize the matrix C_{ES} to obtain the lower triangular matrix B_{ES} of size 14×14 (Eq.3.28).

Step 7: Generate the random number $\hat{\epsilon}_{ES}$ following the normal distribution $N(0, 1)$.

Step 8: Compute the simulated matrix $\hat{E}_S$ using Eq.3.30.

Step 9: Compute the non-standardize values of the matrix $\hat{E}$ by multiplying the standard deviation of the respective month.

After computing the non-standardized simulated matrix $\hat{E}$ separately for each of the months, the results are used in the Eq.3.4 to obtain the final downscaled daily T_{max} and T_{min} .

A-2 Generating residual matrix for four stations in Bangladesh

The following subsections provide detailed description of the steps for SVD-MAR(A-2-1) and MSM (A-2-2), which have been applied to simulate the residual matrix of daily temperature series at four stations in Bangladesh.

A-2-1 SVD-MAR

For 10-year calibration period (1981-1990), for four used stations, and for both T_{max} and T_{min} , the residual matrix E will be of size 10×2920 . The rows are the records in years and the columns are the residuals of 1460 daily T_{max} at the seven stations followed by the residuals of 1460 daily T_{min} at these stations. The computational steps of the SVD-MAR procedures are described in the following:

Step 1: Compute the 10×2920 matrix E_S of standardized values of E (Eq.3.7).

Step 2: Compute the 10×10 matrix N_{ES_0} (Eq.3.12) instead of matrix M_{ES_0} . Because the size 10×10 of N_{ES_0} is smaller than the size 2920×2920 of M_{ES_0} matrix.

Step 3: Decompose N_{ES_0} matrix (by using Eq.3.9 but applied to the matrix N_{ES_0}) to obtain the 9×9 diagonal matrix Ω_{ES} of the ordered 9 non-zero eigenvalues of N_{ES_0} and the 10×9 matrix Γ_{ES} of the corresponding 9 eigenvectors. Here, 9 is the rank r of N_{ES_0} .

Step 4: Compute the matrix Ψ_{Es} of the eigenvectors of M_{Es0} using the matrix Γ_{Es} of the eigenvectors of N_{Es0} (Eq.3.13).

Step 5: Compute 10×9 sized standardized principal components matrix W_{Es} of Es by Eq.3.14.

Step 6: Partition the matrix W_{Es} into three sub matrices like: W_{Es}^1 , W_{Es}^2 , W_{Es}^3 . Their sizes are 10×3 , 10×3 and 10×3 respectively.

Step 7: Compute the lag-one correlation matrices R_{Es1}^1 of W_{Es}^1 of size 3×3 . Note that, since the columns of the principal component matrix are perfectly uncorrelated, the lag-zero correlation matrix R_{Es0}^1 is equal to I_3 (Identity matrix of size 3×3).

Step 8: Calculate ϕ_{Es1}^1 and Σ_{Es}^1 matrices (Eq.3.16 and Eq.3.17) of size 3×3 .

Step 9: Generate 10×3 MAR(1)-residual matrix $\hat{U}_{Es}^1$ following the normal distribution $N\left(0, \left(\Sigma_{Es,j,j}^1\right)^{\frac{1}{2}}\right)$.

Step 10: Compute the matrices $\hat{W}_{Es}^1$ using Eq.3.15 of size 10×3 .

Step 11: Repeat the steps 7-10 for $z = 2, 3$ and obtain the matrices $\hat{W}_{Es}^2$ and $\hat{W}_{Es}^3$ of size 10×3 .

Step 12: Concatenate the 10×9 matrix $\hat{W}_{Es}$ using Eq.3.21.

Step 13: Compute the simulated matrix $\hat{E}s$ following Eq.3.19.

Step 14: Compute the non-standardize values of the matrix $\hat{E}$ using the Eq.3.20.

Finally, when the non-standardized simulated matrix $\hat{E}$ is computed, it is used in the Eq.3.4 to obtain the downscaled daily $Tmax$ and $Tmin$ values over the calibration period.

A-2-2 MSM

The steps for generating the residuals of daily $Tmax$ and $Tmin$ following MSM model for used four stations in Bangladesh are given below.

Step 1: Obtain the residual values, which are the difference between the observed daily data and the estimated ones, for each month at each of the stations. Construct the residual matrix E by

concatenating the elements of E_{Tmax} and E_{Tmin} , which are the residuals obtained for daily $Tmax$ and $Tmin$, respectively. For 10-year calibration period (1981-1990) and for four used stations, and for both $Tmax$ and $Tmin$, the size of the residual matrix E for each month is: 310×8 , for the months Jan, Mar, May, Jul, Aug, Oct and Dec; 300×8 , for the months Apr, Jun, Sep and Nov; 280×8 , for the month Feb (without considering the leap years). Here, each row of matrix E represents a day for a given month and the columns represent the stations for E_{Tmax} and then followed by E_{Tmin} .

Step 2: Compute the matrix E_s of standardized values of E by dividing each element by the standard deviation of their respective column.

The steps onward 3 to 9 are given here to explain the procedures for generating residual matrix for a particular month. The same steps are to be followed for each of the months separately.

Step 3: Compute the 8×8 lag-zero correlation matrix M_{Es0} and lag-one correlation matrix M_{Es1} of E_s .

Step 4: Compute the matrix A_{Es} of size 8×8 using Eq.3.23.

Step 5: Compute 8×8 matrix C_{Es} using Eq.3.29.

Step 6: Factorize the matrix C_{Es} to obtain the lower triangular matrix B_{Es} of size 8×8 (Eq.3.28).

Step 7: Generate the random number $\hat{\epsilon}_{Es}$ following the normal distribution $N(0, 1)$.

Step 8: Compute the simulated matrix $\hat{E}_s$ using Eq.3.30.

Step 9: Compute the non-standardize values of the matrix $\hat{E}$ by multiplying the standard deviation of the respective month.

After computing the non-standardized simulated matrix $\hat{E}$ separately for each of the months, the results are used in the Eq.3.4 to obtain the final downscaled daily $Tmax$ and $Tmin$.

Appendix B

ANALYSIS OF EXTREME TEMPERATURE SERIES IN THE QUEBEC-ONTARIO REGION IN CANADA

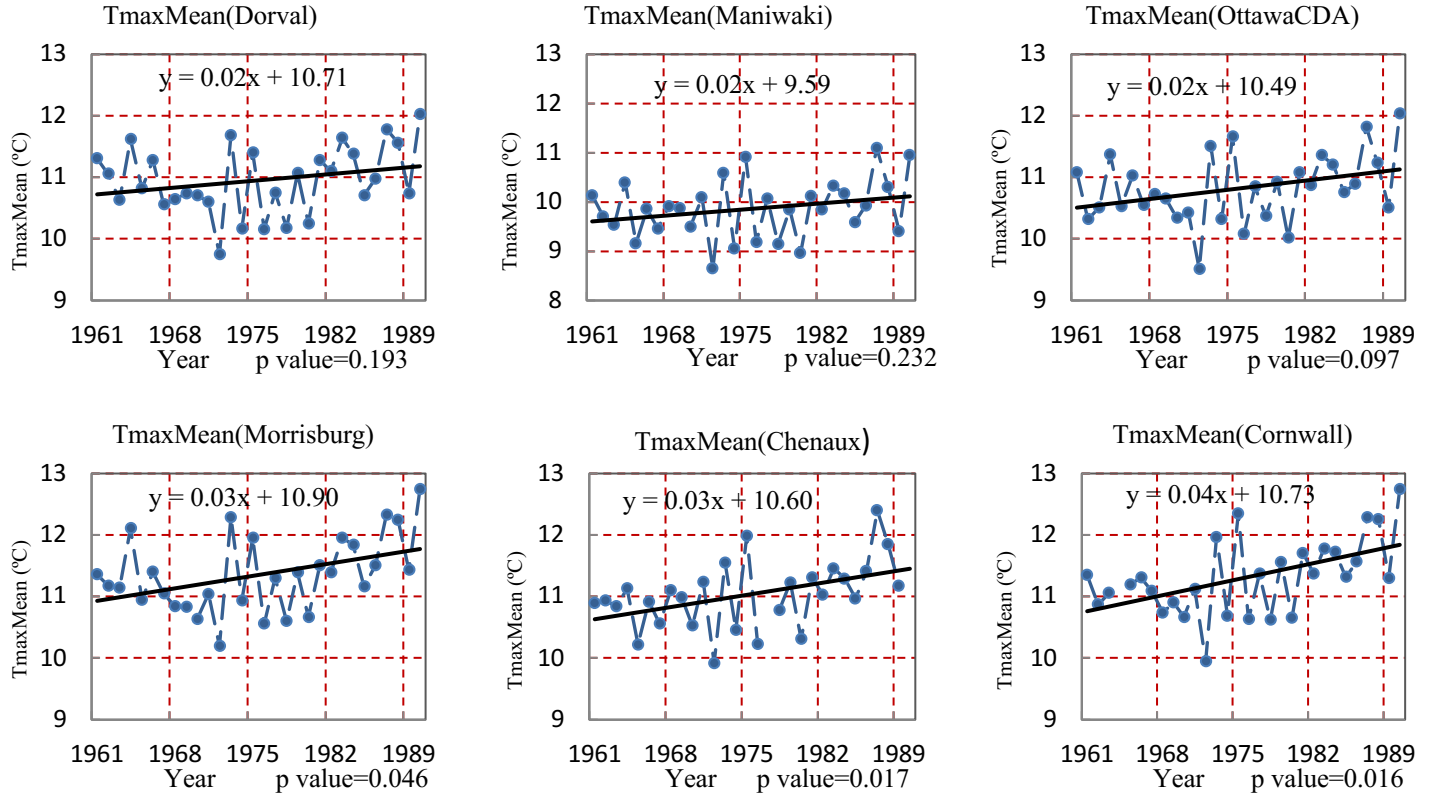
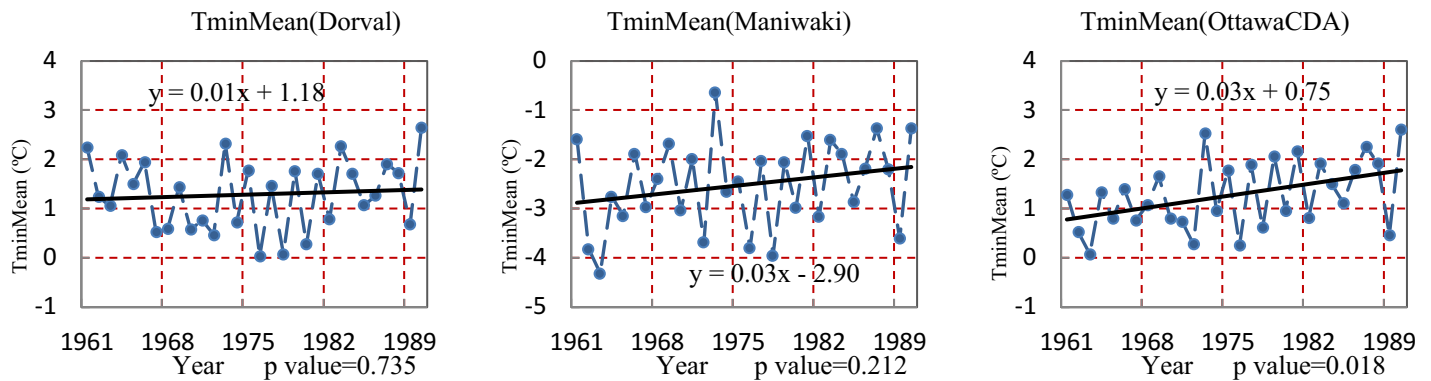


Figure B-1: Trends in TmaxMean at six stations in the southern Quebec-Ontario region.



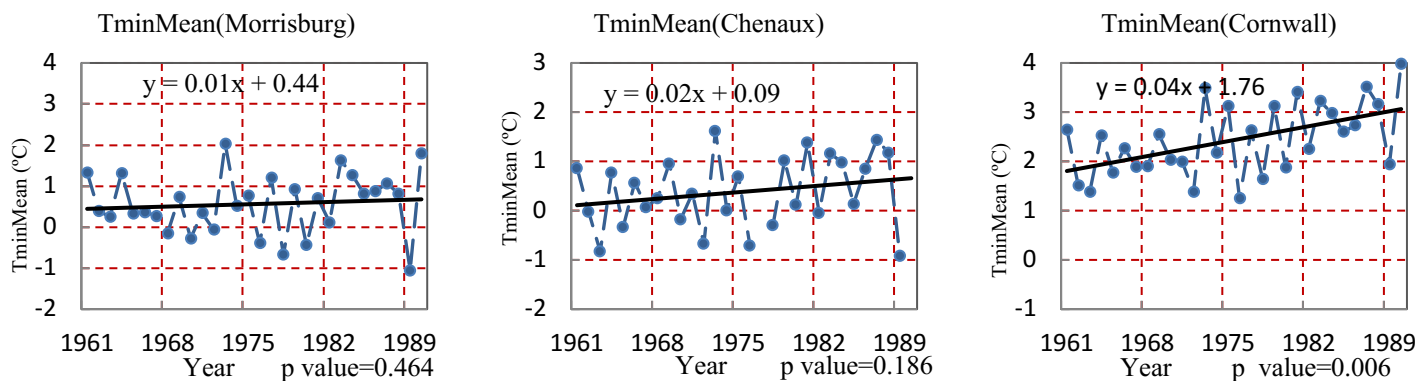


Figure B-2: Trends in TminMean at six stations in the southern Quebec-Ontario region.

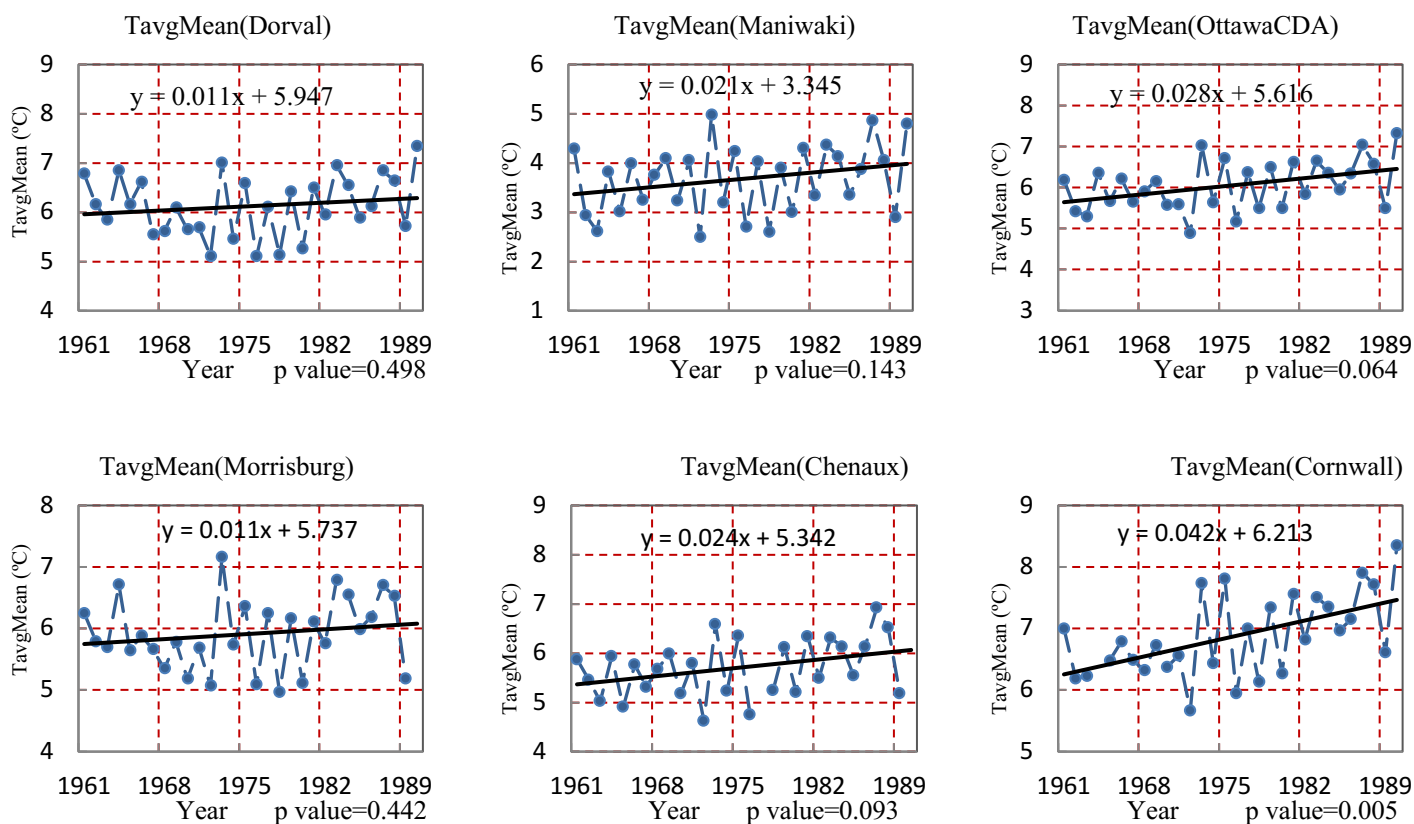


Figure B-3: Trends in TavGMean at six stations in the southern Quebec-Ontario region.

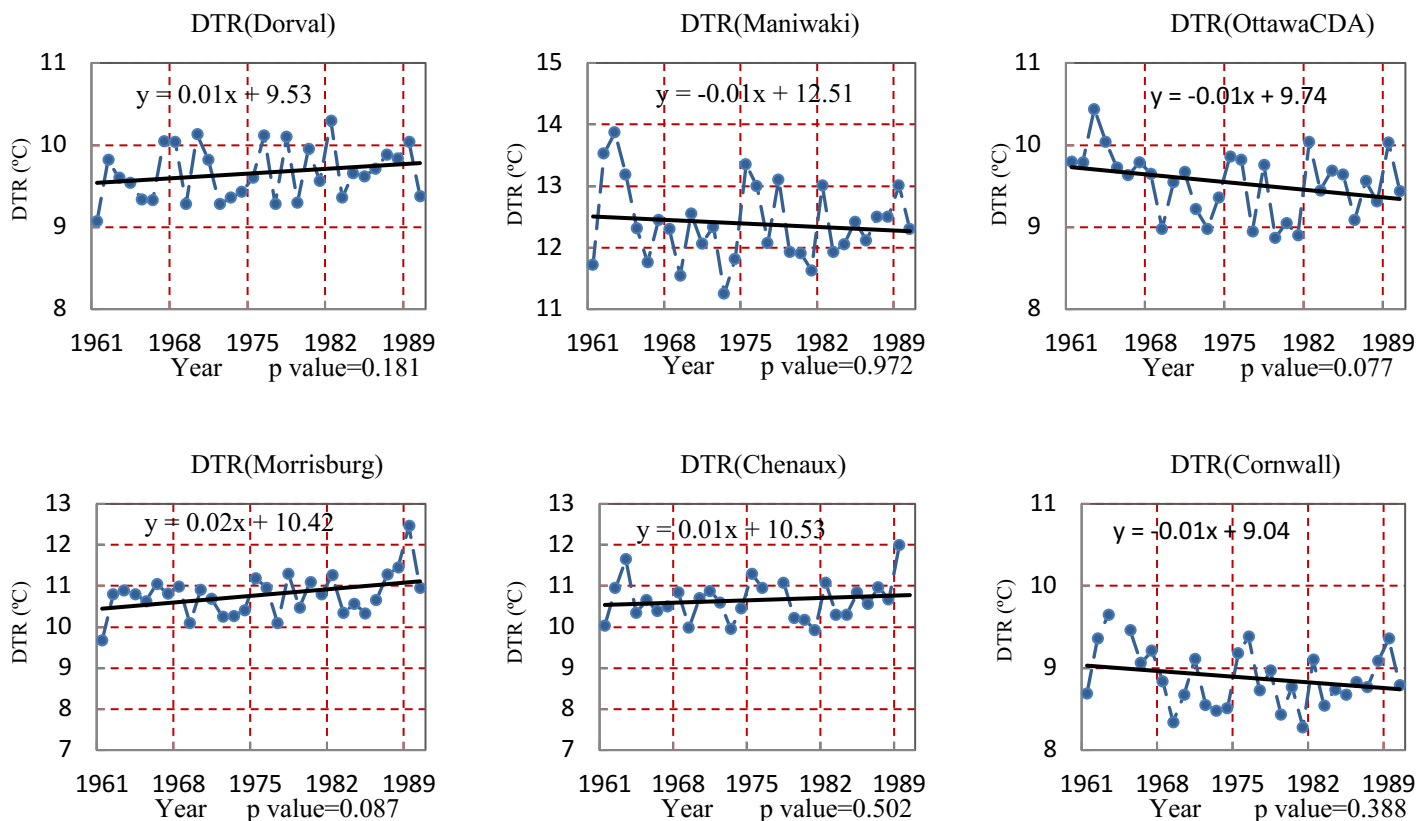
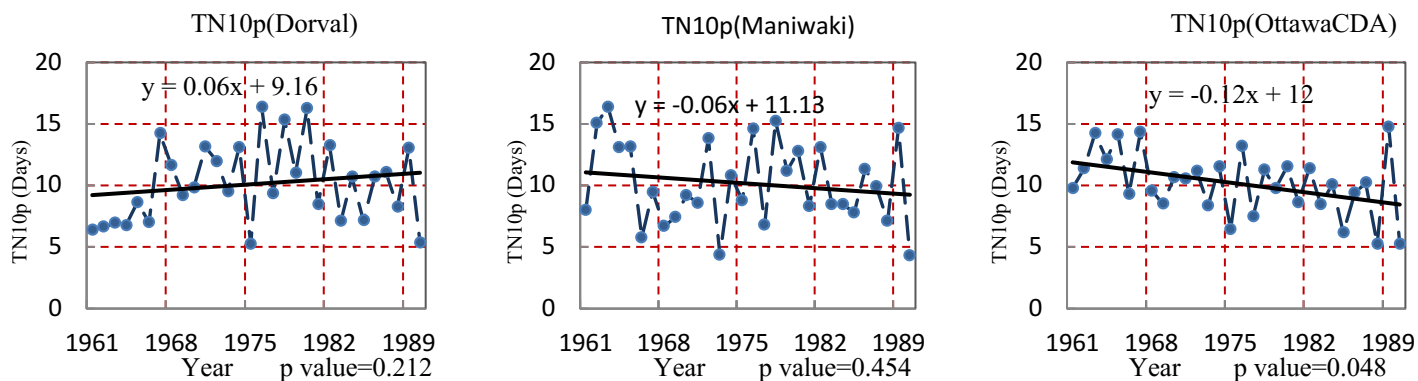


Figure B-4: Trends in DTR at six stations in the southern Quebec-Ontario region.



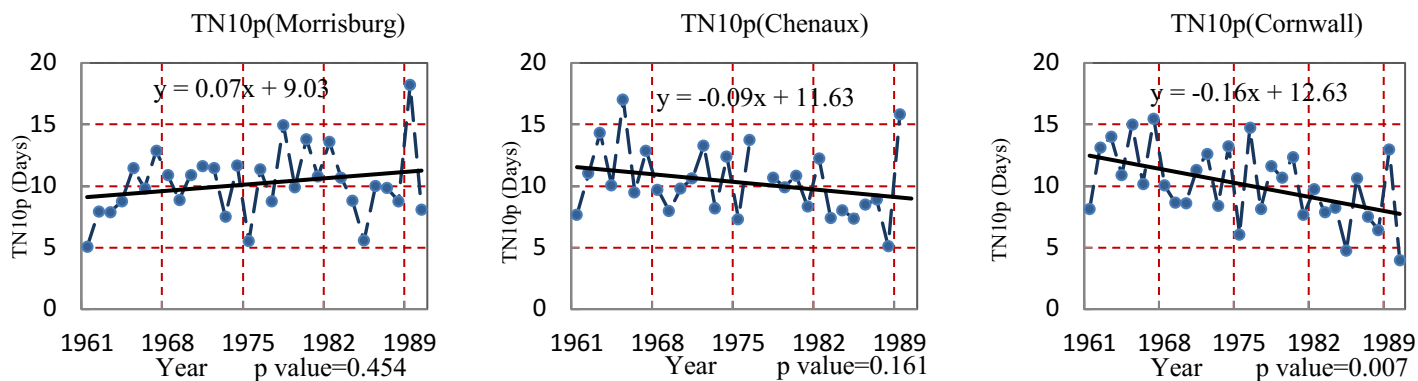


Figure B-5: Trends in cool nights (TN10p) at six stations in the southern Quebec-Ontario region.

