CHANGES IN FUTURE RAINFALL EXTREMES OVER NORTHWEST BANGLADESH USING MULTI-MODEL ENSEMBLE

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CERTIFICATE OF RESEARCH

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DECLARATION

*I hereby declare that this thesis entitled "**CHANGES IN FUTURE RAINFALL EXTREMES OVER NORTHWEST BANGLADESH USING MULTI-MODEL ENSEMBLE**" is an authentic report of study carried out as requirement for the award of degree B.Sc. (Mechanical Engineering) at Islamic University of Technology, Gazipur, Dhaka, under the supervision of*

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in the year 2022 The matter embodied in this thesis has not been submitted in part or full to any other institute for award of any degree.

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ABSTRACT

Bangladesh is rich in nearly every form of natural resource. Underground water and rainfall are critical parameters in civil and mechanical engineering. The impacts of climate change on precipitation across Bangladesh's northwestern zone were explored using daily precipitation data from eight bias-corrected general circulation models (GCMs) under the representative concentration pathway (RCP) 4.5 and RCP 8.5 scenarios. The northwestern zone is particularly prone to drought. CMIP5 models perform a probabilistic forecast of the future using the precipitation indices for the time period of (2010-2099). We will forecast changes in future climate indices for the period 2020-2099 using observed data and GCM model data. Future timespan can be separated into two sections: one is the near future (2020-2059) and another one is the far future (2060-2099). Menn-Kendell Test will give us future trend analysis report. Bayesian Model Averaging (BMA) will be used to do multi-model ensemble. Changes in extreme climate indices will be projected by spatial mapping. Extremely heavy precipitation days & heavy precipitation days are decreasing in almost all stations. But total annual precipitation has an increasing trend. For high emission scenario change in climate indices are more prominent & devastating. These are the major findings of this thesis. Our study only focuses on precipitation. But temperature-related indices are skipped in this case due to time shortage. So, giving a perfect future climate scenario is quite tough. It's a major limitation in our study. But we see that most of the cases the indices are changing insignificantly in Ishwardi station. In some cases, Rangpur & Dinajpur will face some extreme weather events.

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NOMENCLATURE

AOGCM	Atmosphere-Ocean General Circulation Models
AR5	Fifth Assessment Report
AR6	Sixth Assessment Report
BMD	Bangladesh Meteorological Department
CDF	Cumulative Distribution Function
CMIP	Coupled Model Inter-comparison Project
CMIP5	Coupled Model Inter-comparison Project 5
GCM	Global Climate Model
IPCC	Intergovernmental Panel on Climate Change
MME	Multi Model Ensemble
RCP	Representative Concentration Pathway
SQM	Simple Quantile Mapping
SSP	Shared Socio-economic Pathways
WCRP	World Climate Research Program
ETCCDI	Expert Team on Climate Change Detection and Indices

Chapter 1: Introduction

Background

This country is one of the most vulnerable to climate change because of it's low lying flood plain, frequent environmental disasters, high population density, unique geographical location and agriculture-based weak economy, among so many other factors (IPCC, 2007, Islam et al., 2017, Salam et al., 2020, Ghose et al., 2021a). Heavy rainfall causes flash floods, which destroy infrastructure, disrupt natural ecosystems, and even result in human casualties. Furthermore, drought is one of Bangladesh's most common natural disasters due to its prolonged impacts on crop production and the environment. (Kamruzzaman et al., 2019). The country has also reported an increase in the frequency and intensity of rainfall extremes (Basher et al., 2018), (Hasan et al., 2018), (N. Khan et al., 2020),(Mallick et al., 2021), (Shahid, 2011). heavy rainfall or Flash floods, causing infrastructural destruction, significant harm to natural ecosystems, and even human casualties. Moreover, drought is becoming Bangladesh's most common natural catastrophe, owing to its negative influence on crop productivity and the environment (Kamruzzaman et al., 2019). Several studies reveal that the extreme climatic events are likely to exacerbate in future days. Policymakers and the general public are increasingly in need of realistic and thorough future projections of such extreme climate occurrences in order to prepare for regional climatic shifts.

Extreme climate events and it's future projection

Climatic extremes are infrequent events; located at the two-tail end of distribution curves of climate variables like precipitation, temperature, and so on (Zhang et al., 2011). Extreme climate events are the occurrences of such climatic changes. The World Meteorological Organization's Expert Team on Climate Change Detection and Indices (ETCCDI) proposed the usage of a set of 27 climate indices to establish a standard framework for investigating extreme climate events (Alexander et al., 2019). The ETCCDI indices are commonly used in numerous geographic environments to quantify and analyze extreme event trends and intensity (Thibeault & Seth, 2014),(McDowell et al., 2014) .

Research Problem Statement

Many countries, including India, China, North America, and others, have previously done extensive work on future climate modeling. But it's pretty much unheard of in Bangladesh. Forecasting future climate indices is important for policymakers, engineers, and farmers to make critical decision. In this study, we will focus on five weather stations in Bangladesh's northwestern region: Bogura, Dinajpur, Ishwardi, Rajshahi, and Rangpur. CDD, CWD, RX1day, and other precipitation-related climatic indices will be investigated. The northwestern zone is being studied in particular since it is a drought-prone area with no previous research. So, we will fill these information gap.

The following research gaps were addressed in this thesis:

1. What is the future trend of Bangladesh's climate extremes in terms of precipitation related extreme indices?
2. What is the temporal and spatial impact of different emission scenarios (RCP4.5 & RCP8.5)?

Research's major goal is to estimate a future climate scenario for the twenty-first century using a bias-corrected climate model dataset. This thesis has three primary objectives to achieve this goal:

I. To estimate Bangladesh's future extreme climatic events from 2010 to 2099 using BMD data & bias corrected GCM data.

II. Use the Mann-Kendall Test of these extremes to assess future changes and trends under moderate (RCP4.5) and extreme (RCP8.5) future emission scenarios.

III. Using Bayesian model averaging (BMA) to perform multi-model ensemble

IV. To evaluate spatial variability of such extreme indices in Bangladesh's northwestern zone.

Limitations and Scope

I. Limited number of weather stations are used in this study contains missing values. We only included 5 stations in our study; however, including all stations might provide better forecast scenarios.

II. This study used statistical downscaling, but literatures show a dynamic downscaling can give better result. However, statistical downscaling is inexpensive and requires less amount of time (Wang et al., 2018) which is the reason for selecting this method.

III. Due to time constraints, only 8 of the 31 GCM models were investigated. If it was possible to study more models it would be very helpful.

IV. Temperature related extreme indices are not added here. So Temperature related change are being neglected here. Without knowing the rainfall & precipitation extremes, it is completely unrealistic to estimate future climate change.

But by knowing the precipitation we get some important information. Precipitation is one of the most crucial components in Bangladesh, which has a robust agricultural economy. Around 80% of Bangladesh's people live in rural areas and is dependent on agriculture, either directly or indirectly. The unpredictable rainfall and accompanying extreme events may have an impact on ecosystems, land productivity, agriculture, food security, water availability and quality, as well as the health and livelihood of Bangladesh's common people. As a result, a better knowledge of precipitation changes has significant consequences for Bangladesh's economy and society.

Steps & Methods

I. Date Extraction: extraction GCM model dataset of Precipitation & Temperature

II. Post Processing of Data: Down scaling the gridded data to finer resolution & Bias correction using Simple Quantile Method (SQM)

III. Calculation of ETCCDI extreme indices: calculation of climate indices by using 'RClimdex' tool with bias corrected station data.

IV. Multi-model Ensemble: Use of Bayesian Model Averaging (BMA) for Multi-model Ensemble

V. Future Projection: With the MME datasets, future changes of extreme climate indices, trend analysis & spatial analysis have been carried out.

Organization of The Study

This thesis is containing 6 chapters including:

Chapter 1: presents the background, limitations, organization and objectives of the study.

Chapter 2: presents literature review on the current studies of Extreme Climate Events in Bangladesh and use of climate models in predicting future climate extremes under different emission scenarios.

Chapter 3: Includes details about the Climate extremes and Climate models, evaluation of CMIP models and their future emission Scenarios

Chapter 4: presents the materials and methods that have been used in this study

Chapter 5: Includes the key findings regarding the future projections under different emission scenarios.

Chapter 6: Discussion and concluding Remarks

Chapter 2: Literature Review

Introduction

The evaluation of changes in climatic extremes is very essential for Bangladesh. As a result, studies have been undertaken to assess the changes in different rainfall and temperature extremes in Bangladesh. Extreme climate events in Bangladesh focuses on either on the change in mean value (Hafijur Rahaman Khan et al., 2019), (Shahid,2011) or the observed trend (Endo et al., 2015), (Khan et al., 2019b). Later, a number of studies attempted to project the future climate extremes of Bangladesh.

Recent studies regarding Extreme Climate Events in Bangladesh

Climate change is causing temperature rises, heavy rains, droughts, and other phenomena around the planet. Bangladesh is growing faster than the rest of the world. According to certain climate models, temperatures will rise in the near future as rainfall increases. However, precipitation is insignificant compared to temperature rise. As a result, the frequency of droughts and heat waves may rise in the future. The World Meteorological Organization's Expert Team on Climate Change Detection and Indices (ETCCDI) advocated the usage of a set of 27 climate indices to establish a standard framework for investigating extreme climate occurrences. With ETCCDI's 27 core climate indices, we can define temperature and precipitation-related severe occurrences. Rising the global mean, resulting in increasing extreme weather events. Climate extremes occur at the tail of the distribution of critical climate parameters—are expected to become more frequent, intense, and prolonged as a result of these changes. Using Regional Temperature Modeling (M. J. U. Khan et al., 2020), ETCCDI's climate indices of 1.5, 2 and 4 degrees Celsius of global warming were analyzed over Bangladesh, depicting vulnerability to climate change in all over Bangladesh. The precipitation and possible evatransportation in the northwest region were investigated (Karim et al., 2020). Karim used data from 28 (GCMs) for two emission scenarios, based on the IPCC's 5th assessment report (AR5). Projections were generated for 16 administrative districts in the research area from 2045 to 2075, with changes projected on an annual, seasonal, and monthly time scale. Most of the calculation is showing that PET is upgoing. Rainfall has more increasing trend rather than decrease. From projections, rainfall is increasing ranging from 160 to 250 mm (with an average of 200 mm) in Kharif season. Rainfall is higher in the Kharif season, although PET is higher in both the Kharif and Rabi seasons. With exception of rainfall, in most cases, PET rises more in the Rabi season. There is probability of droughts in the future because of high potential evatransportation (PET). Earlier The consequences of climate change on precipitation and drought characteristics over Bangladesh were investigated using daily precipitation data under the RCP 4.5 and 8.5 scenarios from 29 bias-corrected GCMs. However, extreme drought days are expected to increase in most agricultural seasons over the next few years. Drought characteristics suggest that, as a consequence of climate change, drought-prone areas are expected to relocate in the future from the northwest to the central and southern regions under high & moderate emission scenario (Kamruzzaman et al., 2019).

The variability study of extreme rainfall events in Bangladesh from 1958 to 2007 was covered by (Shahid, 2011). The Mann-Kendall statistic shows as well as the trends and magnitude of change were measured using Sen's Slope model. To assess the trends, the Mann-Kendall (MK) test was performed, and the Thiel-Sen’s slope estimator was applied to compute the magnitudes of the trends. According to the findings, all coastal and inland areas were warming markedly, with coastal parts warming quicker. Ignoring the fact that most of the extreme rainfall indices for coastal and inland stations showed statistically negligible changes, localized humidity and greater rainfall have been seen in particular areas. (Shahid, 2011),(Islam et al., 2021), and others worked on trend analysis using historical data. However, no one worked on forecasting future extreme climatic occurrences. Previously, different studies in climate change studies in Bangladesh indicated varied temperature and precipitation extreme indices. CIMP3, GCM models were used in the majority of them. The Rajshahi zone in Bangladesh's northwestern region is prone to drought. As a result, understanding the precipitation pattern in this zone is critical. However, there is no future precipitation estimate that shows how extreme climatic indices will trend in the near and long term.

Use of GCMs in Projecting Future Climate Extremes

Global Climate Models (GCMs), in addition to regional climate models (RCMs), are a very trustworthy instrument for evaluating past and future climate. GCMs from the CMIP have been widely used in climate studies, including assessment reports from the

Intergovernmental Panel on Climate Change (IPCC) (Alexander et al., 2019), (Easterling et al., 2012). Nonetheless, relatively few research in Bangladesh tried to estimate future temperature or climatic extremes using GCM data. (Fahad et al., 2018) used a bias-corrected MME to determine the change in temperature and rainfall across the country and discovered a considerable spike in the pre- and post-monsoon seasons. However, the study did not address the forecast of climatic extremes. Using daily precipitation outputs from bias-corrected 29 GCMs from the CMIP5 under the RCP 4.5 and 8.5 scenarios, (Kamruzzaman et al., 2019) discovered that annual total precipitation would increase in Bangladesh in the twenty-first century, with the largest increase in rainfall in the drought-prone northern area. (Khan et al., 2020) researched climate extremes in Bangladesh at 1.5°C, 2°C, and 4°C of global warming and discovered that severe rainfall grew more than total annual rainfall. (Khan et al., 2019a) recently forecasted future extremes, considering the new RCP4.5 and RCP8.5 emission scenarios over Bangladesh utilizing RCM data produced by GCMs inside the new CMIP5. The study found that general precipitation and temperature trends in this region are projected to rise in the future. These results, however, were not used to estimate drought characteristics.

