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Assessment of Future Climate Change Scenario over Rwanda using Statistical Downscaling Approach

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Declaration

I certify that this work is the result of my own efforts and has not previously been submitted for recognition or awards.

Protais DUSHIMIYIMANA

Signed…………………………………

Date……………………………………………………….

Certification

This is to certify that the master's dissertation entitled "**Assessment of Future Climate Change Scenario over Rwanda using Statistical Downscaling Approach**" was carried out by Protais DUSHIMIYIMANA in partial fulfillment of the requirement for the Award of Master's Degree in Atmospheric and climate science in University of Rwanda, College of Science and Technology.

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Abstract

Rwanda has been facing adverse consequences of climate change affecting its socio-economic sectors. This study adopts a statistical downscaling approach to refine CMIP5 GCM outputs (CanESM2) under three Representative Concentration Pathways (RCP2.6, RCP4.5, and RCP8.5) for 2010-2039 (2020s), 2040-2069 (2050s) and 2070-2099 (2080s) at the meteorological station level, aligning them with local requirements for impact assessment. The screen process was performed to select the predictors for rainfall, minimum temperature and maximum temperature. The performance of CanESM2 model statistically downscaled using statistical downscaling model (SDSM) results was based on evaluation metrics namely correlation (R), Root Mean Square error (RMSE), Mean Square Error (MSE), and Index of Agreement (IOA) during both the calibration and validation phases. Projected changes were performed based on to 1976 – 2005 reference period. The results show that the model is able to capture the annual cycle for both rainfall and temperatures (minimum and maximum). For calibration period (1983-1995), the correlation measure indicated a correlation ranging between 0.99 and 1 for maximum temperature, 0.86 and 0.99 for minimum temperature and 0.83 and 0.99 for rainfall during calibration. The RMSE ranges between 0.01 and 0.03 for maximum temperature, 0.01 and 0.72 for minimum temperature and 0.01 and 1.35 for rainfall. The MSE ranges between 0 and 0.01 for maximum temperature, 0 and 0.51 for minimum temperature and 0 and 1.83 for rainfall while IOA ranges between 0.99 and1 for maximum temperature, 0.23 and 0.99 for minimum temperature and 0.89 and 0.99 for rainfall. For evaluation (1996 -2005), the correlation measure indicated a correlation ranging between 0.36 and 0.99 for maximum temperature, 0.61 and 0.98 for minimum temperature and 0.70 and 0.94 for rainfall during evaluation. The RMSE ranges between 0.11 and 0.51 for maximum temperature, 0.27 and 0.99 for minimum temperature and 0.81 and 2.4 for rainfall. The MSE ranges between 0.01 and 0.26 for maximum temperature, 0.07 and 0.98 for minimum temperature and 0.58 and 3.94 for rainfall while IOA ranges between 0.59 and 0.99 for maximum temperature, 0.63 and 0.98 for minimum temperature and 0.57 and 0.95 for rainfall. It expected that the majority of meteorological stations will experience an increase ranging between 0.05°C and 11.8°C in minimum temperature across all emission scenarios and for all future periods, except for a few stations which are expected to experience a reduction ranging between -1°C and -2.5°C. For

maximum temperature, a projected increase ranging between 0.3°C and 8.5°C is expected in the station located in Kigali city and Eastern region, the remaining stations are expected to experience a reduction ranging between -0.07°C and -17°C across all emission scenarios and for all future periods. It expected that the most of meteorological stations will experience an increase ranging between 11.5mm to 49.97 mm in rainfall across all emission scenarios and for all future periods, while a reduction of -4.11mm to -4.39 mm is expected over a few stations. The obtained results are essential for developing suitable mitigation and adaptation measures to mitigate and adapt to the effect of climate change on socio-economic sectors in Rwanda.

List of symbols and acronyms

AR5: Fifth Assessment Report

CanEMS2: Canadian Second-Generation Earth System Model

CMIP5: Coupled Model Intercomparison Project Phase 5

GCMs: Global climate models or Global circulation Models

IOA: Index of Agreement

IPCC: Intergovernmental Panel on Climate Change

MSE: Mean Square Error

NCEP-NCAR: National Centre for Environmental Prediction

PCA: Partial Correlation Analysis

P.R: Partial Correlation

P.V: P-Value

R: Correlation Coefficient

RCPs: Representative Concentration Pathways

RCP2.6: Representative Concentration Pathway that correspond to the radiative forcing reaches a peak of about 3 W/m2 around mid-century and decreases to 2.6 W/m2 by 2100

RCP4.5: Representative Concentration Pathway that correspond to a rise in radiative forcing to 4.5 W/m2 by 2100 and beyond.

RCP8.5: Representative Concentration Pathway that correspond to a rise in radiative forcing to 8.5 W/m2 by 2100 and beyond.

RMSE: Root Mean Square Error

SD: Statistical downscaling

SDSM: Statistical Downscaling Model

Tmax: Maximum Temperature

Tmin: Minimum Temperature

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Chapter 1: Introduction

1.1 Background

Climate change is a problem of utmost importance that affects the entire planet, and its consequences are being experienced worldwide [1]. For decades, it has been evident that the climate of the Earth is undergoing transformations, and models estimate that the rate of these changes is expected to accelerate [2]. The African continent, specifically East Africa, is at significant risk to variations in climate, including severe weather conditions like frequent droughts, floods, and heavy rainfalls, which are predicted to increase in frequency in the future [3]. the spatial distribution of precipitation has been reported to fluctuate substantially, with a variation of around 25% to 50% decrease and increase [2]. Climate change alterations, such as changes in rainfall patterns, extended periods of dry weather, and reduced agricultural output, have already been observed in Rwanda, a landlocked nation located in East Africa, resulting in food insecurity in certain regions [4]. As a result, it is imperative to assess future climate change scenarios to design effective adaptation and mitigation measures.

Global climate models are critical in assessing future climate change scenarios. The IPCC (Intergovernmental Panel on Climate Change) expresses strong confidence in the ability of GCMs to predict future climate conditions and establish links between observed climate patterns and anthropogenic greenhouse gas emissions [5]. The data derived from these models depicting climate scenarios lack the spatial precision essential for precise local predictions. Consequently, downscaling becomes imperative for studies regarding impact and adaptation, as they necessitate finely-detailed local climate projections at high resolution [6]. Downscaling techniques are categorized into two types: dynamical and statistical downscaling. Statistical downscaling aims at establishing actual association between large-scale climate conditions (atmospheric predictors) and climate conditions at local scale, such as topography, land usage and land-sea contrast [7]. Among the two types of downscaling discussed, this study utilized statistical downscaling through the use of SDSM, a free and open-source tool for generate fine-resolution climate change data from GCMs specifically for conducting research on local-scale climate change at local-scale [8].

To adequately engage in local climate change impact studies, additional focus should be directed towards enhancing the statistical downscaling of GCM outputs to the regional level.

1.2 Problem statement.

Climate change is considered as the most significant and irreversible environmental issue threatening the globe [1], [5]. Like many other countries in East African region, Rwanda is increasingly experiencing the effects of changing climate and it is one of the top ten countries most affected by climate change according to the Global Climate Risk Index ranks of year 2018 [6]. Changes in temperature and rainfall patterns, as well as their distribution, are the primary causes of climate and weather-related disasters affecting Rwandans and the nation's economy. These changes cause catastrophic events such as droughts, floods, and landslides, which have negative consequences such as infrastructure destruction, loss of life and property (including crops), and worsen concerns such as soil erosion and water pollution [7]. Thus, for example, between 1980 and 2017, the effects of climate change, including heavy precipitation, droughts, floods, landslides, crop damage, and famine, caused the deaths, injuries, and displacement of over one million individuals, as well as destruction to 15,000 hectares of cropland and 23,000 homes [8]. Muneza [9] highlight that high temperature and irregular rainfall affect agriculture in such way that, high temperatures lead to decreased crop yields and promote the growth of weeds and pests, while prolonged dry condition contributes to desertification, and irregular rainfall results in flooding, erosion, landslides, and loss of arable soil. Researches on climate change Impacts require a fine resolution climate data however, the available projections from GCMs are at low spatial resolutions. Therefore, there is a strong need to bridge GCMs output with local climate observations. High-resolution climate data is required for driving impact assessment models [10], yet these models typically have low resolution and may not encompass the necessary local climate variability crucial for impact and adaptation studies. To address this challenge, the statistical downscaling approach is required to refine global models to the local level. The statistical downscaling model (SDSM) is employed for the first time to downscale CanESM2 output at different meteorological stations in Rwanda.

1.3 Objectives

The primary aim of this research is to evaluate future climate change scenarios in Rwanda by employing a statistical downscaling model (SDSM). To accomplish this, the following specific objectives were followed:

- To statistically downscale CanESM2 model to local station in Rwanda.
- To examining the efficiency of the statistical downscaling model.
- To produce future climate change scenario data for RCP4.5 and RCP8.5 at different locations in Rwanda.

1.4 Justification of the study

Climate change is now recognized as the most serious environmental threat on the planet. The examination of its local implications necessitates finer spatial scale information than offered by global climate models. Their usefulness for local impact studies is limited by their coarse spatial resolution and inability to resolve critical sub-grid scale elements such as clouds and topography. [11]. Therefore, there is a need to bridge these gaps through statistical downscaling approach. This study found its interest in statistically downscaling simulations of CanESM2 GCM model and produce future climate change scenarios under three representative concentration pathways namely, RCP2.6, RCP4.5 and RCP8.5 for climate variables temperature (maximum and minimum) and precipitation over Rwanda.

1.5 Study Area

Rwanda is a small landlocked Central African country; it falls between 1°4′ and 2°51′ south latitude and 28°45′ and 31°15′ east longitude [6]. With a total land area of 26,338 km2, Rwanda's borders extend to the north, where it neighbors Uganda, to the east with Tanzania, to the south with Burundi, and to the west and northwest, it shares boundaries with the Democratic Republic of Congo. [12]. The country displays four clearly defined climatic zones: the eastern plains, the central plateau, the highlands, and the regions surrounding Lake Kivu along the western boundary. [12]. Rwanda experiences a tropical climate characterized by hilly terrain extending from east towards west. The area of Rwanda is consisting of a variety of ecosystems, including aquatic forests, mountain rainforests, gallery forests, savannah woodland, agroecosystems and wetlands.

The rainfall ranging from 700 mm to 1,100 mm and an average yearly temperature fluctuating from 20°C to 22°C are recorded in eastern plains. The central plateau region experiences rainfall between 1,100 mm and 1,300 mm annually, with mean temperatures ranging from 18°C to 20°C. The highlands, which include the Congo-Nile Ridge and volcanic chains of Birunga, receive annual rainfall between 1,300 mm and 1,600 mm, with average temperatures ranging from 10°C to 18°C. Lastly, regions around Lake Kivu and Bugarama plains receive annual rainfall between 1,200 mm and 1,500 mm, and the average temperatures range from 18°C to 22°C.

As the objective of this research is to assess future climate change scenario over Rwanda, we happened to choose stations that belongs within the four mentioned main climatic regions, in order to be able to capture the general climatic information. (Figure 1) shows the location of total fourteen meteorological stations that we have selected taken into considerations.

Chapter 2: Literature review

2.1 General circulation models

Global Climate Models (GCMs) are the mathematical models employed to simulate the current climate and predict future climate, accounting for greenhouse gas and aerosol forcing [13]. GCMs represent the cutting-edge instruments utilized for precise simulation of the present global climate and projecting future climate scenarios [14]. In most cases, their formulation considers the behavior and interaction of circulation systems in the biosphere, hydrosphere, atmosphere, and geosphere in the climate system [15]. Global Climate Models are Cartesian point models which may be run at various horizontal and vertical resolutions to be used in various portions of the planet. [16]. General circulation model forecasts climate patterns with large spatial coverage, considering factors like clouds, radiation, surface characteristics, ocean dynamics, and model stability for accurate predictions [17]. GCMs have a relatively coarse spatial resolution, typically around 250 x 250 km, resulting in the luck of regional and local climate details influenced by spatial variations in the regional landscape [14], [18], [19]. As a consequence, GCMs cannot adequately capture the dynamics and features at the local sub-grid scale, including specific topographical characteristics and convective cloud processes [18]. Thus, there is a necessity to transform GCM outputs into dependable dataset to be used at the local level [20].

2.2 Downscaling.

Downscaling is a scientific process employed to enhance the resolution of global climate model outputs, thereby providing more detailed and region-specific information pertaining to local climate conditions [21], [22]. The downscaling approach relies on several underlying assumptions and limitations, necessitating careful consideration to avoid potential inaccuracies or misinterpretations in the outcomes. Various research endeavors have been undertaken in the domain of downscaling procedures [20], [23] [24]. Acknowledging the significance impact of large-scale atmospheric phenomena and local-specific elements on local climate conditions is crucial [24]. As a result, downscaling techniques can be classified widely into two broad categories: dynamical and statistical downscaling [22],[15]. (Figure 2) illustrate the approaches proposed for downscaling GCMs.

2.2.1 Dynamical downscaling

Dynamical Downscaling is an approach utilized to create a regional climate model that requires an in-depth Comprehension of physical processes occurring in the atmosphere, along with detailed interactions and feedbacks at the local or regional level [25]. In general, the Dynamical Downscaling (DD) approach is used in places with complex topography, coastal or island environments, and locations with very variable land cover patterns [22].

The benefits attributed to dynamical downscaling include its capability to react in a manner that maintains physical consistency to various external influences, its capacity to capture atmospheric processes like topographic precipitation, and its alignment with Global Climate Models (GCM) for greater coherence[21]. The limitations of dynamical downscaling involve its reliance on considerable computational resources and its susceptibility to the accuracy of GCM boundary forcing and initial boundary conditions, which can influence results [26].

One critical characteristic of dynamical downscaling approaches is determining if the high-resolution scenarios produce significantly distinct effect calculations than the coarser resolution GCM from which the high-resolution scenario was produced in part [27].

2.2.2 Statistical downscaling

Statistical downscaling is a useful approach for refining climate data from larger spatial scales to finer scales [28]. It involves creating direct statistical associations between large-scale atmospheric patterns and local parameters, like temperature and precipitation, to obtain climate change data at a more detailed resolution [29].

Compared to alternative downscaling techniques, such as dynamical downscaling, statistical methods are relatively user-friendly and provide climate information at a station level based on simulations of GCMs [30]. Consequently, they are widely utilized in hydrologic impact studies concerning climate change scenarios. It offers several advantages, including cost-effectiveness, low computational demands, and ease of implementation, making it a practical choice for various climate change impact applications and uncertainty analyses [19], [31]. Furthermore, statistical downscaling becomes especially attractive when computational resources are limited, particularly in developing nations [32]. Statistical approaches have been recognized as having practical benefits over dynamical downscaling techniques, such as adaptability to specific study purposes and less demand for expensive computing resources.

However, there are disadvantages to consider. High-quality observation data is necessary for model calibration, and the relationships between predictors and predictands are often non-stationary [33]. Furthermore, empirical methods may fail to account for potential systematic changes in regional driving conditions or feedback processes [34].

Weather typing approach, regression methods, and stochastic weather generators are the three primary forms of statistical downscaling methodologies [35]. These methods are based on three basic assumptions: (i) Local-scale parameters are affected by synoptic forcing, (ii) the GCM used to derive relationships is valid at the scale under consideration, and (iii) the obtained relationships are applicable under changing climate conditions [15].