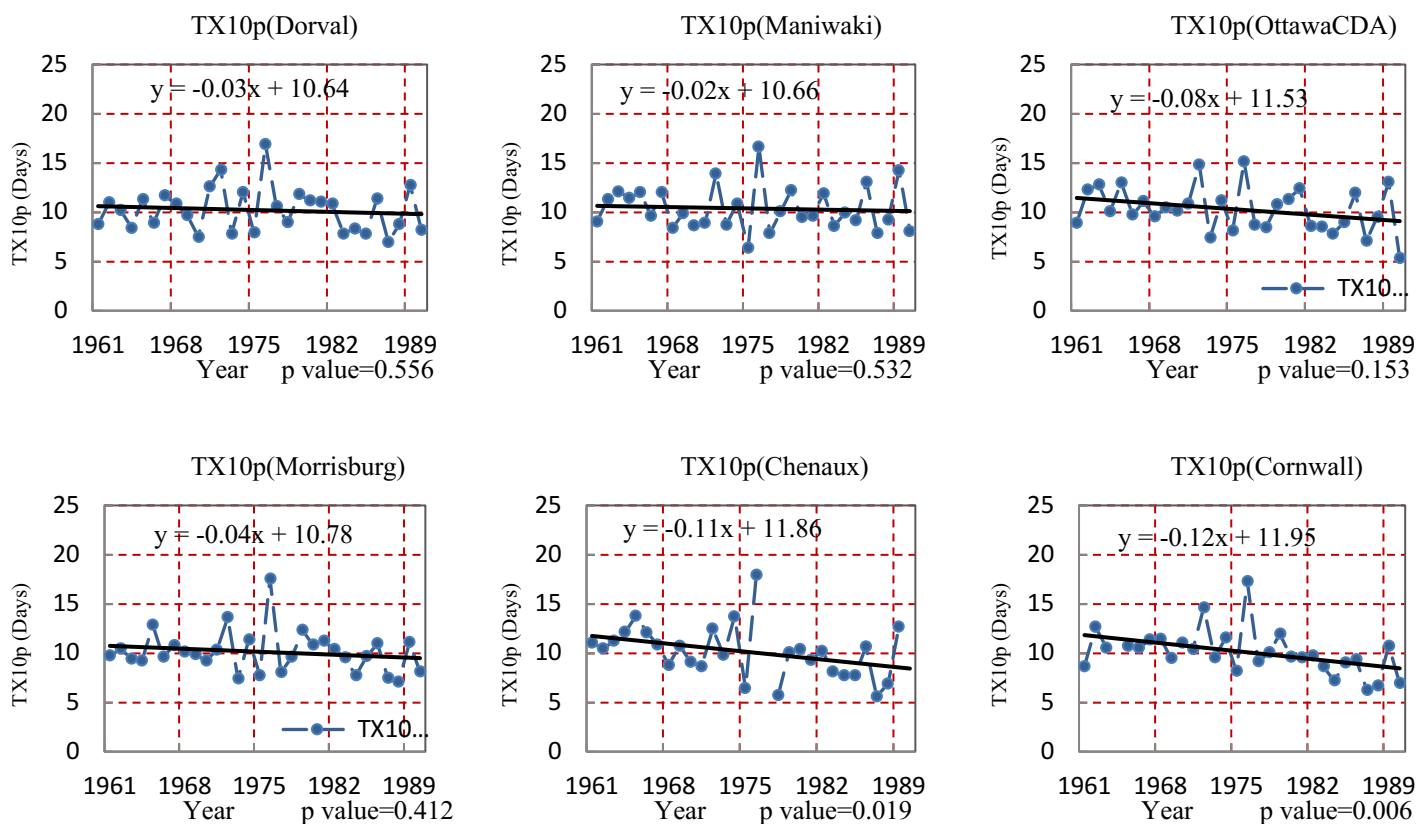


Figure B-6: Trends in cool days (TX10p) at six stations in the southern Quebec-Ontario region.

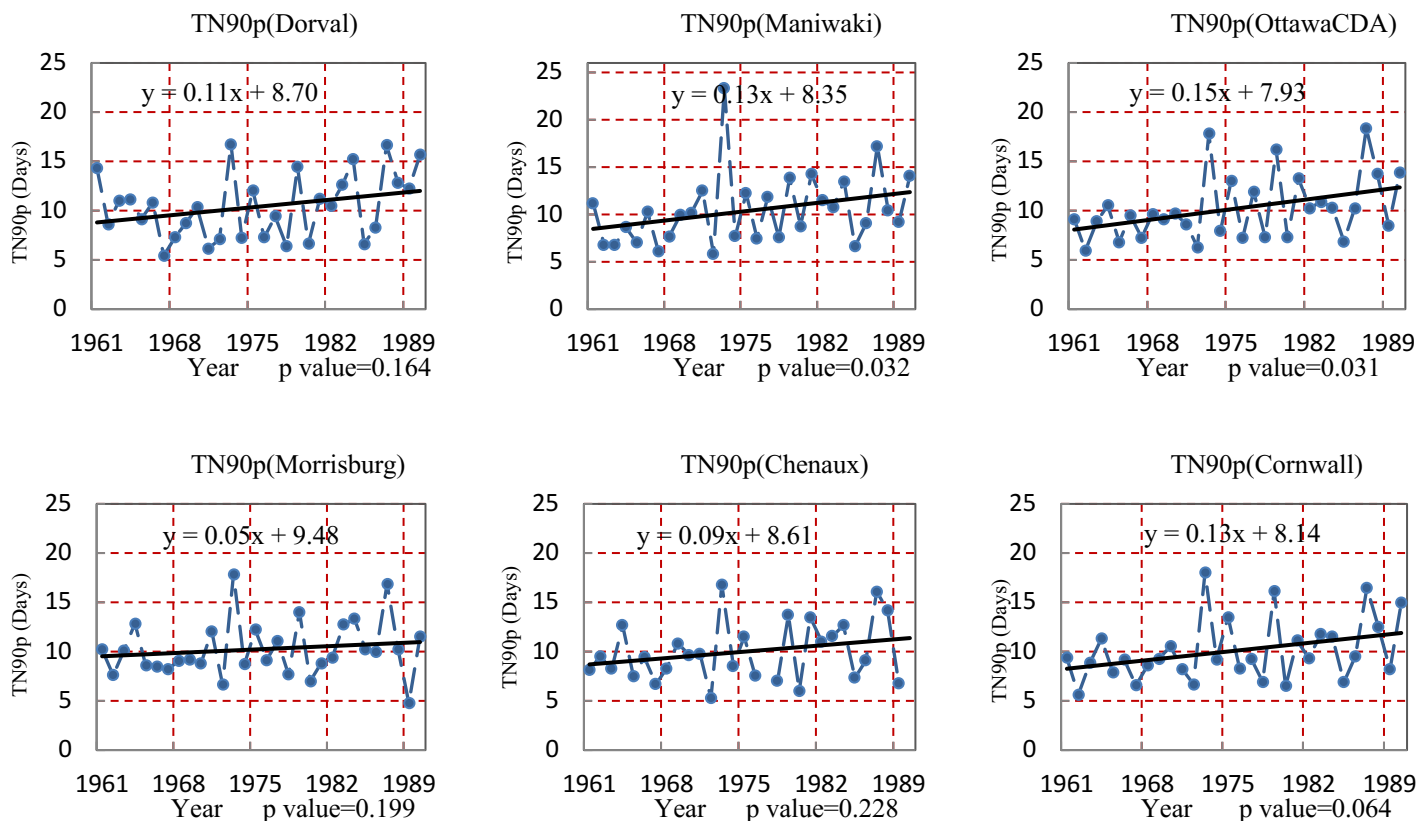
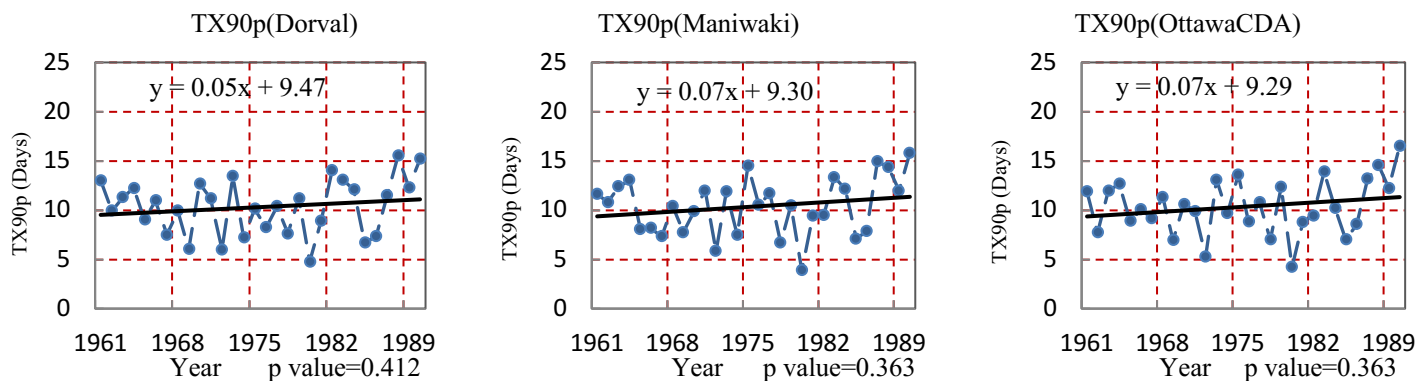


Figure B-7: Trends in warm nights (TN90p) at six stations in the southern Quebec-Ontario region.



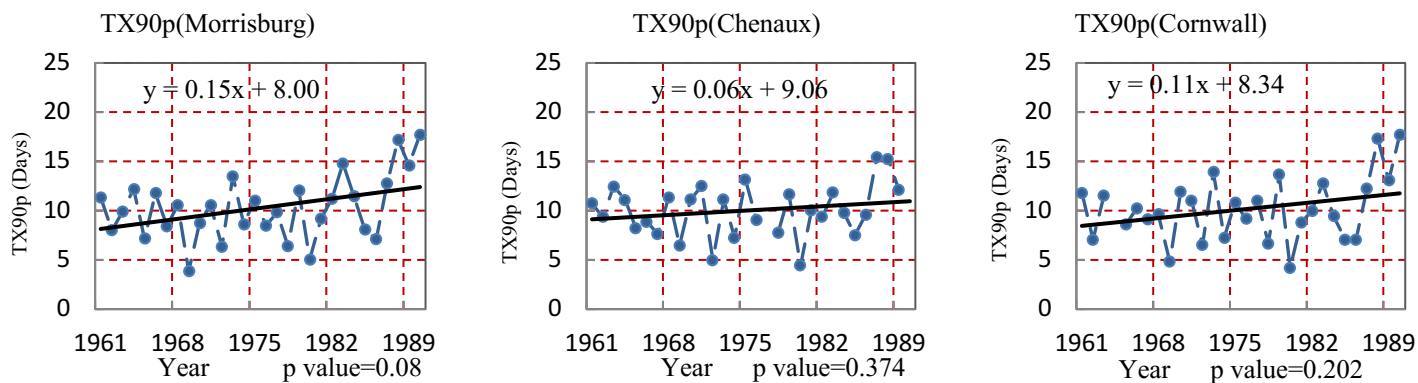


Figure B-8: Trends in warm days (TX90p) at six stations in the southern Quebec-Ontario region.

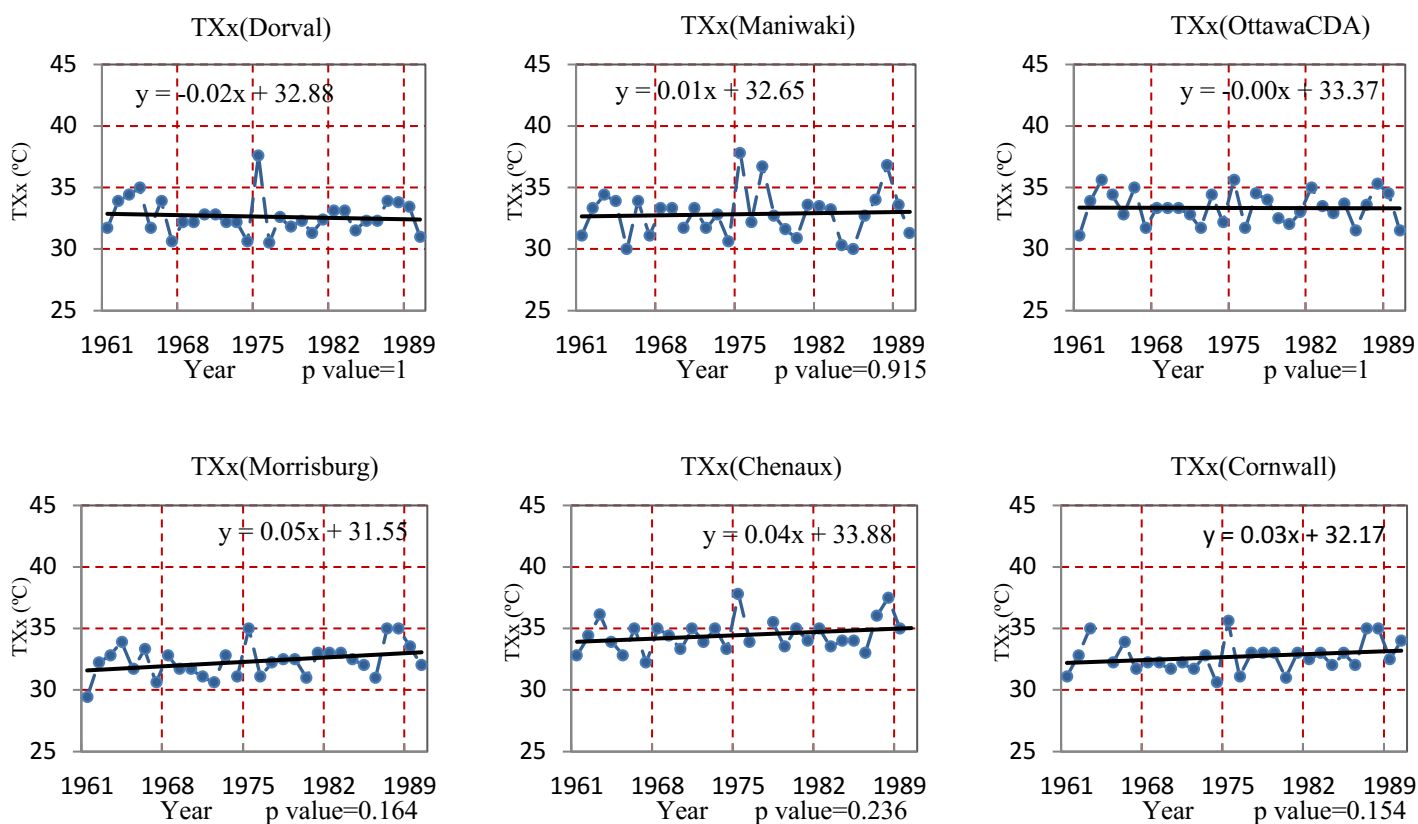


Figure B-9: Trends in MaxTmax (TXx) at six stations in the southern Quebec-Ontario region.

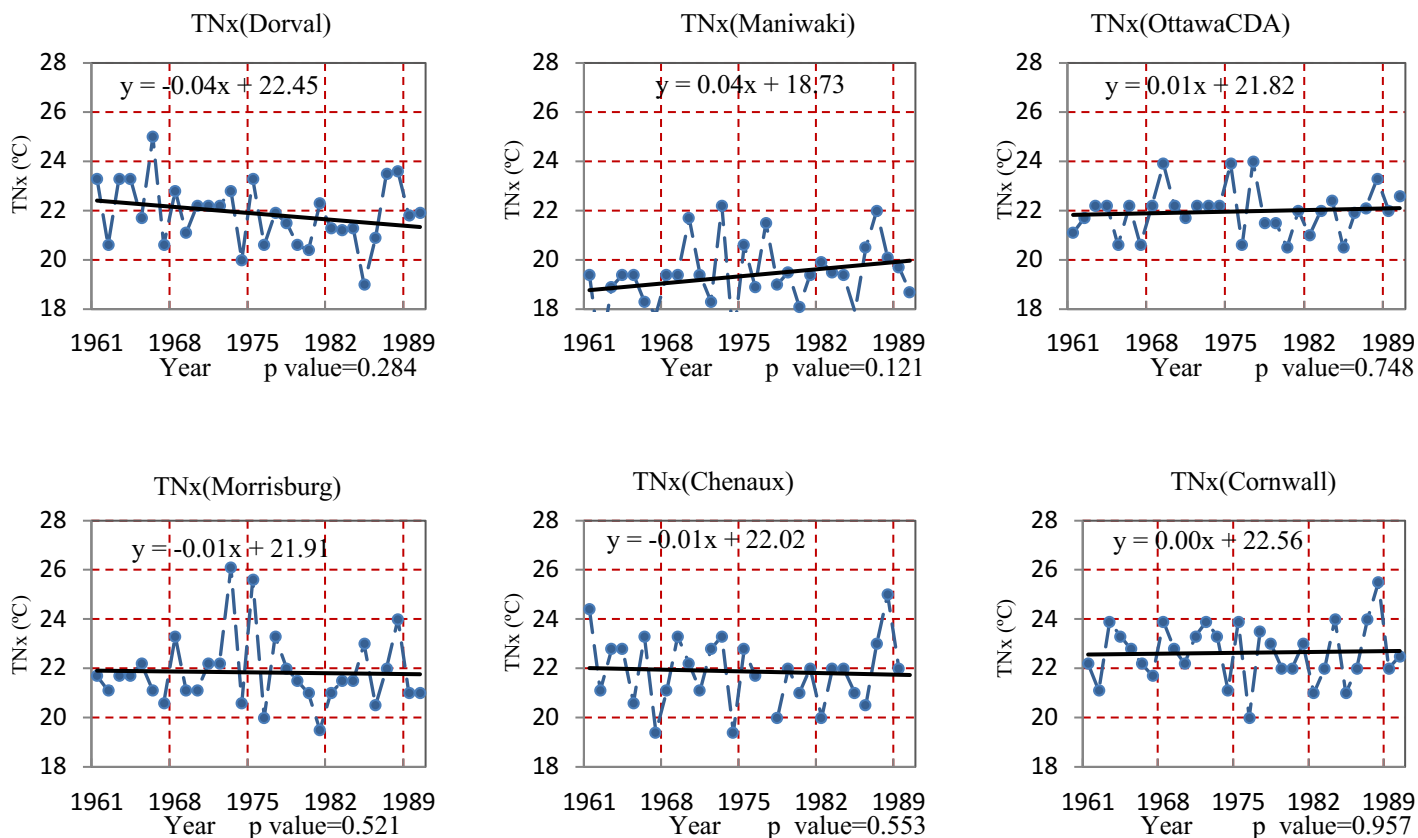
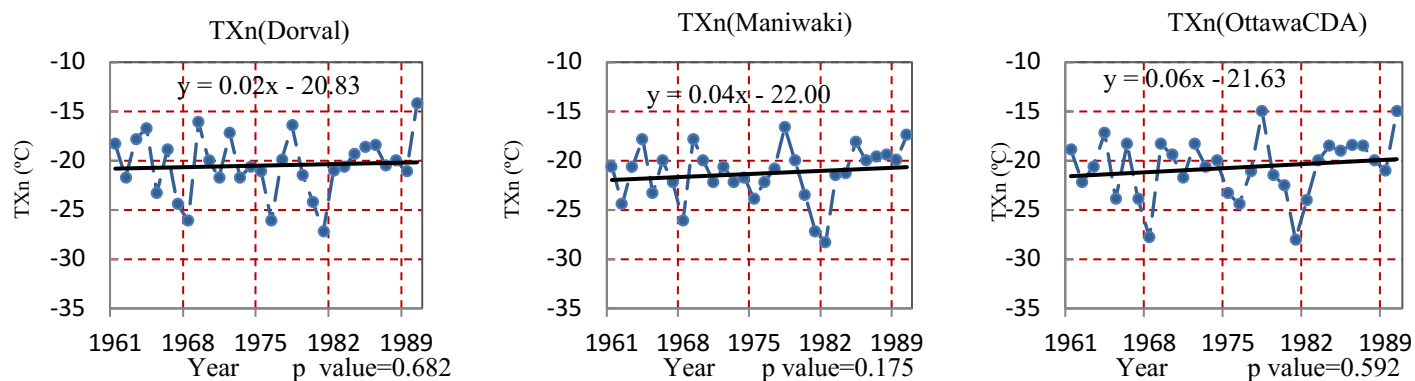


Figure B-10: Trends in MaxTmin (TNx) at six stations in the southern Quebec-Ontario region.



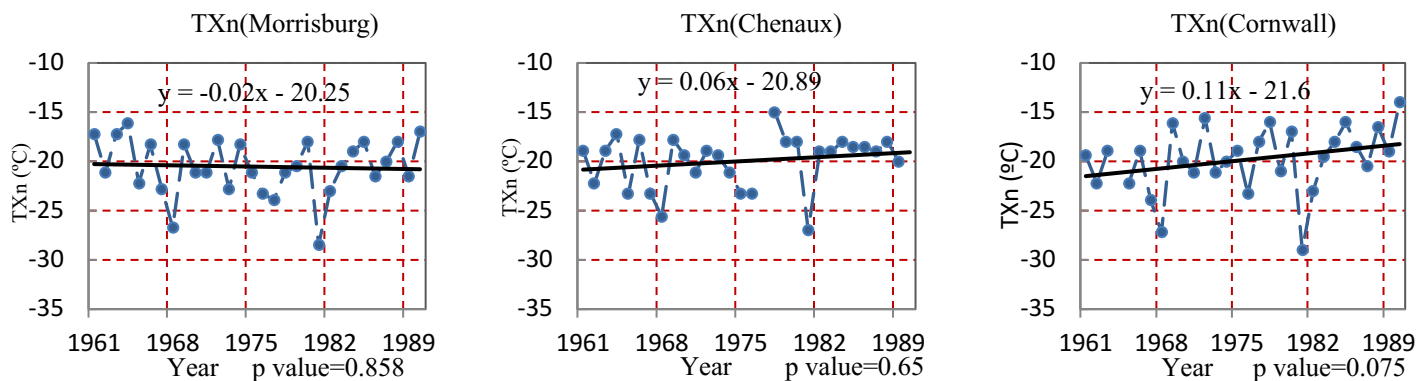


Figure B-11: Trends in MinTmax (TXn) at six stations in the southern Quebec-Ontario region.

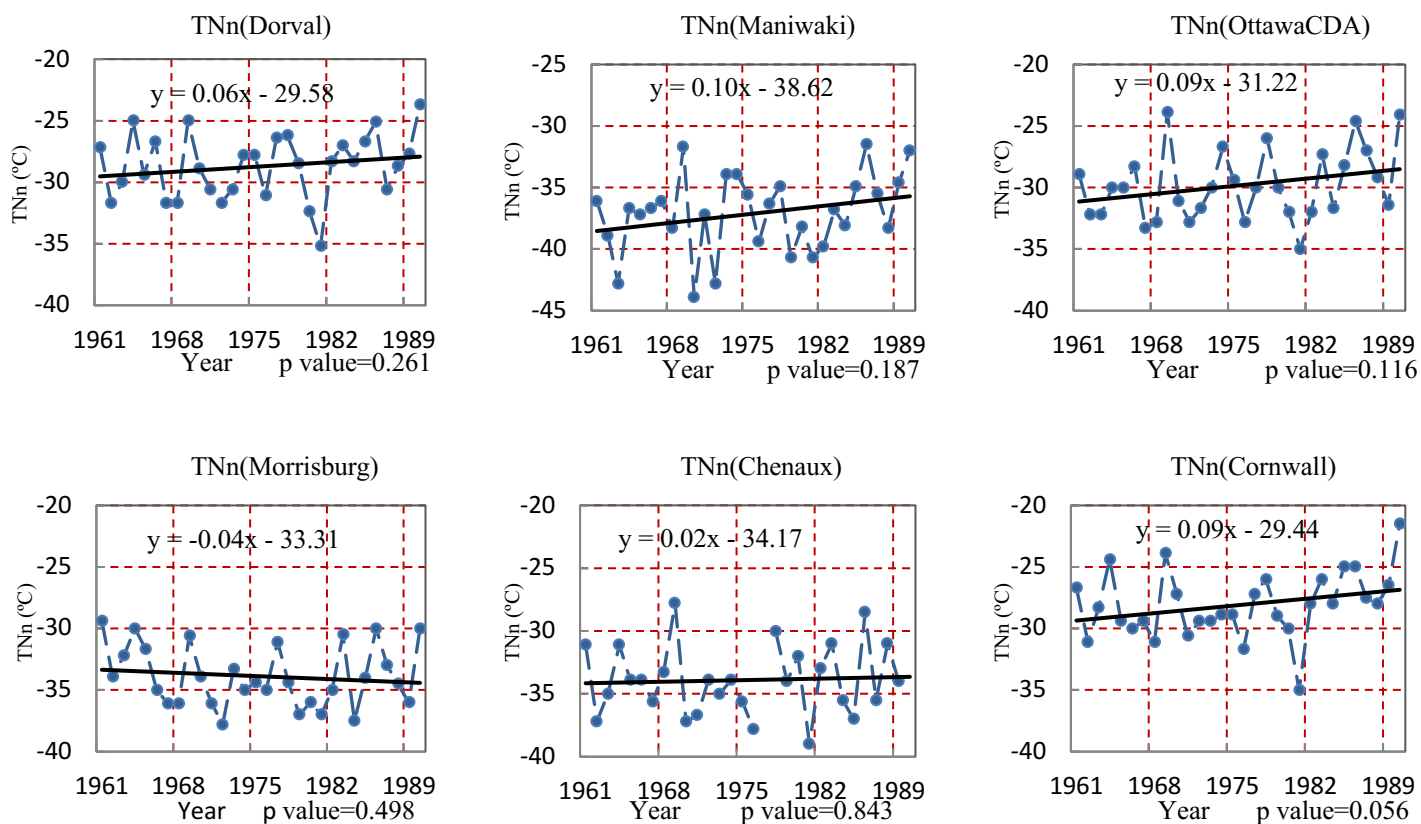


Figure B-12: Trends in MinTmin (TNn) at six stations in the southern Quebec-Ontario region.