The Fundamentals of GCMs

Many Geophysical Fluid Dynamics "fundamental equations" are used in climate models to depict the interrelations of the atmosphere and ocean on large enough scale. To obtain the basic equations, the whole three-dimensional Navier–Stokes equations can be employed. Bjerknes described the the 'equation of state for the atmosphere, hydrodynamic equations of motion, the continuity equation and the two essential theorems of heat transfer (Bjerknes et al., 2009). Seven variables may be estimated using this set of equations that determine the condition of the atmosphere: humidity, density, air pressure, temperature, and velocity in three directions. In general, finding an exact solution is the best acceptable strategy for accurately estimating future atmospheric conditions, although this is not always possible. However, this equation system is obviously too complicated to be transformed into an accurate solution. In order for a numerical climate model to function, Bjerknes' equation set must be translated into a set of processes that splits the atmosphere into grid cells. Thus, influence of physical and mechanical forces on fluids on the grid cells are described (Goldstine, 2012)

GCM Spatial Resolution

A model cannot practically simulate all of these functions for every cubic meter of the geographic system due to the complexity of the climate system and computer resource limitations. A climate model, on the other hand, splits the Earth into a series of boxes known as "grid cells."The "spatial resolution" of a model refers to the size of the grid cells. Grid cells in a crude global climate model are typically roughly 100 kilometers longitude and latitude in the mid-latitudes. There should be 10–20 vertical layers and 30 layers in the atmospheric and oceanic realms, respectively. Furthermore, the horizontal resolution must be between 250 and 600 kilometers. To estimate feedback mechanisms, GCM evaluates many natural statistics such as ocean circulation, clouds and radiation, water vapor and warming and ice and snow albedo (IPCC, 2007).

Global Climate Model Time Step

As previously stated, GCMs solve the complicated equations that represent the atmosphere using time stepping numerical approximations. The "leapfrogging method," in which a model extrapolates climate information from past and current time steps and advances to the next, and so on through time, is a highly prevalent approach for time stepping approximation in a GCM. A smaller time step, like the size of grid cells, allows the model to output more comprehensive climate data. However, this means that the model must perform more calculations in each run (Goldstine, 2012).

Global Climate Model Downscaling and Bias Correction

Climate models with coarse resolution is insufficient for providing actionable information for localized climate study research. Furthermore, they can have significant systematic biases when compared to observational datasets. As a result, in order to generate reliable climate estimations at the local scale, the simulations must be post-processed.

The Importance of Downscaling

GCM is a numerical model that uses data from a variety of climatic characteristics to simulate large-scale weather conditions. However, projection on a small spatial scale is difficult. To close this spatial gap, large-scale GCM results should be converted into high-resolution grids using the "downscaling" method. Downscaling is often implemented using both dynamic and statistical methods. The dynamical downscaling approach is used to include a high-resolution RCM model into a GCM model. Statistical methodologies are used to create empirical correlations between large-scale low-resolution climatic variables (predictors) and local high-resolution parameters (predictands) in a specific area, which are subsequently applied to GCM outputs (Alexander et al., 2006).

Correction for Bias

The Bias Correction (BC) approach evaluates discrepancies in the mean and variability between GCM and observations in a reference period to correct the anticipated raw daily GCM output. In climate impact modeling, statistical bias correction is often used to modify climate model data for consistent divergence of simulated historical data from observations. Transfer functions are used in the ways to relate the distribution of simulated historical data to the distribution of observations. The findings are then utilized to improve future estimates. There are six ways to correct rainfall bias and four ways to fix temperature bias. They address the most popular types of bias correction approaches.

(a) Rainfall bias correction:

I. Linear Scaling, I (LS)
II. Every Day Translation (DT)
III. Scaling of Local Intensity (LOCI)
IV. Bias Correction Every Day (DBC)
V. Transformation of Power (PT)
VI. Quantile Mapping (Simple) (SQM)

(b) Temperature bias correction:

I. Linear Scaling I (LS)

Daily Translation (DT)

II. Quantile Mapping (Simple) (SQM)

III. Scaling Variance (VARI)

For both precipitation and temperature data, Simple Quantile Mapping (SQM) is a very helpful bias reduction technique. We will apply SQM for GCM output: precipitation data.

Bias Sources

Different sources of mistakes in climate models could exist. Eden and colleagues (2012) classify mistakes due to - in GCMs

i. Large-scale variation or responses to climate changes that are unrealistic
ii. Internal variability that is unpredictable and varies from observations (for example, if the sampled historical period occurs within the positive phase of the Pacific decadal oscillation in data but the negative phase in the climate model).
iii. Unexplained sub grid-scale orography and errors in convective parameterizations

The Multi-model Ensemble (MME)

Model resolution, mathematical formulation, initial assumptions, and calibration methods, among other things, can cause various uncertainties in climate model simulations. These uncertainties limit the accuracy of regional or local usage forecasts (Northrop, 2013).

MME has the ability to reduce uncertainties in future simulations, is a good technique to avoid the uncertainty(Shahid et al., 2016). Several studies have used alternative types of MME, other than the arithmetic mean, to produce more robust projections.

i. Several studies have demonstrated the effectiveness of a weighted ensemble technique that is based on the models' simulation capability and sometimes takes account of model dependencies (Annan & Hargreaves, 2017). Model weighting, on the other hand, is not a conventional approach in climate modeling. The most recent IPCC report admits that the climate community does not know how to weight models to provide the best estimation of future climate change. Climate model performance varies depending on variable and geography.

ii. BMA has been widely used to aggregate climate projections from individual models and quantify the uncertainty caused by the model structure (Xu et al., 2015). BMA has model uncertainty and then performs Bayesian modification of assumptions in response to observations. The BMA framework offers a number of advantages over single-model selection: When model uncertainty is disregarded, BMA lowers overconfidence (i.e., underestimated uncertainty).

iii. (Herger et al., 2015) devised a unique technique for modeling weighting that employs the Model observation distance matrix as an indicator of model performance and dependency.

iv. Broad spectrum of climate change research and forecast issues using machine learning (ML) technologies have gained recognition in recent years. ML is an excellent choice due to its primary advantage of analyzing nonlinear and hierarchical interactions between variables and outputs using an ensemble learning approach. Acharya et al. (2014) employed an extreme learning machine on seven GCMs to generate an MME-based estimate of northeast monsoon rainfall across south peninsular India. ML is more robust compared other MME techniques.

The nature of extreme climate indexes and their significance

Before analyzing extreme climate events, it is necessary to have a full understanding of the nature of these indexes and the "extreme events" that they reflect. Climate extremes are rare occurrences that occur at the extremes of the climate variable distribution curve (Zhang et al., 2011).If temperature is regularly distributed over time, for example, the two climate extremes (extreme cold and extreme heat) would be at the two extreme ends of the distribution curve (Peterson, 2006). Even though rainfall does not follow a normal distribution, its curve follows a similar principle, with the extreme ends representing light and heavy rainfall events (Zhang et al., 2011).

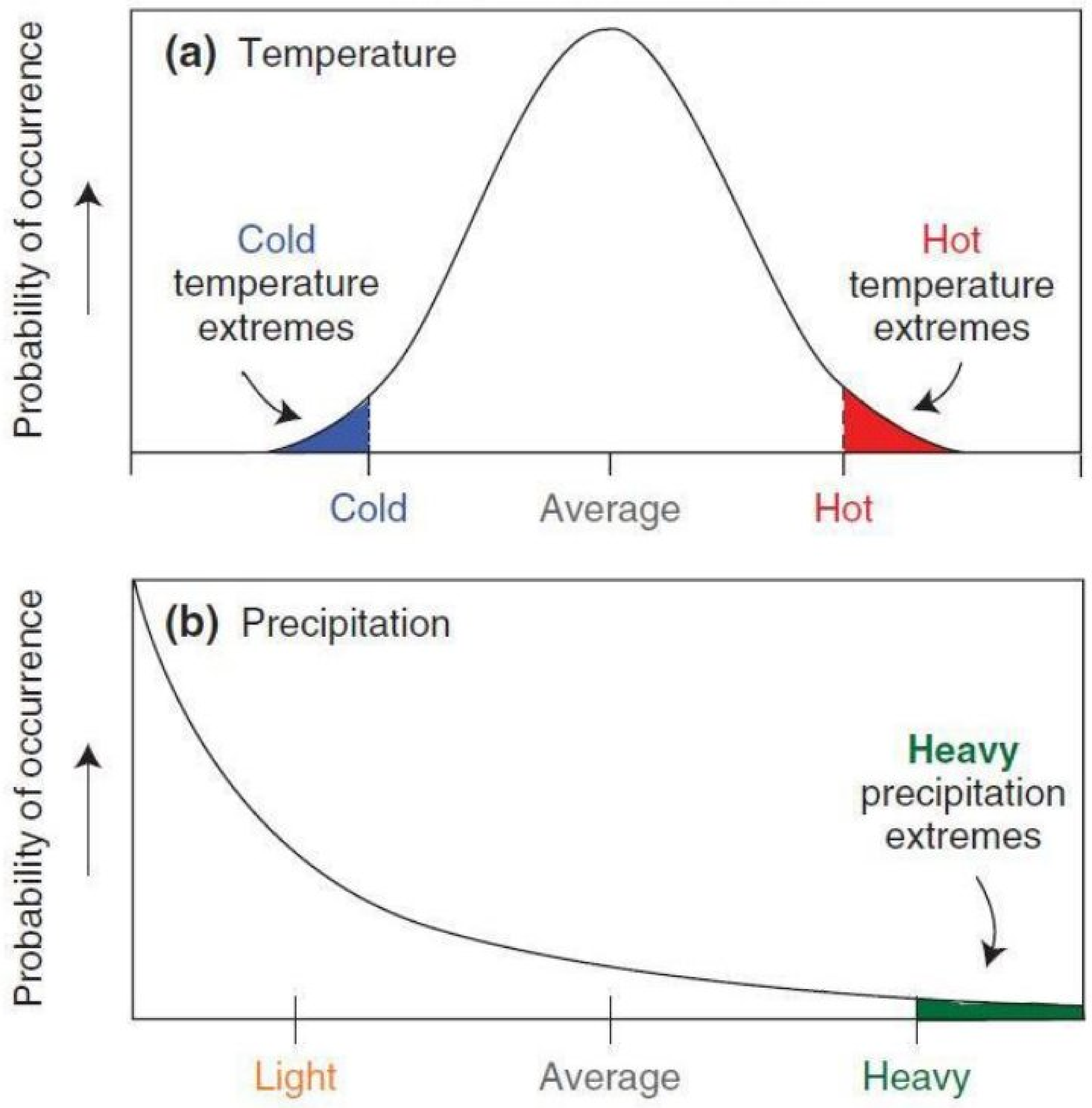

Figure 1:The probability distributions of daily temperature and precipitation.

The higher the black line in Figure 1, the more frequently weather with those qualities occurs. The colored regions signify extremes and are derived from (Zhang, et al., 2011).

A set of 27 climate indices for the study of extreme climate events are recommended by ETCCDI ((Abdullah et al., 2022).

Chapter 3: Materials & Method

Study area

In North-West Bangladesh, only five of the 16 administrative districts have a meteorological station. This research looked at five of them: Bogura, Rajshahi, Rangpur, Pabna, and Dinajpur. The North-West region spans the latitudes of 23°47′N and 25°50′N, as well as the longitudes of 88°01′E and 89°48′E. This region of the country has a sub-humid agro-climatic classification. This region is classified as extremely close to dry because total annual evapotranspiration equals annual rainfall in some spots (Shahid et al., 2005). The annual rainfall ranges between 1400 and 2000 mm. During the dry months in this region, meteorological drought is a typical occurrence (Shahid & Behrawan, 2008). Aside from the massive population expansion, Bangladesh has a slew of other issues, including a lack of land to house people, food security, human health, illiteracy, and so on. The country is one of the most vulnerable to global climate change's escalating effects.

Table 1: Station information

Longitude	Latitude	Elevation	Station ID	Ename
89.37	24.85	17.9	BD41883	BOGRA
88.68	25.65	37.58	BD41863	DINAJPUR
89.05	24.13	12.9	BD41907	ISHWARDI
88.7	24.37	19.5	BD41895	RAJSHAHI
89.23	25.73	32.61	BD41859	RANGPUR

Data

The thesis employs two unique types of data: the CMIP5 data, which consists of eight models, each with a historical dataset and two separate datasets corresponding to future scenarios, and a daily observational dataset.