2.2.3 Research on statistical downscaling

The application of General Circulation Models (GCMs) to project climate change is commonly used, but these models are of low resolution and often cannot provide data on local climate variability [36]. In contrast, the statistical Downscaling Model (SDSM software) can provide detailed climate projections at a regional and local level [11].

In previous studies, SDSM software has successfully applied to assess future possibilities of climate change in diverse parts of the world. A research conducted by Shitu et al. (2019) used SDSM software as statistical downscaling techniques for projecting future daily maximum temperature, daily minimum temperature, and precipitation values in Kombolcha Town, South Wollo, Ethiopia, and the findings showed that mean value of annual rainfall undergo reduction of 1.36% - 7.03% and 5.37% -13.8% for RCP4.5 and RCP8.5 emission scenarios in the last 21 century respectively, on the other side, maximum and minimum temperature of the town showed a rising trend in future for RCP4.5 and RCP8.5 emission scenarios [37]. Similarly, another study by Ncoyini et al. (2022) assessed Future Air Temperature and Rainfall Changes in South Africa, specifically, KwaZulu-Natal midlands of and found a rise in both minimum and maximum air temperatures for the entire study period and the model predicted positive trend in precipitation despite the fact that all scenarios forecast a falling trend in the 2020s and a rising in the 2050s [38].

Closer to Rwanda, a study by Gebrechorkos et al. (2018) used the SDSM software to downscale statistically the East Africa's climate dataset, and the results showed the ability of the model in replicating he observed precipitation characteristics and if is found that there is a strong correlation (R^2) between observed and downscaled precipitation and model biases were lower. the model also showed great ability in replicating maximum and minimum temperature [32]. These are the evidence that the model can also be applied in Rwanda.

In conclusion, while GCMs are widely used for climate change assessments, the SDSM software offers a robust solution for assessing future climate change scenarios at a local and local level. This method should be considered for assessing future climate change projections over Rwanda given its relative accuracy and high special resolution.

2.3 Scenarios under RCPs

The Representative Concentration Pathways (RCPs) are a collection of greenhouse gas concentration and emissions pathways aimed to facilitate studies on the consequences of climate change and possible policy measures in response to it [39]. The Representative Concentration Pathways (RCPs) are used in the CMIP5 forecasts to show several future scenarios of human-induced climate change [40]. These RCPs range from a low-emission scenario (RCP 2.6), characterized by active mitigation, through intermediate scenarios (RCP 4.5 and 6.0), to a high-emission scenario (RCP 8.6) [41]. These RCPs are associated with possible combinations of population increase, economic activity, socioeconomic development, and energy consumption [39]. The names of the RCP scenarios are based on their total radiative forcing by the year 2100 [41]. RCP 2.6 envisions a significant reduction in radiative forcing compared to other trajectories. In this scenario, greenhouse gas emissions peak around 2020 and then decline. The radiative forcing reaches a peak of about 3 W/m2 around mid-century and decreases to 2.6 W/m2 by 2100 [42]. RCP 4.5 follows a stabilization pathway where radiative forcing peaks around 2040 and remains stable thereafter without any further increase. The radiative forcing level is around 4.5 W/m2 by the year 2100 [43]. RCP 6.5 is also a stabilization pathway, representing the application of non-climate policies. The radiative forcing stabilizes at around 6.5 W/m2 by the year 2100 [42].

On the other hand, RCP 8.5 illustrates an increasing trend of radiative forcing even beyond 2100. Addressing this scenario requires strict implementation of non-climate policies. The radiative forcing is projected to reach approximately 8.5 W/m2 by the year 2100 [44].

In summary, RCP 2.6 scenario indicates a mid-century peak of approximately 3 W/m2 in radiative forcing before decreasing to 2.6 W/m2 by 2100. for RCP 4.5, radiative forcing is expected undergo stability at 4.5 W/m2 after 2100. Meanwhile, the worst scenario (RCP 8.5) forecast a rise in radiative forcing to 8.5 W/m2 by 2100 and beyond.

Chapter 3: Data and Methodology

3.1 Data

3.1.1 Station data

Actual Meteorological station data were collected from Rwanda Meteorological agency. The data collected includes: daily rainfall data spanning from 1981 to 2021 and surface minimum and maximum temperature from 1983 to 2021. (Table 1) shows all fourteen meteorological stations known as synoptic stations at Meteo Rwanda, selected for data collection.

3.1.2 GCM data

This study focuses on CanESM2 model simulations (RCPs scenario). The selection of CanESM2 for this work is based on its extensive application in numerous climate change impact researches and the fact that model offers predictor variables that are suitable for use in SDSM [2], [37], [45], [46]. The second-generation Canadian Earth System Model (CanESM2), is built upon CMIP5 experiments and is a fourth-generation coupled global climate model (CGCM4) created by the Canadian Centre for Climate Modelling and Analysis (CCCma) within Environment and Climate Change Canada. It serves as Canada's contribution to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC).

The data files for the CanESM2 model are downloaded from the Canadian Climate Data and Scenarios website (http://climate-scenarios.canada.ca/). CanESM2 predictor variables are provided on a grid box per grid box basis with dimensions of 2.5° latitude x 3.75° longitude. The study area is registered within Grid BOX_012X_32Y with Box Centre of (lat.-1.395 *and* 30.9375long.) and BOX_011X_32Y with Box Centre of (lat. -1.395 and 28.125long.) which are simply noted as Grid box 1 and Grid box 2 respectively in our study. (Figure 3) represent the Grid box of CanESM2 that covers Rwanda, letter A and B shows BOX_012X_32Y and BOX_011X_32Y respectively. Among fourteen meteorological stations we have in our study area, ten of them are found to be in Grid box 1 while the remaining four belong in Grid box 2.

The predictor can be accessed in a compressed zip file type. Upon opening the zip file, you will find the following weather parameters were included:

NCEP-NCAR_1961-2005: This directory contains a collection of 44 years of daily observed data for predictors derived from the NCEP reanalysis. These data have been normalized by using the mean and standard deviation values from 1961 to 1990. (Table 2) provides an overview of the 26 NCEP-NCAR predictor variables.

CanESM2_historical_1961_2005: This Directory contains 44-year daily GCM predictor data from CanEsm2 experiment, normalized 1961-1990.

CanESM2_rcp2.6_2006_2100: Directory contains 95 years of daily GCM predictor data from RCP2.6 experiment, normalized using 1961-1990 reference.

CanESM2_rcp45_2006_2100: Directory contains 95 years of daily GCM predictor data from RCP4.5 experiment, normalized using 1961-1990 reference.

CanESM2_rcp8.5_2006_2100: Directory contains 95 years of daily GCM predictor data from RCP8.5 experiment, normalized using 1961-1990 reference.

3.2 Methodology

3.2.1 Statistical Downscaling Model (SDSM)

The overall process followed to downscale rainfall, maximum and minimum temperature by using SDSM (Statistical Downscaling Model) is demonstrated in (Figure 4). The same process was previously applied in many studies as highlighted by [28]. the SDSM software simplifies the process of statistically downscaling daily weather series into seven distinct stages as described in subsequent sections. These processes include: 1) quality control and data transformation; 2) selection of predictor variables; 3) model calibration; 4) weather generation (utilizing observed predictors); 5) statistical analyses; 6) visualization of model output; 7) scenario generation (using climate model predictors) [47]. (Figure 5) presents how all these processes appear in SDSM homepage.

The statistical downscaling models (SDSM) utilized to downscale daily time-series of CanESM2 GCM outputs (from 1961 to 2099) at each meteorological station selected in the study area is a powerful tool created by [47], and has since become a popular tool for regional climate change studies [15], [34], [48]. The SDSM is a hybrid model that combines multi-linear regression methods with a stochastic weather generator to encompass both the predictable and random aspects of weather patterns [31]. By utilizing this approach, SDSM can simulate the frequency of extreme weather events and long-term changes in regional climate variables, considering the influence of large-scale climate processes[49]. The downscaled process has two modes: unconditional, presuming a straightforward correlation between large-scale predictors and ground observed data (e.g., wet-day occurrence or air temperature), and conditional, applied for specific events (e.g., rainfall amounts) [47].

Regarding wet-day occurrence (O_i), a direct linear dependency on n predictor variables (P_{ij}) for day i can be expressed as:

$$\boldsymbol{O_i = \varphi_0 + \sum_{j=1}^{n} \varphi_j P_{ij}} \quad (1)$$

where $0 \leq O_i \leq 1$. Precipitation occurs when a uniform random number (r) is less than or equal to O_i. If a wet-day is detected, the precipitation total (R_i) is downscaled using the equation:

$$\boldsymbol{R_i{}^k = \beta_0 + \sum_{j=1}^{n} \beta_j\ P_{ij} + e_i} \quad (2)$$

Here, k represents a transformation (e.g., fourth root, inverse normal, or logarithmic) applied to account for the skewed nature of precipitation data.

For unconditional processes like daily temperature (T_i), a direct linear relationship is established between the predictand T_i and selected predictors P_{ij} on individual station:

$$\boldsymbol{T_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j P_{ij} + e_i} \quad (3)$$

where T_i and P_{ij} are temperature and the selected predictors, respectively, for day i. The regression coefficients φ_j, β_j, and γ_j are estimated for each month using least squares regression as model optimization method, while e_i represents the model error. This error is stochastically generated using a series of serially independent Gaussian numbers and added to the deterministic components on a daily basis. More detailed technical information on SDSM can be found in [39].

3.2.2 Quality control

This represents the initial stage of the downscaling process. The data acquired for the local climate is subject to examination in order to identify any potential errors, missing values, variations in values, as well as maximum and minimum values. SDSM employs a designated missing value code, typically set at -999. While quality control does not directly impact the subsequent downscaling process, it is advised and considered good practice. In this study, quality control is performed on observed Temperature and Rainfall data from each station.

3.2.3 Screening of predictor variables

The most essential stage in various statistical downscaling methods is the screening of predictor variables, as highlighted in [28]. In the SDSM tool, this task involves assessing several indicators such as partial correlations, correlation matrices, explained variance, P-values, histograms, and scatter plots, which aid in simplifying the process [40]. In this study, good predictors were chosen based on their correlation matrix, partial correlation, and P-value with a significance level set at ninety-five per cent (0.05) using observed data. The same approach was also utilized in previous studies, as mentioned in [41,18].

A correlation matrix was generated to analyze the relationship between 26 NCEP predictors and the predictand. Subsequently, the predictors with high correlation coefficients were selected from the initial set of 26. The correlation matrix, denoted as r_{ab} in Equation (4), provides insight into the strength and direction of associations between variables, ranging from -1 to 1. A positive value indicates a direct positive association between the predictand and predictor variables, while a negative value suggests an inverse relationship. The formula for the correlation matrix r_{ab}, as shown in Equation (4), is computed by considering the covariance between the predictands and predictors (Cov(ab) and dividing it by the product of their standard deviations (S_a and S_b).

$$\boldsymbol{r_{ab} = \frac{Cov(ab)}{\sqrt{S_a^2 S_b^2}}} \qquad (4)$$

Provided that: $\boldsymbol{Cov(ab) = \frac{1}{N}\sum\left(a_{i,j}b_{i,j} - \overline{ab}\right)}$

Where, a_{ij} and $b_{i,j}$ represents the data of predictands and predictors at the respective indices (i, j). The term ab represents the mean value of both variables.

Partial correlation analysis (PCA) is used to acquire a deeper understanding of the underlying correlation between the two parameters of concern while accounting for the influences of additional associated variables. [42]. This technique is particularly useful in statistical downscaling studies, and it is commonly used by academics to discover significant predictors. [43, 31]. A higher partial correlation value implies a stronger association.

From the research conducted by [50], The partial correlation of variables x and predictand y, with the influence of a third variable z taken into account, can be expressed as:

$$r_{xy,z} = \frac{r_{xy} - r_{xz} r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}} \tag{5}$$

Here, r_{xy}, r_{xz}, and r_{yz} are the correlation coefficients between x and y, x and z, and y and z, respectively.

3.2.4 Model Calibration and validation

In SDSM, the model calibration involves generation downscaled data through multiple regression equations using predictand and selected predictors at each station. The model is constructed as a monthly-based model for daily precipitation and temperature, utilizing the identical set of chosen NCEP predictors throughout the calibration period. Consequently, 12 regression equations were formulated, each corresponding to one of the 12 months.

The model validation process involved assessing the model's performance using an independent dataset. To make a comparison between observed and simulated data, SDSM utilized a summary statistics function to presents results of both datasets. Station data and NCEP reanalysis data were separated into two groups: one for the calibration period (1981-1995 for rainfall, 1983-1995 for temperature) and the other for validation (1996-2005) for both rainfall and temperature.

3.2.5 Future climate change scenario generation.

The scenario generator function generates sets of synthetic daily weather series using observed daily atmospheric predictor variables provided by a GCM, applicable to either current or future climates [47]. For this study, the scenario generation resulted in 20 sets of synthetic weather data, forming an ensemble that spans 95 years (2006–2100) based on canESM2 for RCP2.6, 4.5, and 8.5 scenarios. The mean value of the ensemble members was then computed and utilized for further climate change analysis. Based on the World Meteorological Organization recommendation of a

30-year interval, the generated scenario was subsequently divided into three-time periods, 2010–2039, 2040–2069, and 2070–2099 which are represented the 2020s, 2050s, and 2080s, respectively. Therefore, the 30- year data for historical period was compared to the average of the twenty ensembles of produced scenarios. The anomaly was highlighted by difference between the average future period and the monthly average of the historical period. The negative or positive anomaly indicated a drop or increase in the predictand in future periods.

3.2.6 Model performance evaluation

To compare modelled and observed data, SDSM incorporates various graphical and statistical comparison techniques, consisting of both conditional and generic parameters. The generic statistics in SDSM cover extreme ranges, variance, maximum, and mean whereas the conditional statistics involve the standard deviation and the percentage of dry and wet periods. In this study, the statistics integrated within the SDSM were combined with commonly employed model evaluation methods, which include the Correlation Coefficient (R) (Eq. (6)), Root Mean Square Error (RMSE) (Eq. (7)), Mean Square Error (MSE) (Eq. (8)), and Index of Agreement (IOA) (Eq. (9)).

RMSE served as a method to assess the goodness of fit, indicating the model's standard deviation in replicating the observed data. The MSE was used to evaluates the mean squared difference between the predicted and observed values. The MSE value increases as the model's error increases. A model's performance is considered better when both RMSE and MSE approach 0, means that the prefect score is zero [51].

The R serves as a statistical indicator of the degree of association between the relative changes in two variables. Its values lie between -1.0 and 1.0. If the calculated number falls below -1.0 or exceeds 1.0, it indicates a measurement error. A correlation of -1.0 represents a perfect negative correlation, while a correlation of 1.0 signifies a perfect positive correlation. A correlation of 0.0 indicates no relationship between the modelled and observed data [51].