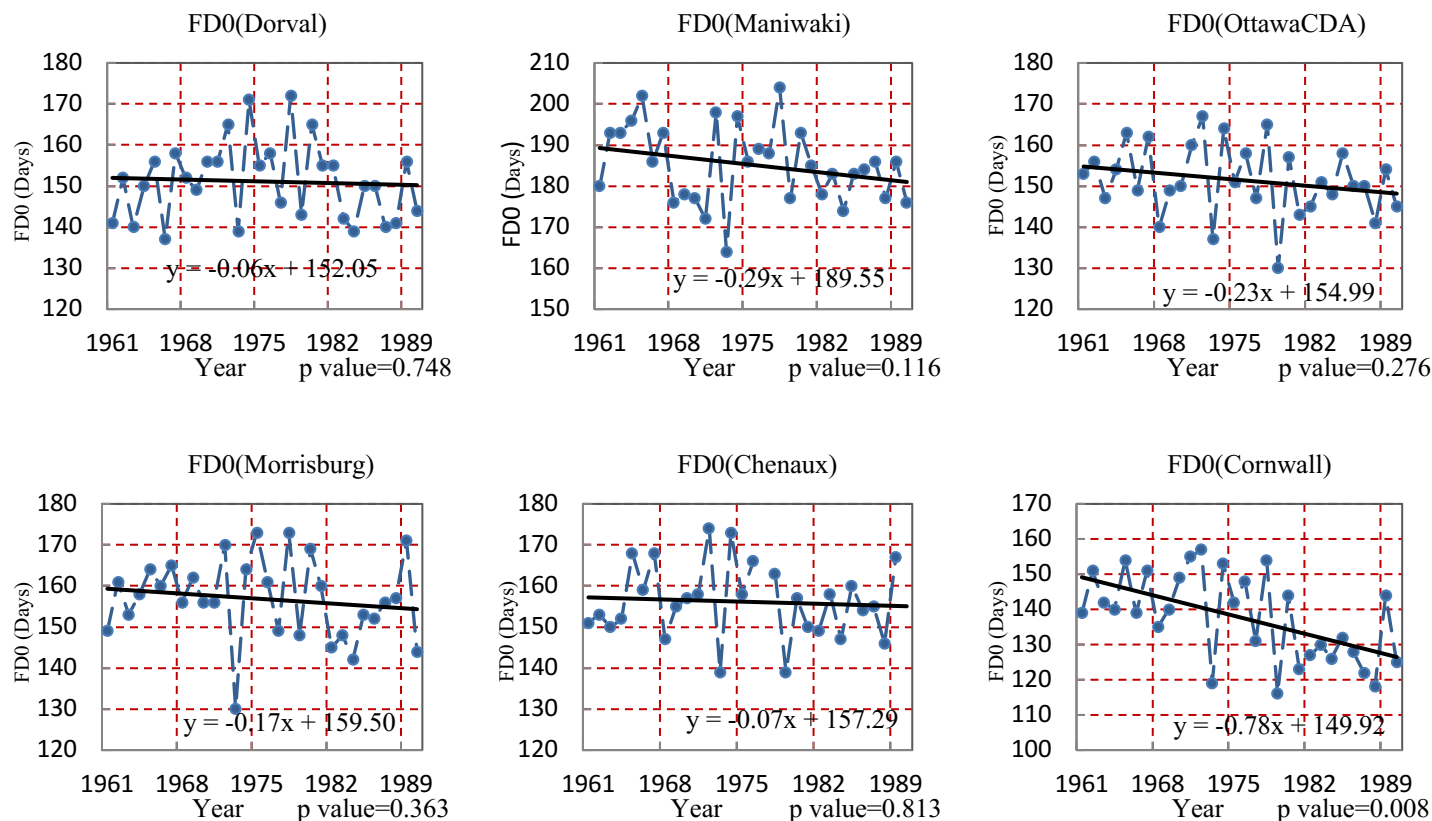
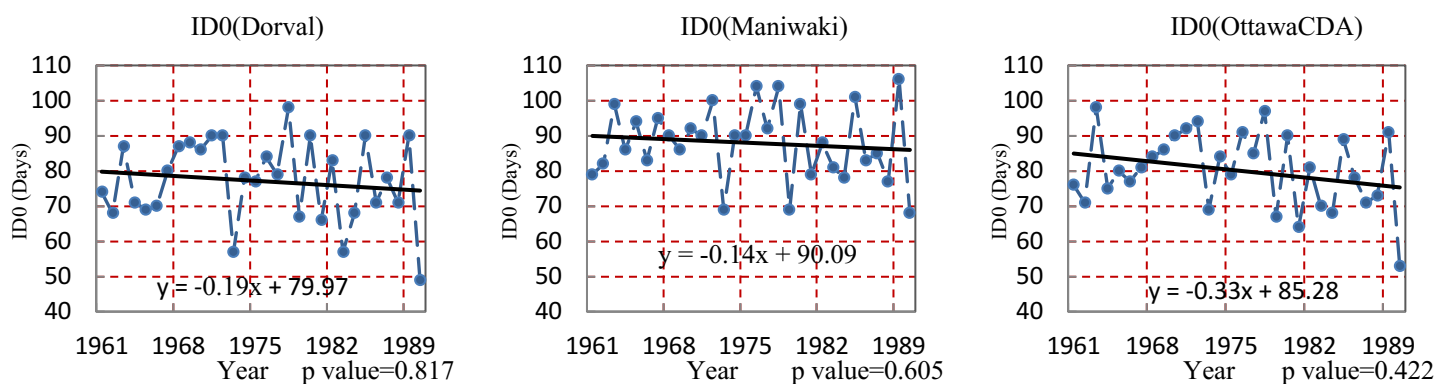


Figure B-13: Trends in frost days (FD0) at six stations in the southern Quebec-Ontario region.



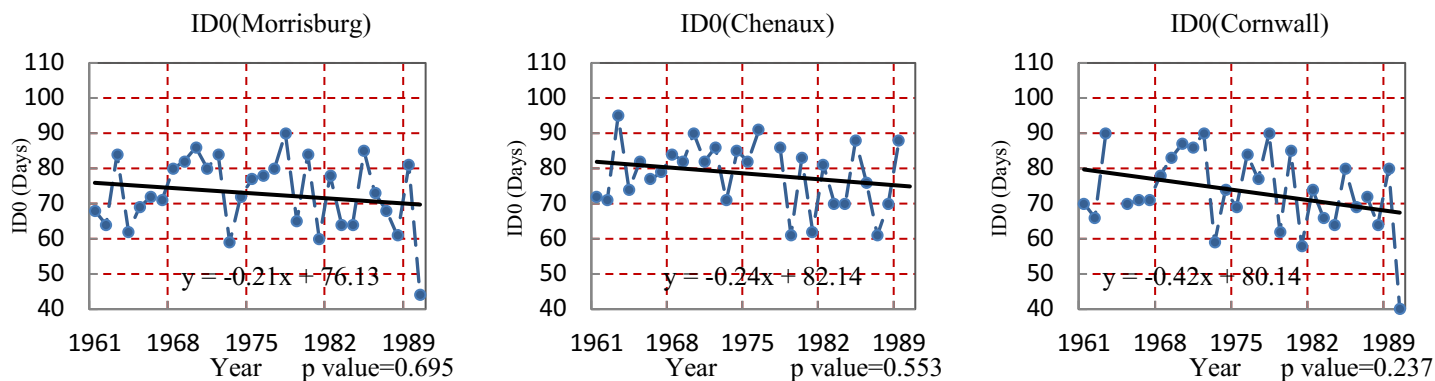


Figure B-14: Trends in ice days (ID0) at six stations in the southern Quebec-Ontario region.

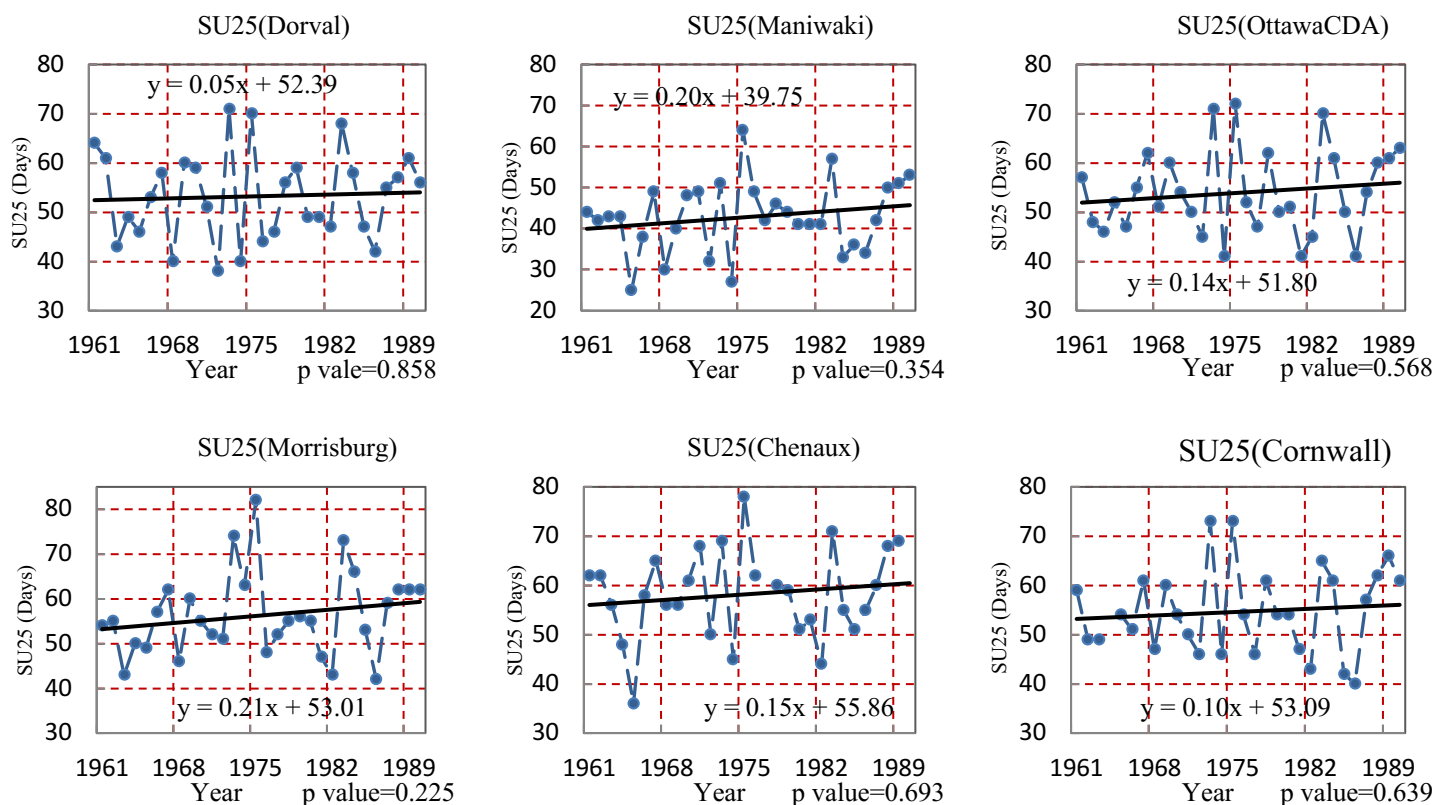


Figure B-15: Trends in summer days (SU25) at six stations in the southern Quebec-Ontario region.

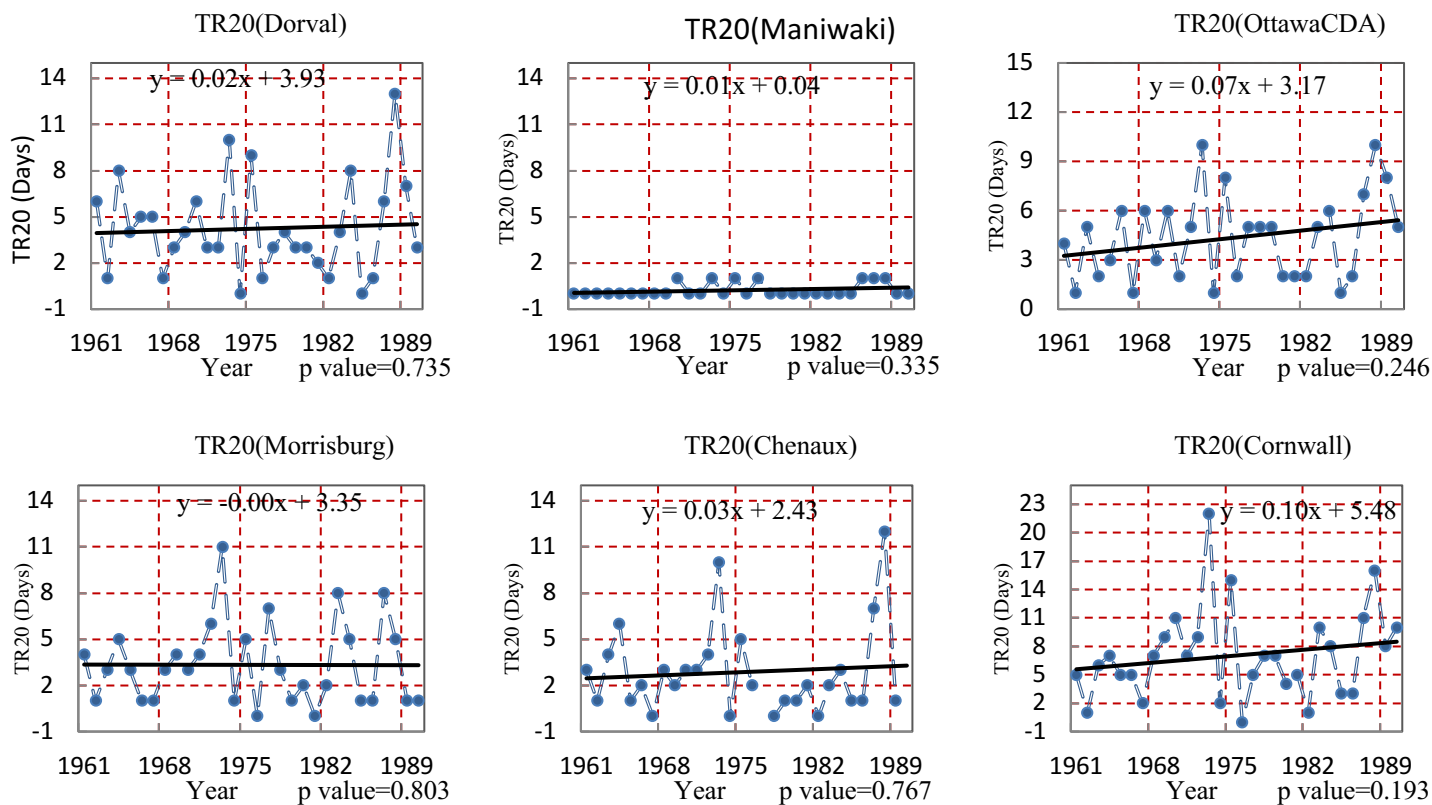
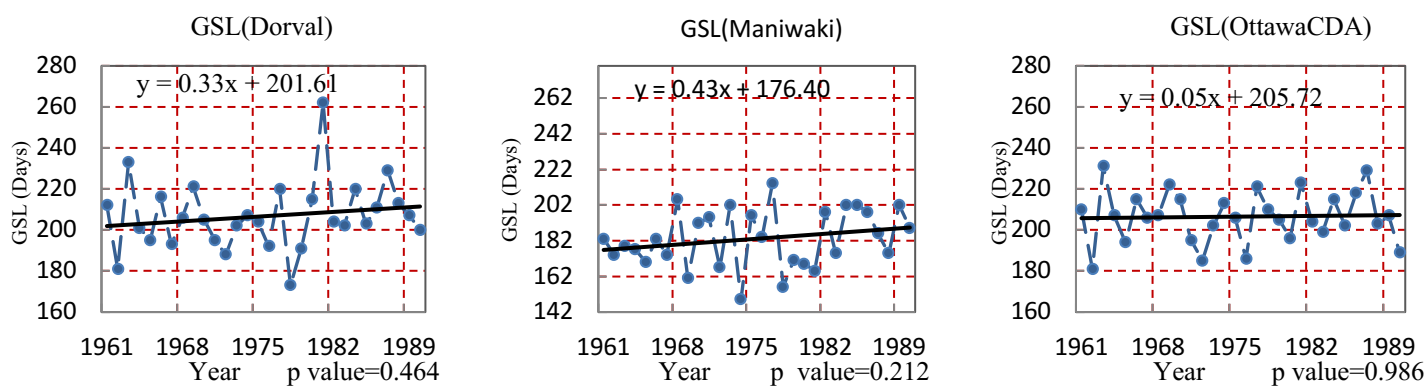


Figure B-16: Trends in tropical nights (TR20) at six stations in the southern Quebec-Ontario region.



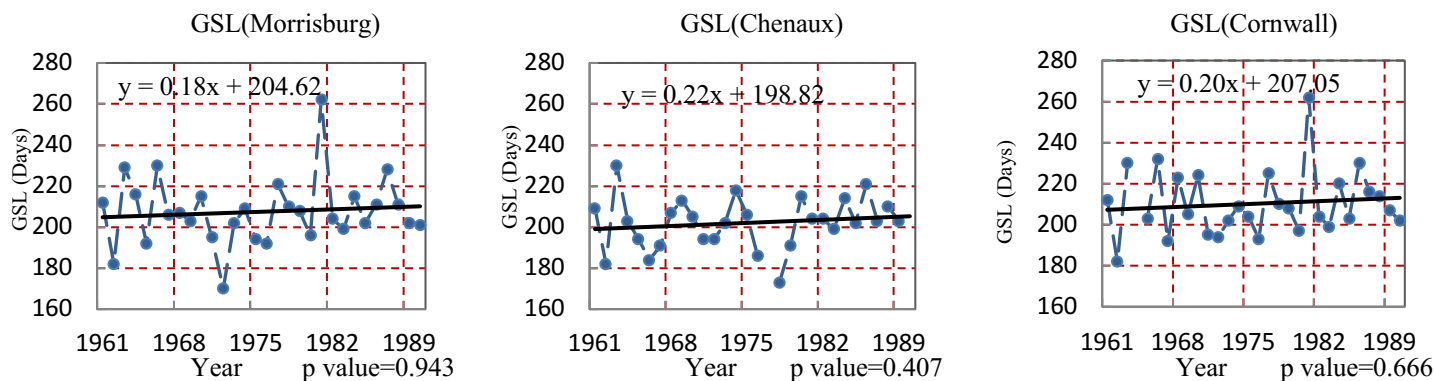


Figure B-17: Trends in growing season length (GSL) at six stations in the southern Quebec-Ontario region.

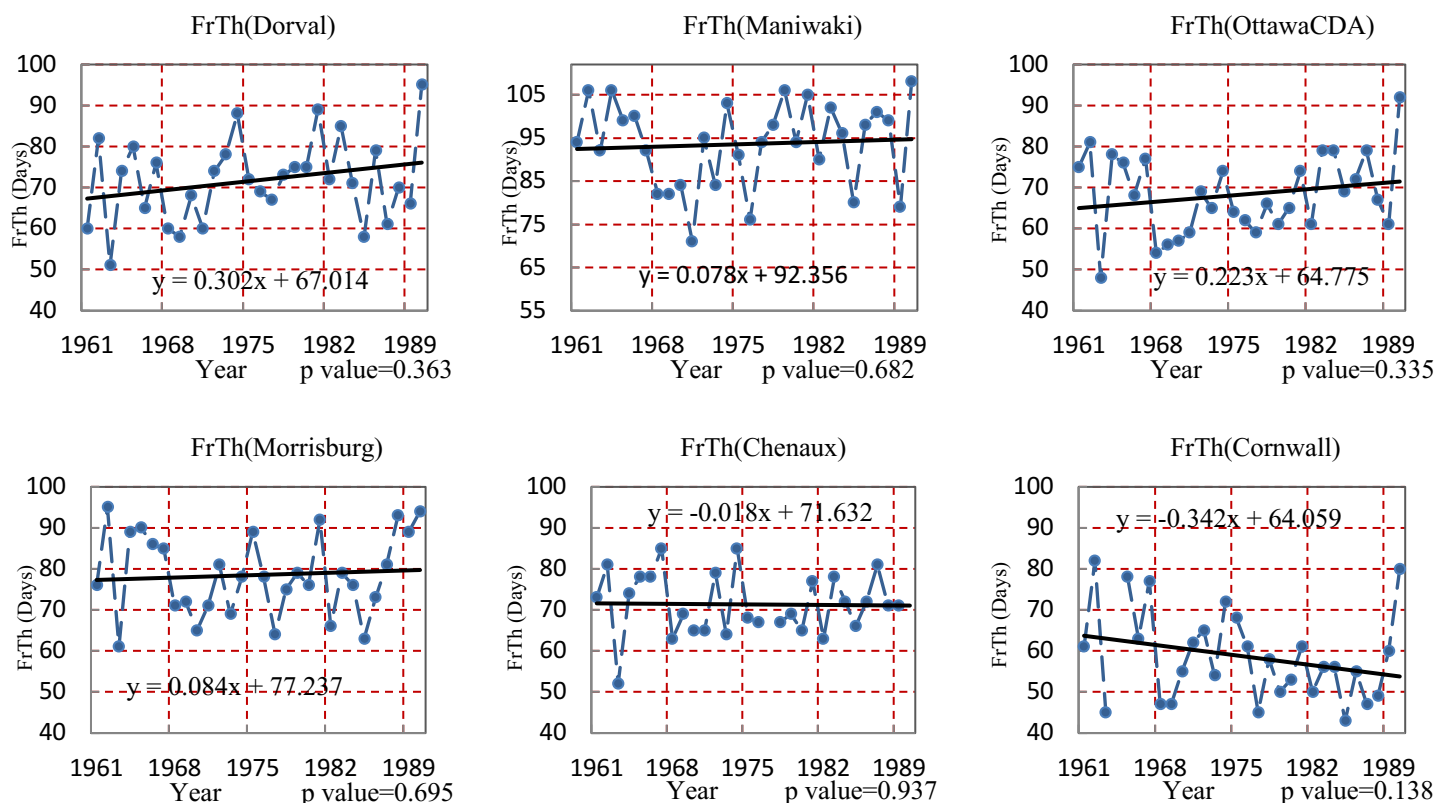


Figure B-18: Trends in freeze and thaw cycle (Fr-Th) at six stations in the southern Quebec-Ontario region.

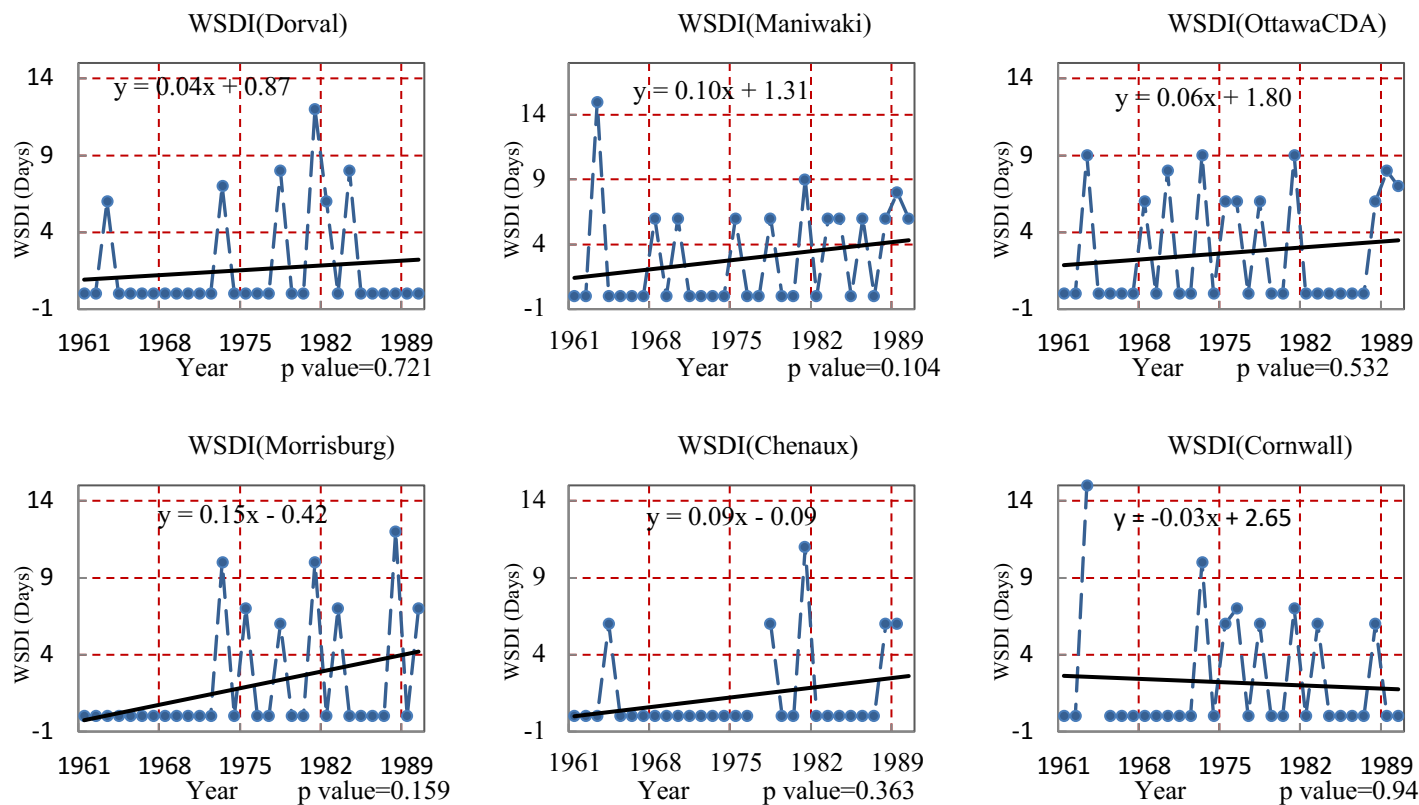
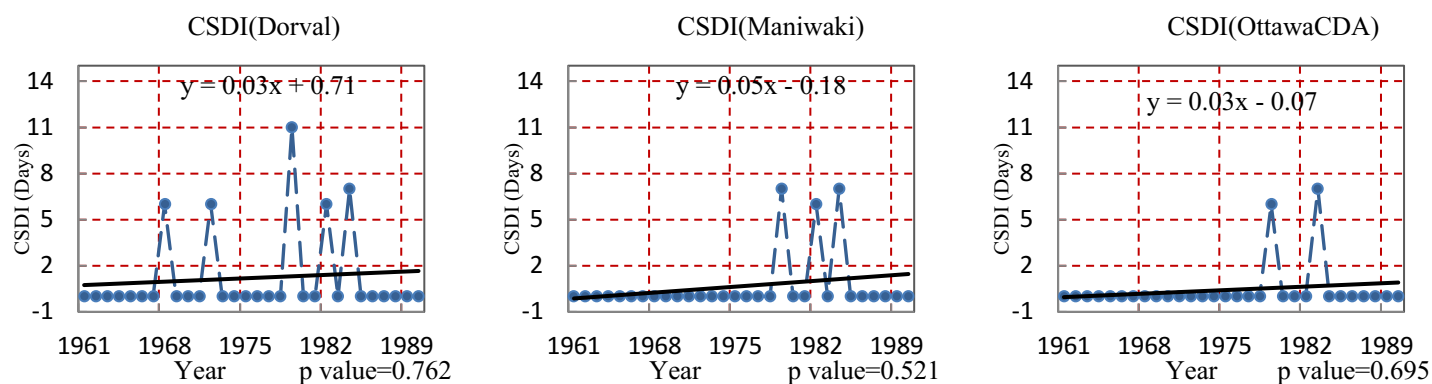


Figure B-19: Trends in warm spell duration indicator (WSDI) at six stations in the southern Quebec-Ontario region.