We have 2 types of data set

1. Station data/ BMD data (1975-2005)
2. GCM model data

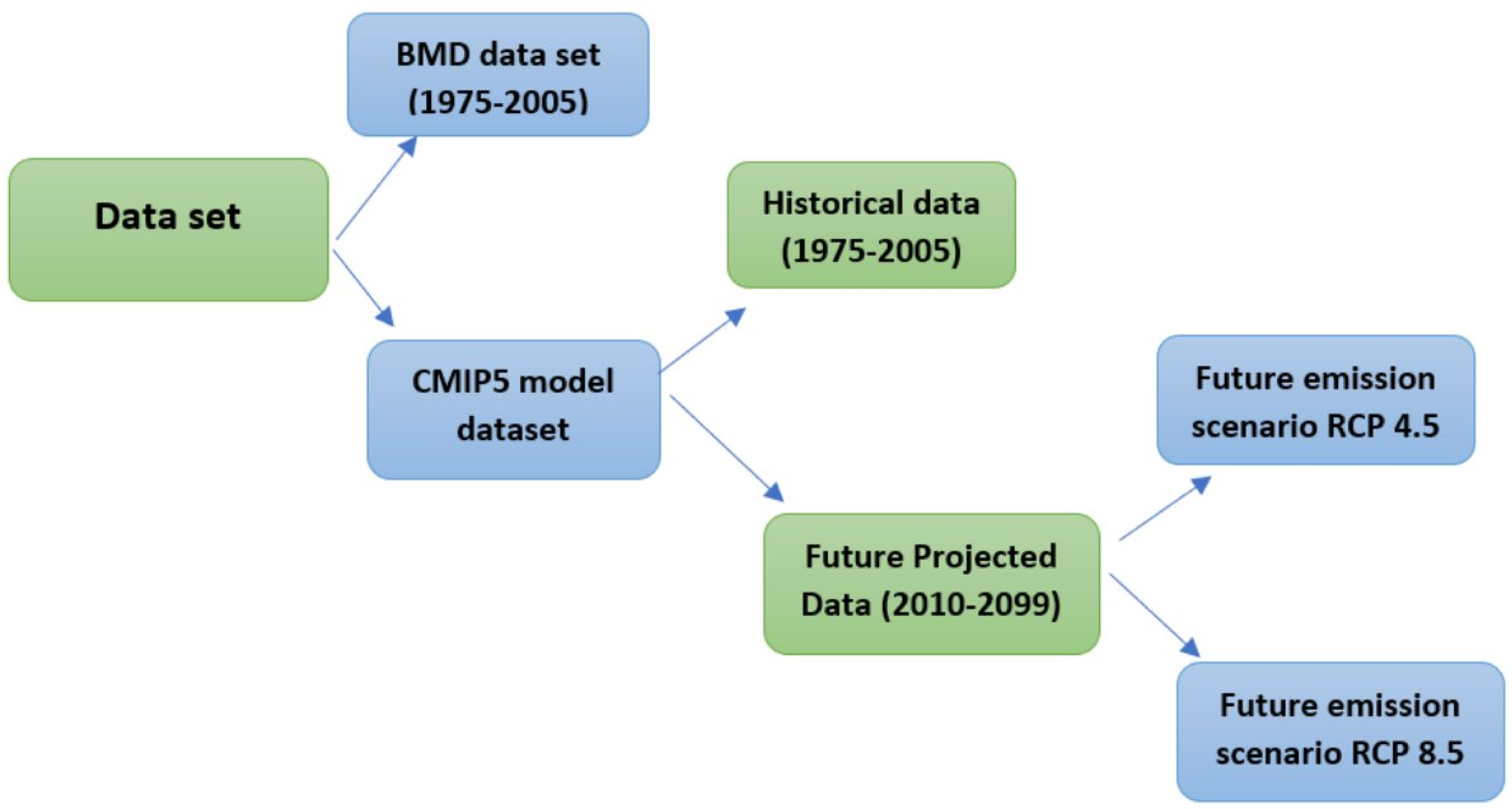

Figure 2 Flowchart of Dataset

Calculation of Climate indices using RClimdex:

It requires high quality homogeneous meteorological data to calculate the extreme indices (Zhang et al., 2011). The indices used in this study are generally derived from bias corrected CMIP-5 model outputs. Daily precipitation and Maximum and Minimum temperature datasets converted into station level are used to calculate such indices. This study used *RClimDex* software which is capable of computing all 27 core indices listed in ***Chapter 3*** In this study, the threshold values are the observed annual average value of Daily precipitation, Tmax and Tmin. The base period is from 1975-2005. Details of the software is added in ***Appendix.*** Input data sets are added in the appendix section. RClimdex gives us ' observed data' for climate indices. Here it also gives us the plot for observed period. So we can see the trend for previous period. In our thesis we considered (1975-2005) as hitorical period. For future projection RCP4.5-1 & RCP8.5-1 show the change in near future (2010-2054) .RCP4.5-2 & RCP8.5-2 show the change in far future(2055-2099) .

Extreme Climate Indices used in this study

A subset of 27 ETCCDI defined extreme climate indices were used in this study (8 temperature indices) used in this study. Table 4 represents their list along with definitions. The further detail of the indices are discussed below.

Table 2 : Precipitation Indices

Index ID	**Descriptive Name**	**Definition**	**Unit**
CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days
PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR>=1mm)	mm
R99p	Very wet days	Annual total PRCP when RR>95th percentile	mm
R10mm	Number of heavy precipitation days	Annual count of days when PRCP>=10mm	Days
R20mm	Number of very heavy precipitation days	Annual count of days when PRCP>=20mm	Days
RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
RX5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm

GCM Models Used in this study

Among 31 GCM models we studied 8 models. Description of the models are given below:

Table 3 Description of GCM models

Models	Spatial resolution	Organization

CanESM2	2.8° × 2.8°	Canadian Centre for Climate Modelling and Analysis, Canada
CNRM-CM5	1.4° × 1.4°	Centre National de Recherches Météorologiques and Centre Européen de Recherche et Formation Avancées en Calcul Scientifique, France
INM-CM4.0	1.5° × 2°	Institute of Numerical Mathematics, Russian Academy of Sciences, Russia
MIROC5	1.4° × 1.4°	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, Japan agency for Marine-Earth Science & Technology, Japan
MPI-ESM-LR MPI-ESM-MR	1.8° × 1.8°	Max Planck Institute for Meteorology, Germany
MRI-CGCM3	1° × 1°	Meteorological Research Institute, Japan Meter ological Agency, Japan
NorESM1	2°× 2°	Norwegian Climate Centre, Norway

Data Post Processing: Statistical Downscaling and bias correction

It has been found that quantile mapping can artificially capture future model-projected trends. Hence, a simple quantile-mapping algorithm has been used in this study to downscale GCM output at the daily scale and then bias correction. The Simple quantile mapping (SQM) approach is ideal for biasing accurate time-series data, such as precipitation and temperature data. Transformation of modeled variable is found by Quantile mapping (also referred to as quantile-quantile transformation, quantile matching, cumulative distribution function matching) such that its new & observed variable (P_o) distribution is equal (Gudmundsson et al., 2012). parametric and non-parametric techniques are usedin bias correction method for scaling the mean, varianc e, and higher distribution moment (Eum and Cannon, 2017). SQM: a non-parametric bias correction approach that may eliminate biases in climate models reliably and precisely replicate temporal trends using weather variables and is ideal for hydrological applications. (Eden et al., 2012).

SQM Algorithm

Through empirical quantile mapping, the SQM approach conducts different modifications by observation sites and meteorological factors. As indicated by (Cho et al., 2016), the following three-step approach was employed in this study:

i. To begin, a single grid encompassing the target station was extracted.

ii. The historical simulations' biases were then calculated in compared to observation.

iii. Finally, bias-correction of future forecasts was performed using the distributions of the retrospective simulations.

The SQM algorithm computes the differences between observed and simulated cumulative distribution functions (CDFs) during the historical era, which it then applies to future simulations for a particular percentile using the equation below.

$$x'_p(t) = x_p(t) + F^{-1}_{obs}(F_{p.sim}(x_p(t)) - F^{-1}_{r.sim}(F_{p.sim}(x_p(t)))$$

where

$x'p(t)$ & $x_p(t)$ = bias-corrected and raw future projections on day t, correspondingly

$F(x)$ & $F^{-1}(x)$ = CDF of the daily data and its inverse.

The subscripts p.sim, r.sim, and obs denote future projection, retrospective simulation, and observed daily data, in that order. SQM, like all statistical post-processing algorithms, is highly reliant on the assumption that the preset climate model biases are stable (Cannon et al., 2015). Following the projection of all The SQM approach was implemented in this work using the Statistical software package RSQM. RSQM uses the empirical quantile mapping approach to perform statistical downscaling of daily CMIP model datasets at the station level (Cho et al., 2016).

Baysian model averaging (BMA):

$M = (M_1, ..., M_k)$ denotes the collection of models under evaluation. A model can be characterized by a number of properties, such as the the form of the error variance or model's subset containing explanatory variables. If the quantity of interest is, for example, a future variable or a model parameter, then the posterior distribution of supplied data Z is:

$$p(\Delta \mid \boldsymbol{Z}) = \sum_{k=1}^{K} p(\Delta \mid \boldsymbol{Z}, M_k) p(M_k \mid \boldsymbol{Z}),$$

This is the weighted average of the posterior probability distribution for for each of the models evaluated. Model M_k's posterior probability is provided by

$$p(M_k \mid \boldsymbol{Z}) = \frac{p(\boldsymbol{Z} \mid M_k) p(M_k)}{\sum_{l=1}^{K} p(\boldsymbol{Z} \mid M_l) p(M_l)}$$

where

$$p(\boldsymbol{Z} \mid M_k) = \int \cdots \int p(\boldsymbol{Z} \mid \boldsymbol{\theta}_k, M_k) p(\boldsymbol{\theta}_k \mid M_k) d\boldsymbol{\theta}_k$$

is the integrated probability of model $M_k, \boldsymbol{\theta}_k$ & the vector of parameters of model $M_k, p(\boldsymbol{\theta}_k \mid M_k)$ is the prior density of the parameters under model $M_k, p(\boldsymbol{Z} \mid \boldsymbol{\theta}_k, M_k)$ is the probability, and $p(M_k)$ is the prior probability that M_k is the true model. All probabilities are implicitly conditional on $\mathcal{M}$, the set of all models being considered.

Parameter estimates and other quantities of interest are provided via straightforward application of the principles described above. For example, the Bayesian model averaging (BMA) estimate of a parameter θ is

$$\hat{\theta}_{\text{BMA}} = \sum_{k=1}^{K} \hat{\theta}_k p(M_k \mid \boldsymbol{Z})$$

Evaluation of the GCM models

There may be some deviation between observed data & historical model data. Which model has less error/deviation for base period can be used for future forecasting. Error is predicted by MAD, MSE, RMSE, RMSE, MAPE. Another approach is Taylor Diagram.

MAD: The mean absolute deviation (MAD) is the summation of the absolute deviations between the actual and predicted values divided by the number of observations.

$$\text{MAD} = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n}$$

MSE: The most typical error measure is probably mean square error (MSE). Because squaring larger numbers has a higher impact than squaring smaller ones, it marginalizes more errors. The MSE is calculated as the sum of squared errors divided by the number of observations.

$$\text{MSE} = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}$$

RMSE: the root mean square error (RMSE) is the square root of the MSE.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}}$$

MAPE: The average of absolute errors divided by actual observation values is the mean absolute percentage error (MAPE). $\text{MAPE} = \frac{\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|}{n} \times 100$

Less the magnitude (RMSE, MAPE, MAD), better the quality of dataset.

Taylor Diagram

Taylor diagrams are quantitative diagrams that show which of numerous approximate representations (or models) of a system, process, or phenomena is the most accurate or authentic. We may learn three things from the Taylor diagram:

I. **Correlation Coefficient:** In a correlation analysis, the correlation coefficient is the precise measure that measures the strength of the linear relationship between two variables.

II. **Standard Deviation:** The standard deviation of a set of statistics is the distance between them and the mean.

III. **Centered RMS value:** RMSE is commonly used to calculate prediction error.

Mann-Kendall Test

The Mann-Kendall test revealed trends in the time series of all the indicators evaluated. This is a rank correlation statistic test that compares the number of discordances observed to the value of the same quantity anticipated from a random series. Mann-Kendall approach for trend analysis related to environmental data time series is highly recommended by The World Meteorological Organization. This test compares each value in the time-series against the others that remain, always in sequential order. The number of times the remaining terms are larger than the term under consideration is recorded. The Mann-Kendall statistic is calculated using the following equation:

$$S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} \operatorname{sign}(x_i - x_j)$$

where n = length of the data set,

x_i and x_j = generic sequential data values,

and the function $\operatorname{sign}(x_i - x_j)$ assumes the following values:

$$\operatorname{sign}(x_i - x_j) = \begin{cases} 1, \text{ if } (x_i - x_j) > 0, \\ 0, \text{ if } (x_i - x_j) = 0, \\ -1, \text{ if } (x_i - x_j) < 0. \end{cases}$$

The S statistic thus shows the number of positive differences identified in the investigated time series minus the number of negative differences found. If there is no trend in the data and no link between the investigated variable and time, then each ordering of the data set is equally likely. The statistic S is essentially normally distributed under this hypothesis, with the mean E(S) and variance Var(S) as follows:

$$E(S) = 0$$

$$\operatorname{Var}(S) = \frac{1}{18}\left[n(n-1)(2n=5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right]$$

where n is the length of the times-series, t_p denotes the number of ties for the "pth " value, and q denotes the number of tied values, i.e., equals values. The second term suggests a correction for tied or filtered data. Z is the standardized test statistic.

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\operatorname{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \dfrac{S-1}{\sqrt{\operatorname{Var}(S)}} & \text{if } S < 0 \end{cases}$$

$$b = \text{ Median } \left[\frac{(X_j - X_i)}{(j - i)}\right], \text{ for all } i < j$$

where is the slope between data points X_j and X_i; measured at times j and i; respectively.

Spatial Analysis

A thorough spatial analysis has been carried out to assess the spatial. variability of the extreme indices using IDW (Inverse Distance Weighing) method using Arc RStudio code.