Finally, the IOA is a standardized measure of the magnitude of model prediction error, ranging from 0 to 1. The index of agreement is determined by the ratio of mean square error to potential error. An agreement rating of 1 implies a perfect match, whereas 0 shows no agreement at all [51].

$$R = \frac{\sum_{i=1}^{n}(O_i - \bar{F})(F_i - \bar{F})}{\sqrt{\sum_{i=1}^{n}(O_{i-}\bar{O})^2}\sqrt{\sum_{i=1}^{n}(F_{i-}\bar{F})^2}} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_{i-}F_i)^2}{N}} \quad (7)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(O_{i-}F_i)^2 \quad (8)$$

$$IOE = 1 - \frac{\sum_{i=1}^{n}(O_{i-}F_i)^2}{\sum_{i=1}^{n}\sqrt{(|F_i - \bar{O}| + |O_i - \bar{O}|)^2}} \quad (9)$$

In this context, O_i refers to the observed values (Prcp, Tmax, and Tmin), while F_i represents the predicted values (Prcp, Tmax, and Tmin). $\bar{O}$ denotes the average of the observed values (Prcp, Tmax, and Tmin), $\bar{F}$ stands for the average of the observed values (Prcp, Tmax, and Tmin) and N represents the total number of observations.

Chapter 4: Results and Discussion

4.1 Screening of predictors

The screening of predictors is the most important phase during the downscaling process, primarily aimed at establishing the relationship between predictors and predictands. Screening is essential because the predictors identified in this stage are utilized in model calibration [31]. NCEP/NCAR reanalysis data obtained from CanESM2 undergoes this crucial step, along with the predictand (local meteorological observation). Potential predictors are chosen based on partial correlation and p values. Selected predictors for rainfall, maximum temperature and minimum temperature are presented in (Table 3), (Table 4), and (Table 5) respectively. Considerable variation in the selected predictors is found as a result of the complex topography of the country.

In general, the following predictors, Surface specific humidity (shum), 850 hpa geopotential height (p850), Surface meridional velocity (p1_v), Specific humidity at 850 hpa (s850) and Surface zonal velocity (p1_u) were obtained as predominant predictors for maximum temperature over Rwanda for most stations (Table 3).

For minimum temperature the predominant predictors are: Surface divergence (p1zh), Surface specific humidity (shum), 500 hpa geopotential height (p500), 850 hpa Divergence (p8zh), and Precipitation (prcp) for most stations over Rwanda (Table 4).

For precipitation, there is no predictors obtained as main for different stations. each station was found to have its own predictors. This is due to the property of rainfall of being unevenly distributed in space and time (Table 5).

4.2 SDSM Model Calibration and Validation Performance

Through the process of model performance evaluation, the observed data of minimum and maximum temperature and precipitation are correlated with the downscaled data during the calibration and validation periods using the R, RMSE, MSE, IOA. The calibration and validation periods for maximum and minimum temperature at each station are 1983-1995 and 1996-2005 respectively, while for rainfall, 1981-1995 have used for calibration and 1996-2005 for validation.

In the unconditional process, the simulated and observed values showed a very high correlation of 0.99 for both minimum and maximum temperature, except Kamembe station having 0.74 for minimum temperature during calibration. Also, during validation, the data showed a great correlation mostly ranging from 0.7 to 0.99 with few stations falling below the range.

The correlation coefficient for precipitation is almost above 0.99 during calibration and range from 0.7 to 0.9 during validation. Unconditional models assume a direct relationship between regional-scale predictors and local predictand. In contrast, conditional models, like those for daily precipitation amounts, rely on an intermediate variable, such as the probability of precipitation occurrence [11].

4.1.1 Maximum temperature

After calibration and validation processes, the model was evaluation for its performance in replicating maximum temperature using were different model evaluation metrics namely, R, RMSE, MSE and IOA. The overall results are presented in (Table 6). The calibration results indicate that the downscaled maximum temperature is quite well correlated with observed maximum temperature with R being 0.99 at all stations, the index of agreement, is found to be 0.99 which simply show a good agreement between downscaled and observed maximum temperature. The RMSE and MSE tends to zero meaning that model is accurately replicating the maximum temperature. The results of model validation show a good correlation between modeled and observed maximum temperature with R ranging between 0.36 and 0.99, the IOA ranges between 0.24 and 0.99, RMS and MSE are below 0.51 and 0.26 respectively.

In general, for both calibration and validation, the correlations between downscaled maximum temperature and observed maximum temperature ranges between 0.74 and 0.99 for most stations except for Gisenyi and Rubengera stations which indicated a correlation of 0.36 and 0.47 respectively. Index of agreement shows a great agreement between model and observation data which ranges between 0.76 and 0.99 for most of stations except, Gisenyi and Rubengera stations indicated an index of agreement of 0.24 and 0.59 respectively. The error measures are in good range just below 0.51 and 0.26 for RMSE and MSE respectively at all stations. The graphical representation of observed versus downscaled maximum temperature for model calibration process (Figure 6) and validation process (Figure 7), shows that the model understands the annual cycle of maximum temperature. These results indicate that the model can be used to predict maximum temperature for a particular month or season over Rwanda. The understanding of model on capturing the annual cycles give more confidence on the model to be used as the temperature over Rwanda varies with months and region mainly due to difference in topography.

4.1.2 Minimum temperature

The outcome of downscaling minimum temperature shows that the observed and simulated minimum temperatures match quite well. (Table 7) shows the results of model calibration and validation for minimum temperature in terms R, RMSE, MSE and IOA. During the model calibration process, it is evident that the downscaled maximum temperature exhibits a strong correlation with the observed minimum temperature at thirteen stations, namely Bugarama, Busogo, Byimana, Byumba, Gikongoro, Gisenyi, Gitega, Kawangire, Kibungo, Kigali, Nyagatare, Rubengera, and Ruhengeri. The correlation coefficient (R) was found to be 0.99 for these stations, except for Kamembe station, where it was 0.86. Regarding the index of agreement, the results reveal a value of 0.99 for the same thirteen stations mentioned for R, while the Kamembe station shows an index of agreement of 0.23. According to errors, both RMSE and MSE values approach zero, indicating that the model's performance is approaching perfection. This suggests that the model effectively simulates minimum temperature with minimal bias. For model validation, R ranges between 0.67 and 0.98 across all stations, index of agreement is above 0.72 for most of stations, except Kamembe and Byumba stations have -0.34, 0.63 respectively. Both RMSE and MSE falls below 1. The rusults of model evaluation during calibration and validation are presented in (Figure 8) and (Figure 9), respectively.

4.2.2 Rainfall

Regarding the variation in rainfall compared to minimum and maximum temperatures, it cannot be precisely replicated due to the complexity of rainfall processes and their spatial and temporal distribution [26]. Although climate model simulations have improved over time, they still encounter challenges. Notably, rainfall forecasts are more uncertain than temperature forecasts due to the high spatial variability of rainfall, which the current generation of climate models with relatively coarse spatial resolution cannot fully capture.

The results of calibration and validation period presented in (Table 8) indicate that the correlation coefficient between observed and simulated data range in between 0.83 and 0.99 implies a good correlation, IOA range from 0.57 to 0.95 which means that model have a good agreement with observed data, the calculated error metrics (RMSE, MSE) are found to approach zero which is a good indicator of model accuracy are in good range. Similarly, during the validation period, model gives a good result with respect to R and IOA, however, RMSE and MSE indicated a little more increase compared to their values during validation period. (Figure 10) and (figure 11) present the results of calibration and validation respectively.

4.3 Projected future climate change scenario

After the exhaustive calibration and validation of the SDSM model, the daily climate variables of Rainfall, Maximum and Minimum temperature were projected using RCP2.6, RCP4.5, and RCP8.5 of CanESM2 Global Circulation Model. This projection resulted in 20 equally plausible ensembles of daily climate variables. To capture the characteristics of all these ensembles, an averaging process was performed to obtain ensemble mean. By the help of SDSM, the global predictors from the GCMs were employed to develop future climate scenarios. The analysis was conducted for three time periods: the 2010-2039, 2040-2069, and 2070-2099 which are simply noted as 2020s, 2050s, and 2080s respectively.

4.3.1 Maximum temperature

In all RCPs scenarios, the maximum temperature is expected to rise at certain stations while decrease at others during future periods. Among fourteen downscaled stations, two stations namely KigaliAero and Gitega stations located in Kigali city and three stations namely Kawangire, Kibungokazo and Nyagatare stations located in Eastern province of Rwanda show an increase in maximum temperature under all RCPs. The two stations namely Busogo_ISAE and Byumba stations located in the northern province are expected to have slight increase and decrease under all RCPs. however, the remaining seven station including Bugarama, Kamembe, Rubengera and Gisenyi located in western province, Byimana and Gikongoro in Southern province and Ruhengeri in northern province show the decrease in maximum temperature across all RCPs. More details on projected maximum temperature are shown in (Table 9) and (Figure 12)

In general, it is expected that maximum temperature will increase in range of 0.3°C and 8.5°C at stations located in Kigali city and Eastern region, the remaining stations are expected to experience a reduction ranging between -17°C and -0.07 across all emission scenarios and for all future periods.

4.3.2 Minimum temperature

The projected trend for future periods indicates a general increase in minimum temperature, although a few stations have registered slight decreases across all RCPs. Minimum temperature is expected to increase in 2020s, 2050s and 2080s under RCP2.6, RCP4.5, and RCP8.5 at eleven stations namely Bugarama, Byimana, Byumba, Gikongoro,Gitega, Kamembe, Kawangire, Kibungo Kazo, Kigali Aero, Nyagatare and Rubengera and reduction is expected at Busogo, Gisenyi and Ruhengeri stations. The minimum temperature is expected to rise from 0.9°C to 5.3°C at Bugarama, 1.7°C to 5.2°C at Byimana, 3.3°C to 9.5°C at Byumba, 1.0°C to 3.2°C at Gikongoro, 2.3°C to 8.5°C at Gitega, 0.7°C to 3.2°C at Kamembe, 2.17°C to 7.1°C at Kawangire, 3.0°C to 11.8°C at Kibungo, 2.5°C to 8.6°C at Kigali, 1.3°C to 4.3°C at Nyagatare and 0.05°C to1.8°C at Rubengera, under all RCPs in all future periods. Three stations namely Busogo, Gisenyi and Ruhengeri show a decrease in minimum temperature ranging from -2.9 to -0.55 for Busogo, -1.4 to -1.05°C for Gisenyi Aero and -0.48°C to -0.43°C, -0.8°C to -0.5°C and -1.1°C to –0.43°C at Ruhengeri, under all RCPs in all future periods. The detailed description of projected minimum temperature is presented in (Table 11) and (figure 10).

4.3.3 Rainfall

The projected rainfall in future periods (2020s,2050s and 2080s) under all representative concentration pathways generally show an increase in mean annual rainfall over the baseline period (1976-2005) as indicated in (table11). Under RCP2.6 the mean annual rainfall is expected to increase at Bugarama, Busogo, Gikongoro, Gisenyi, Kamembe, Kibungo, Kigali and Rubengera stations in the 2020s, 2050s, and 2080s. the projections under the intermediate emmissions (RCP4.5) show an increase ai the same stations as with RCP2.6, Byumba stations also recorded an increase in all future periods an Byimana marked an increase only in 2050s. under RCP8.5 which is known as the worst case scenario, the increase in mean annual rainfall is also expected in the same stations as projected in RCP2.6 and two more stations namely Byimana and Byumba are found to have an increase in 2050s and 2080s. finally under all scenarios, Gitega, Kwawangire, Ruhemgeri and Nyagatare station was found to decrease in annual mean rainfall in all future periods.

It expected that the most of meteorological stations will experience an increase ranging between 11.5 mm to 49.97 mm in rainfall across all emission scenarios and for all future periods, however, a reduction of -4.11mm to -4.39 mm is expected over a few stations. (Figure 14) represent the results of future daily mean monthly rainfall.

Chapter 5. Conclusion and Recommendations

5.1 Conclusion

This study applied a statistical downscaling approach to refine CMIP5 GCM outputs (CanESM2) under three Representative Concentration Pathways (RCP2.6, RCP4.5, and RCP8.5) for different future period namely 2020s spanning from 2010 to 2039, 2050s spanning from 2040 to 2069 and 2080s spanning from 2070-2099, at the meteorological station level in Rwanda, matching them with local requirements for impact assessment. The screen process was performed to select the predictors for rainfall, minimum temperature and maximum temperature. The performance of CanESM2 model statistically downscaled using statistical downscaling model (SDSM) results was based on evaluation metrics namely correlation (R), Root Mean Square error (RMSE), Mean Square Error (MSE), and Index of Agreement (IOA) during both the calibration and validation phases. Projected changes were performed based on to 1976–2005 reference period.

The results show that the model is able to capture the annual cycle for both rainfall and temperatures (minimum and maximum). For calibration period (1983-1995), the correlation measure indicated a correlation ranging between 0.99 and 1 for maximum temperature, 0.86 and 0.99 for minimum temperature and 0.83 and 0.99 for rainfall during calibration. The RMSE ranges between 0.01 and 0.03 for maximum temperature, 0.01 and 0.72 for minimum temperature and 0.01 and 1.35 for rainfall. The MSE ranges between 0 and 0.01 for maximum temperature, 0 and 0.51 for minimum temperature and 0 and 1.83 for rainfall while IOA ranges between 0.99 and1 for maximum temperature, 0.23 and 0.99 for minimum temperature and 0.89 and 0.99 for rainfall. For evaluation (1996 -2005), the correlation measure indicated a correlation ranging between 0.36 and 0.99 for maximum temperature, 0.61 and 0.98 for minimum temperature and 0.70 and 0.94 for rainfall during evaluation. The RMSE ranges between 0.11 and 0.51 for maximum temperature, 0.27 and 0.99 for minimum temperature and 0.81 and 2.4 for rainfall. The MSE ranges between 0.01 and 0.26 for maximum temperature, 0.07 and 0.98 for minimum temperature and 0.58 and 3.94 for rainfall while IOA ranges between 0.59 and 0.99 for maximum temperature, 0.63 and 0.98 for minimum temperature and 0.57 and 0.95 for rainfall.

It expected that the majority of meteorological stations will experience an increase ranging between 0.05°C and 11.8°C in minimum temperature across all emission scenarios and for all future periods, except for a few stations which are expected to experience a reduction ranging between -1°C and -2.5°C. For maximum temperature, a projected increase ranging between 0.3°C and 8.5°C is expected in the station located in Kigali city and Eastern region, the remaining stations are expected to experience a reduction ranging between -0.07°C and -17°C across all emission scenarios and for all future periods. It expected that the most of meteorological stations will experience an increase ranging between 11.5mm to 49.97 mm in rainfall across all emission scenarios and for all future periods, while a reduction of -4.11mm to -4.39 mm is expected over a few stations.

5.2 Recommendations

This research produces data about future climate change scenario in Rwanda, which will undoubtedly have practical applications for various impact assessments and decision-making processes. Nonetheless, this study has also revealed new avenues for potential future research, including the following:

- The current study relies exclusively on the outputs of a single GCM. Conducting climate change investigations using an ensemble of multiple GCMs could offer a clearer perspective of future scenarios. Thus, it is advisable to analyze additional suitable CMIP5 GCMs and incorporate their data into a statistical downscaling model for comparing outcomes across all GCMs and ensembles as well as and to obtain the big picture of climate change scenario over Rwanda.
- It could be better if future research using statistical downscaling could be extended at a particular region such at a catchment level, district level and so on in order to gain more detailed climate information.