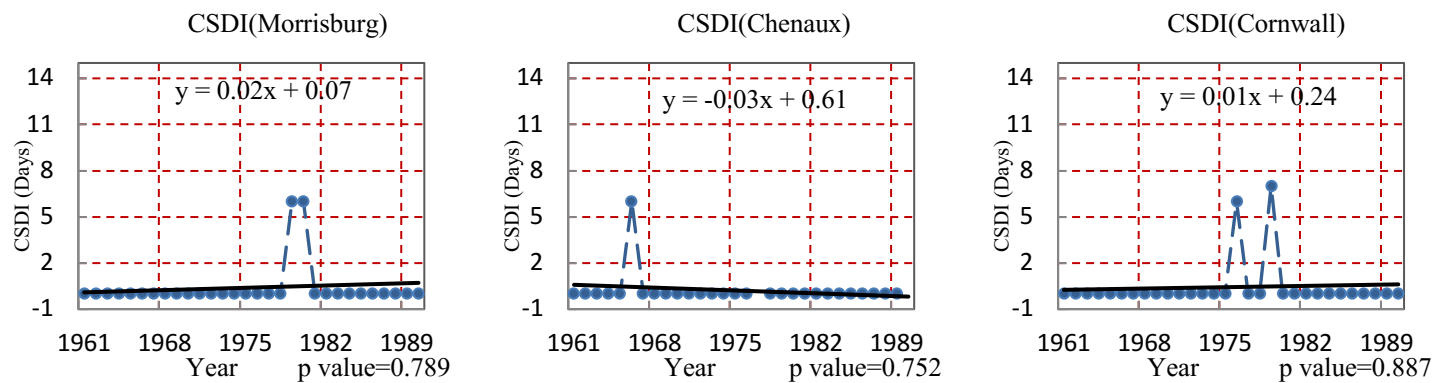


Figure B-20: Trends in cold spell duration indicator (CSDI) at six stations in the southern Quebec-Ontario region.

Appendix C

ANALYSIS OF EXTREME TEMPERATURE SERIES IN BANGLADESH

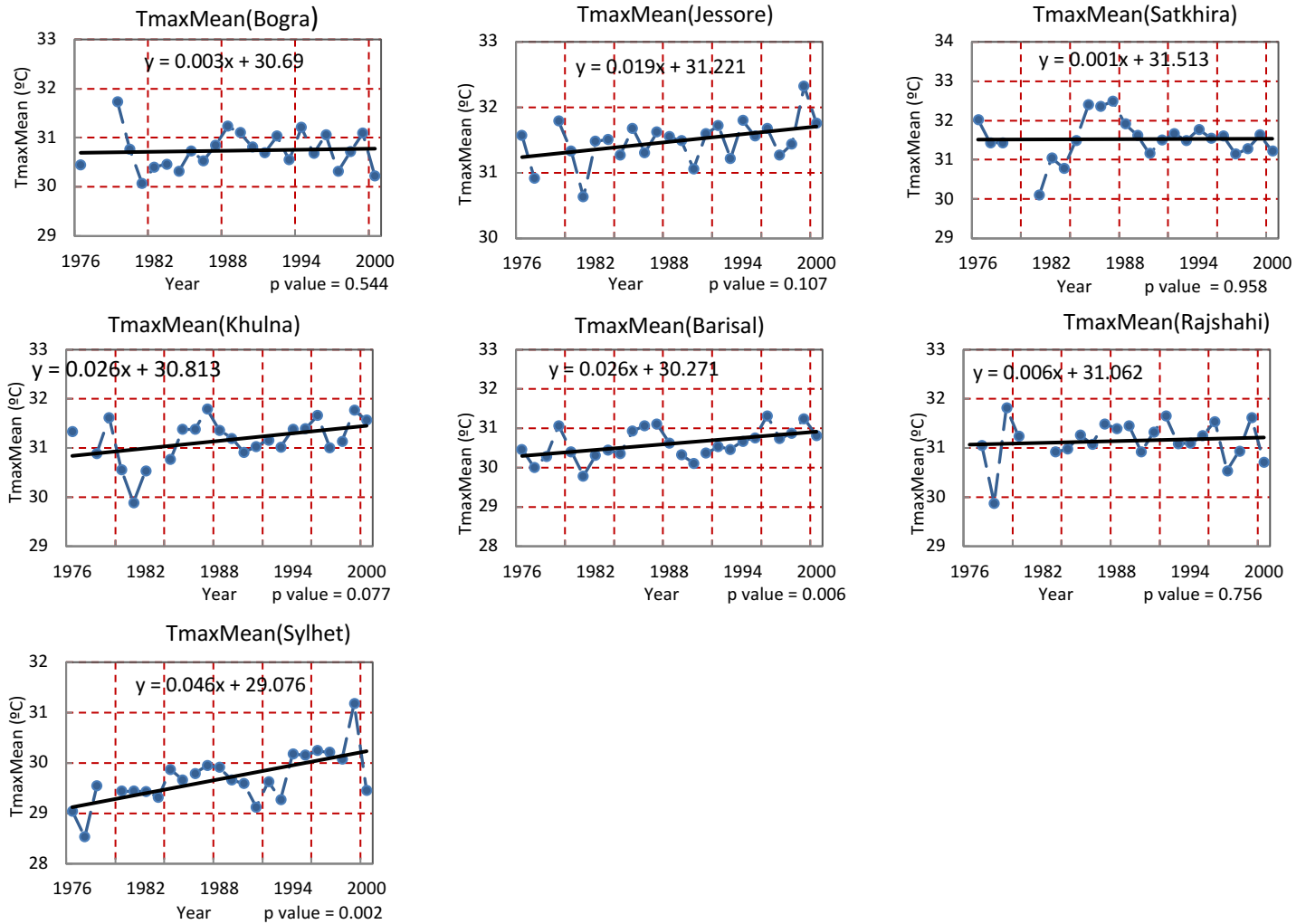
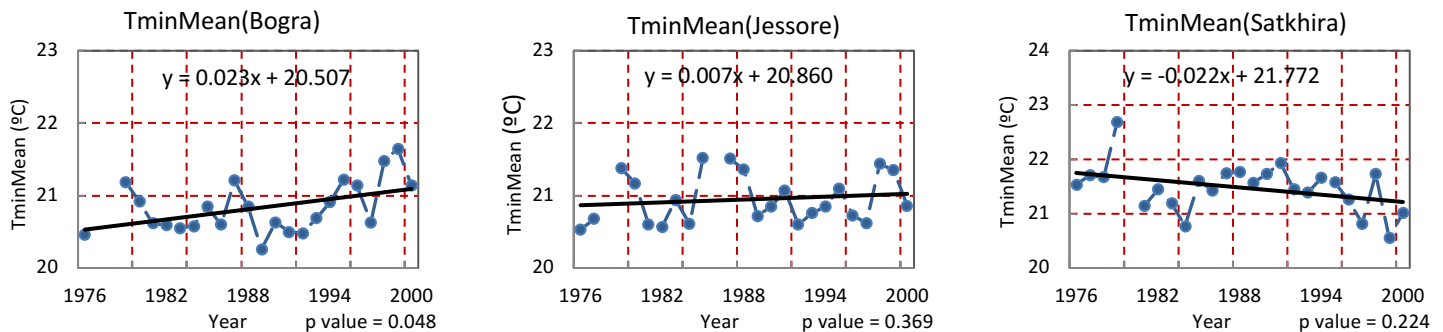


Figure C-1: Trends in TmaxMean at seven stations in Bangladesh.



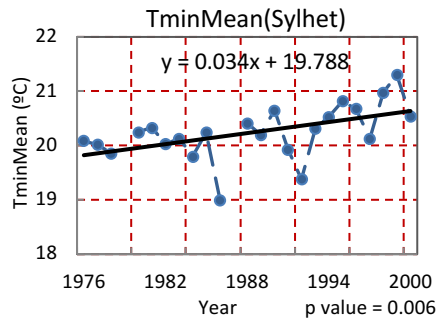
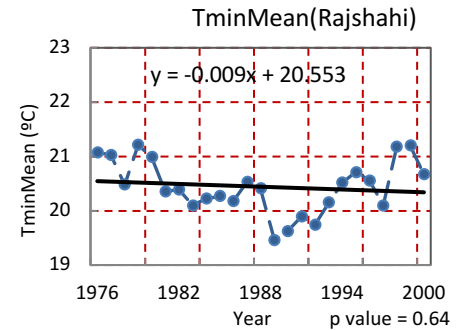
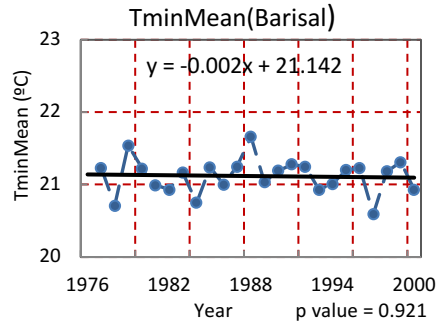
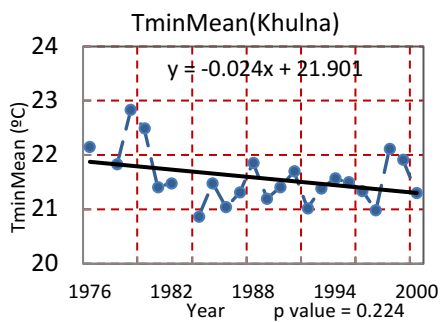
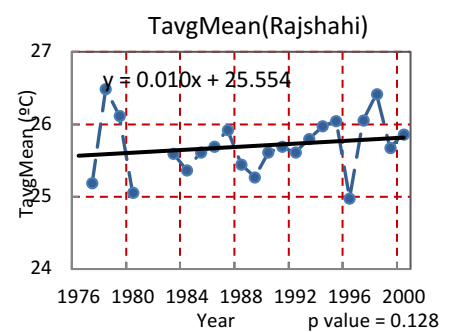
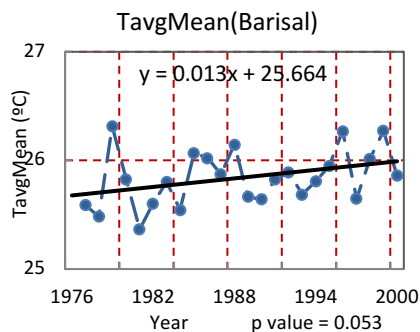
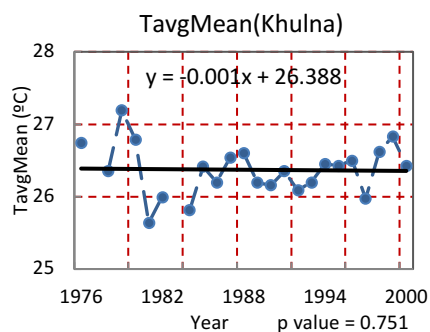
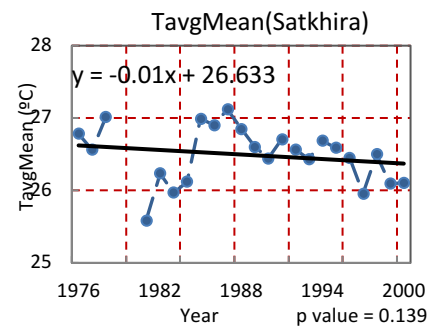
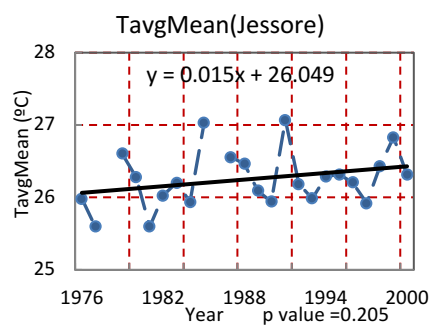
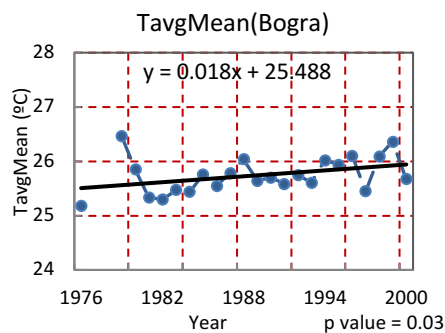


Figure C-2: Trends in TminMean at seven stations in Bangladesh.



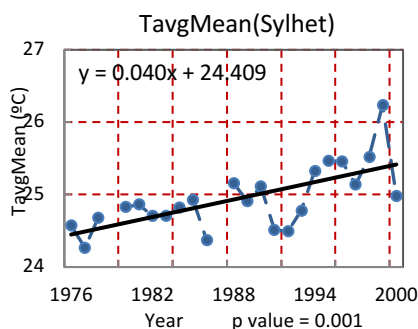


Figure C-3: Trends in TavGMean at seven stations in Bangladesh.

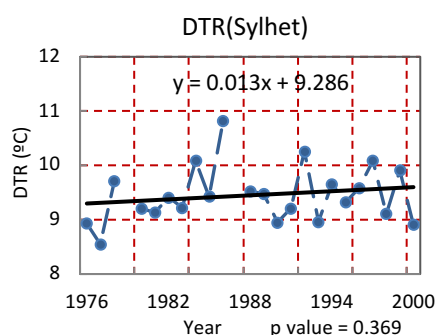
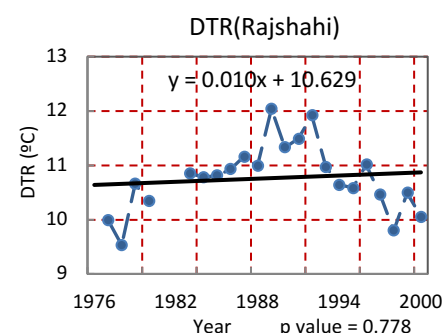
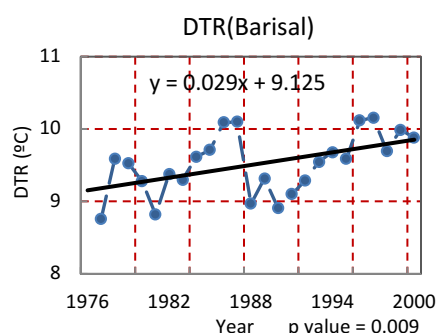
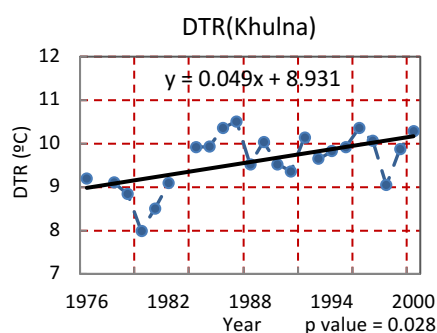
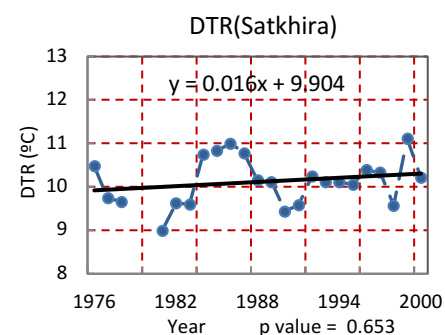
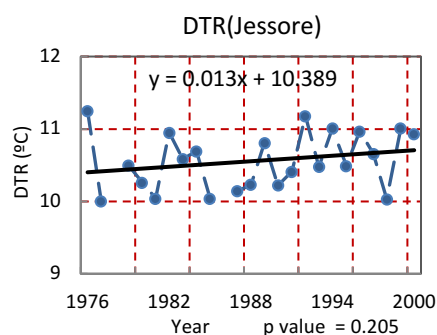
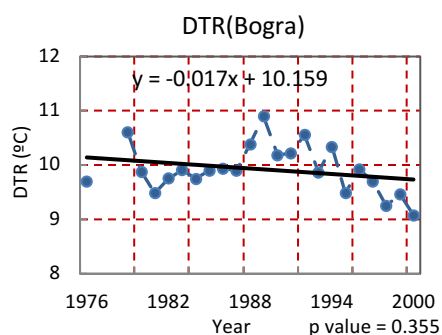


Figure C-4: Trends in DTR at seven stations in Bangladesh.

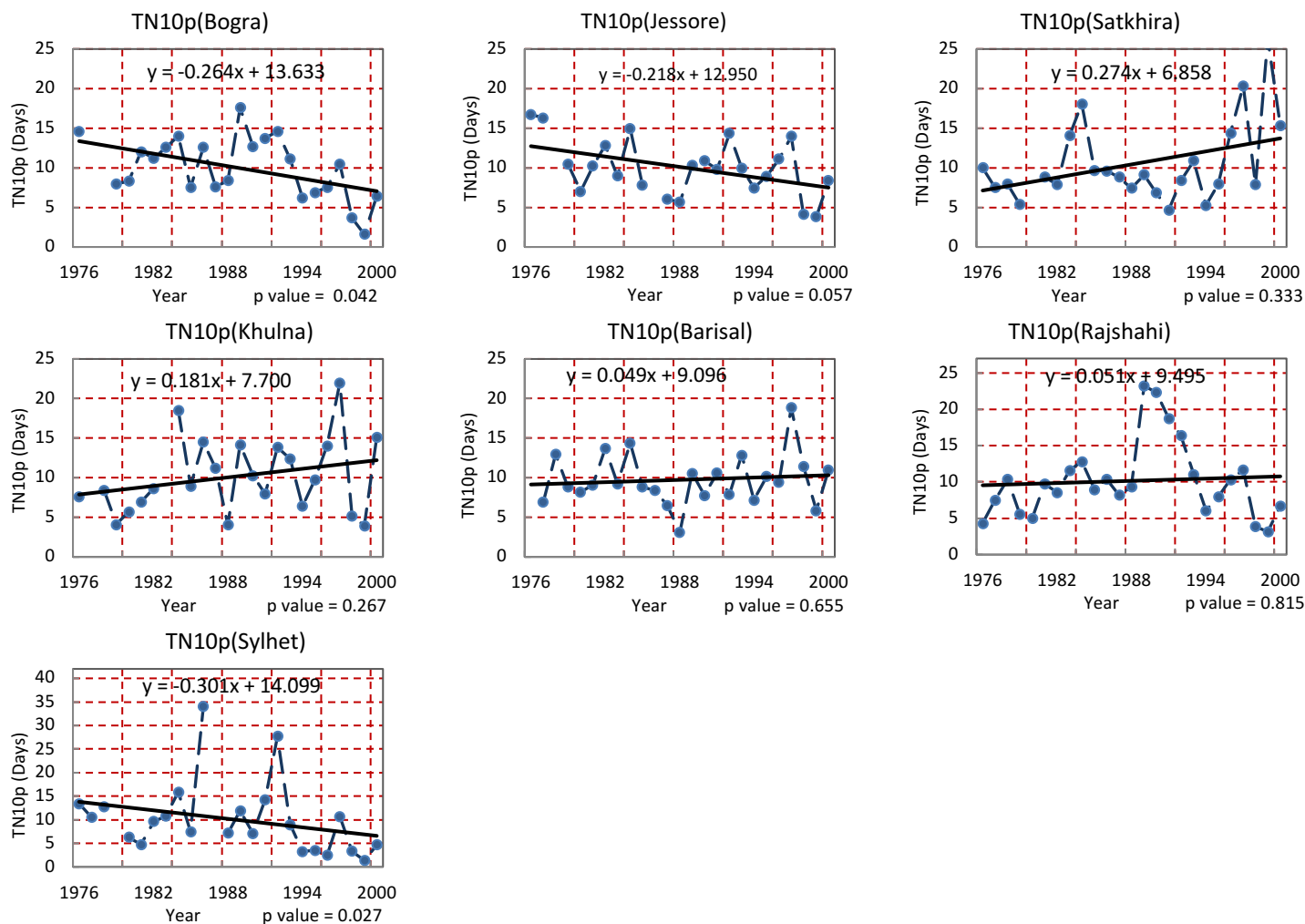
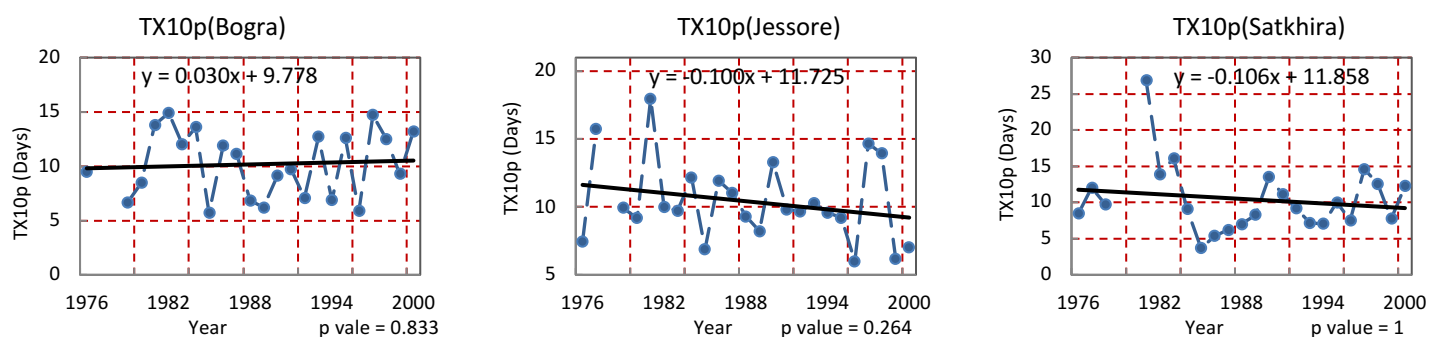


Figure C-5: Trends in cool nights (TN10p) at seven stations in Bangladesh.