So, the summary if the entire methodology is –

1. **Data Collection>** From BMD (observed) and ESGF web portal (simulated)

2. **Data Post processing>** Statistical Downscaling and Bias correction using simple quantile mapping method ***SQM.***

3. **Extreme Index Calculation>** From the bias corrected daily Precipitation, Tmax and Tmin data, indices were calculated for historical (1975-2005) and future period (2010-2100) **using *RClimdex.***

4. **MME>** Multimodel Ensemble mean by using ***BMA*** from the calculated indices.

5. **Assessment of Future changes**> Using the MME, future trends are quantified .

Chapter 4: Results

This chapter analyzes the overall outputs and the results of the thesis. At first the CMIP5 models are validated against the observed datasets and the GCM reproducibility are assessed. In this study with the help of spatial mapping change in climate indices will be shown.At first we will determine which model/averaging technique is more suitable for climate forecasting. Taylor diagram & MAD, MSE, RMSE, MAPE values of a climate indices can give approxmaty accurate decision. We will do Arithmetic averaging(AM) & Baysian model averaging (BMA) of 8 GCM models. For example we are taking the historical data set of 8 GCM models of Rajshahi containing the precipitation data (Table 4). Baysian model average & Arithmetic Mean is determined & given in the Table 4.

Table 4 GCM models and Arithmetic mean & Baysian model Average (BMA) data of Rajshahi PRCPTOT (1976-2005)

year	CanESM2	CNRM-CM5	Inmcm4	MIROC5	MPI-ESM-LR	MPI-ESM-MR	MRI-CGCM3	NorESM1	Observed	Arithmetic Mean	BMA
1976	2252.577	1591.296	1678.091	936.4738	485.4695	1730.659	1212.723	1115.755	1441	1375.381	1485.122
1977	1564.766	2097.438	3665.296	1903.504	1350.027	1055.521	1688.573	1277.768	1946	1825.362	1608.083
1978	1949.711	1315.232	2359.771	2436.506	1866.166	1770.555	2441.26	1496.042	1765	1954.405	1539.331
1979	1260.332	1213.658	1457.421	1426.915	1352.473	2554.998	1235.665	1751.874	1631	1531.667	1552.398
1980	1702.803	1644.426	1738.502	1282.996	1785.014	1485.551	1415.854	1625.046	1581	1585.024	1554.122
1981	1131.532	1862.716	1467.378	539.8297	1469.741	1215.366	1724.82	2339.111	2217	1468.812	1595.615
1982	2126.578	1499.386	1091.434	1256.419	1292.016	1603.414	1658.886	1506.132	1083	1504.283	1494.791
1983	1477.211	1622.705	2343.849	1684.759	2214.692	1166.175	1066.243	1350.769	1712	1615.8	1590.399
1984	1372.782	1958.147	1208.945	851.2859	3085.258	1245.94	768.6661	1070.193	1604	1445.152	1593.334
1985	1701.833	1678.504	1533.017	1414.571	1558.66	2068.073	1133.236	1667.623	1309	1594.44	1539.194
1986	1184.265	1808.812	672.3516	1270.097	941.6997	1438.849	1880.528	1506.04	1557	1337.83	1543.983
1987	1505.531	1343.366	1547.057	1184.448	2214.43	1571.368	1616.353	1413.905	1472	1549.557	1565.071
1988	1034.351	1360.857	1732.787	1405.595	1825.939	2556.452	1252.194	921.5112	1580	1511.211	1579.842
1989	1947.491	1125.613	1237.615	1964.117	742.5423	1599.868	1566.391	1267.202	1299	1431.355	1485.68
1990	1577.153	1290.269	1292.903	2014.605	1597.448	1166.48	1712.1	1494.8	1801	1518.22	1536.526
1991	1938.454	2192.816	1192.167	3017.595	1703.115	1157.608	964.3892	1279.298	1538	1680.68	1514.378
1992	1089.804	1660.873	2118.71	1974.744	702.4146	1630.244	1775.784	1775.875	887	1591.056	1577.192
1993	1870.055	1372.906	1548.224	1139.246	1337.709	1788.519	1631.719	1071.096	1620	1469.934	1519.147
1994	1541.415	1684.478	1513.677	1463.168	1799.247	1701.072	1246.826	1398.561	1134	1543.556	1554.392
1995	2017.427	1417.473	1638.361	2034.988	1162.79	1063.076	1535.833	1885.467	1395	1594.427	1513.453
1996	1329.248	954.0311	851.3539	1579.151	1983.652	1336.233	1677.238	2281.965	1252	1499.109	1553.221
1997	1137.207	1379.178	1831.756	1622.609	1583.448	1331.746	1444.01	1536.074	1997	1483.253	1583.447
1998	1985.878	1871.875	2110.16	1167.297	1044.329	2333.689	1546.452	2210.8	1506	1783.81	1533.27
1999	957.9745	1462.5	2269.551	1301.862	1703.599	2162.228	1007.419	2195.726	1841	1632.607	1612.824
2000	1310.062	1502.392	694.7576	1478.896	1507.046	1144.444	2779.631	1243.909	1737	1457.642	1542.371
2001	1460.606	1853.02	1349.725	1314.798	1732.359	701.6232	1519.257	872.0564	1404	1350.431	1560.579
2002	1696.56	1140.064	1630.229	1578.65	1586.809	1790.302	1515.465	1526.698	1507	1558.097	1534.697
2003	1204.152	1403.124	923.4159	1545.948	1250.021	1281.291	1860.715	1522.164	1445	1373.854	1548.98
2004	1358.846	1340.346	668.0548	1635.538	1424.544	1708.171	792.7462	1813.837	1822	1342.76	1532.467
2005	1489.733	1417.971	710.0076	1604.181	1847.789	792.7633	2246.658	1729.414	1403	1479.815	1542.094

Data Validation

For model validation we can take any datasets. We have taken the precipitation dataset of Rajshahi weather station in base period of 1976-2005.In Table 5 MAD is lowest for CanESM2 model & BMA. Arithmetic Mean is close to Baysian Model Average (BMA). But BMA is better here. Mean absolute deviation (MAD) is very high for MIROC5, Inm-CM4, MPI-ESM-LR, MPI-ESM-MR.

Table 5 GCM models & averaging technique evaluation for Rajshahi -PRCPTOT

Model Name	MAPE	RMSE	MSE	MAD
CanESM2	13.82	263.359	250102.94	196.716
CNRM-CM5	21.9596	373.22286	139295.299	319.9187
Inmcm4	30.6	617.303	381063	467.75
MIROC5	28.15	573.927	329392.3	419.616
MPI-ESM-LR	27.89	515.98	266233.64	421.262
MPI-ESM-MR	31.27	554.336	307288.433	469.169
MRI-CGCM3	27.99	521.867	272345.437	421.145
NorESM1	25.15	444.122	197244.633	359.673
Arithmetic Mean	15.7	293.822	86331.601	227.79
BMA	13.82	263.359	69358.161	196.716

Mean squred error (MSE) is lowest for BMA & highest for MPI-ESM-MR & INM-CM4. Table 6 showing a good RMSE value for CanESM2 & BMA. It's also same for MAPE. Overall it can be said that Baysian Model Average (BMA) has the lowest deviation (error) from observed dataset. So taking BMA rather than any single model is the best option for future climate modelling .

Taylor Diagram

Another approach to data validation is Taylor diagram. It will validate which model/ method is best for future climate indices. Taylor's diagram gives a graphical representation. Here PRCPTOT of Rajshahi for the historical period of (1975-2005) is used to draw the Taylor Diagram. From the Taylor diagram, we see that the standard deviation value for BMA is very close to zero. The correlation coefficient is high; nearly 90%. The centered RMSE value is 0.95, which is close to 1.0. So overall from the diagram we see that Bayesian Model Averaging (BMA) is giving us more reliable weather forecasting. Observed data is compared with each model & Arithmetic Mean (AM) data.

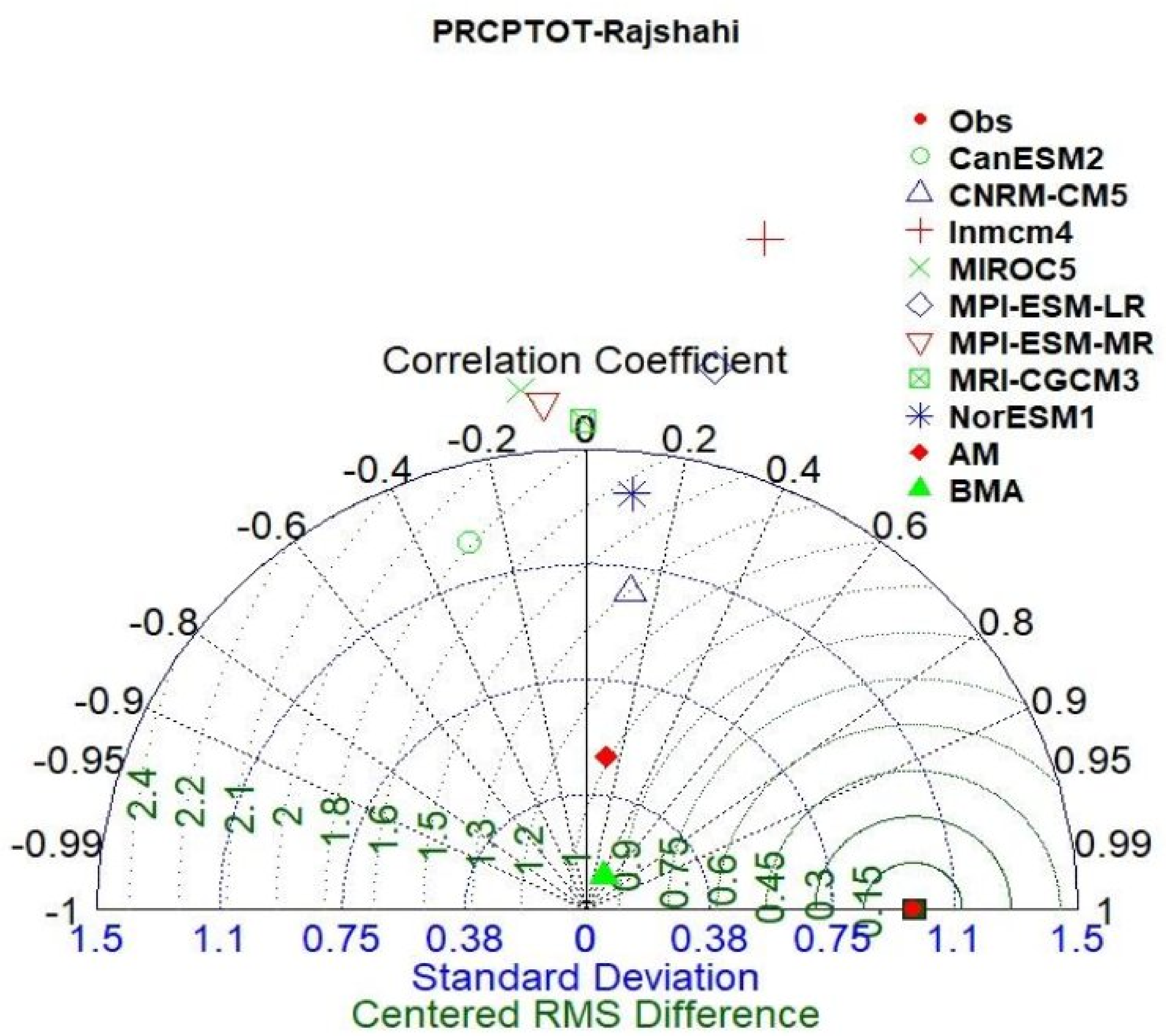

Figure 3 Taylor Diagram for PRCPTOT in Rajshahi (1975-2005)

Comparing each model, we see that BMA is more sophisticated. Related datasets are given in the Appendix section. Comparing each model, we see that BMA is more sophisticated. Related datasets are given in the Appendix section. Here in the next section Baysian model averaging (BMA) is used to generate one single data from 8 model data. So BMA has made our calculation more easier. Bayesian model averaging (BMA) is used as MME technique. It's now very easy for projection the change in extreme indices.

Future Trend analysis

Future Trend analysis is done by modified Man-Kendell Test. Table 6 is added in this section showing the trends are increasing or decreasing with respect to time series & level of significance.

CDD: With high emission scenario, CDD trend of Ishwardi in near future is changing very significantly. From the Sen's slope, the consecutive Dry day increasing trend is 0.34days/decade. Also for high emission scenario RCP 8.5, CDD is decreasing significantly for Rajshahi & Rangpur in near future & far future respectively. No significant trend in other cases as p-value is greater than 0.05.

CWD: Table 6 is showing trend for CWD. P-value is significant in Rangpur at the end of 21^{st} century with high emission scenario. Consecutive wet days are decreasing by 0.35days/decade. For other weather stations, the CWD change is insignificant.

R99p : From **Table 6** in far future with moderate emission scenario, Rangpur will have significantly increasing trend of R99p. Extremely wet days (R99p) will increase by 12.7days/decade. Other stations have insignificant trend for both emission scenario.

PRCPTOT: In future overall in all stations precipitation will be increased is depicted in Table 6. In near future (20010-2054) with high emission scenario , Ishwardi & Rangpur will have increasing trend of 12.5mm/decade & 5.2mm/ decade respectively. In far future with high emission scenario (RCP 8.5) Dinajpur, Ran gpur will face an increasing trend of rainfall; 4mm/decade & 6mm/decade respectively.Increase in rainfall in other stations.Only for Rajshahi in near future with moderate emission scenario (RCP 4.5) rainfall is decreasing significantly.