Addendum 1: list of tables

Table 1 Selected meteorological station

NO	Station	Latitude	Longitude
1	Gitega	-1.96	30.06
2	Kigaliaero	-1.95	30.11
3	Gikongoromet	-2.48	29.55
4	Byimana	-2.16	29.71
5	Rubengeramet	-2.07	29.41
6	Gisenyiaero	-1.68	29.26
7	Kamembeaero	-2.46	28.91
8	Busogoisae	-1.56	29.55
9	Ruhengeriaero	-1.48	29.61
10	Byumbamet	-1.6	30.05
11	Nyagatare	-1.28	30.31
12	Kawangire	-1.81	30.43
13	Kibungokazo	-2.15	30.5
14	Bugaramariz	-2.68	29.02

Table 2 List of 26 NCEP predictor variables with their definitions

No	Long-name	Sort-name
1	Mean sea level pressure	msl
2	Surface airflow strength	p1_f
3	Surface zonal velocity	p1_u
4	Surface meridional velocity	p1_v
5	Surface vorticity	p1_z
6	Surface wind direction	p1th
7	Surface divergence	p1zh
8	500 hpa airflow strength	p5_f
9	500 hpa zonal velocity	p5_u
10	500 hpa merdional velocity	p5_v
11	500 hpa vorticity	p5_z
12	500 hpa geopotential height	p500
13	500 hpa wind direction	p5th
14	500 hpa divergence	p5zh
15	850 hpa airflow strength	p8_f
16	850 hpa zonal velocity	p8_u
17	850 hpa merdional velocity	p8_v
18	850 hpa vorticity	p8_z
19	850 hpa geopotential height	p850
20	850 hpa Wind direction	p8th
21	850 hpa Divergence	p8zh
22	Precipitation	prcp
23	Specific humidity at 500 hpa	s500
24	Specific humidity at 850 hpa	s850
25	Surface specific humidity	shum
26	Mean temperature at 2m	temp

Table 3 Selected predictor variables for maximum temperature

Station	Grid box	Predictor	P. R	P. V	Station	Grid box	Predictor	P. R	P. V
Bugarama	2	Mslp	0.127	0	Kamembe	2	mslp	0.054	0.0005
		p1_f	0.054	0.0005			p1_v	-0.066	0
		p1_v	-0.193	0			p5_v	0.035	0.0293
		p5zh	0.179	0			p8_z	0.065	0
		p8_z	0.051	0.0011			p850	-0.076	0
		p850	-0.094	0			prcp	-0.087	0
		Prcp	-0.067	0			s850	0.046	0.004
		Shum	0.122	0			temp	-0.068	0
Busogoisae	1	p1_u	0.092	0	Kawangire	1	mslp	0.097	0
		p1_v	0.077	0			p1zh	-0.074	0
		p1_z	0.041	0.0097			p8_z	-0.053	0.0007
		p8_u	0.075	0			p850	0.041	0.0108
		p8_v	0.071	0			p8zh	0.073	0
		p8_z	0.13	0			s850	-0.068	0
		shum	0.162	0			shum	0.055	0.0004
							temp	0.047	0.0029
Byimana	1	mslp	0.044	0.0055					
		p1_u	0.039	0.0161	Kibungo	1	mslp	0.119	0
		p8_u	0.039	0.014			p1zh	-0.057	0.0003
		p850	0.067	0			p8_f	0.109	0
		shum	0.056	0.0003			p850	0.038	0.0198
		temp	0.036	0.0276			p8zh	-0.076	0
							s850	0.037	0.0232
Byumba	1	mslp	0.109	0			temp	-0.063	0
		p1_u	0.037	0.0212					
		p5_u	0.037	0.0212	Kigali	1	mslp	0.097	0
		p5_v	0.043	0.0071			p8_f	0.034	0.0392
		p850	0.161	0			p850	0.103	0
							shum	0.032	0.0495
Gikongoro	1	mslp	0.049	0.0029			temp	0.043	0.0067
		p1_u	0.043	0.0066					
		p8_u	0.048	0.0026	Nyagatare	1	mslp	0.053	0.0007
		p850	0.085	0			p1_z	0.046	0.0039
		shum	0.046	0.0034			p1zh	-0.061	0.0001
							p8_z	0.048	0.0085
Gisenyia	2	p1_v	-0.072	0			p850	0.038	0.0195
		p500	0.044	0.0062			p8zh	-0.058	0.0002
		p850	-0.059	0.0001					
		p8zh	-0.051	0.0012	Rubengera	2	mslp	0.061	0.0001

		prcp	-0.043	0.063			p1_v	-0.086	0
		s850	-0.046	0.0039			p1zh	-0.065	0
							p500	-0.066	0
Gitega	1	mslp	0.081	0			p8_v	-0.06	0.0001
		p8_f	0.033	0.033			p850	0.08	0
		p8_u	0.032	0.032			p8zh	-0.062	0.0001
		p850	0.091	0			s850	-0.062	0.0001
		shum	0.056	0.0003					
		temp	0.046	0.0035	Ruhengeri	1	mslp	0.037	0.0215
							p1_u	0.044	0.0058
							p1zh	-0.063	0
							p500	0.087	0
							p850	-0.062	0
							p8zh	-0.098	0.0001
							s850	-0.068	0
							shum	0.039	0.0162

Table 4 Selected predictor variables for minimum temperature

Station	Grid box	Predictor	P. R	P. V	station	Grid box	Predictor	P. R	P. V
Bugarama	2	p1_u	0.043	0.0072	Kamembe	2	p1_v	0.037	0.0225
		p1th	0.058	0.0002			p500	0.108	0
		p1zh	0.04	0.0136			p8zh	0.102	0
		p500	0.103	0			prcp	0.093	0
		p8zh	0.127	0			shum	0.085	0
		prcp	0.137	0			temp	0.037	0.0225
		shumg	0.184	0					
					Kawangire	1	p1zh	0.043	0.007
Busogo	1	p1_v	0.067	0			p500	0.135	0
		p1zh	0.042	0.0078			p8zh	0.075	0
		p500	0.11	0			prcp	0.05	0.0013
		p8zh	0.099	0			shum	0.047	0.0031
		prcp	0.04	0.0128			temp	0.089	0
		s850	0.07	0					
					Kibungo	1	mslp	0.035	0.0321
Byimana	1	p1zh	0.101	0			p1_v	-0.46	0.0118
		p500	0.186	0			p500	0.04	0.0005
		p8zh	0.123	0			p8_v	-0.066	0
		prcp	0.108	0			temp	-0.46	0.0035
		shum	0.093	0					
		temp	0.116	0	Kigali	1	p1zh	0.042	0.0083
							p500	0.115	0
Byumba	1	msl	-0.05	0.0014			p8zh	0.048	0.0026
		p500	0.04	0.0127			shum	0.051	0.0011
		p850	-0.057	0.0002			temp	0.089	0
		temp	0.036	0.0274					
					Nyagatare	1	p1_u	0.07	0
Gikongoro	1	p1_v	0.082	0			p1_z	0.16	0
		p1zh	0.073	0			p1zh	0.125	0
		p500	0.155	0			p500	0.111	0
		p8zh	0.112	0			p8_u	0.137	0
		prcp	0.061	0.0001			p8_z	0.248	0
		s500	0.057	0.0002			shum	0.265	0
		s850	0.061	0.0001					
		temp	0.048	0.0024	Rubengera	2	p1_v	0.06	0.0001
							p500	0.073	0
Gisenyi	2	p1_v	0.069	0			p8zh	0.083	0
		p500	0.123	0			prcp	0.067	0
		p8zh	0.103	0			shum	0.049	0.0017
		prcp	0.082	0					

		s850	0.041	0.041	Ruhengeri	1	p1_v	0.074	0
		shum	0.057	0.0002			p5_z	0.059	0.0002
		temp	0.069	0			p500	0.172	0
							p8zh	0.147	0
Gitega	1	p1zh	0.047	0.003			prcp	0.057	0.0003
		p500	0.11	0			s500	0.07	0
		p8_u	0.047	0.0028			s850	0.185	0
		p8_z	0.066	0					
		prcp	0.037	0.0203					
		shum	0.125	0					
		temp	0.099	0					

Table 5 Selected predictor variables for rainfall

Station	Grid box	Predictor	P. R	P. V	Station	Grid box	Predictor	P. R	P. V
Bugarama	2	msl	0.041	0.0426	Kamembe	2	p1th	-0.049	0.0314
		p1_f	-0.036	0.0469			p5_v	0.051	0.0257
		p8_z	-0.06	0.0021			p8th	-0.038	0.0452
		p850	0.036	0.0417					
		rcp	0.063	0.0012	Kawangire	1	p1_v	0.061	0.0205
		temp	-0.055	0.0047			p5_v	-0.087	0.0006
							p5_z	-0.046	0.0477
Busogo	1	p1_v	0.087	0.0004			p5th	-0.056	0.0326
		p5_v	-0.044	0.0309					
		p8_v	0.078	0.0017	Kibungo	1	p1_u	-0.074	0.0145
		p8_z	-0.049	0.0493			p8_u	-0.057	0.0419
							s500	-0.058	0.0326
Byimana	1	p1_v	0.069	0.0085					
		p8_v	0.08	0.0021	Kigaliaero	1	p1_v	0.051	0.0311
		s500	0.05	0.0471			p5zh	-0.049	0.043
							p8zh	0.057	0.0406
Byumba	1	P1_v	0.048	0.0493					
		p1zh	0.059	0.0294	Nyagatare	1	msl	0.11	0.0001
		p8_z	0.077	0.0022			p1_v	0.083	0.0033
		rcp	0.066	0.0101			p8_v	0.09	0.013
		s500	0.058	0.0247			p8_z	-0.067	0.0197
		s850	0.078	0.0021			p850	0.107	0.0001
							s500	0.06	0.0397
Gikongoro	1	p1_u	-0.067	0.0116			temp	-0.078	0.059
		p1_v	0.057	0.033					
		p1th	0.047	0.0491	Rubengera	2	temp	0.046	0.0473
		p8_v	0.05	0.0368			p850	0.05	0.0499
		p8zh	0.062	0.0191			p500	0.052	0.0496
		s500	0.08	0.002					
					Ruhengeri	1	p8_f	0.046	0.04002
Gisenyi	2	p1_u	-0.044	0.0411					
		p5zh	-0.041	0.05	Gitega	1	p1zh	0.052	0.0417
		p8_u	-0.041	0.0382			p5_v	0.071	0.0082

Table 6 Results of model calibration and Validation for maximum temperature

Predictand	Station	Calibration				Validation			
		R	RMSE	MSE	IOA	R	RMSE	MSE	IOA
Tmax	Bugarama	0.99	0.02	0.00	0.99	0.99	0.11	0.01	0.99
	Busogo	0.99	0.02	0.00	0.99	0.94	0.49	0.24	0.93
	Byimana	0.99	0.02	0.00	0.99	0.82	0.38	0.15	0.87
	Byumba	0.99	0.11	0.01	0.99	0.99	0.14	0.02	0.99
	Gikongoro	0.99	0.02	0.00	0.99	0.78	0.36	0.13	0.85
	Gisenyi	0.99	0.03	0.00	0.99	0.36	0.46	0.21	0.24
	Gitega	0.99	0.03	0.00	0.99	0.87	0.39	0.15	0.91
	Kamembe	0.99	0.02	0.00	0.99	0.83	0.32	0.10	0.86
	Kawangire	0.99	0.02	0.00	0.99	0.82	0.44	0.19	0.88
	Kibungo	0.99	0.03	0.00	0.99	0.84	0.43	0.19	0.87
	Kigalia	0.99	0.01	0.00	0.99	0.89	0.38	0.14	0.91
	Nyagatare	0.99	0.03	0.00	0.99	0.76	0.43	0.19	0.76
	Rubengera	0.99	0.02	0.00	0.99	0.47	0.47	0.22	0.59
	Ruhengeri	0.99	0.02	0.00	0.99	0.74	0.51	0.26	0.84

Table 7 Results of Model calibration and validation for minimum temperature

Predictand	Station	Calibration				Validation			
		R	RMSE	MSE	IOE	R	RMSE	MSE	IOA
Tmin	Bugarama	0.99	0.06	0.00	0.99	0.93	0.35	0.12	0.94
	Busogo	0.99	0.01	0.00	0.99	0.89	0.32	0.10	0.91
	Byimana	0.99	0.01	0.00	0.99	0.93	0.33	0.11	0.95
	Byumba	0.99	0.01	0.00	0.99	0.61	0.31	0.10	0.63
	Gikongoro	0.99	0.01	0.00	0.99	0.87	0.27	0.07	0.91
	Gisenyi	0.99	0.01	0.00	0.99	0.91	0.37	0.14	0.87
	Gitega	0.99	0.01	0.00	0.99	0.77	0.38	0.14	0.82
	Kamembe	0.86	0.72	0.51	0.23	0.72	0.99	0.98	-0.34
	Kawangire	0.99	0.01	0.00	0.99	0.90	0.41	0.16	0.90
	Kibungo	0.99	0.01	0.00	0.99	0.84	0.39	0.15	0.78
	Kigalia	0.99	0.01	0.00	0.99	0.67	0.38	0.15	0.72
	Nyagatare	0.99	0.01	0.00	0.99	0.98	0.39	0.15	0.98
	Rubengera	0.99	0.01	0.00	0.99	0.83	0.33	0.11	0.86
	Ruhengeri	0.99	0.01	0.00	0.99	0.94	0.31	0.10	0.96

Table 8 Results of model calibration and validation for rainfall

Predictand	Station	Calibration				Validation			
		R	RMSE	MSE	IOE	R	RMSE	RMSE	IO
RAINFALL	Bugarama	0.99	0.12	0.01	0.99	0.92	1.31	1.71	0.95
	Busogo	0.99	0.07	0.01	0.99	0.86	1.84	3.40	0.73
	Byimana	0.99	0.14	0.02	0.99	0.72	1.93	3.73	0.68
	Byumba	0.99	0.05	0.00	0.99	0.92	0.76	0.58	0.95
	Gikongoro	0.99	0.48	0.23	0.98	0.90	1.24	1.53	0.87
	Gisenyi	0.99	0.14	0.02	0.99	0.73	1.31	1.70	0.69
	Gitega	0.99	0.09	0.01	0.99	0.70	2.40	5.77	0.57
	Kamembe	0.83	1.35	1.83	0.89	0.71	1.69	2.84	0.79
	Kawangire	0.99	0.28	0.08	0.98	0.94	0.84	0.71	0.91
	Kibungo	0.99	0.10	0.01	0.99	0.94	1.37	1.88	0.88
	Kigali	0.99	0.11	0.01	0.99	0.90	1.99	3.94	0.70
	Nyagatare	0.99	0.08	0.01	0.99	0.88	0.81	0.66	0.90
	Rubengera	0.99	0.07	0.00	0.99	0.84	0.92	0.84	0.88
	Ruhengeri	0.99	0.10	0.01	0.99	0.90	1.30	1.70	0.88