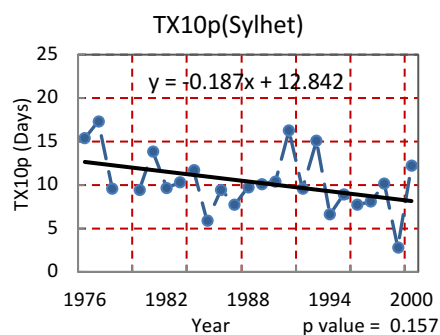
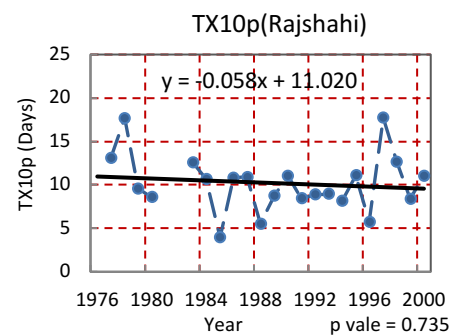
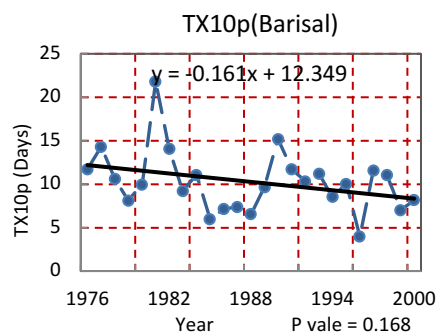
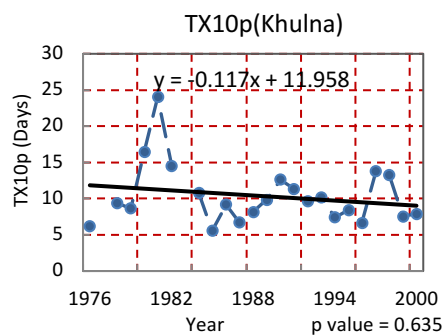
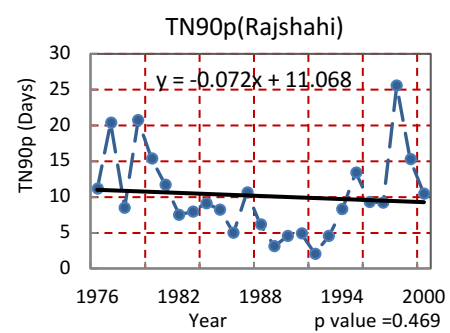
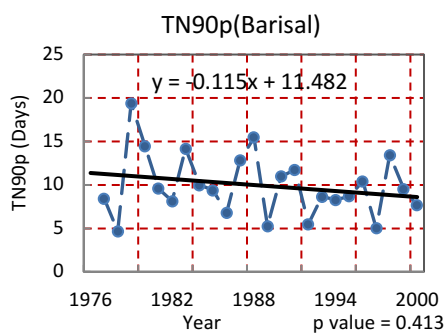
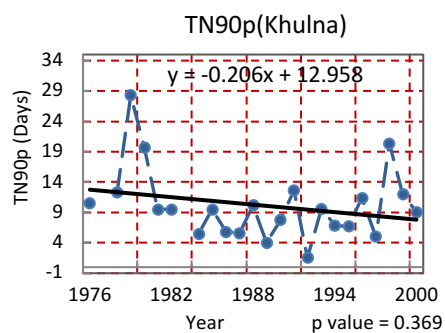
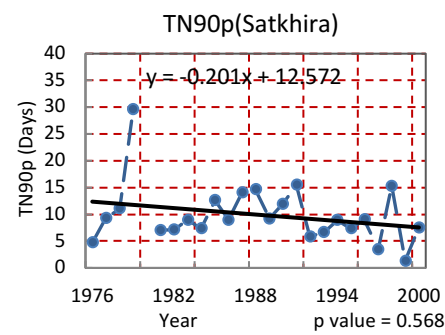
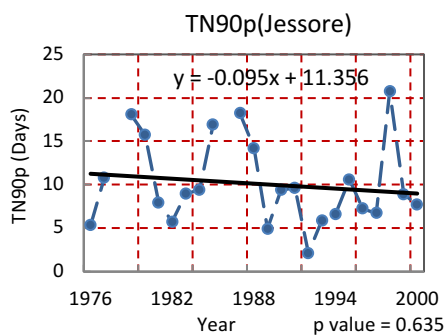
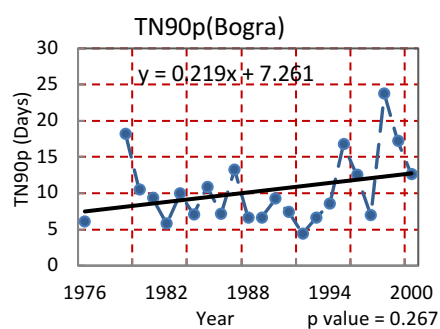


Figure C-6: Trends in cool days (TX10p) at seven stations in Bangladesh



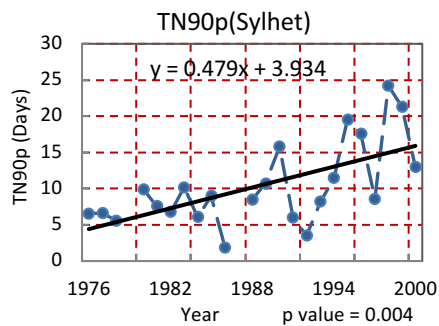


Figure C-7: Trends in warm nights (TN90p) at seven stations in Bangladesh.

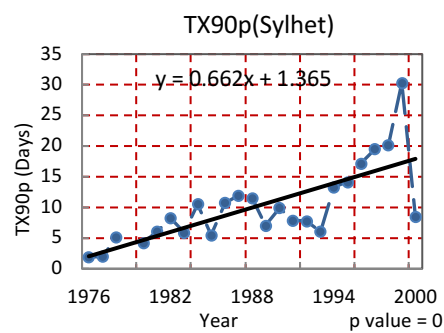
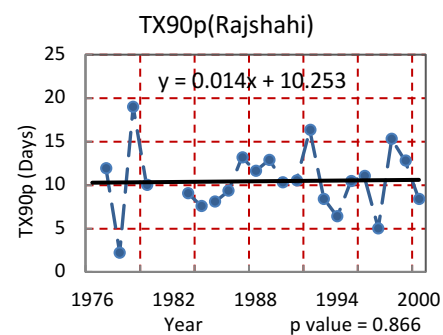
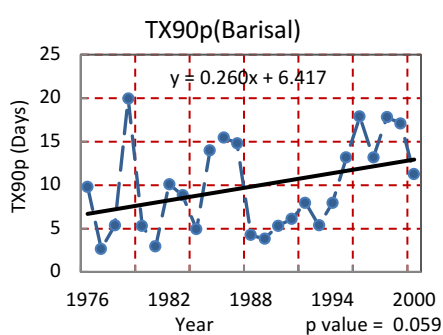
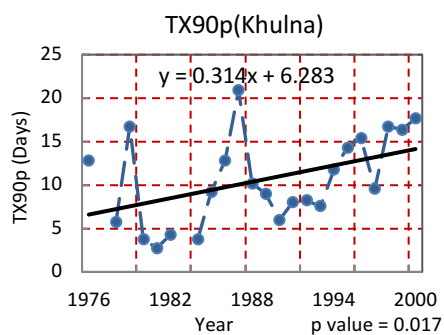
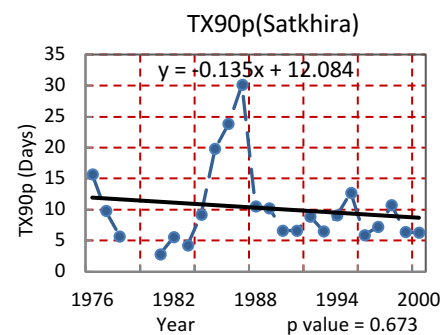
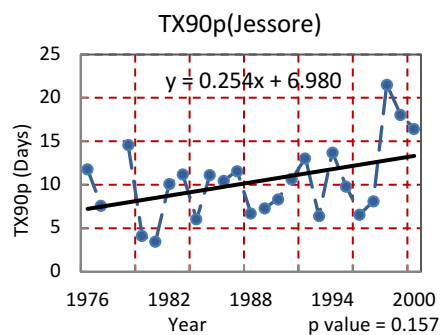
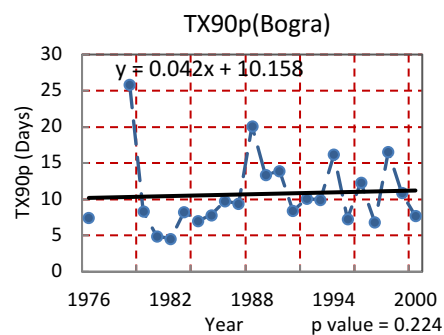


Figure C-8: Trends in warm days (TX90p) at seven stations in Bangladesh.

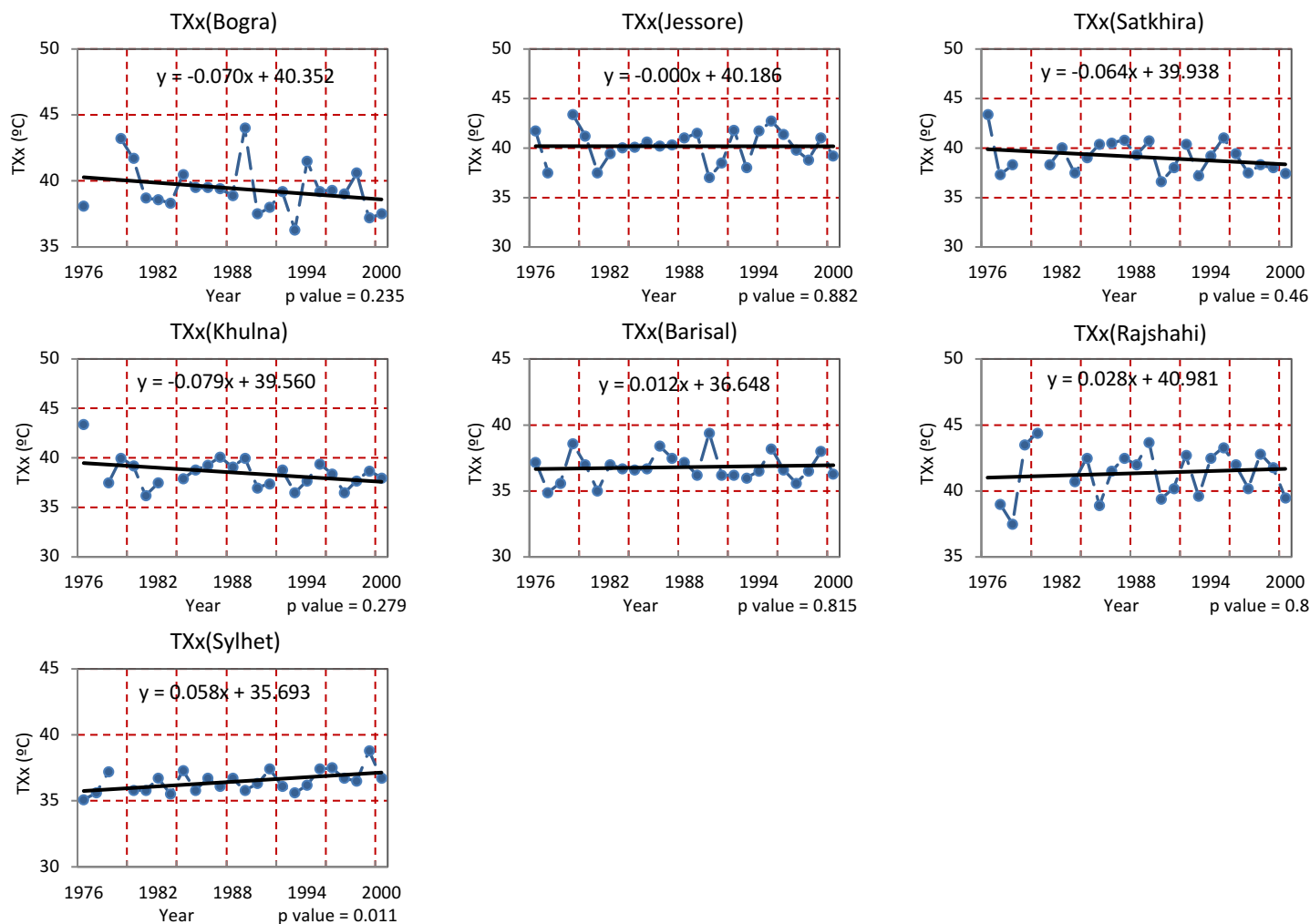
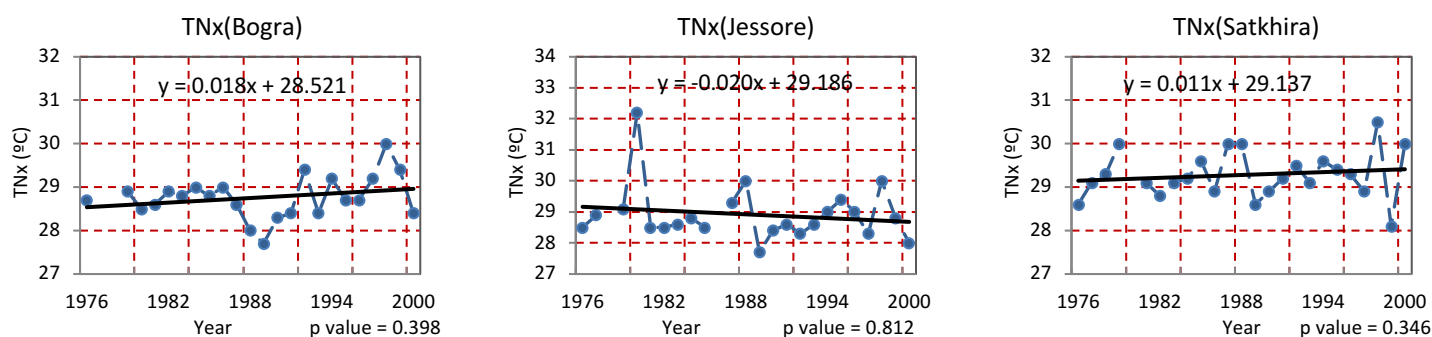


Figure C-9: Trends in MaxTmax (TXx) at seven stations in Bangladesh.



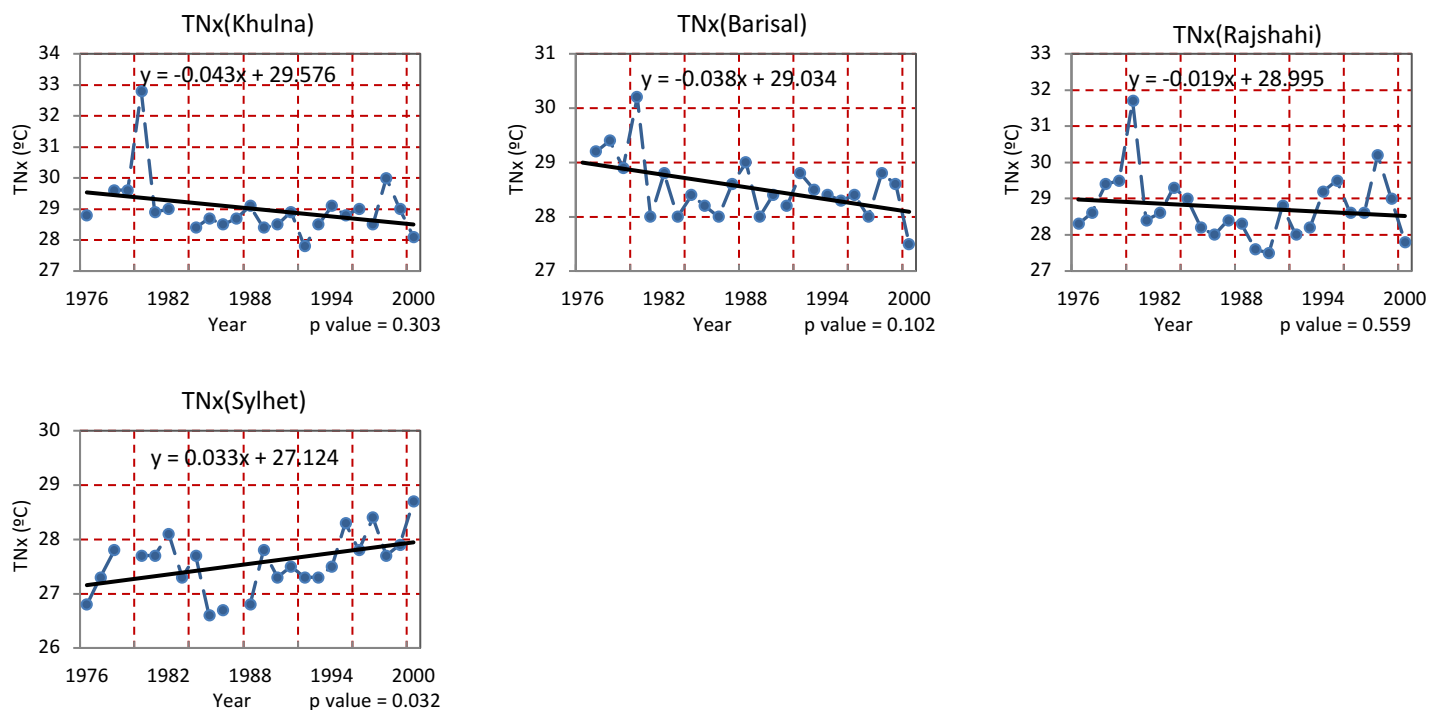
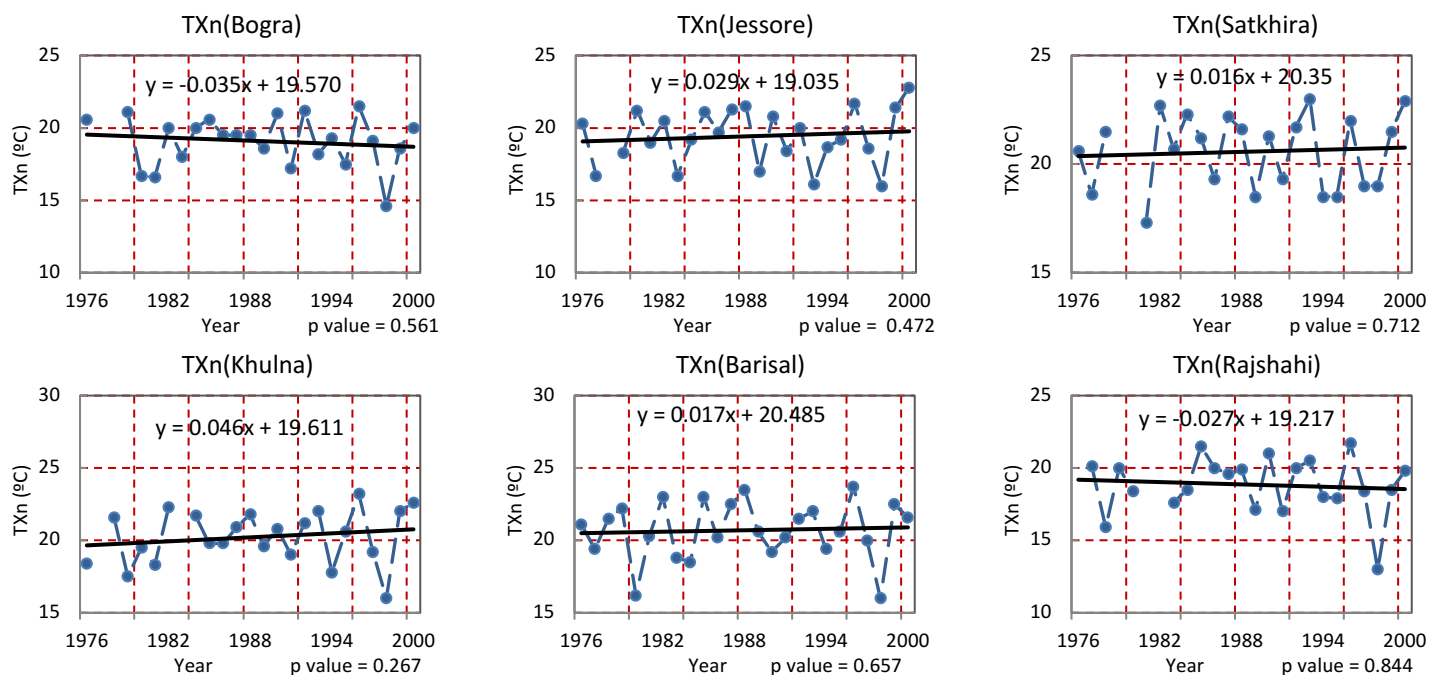


Figure C-10: Trends in MaxTmin (TNx) at seven stations in Bangladesh.



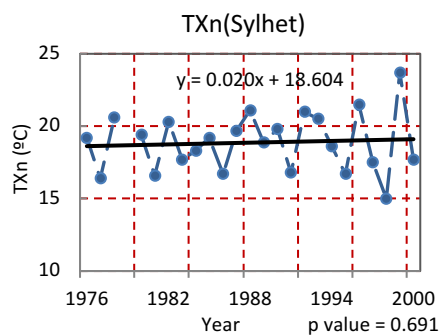


Figure C-11: Trends in MinTmax (TXn) at seven stations in Bangladesh.

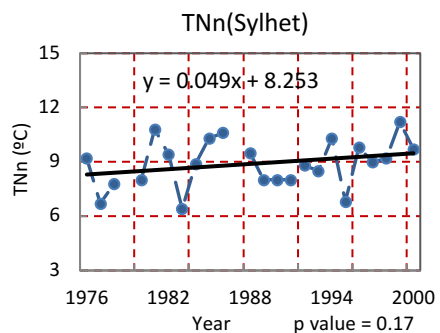
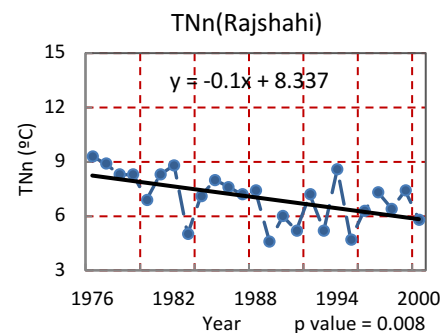
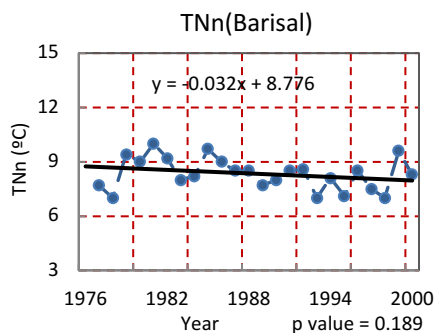
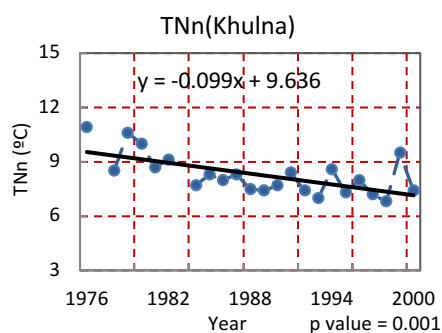
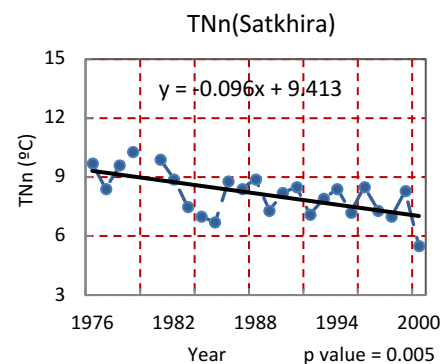
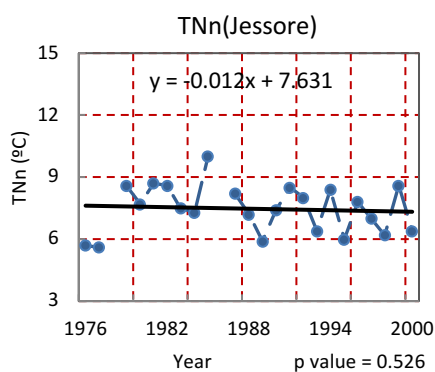
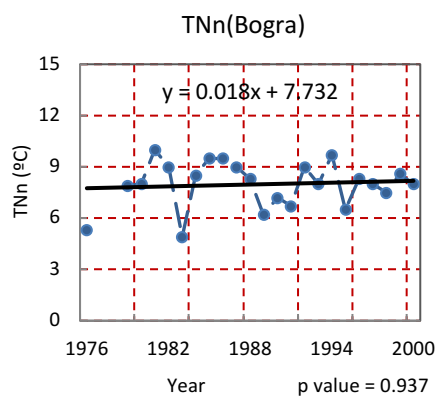


Figure C-12: Trends in MinTmin (TNn) at seven stations in Bangladesh.