R10mm:Table 6 shows increasing trend in Bagura by 0.01days/yr & decreasing trend in Rajshahi by 2.513days/decade in near future with high emission scenario. For confidence level 0.05 other changes are in insignificant.

R20mm: In near future Extremely heavy precipitation days are increasing in Ishwardi & decreasing in Rajshahi for high emission scenario (RCP 4.5).In far future in Rangpur R20mm will be increased by 1.07days/decade.

RX1day: RX1day is decreasing in most of the cases accroding to Table 6. In Rangpur with moderate emission scenario RX1day increases significantly by 1.28144mm/decade. RX1day will be decreased by 1.328mm/decade significantly in near future with moderate emission (RCP 4.5) scenario.

RX5day: Highest five days precipitation amount (**RX5day**) is decreasing. But for moderate emission condition in far future the trend in Ishwardi decreases by 1.244mm/decade & in Rangpur trend slope is 16.55mm/decade. In near future with high emission scenario, Rajshahi will have decreasing trend of highest five days precipitation (RX5day) amount 2.5135mm/decade.

Table 6 Sen's slope & significance level of precipitation related indices

		CDD (days/decade)		**CWD (days/decade)**		**R99p**		**PRCPTOT**	
		Near future (2010-2054)	**Far Future (2055-2099)**	**Near future (2010-2054)**	**Far Future (2055-2099)**	**Near future (2010-2054)**	**Far Future (2055-2099)**	**Near future (2010-2054)**	**Far Future (2055-2099)**
Bogura	RCP 4.5	-0.0178	-0.05566	0.30668	0.46	-4.738	1.90842	-1.4836	6.3743
	RCP 8.5	0.03466	-0.00407	-0.834	0.30474	1.0148	-0.77	-1.6691	-0.64
Dinajpur	RCP 4.5	-0.2362	-0.25415	1.87	4.9044	-6.9621	-4.6735	5.2403	16.82
	RCP 8.5	0.5392	-0.24	0.727	6.613	5.7103	3.5405	9.9024	**30.798**
Ishwardi	RCP 4.5	0.033	0.02575	-0.0071	-0.0921	0.53035	2.176266	1.608	6.359
	RCP 8.5	**0.34**	0.1471	-0.0122	0.01585	2.58245	-0.18765	**12.447**	4.286
Rajshahi	RCP 4.5	-1.426	-0.2915	-0.0072	-0.0389	3.66269	-9.2296	**-8.131**	-2.3157
	RCP 8.5	**-2.5135**	-1.3252	-0.0265	-0.027	9.00731	-2.419	0.11003	**-10.18**

Rangpur	RCP 4.5	0.09226	0.340	-0.0657	-0.2905	-6.633	**12.7471**	6.8685	46.8055
	RCP 8.5	0.63106	**1.06764**	-0.0481	**-0.35**	1.5885	4.53393	**51.83**	**59.9123**
		R10mm		**R20mm**		**RX1day**		**RX5day**	
		Near future	**Far Future**	**Near future**	**Far Future**	**Near future**	**Far Future**	**Near future**	**Far Future**
Bogura	RCP 4.5	-0.1176	-0.0777	-0.0178	-0.0557	-1.4222	0.11343	-0.4473	0.38553
	RCP 8.5	**0.09765**	0.011	0.03466	-0.0041	0.34143	0.92617	-0.27367	-0.3188
Dinajpur	RCP 4.5	-0.244	-0.3637	-0.2362	-0.2542	-2.1316	2.1346	3.120715	0.5567
	RCP 8.5	0.03564	-0.1624	0.5392	-0.24	-0.7175	0.82987	-0.9116	3.21484
Ishwardi	RCP 4.5	0.05574	0.1385	0.033	0.02575	-0.2846	-0.34304	-0.21406	**-1.244**
	RCP 8.5	0.0936	0.0774	**0.33935**	0.1471	-0.3446	-0.2853	0.25604	-2.083
Rajshahi	RCP 4.5	-1.426	-0.2915	-1.426	-0.29146	**-1.32814**	-0.55152	-1.42603	-0.2915
	RCP 8.5	**-2.5135**	-1.3252	**-2.5135**	-1.3252	-0.83026	-0.21836	**-2.5135**	-1.3252
Rangpur	RCP 4.5	0.5409	1.68622	0.09226	0.34	-0.4209	**1.281443**	3.46721	**16.54744**
	RCP 8.5	0.55673	1.21845	0.63106	**1.0677**	-0.0482	0.3576	8.543325	7.83619

***Bold numbers are showing that trends are significant**

Spatial change of extreme Indices

Spatial map of climate indices are derived with the help of observed data & BMA data of future projection.The data tables are added in the appendix section. From IDW mapping & table, future changes of extreme indices are discussed below

CDD: Here in this section we will show the changes through spatial map. 5 weather station data is considered for mapping. 5 stations are Bagura, Dinajpur, Ishwardi, Rangpur, Rajshahi. Both in near & far future for RCP 4.5 CDD increases by average 9.5 days. But in far future for RCP4.5 scenario, CDD is decreasing in Bagura, Rajshahi, Rangpur.

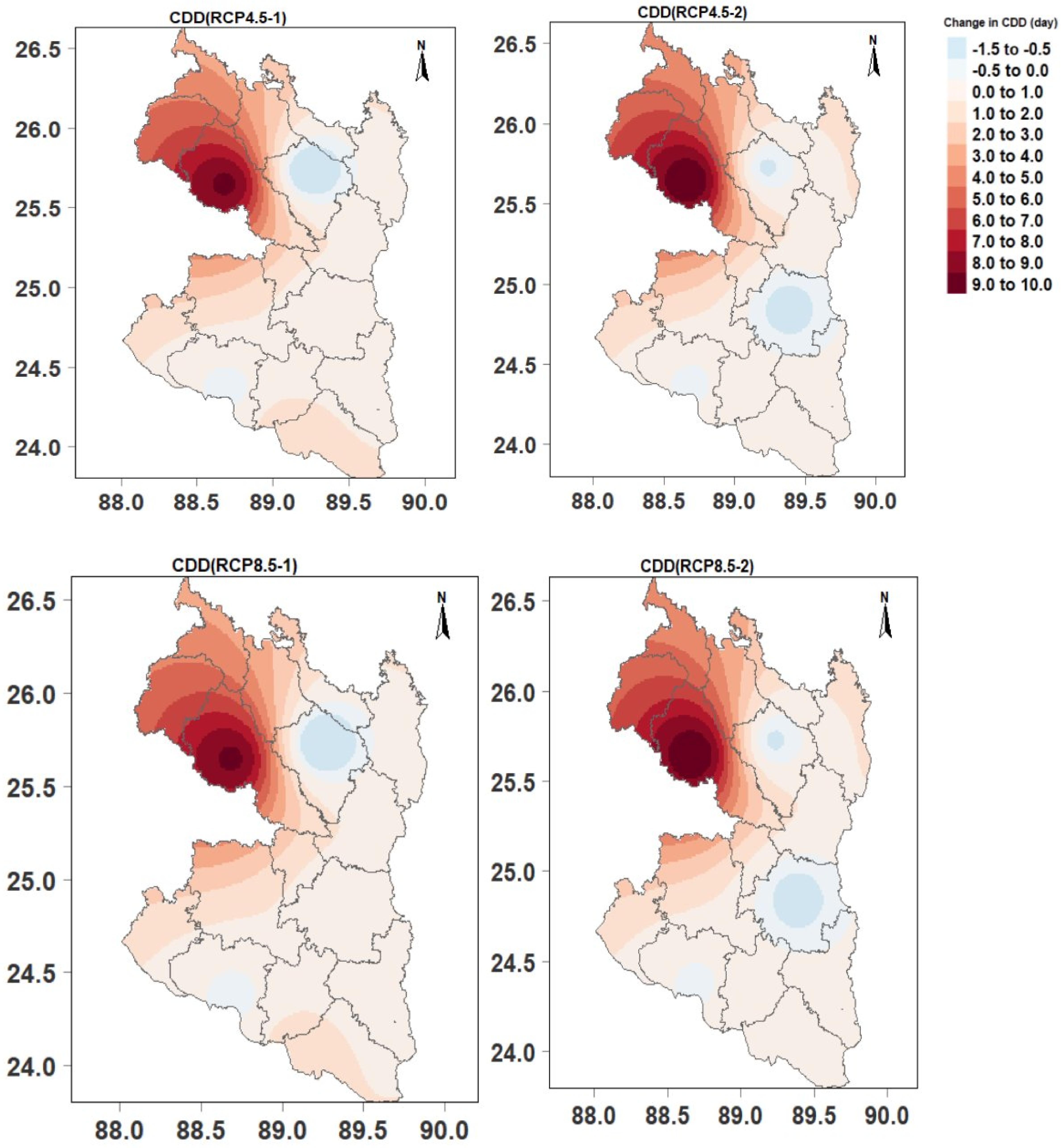

Figure 4 Spatial Change in CDD

In Figure 4, RCP 8.5 emission scenarios, CDD is increasing significantly. Consecutive day is decreasing in Bagura, Rajshahi, Rangpur in a very insignificant for both near & far future.

CWD: Figure 5 shows that for all cases of CWD, wet days are decreasing. For RCP4.5, CWD is decreasing very significantly in Dinajpur. But for high emission scenario (RCP8.5), Dinajpur will have slightly decreased CWD. The decreasing rate in near future & far future is 8 & 14.4 days/year respectively. For RCP 8.5 scenarios, Ishwardi station shows almost constant CWD. But for other **stations the CWD is decreasing slightly.**

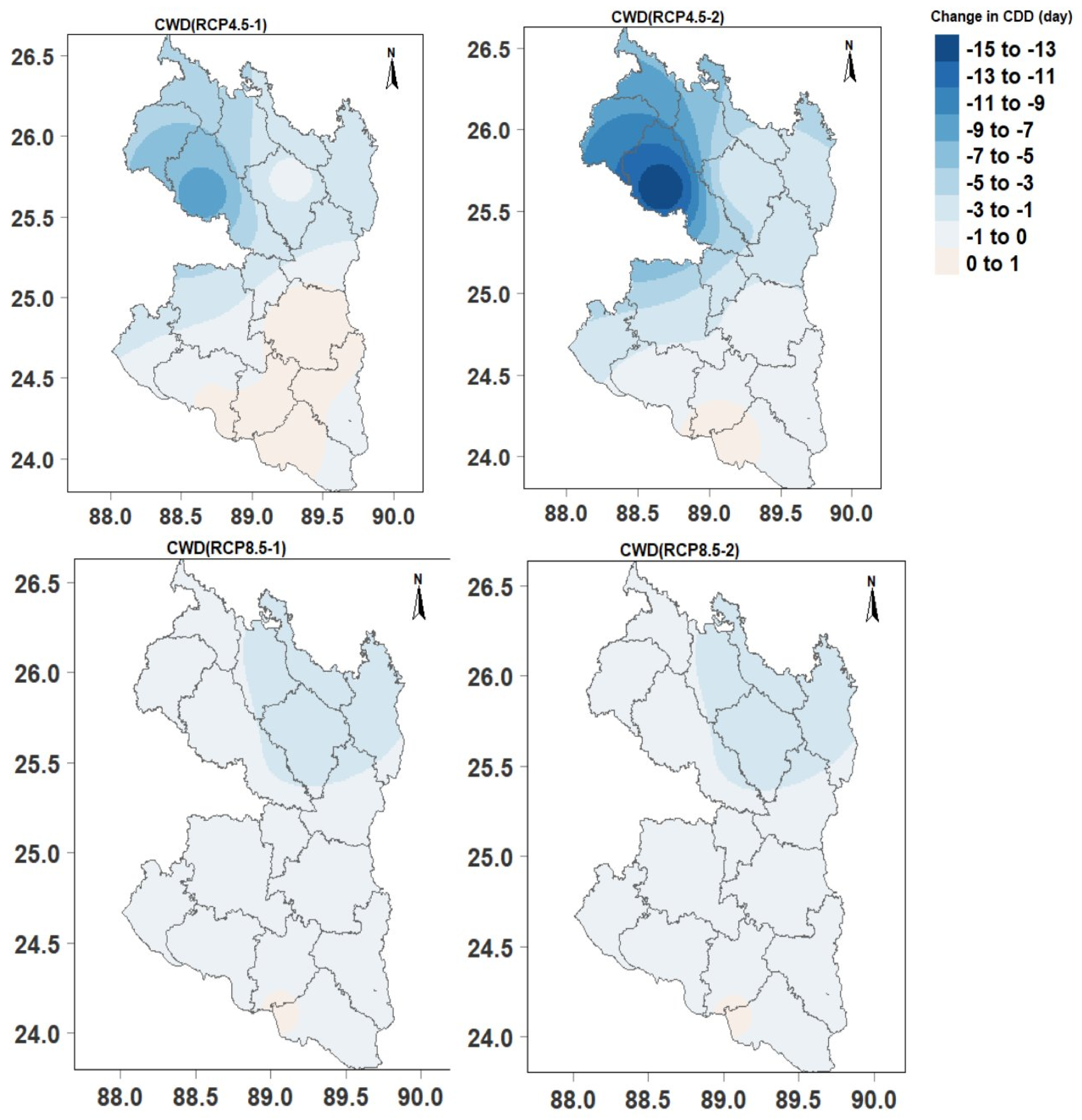

Figure 5: Spatial Change in CWD

PRCPTOT: The total annual precipitation tended to increase gradually in the future periods under all the RCP scenarios; however, the changes are more pronounced at the end of the century according to Figure 6. Rangpur will have highest precipitation. For extreme emission scenario RCP 8.5, total precipitation will be increased by 11.5% in far future & 4.43% in near future. In near future, for both emission scenario precipitation is decreasing in Ishwardi & Bogura; but it’s very insignificantly.