Table 9 Future change in daily mean monthly maximum temperature

	RCP2.6			RCP4.5			RCP8.5		
Station	2020S	2050S	2080S	2020S	2050S	2080S	2020S	2050S	2080S
Bugarama	-2.9	-3.8	-3.6	-3.3	-4.4	-5.1	-3.1	-5.7	-8.3
Busogo	-0.3	0.09	0.09	0.04	0.02	-0.07	-0.2	-0.01	-0.1
Byimana	-0.4	-0.6	-0.5	-0.3	-0.9	-0.9	-0.6	-1.1	-2.1
Byumba	-0.07	-0.2	-0.06	0.008	-0.3	-0.2	-0.2	-0.3	-0.2
Gikongoro	-1.6	-2.5	-2.1	-1.5	-2.8	-3.2	-2.0	-3.6	-5.9
Gisenyi	-5.07	-6.8	-6.2	-5.4	-7.9	-9.4	-5.7	-10.3	-15.
Gitega	1.2	1.5	1.8	1.2	1.7	1.9	1.1	2.6	3.5
Kamembe	-3.8	-4.8	-4.7	-4.0	-5.7	-7.0	-4.4	-7.5	-11.0
Kawangire	1.3	1.9	2.4	0.9	2.1	2.3	1.1	3.1	4.5
Kibungo	0.3	0.8	1.1	0.06	0.7	1.1	0.1	1.5	2.2
Kigali	1.1	1.5	1.8	0.9	0.9	1.8	0.9	2.5	3.6
Nyagatare	2.8	4.0	4.0	2.3	3.9	4.7	2.6	5.9	8.5
Rubengera	-6.3	-8.1	-7.7	-6.47	-9.1	-10.8	-6.8	-11.5	-17.1
Ruhengeri	-3.2	-4.8	-4.3	-3.2	-5.2	-6.3	-3.7	-7.2	-11.4

Table 10 Future change in daily mean monthly minimum temperature

	RCP2.6			RCP4.5			RCP8.5		
Station	2020S	2050S	2080S	2020S	2050S	2080S	2020S	2050S	2080S
Bugarama	0.9	1.5	1.5	1.08	2.18	2.6	1.09	3.05	5.3
Busogo	-0.5	-0.9	-0.8	-0.5	-1.1	-1.5	-0.7	-1.8	-2.9
Byimana	1.8	2.3	2.2	1.7	2.7	2.9	1.9	3.4	5.2
Byumba	3.3	4.3	4.0	4.3	4.0	5.3	3.5	6.3	9.5
Gikongoro	1.05	1.47	1.43	1.05	1.6	1.8	1.2	2.1	3.2
Gisenyi	-1.0	-1.1	-1.0	-1.0	-1.1	-1.3	-1.05	-1.3	-1.4
Gitega	2.3	3.3	3.2	2.2	3.9	4.5	2.7	5.2	8.5
Kamembe	0.7	1.08	1.03	0.7	1.3	1.4	0.8	1.7	3.2
Kawangire	2.3	3.0	3.09	2.1	3.5	3.9	2.5	4.6	7.1
Kibungo	3.1	4.6	4.4	3.0	5.4	6.3	3.5	7.4	11.8
Kigali	2.5	3.5	3.4	2.5	4.2	4.7	2.8	5.6	8.6
Nyagatare	1.4	1.9	1.8	1.3	2.1	2.5	1.6	2.8	4.3
Rubengera	0.05	0.28	0.20	0.1	0.5	0.6	0.16	0.8	1.8
Ruhengeri	-0.4	-0.6	-0.6	-0.4	-0.5	-0.8	-0.4	-0.8	-1.1

Table 11 Future change in daily mean monthly rainfall

	RCP2.6			RCP4.5			RCP8.5		
Rainfall	2020S	2050S	2080S	2020S	2050S	2080S	2020S	2050S	2080S
Bugarama	11.54	15.82	15.36	11.12	19.00	22.06	13.90	24.19	47.29
Busogo	0.51	1.08	1.01	1.05	0.82	0.88	0.58	0.69	0.19
Byimana	-0.32	0.03	-0.36	-0.14	0.71	-0.01	-0.32	0.71	1.81
Byumba	-1.21	-0.54	-0.74	0.02	0.23	1.03	-0.74	0.77	3.28
Gikongoro	5.14	6.92	5.80	5.50	6.23	6.65	4.87	6.90	8.96
Gisenyi	0.51	0.71	0.32	0.82	0.68	0.90	0.57	0.70	0.76
Gitega	-0.52	-0.34	-0.09	-0.21	-0.09	-0.41	-0.16	-0.45	-0.69
Kamembe	0.30	0.05	0.33	0.001	-0.03	0.30	0.20	0.43	0.59
Kawangire	-1.16	-1.41	-1.34	-1.47	-1.69	-1.88	-1.31	-1.87	-1.94
Kibungo	1.16	1.79	1.87	1.29	1.79	3.30	1.22	3.27	5.97
Kigali	1.05	0.89	1.27	1.34	1.00	1.53	1.25	1.08	1.01
Nyagatare	-4.11	-3.87	-4.02	-4.00	-4.02	-3.30	-4.39	-3.26	-1.85
Rubengera	5.43	9.65	8.63	5.56	13.84	18.18	6.87	22.31	49.97
Ruhengeri	-0.75	-0.74	-0.83	-0.82	-0.70	-0.88	-0.65	-0.68	-0.86

Addendum 2: List of figures

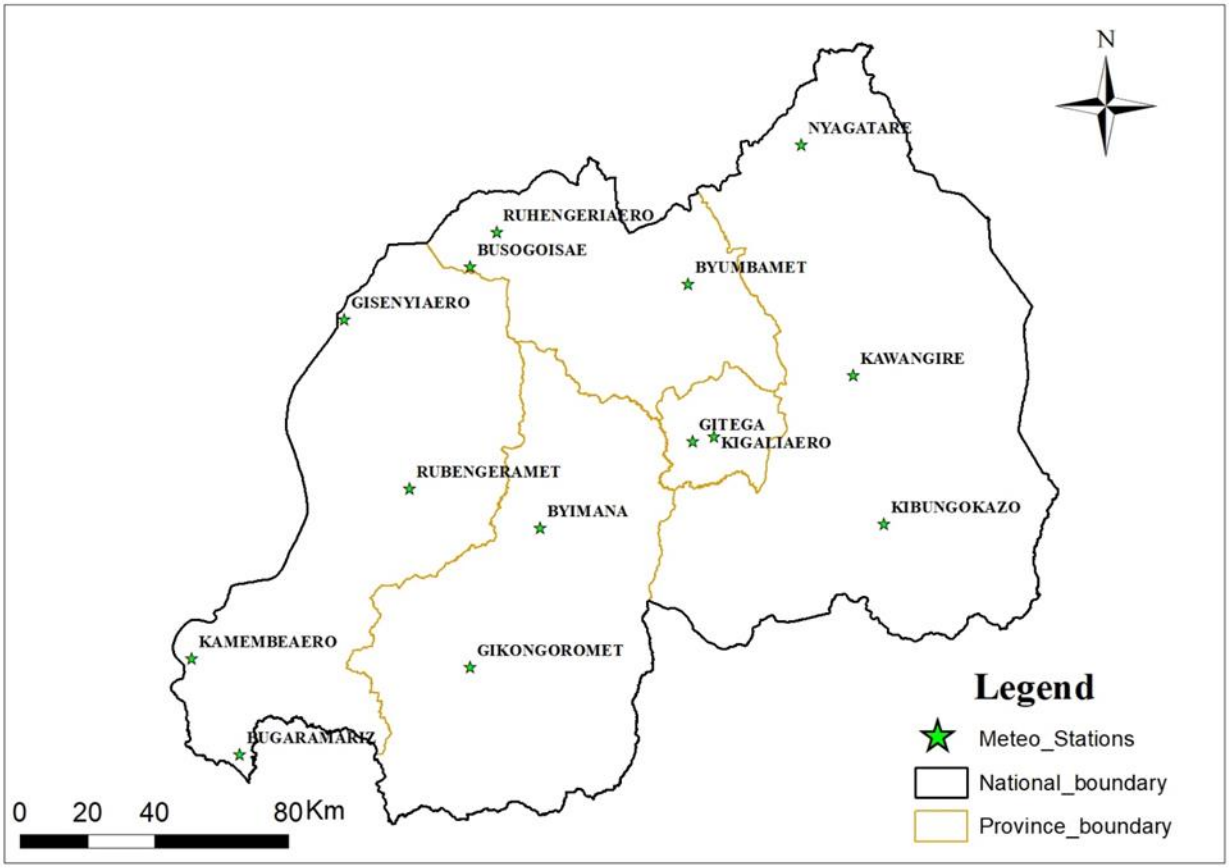

Figure 1 Map showing selected meteorological stations

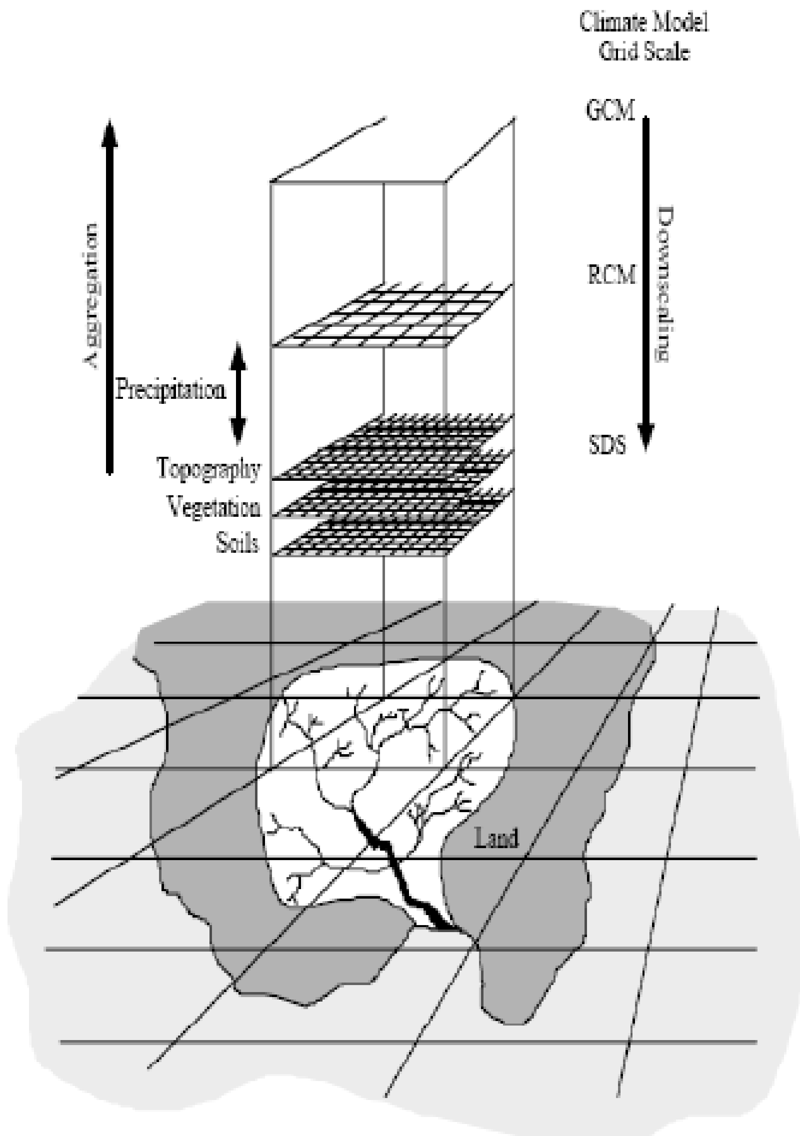

Figure 2 A diagram depicting the overall method of downscaling [11]