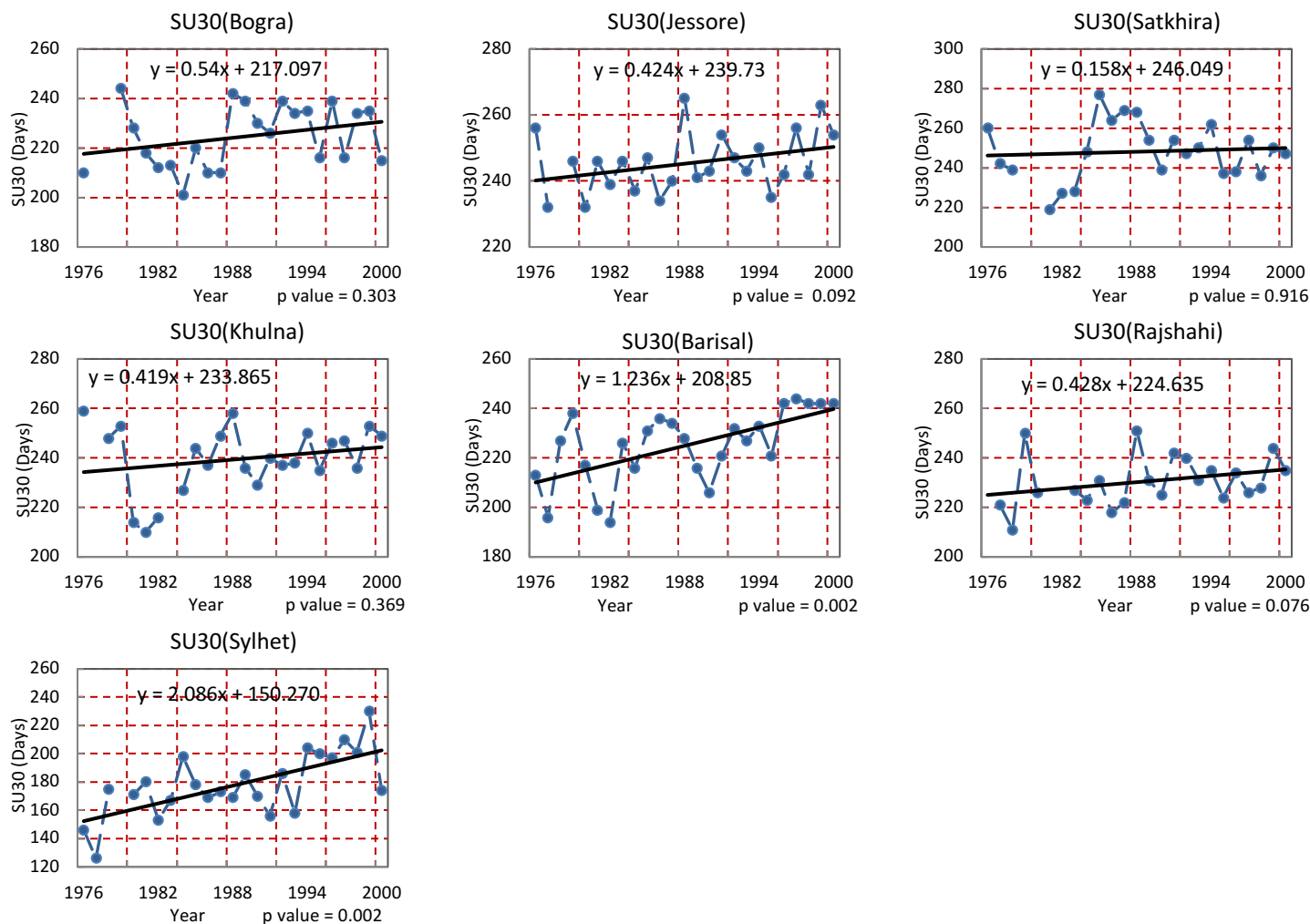
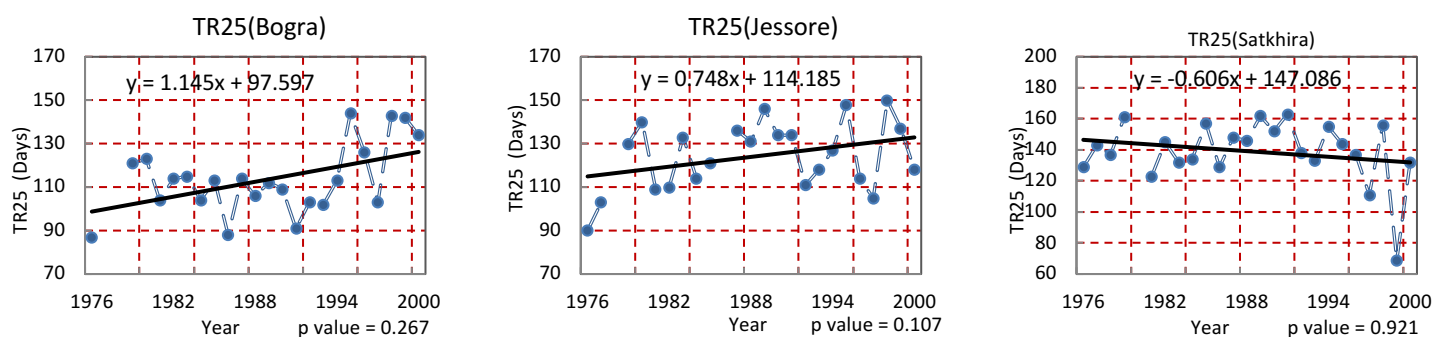


Figure C-13: Trends in summer days (SU30) at seven stations in Bangladesh.



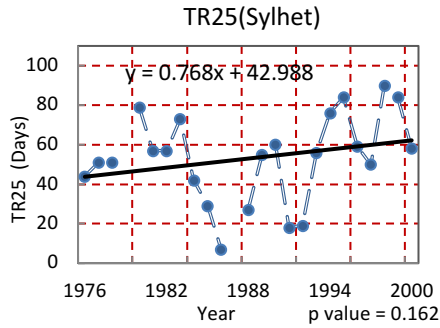
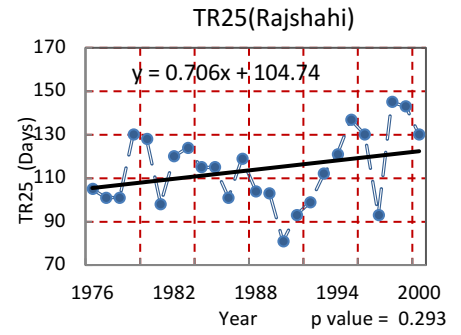
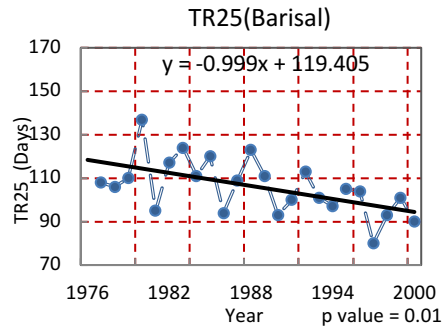
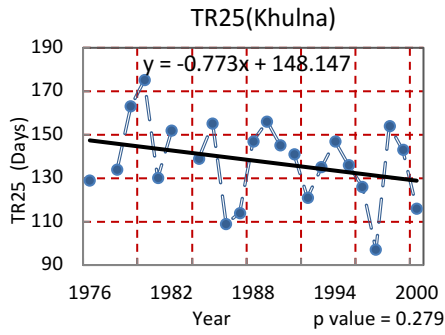
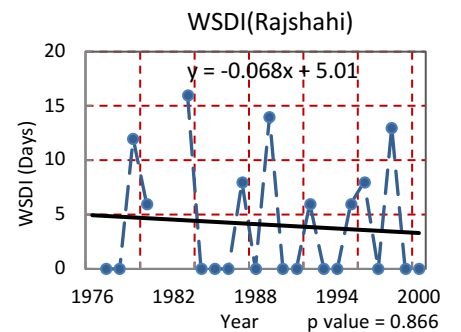
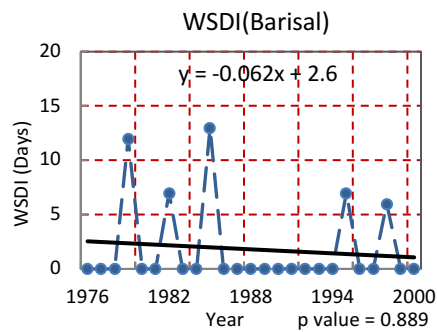
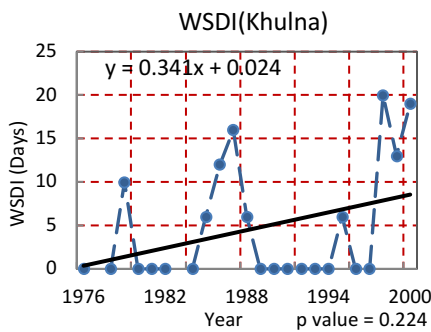
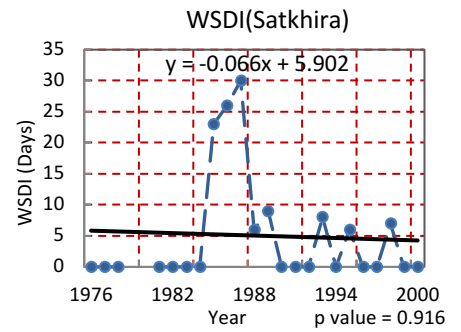
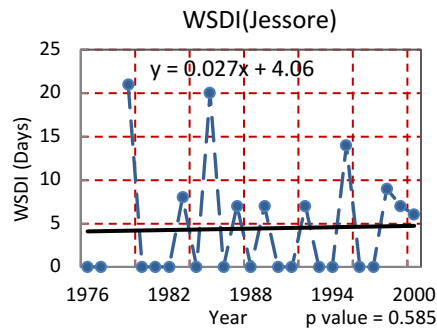
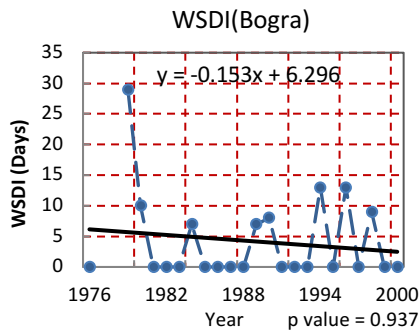


Figure C-14: Trends in tropical nights (TR25) at seven stations in Bangladesh.



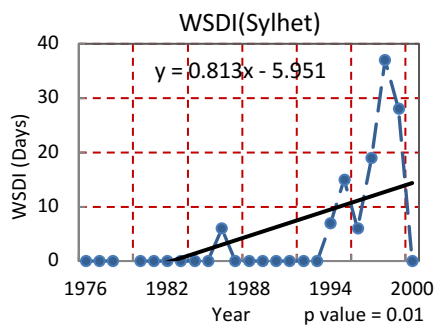


Figure C-15: Trends in warm spell duration indicator (WSDI) at seven stations in Bangladesh.

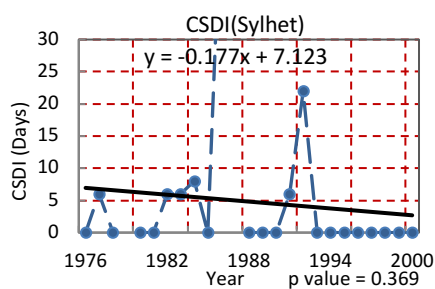
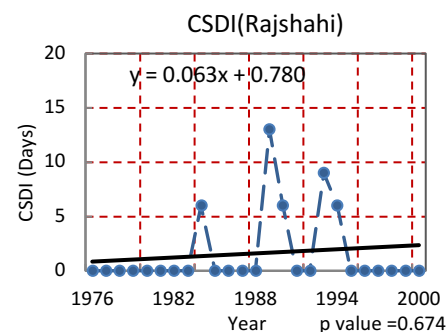
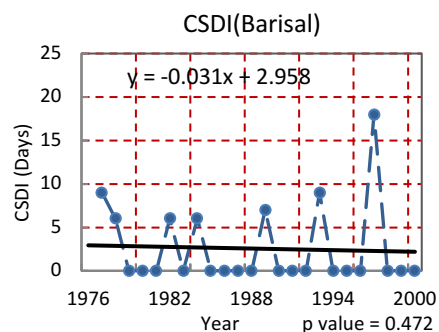
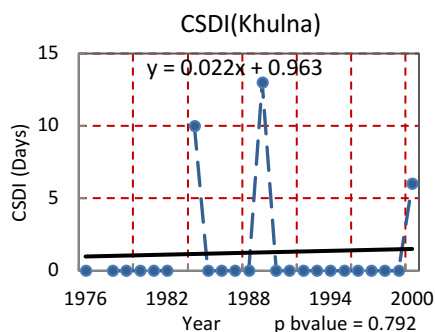
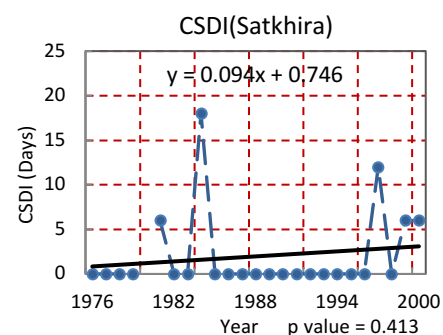
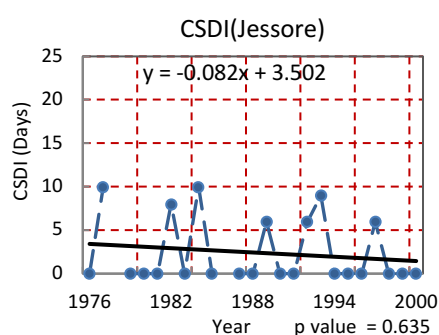
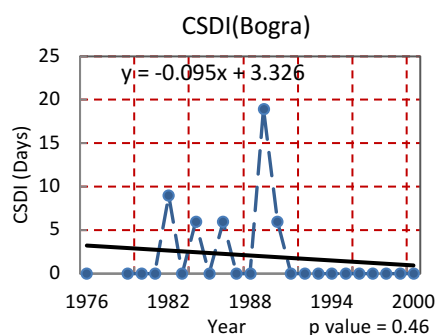
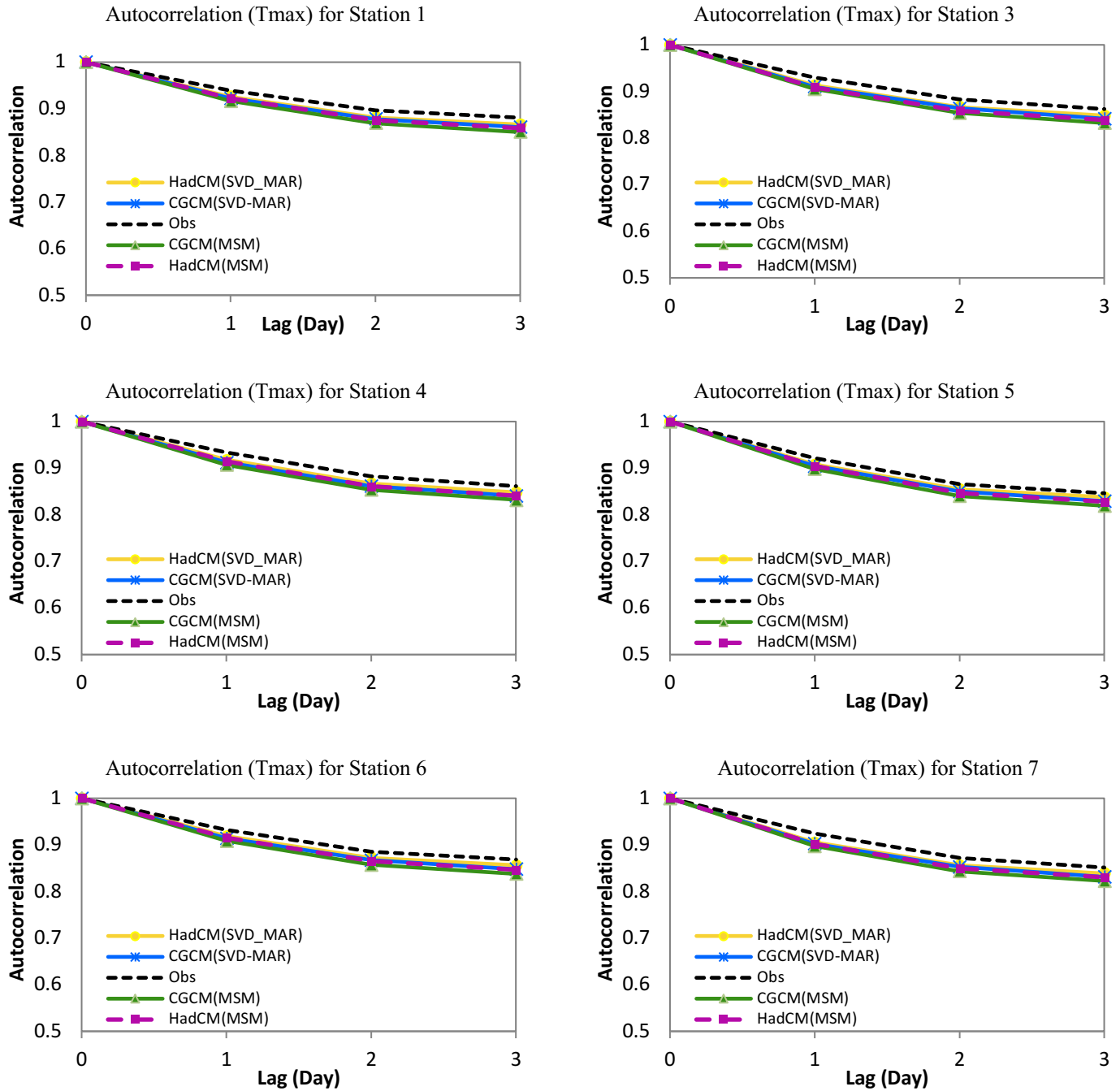
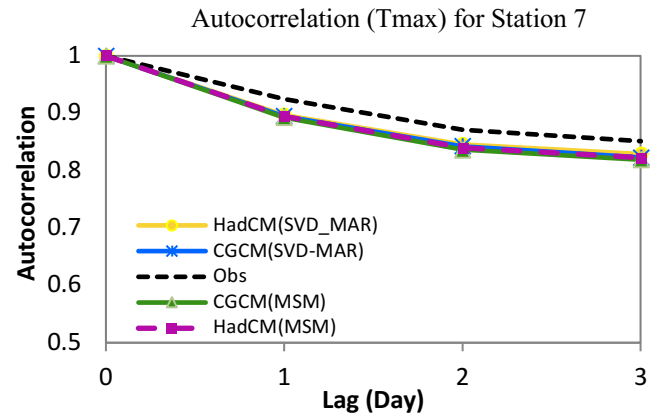
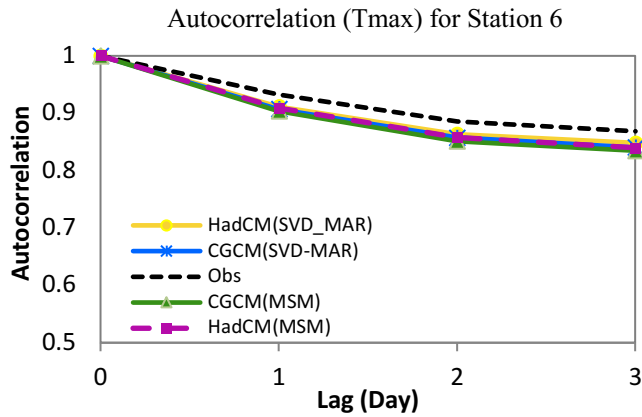
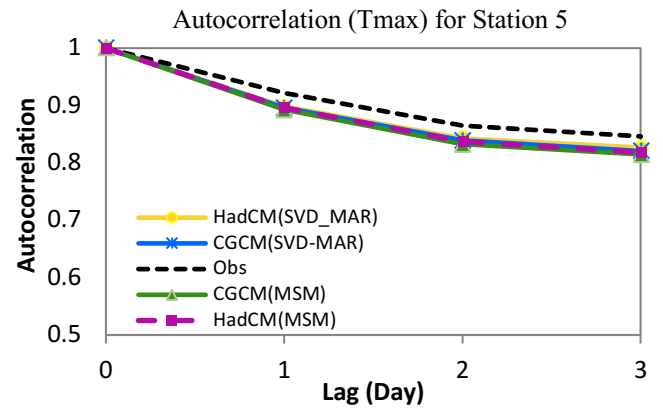
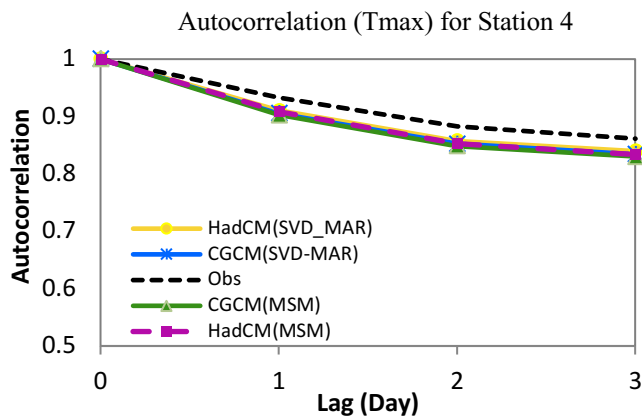
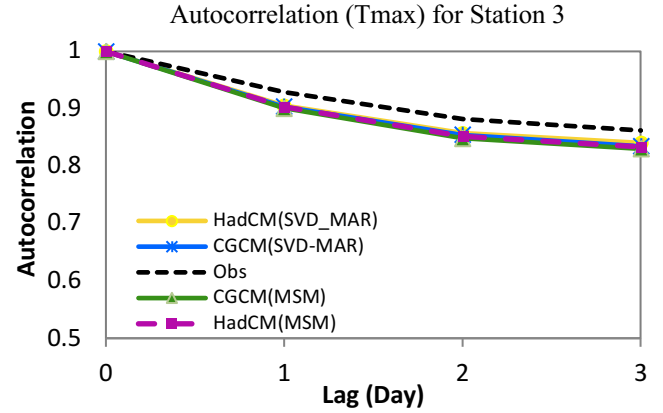
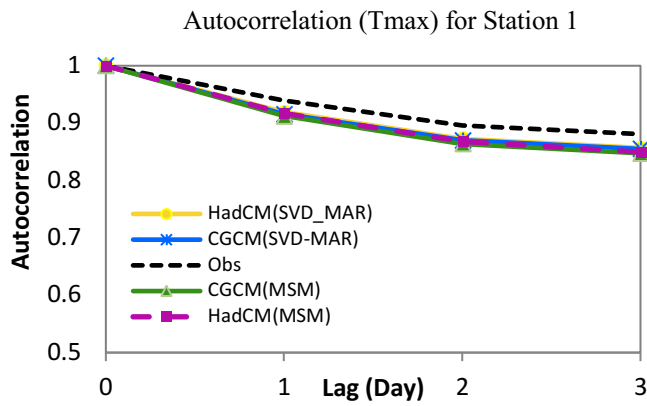


Figure C-16: Trends in cold spell duration indicator (CSDI) at seven stations in Bangladesh.