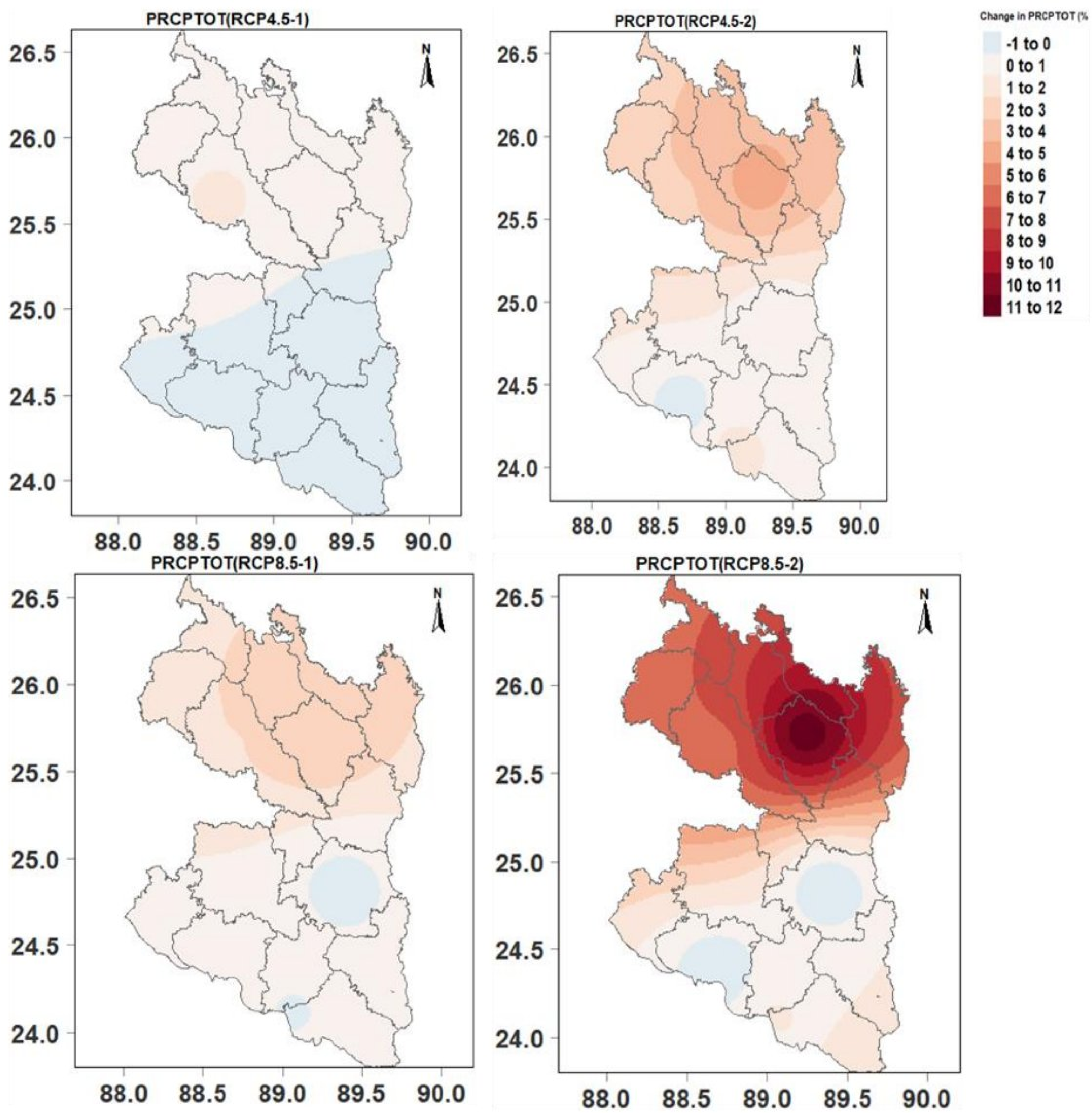

Figure 6 Spatial Change in PRCPTOT

R10mm :R10mm is decreasing for each emission scenario of case RCP 4.5 & RCP8.5 in Bogura & Dinajpur. Rajshahi weather station has insignificant change .Rangpur will face highest increase in R10mm ; In far future R10mm increased by 5.8% & 11.42% respectively for both RCP 4.5 & RCP 8.5 scenarios. Figure 7 shows that for RCP 8.5, R10mm is very high for Rangpur.

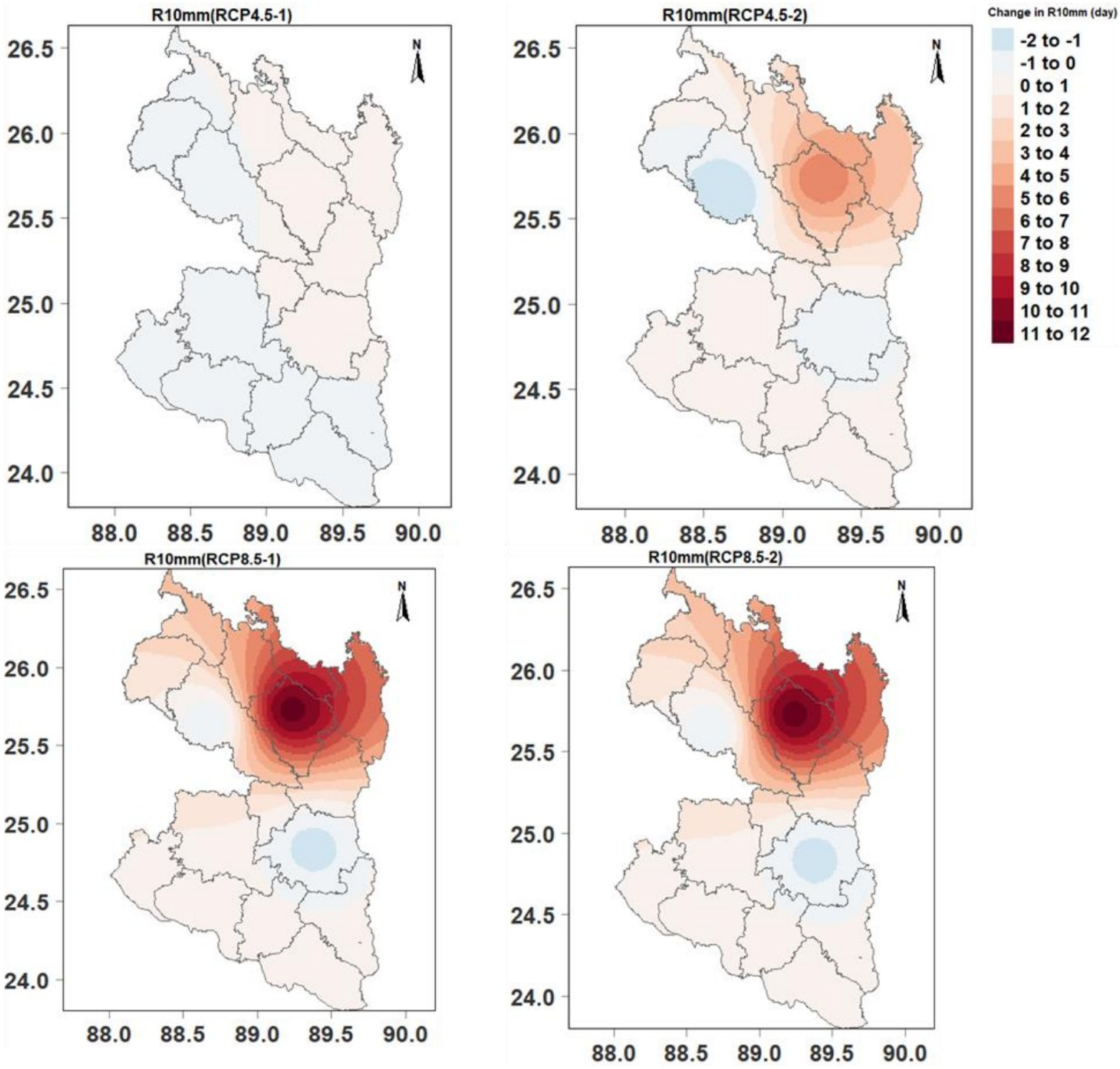

Figure 7 Spatial Change in R10mm

R20mm: Figure 8 showing showing that Rajshahi station will face highest change in heavy rainfall (R20mm) events. Heavy rainfall days will be increased by approx. 18.5days in near future & far future for both RCP 4.5 & RCP 8.5 emission scenarios.

For both scenario, Iswardi station showing that in near future heavy rainfall (R20mm) will be decresed & in far future R20mm will be sightly incresed.

In near future, Rangpur will face .56 & 1.31days & in far future, 1.68 & 5.46 days of increase in heavy rainfall days respectively with RCP 4.5 & RCP8.5.

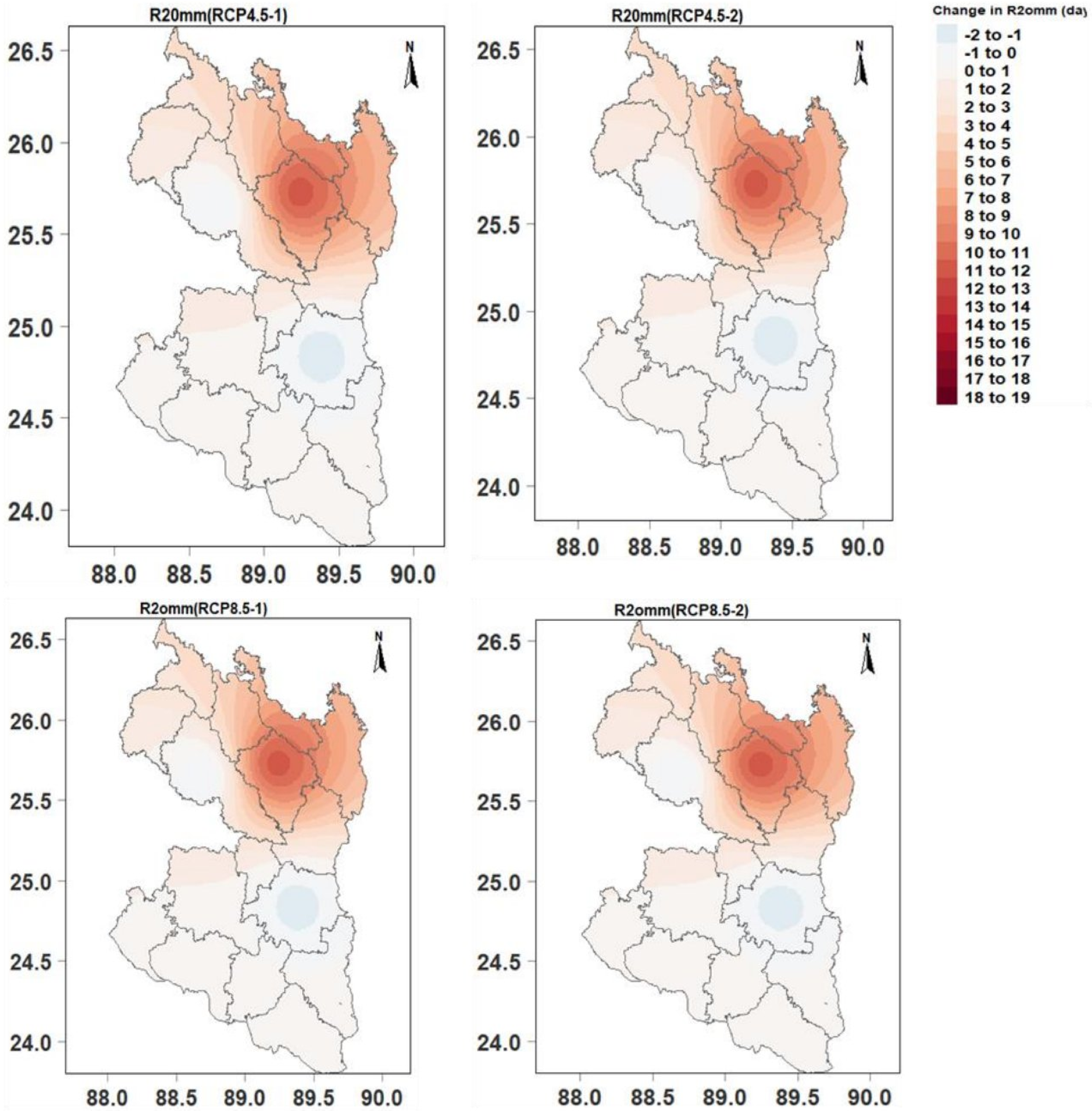

Figure 8 Spatial Change in R20mm

R99p: Figure 9 represents Extremely wet day rainfall (R99p) will be increased by 29.5% in Rajshahi & decreased by 4.4% in Rangpur for high emission scenario (RCP8.5) in far future. The result for Bogura is quite unpredictable here. For emission scenario RCP 4.5 R99p is increasing 0.18% near future & 6.5% in far future compared to historical period. But for high emission scenario (RCP8.5), R99p increasing rate is completely reverse; 8.81% to 1.96%.