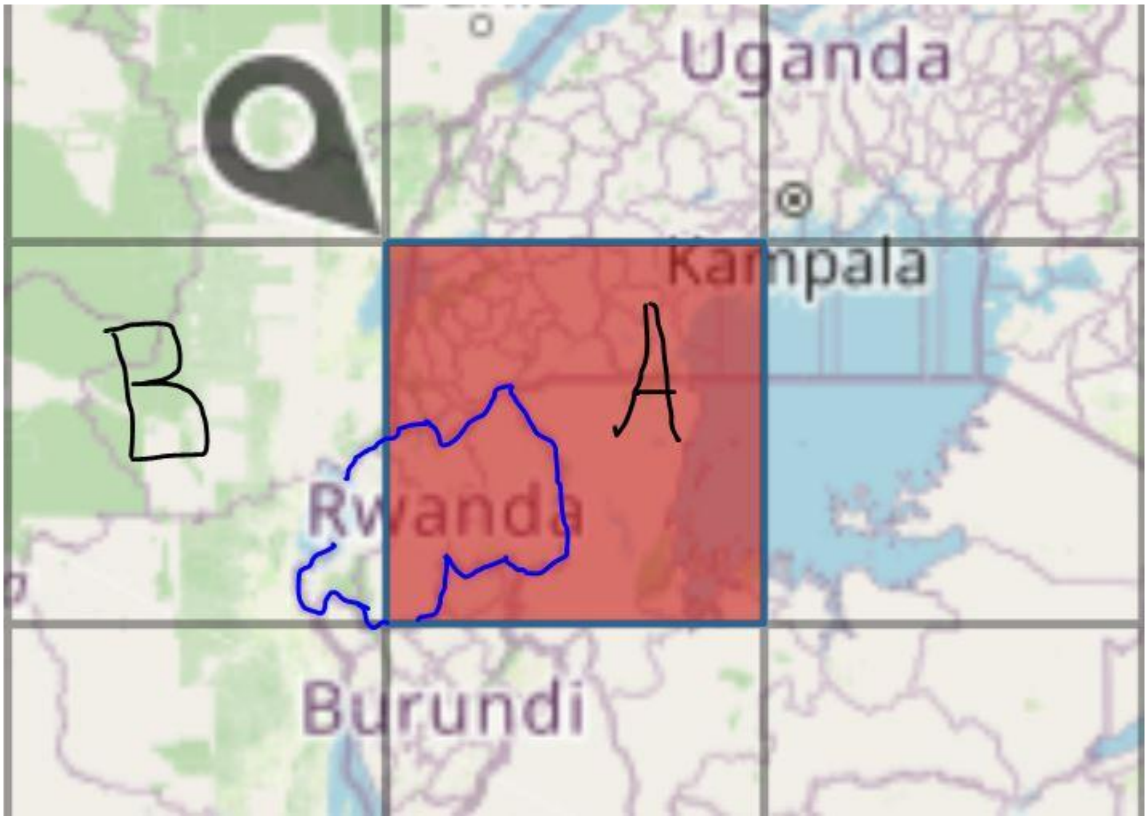

Figure 3 The CanESM2 grid box that covers Rwanda

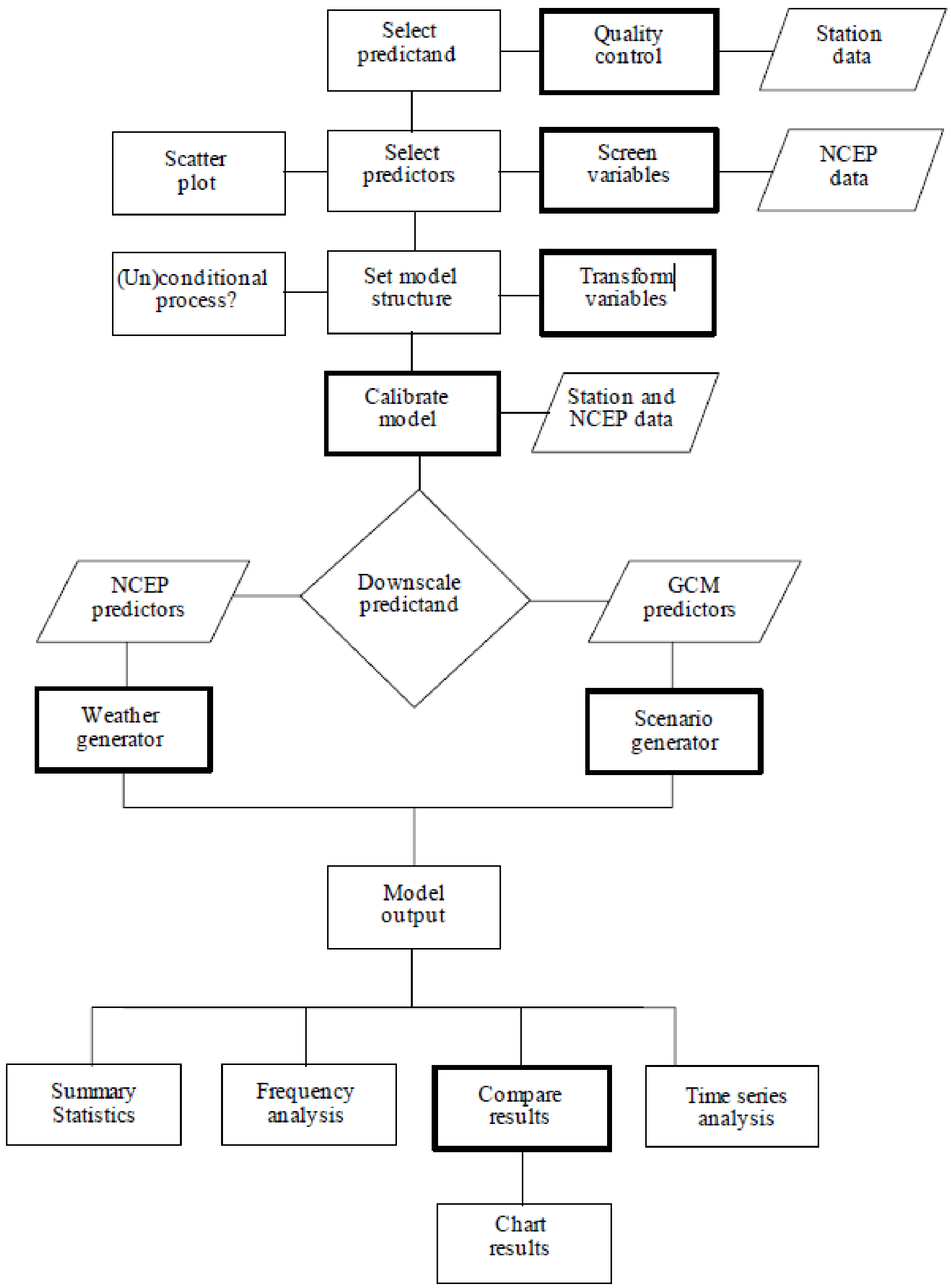

Figure 4 SDSM version 2 climate scenario generation [11]