Appendix D

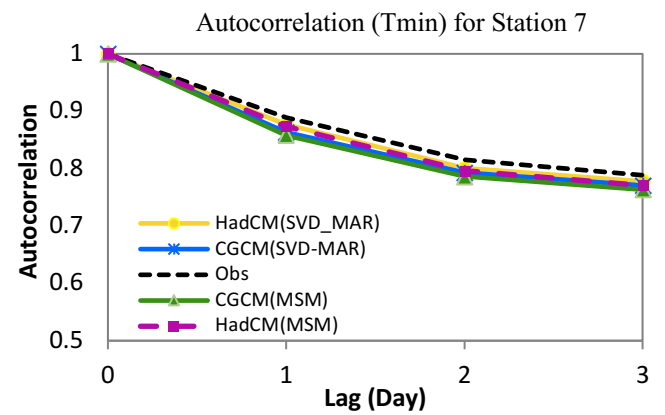
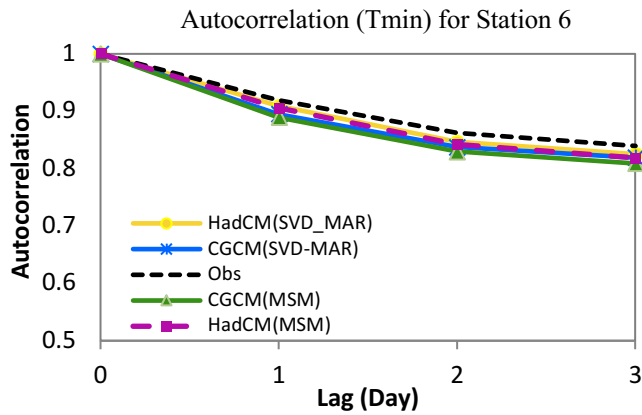
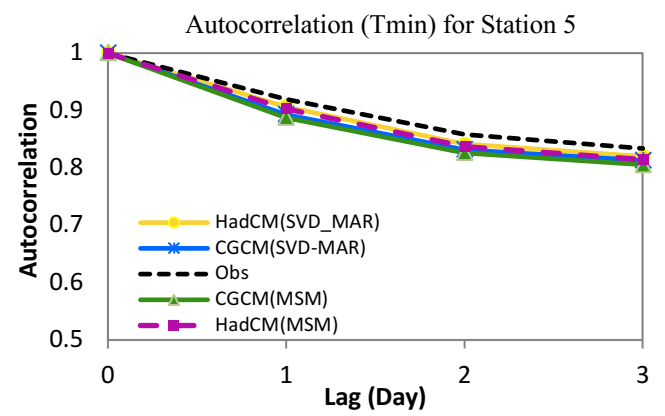
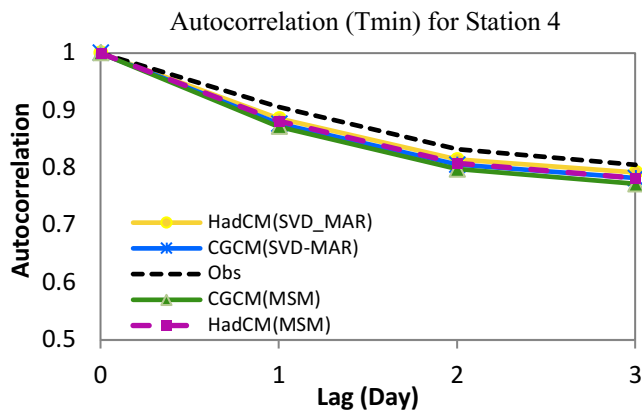
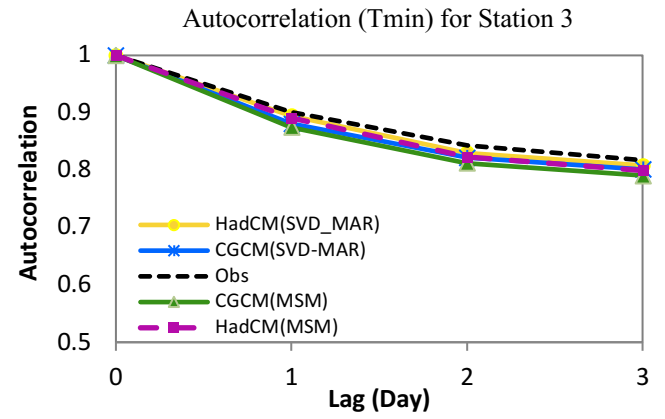
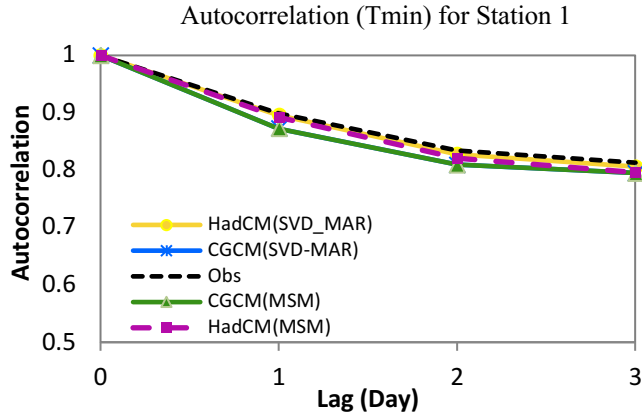
THE OBSERVED AND SIMULATED AUTOCORRELATION COEFFICIENTS AT THE STATIONS IN SOUTHERN QUEBEC-ONTARIO REGION AND BANGLADESH



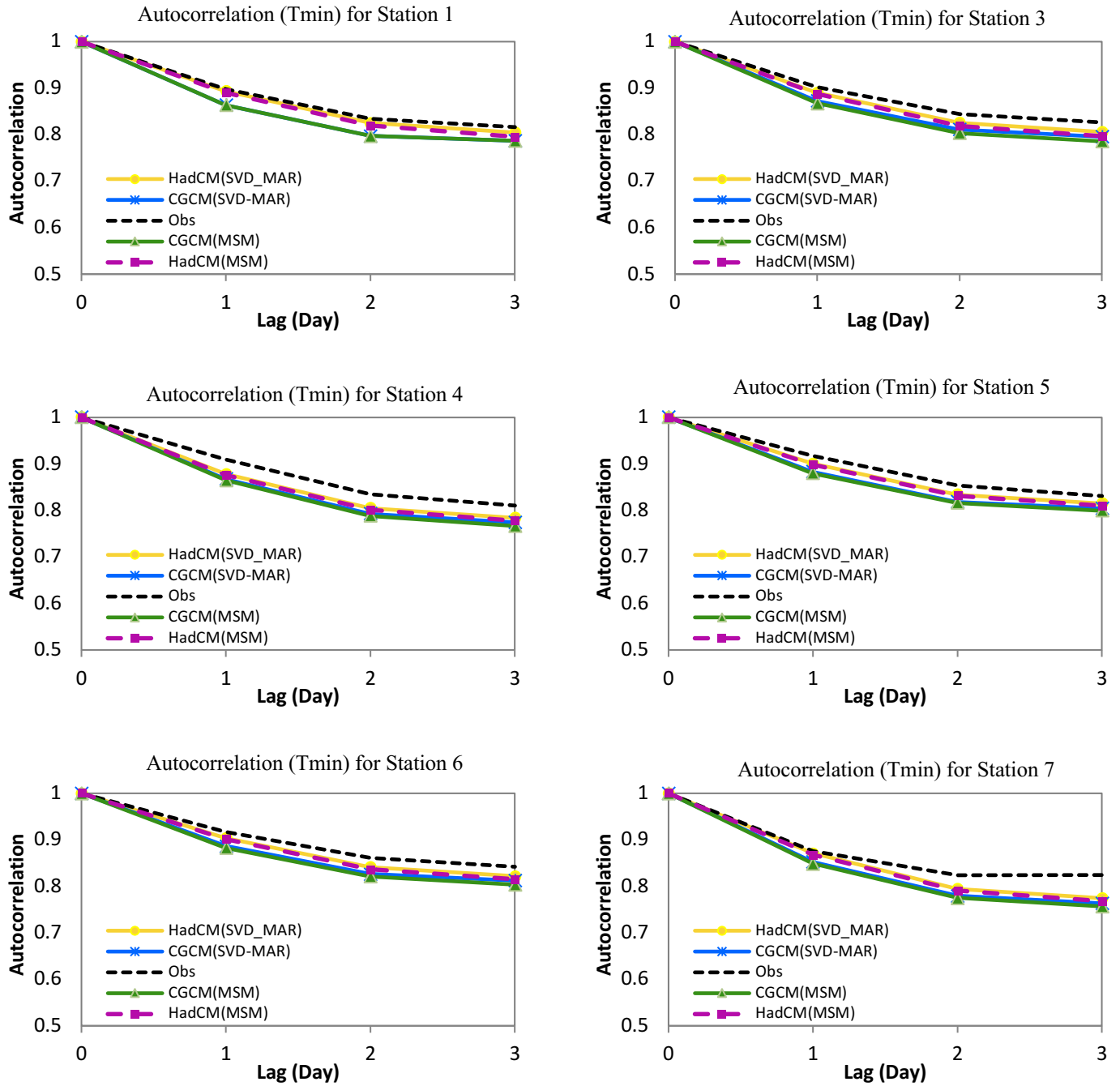


(b)

Figure D-1: Observed and simulated autocorrelation coefficients of T_{max} at the stations in Quebec-Ontario region during (a) calibration and (b) validation period for NCEP data.

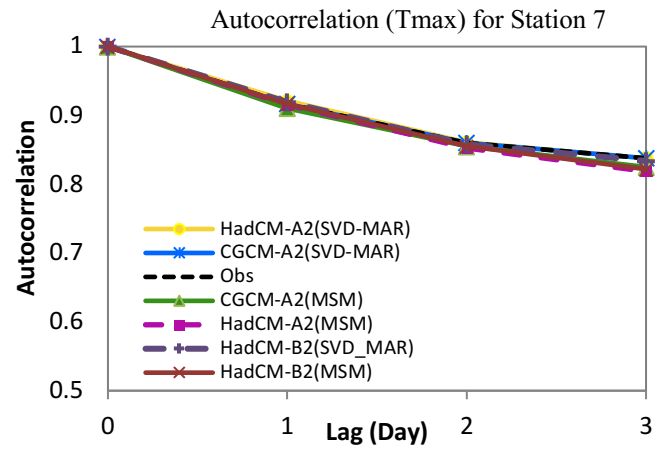
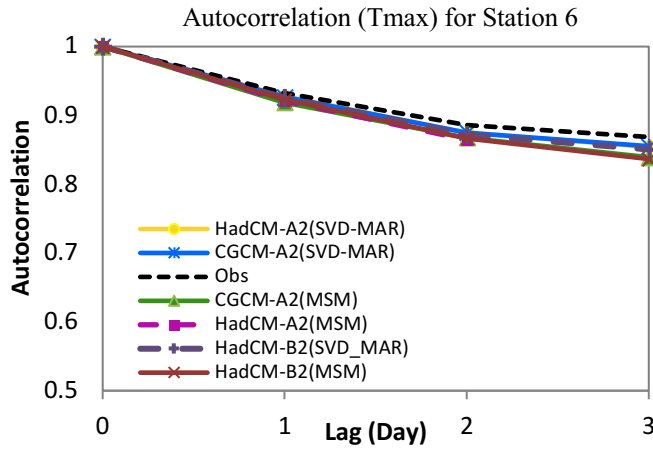
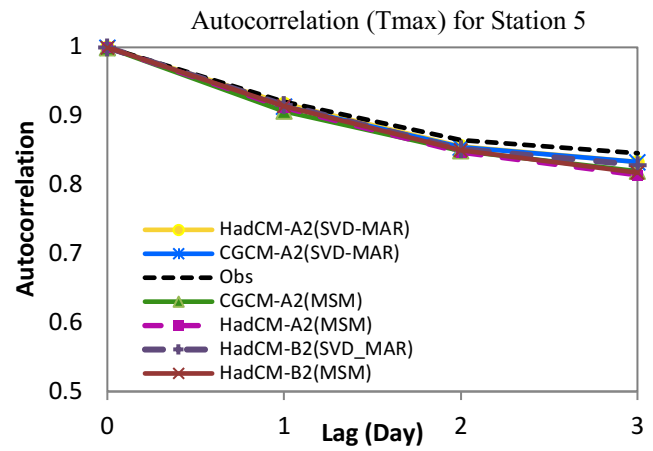
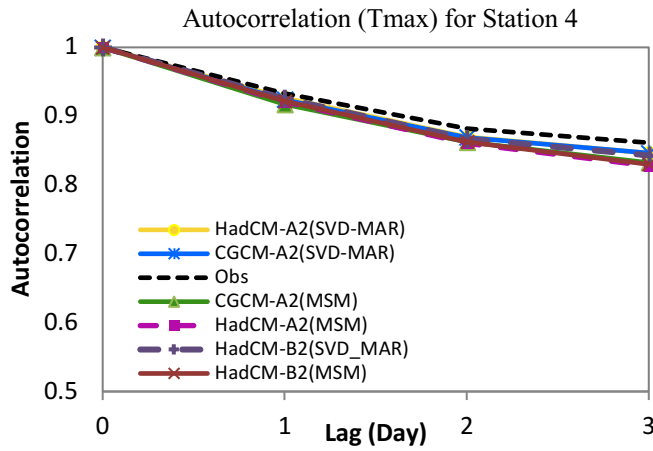
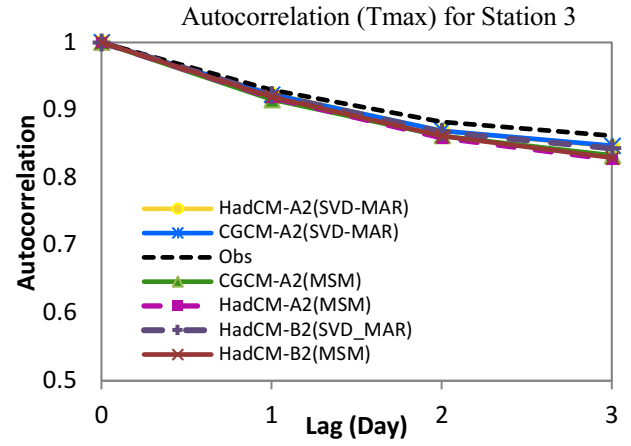
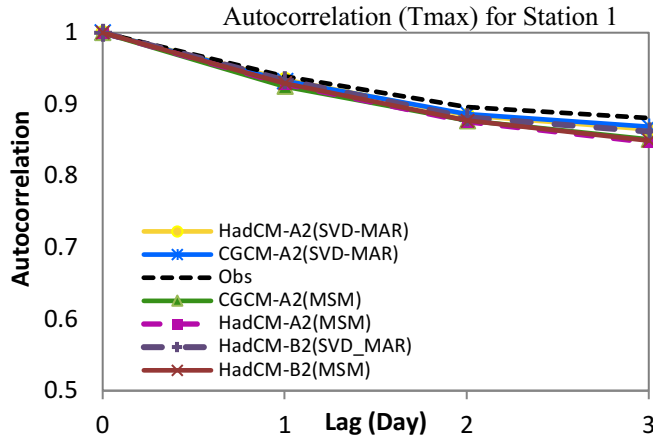


(a)



(b)

Figure D-2: Observed and simulated autocorrelation coefficients of T_{min} at the stations in Quebec-Ontario region during (a) calibration and (b) validation period for NCEP data.



(a)

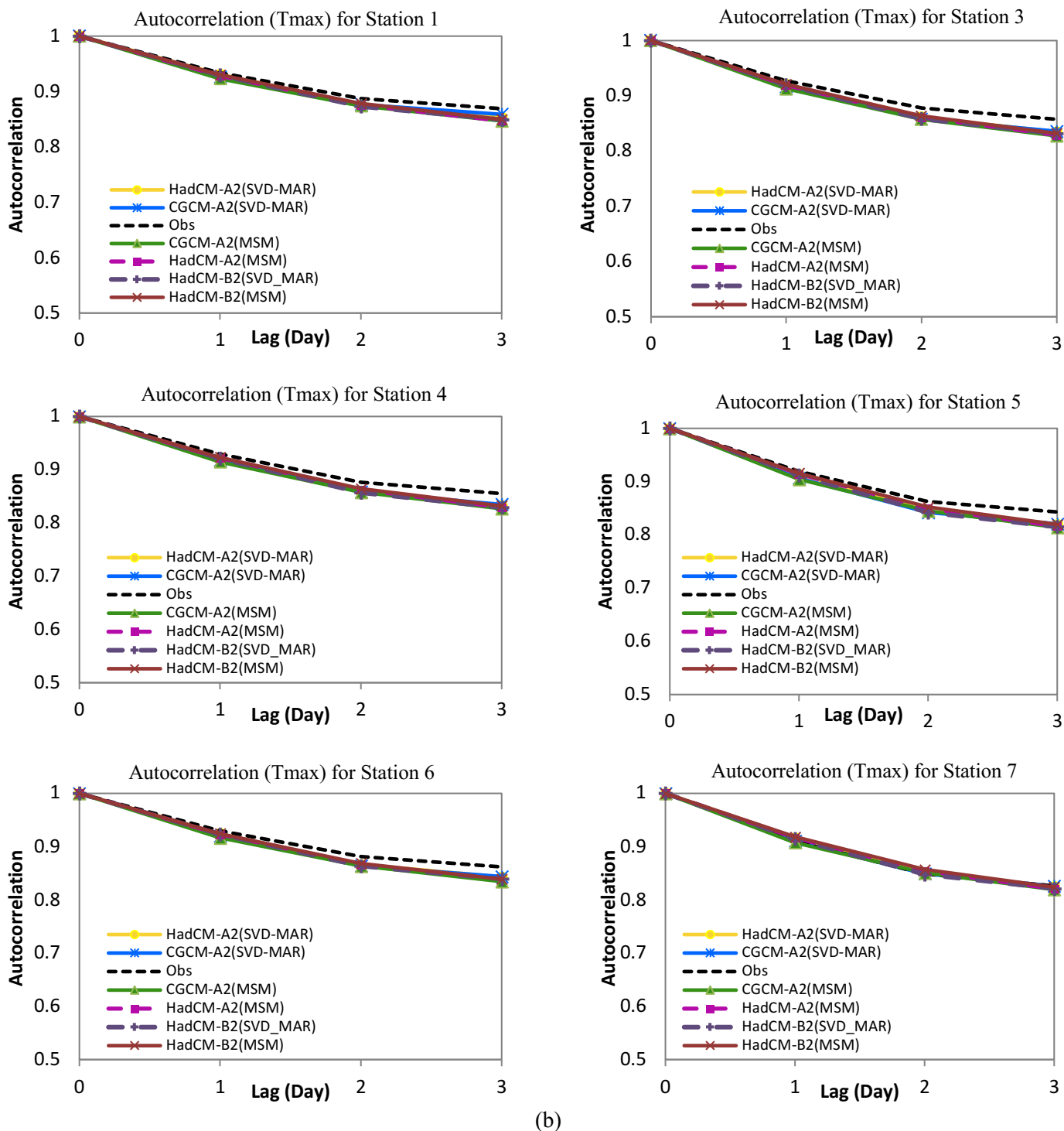
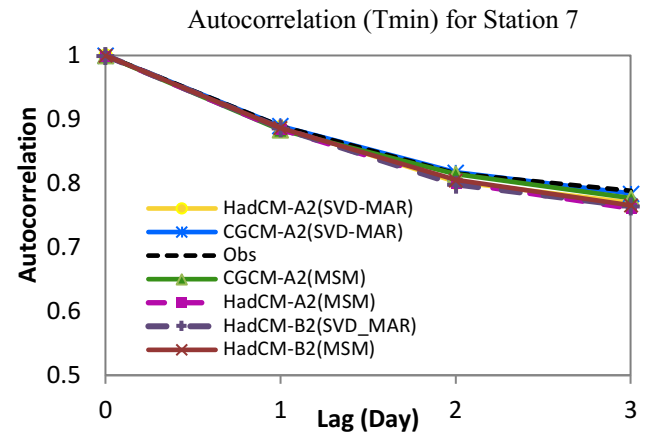
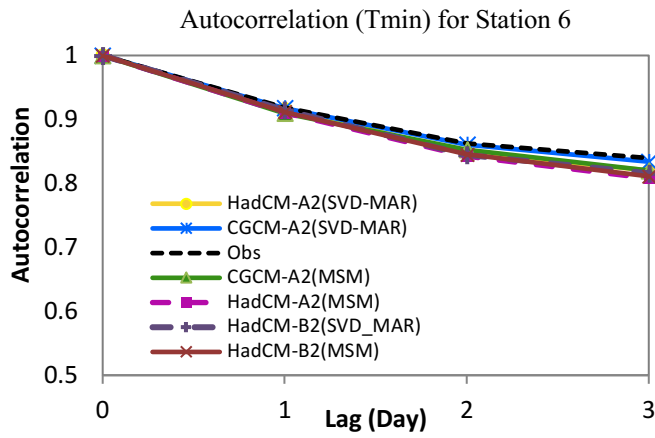
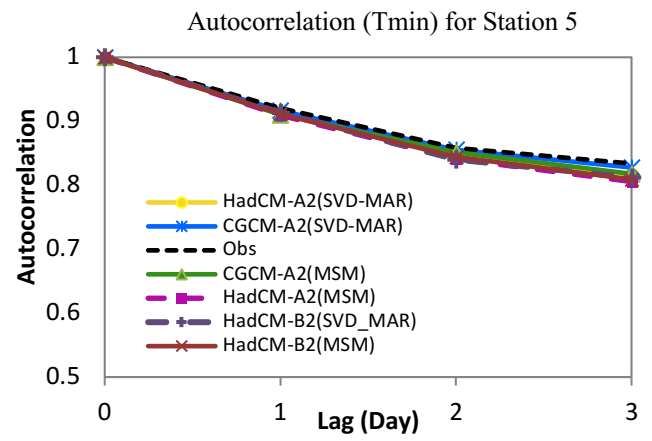
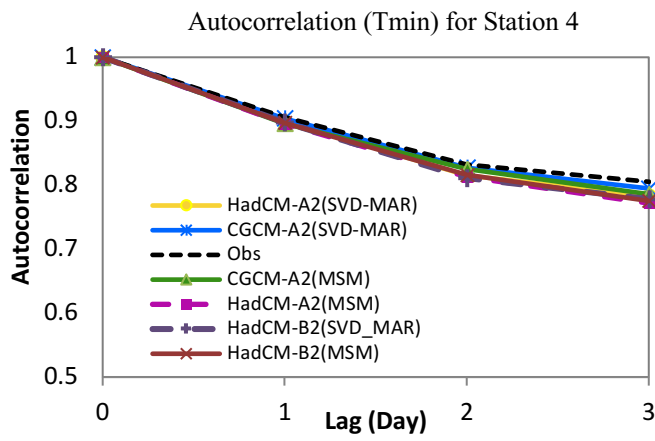
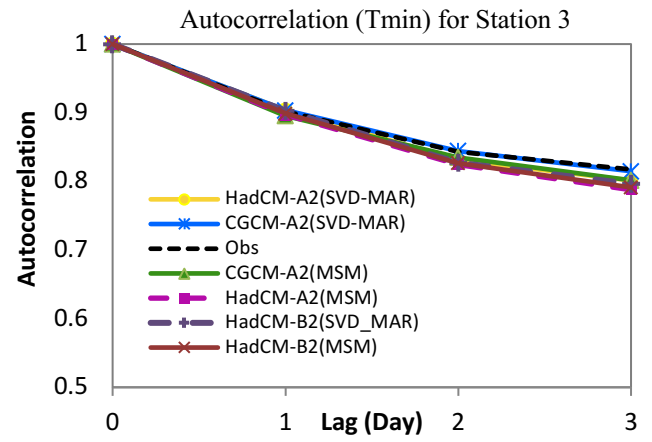
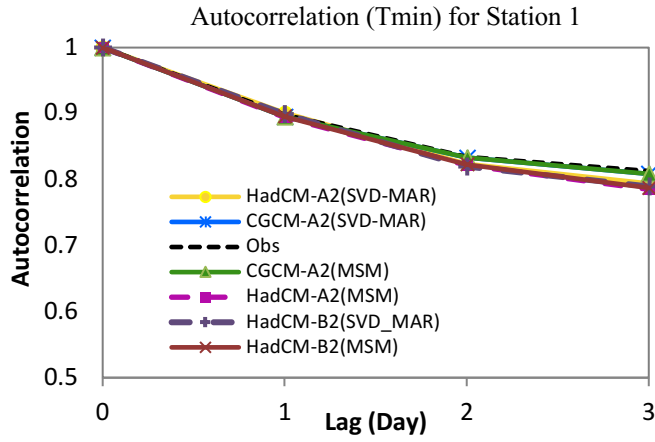
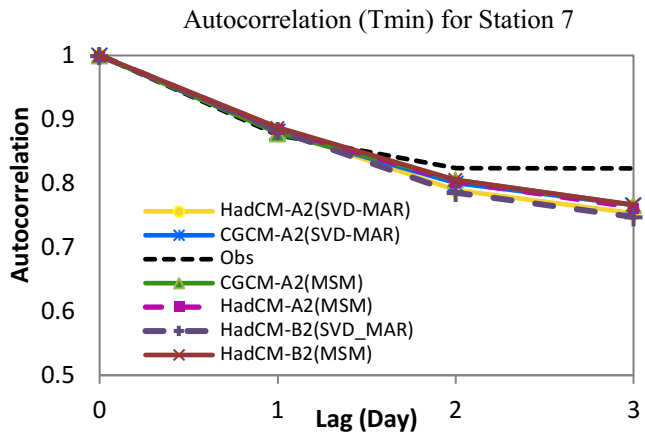
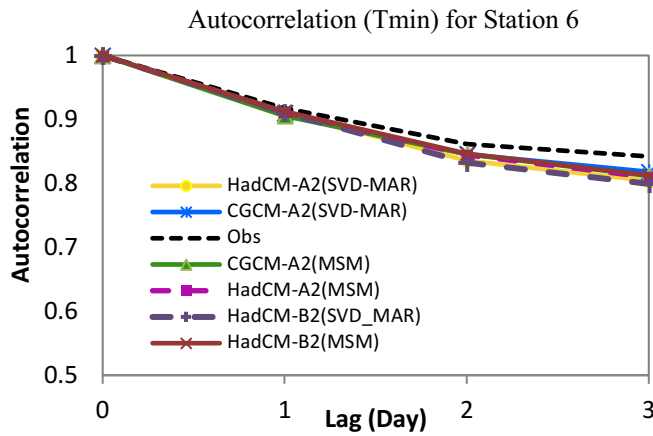
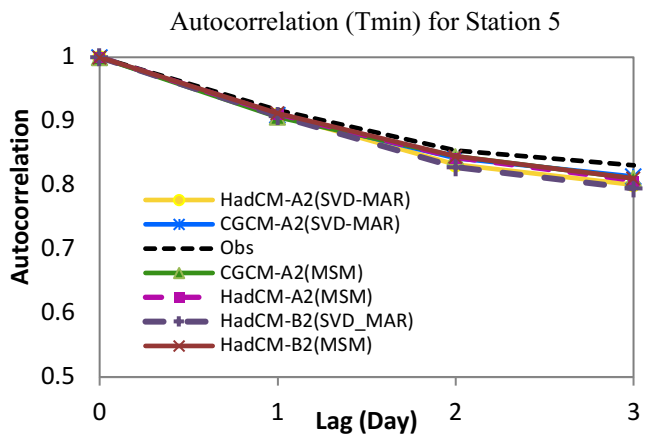
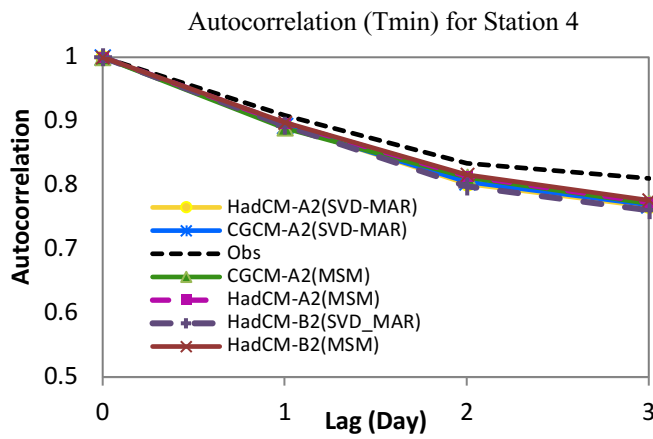
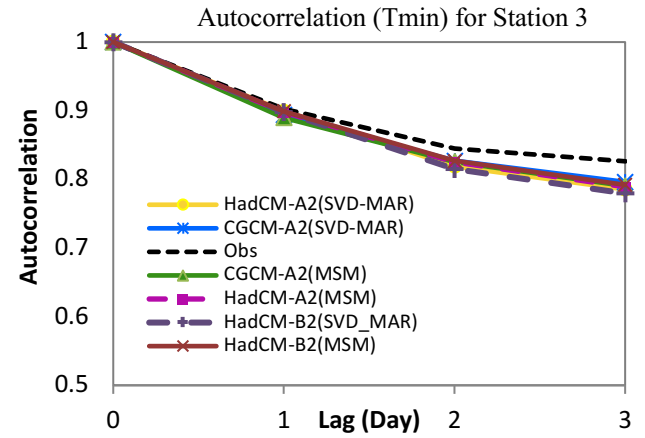
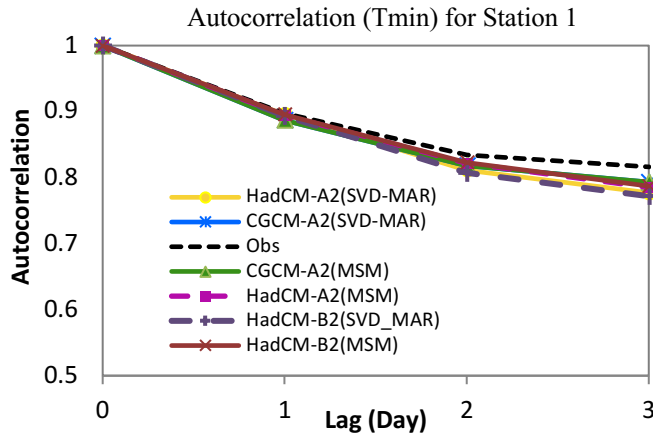


Figure D-3: Observed and simulated autocorrelation coefficients of T_{max} at the stations in Quebec-Ontario region during (a) calibration and (b) validation period for different climate scenarios.

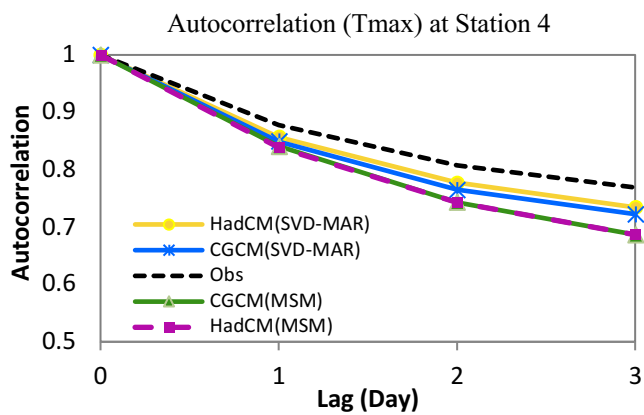
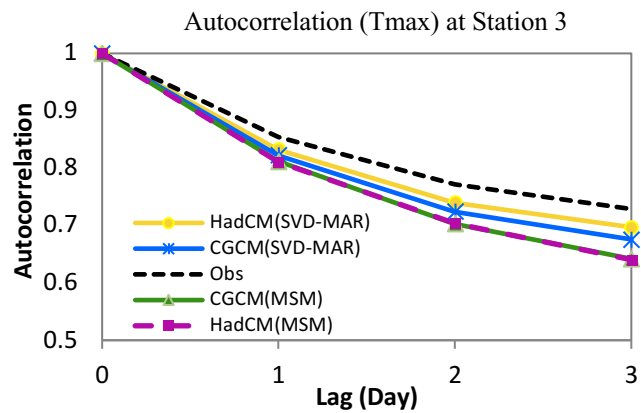
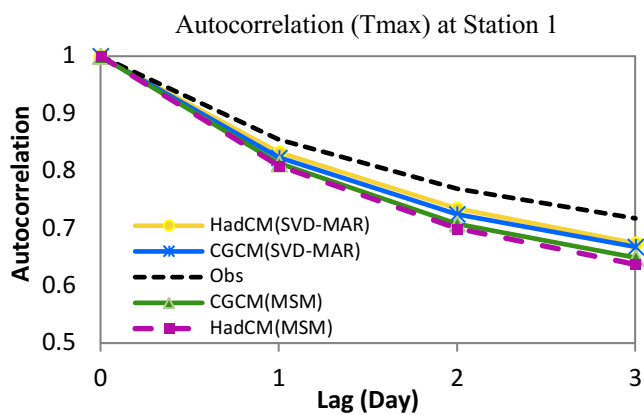


(a)

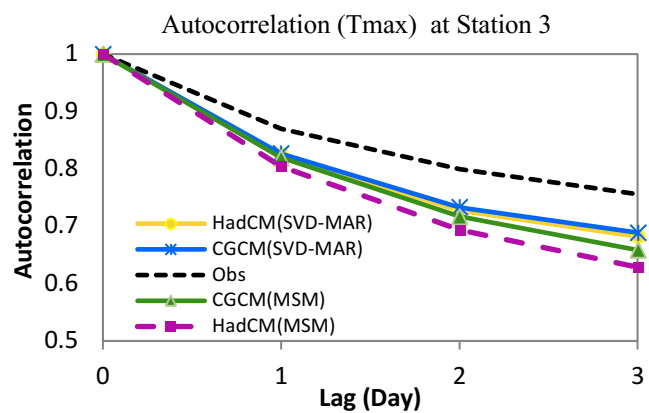
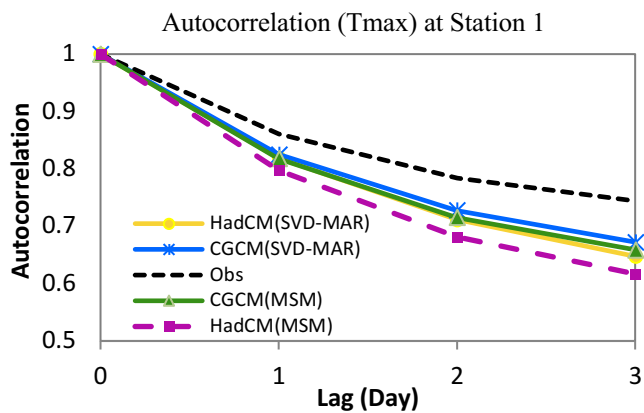


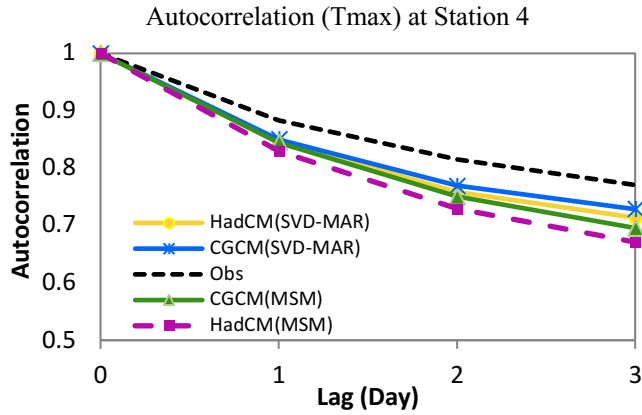
(b)

Figure D-4: Observed and simulated autocorrelation coefficients of T_{min} at the stations in Quebec-Ontario region during (a) calibration and (b) validation period for different climate scenarios.



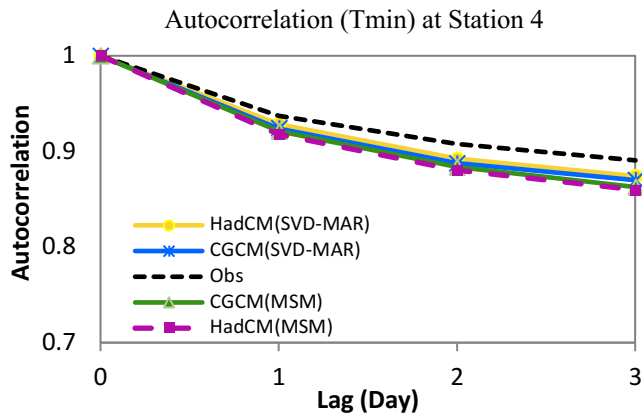
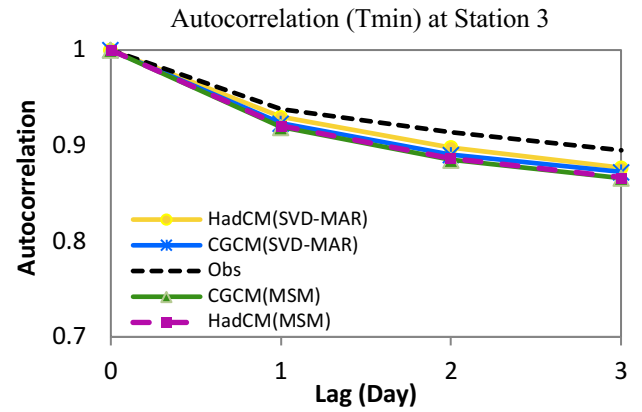
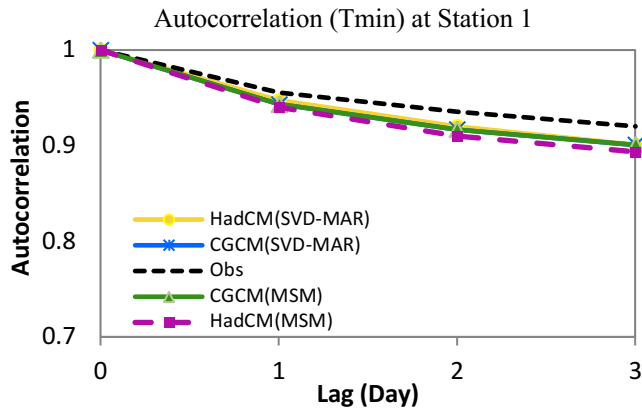
(a)



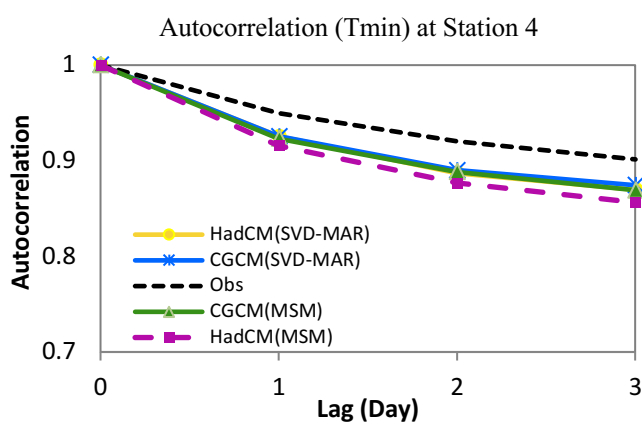
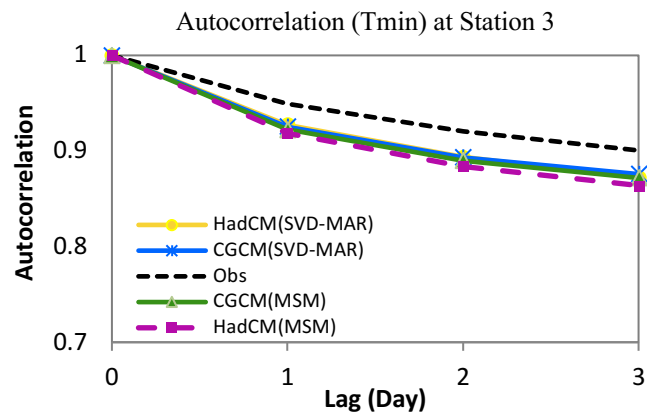
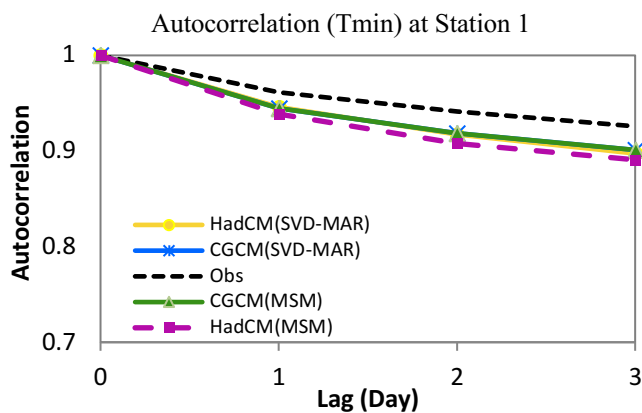


(b)

Figure D-5: Observed and simulated autocorrelation coefficients of T_{max} at the stations in Bangladesh during (a) calibration and (b) validation period for NCEP data.

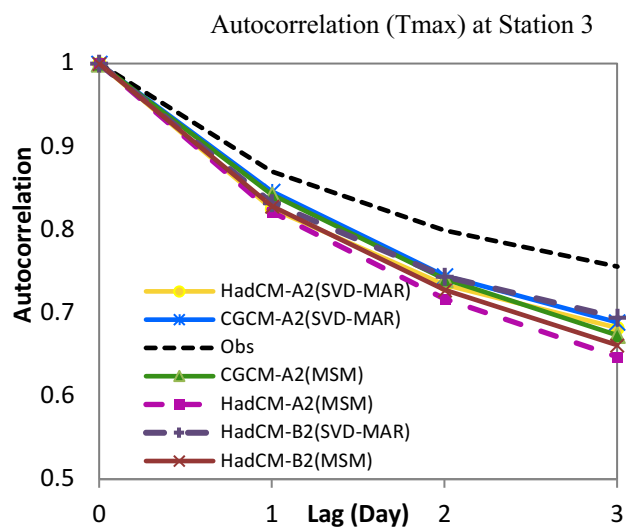
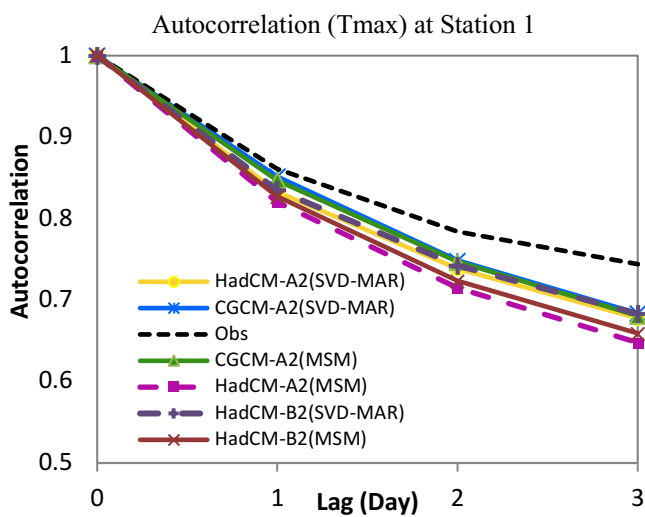


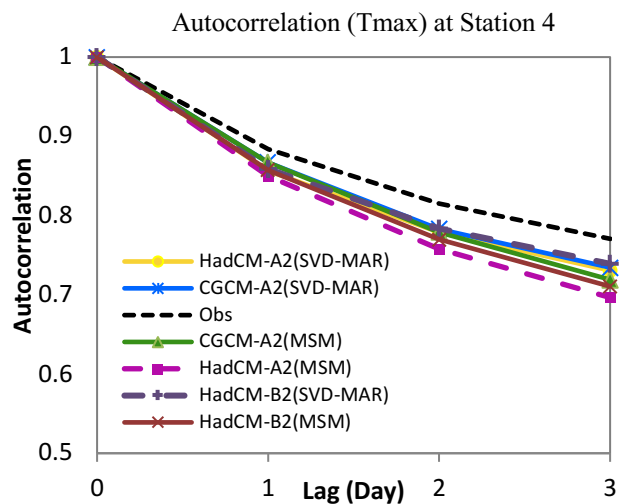
(a)



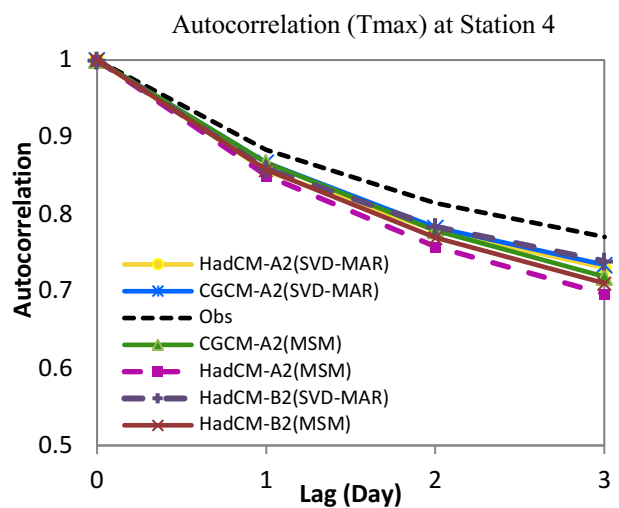
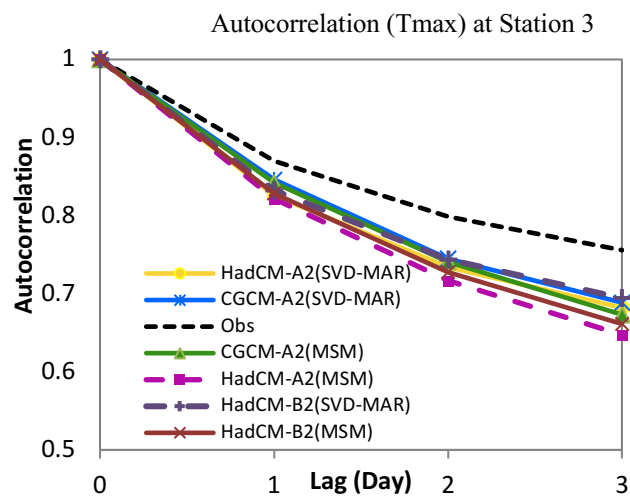
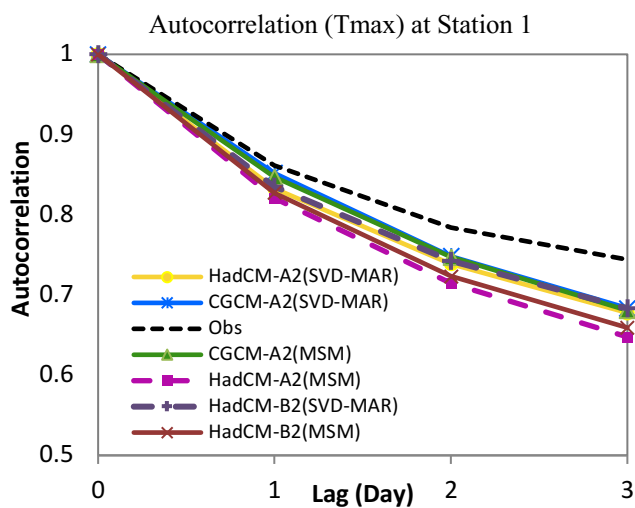
(b)

Figure D-6: Observed and simulated autocorrelation coefficients of *Tmin* at the stations in Bangladesh during (a) calibration and (b) validation period for NCEP data.



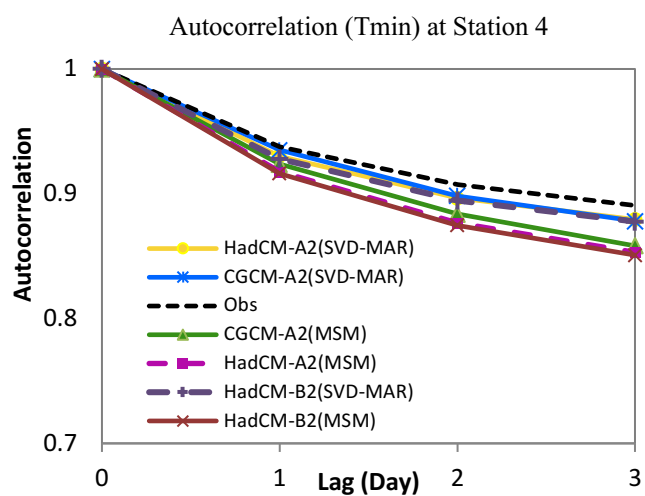
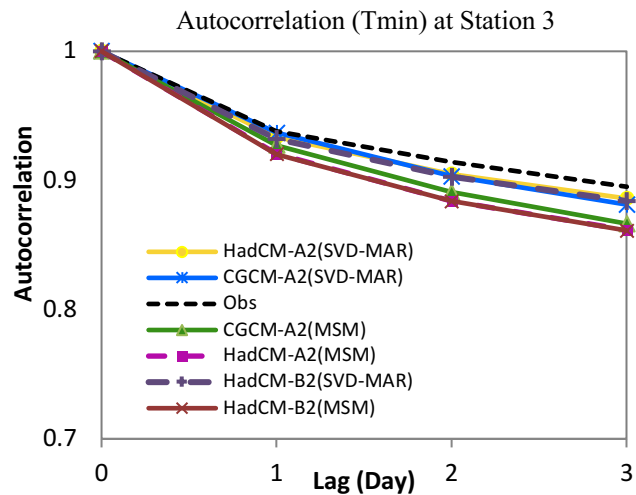
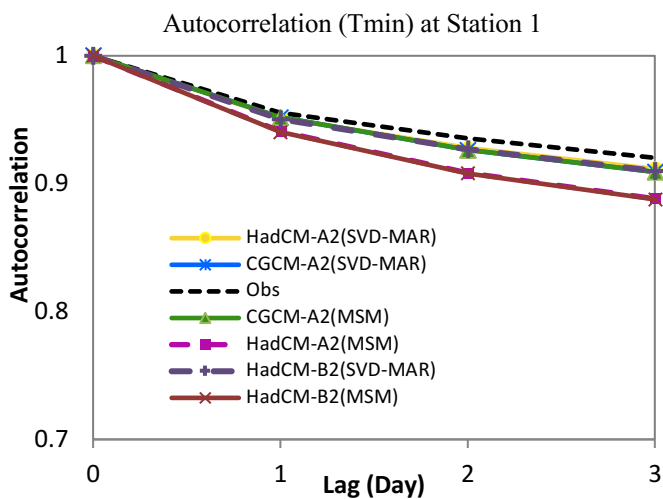


(a)

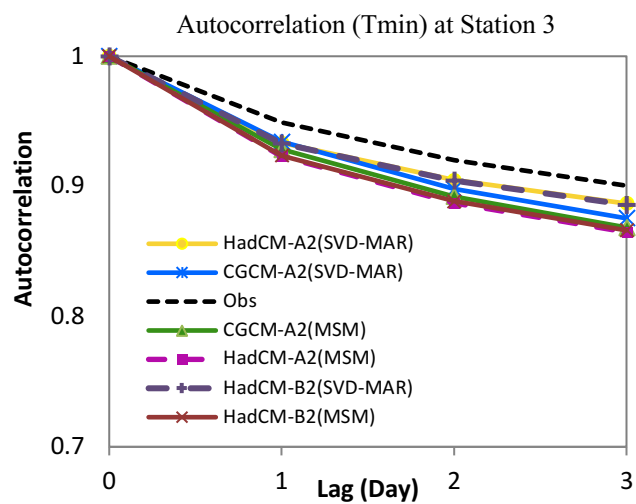
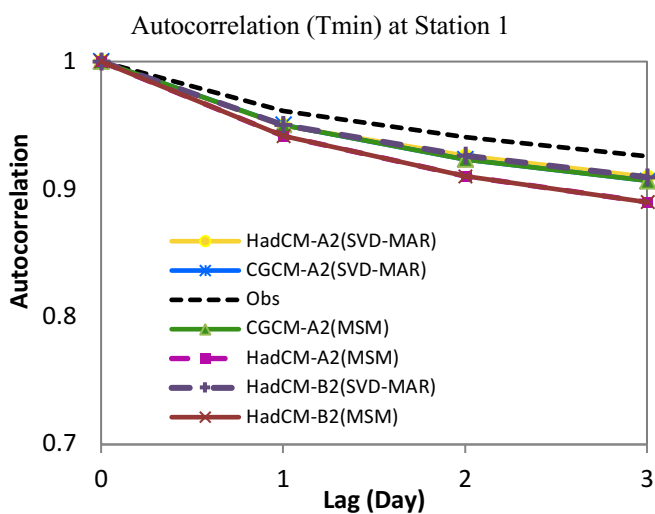


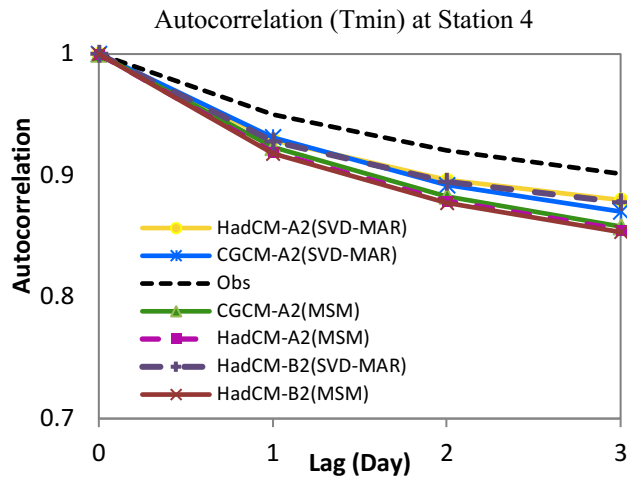
(b)

Figure D-7: Observed and simulated autocorrelation coefficients of T_{max} at the stations in Bangladesh during (a) calibration and (b) validation period for different climate scenarios.



(a)





(b)

Figure D-8: Observed and simulated autocorrelation coefficients of T_{min} at the stations in Bangladesh during (a) calibration and (b) validation period for different climate scenarios.