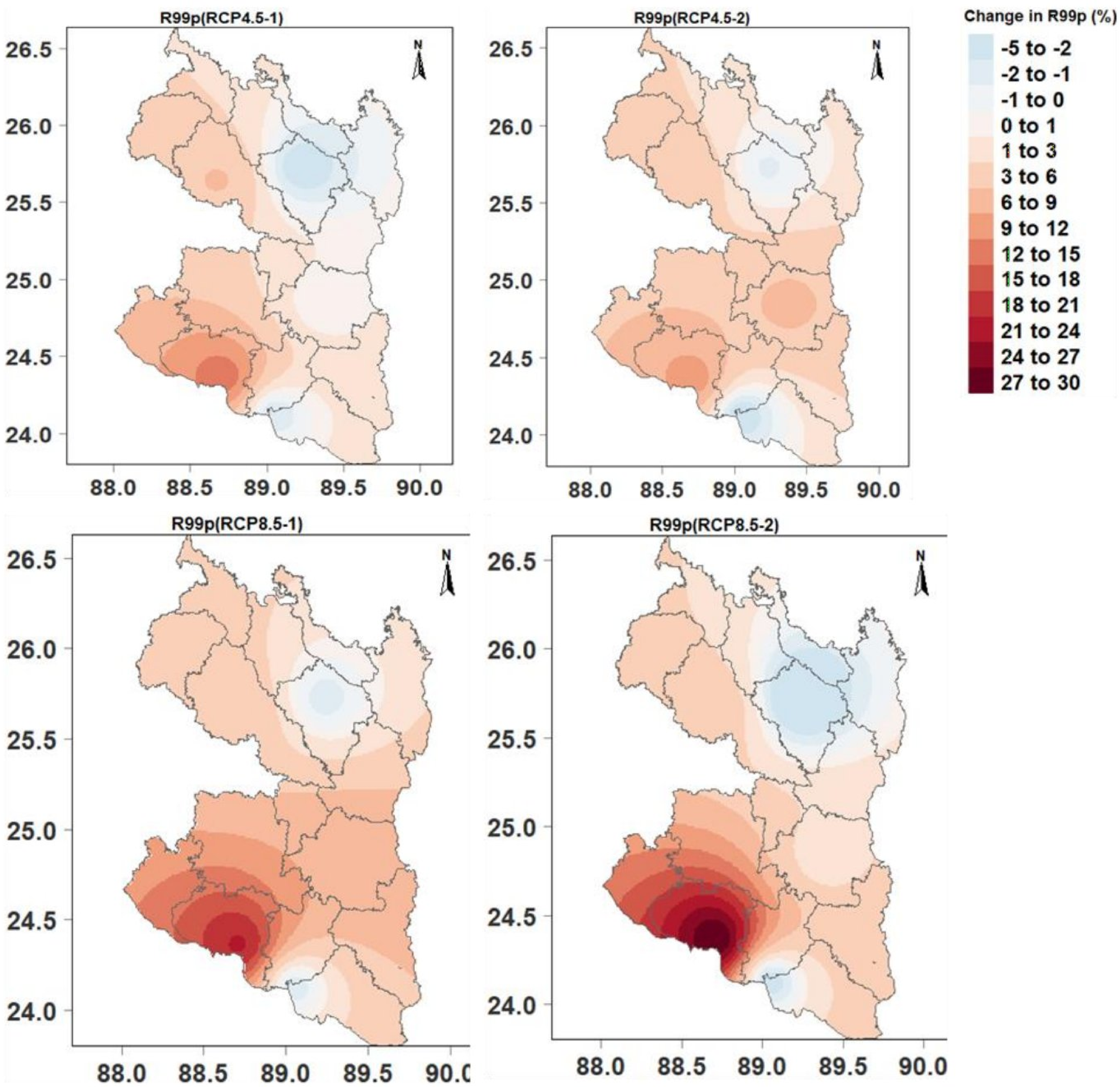

Figure 9 Spatial Change in R99p

RX1day: Spatial map in Figure 10 shows that with RCP 4.5, Maximum 1 day precipitation (RX1day) decreses by 0.5mm to 2mm in Ishwardi, Rajshahi, Rangpur station in future. For the same stations with maximum emission scenario (RCP8.5), RX1day is slightly decresing more compared to RCP4.5. Dinajpur has more incresing result than other weather stations .

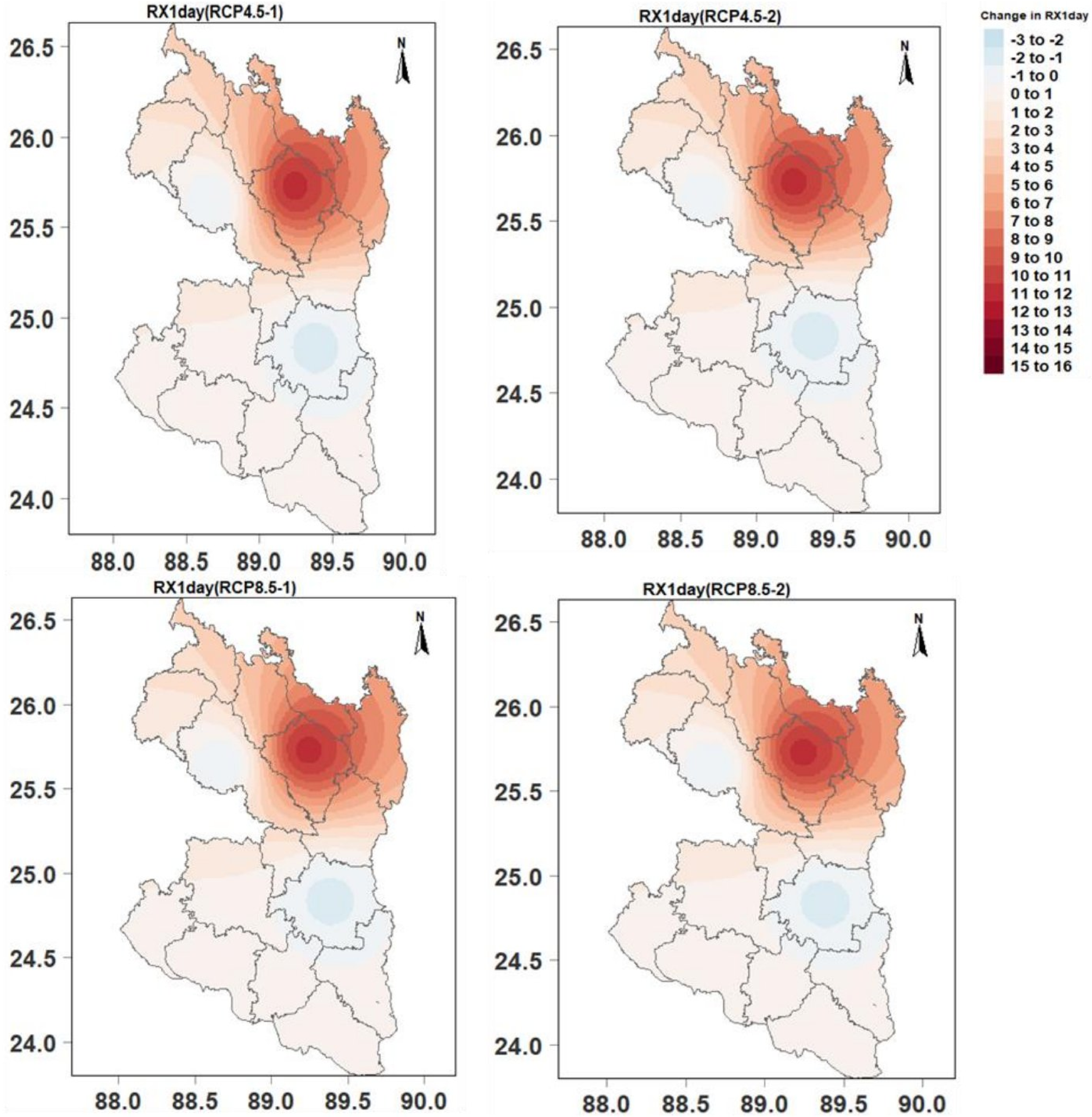

Figure 10:Spatial Change in RX1day

With Moderate emission scenario RX1day will be increased by 10.26mm &15.535mm respectively in near future & far future. For high emission scenario increasing rate is 12.7mm & 13.08mm respectively.

RX5day: Monthly maximum consecutive 5-day precipitation (Rx5day) change will be highest in far future. Figure 11 shows RX5day change will be highest in each case compared to baseline period in Dinajpur station. Monthly maximum consecutive 5-day precipitation will be increased by 26mm &31.9mm respectively compared to baseline period in RCP4.5. In RCP8.5, RX5day increases by 22.89mm &33.3mm respectively. The figure also shows that RX5day will be decreased in future in Ishwardi & Rajshahi.

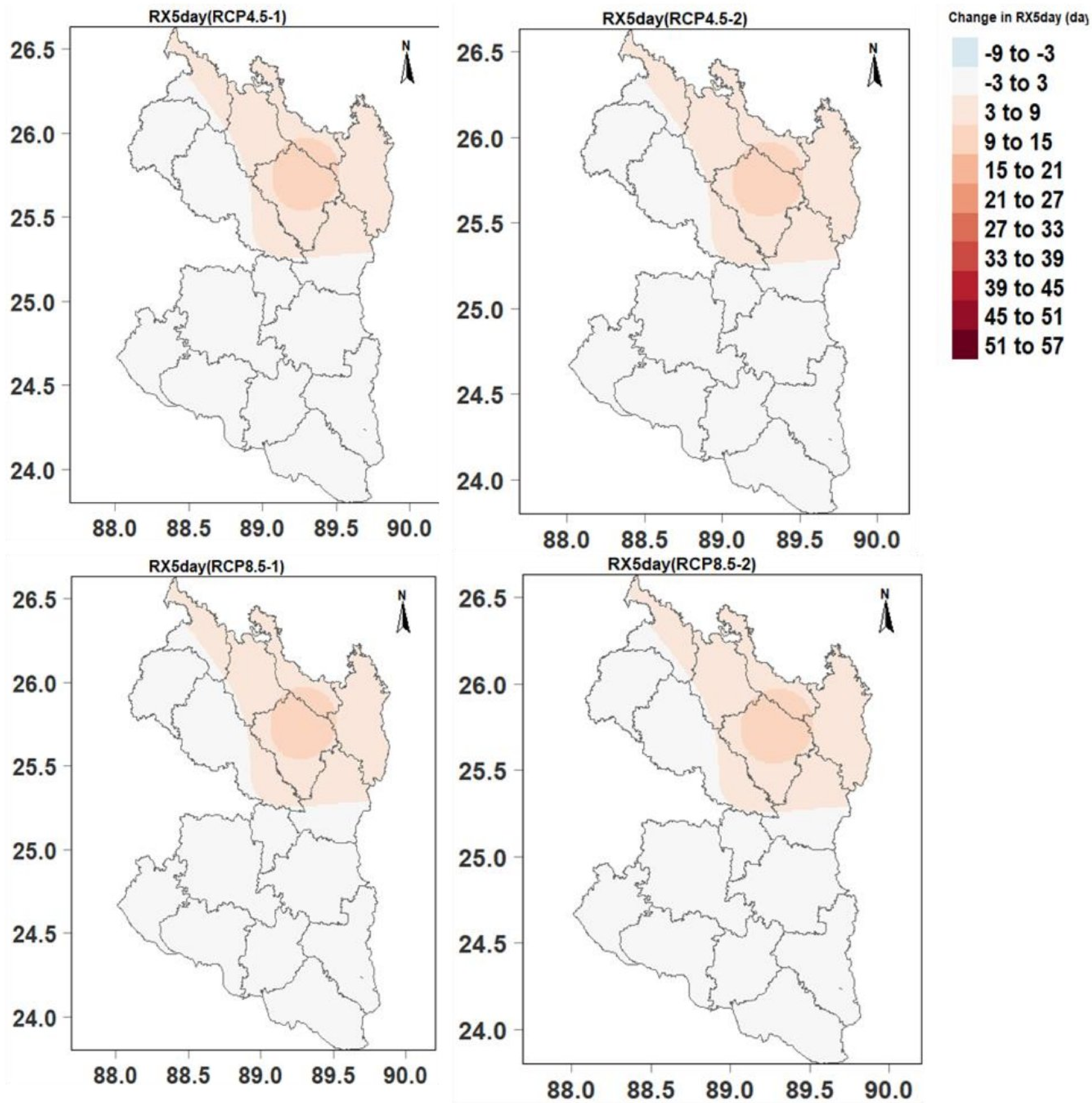

Figure 11 : Spatial Change in RX5day

Chapter 5: Discussion and Conclusion

Major Findings

This study investigates the changes in temperature and precipitation extremes over Bangladesh from the period 2010-2099 as well as their future trends and spatial variability considering 1975-2005 as the baseline period using 8 CMIP5 models. The findings give the most recent information on Bangladesh's climate response to various emission scenarios in the twenty-first century. The key findings are stated below:

I. The CMIP5 Bayesian model average (BMA) showed high climate responses under different radiative forcing levels. Results suggest that the indices tend to increase at a higher magnitude under the higher emission scenarios like RCP4.5 & RCP 8.5. However, the change is robust at the end of the century.