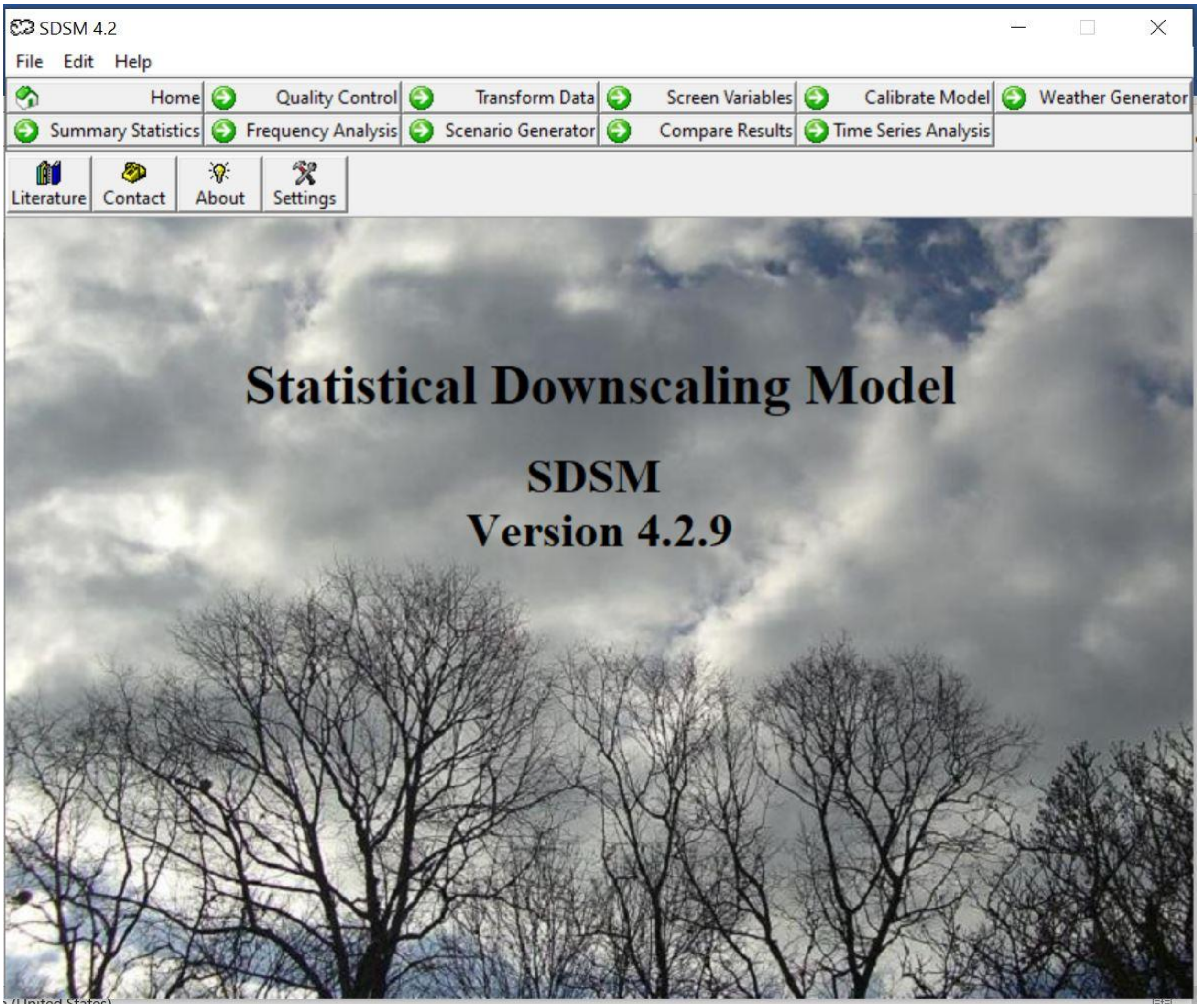

Figure 5 Image capturing the SDSM interface

Figure 6 Calibration results of observed and downscaled mean maximum temperature

Figure 7 Validation results of observed and downscaled mean maximum temperature

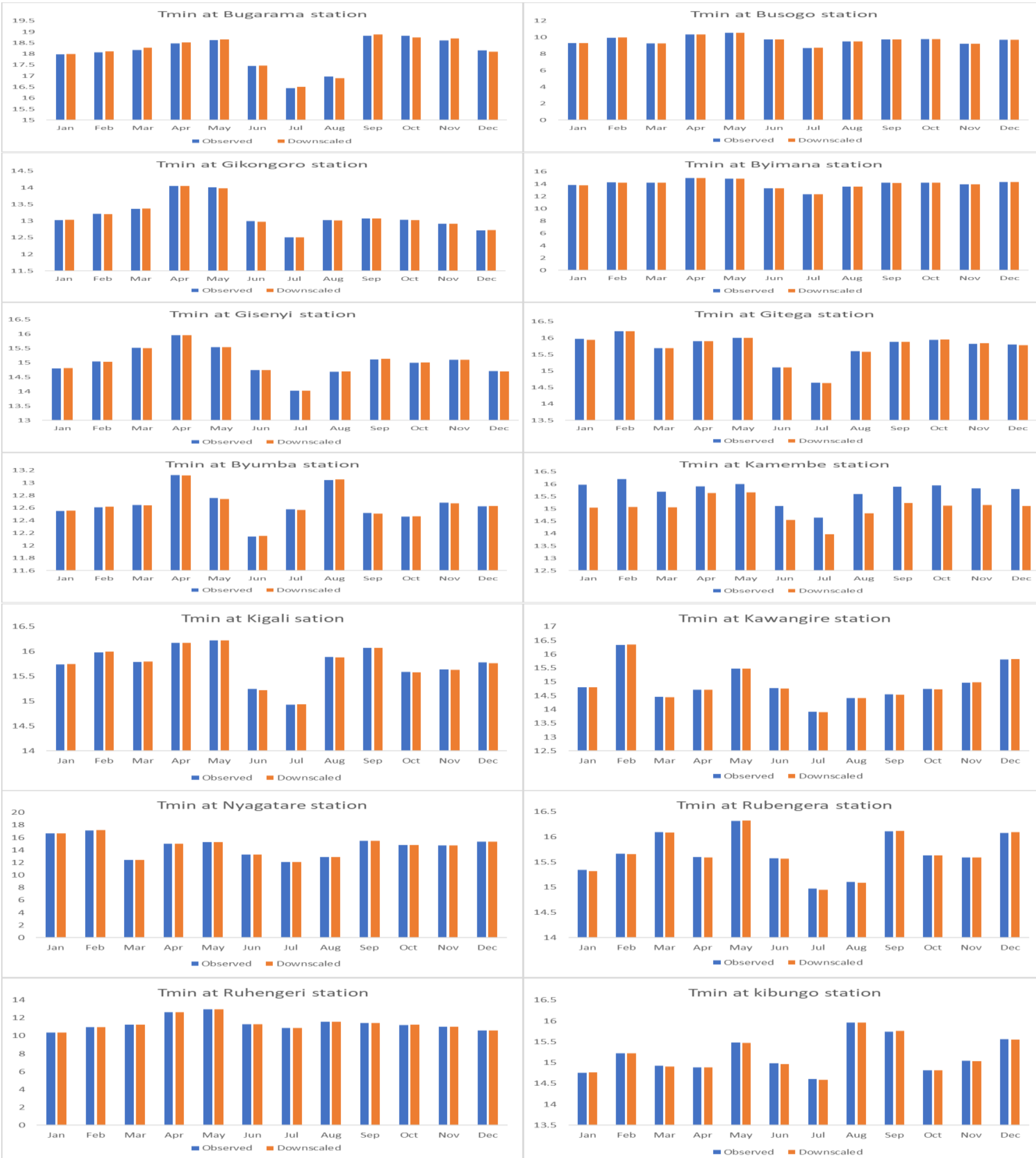

Figure 8 Calibration results of observed and downscaled mean minimum temperature

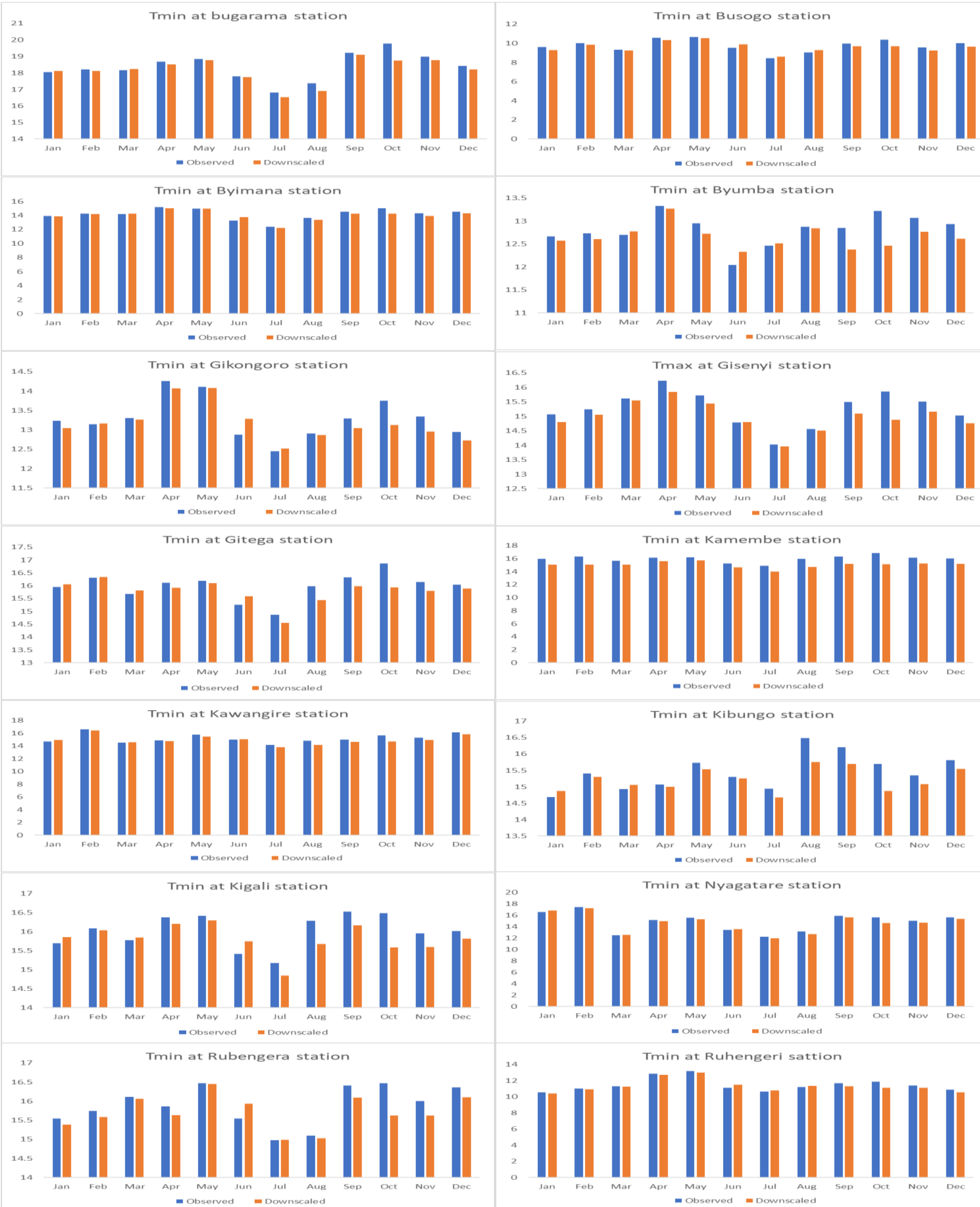

Figure 9 Validation results of observed and downscaled mean minimum temperature

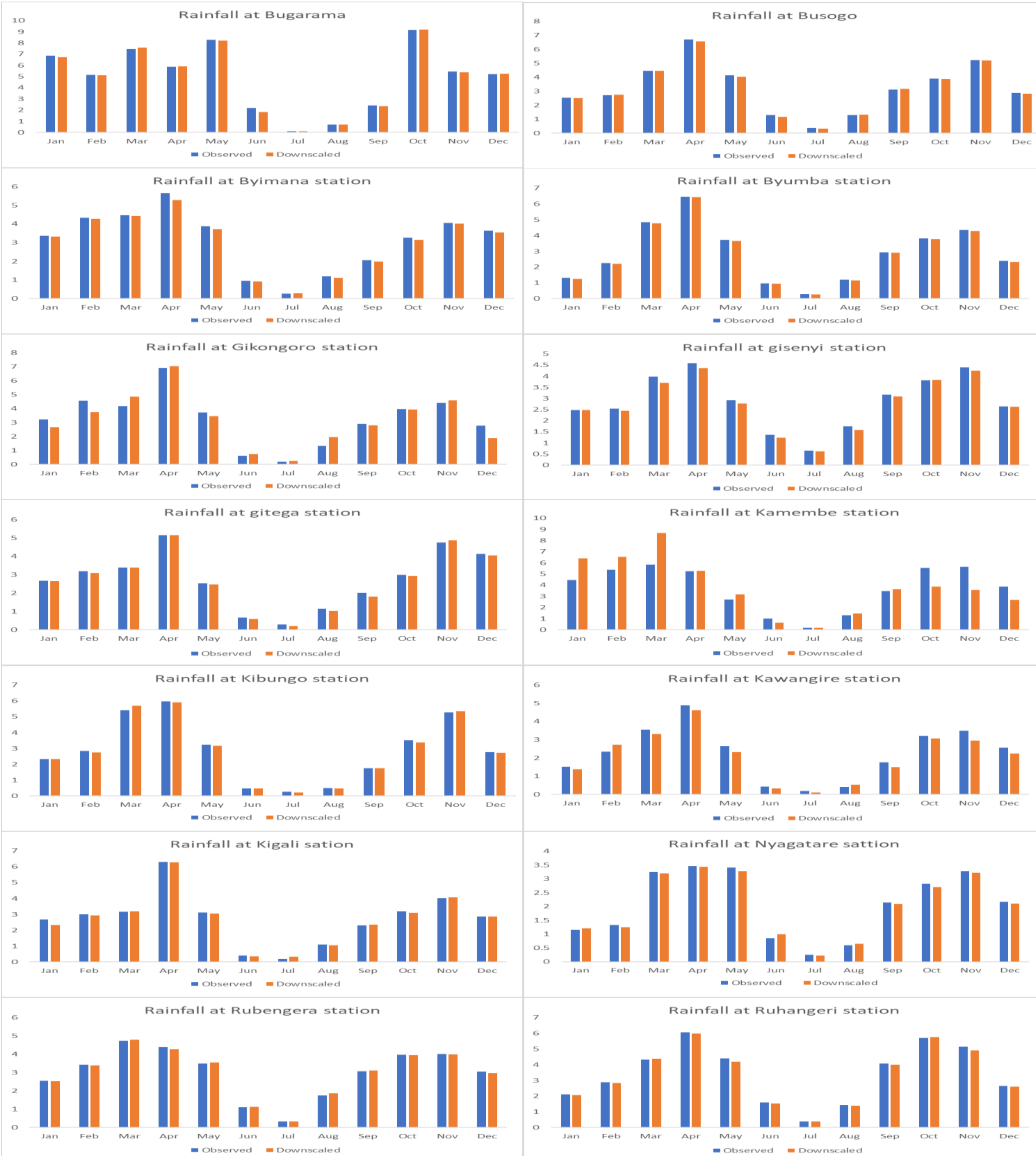

Figure 10 Calibration results of observed and downscaled mean rainfall

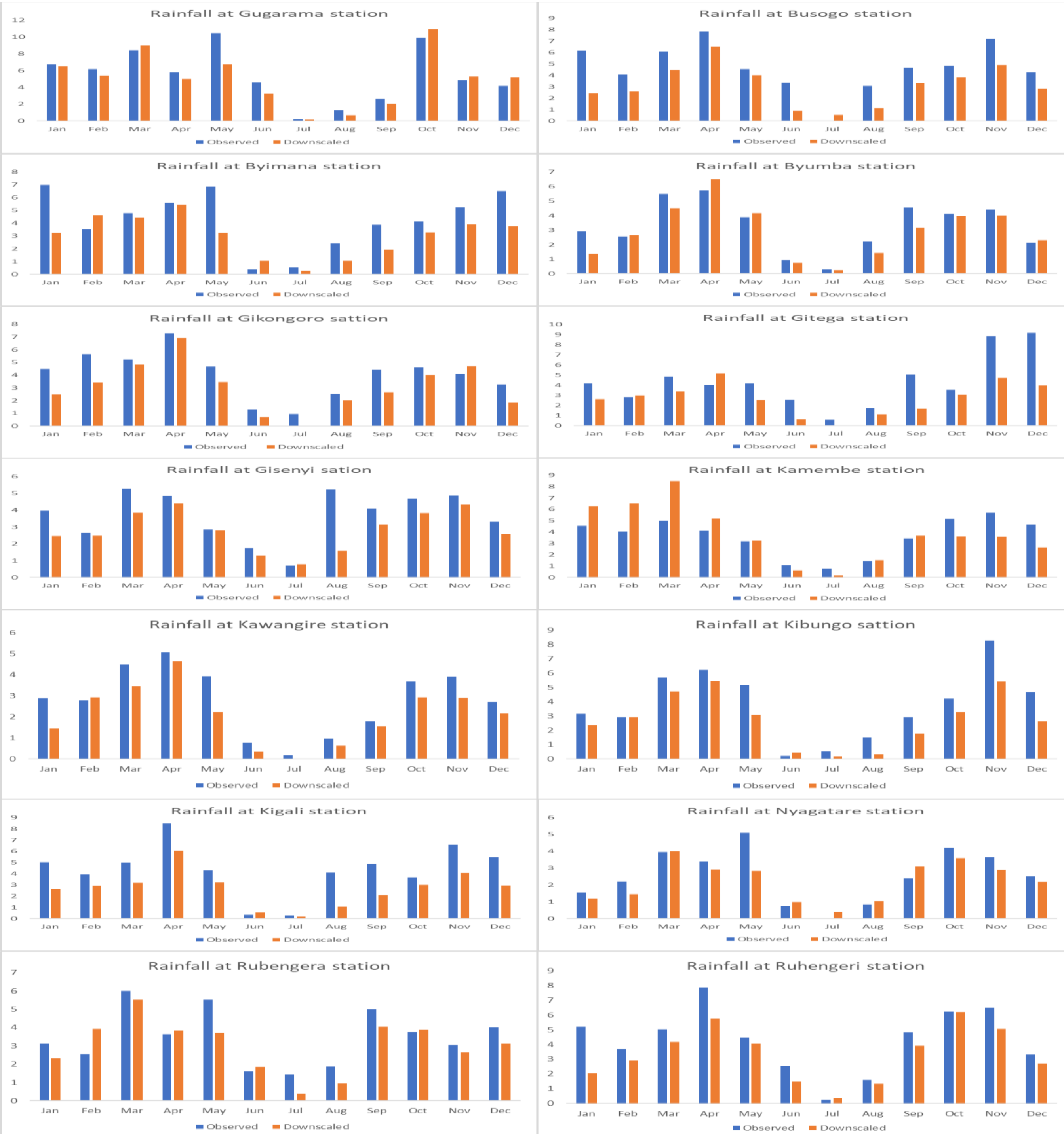

Figure 11 Validation results of observed and downscaled mean rainfall

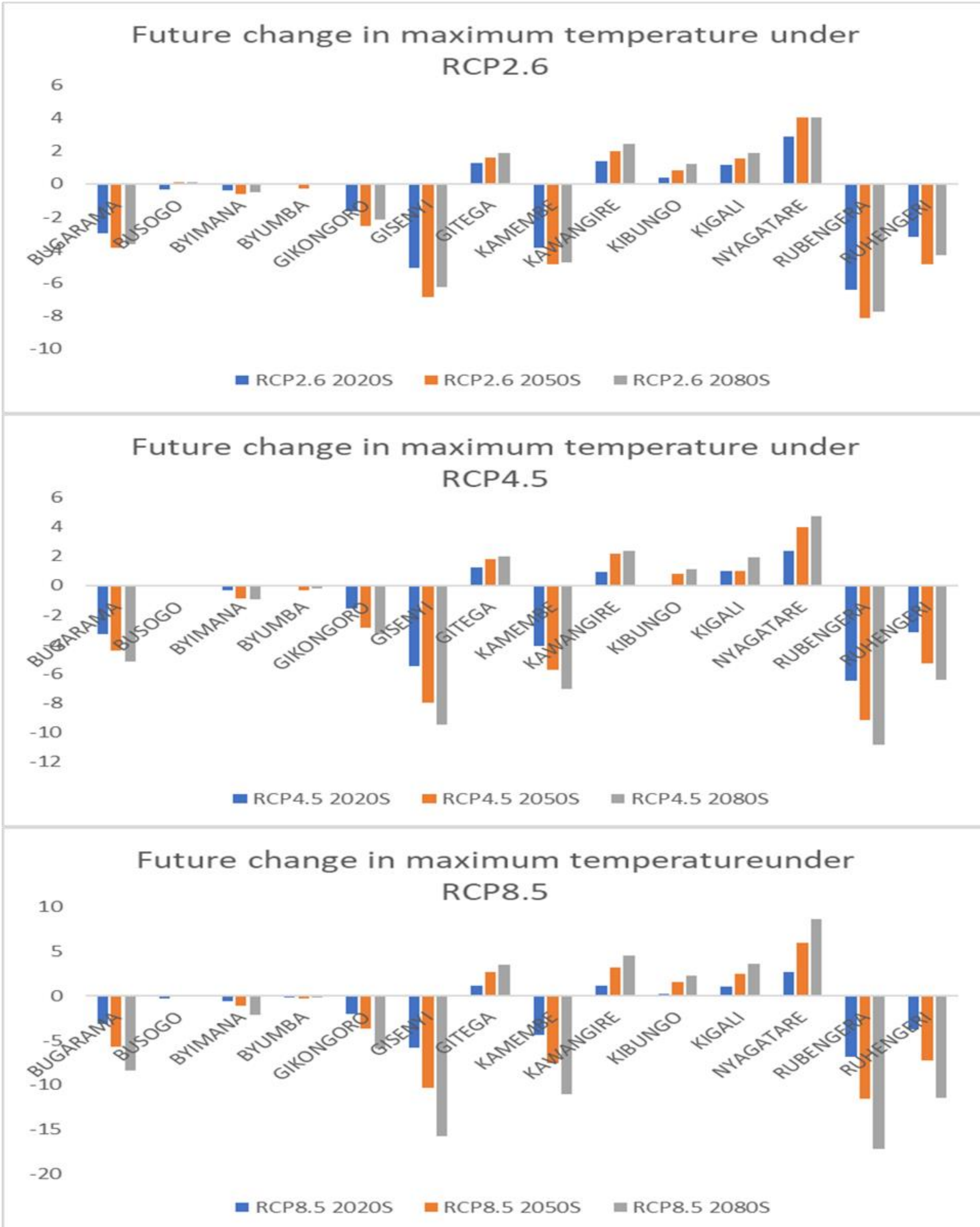

Figure 12 Future change in daily mean monthly maximum temperature

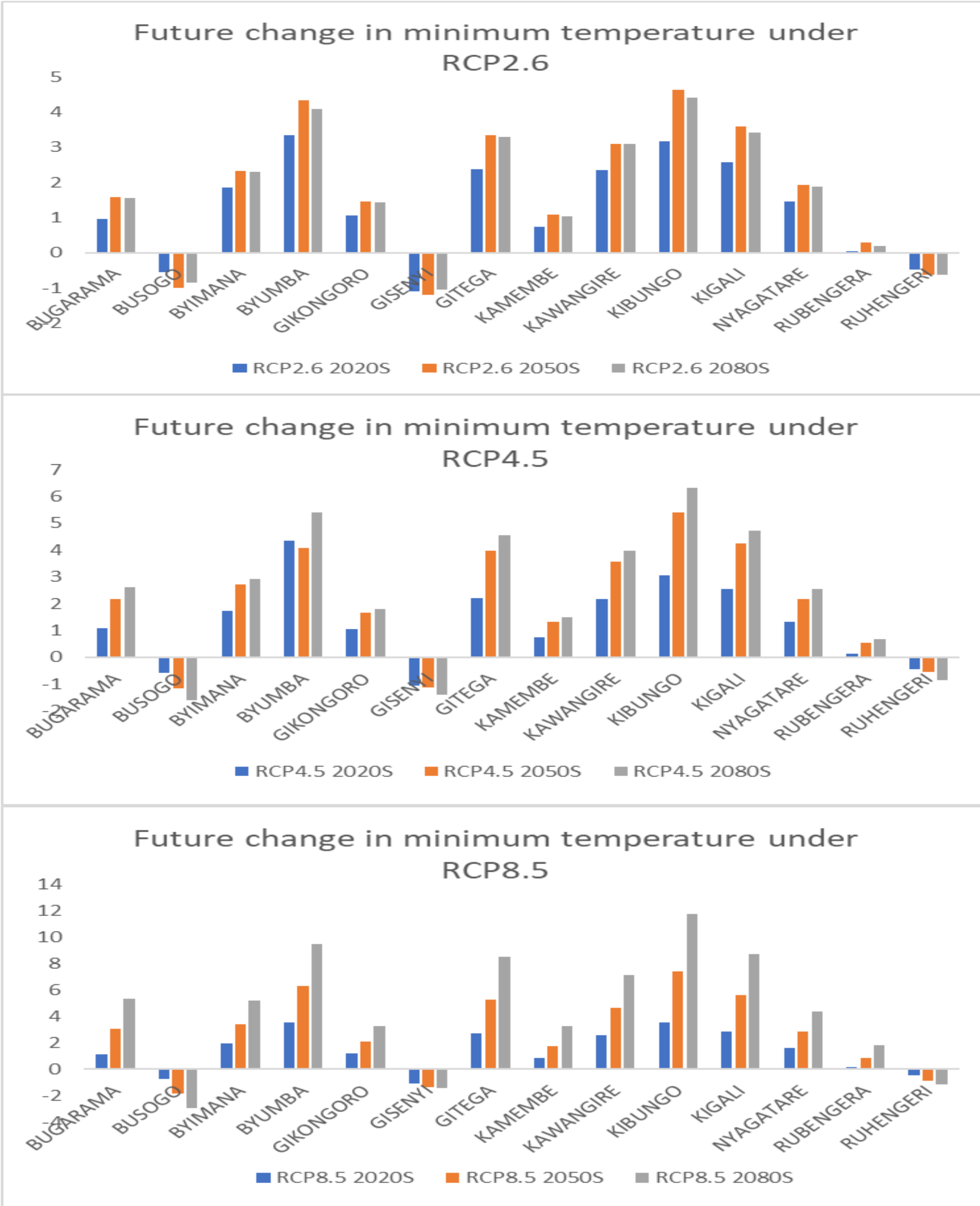

Figure 13 Future change in daily mean monthly minimum temperature

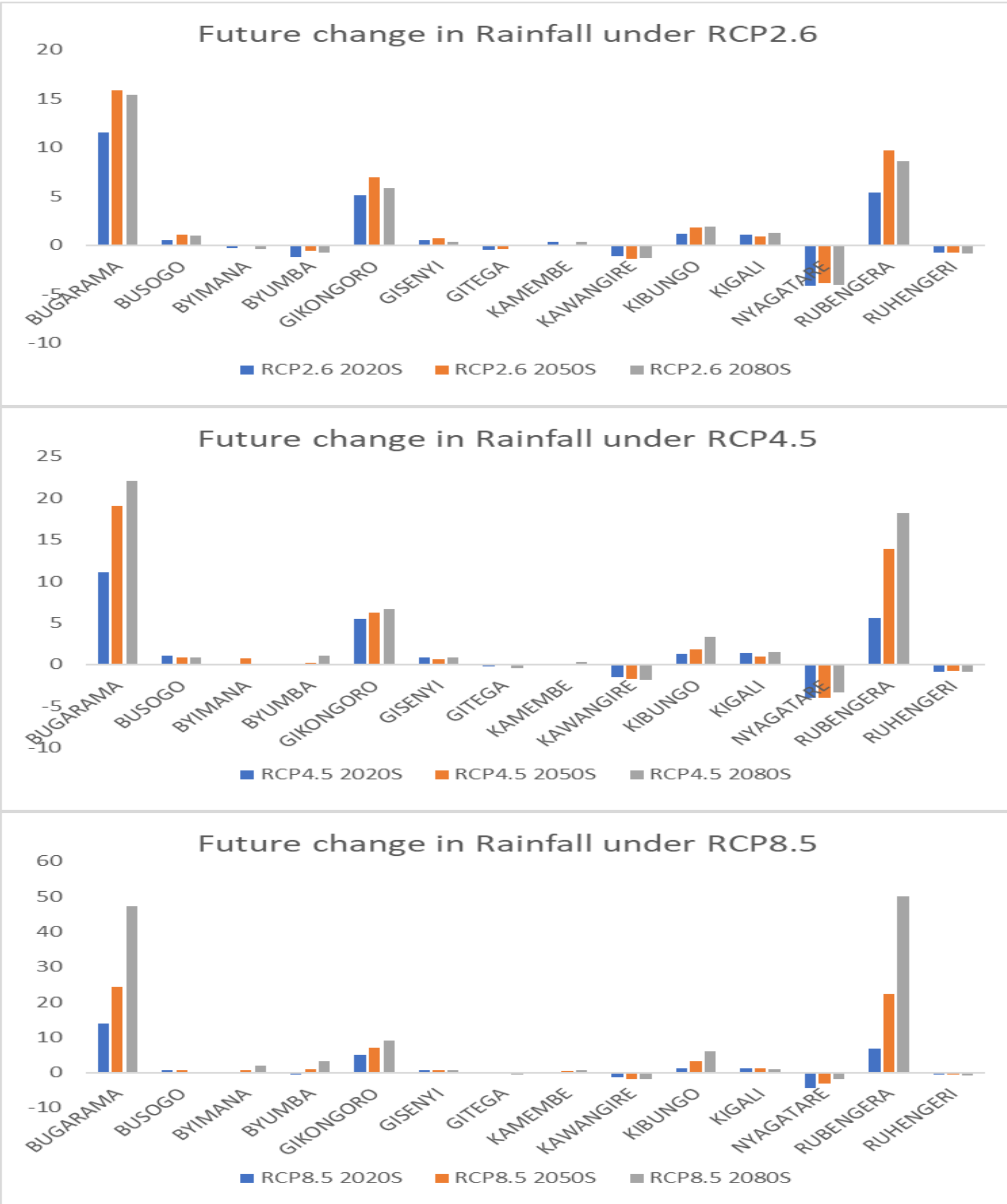

Figure 14 Future change in daily mean monthly rainfall

REFERENCES

[1] D. Ayalew, K. Tesfaye, G. Mamo, B. Yitaferu, and W. Bayu, 'Outlook of future climate in northwestern Ethiopia', *Agricultural Sciences*, vol. 03, no. 04, pp. 608–624, 2012, doi: 10.4236/as.2012.34074.

[2] T. Abebe, L. Bekele, and M. T. Hessebo, 'Assessment of Future Climate Change Scenario in Halaba District, Southern Ethiopia', *Atmospheric and Climate Sciences*, vol. 12, no. 02, pp. 283–296, 2022, doi: 10.4236/acs.2022.122018.

[3] S. H. Gebrechorkos, S. Hülsmann, and C. Bernhofer, 'Statistically downscaled climate dataset for East Africa', *Sci Data*, vol. 6, no. 1, 2019, doi: 10.1038/s41597-019-0038-1.

[4] 'Climate Risk Profile: Rwanda (2021): The World Bank Group.' [Online]. Available: www.worldbank.org

[5] M. Abbasnia and H. Toros, 'Future changes in maximum temperature using the statistical downscaling model (SDSM) at selected stations of Iran', *Model Earth Syst Environ*, vol. 2, no. 2, Jun. 2016, doi: 10.1007/s40808-016-0112-z.

[6] Republic of Rwanda, 'Updated Nationally Determined Contribution', 2020.

[7] USAD, 'Climate risk in Rwanda: Country risk profile.', Kigali, 2019.

[8] MIDIMAR, 'The monthly and annual data on disasters countlywide', Kigali, Rwanda, 2017.

[9] M. Lydie, 'Droughts and Floodings Implications in Agriculture Sector in Rwanda: Consequences of Global Warming'. [Online]. Available: www.intechopen.com

[10] C. Tisseuil, M. Vrac, S. Lek, and A. J. Wade, 'Statistical downscaling of river flows', *J Hydrol (Amst)*, vol. 385, no. 1–4, pp. 279–291, May 2010, doi: 10.1016/j.jhydrol.2010.02.030.

[11] R. L. Wilby and C. W. Dawson, 'SDSM 4.2— A decision support tool for the assessment of regional climate change impacts, User Manual', *Department of Geography, Lancaster University, UK*, no. August, 2007.

[12] World Bank GROUP, 'Rwanda Climate Risk Country Profile', 2021. [Online]. Available: www.worldbank.org

[13] R. L. Wilby and T. M. L. Wigleyb, 'Downscaling general circulation model output: a review of methods and limitations.

[14] R. L. Wilby, L. E. Hay, and G. H. Leavesley, 'A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado'. [Online]. Available: www.elsevier.com/locate/jhydrol

[15] D. Chaudhary, D. Kumar, R. K. Jaiswal, and A. K. Nema, 'A Statistical Downscaling Technique for Assessment of Meteorological Parameters under Climate Change Condition Using SDSM-DC

Model in Raipur District', *International Journal of Bio-resource and Stress Management*, vol. 9, no. 4, pp. 489–498, Aug. 2018, doi: 10.23910/IJBSM/2018.9.4.3C0268.

[16] R. Mahmood and M. S. Babel, 'Evaluation of SDSM developed by annual and monthly sub-models for downscaling temperature and precipitation in the Jhelum basin, Pakistan and India', *Theor Appl Climatol*, vol. 113, no. 1–2, pp. 27–44, Jul. 2013, doi: 10.1007/s00704-012-0765-0.

[17] R. L. Wilby, C. W. Dawson, C. Murphy, P. O'Connor, and E. Hawkins, 'The Statistical DownScaling Model -Decision Centric (SDSM-DC): Conceptual basis and applications', *Clim Res*, vol. 61, no. 3, pp. 251–268, Oct. 2014, doi: 10.3354/cr01254.

[18] A. Lupo and W. Kininmonth, 'Global Climate Models and Their Limitations'.

[19] J. Guo, G. Huang, X. Wang, Y. Li, and Q. Lin, 'Dynamically-downscaled projections of changes in temperature extremes over China', *Clim Dyn*, vol. 50, no. 3–4, pp. 1045–1066, Feb. 2018, doi: 10.1007/s00382-017-3660-7.

[20] R. L. Wilby and T. M. L. Wigleyb, 'Downscaling general circulation model output: a review of methods and limitations.

[21] R. Le Roux, M. Katurji, P. Zawar-Reza, H. Quénol, and A. Sturman, 'Comparison of statistical and dynamical downscaling results from the WRF model', *Environmental Modelling and Software*, vol. 100, pp. 67–73, Feb. 2018, doi: 10.1016/j.envsoft.2017.11.002.

[22] J. Boé, L. Terray, F. Habets, and E. Martin, 'Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies', *International Journal of Climatology*, vol. 27, no. 12, pp. 1643–1655, Oct. 2007, doi: 10.1002/joc.1602.

[23] S. Gagnon, B. Singh, J. Rousselle, and L. Roy, 'An Application of the statistical downscaling model (SDSM) to simulate climatic data for streamflow modelling in Québec', *Canadian Water Resources Journal*, vol. 30, no. 4, pp. 297–314, 2005, doi: 10.4296/cwrj3004297.

[24] 'CLIMATE RESEARCH Clim Res Climate downscaling: techniques and application'.

[25] J. Murphy, 'An Evaluation of Statistical and Dynamical Techniques for Downscaling Local Climate'.

[26] R. L. Wilby, C. W. Dawson, and E. M. Barrow, 'sdsm-a decision support tool for the assessment of regional climate change impacts', 2002. [Online]. Available: www.elsevier.com/locate/envsoft

[27] J. Guo, G. Huang, X. Wang, Y. Li, and Q. Lin, 'Dynamically-downscaled projections of changes in temperature extremes over China', *Clim Dyn*, vol. 50, no. 3–4, pp. 1045–1066, Feb. 2018, doi: 10.1007/s00382-017-3660-7.

[28] R. L. Wilby and C. W. Dawson, 'The statistical downscaling model: Insights from one decade of application', *International Journal of Climatology*, vol. 33, no. 7, pp. 1707–1719, Jun. 2013, doi: 10.1002/joc.3544.

[29] C. Yang, N. Wang, and S. Wang, ‘A comparison of three predictor selection methods for statistical downscaling’, *International Journal of Climatology*, vol. 37, no. 3, pp. 1238–1249, Mar. 2017, doi: 10.1002/joc.4772.

[30] R. L. Wilby and T. M. L. Wigleyb, ‘Downscaling general circulation model output: a review of methods and limitations.

[31] R. L. Wilby, C. W. Dawson, and E. M. Barrow, ‘sdsm-a decision support tool for the assessment of regional climate change impacts’, 2002. [Online]. Available: www.elsevier.com/locate/envsoft

[32] S. H. Gebrechorkos, S. Hülsmann, and C. Bernhofer, ‘Statistically downscaled climate dataset for East Africa’, *Sci Data*, vol. 6, no. 1, Dec. 2019, doi: 10.1038/s41597-019-0038-1.

[33] O. Moses and M. Gondwe, ‘Simulation of changes in the twenty-first century maximum temperatures using the statistical downscaling model at some stations in Botswana’, *Model Earth Syst Environ*, vol. 5, no. 3, pp. 843–855, Sep. 2019, doi: 10.1007/s40808-019-00571-5.

[34] D. S. N. A. P. A. Hasan, U. Ratnayake, S. Shams, Z. B. H. Nayan, and E. K. A. Rahman, ‘Prediction of climate change in Brunei Darussalam using statistical downscaling model’, *Theor Appl Climatol*, vol. 133, no. 1–2, pp. 343–360, Jul. 2018, doi: 10.1007/s00704-017-2172-z.

[35] A. Busuioc, D. Chen, and C. Hellström, ‘Performance of statistical downscaling models in GCM validation and regional climate change estimates: Application for Swedish precipitation’, *International Journal of Climatology*, vol. 21, no. 5, pp. 557–578, 2001, doi: 10.1002/joc.624.

[36] S. K. Jain, ‘DOWNSCALING METHODS IN CLIMATE CHANGE STUDIES’.

[37] K. Shitu and M. Tesfaw, ‘Downscaling Future Temperature and Precipitation Values in Kombolcha Town, South Wollo in Ethiopia’, 2021. [Online]. Available: https://www.sdsm.org.uk/for

[38] Z. Ncoyini-Manciya and M. J. Savage, ‘The Assessment of Future Air Temperature and Rainfall Changes Based on the Statistical Downscaling Model (SDSM): The Case of the Wartburg Community in KZN Midlands, South Africa’, *Sustainability (Switzerland)*, vol. 14, no. 17, Sep. 2022, doi: 10.3390/su141710682.

[39] R. H. Moss *et al.*, ‘The next generation of scenarios for climate change research and assessment’, *Nature*, vol. 463, no. 7282. pp. 747–756, Feb. 11, 2010. doi: 10.1038/nature08823.

[40] M. Meinshausen *et al.*, ‘The RCP greenhouse gas concentrations and their extensions from 1765 to 2300’, *Clim Change*, vol. 109, no. 1, pp. 213–241, Nov. 2011, doi: 10.1007/s10584-011-0156-z.

[41] J. Strandsbjerg Tristan Pedersen *et al.*, ‘An assessment of the performance of scenarios against historical global emissions for IPCC reports’, *Global Environmental Change*, vol. 66, Jan. 2021, doi: 10.1016/j.gloenvcha.2020.102199.

[42] D. P. van Vuuren *et al.*, ‘RCP2.6: Exploring the possibility to keep global mean temperature increase below 2°C’, *Clim Change*, vol. 109, no. 1, pp. 95–116, Nov. 2011, doi: 10.1007/s10584-011-0152-3.

[43] A. M. Thomson *et al.*, 'RCP4.5: A pathway for stabilization of radiative forcing by 2100', *Clim Change*, vol. 109, no. 1, pp. 77–94, Nov. 2011, doi: 10.1007/s10584-011-0151-4.

[44] K. Riahi *et al.*, 'RCP 8.5-A scenario of comparatively high greenhouse gas emissions', *Clim Change*, vol. 109, no. 1, pp. 33–57, Nov. 2011, doi: 10.1007/s10584-011-0149-y.

[45] G. Feyissa, G. Zeleke, W. Bewket, and E. Gebremariam, 'Downscaling of future temperature and precipitation extremes in Addis Ababa under climate change', *Climate*, vol. 6, no. 3, Sep. 2018, doi: 10.3390/cli6030058.

[46] V. E. Weli, M. O. Nwagbara, and F. Ozabor, 'The Minimum and Maximum Temperature Forecast Using Statistical Downscaling Techniques for Port-Harcourt Metropolis, Nigeria', *Atmospheric and Climate Sciences*, vol. 07, no. 04, pp. 424–435, 2017, doi: 10.4236/acs.2017.74031.

[47] R. L. Wilby, C. W. Dawson, and E. M. Barrow, 'sdsm-a decision support tool for the assessment of regional climate change impacts', 2002. [Online]. Available: www.elsevier.com/locate/envsoft

[48] D. T. Bulti, B. G. Abebe, and Z. Biru, 'Analysis of the changes in historical and future extreme precipitation under climate change in Adama city, Ethiopia', *Model Earth Syst Environ*, vol. 7, no. 4, pp. 2575–2587, Nov. 2021, doi: 10.1007/s40808-020-01019-x.

[49] R. Kabiri, V. Ramani Bai, and A. Chan, 'Assessment of hydrologic impacts of climate change on the runoff trend in Klang Watershed, Malaysia', *Environ Earth Sci*, vol. 73, no. 1, pp. 27–37, Jan. 2015, doi: 10.1007/s12665-014-3392-5.

[50] C. Yang, N. Wang, and S. Wang, 'A comparison of three predictor selection methods for statistical downscaling', *International Journal of Climatology*, vol. 37, no. 3, pp. 1238–1249, Mar. 2017, doi: 10.1002/joc.4772.

[51] D. N. Moriasi, J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith, 'MODEL EVALUATION GUIDELINES FOR SYSTEMATIC QUANTIFICATION OF ACCURACY IN WATERSHED SIMULATIONS', 1983.