II. The total precipitation amount PRCPTOT will likely to increase in the upcoming days of twenty-first century. Along with the total amount, the maximum 1day precipitation amount will likely to decrease in upcoming days. Likewise, the duration index, R20mm or heavy precipitation days (precipitation days with >20 mm rainfall) showed an increase with higher magnitudes than the baseline period in Rajshahi & Rangpur. For other stations heavy precipitation days are decreasing.

III. In contrary to these rainfall indices, the Consecutive Dry Days or CDD showed a decreasing trend in the lower emission scenarios, indicating a decrease of dry spells in future periods. CDD is expected to decrease in Bagura, Rajshahi, Rangpur at the end of the century. Dinajpur & Ishwardi may have increasing CDD. The study uses CMIP data to project future changes of precipitation and drought characteristics in Bangladesh and reveals that the due to the spatial change in drought characteristics and precipitation, the central and north-western regions might also be vulnerable to drought.

IV. The northwestern parts of the country exhibited higher increase in rainfall indices than the past in terms of precipitation amount, intensity and duration. The highest change in terms of Maximum 1day observed (RX1day) change was found in Dinajpur. Ishwardi, Rajshahi, Rangpur had decreasing change compared to baseline period.

Consequences of Climate Extremes and Recommendations

Several researchers have discovered that current rapid global warming-induced changes in atmospheric circulation patterns, moisture supply & water vapor content have inclined to ramp up precipitation extremes in tropical regions, affecting water management, agriculture & natural ecosystems in less-developed countries.(Allen and Ingram 2002, Zhai et al 2005,Sillmann et al 2017, Chen and Sun 2018). Bangladesh is one of the world's most susceptible countries to climate change. Bangladesh's northeastern and northern districts are subject to flash floods (Mirza and Ahmed, 2005). Rising annual rainfall, intensity, and duration in north and northwest Bangladesh may lead to more flash floods in the region. Local runoff accumulates in depressions as a result of heavy pre-monsoon rainfall.

Agriculture is crucial to Bangladesh's economy, which is strongly dependent on rainfall. Higher annual and pre-monsoon rainfalls, as well as a reduction in the number of dry days, may contribute to improving soil moisture content and agricultural production in various regions of Bangladesh. Increased rainfall and wet days during the pre-monsoon irrigation period in Bangladesh might also lessen the demand on groundwater. Increased heavy rainfall incidents, on the other hand, during the rice harvesting season, might cause crop field flooding and significant losses. Runoff from increasing heavy precipitation occurrences may cause river water levels to rise and flash floods to occur. Water logging is often a problem in metropolitan areas. Furthermore, Due to the rapid rising of temperature and GHG emission, the urban temperature is increasing which is responsible for the surface urban heat island (SUHI). An increasing trend in urban hit islands is seen in the megacities of Bangladesh recently Dewan, et, al, 2021).

Additionally, due to fast temperature goes up and GHG emissions, urban temperatures are rising, contributing to the surface urban heat island (SUHI). Bangladesh's megacities are facing a growing trend in urban hit islands in recent time (Dewan et al, 2021).

Conclusion

The findings of eight bias-corrected GCMs from the CMIP5 were used to project future changes in temperature and precipitation extremes in Bangladesh over the twenty-first century. Despite being the world's seventh most vulnerable country to climate change, the study's findings seem frightening. The quick rise in severe temperatures and precipitation might worsen future scenarios. Based on our CMIP5 results, we highlight the need of limiting global warming in order to alleviate climatic extremes at the regional level.

The study's conclusions have significant consequences for Bangladesh. During the period 1998-2014, Bangladesh is projected to have lost $3 billion owing to catastrophic occurrences such as floods and droughts (Kamruzzaman et al., 2019). As a result, spatiotemporal analysis of severe climate indices produced from CMIP5 datasets may be highly beneficial in identifying meteorologically sensitive parts of Bangladesh in the future days. The findings can assist policymakers in developing robust mitigation measures to combat climate extremes in Bangladesh in the twenty-first century.

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Appendix

Procedure for determining Observed Climate indices from RClimdex:

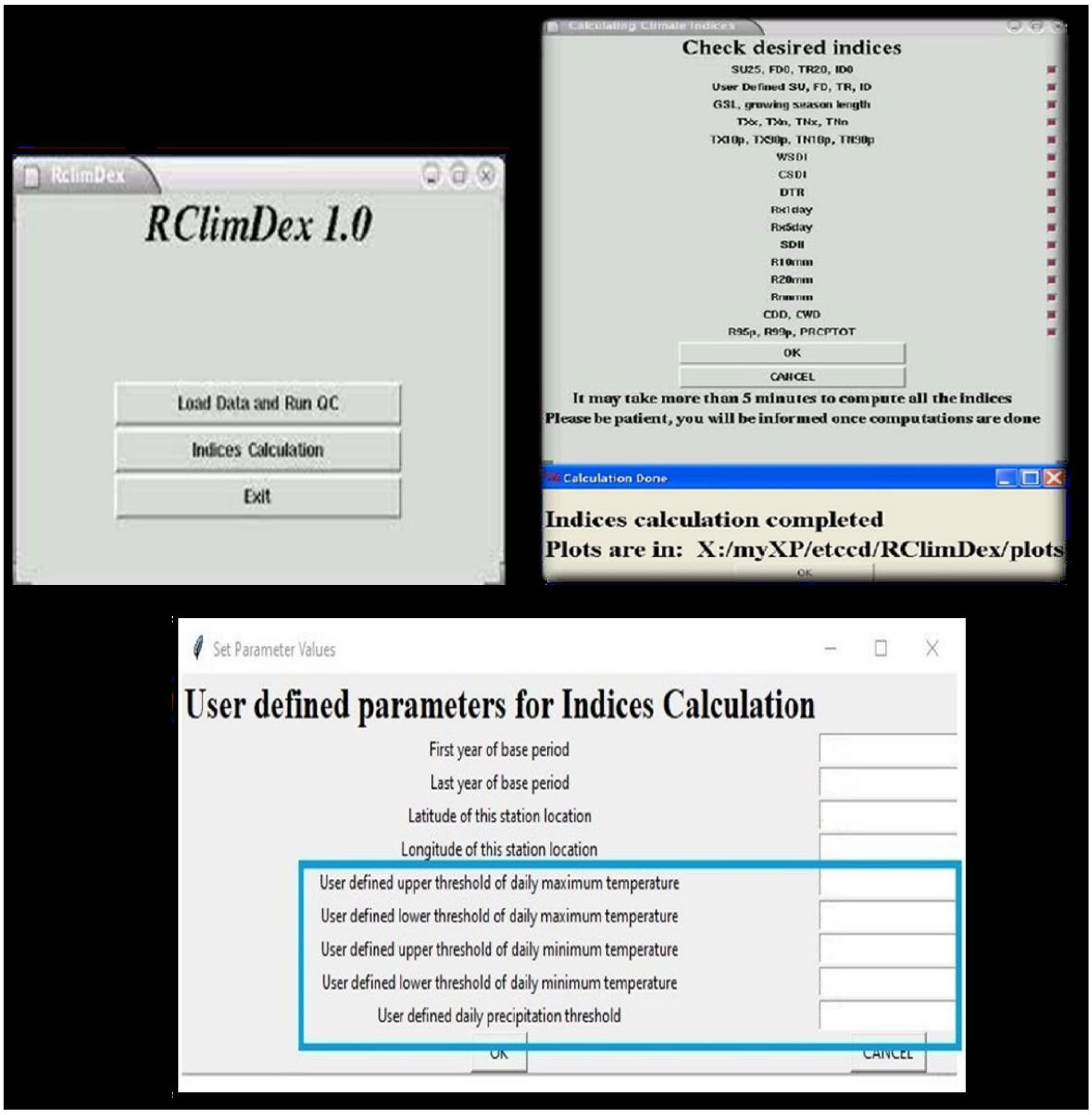

Table 7: Model & Observed precipitation data of Rajshahi (1975-2005)

Sample code for modified MK test

```
#R10mm

#RCP4.5_01

        setwd("G:/1.Split Data/Ishwardi")

        library(modifiedmk)

        df<-read.csv("Ishwardi_R10MM_rcp45_BC_01.csv", header = T)

         for( i in 2:ncol(df)) {

          if(i==2) tres<-mmkh(df[,i])

          if(i>2) tres<-rbind(tres,mmkh(df[,i]))

        }

       row.names(tres)<-c("CanESM2","CNRM-CM5","Inmcm4","MIROC5","MPI-
ESM-LR","MPI-ESM-MR","MRI-CGCM3","NorESM1")

   setwd("G:/MK Trend")

  write.csv(tres,"Ishwardi_R10MM_rcp45_BC_01trend.csv")


#RCP 4.5_02

setwd("G:/1.Split Data/Ishwardi")

library(modifiedmk)

df<-read.csv("Ishwardi_R10MM_rcp45_BC_02.csv", header = T)

        for( i in 2:ncol(df)) {

          if(i==2) tres<-mmkh(df[,i])

          if(i>2) tres<-rbind(tres,mmkh(df[,i]))

        }
```

```
row.names(tres)<-c("CanESM2","CNRM-CM5","Inmcm4","MIROC5","MPI-ESM-LR","MPI-ESM-MR","MRI-CGCM3","NorESM1")

setwd("G:/MK Trend")

write.csv(tres,"Ishwardi_R10MM_rcp45_BC_02trend.csv")
```

Sample Code for Baysian Model Averaging (BMA)

```
#R10mm

library(BMS)

setwd("G:/1.Split Data for ensamble/Bogra")

dat<-read.csv("Bogra_R10MM_historical_BC.csv")

pdat<-read.csv("Bogra_R10MM_rcp85_BC_01.csv")


bmod = bms(dat, burn = 50000, iter = 1e+05, g = "BRIC",

        mprior = "uniform", nmodel = 2000, mcmc = "bd", user.int = F)


plot(bmod)

hist<-predict(bmod)

hisR<-cbind(dat[,2],hist)

colnames(hisR)<-c("Observed","Ensemble")

proj<-predict(bmod,newdata=data.frame(pdat))

setwd("G:/BMA output")

#write.csv(hisR,"BMA_Bogra_R10mm_historical.csv")

write.csv(proj,"BMA_Bogra_R10mm_rcp85.csv")
```

library(gstat) # Use gstat's idw routine

library(sp)   # Used for the spsample function

Sample Code for IDW mapping

```
library(raster)

library(tmap)

library(rgdal)

library(viridis)

library(maptools)

library(ggplot2)

library(ggmap)

library(Rcpp)

library(xts)

library(rgeos)

library(spData) # example datasets

library(sf)     # spatial data classes


setwd("E:\\Abedin\\Map Input\\Map Input 3")

df=read.csv("CWD.csv",header = T)

df

#setup coordinate system

dsp <- SpatialPoints(df[,1:2], proj4string=CRS("+proj=longlat +datum=WGS84"))

# make dataframe

dsp <- SpatialPointsDataFrame(dsp, df)

# Import shape file
```

```
CA <- readOGR("North-waestern_region_shape/North-weastern_region.shp")

# Replace point boundary extent with that of BGD
dsp@bbox <- CA@bbox

# write a shapefile
#writeOGR(dsp, getwd(),"pointfile", driver="ESRI Shapefile")
# define groups for mapping
#cuts <- c(-3,-2,-1.5,-1,0)
# set up a palette of interpolated colors
#blues <- colorRampPalette(c('yellow', 'orange', 'blue', 'dark blue'))
#pols <- list("sp.polygons",CA, fill = "lightgray")
#spplot(dsp,'Feb.95', cuts=cuts, col.regions=blues(4), sp.layout=CA, pch=20, cex=2,
axes=T)

# Create an empty grid where n is the total number of cells
grd              <- as.data.frame(spsample(dsp,"regular", n=50000))
names(grd)       <- c("X", "Y")
coordinates(grd) <- c("X", "Y")
gridded(grd)     <- TRUE  # Create SpatialPixel object
fullgrid(grd)    <- TRUE  # Create SpatialGrid object

# Add dsp's projection information to the empty grid
proj4string(grd) <- proj4string(dsp)
```

```
# Interpolate the grid cells using a power value of 2 (idp=2)

dsp.idw <- gstat::idw(dsp$ChangeRCP8.5.1~ 1, dsp, newdata=grd, idp=2)


# Convert to raster object then clip to Texas

r      <- raster(dsp.idw)

r.m    <- mask(r, CA)

#plot(r.m)

tm1=tm_shape(r.m) +

  tm_raster(n=12,palette = "-RdBu", breaks = c(-1.5,-0.5,0,1,2,3,4,5,6,7,8,9,10),

        legend.is.portrait = T,title="Change in CDD (day)") + tm_shape(CA)+tm_borders() +

  tm_layout(

    main.title=c("CDD(RCP8.5-1)"),main.title.size=1,main.title.position=c("center"),

    asp =.8,fontface="bold",

    legend.title.size=1.5,

    legend.text.size =1.5,

    legend.only =F,

    legend.width =1.5,

    legend.outside=T,

    )

#tm1

tm2=tm1+tm_legend(show=F)

tm3=tm2+tm_grid(lines = FALSE,labels.size = 1.5)+ tm_compass(cardinal.directions = c("N", "E", "S", "W"),position=c("right", "top"))

tm3
```

```
#legend.outside.position = c("bottom")
```

Summary of Spatial Mapping showing Change in Climate Indices: