Comparison between statistical and dynamical downscaling of rainfall under Representative Concentration Pathways scenarios over the Gwadar- Ormara basin, Pakistan

RAAZIA ATTIQUE
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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

For climate change impact assessment studies, GCMs outputs commonly cannot be directly used because of their coarse spatial resolution. As such the provided atmospheric and meteorological information is not directly suitable for hydrological studies due to mismatch of scale. Therefore, GCM outputs are downscaled to a finer resolution so that projections can serve hydrological modelling studies on water resources under climate change at regional level. Two main types of downscaling methods exist; statistical and dynamical. Both techniques have their own pros and cons. Understanding the limitations and strengths of each of the downscaling methods is important to ensure that for a particular terrain the suitable approach is being implemented to serve specific research purposes. Thus, the main objective of this study was to evaluate and compare the performance of the two downscaling approaches on the Gwadar-Ormara basin, Pakistan to analyse which technique can better simulate and predict the spatial-temporal rainfall distribution. The downscaled outcomes of monthly rainfall were evaluated for a baseline period, compared to in-situ observations. The evaluation was for rainfall only and was based on climatological averages and standard deviation for both historic (1971-2000) and future (2041-2070) time periods under RCPs 4.5 and RCPs 8.5 scenarios. This study also assessed the reliability of observed rainfall time series with grid-based rainfall time series of the APHRODITE dataset, which resulted that APHRODITE data cannot be used in place of observed data to overcome the problem of inconsistency in the observed dataset.

For statistical downscaling the CanESM2 AOGCM was used whereas for dynamical downscaling the RegCM4 RCM, using outputs from the same CanESM2 AOGCM, was used. The latter data is provided under the Coordinated Regional Climate Downscaling Experiment – South Asia (CORDEX-SA) initiative. The performance evaluation of the two downscaling techniques led to the conclusion that statistical downscaling is preferred to simulate and to project rainfall pattern in the study area where in-situ data available is scarce with unreliability in time series. The Statistical DownScaling Model (SDSM) used showed relatively poor performance in calibrating and validating the simulations with respect to observed data in the historic period. But overall the SDSM generated satisfactory results in terms of projecting monthly rainfall cycle for the entire basin. On the contrary, RCM showed high biased rainfall simulations for both historic as well as future time periods. Dynamical downscaling may show large uncertainties in coastal terrains where rainfall patterns are highly variable. However, the use of a multi-model ensemble of regional climate models can be a viable option in such cases to simulate rainfall variability and patterns if there is confidence in the observed dataset to be used for bias correction of the RCMs outputs. Different combinations of RCMs and GCMs may perform differently to simulate and project climatic variations depending upon the season, topography, model initialization, parametrization, boundary conditions, etc. Thus, the performance of more than one climate model should be tested before using the RCMs outputs in climate change impact and adaptation studies.

Keywords: statistical downscaling, dynamical downscaling, RCPs, CORDEX-SA, Gwadar- Ormara basin Pakistan

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LIST OF ABBREVIATIONS

AOGCM(s)	Atmosphere Ocean General Circulation Models
AR	Assessment Report
CCCma	Canadian Centre for Climate Modelling and Analysis
CDO	Climate Data Operators
CMIP5	Coupled Model Inter-comparison Project Phase 5
CORDEX-SA	COordinated Regional climate Downscaling EXperiment- South Asia
CPEC	China Pakistan Economic Corridor
CRU	Climate Research Unit
CV	Coefficient of Variation
DJF	December, January, February
DS	Dual Simplex
ECMWF	European Centre for Medium Range Weather Forecast
EDCDFm	EquiDistant Cumulative Distribution Functions matching
GCISC	Global Change Impact Studies Centre
GCM(s)	Global/ General Circulation Models
GHG	Greenhouse Gas
IDW	Inverse Distance Weighting
IPCC	Inter- governmental Panel on Climate Change
JJA	June, July, August
LAM(s)	Limited Area Models
LR	Linear Regression
MICE	Multivariate Imputation via Chained Equations
MLP	Multi – Layer Perceptron
MLR	Multiple Linear Regression
NCAR	National Center for Atmospheric Research
NCEP	National Center for Environmental Prediction
OLS	Ordinary Least Squares
OSR	Optimal Subset Regression
R^2	Coefficient of Determination
RCM(s)	Regional Climate Models
RCP(s)	Representative Concentration Pathways
RF	Radiative Forcing
SD	Standard Deviation
SDSM	Statistical DownScaling Model
SRES	Special Report on Emission Scenarios
SWG	Stochastic Weather Generator
WCRP	World Climate Research Program
WRI	World Resources Institute

1. INTRODUCTION

1.1. Background

According to the 5th Assessment Report (AR5) of the Inter- governmental Panel on Climate Change (IPCC), the global (land and ocean) average temperature has shown a 0.85 ^{o}C increase over the period of 1800–2012 (IPCC, 2013), and a 0.74 ± 0.18 ^{o}C increase during the last hundred years (1906– 2005) (IPCC, 2007). The impacts of climate change extend well beyond the increase in temperature alone. Nowadays there is clear evidence that sectors like water, energy, wildlife, agriculture, ecosystems, and human health are affected out of which the water sector is crucial, as availability of sufficient and non-polluted water is indispensable for all forms of life.

Most of the studies in the world on climate change impact assessment on water resources focus on key indicative variables like temperature, precipitation and evaporation for water resources management (Wang et al., 2012). Hence, it is of great importance to evaluate the possible impacts of climate change on these climatic variables in order to get a better understanding about how long term changes of these variables affect the hydrological cycle behaviour, water balance and water availability to ensure sustainable development in any region. Such studies, consequently, can help in achieving meaningful insights to address extreme events related to water such as water scarcity, flooding, drought. In this regard, since the 1970's, General Circulation Models (GCMs) have been developed to simulate the average, synoptic-scale, general-circulation patterns of the atmosphere for present climate and to predict future climate change (Kour, Patel, & Krishna, 2016).

GCM outputs based on the Special Report on Emission Scenarios (SRES) have been used extensively to project future meteorological variables for use as inputs into hydrological models at a regional scale (Kour et al., 2016). The direct representations of hydrological quantities from GCMs are large-scale averages with little spatial reliability for specific regions. Moreover, the coarse spatial resolution and temporal deficiencies of GCM model output limit the effectiveness of the model in providing useful information at the regional scale (Wilby and Wigley, 1997). Therefore, there is a need to convert GCM outputs into regional high-resolution meteorological fields required for reliable hydrological modelling, and this process is generally referred to as 'downscaling' (Hewitson and Crane, 1992).

There are two main downscaling approaches: 'Dynamical downscaling' and 'Statistical downscaling'. Dynamical downscaling is commonly carried out using a Regional Climate Model (RCM) set up for an area of interest and nested within a GCM. "The RCM uses time-varying atmospheric boundary conditions around a finite domain from the GCM (one-way nesting)" (Sunyer, Madsen, & Ang, 2012). Whereas, statistical or empirical downscaling methods are more straightforward as they define a statistical relationship between large-scale variables ('predictor' – either from GCM or RCM) and observed small-scale meteorological variables ('predictand') using techniques which range from simple interpolation to complex statistical neural networks and weather generators (Kour et al., 2016).

1.2. Problem Statement

There can be different sources of uncertainty in undertaking climate change impact studies. The first and primary source of uncertainty evolves when representing different emission scenarios for future climate. The change in atmospheric variables (like precipitation, temperature) may largely depend upon different emission scenarios as well as on future climatic windows. Choudhary and Dimri, (2017) studied the COordinated Regional climate Downscaling EXperiment for South Asia (CORDEX-SA) to determine probable changes in monsoonal rainfall over the Himalayan region for three different greenhouse gas emission scenarios (i.e. Representative Concentration Pathways or RCPs[1]) and two future time slices. They discovered that change in rainfall variability increases from the least intensive carbon emission scenario to the most intensive scenario and from the near (2020-2049) to the far future (2070-2099).

Another source of uncertainty may arise due to the coarse spatial resolution of GCMs. GCMs provide projections at a resolution of approximately 150–300 km and are often biased and hence should not be used directly in hydrological models (like rainfall-runoff models, water balance models) for climate change impact assessments (Fowler et al., 2007). Because of the coarse spatial resolution of GCMs, they become unsuitable to represent climate variations at the scale of 20-50 km (Wilby et al., 2000). Accurate and reliable simulation and (future) projections of the climate over a region of interest remains a challenge mainly because of scale issues by " i) large differences in the spatial and temporal scales on which the processes occur, ii) the processes are observed and iii) the processes are simulated" (Haile and Rientjes, 2015).

As already mentioned, GCM outputs require downscaling to finer spatial resolution to assess future climatic changes. These downscaled outputs are then used to drive other sector-specific models for climate change impact studies. The two downscaling methods both can exhibit uncertainty in their results. Although RCMs might simulate meteorological variables better than GCMs because of their finer resolution; they also might not precisely match with observed meteorological variables and inherit biases from their driving GCM. The reason of uncertainty from RCMs can be due to imperfect model conceptualization, parameterization physics, choice of initial conditions, boundary conditions and spatial averaging over grid cells.

A large number (>100) of climatic models have been developed over the past decades. Different climatic models (GCMs as well as RCMs) since differ in their approach which causes simulation results and projections for the future dissimilar and thus, the outcome from the models becomes associated to uncertainty. Also, the unique characteristics of each downscaling method leads to different future climate scenarios, indicating that the downscaling approaches adds uncertainty in climate projections. This leads to the requirement to inter-compare the performance of models and/or methods before utilization of the model outputs in impact, climate mitigation and adaptation studies. In addition, it is unclear which method or approach is more suitable or appropriate for a particular study area and for a specific purpose of research. Hence, the final selection of the climate model and/ or downscaling approach becomes problematic and questionable.

1.3. Literature Review

1.3.1. Statistical Downscaling

Statistical downscaling is a two-step process consisting of: i) the development of statistical relationships between long term, historic, observations of local climate surface variables (predictands) and large scale atmospheric variables (predictors). ii) application of such relationships to projected output of GCMs for selected future time windows to simulate local and regional climate variables (Hoar and Nychka, 2008). The most common form of a statistical downscaling model is that the predictand is described as a regression function of pre-selected predictor(s). In mathematical terms:

[1] RCPs are elaborated in section 1.3.3

$$R = F(L)$$

Where, R represents the predictand, L represents the predictor, and F is a deterministic/ stochastic function conditioned by L and has to be found empirically from historical observation or reanalysis data sets (Abdo, 2008).

Statistical downscaling methods can be classified according to the techniques used (Wilby and Wigley, 1997) or according to the chosen predictor variables (Rummukainen, 1997). In Wilby and Wigley's study, statistical downscaling techniques are categorized in three classes, namely: *(a) Regression Methods, (b) Weather pattern- based approaches, and (c) Stochastic Weather Generators*. Whereas, in Rummukainen's (1997) study, statistical downscaling methods are classified as: *(a) Downscaling with surface variables, (b) The perfect prog(nosis) (PP) method, and (c) The model output statistics (MOS) method*. A summary of how these different techniques establish statistical relationships between predictors and predictands is provided in the literature by Kour et al., (2016) and Xu, (1999b). Many downscaling approaches embrace attributes of more than one of the above mentioned techniques and therefore, are hybrid in nature.

Statistical downscaling methods are computationally inexpensive and efficient as compared to dynamical downscaling methods and thus can be easily applied to the output from different GCM experiments. This is one of the major practical advantages of statistical downscaling over dynamical downscaling. Another advantage is that empirical methods can be used to provide site- specific information, which can be useful for many climate change impact studies. On the other hand, the main theoretical weakness of empirical downscaling is the basic assumption that "the relationship between large and local scale will remain constant in the future" (Fowler et al., 2007). This means that the statistical relationships developed for the present day climate are assumed to be valid for possible future climates under different radiative forcings (Wilby et al., 2004). This is also referred to as the "Stationarity Assumption".

Another disadvantage of statistical techniques (like the regression method) is that the method tends to underestimate the variance of climatic patterns. Also the partial statistical relationship between regional or local climate and large scale climate variables represent extreme events poorly (Fowler, Blenkinsop, & Tebaldi, 2007). The advantages and disadvantages of statistical and dynamical downscaling methods are well summarized in Kour et al., (2016).

1.3.2. Dynamical Downscaling

The aim of dynamical downscaling, i.e.; to extract local-scale information from large-scale GCM data, is achieved by limited-area models (LAMs) or regional climate models (RCMs). Dynamical downscaling involves the nesting of RCMs in GCMs; thus, this method is also called a 'nested' RCM approach (Teutschbein, 2013). There are two kinds of nesting approaches: one-way or two-way nesting (Harris and Durran, 2010). If the RCM uses the GCM output to define the initial and lateral boundary conditions, it is termed as 'one-way nesting approach' (without feedback from the RCM to GCM). Whereas, the 'two-way nesting approach' comprises a feedback from RCM simulations back to the GCM (Kour et al., 2016). According to Rummukainen (1997), dynamical downscaling can be performed in three ways:

1) "Running a regional-scale limited-area model with the coarse GCM data as geographical or spectral boundary conditions ('one-way/ two-way nesting')"
2) "Performing global-scale experiments with high-resolution atmosphere GCMs, with coarse GCM data as initial (and partially also as boundary) conditions"
3) "Using a variable-resolution global model (with the highest resolution over the area of interest)"

Recently RCMs have been developed having horizontal resolution in the order of tens of kilometres or less over areas of interest. Compared to previous generation RCMs, such RCMs can provide a better agreement with observations on synoptic and regional scales and on monthly, seasonal and inter-annual timescales. While nested modelling is likely to be the most informative and widely used approach to drive regional information for 20–50 km horizontal grid spacing and 100–1000 m vertical resolution, there are several admitted restrictions of the approach (Xu, 1999b). In principle RCMs cannot remove GCM biases related to large scale variables. However, RCMs may lead to improved simulation of downscaled GCM outputs at the GCM sub-grid scale because of using relatively high resolution data of for instance topography and land cover (Haile and Rientjes, 2015). One major disadvantage of RCMs is that they require substantial computing resources and are as expensive to run as a global GCMs (Abdo, 2008).

Dynamical downscaling methods have gained importance over statistical downscaling primarily due to the lack of in-situ data required for statistical downscaling. They have a better skill to simulate small scale atmospheric features, such as orographic precipitation than statistical methods. RCMs due to relatively high spatial resolution allow use of circulation to regional scale climate impact assessments. Also algorithms that drive and represents climate circulation patterns represent real world atmospheric physics that as such often is considered more reliable and preferred above statistical relations that are established at point scale only. Another advantage of dynamical downscaling over statistical downscaling is that the "Stationarity Assumption" is not applied, as dynamical downscaling methods have the ability to respond in a physically consistent way to different external forcing signals, such as land surface or atmospheric chemistry changes. Given the range of downscaling methods and the fact that each method has its own advantages and disadvantages, there exists no universal approach which works for all situations. It is recommended through different research studies that arduous testing and comparison of statistical and dynamical downscaling approaches should be undertaken.

1.3.3. Representative Concentration Pathways (RCPs)

IPCC in its 5th assessment report has introduced a new set of emission scenarios called Representative Concentration Pathways (RCPs) (Van Vuuren et al., 2011; Taylor et al., 2012), based on a set of scenarios of anthropogenic forcings which are used under the framework of CMIP5 for the new climate model simulations carried out. RCP scenarios represent a high potential proposition for research and assessment, including emissions' impact and mitigation analysis (Van Vuuren et al., 2011) and they represent a wide variety of possible future climate scenarios. Till the release of the AR5, IPCC used climate change scenarios based on the Special Report on Emission Scenarios (SRES), which are outdated and these scenarios are now replaced with RCPs. The RCPs provide combination of adaptation and mitigation to greenhouse gas (GHG) concentrations and therefore, future climate projections based on RCPs are more realistic compared to SRES (Taylor et al., 2012). SRES explicitly used to consider the effects of prescribed levels of emissions into the atmosphere, offering 'what if' scenarios that if a given amount of carbon dioxide equivalent is emitted what will happen to the atmosphere. Thus they were more uncertain regarding contributing factors such as population growth, economic development and technological advances. Whereas, RCPs relate to concentrations of greenhouse gas that represent cumulative emission budgets, hence these are considered more realistic.

RCPs produce a range of responses from continued warming, to approximately steady forcing, to an emission mitigation (or reduction) scenario that stabilizes and then gradually reduces the radiative forcing (RF) after the mid-21st century. Four RCPs have been used in AR5 to represent future scenarios. They are RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5. These RCPs together span the range up to 2100 with radiative forcing values and their descriptions are presented in Table-1. In all RCPs, the atmospheric GHG concentrations are assumed to be higher in 2100 as a result of a further increase of cumulative emissions of GHGs to the atmosphere during the 21st century. The reason of taking different RCPs is to understand how the rainfall is being affected under a changing climate of increased radiative forcing and concentration of CO_2. Generally, most of the climate change impact studies try to evaluate climate projections using low, medium and high emission scenarios.

Table 1: Overview of RCPs (source: Van Vuuren et al., 2011)

	Description
RCP 2.6 (low emission scenario)	Radiative forcing rise at 3.1 W/m² (~490 ppm CO_2 eq) in the middle period of the 21st century and then decline to 2.6 W/m² by 2100
RCP 4.5 (intermediate stabilization scenario)	Stabilization without overshoot pathway to 4.5 W/m² (~650 ppm CO_2 eq) before 2100 by employment of a range of technologies and strategies for reducing greenhouse gas emissions.
RCP 6	Stabilization scenario without overshoot pathway to 6 W/m² (~850 ppm CO_2 eq) after 2100
RCP 8.5 (high emission scenario)	Rising radiative forcing to 8.5 W/m² (~1370 ppm CO_2 eq) by 2100.

1.3.4. Overview of Climate Change Impact Studies on Pakistan

Under Global Change Impact Studies Centre (GCISC), which is a dedicated research institute for climate change in Pakistan (http://www.gcisc.org.pk/index.php), studies have been performed in water related sectors over South Asia with a focus on Pakistan in a few. These studies have mostly conducted climate change projections over entire Pakistan using PRECIS and RegCM3 regional climate models (focusing on dynamical downscaling only) under the SRES – A2 scenario. For example:

1) Saeed et al., (2009) attempted to validate the regional climate model PRECIS over South Asia by simulating the summer monsoon and winter seasons in 1992, an extreme precipitation event of September, 1992 over Jhelum river basin and the Super Cyclonic storm of 1999 in the Bay of Bengal. The study investigated the performance of the model for synoptic events and large scale monsoon circulation when driven by the European Centre for Medium Range Weather Forecast (ECMWF) reanalysis datasets- which are merged climate model and observed datasets.
2) Mehmood et al., (2009) tried to develop high resolution climate change scenarios for the South Asian region using RegCM3 for the period 2041-2070 and 2071-2100. They carried out the study first on South Asia and then focused on entire Pakistan producing simulations driven by the lateral boundary conditions from two GCMs (ECHAM5 and FVGCM), with an additional analysis of temperature and precipitation prediction for the Upper Indus basin, Kabul River basin and Jhelum River basin.
3) Islam et al., (2009) performed a similar kind of study in which they developed high resolution climate change scenarios over South Asia and Pakistan using the PRECIS RCM nested within HadAM3P GCM for the future time slice of 2071-2100 under the A2 scenario.

Other studies used only statistical downscaling methods for climate change assessment over entire or some part of Pakistan. For instance, Khattak et al., (2011) examined trends in several hydro meteorological variables (minimum temperature, maximum temperature, precipitation and stream flow) over the Upper Indus Basin using the non-parametric Mann-Kendall test in combination with Sen's slope method, a non-parametric alternative for estimating a slope for a uni-variate time series to determine the magnitude of trends. Khan et al., (2017) studied the future availability of water for the Upper Indus Basin under the A2, B2, RCP4.5 and RCP8.5 emission scenarios. They conducted a meta-analysis (a statistical method which can be used to produce combined projections from individual model outputs) to present a collective picture by combining the results from the emission scenarios. The meta-analysis showed higher confidence in RCPs projections. Ghumman et al. (2013) studied the variability in precipitation patterns of Pakistan due to environmental and climatic changes using different GCMs downscaled using the k-NN statistical method under the A2 scenario. They concluded that the average annual precipitation of the country will undergo an increase in the range of +57 to +71% as compared to the average of the base period (1971-2000).

Mahmood & Babel, (2014) projected future changes in extreme temperature events under A2 and B2 climate scenarios using a Statistical DownScaling Model (SDSM) in the trans-boundary region of the Jhelum river basin. Kazmi et al., (2015) employed SDSM for downscaling of daily minimum and maximum temperature for Pakistan and projected future scenarios using HadCM3 daily data for A2 and B2 story lines. Mahmood et al., (2016) investigated the possible impacts of climate change on the water resources of the Kunhar River basin, Pakistan, under A2 and B2 scenarios of HadCM3 GCM. They also used SDSM to downscale and further used GCM simulations to predict stream flow in the basin for three future periods (2011–2040, 2041–2070, and 2071–2099).

Recently many studies have used statistical downscaling approaches with RCP scenarios for climate change projections. For example, Su et al., (2016) attempted to analyse the impacts of climate change on climatic parameters (temperature and precipitation) by evaluating the simulation ability of multi- GCM models ensembles within the Coupled Model Inter-comparison Project Phase 5 (CMIP5) over the Indus River Basin using different RCP scenarios (2.6, 4.5 and 8.5). They applied the Equidistant Cumulative Distribution Functions matching (EDCDFm) method to correct systematic biases and applied statistical downscaling to GCM simulations. Amin et al., (2017) did a statistical analysis of monthly, seasonal and annual precipitation trends for Pakistan at different temporal (1996-2015 and 2041-2060) scales. They used the SimCLIM model for future precipitation projections using RCP 6.0 alone. Similar studies have been performed in other areas of Nepal, China and India (e.g. Khadka & Pathak, 2016; Zhang et al., 2016; Shivam, Goyal & Sarma, 2017; Singh & Goyal, 2016) which have employed SDSMs forced under different RCPs.

Some other studies like Ding & Ke, (2013) compared two statistical approaches for improving seasonal precipitation prediction skills for Pakistan. They employed the statistical regression method and statistical downscaling to perform rainfall predictions for the monsoon season in Pakistan. They used Linear Regression (LR) and Optimal Subset Regression (OSR) for each approach, and compared the raw model outputs with the regression forecast methods. Ahmed et al., (2015) applied a multilayer perceptron (MLP) neural network for the downscaling of rainfall in the data scarce arid region of Baluchistan province of Pakistan. While many studies including (Akhtar, Ahmad, & Booij, 2008; Hewitt, 1998; Hewitt, 2005; Mayer et al., 2006; Fowler and Archer, 2006; Bhutiyani et al., 2007; Tahir et al., 2011; Naeem et al., 2013; Immerzeel et al., 2009; Reggiani and Rientjes, 2015; Tahir et al., 2016; Tiwari et al., 2014) have evaluated the impact of climate change on the surface waters in the Northern part (Hindukush – Karakoram – Himalaya belt) of Pakistan.

1.4. Research Gap

By effects of climate change, Pakistan will become one of the most water stressed countries in the world according to a study conducted by Maddocks et al., (2015) for the World Resources Institute (WRI). The country faces challenges like high glacial melt, prolonged droughts, flash floods and rise in sea levels. A significant research gap exists in this regard to assess the impact of climate change on water resources specifically in the southern part of Pakistan. The southern part is more arid and downscaling rainfall in such regions is more challenging compared to wet regions due to erratic and infrequent rainfall. The complexity is further enhanced due to scarcity of data in such regions and rapidly changing climatic settings from Arabian see towards the Upper Indus area. Baluchistan being geographically Pakistan's largest province, having an area of 347,190 km^2, has a climate lying in hyper-arid, arid and semi-arid domains. The Gwadar-Ormara basin that is the area of study in this research, is located on the south western fringe of Baluchistan. From literature review, it appears that Ahmed et al., (2015) is the only study that has been conducted on the southern part (Baluchistan) of Pakistan, using statistical techniques only to downscale rainfall. Further, this study took the province in its entirety and has not focused specifically Gwadar-Ormara basin.

All the studies as cited in section 1.3.4, have evaluated rainfall and/or temperature variability and change over Pakistan using only one downscaling approach (statistical or dynamical). To the best of the author's knowledge, no study has been performed to compare statistical downscaling with dynamical downscaling over Pakistan or on any part of it, which is a significant research gap. Further, before the AR4 SRES scenarios were not obsolete, statistical and dynamical methods were being used with IPCC AR4 SRES emission scenarios (A1, A2, B1, B2) in climate research community. Fewer studies have recently tried to analyse climate change impacts on atmospheric variables (rainfall and/or temperature) using RCPs. These studies focused on particular regions in Pakistan and have performed the analysis using only one downscaling method. Therefore, there still exists a gap to assess and compare the impacts of climate change on the spatial-temporal trends and variation of atmospheric variables using different RCPs and using both statistical and dynamical approaches together over any region or entire Pakistan for future climatic windows. In this study due to time limitation, an attempt has been made to address the research gap of comparing statistical downscaling with dynamical downscaling under RCPs to identify which downscaling method provides the most reliable simulations and projections over the Gwadar-Ormara basin, without performing the climate change impact assessment.

1.5. Research Objectives

The main objective of the study is to evaluate and compare the performance of two downscaling approaches to analyse which technique can better simulate and predict the spatial-temporal rainfall distribution over the Gwadar- Ormara basin, Pakistan. For both approaches model outcomes of CanESM2 AOGCM are used to make evaluation more objective. The comparison of the two downscaling methods includes first the evaluation of the performance of the downscaling approach individually, for the baseline period (1971-2000) over the Gwadar-Ormara basin of Pakistan. Secondly, for the future climatic window (2041-2070) using RCP 4.5 and RCP 8.5 scenarios. In this study, only RCP 4.5 and RCP 8.5 are used following the priority set by CMIP5 and furthermore one future time period is considered only due to time constraints. The analysis and comparison of the downscaling methods is based on the evaluation using first order statistics (mean and standard deviation) of rainfall in the reference period (1971-2000), for which daily observed data was used from weather stations. The evaluation is done based on climatological averages at a monthly time scale to understand the limitations and strengths of the two downscaling approaches driven by the same climate model.

1.6. Research Identification and Novelty

Previous studies have tried to project future changes in temperature and/or rainfall either for the entire region of Pakistan, the Upper Indus area or for the Jhelum river basin specifically. None of the studies have explicitly focused the Gwadar-Ormara catchment in Baluchistan, Pakistan. To choose this study area is in itself a novelty as general circulation models may perform and project future changes differently for different regions with specific climatic conditions, rapidly changing topography and observational scale. The challenging task of the research was to analyse the performance of the two downscaling approaches in simulating and predicting spatial-temporal rainfall distribution over the Gwadar-Ormara basin, where the available observed data was not only scarce but also uncertain to some extent. The uncertainty of observed meteorological data was evaluated with the APHRODITE gridded rainfall product and the results of this analysis added another novelty to the work.

Also, most of the climate change impact studies in Pakistan have focused on analysing future climate variability under SRES emission scenarios, which are now outdated. Hence, the idea to compare the two downscaling methodologies under RCPs scenario is new for Pakistan, as no such study has been done before for whole or for any region of Pakistan.

1.7. Thesis Layout

This thesis consists of five chapters and is organized as follows:

- Chapter-1 is the introduction to the study.
- Chapter-2 describes the study area, the data sets and the models to be used.
- Chapter-3 explains the methodology applied.
- Chapter-4 shows the results and discussion about the results obtained.
- Chapter-5 finalizes the thesis by conclusions and recommendations.

2. STUDY AREA, DATA AND MODEL

2.1. Study Area

2.1.1. Location

Gwadar- Ormara basin is the largest coastal district of Pakistan. It is located between 25º - 27º north latitude and 60º – 65º east longitude. The district is bounded on the north by other two districts namely Kech and Awaran, on the east by district Lasbela, on the south by the Arabian Sea and on the west by Iran. It has a total area of 12,637 km². The area is geo-strategically important to Pakistan because of the 46 billion US dollars CPEC (China Pakistan Economic Corridor) project under way. Gwadar district will serve as a key centre for future industrial and shipping activity, once the project will be completed. The district's coastline stretches for 600 kilometres comprising 78 percent of the provincial coastline and 55 percent of the entire coastline of Pakistan. In places, the topography climbs to 300 metres above sea level with a few mountain peaks up to 1,000 metres above sea level. Figure-1 shows the location, topography and meteorological stations of the study area.

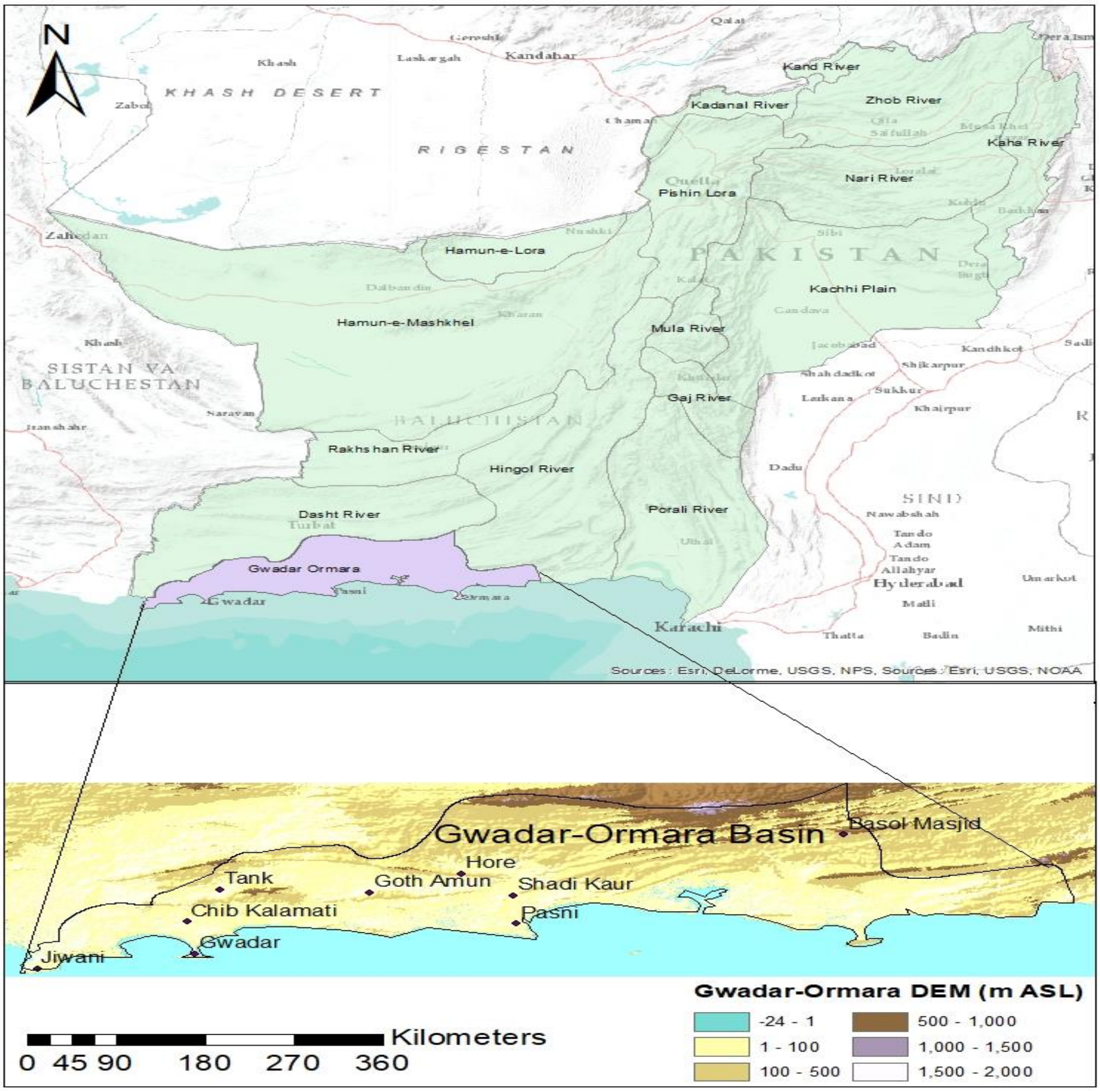

Figure 1: Location, topography and meteorological stations of Gwadar-Ormara basin, Pakistan

2.1.2. Climate

The climate of Gwadar-Ormara basin can be classified as arid with warm summers, mild winters and erratic rainfall patterns. The winter lasts for three months from December to February and is pleasant except for occasional and brief cold spells. May and June are the hottest months with a mean maximum temperature of around 35°C and December- January are the coldest months with a mean minimum temperature of around 13°C. The mean annual rainfall varies from 75 to 100 mm. Most rainfall occurs between December and February with a monthly average rainfall of 20 mm.

2.2. Datasets

2.2.1. Observed Data

Observed rainfall data were required for downscaling AOGCM and National Center for Environmental Prediction (NCEP) data using statistical downscaling model (SDSM) and to validate the downscaled RCM simulations. Daily rainfall time series data for all 9 stations, as shown in Figure-1, is collected from the archive of the National Engineering Services Pakistan (NESPAK). The stations in the study area are non-uniformly distributed. The in-situ station data obtained from NESPAK was having lot of missing values over the requisite time period of 1971-2000. This can be observed in Figure-2. The daily mean monthly rainfall for the period 1971-2000 recorded at 9 different rainfall gauging stations over the study area is shown in Figure-3.

From the 9 gauging stations for which the daily rainfall data for a certain time period was available, Gothamun showed very high mean monthly rainfall values. This can be clearly witnessed in Figure-3. Therefore, to ensure that the observed data to be used for analysis is free from anomalies, Gothamun station data was not further incorporated in the study. Figure-4 and Figure-5 represent the mean daily standard deviation (SD) and mean daily coefficient of variation (CV) of observed rainfall data averaged over months for the period of 1971-2000, respectively.

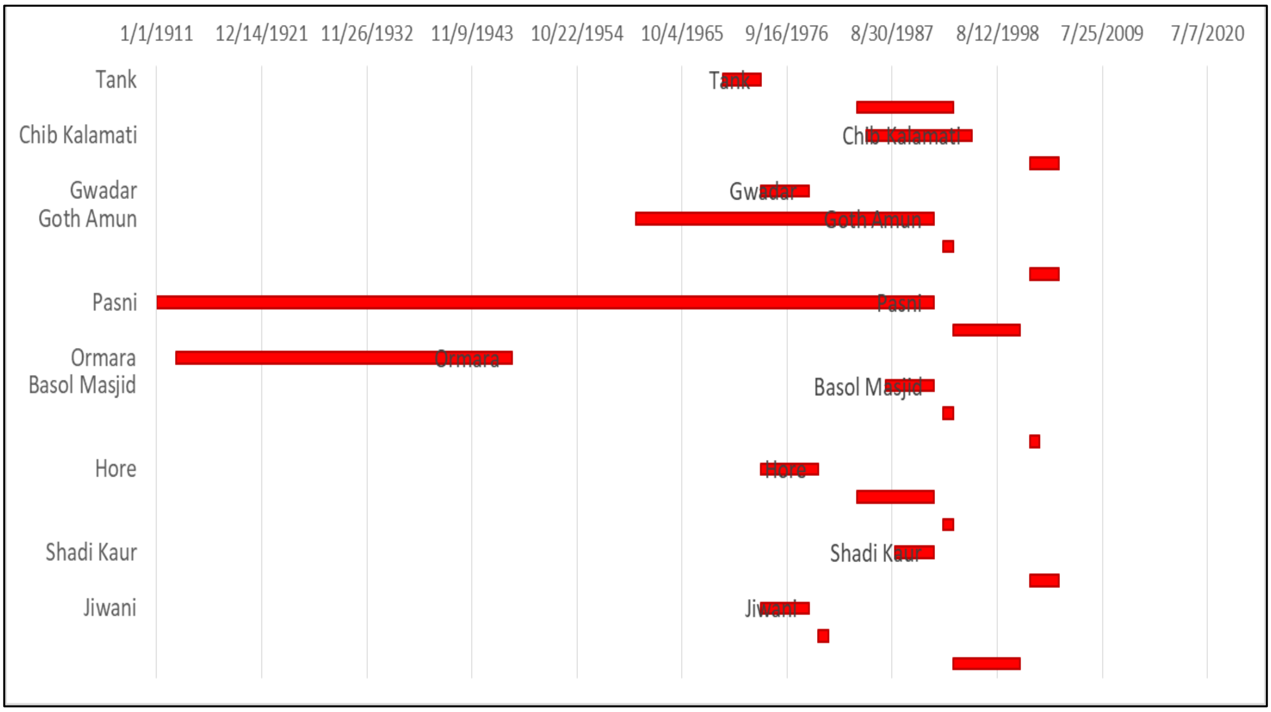

Figure 2: Daily rainfall data available for the study area from the archive of NESPAK

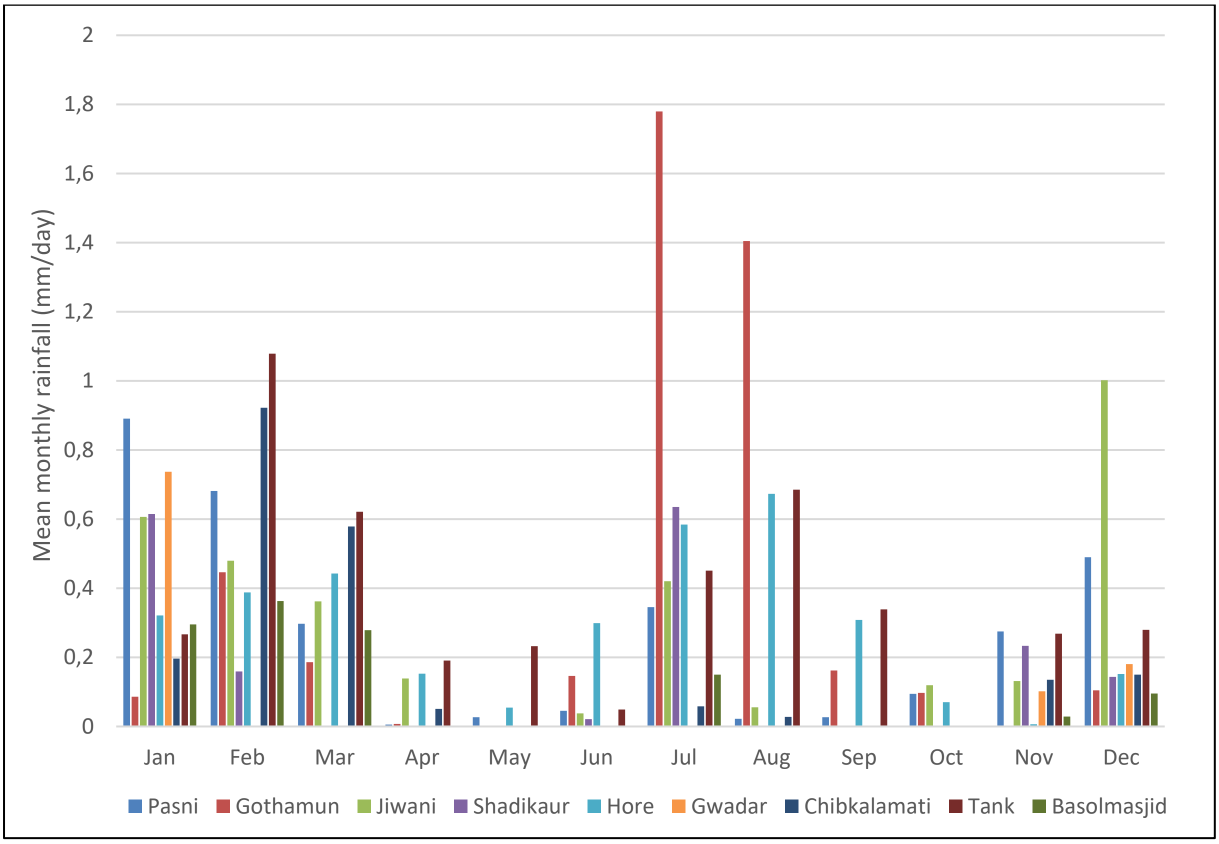

Figure 3: Daily mean monthly rainfall for the baseline period (1971-2000)

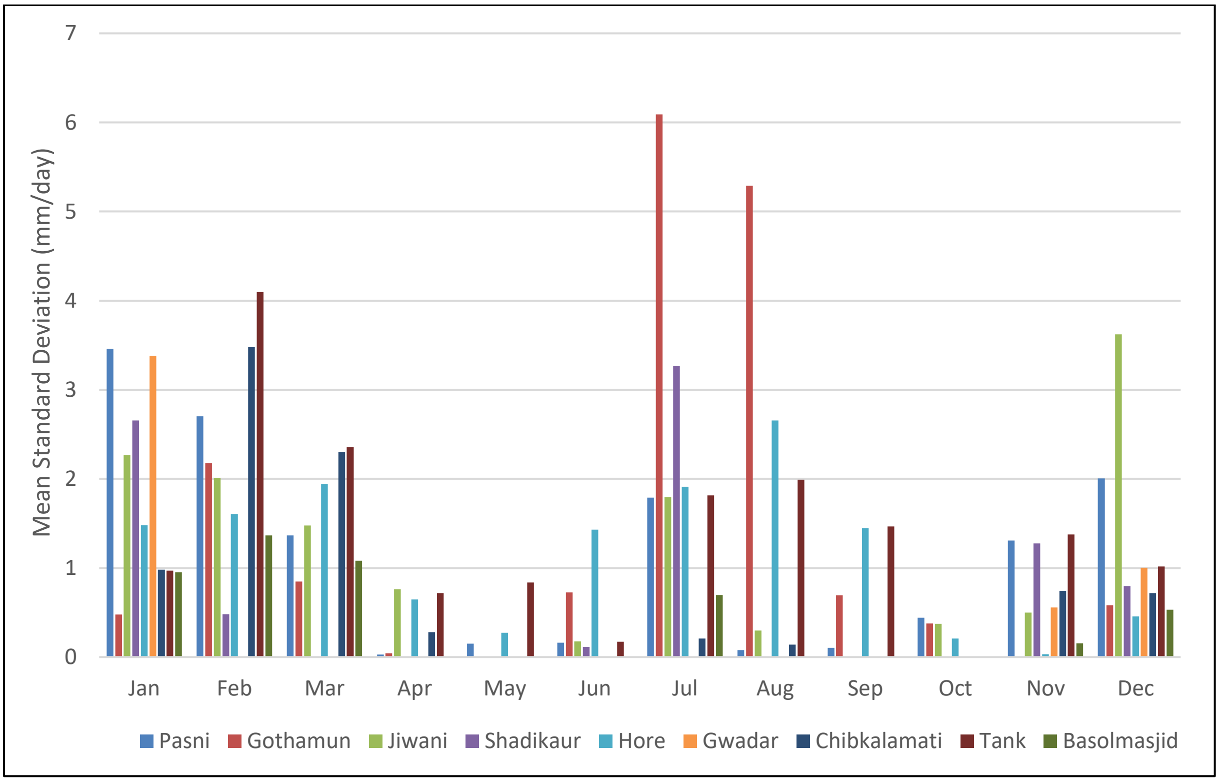

Figure 4: Mean monthly standard deviation of rainfall for the baseline period (1971-2000)

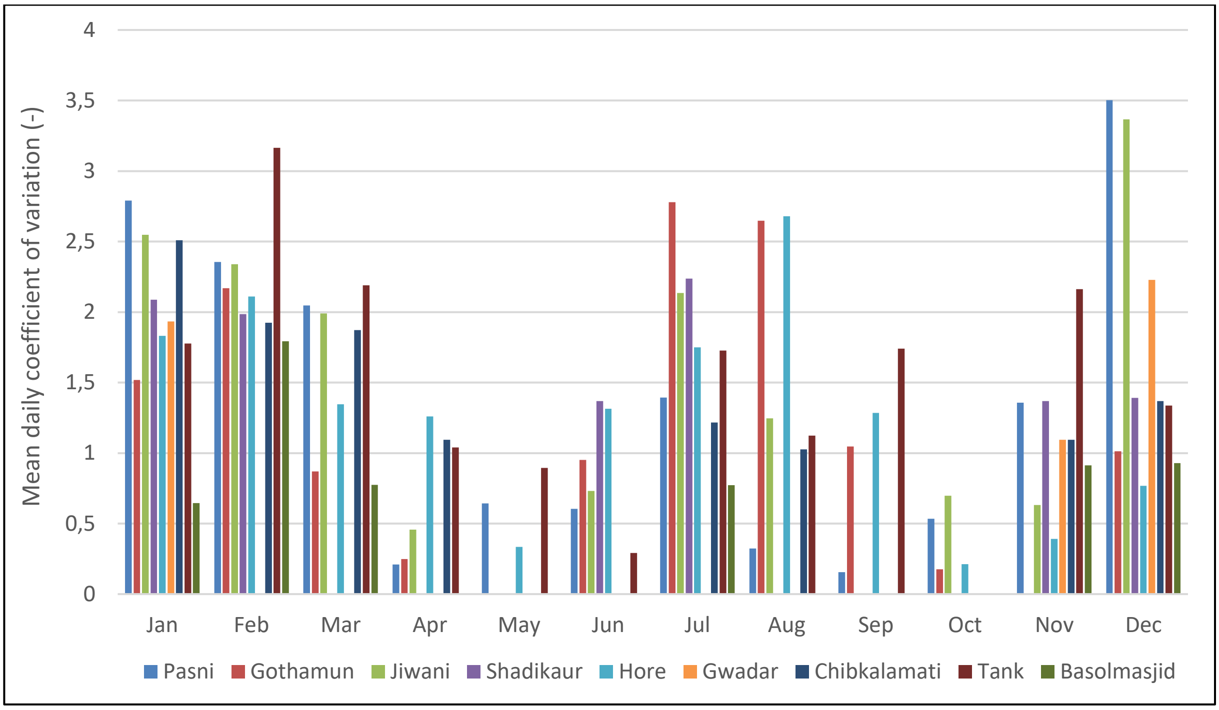

Figure 5: Mean monthly coefficient of variation of rainfall for the baseline period (1971-2000)

2.2.2. APHRODITE Gridded Data

In order to overcome the problem of missing data in the observed rainfall time series, gridded dataset of the Asian Precipitation - Highly Resolved Observational Daily Integration Towards Evaluation of Water Resources (APHRODITE) project for daily rainfall was evaluated to fill observed rainfall time series. APHRODITE's Water Resources data consists of daily gridded precipitation data (version V1101) for monsoon Asia (60˚ - 150˚E, 15˚ - 55˚N) for the period 1951 to 2007 available at both 0.25º and 0.5º resolutions (Shrestha, 2017). These high resolution daily gridded datasets are outcomes of data collected from 5,000 – 12,000 stations, with significant improvement in description of areal distribution and variability of rainfall around the Himalaya compared to other available products (Yatagai et al., 2012). Information on the APHRODITE's product was retrieved from http://www.chikyu.ac.jp/precip/english/products.html.

2.2.3. NCEP Reanalysis Data

For this study, daily reanalysis data from the NCEP/NCAR (National Center of Environmental Prediction/ National Center for Atmospheric Research) for the period of 1961-2005 was used for establishing statistical relationships with observed station data. NCEP reanalysis data is required to calibrate and validate statistical downscaling model. Also, in statistical downscaling daily atmospheric predictors' (NCEP) data is required to quantify the relative change of climatic variables between the current and the future time periods (Abdo, 2008). The NCEP data is usually regarded as a set of observed large-scale atmospheric variables with a resolution of 2.5° (longitude) × 2.5° (latitude). NCEP predictors' variable data interpolated and normalized with CanESM2 predictors is provided on a grid box by grid box basis, hence the data was downloaded from the grid box that represented the study area best. Because of the large differences between observed and GCM-simulated conditions, the GCM bias may give poor results through statistical downscaling and therefore, a normalisation process is required to reduce the bias. Table-2 below shows a list of large-scale atmospheric variables which are used as predictors in SDSM.

Table 2: List of predictor variables in NCEP reanalysis data

S.N.	Predictor variables	Description of predictor variables	S.N.	Predictor variables	Description of predictor variables
1	**mslpgl**	Mean seal level pressure	14	**p5zhgl**	500hPa Divergence
2	**p1_fgl**	1000hPa Wind speed	15	**p850gl**	850hPa Geopotential height
3	**p1_ugl**	1000hPa Zonal wind component	16	**p8_fgl**	850hPa Wind speed
4	**p1_vgl**	1000hPa Meridional wind component	17	**p8_ugl**	850hPa Zonal wind component
5	**p1_zgl**	1000hPa Relative vorticity of wind	18	**p8_vgl**	850hPa Meridional wind component
6	**p1_thgl**	1000hPa Wind direction	19	**p8_zgl**	850hPa Relative vorticity of wind
7	**p1_zhgl**	1000hPa Divergence	20	**p8thgl**	850hPa Wind direction
8	**p500gl**	500hPa Geopotential height	21	**p8zhgl**	850hPa Divergence
9	**p5_fgl**	500hPa Wind speed	22	**s500gl**	Specific humidity at 500hPa
10	**p5_ugl**	500hPa Zonal wind component	23	**s850gl**	Specific humidity at 850hPa
11	**p5_vgl**	500hPa Meridional wind component	24	**prcpgl**	Total precipitation
12	**p5_zgl**	500hPa Relative vorticity of wind	25	**shumgl**	Surface specific humidity
13	**p5thgl**	500hPa Wind direction	26	**tempgl**	Mean temperature at 2m

2.2.4. Climate Models Data

In this study, also dynamically downscaled output of the CanESM2 GCM was evaluated. CanESM2 is one of the ensemble members of a RCM (IITM-RegCM4) in the Coordinated Regional Climate Downscaling Experiment (CORDEX) – South Asia. The CORDEX program was initiated under the support of the World Climate Research Program (WCRP) to bring forth an ensemble of high-resolution past and future climate projections at the regional scale. The CORDEX dataset, utilized in this research, comprises downscaled climate scenarios for the South Asian region that are drived from the CanESM2 AOGCM runs conducted under the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Taylor et al., 2012). The CORDEX- SA dataset, used in this study includes two (4.5 and 8.5) of the four greenhouse gas concentration scenarios – RCPs (Meinshausen et al., 2011). In general, CORDEX- South Asia consists of thirteen downscaled RCMs driven by different AOGCMs' initial and boundary forcing, details of which are shown in Table-3. The RCMs' information and models' outputs was obtained from the CCCR website (http://cccr.tropmet.res.in/home/aboutus.jsp).

Table 3: List of the 13 CORDEX South Asia downscaled RCM simulations driven by 10 CMIP5 AOGCMs (source: http://cccr.tropmet.res.in/home/esgf_data.jsp)

CORDEX South Asia RCM	RCM Description	Contributing CORDEX Modeling Center	Driving CMIP5 AOGCM	Contributing CMIP5 Modeling Center
IITM-RegCM4 (6 ensemble members)	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climatic Model version 4 (RegCM4)	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	CCCma-CanESM2	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada
			NOAA-GFDL-GFDL-ESM2M	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA
			CNRM-CM5	Centre National de Recherches Me´te´orologiques (CNRM), France
			MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M), Germany
			IPSL-CM5A-LR	Institut Pierre-Simon Laplace (IPSL), France
			CSIRO-Mk3.6	Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia
SMHI-RCA4 (6 ensemble members)	Rossby Centre regional atmospheric model version 4 (RCA4)	Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden	ICHEC-EC-EARTH	Irish Centre for High-End Computing (ICHEC), European Consortium (EC)
			MIROC-MIROC5	Model for Interdisciplinary Research On Climate (MIROC), Japan Agency for Marine-Earth Sci. & Tech., Japan
			NOAA-GFDL-GFDL-ESM2M	NOAA, GFDL, USA
			CNRM-CM5	CNRM, France
			MPI-ESM-LR	MPI-M, Germany
			IPSL-CM5A-MR	IPSL, France
MPI-CSC-REMO2009 (1 ensemble member)	Max Planck Institute (MPI) Regional model 2009 (REMO2009)	Climate Service Center (CSC), Germany	MPI-ESM-LR	MPI-M, Germany

The main reason of selecting CanESM2 as a driving model to assess the impact of climate, is its ready-to-use atmospheric variables available in coherence with atmospheric variables of NCEP reanalysis data to be used directly in SDSM (Wilby et al., 2002). Both CanESM2 output and NCEP/NCAR reanalysis data use the same set of 26 predictor variables to keep consistency. It is important to mention here that the number and attributes of NCEP atmospheric predictors and any GCM daily atmospheric variables should be the same to perform spatial downscaling statistically, as it is a designed requirement of SDSM. The GCM predictor variables must be normalized with respect to a reference period and available for all variables used in model calibration (Wilby and Dawson, 2007). Keeping this in mind, only CanESM2 GCM under CMIP5 has the data available normalized with NCEP predictors, which makes CanESM2 a reasonable choice to evaluate the two main downscaling methodologies. Other GCMs do not include all atmospheric predictors needed to be used for statistical downscaling in SDSM, and hence require additional extraction and time consuming processing to match resolution with NCEP reanalysis predictors' set.

CanESM2 is a fourth generation coupled global climate model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma) contributing to the IPCC 5th Assessment Report. The 128x64 grid cells of CanESM2 cover the global domain according to the T42 Gaussian grid. This grid is uniform along the longitude with a horizontal resolution of 2.8125° and nearly uniform along the latitude with a horizontal resolution of roughly 2.8125°. It is generally recommended to use multiple GCMs while studying the potential future change in climate. However, this study included only one model due to the time limitation to reach the study objectives. The CanESM2 daily atmospheric predictors for baseline (1971-2000) and future (2041-2070) periods and for the two climate scenarios under RCP 4.5 and RCP 8.5 were downloaded from the website: http://climate-scenarios.canada.ca/?page=pred-canesm2

The choice for the IITM –RegCM4 RCM, to evaluate dynamical downscaling, was made because this is the only RCM available having CanESM2 as driving AOGCM in the CORDEX-SA experiment. The IITM-RegCM4 dataset of precipitation (pr) at a spatial resolution of 0.44° x 0.44° (~50 km x 50 km) and daily temporal resolution for historic (1971-2000) as well as future (2041-2070) climate windows was downloaded from: https://climate4impact.eu/impactportal/data/esgfsearch.jsp.

2.3. Model Used- Statistical DownScaling Model (SDSM)

2.3.1. Generic Description

Among the downscaling models, the Statistical DownScaling Model (SDSM) has been used widely throughout the world in climate change assessment studies (Wilby et al., 2002; Gagnon et al., 2005; Chu et al., 2010; Huang et al., 2011; Mahmood and Babel, 2014). The model was developed by Dawson & Wilby (2007), supported by the Environment Agency of England and Wales. SDSM is based on a combination of Multiple Linear Regression (MLR) and the Stochastic Weather Generator (SWG) empirical approaches. The model establishes a statistical relationship between large-scale variables and local-scale variables, producing regression parameters, and facilitates the rapid development of multiple, single-site scenarios of daily surface weather variables under current and future climate forcing. These relationships are developed using daily observed weather data – local climate data for a specific location for the predictand and larger-scale NCEP data for the predictors. Assuming that these relationships remain valid in the future, these relationships are then used to obtain downscaled daily weather local information for some future time period by driving the relationships with GCM-derived predictors (modified after Dawson & Wilby (2007)).

In SDSM, there are two kinds of methods to optimize parameters of regression equations and thus optimizing model results: *i. Ordinary least squares (OLS)* and *ii. Dual simplex (DS)*. Ordinary least squares is faster than dual simplex and produces comparable results with DS (Huang et al., 2011). There are three kinds of sub-models present for periodic analysis namely, *monthly, seasonal,* and *annual* for developing of empirical relationship between the local-scale and large-scale atmospheric variables. Annual sub-model establishes the same regression parameters for 12 months. The monthly sub-model denotes 12 regression equations, giving different calibrated parameters for each of the 12 months. Whereas, seasonal sub- model produces 4 regression equations, each for a set of 3 months. There are also two other types of sub-models, *conditional* and *unconditional* which can be used according to the local-scale variables. The 'Unconditional' model assumes a direct link between the predictors and the predictand. While the 'Conditional' model is used when there is an intermediate process between regional forcing and local weather. For example, in case of local precipitation that depends on the occurrence of wet days, further depends on regional-scale predictors such as humidity and atmospheric pressure (Wilby and Dawson, 2007).

There are few other options in SDSM that can be used as required like 'model transformation' option to transform the predictand data in conditional sub-model types. Four types of transformation options exist namely; *None, Fourth root, Natural log* and *Inverse Normal*. The default (None) is used whenever the predictand is normally distributed (in case of temperature). The others are used when data are skewed (in case of daily rainfall). Two other options of '*Variance Inflation*' and '*Bias Correction*' offered by SDSM can be used and adjusted to force the model to replicate the observed climate. Variance inflation controls the magnitude of variance in the downscaled daily weather variables. Whereas, bias correction option compensates for any tendency to over or under estimate the mean of conditional processes (like rainfall) by the downscaling model (Wilby and Dawson, 2007). The default value of 12 for variance inflation produces approximately normal variance inflation, while the default value of 1 in bias correction indicates no bias correction.

2.3.2. Key Functions of SDSM

The model can perform statistically downscaling of daily weather series by executing six discrete tasks or functions. The purpose of each function is described below:

1- *Quality control and data transformation:*

The quality, accuracy and completeness of the input dataset is checked by the identification of gross data errors, specification of missing data codes and outliers prior to model calibration. Whereas the data transformation option offers to transform the predictors and/or the predictand data prior to model calibration. The transformations available are logarithmic, power, inverse, lag, binomial, etc.

2- *Screening of downscaling predictor variables:*

The function of screening of appropriate downscaling predictor variables involves identification of large-scale predictor variables (NCEP) which are significantly correlated with observed station (predictand) data. In SDSM, various indicators like partial correlation, correlation matrix, explained variance, P-value, histograms, and scatter plots can be used to select some suitable predictors from a group of atmospheric predictors (Mahmood and Babel, 2014). The screening of predictors is the most important process in all types of statistical downscaling (Wilby et al., 2002; Huang et al., 2011) since, the choice of the predictors mainly determines the character of the downscaled climate scenario. During screening of predictor variables, multiple co-linearity between the predictor variables themselves is the major problem that occur which can cause high correlated predictors to be screened out. Thus, this problem should be considered during the selection of predictors.

3- *Model calibration:*

Model calibration function takes a user-specified predictand along the screened set of predictor variables to compute the parameters of multiple regression equations via an optimisation algorithm (either dual simplex or ordinary least squares) to calibrate the model. Before performing calibration, the user has to specify the model structure: whether monthly, annual or seasonal sub-models are required; or whether the process is unconditional or conditional.

4- *Weather generator:*

The weather generator operation produces an ensembles of synthetic daily weather series from observed (or re-analysis) atmospheric predictor variables. This function allows the verification of the calibrated model (using independent data of observed predictors) and produces the artificial time series for present climatic conditions. The user has to specify the period of record to be synthesized as well as the desired number of ensemble members. The stochastic component of SDSM allows the generation of up to 100 ensembles of data which have the same statistical characteristics but which vary on a day-to-day basis.

5- *Scenario generation:*

The scenario generator function produces ensembles of synthetic daily weather series from GCM-derived atmospheric predictor variables (either for present or future climate), rather than observed predictors using the already developed statistical relationship established by model calibration function. Scenario generation is a similar function like weather generation. Except in the case of scenario generator input files need not be the same length as those used to obtain the regression weights during calibration, as in the case of weather generator.

6- Diagnostic testing/analysis:

The statistical characteristics of both the observed and synthetic data can be compared by use of 'Summary Statistics' and 'Compare Results' options in SDSM, thus determining the effect of spatial downscaling. Summary statistics summarizes the result of both the observed and simulated data. Whereas, compare results enables to plot the result of summary statistics.

3. METHODOLOGY

This chapter describes the steps performed to achieve the study objectives through: i- quality assessment of observed in-situ and APHRODITE rainfall data (section 3.1); ii- statistical downscaling of CanESM2 AOGCM data (section 3.2); and iii- dynamical downscaling using IITM – RegCM4 RCM (section 3.3).

3.1. Data Quality Assessment

In order to validate the outcomes of the RCM as well as for downscaling of AOGCM data using SDSM for the reference period, a reliable in-situ dataset without any gaps and errors is necessary. Initially, the research aimed to correct the inconsistencies and to fill gaps of the in-situ data with the APHRODITE climatic dataset. However the question arises how reliable the APHRODITE data is so that it could be used instead of observed rainfall data as ground truth. To address this issue, the spatial correlation structure of the two datasets, i.e., in-situ and APHRODITE data, was compared. A summary of this spatial correlation analysis is provided in section 3.1.1.

3.1.1. Spatial Correlogram

The quality of the observed gauged as well as the APHRODITE data was assessed by comparing individual correlograms of the two datasets. A correlogram is a statistical plot used to determine the spatial (or temporal) dependence or correlation of a specific variable. The correlation $\rho(h)$ is defined as:

$$\rho(h) = \frac{C(h)}{C(0)}$$

Where, C(h) is the covariance, C(0) is the variance of a variable and h is the distance (or lag). The correlation values always range between +1 and -1. A spatial correlogram, where the correlation coefficient is plotted as a function of the distance (or time lag) was produced for both in-situ and APHRODITE data to check which dataset shows high correlations for closely located points and smaller values for points at larger distances, thus following the Tobler's first law of Geography (Tobler, 1970).

For the purpose to produce spatial correlograms, daily rainfall values in mm/day were spatially interpolated using the Inverse Distance Weighting (IDW) method in ArcMap using 6 stations namely Pasni, Shadikaur, Tank, Hore, Chibkalamati and Basolmasjid. Out of the period 1971-2000 for which data has been collected for this study, the four year period (1988- 1991) was chosen since only for this period daily time series were available without gaps for a maximum number of gauge stations in the study area. After interpolation, mean monthly maps were produced from interpolated daily rainfall raster maps. The interpolated maps were resampled at a grid scale equal to that of APHRODITE (25km x 25 km) for comparison purposes. This gave 27 grid cells in total covering the whole study area (shown in Figure-6). The center pixel values were extracted from each grid. Cross-correlation coefficients were then calculated between all combinations of cells. Finally, these cross-correlation coefficients were plotted against the corresponding distance (in km) for all combinations of cells. The same procedure was repeated for the APHRODITE dataset, except that no interpolation was needed in this case. Also, the APHRODITE daily data were first converted into monthly mean estimates using Climate Data Operators (CDO) toolkit before APHRODITE's centered pixel values were extracted for each cell.

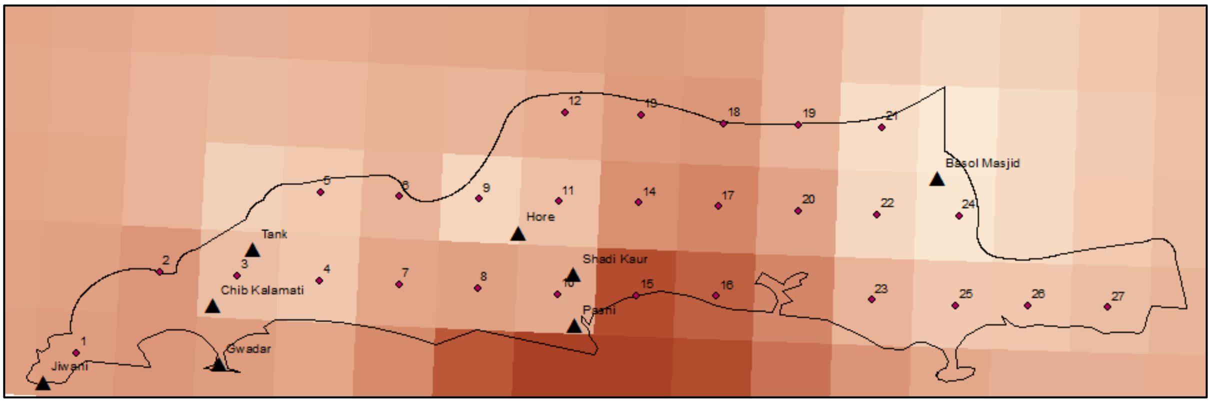

Figure 6: Location of 27 grid cells (25x25 km size) covering study area along with position of gauge stations (represented by triangle)

3.1.2. Filling in Gaps of In-situ data

To overcome the gaps in in-situ data, missing daily rainfall data were imputed using two packages in R software, namely; MICE (Multivariate Imputation via Chained Equations) and missForest. MICE creates multiple imputations as compared to a single imputation (such as the mean) and takes the uncertainty of missing values into account. MICE assumes that the missing data are randomly missing, which means that the probability that a value is missing depends only on the observed value and can be predicted using them. MissForest is an implementation of the random forest algorithm. It is a non-parametric imputation method, meaning it does not make explicit assumptions about the functional form of any arbitrary function 'f.' Instead, it estimates 'f' such that values imputed can be as close to the data points without seeming impractical.

Both methods were applied and checked for each rainfall station in the study area. The results of these methods were then compared with available observed rainfall data. The method giving a more reasonable and closer match to available observed rainfall data was selected for every station.

3.2. SDSM Methodology

3.2.1. Model Setup

Before constructing the relationship between predictand and predictors, some important model parameters were setup to achieve the best statistical agreement between observed and NCEP data as well as CanESM2 AOGCM data. The model setup for this study is described below whereas, terminologies used in settings are explained already in section 2.3.1.

i- Generally the predictand is an individual daily weather series, obtained from meteorological observations at a single station. In this study, daily rainfall time series extracted for each of 27 grid cells covering the entire basin were used as predictand in SDSM. Predictand rainfall data (in mm/day) was retrieved by first interpolating data of 8 gauge stations for the period 1971-2000 using IDW and then resampling it to 25km x 25 km grid cell size.

ii- A calibration period of 20 years was taken starting from 01-01-1971 to 31-12-1990. A validation period of 10 years was considered starting from 01-01-1991 to 31-12-2000 for both NCEP reanalysis data and observed data. CanESM2 GCM data ranged from 1961 to 2005 for the historic period and 2006 to 2100 for the future period. The same range was used for generating GCM outputs.

iii- The event threshold was set to be 0.3 mm/day for precipitation to treat trace rain days as dry days.

iv- For rainfall periodic analysis, *seasonal- June, July, August* (further referred as JJA) along with *conditional* sub-model options were selected. Furthermore, *ordinary least squares* optimization algorithm was selected. Seasonal sub-model type was selected because according to Wilby and Dawson (2007), this model is appropriate to be used in situations where data are too sparse at the monthly level for model calibration or where there is low incidence of precipitation in semi-arid regions. While, JJA season was selected to analyse the model performance for wet monsoon months. Due to time restriction, only one season was analysed.

v- The model was allowed to generate the random number sequences each time the weather generator or scenario generator is run.

vi- In most of the cases, precipitation data is not distributed normally. Therefore, fourth root transformation was applied for precipitation to render it normal before using it in a regression equation, following the precedent set by other studies to downscale rainfall.

3.2.2. Procedure to Downscale

The functionality of SDSM operations to perform the main tasks is explained in section 2.3.2. The following procedure was adopted to statistically downscale rainfall data. Figure-7 represents the same methodology of statistical downscaling in terms of a flow chart.

1- *Quality control and data transformation:*

Quality control check was made for all predictand files and no data transformation was performed on predictand and/or predictor data.

2- *Screening of downscaling predictor variables:*

In order to identify the most suitable predictor variables for the predictand, the correlation statistics and p-values for each of the predictor variables available from NCEP and the GCM were examined. The correlation matrix and p-values indicate the strength of the association between two variables. Higher correlation values imply a higher degree of association. Smaller p-values indicate that this association is less likely to have occurred by chance. A p-value less than 0.05 is generally used as a threshold value. A higher value than 0.05 means that the correlation between the predictor and predictand is likely to be due to chance and the use of such a predictor might lead to multi-co-linearity between the variables.

SDSM allows a maximum of 12 predictors correlated with a predictand at one time. Therefore, multiple combinations of 12 predictor variables with a predictand were checked. After several trials for each of the 27 predictands (for 27 grid cells), only those variables out of 26 NCEP predictor variables were shortlisted which were highly correlated with the predictand and having a p-value less than 0.05. It was observed that mostly two to five predictors were enough to best explain the predictand during calibration and without multi-co-linearity. The shortlisted predictor variables remained more or less constant for all 27 predictands giving confidence that the predictor variables were appropriately screened. The most frequently screened predictor variables for the majority of the 27 predictand (grid cells) can be found in Table-4.

Table 4: List of most effective predictor variables over the study area

S.N.	Predictor variables	Description of predictor variables
1	p8_vgl	850hPa Meridional wind component
2	p5_vgl	500hPa Meridional wind component
3	p1_ugl	1000hPa Zonal wind component
4	s500gl	Specific humidity at 500hPa
5	p1_zhgl	1000hPa Divergence
6	p5zhgl	500hPa Divergence

3- Model calibration:

The model calibration was performed by establishing transfer function based on the multiple regression equations (4 in number for seasonal analysis) via an optimisation algorithm (OLS in this case), using predictand and screened predictor variables. The regression equations are then used for generating new synthetic data. The coefficient of determination (R^2) was used to evaluate the model performance for the calibration period. The default values of variance inflation and bias correction factors were adjusted several times until the best statistical agreement between observed and simulated outputs were achieved to calibrate the model well.

4- Weather generator:

For period 1971-1990, synthetic daily weather data was generated with the regression model weights determined during the model calibration and from NCEP predictor variables. SWG can simulate up to 100 daily time series, using the calibrated parameters along with NCEP in order to fit closely with the observed data (Wilby et al., 2002; Mahmood and Babel, 2013). Twenty time series are normally considered as the standard precedent for validation purposes (Mahmood and Babel, 2014). Therefore, an ensemble of 20 members was generated and the mean of these ensembles was used to compare with the observed data.

5- Scenario generation:

Similar to the weather generator function, the scenario generator operation also generates the ensembles of synthetic daily weather time series. The output of the scenario generator was used to validate the model calibration. First, both NCEP/NCAR reanalysis data and CanESM2 data were used as large-scale atmospheric predictor variables for validation of SDSM for the period 1991-2000. Then, only CanESM2 data was used for future scenario generation using two emission scenarios, i.e., RCP 4.5 and RCP 8.5. The same regression model weights that were used for weather generation were used for downscaling the future data. For each emission scenario, twenty ensembles of synthetic daily time series were generated for the period of 2006 to 2099 and the mean of these twenty ensembles was used as final daily weather data for the future period of 2041-2070 only.

6- Graphical Analysis:

Observed vs. simulated daily weather time series were compared in form of graphical plots. The comparison was performed using 'Summary Statistics' and 'Compare Results' functions in SDSM, results of which are provided in section 4.2.1. There are varieties of statistical options that can be chosen to summarize results. For this study, the comparison was made for mean and variance only. Validation of the model results was performed by visual inspection of these observed vs. simulated graphs.

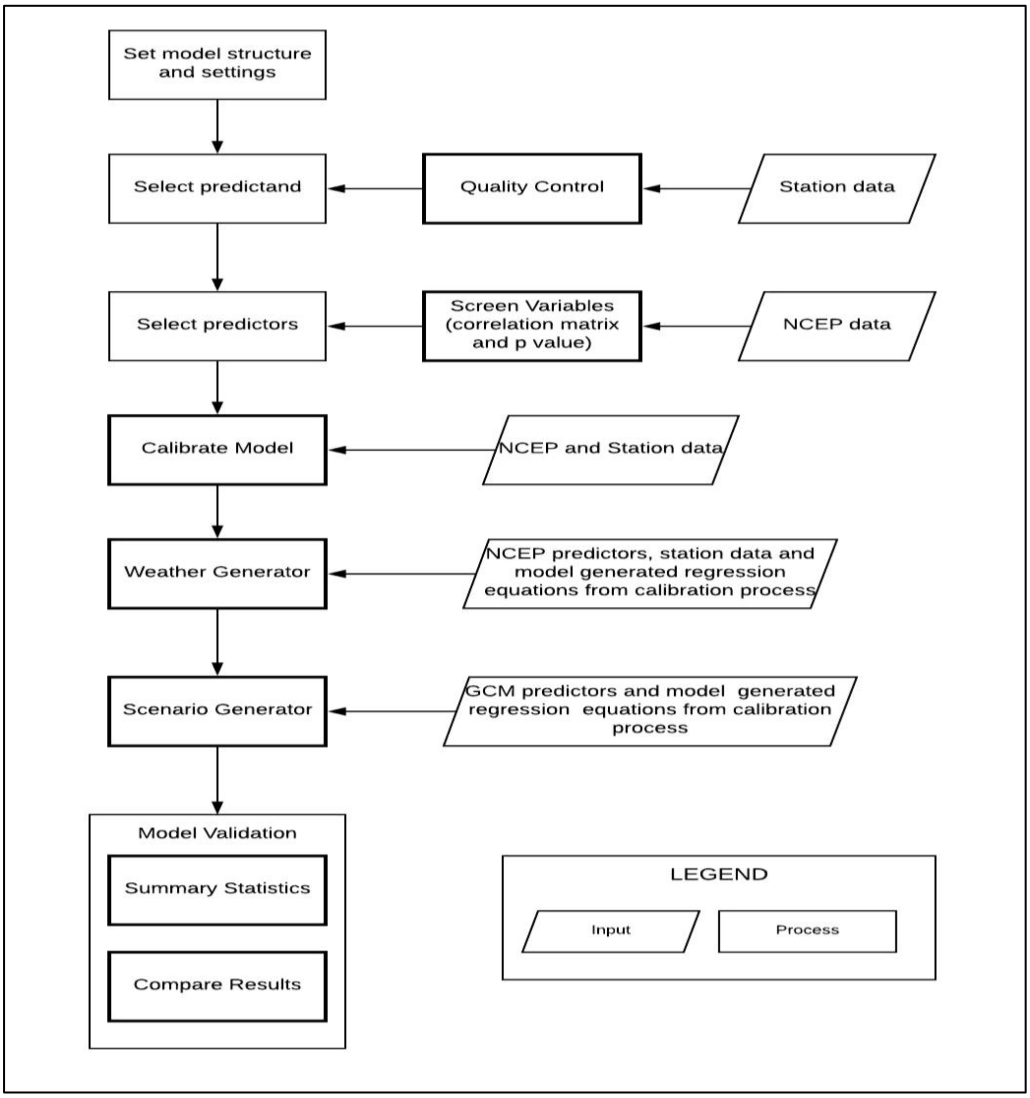

Figure 7: SDSM work methodology used in the study

3.3. RegCM4 RCM Methodology

Raw IITM-RegCM4 regional climate model (RCM) data from the CORDEX-SA dataset available in rotated - polar grids was firstly re-gridded to a regular geographic grid with a spatial resolution of 0.44^{o} x 0.44^{o} (50km x 50km) using Climate Data Operators (CDO) to be further used for analysis in the study. RegCM4 RCM which is a numerical climate prediction model forced by specified lateral and ocean conditions from the CanESM2 AOGCM, offers ready – to –use dynamical downscaled simulations for the 1951-2100 time period which was divided into two periods for this study: historical (1971-2000) and scenario (2041-2070) periods. After re-gridding of RCM data, precipitation values in mm/day were extracted for each grid cell (size 50x50 km) covering the study area. The extracted values were then utilized directly, without performing any bias correction, to calculate the monthly climatological average and monthly climatological standard deviation in order to compare with the final simulated results from statistically downscaled CanESM2 AOGCM data. The results obtained from RegCM4 RCM are provided and discussed in section 4.3.

4. RESULTS AND DISCUSSION

This chapter presents and discusses the results. Results of data reliability analysis through spatial correlogram of observed rainfall and APHRODITE data are discussed in section 4.1. Section 4.2 deals with the calibration and validation of the Statistical DownScaling Model and the performance of the statistical downscaling technique is discussed. Results of the performance evaluation of the dynamically downscaled RegCM4 data are presented in section 4.3. The comparison in terms of strengths and limitations of each of the two downscaling approaches is provided in section 4.4. Finally, the results of this study are compared with other studies in section 4.5.

4.1. Spatial Correlograms

The correlation of both observed and APHRODITE data over distance (km) was assessed to check the quality of each dataset using spatial (cross) correlogram. Results of individual spatial correlogram of the observed and APHRODITE dataset and the comparison between them shows that the observed data follows Tobler's law better than the APHRODITE data. As it can be seen from Figure-8, the correlogram for observed data shows a pattern that follows Tobler's law; i.e., with the increase in distance the correlation coefficient decreases for all combinations among 27 central points of the grid cells covering the study area. Despite that Figure-8 shows a lot of noise, the sequence of grid cells' values at increasing distances show generally same and overall the decreasing trend. To reduce the noise in the spatial correlogram, average values of correlation coefficients at each distance step of 10 km were calculated and plotted as shown in Figure-9. This shows a more lucid shape of the correlogram. A 10 km average was taken assuming that spatial rainfall occurrence over the study area is homogeneous. On the other hand, the APHRODITE data shows a very high correlation (0.8) at distance of 200 km that must be considered unrealistic. The correlogram in Figure-10 suggests that pronounced correlation even extends up to a distance of 350km but such also must be considered unrealistic. The correlogram in Figure-10 does not suggests any aspect of decorrelation, so the APHRODITE data set must be considered not reliable for further use. Based on this result, APHRODITE was rejected and was not further used in the research because of its highly processed dataset and correlogram which is not logical compared to the observed correlogram,. It can be concluded that in regions with scarce coverage of climate stations APHRODITE may provide unrealistic spatial patterns of precipitation (Climate Data Guide, 2017).

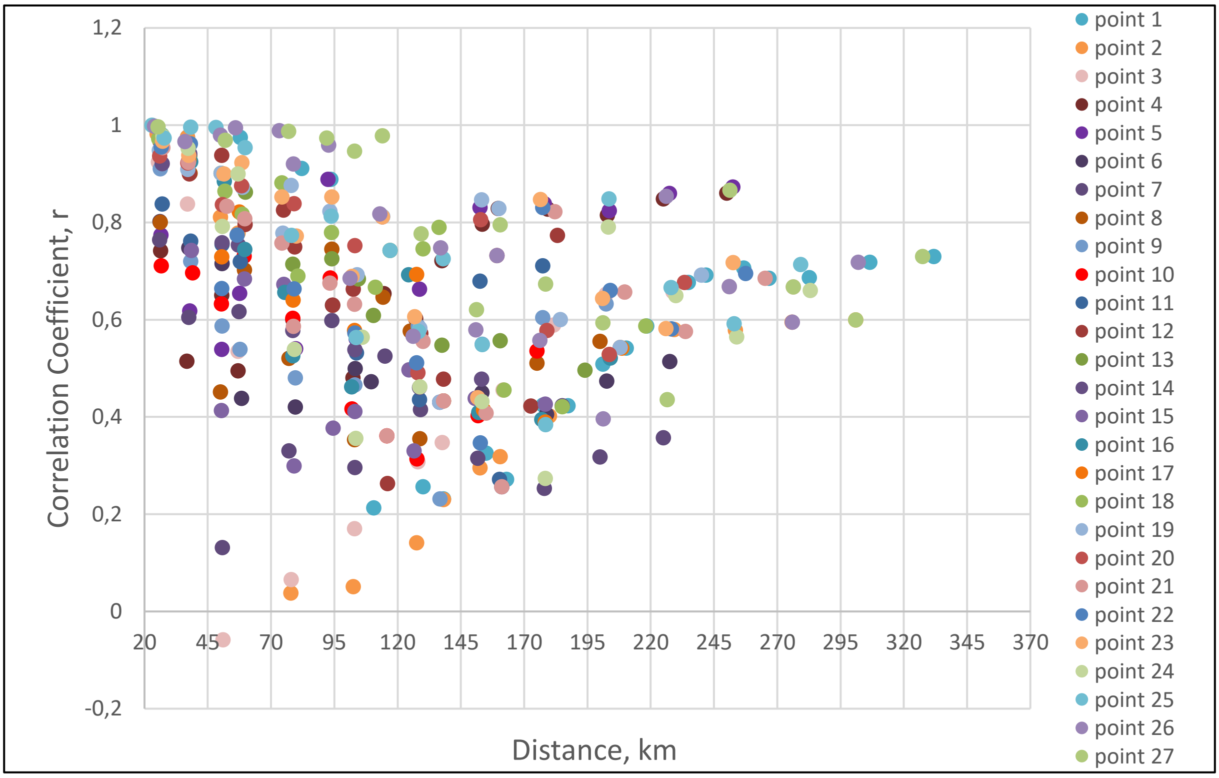

Figure 8: Spatial correlogram of in-situ data for all combination of pixels covering the study area

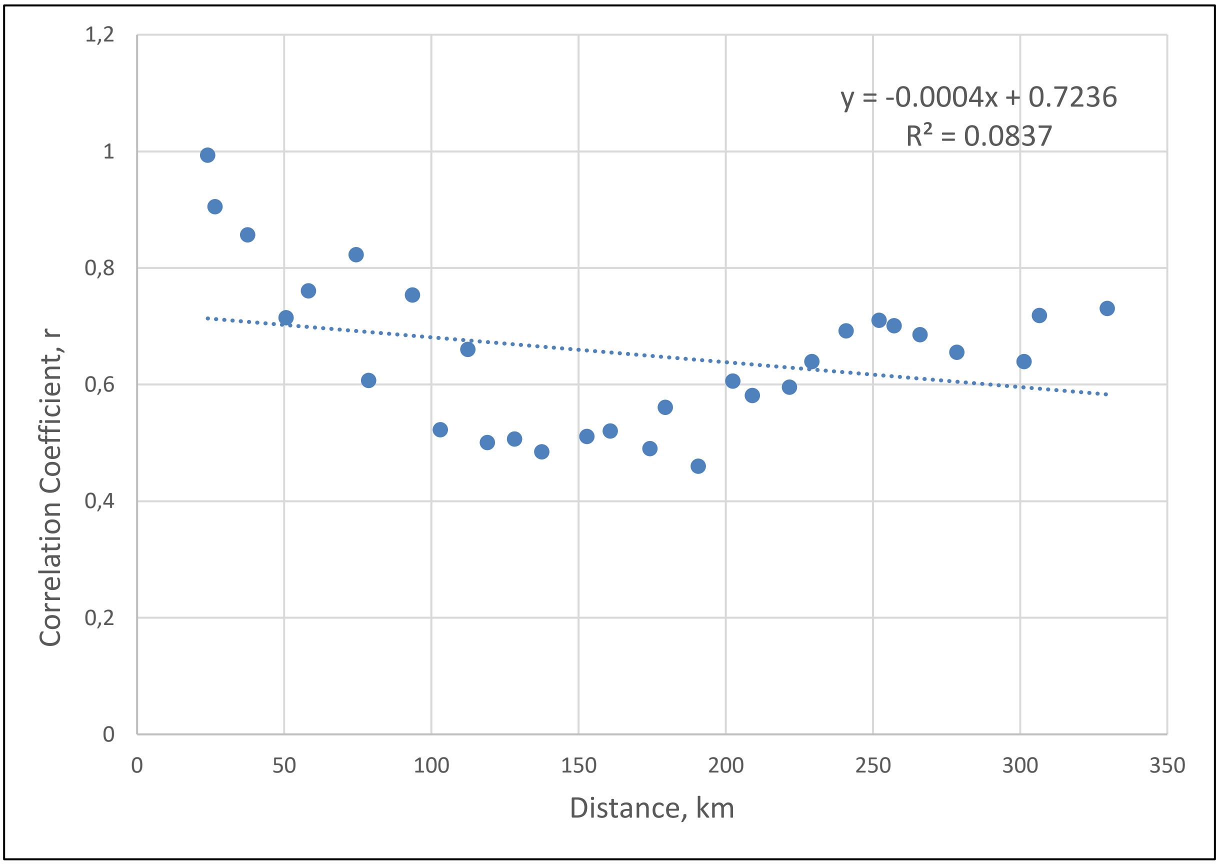

Figure 9: 10-km averaged correlogram of in-situ data for all combination of pixels covering the study area

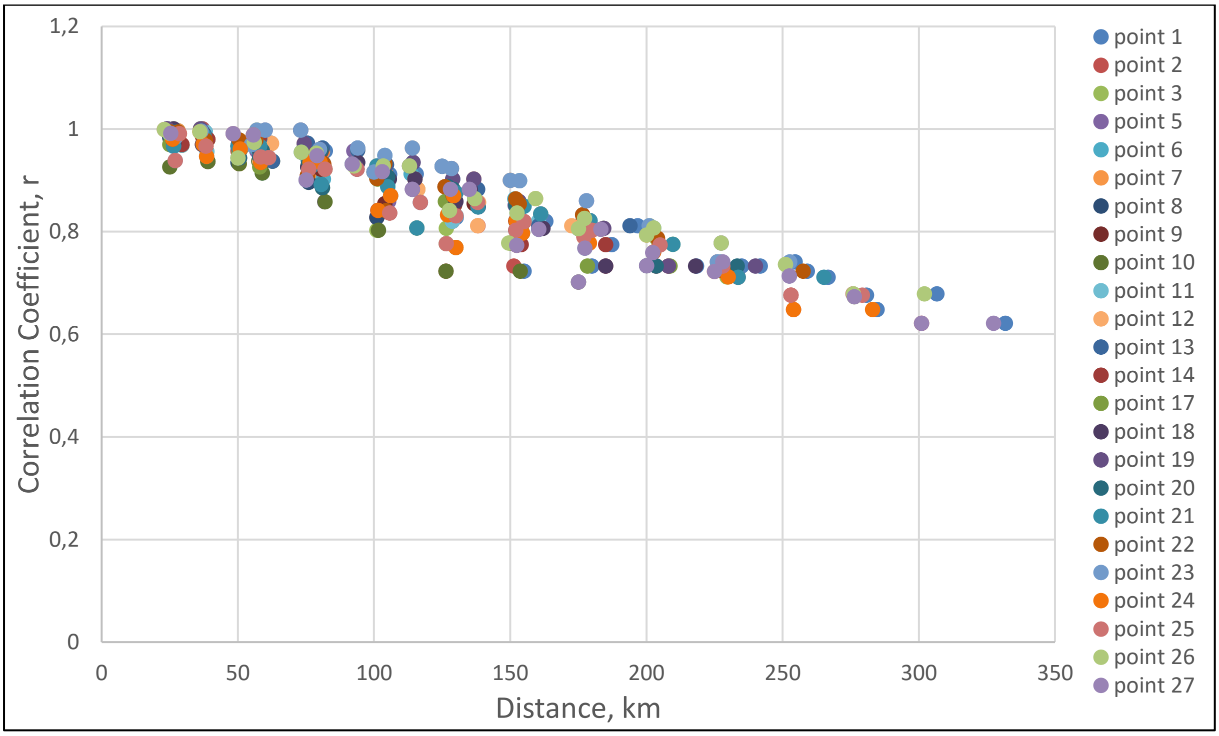

Figure 10: Spatial correlogram of APHRODITE data for all combination of pixels covering the study area

4.2. Statistical Downscaling

4.2.1. Results of Calibration and Validation of Model

For all 27 grid cells, the coefficient of determination (R^2) after calibration ranged between 0.2 and 0.08. The reason for these low R^2 values can be the erratic rainfall values in the dataset with observations that is used as predictand. Also, it might be the limitation of the transfer function used that it sometimes explains a fraction of the climate variability, mostly in case of precipitation (Wilby and Dawson, 2007) thus producing poor results in the model calibration. Moreover, the unique topography and climatic conditions of the coastal basin can be a major reason why statistically downscaled CanESM2 GCM and NCEP reanalysis data did not show a correspondance with the observed data. It is important to mention here that the observed dataset used is not completely reliable, however it was the only available limited dataset as ground truth which proved to be a better option than gridded rainfall data of APHRODITE.

Regardless of the low R^2 values, the observed vs. simulated NCEP and GCM plots as shown in Figure-11, 13, 15, 17 and 19 show that the calibration performed is still considerable, as the overall rainfall trend over the months represented by observed and simulated data is comparable (refer Figure-23). Out of 27 grid cells, calibration and validation graphs for only 5 grid cells are provided in the report. Five grid cells numbered as grid 1, 3, 10, 11 and 24 (see Figure-6), are selected because inside these grid cells gauging stations are located. The validation graphs (Figure-12, 14, 16, 18 and 20) show poorer results than in the calibration, as the seasonal rainfall patterns of observed and simulated datasets do not correspond well. Furthermore, it was found that the comparison between observations and simulations at a daily time step was not meaningful, as most of the days in a year have no rainfall. Therefore, this study solely focused on the evaluation of rainfall patterns at a monthly time scale.

The graphs of observed and downscaled data for monthly precipitation show that NCEP and CanESM2 AOGCM were not able to simulate the maximum monthly rainfall well. This can be observed in all calibration and validation graphs where observed maximum monthly rainfall is higher than the simulated counterparts because of the erratic observed data used. From calibration and validation graphs, it can be concluded that both observed and simulated results are uncertain. To investigate the degree of uncertainty in statistically downscaled CanESM2 AOGCM rainfall compared to observed data, dynamically downscaled results of RegCM4 RCM driven by the same AOGCM were compared with SDSM's results. The sources of uncertainty and comparison of the results of the two downscaled methods are discussed in section 4.4. Due to the uncertainty in observed and statistically downscaled GCM results, a bias correction procedure was not carried out. Bias correction is generally performed on downscaled climate model data (see e.g. Salzmann et al., 2007; Mahmood and Babel, 2013; Khadka & Pathak, 2016; Mahmood and Babel, 2014) when there is sufficient confidence in the observed dataset. However, this is not the case for the observed data in this study.

Model calibration and validation are essential steps to analyse the performance of any model showing how well the model can replicate the observed data. Figure-21 and 22 show the plots of observed and simulated data for all the five grid cells with gauging stations for the calibration and validation period separately. From Figure-21, it can be observed that December, January, February (DJF) and June, July, August (JJA) are wet months and observed, NCEP and CanESM2 all show somewhat higher rainfall amounts in these seasons. Whereas, March, April, May (MAM) and September, October, November (SON) are dry months. Observed, NCEP and CanESM2 all show smaller rainfall amounts in these dry months. On the contrary, no clear rainfall pattern can be observed for the validation period as shown in Figure-22.

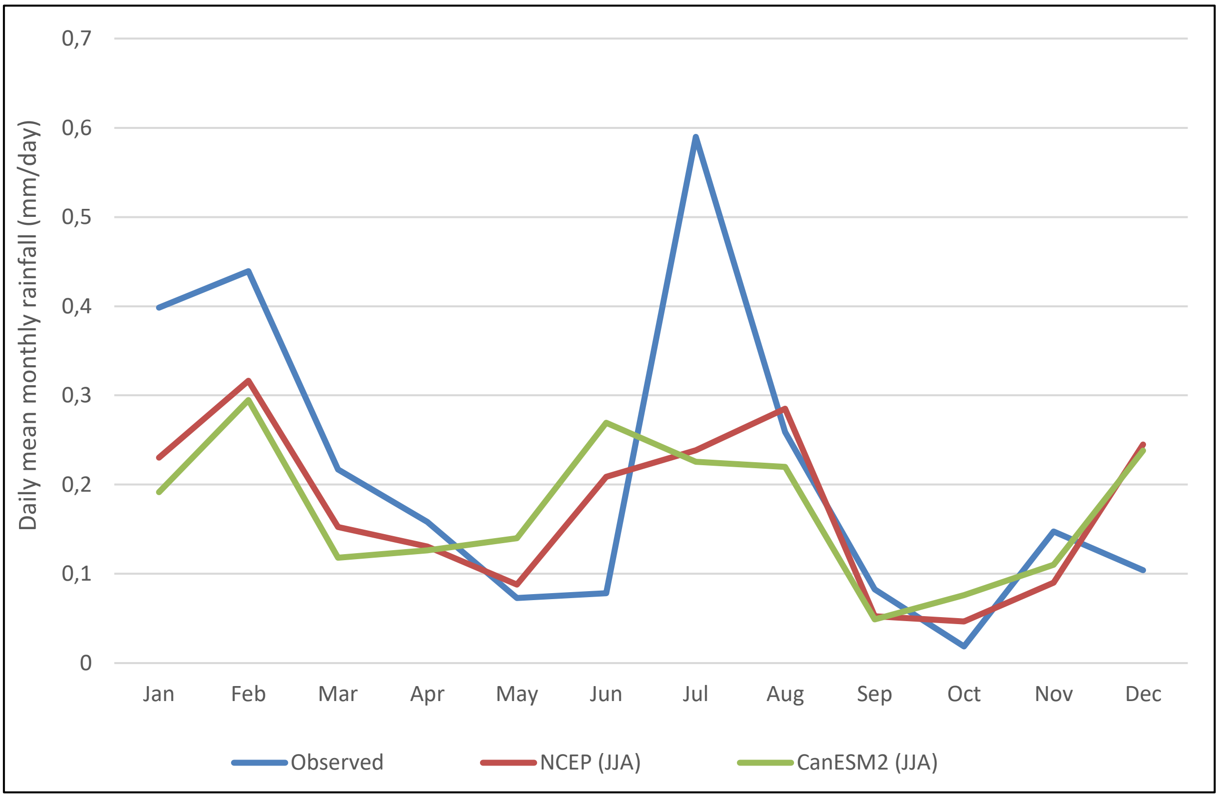

Figure 11: Observed vs. simulated daily mean monthly rainfall for the calibration period for grid cell-1

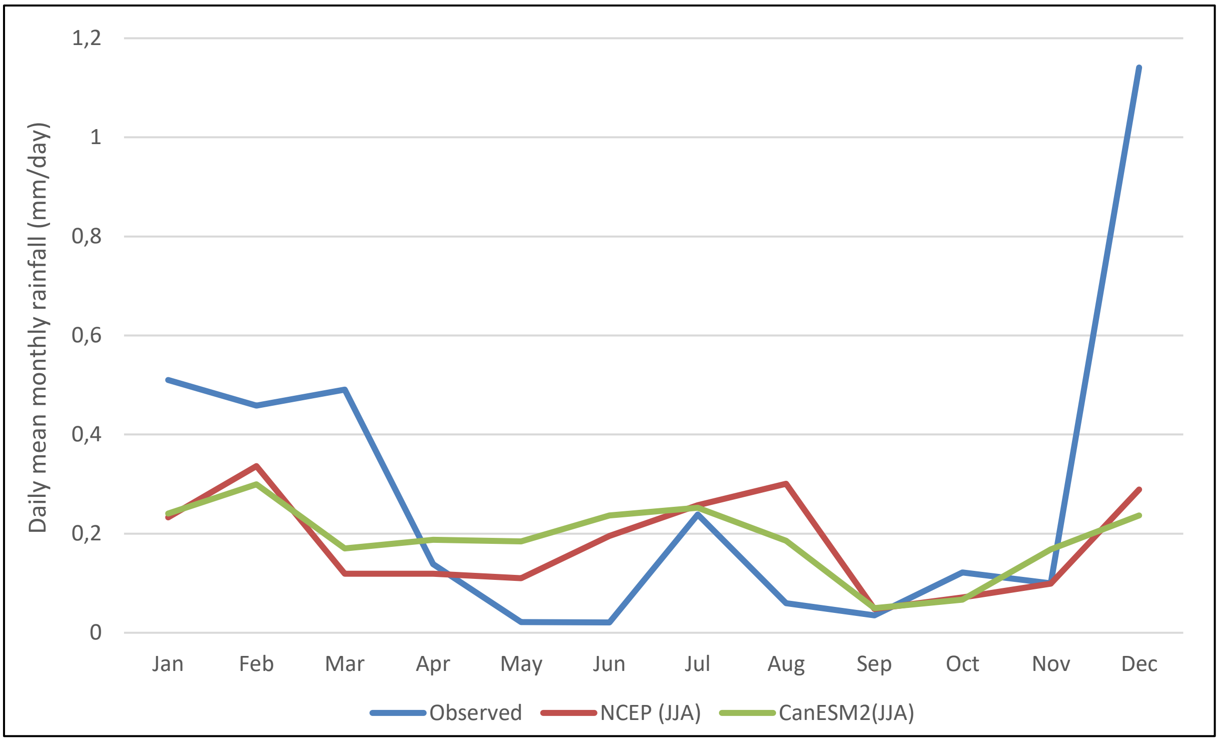

Figure 12: Observed vs. simulated daily mean monthly rainfall for the validation period for grid cell-1

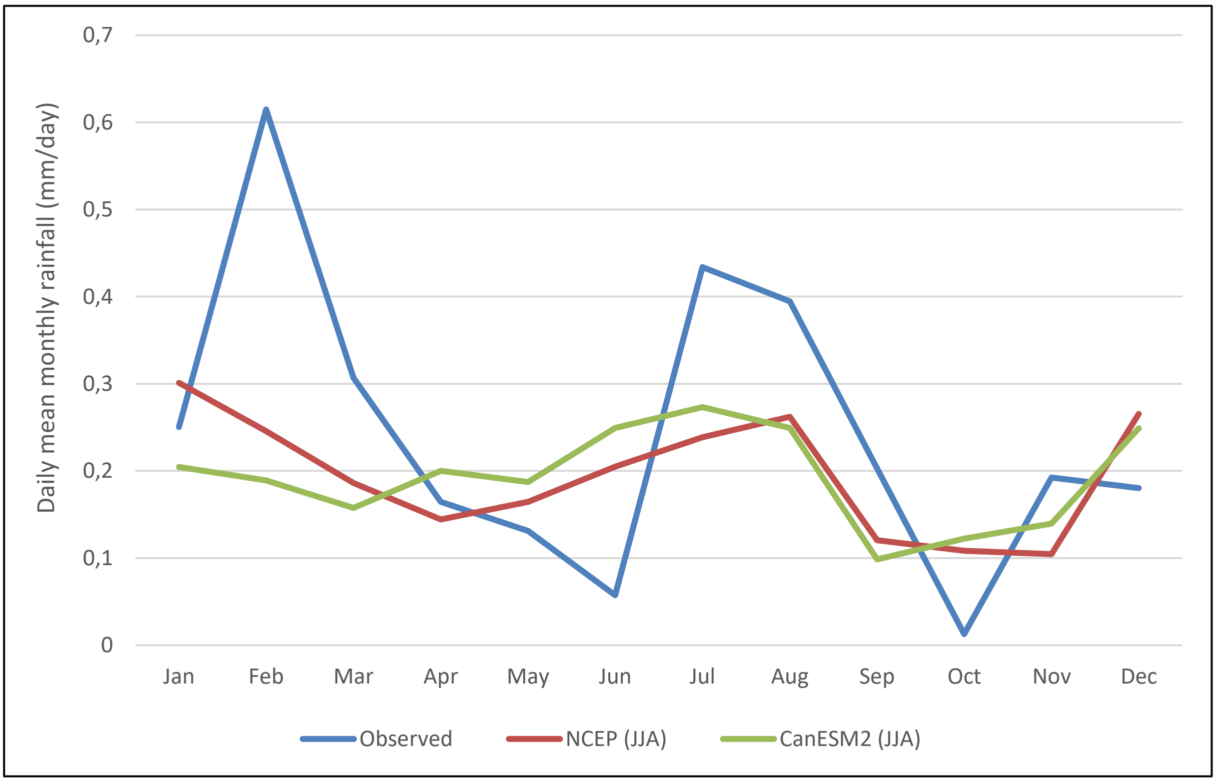

Figure 13: Observed vs. simulated daily mean monthly rainfall for the calibration period for grid cell-3

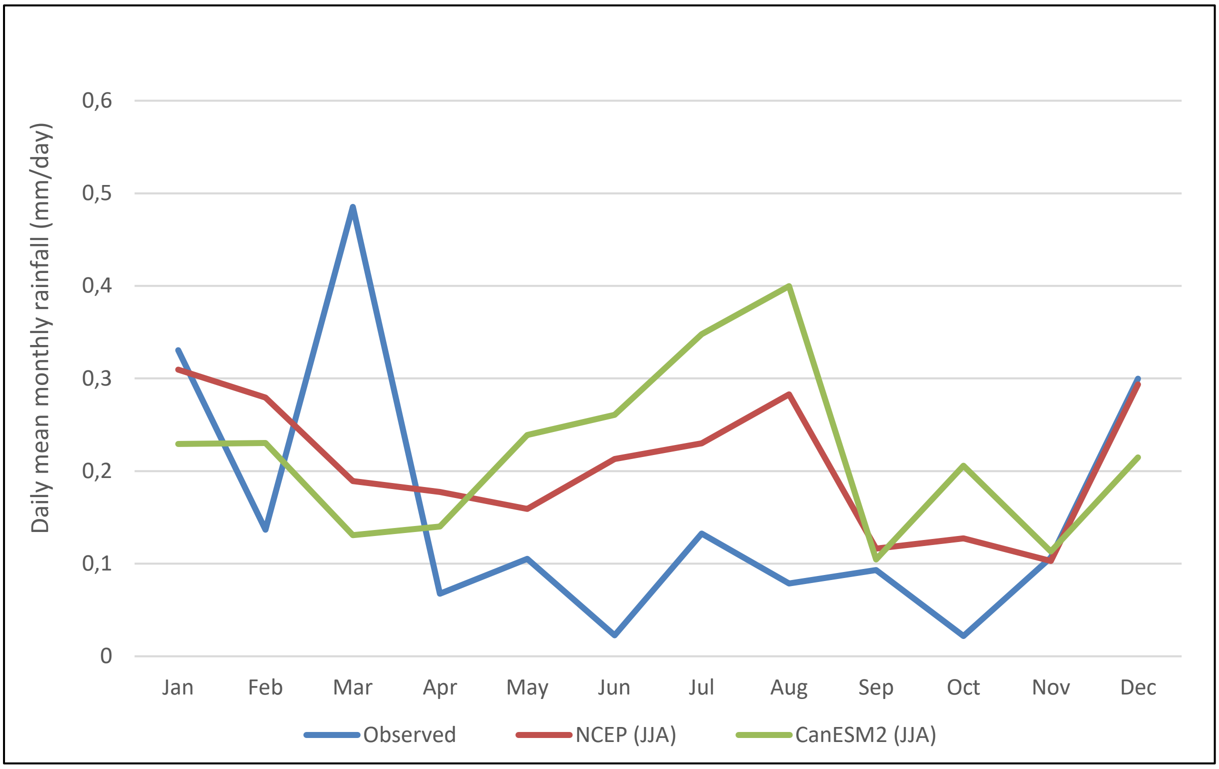

Figure 14: Observed vs. simulated daily mean monthly rainfall for the validation period for grid cell-3

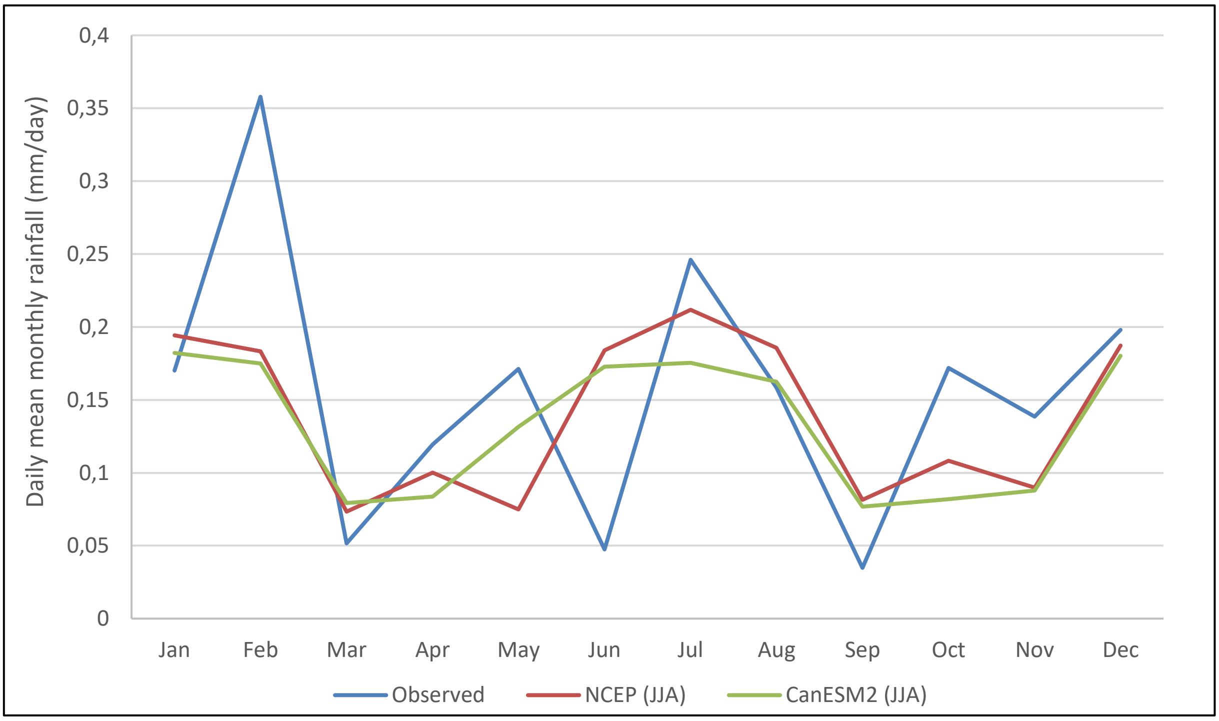

Figure 15: Observed vs. simulated daily mean monthly rainfall for the calibration period for grid cell-10

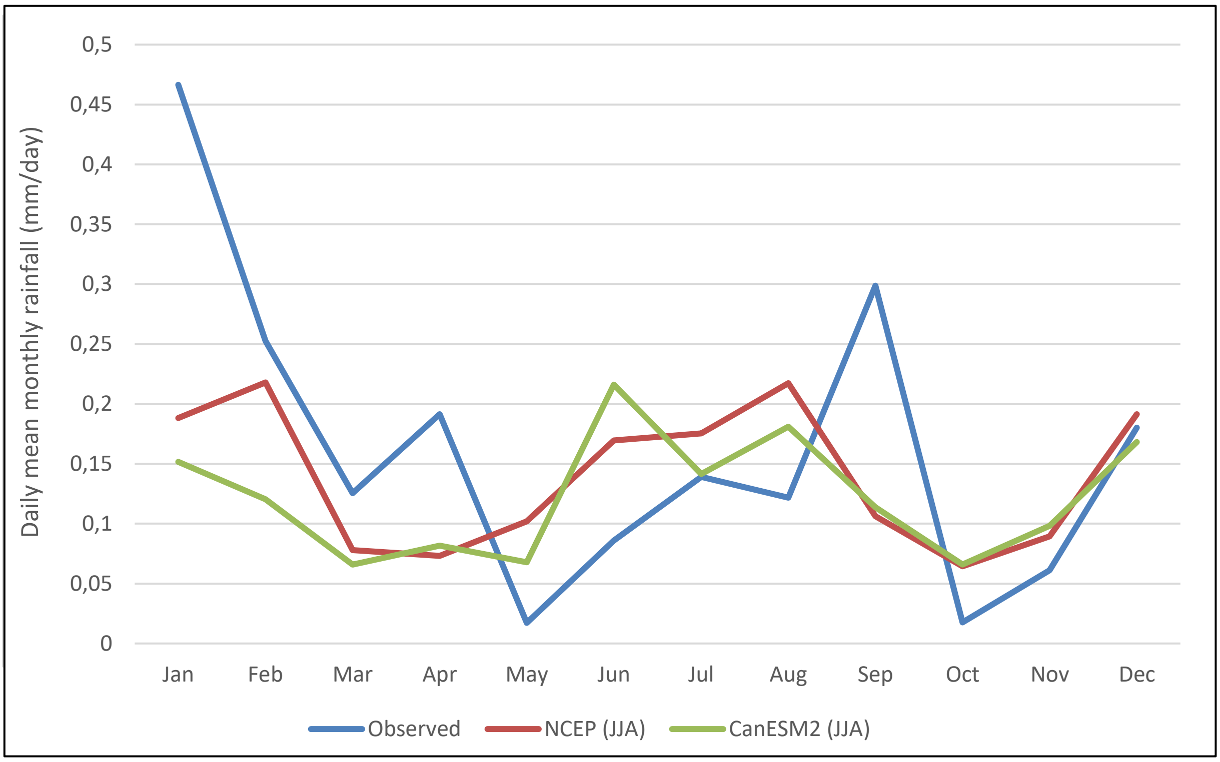

Figure 16: Observed vs. simulated daily mean monthly rainfall for the validation period for grid cell-10

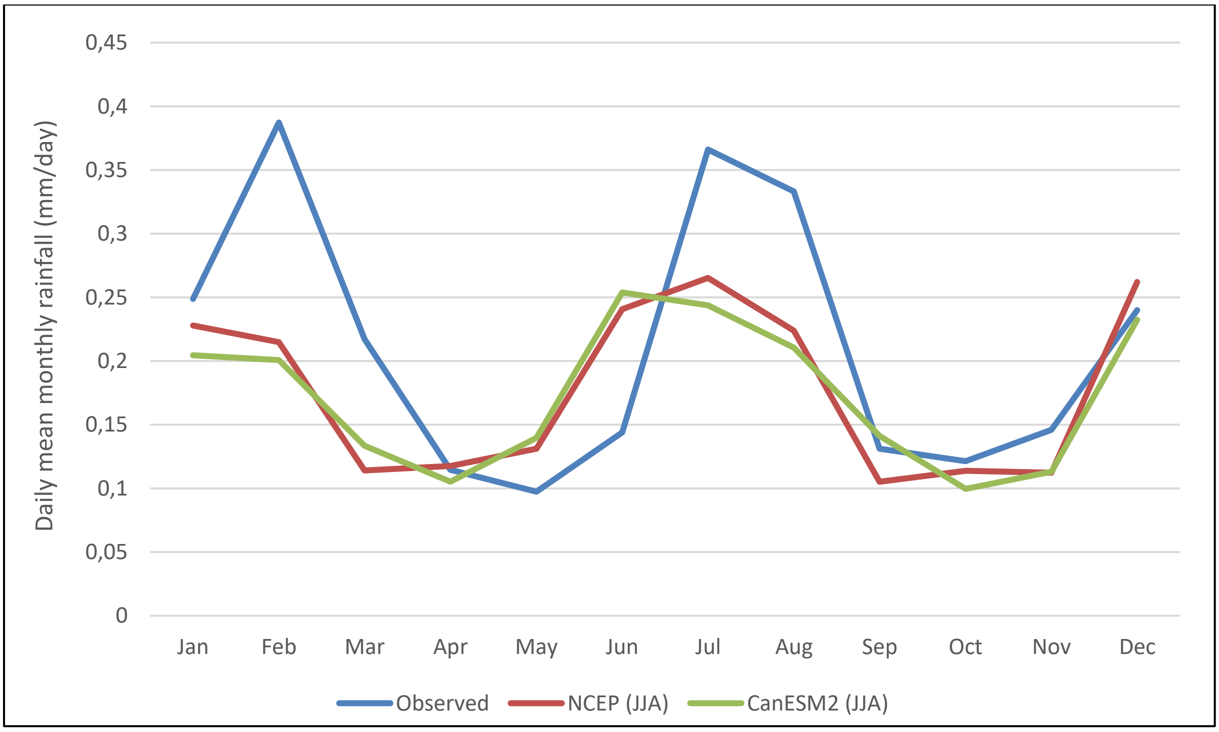

Figure 17: Observed vs. simulated daily mean monthly rainfall for the calibration period for grid cell-11

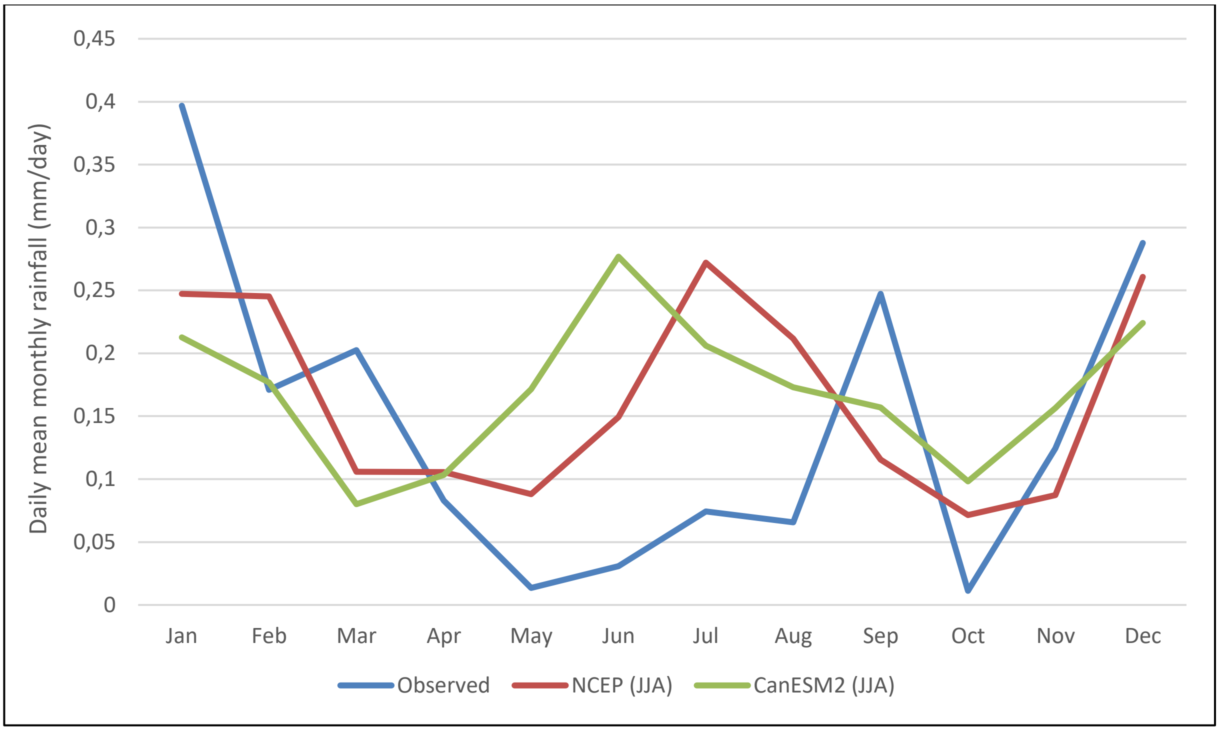

Figure 18: Observed vs. simulated daily mean monthly rainfall for the validation period for grid cell-11

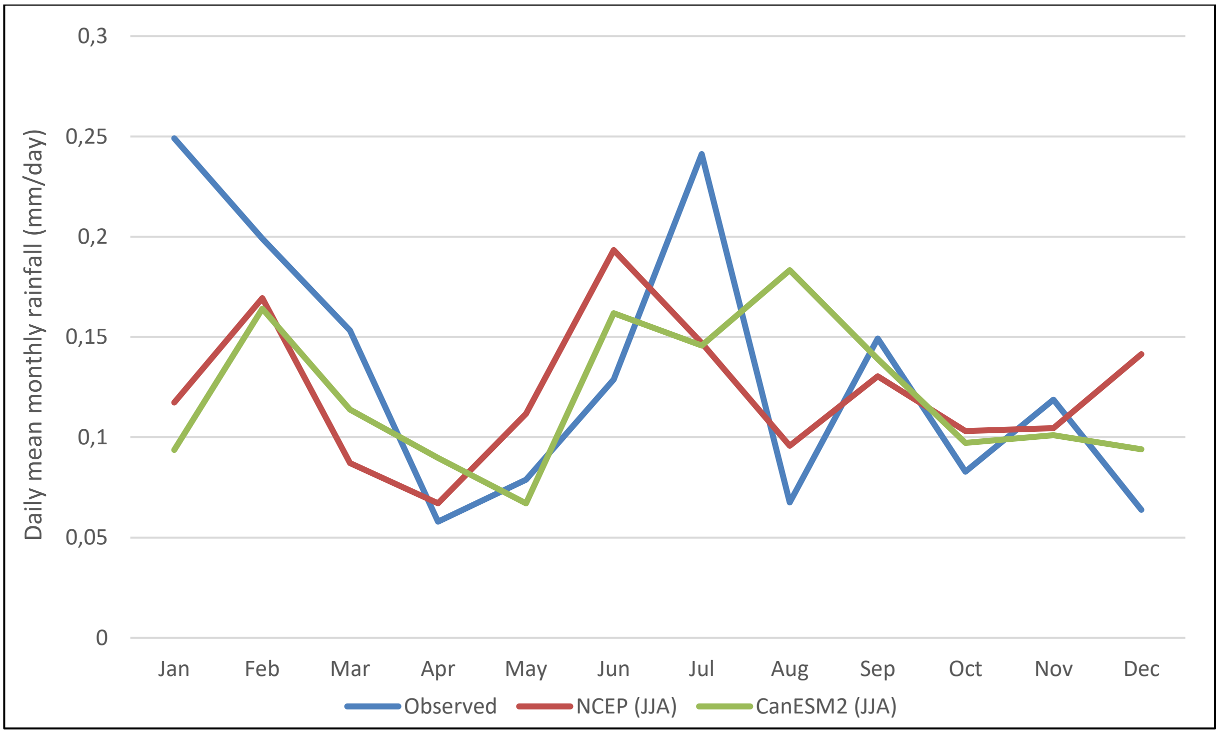

Figure 19: Observed vs. simulated daily mean monthly rainfall for the calibration period for grid cell-24

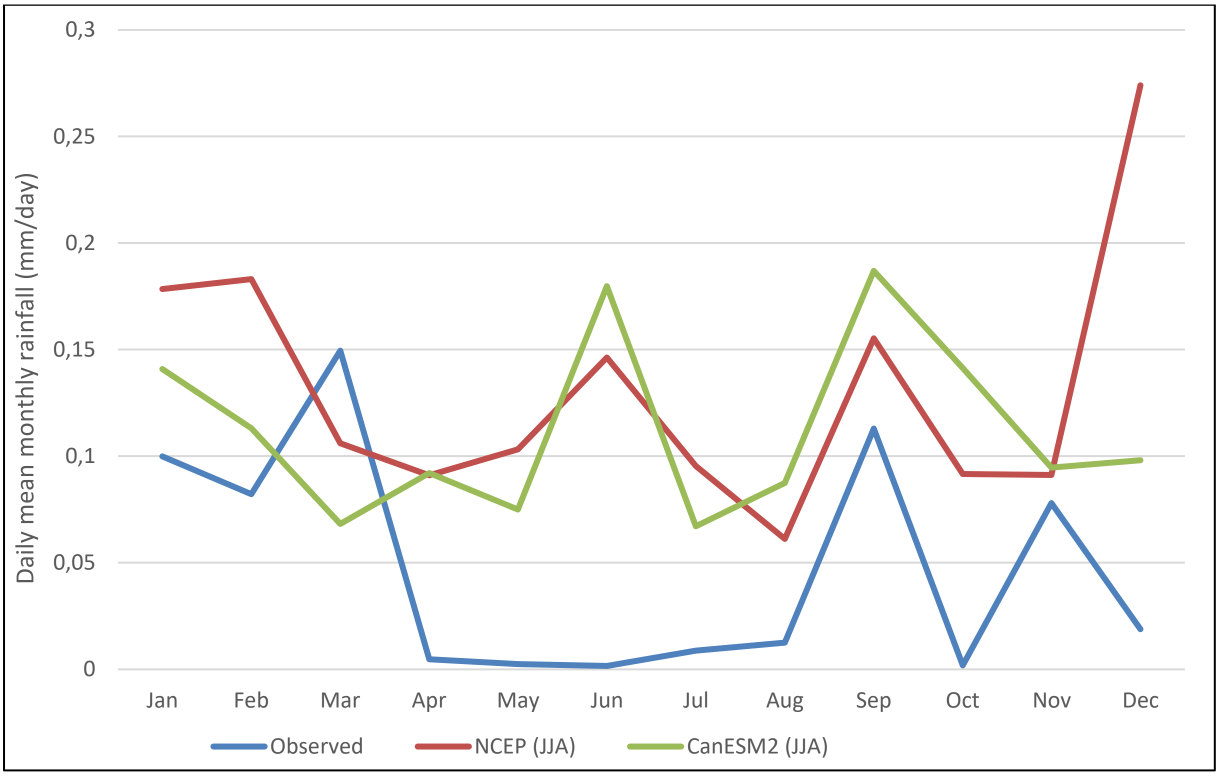

Figure 20: Observed vs. simulated daily mean monthly rainfall for the validation period for grid cell-24

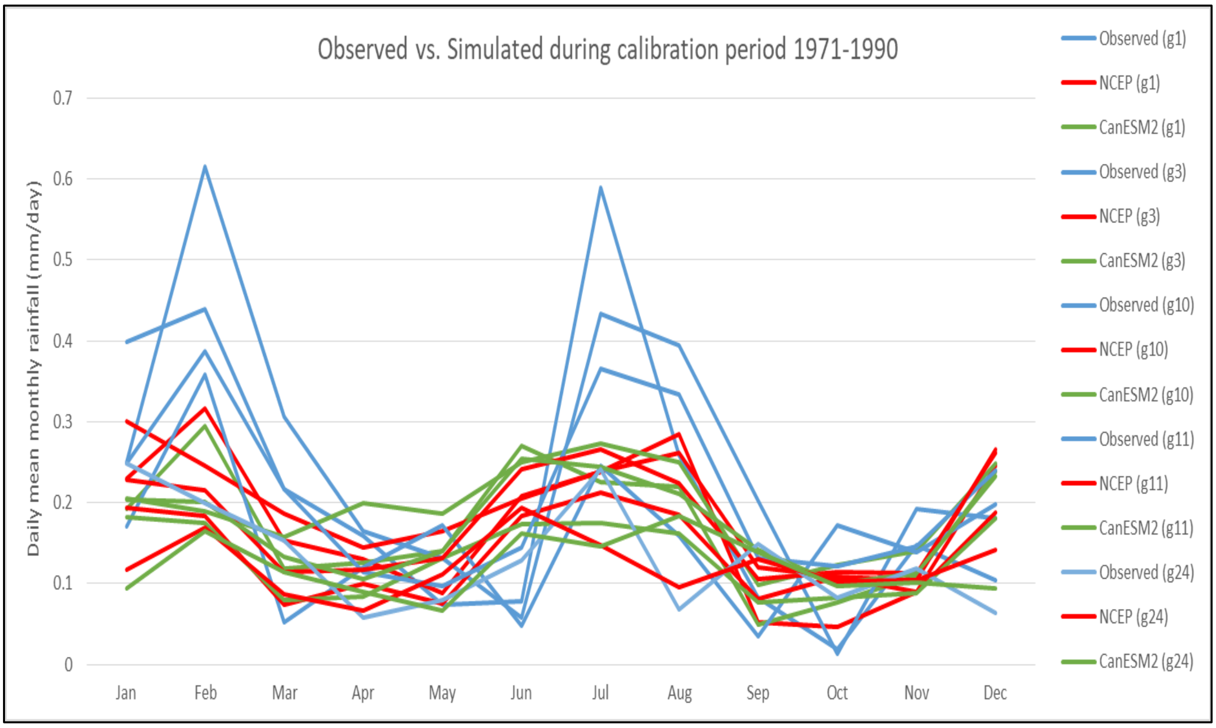

Figure 21: Calibration graph for all 5 grid cells combined

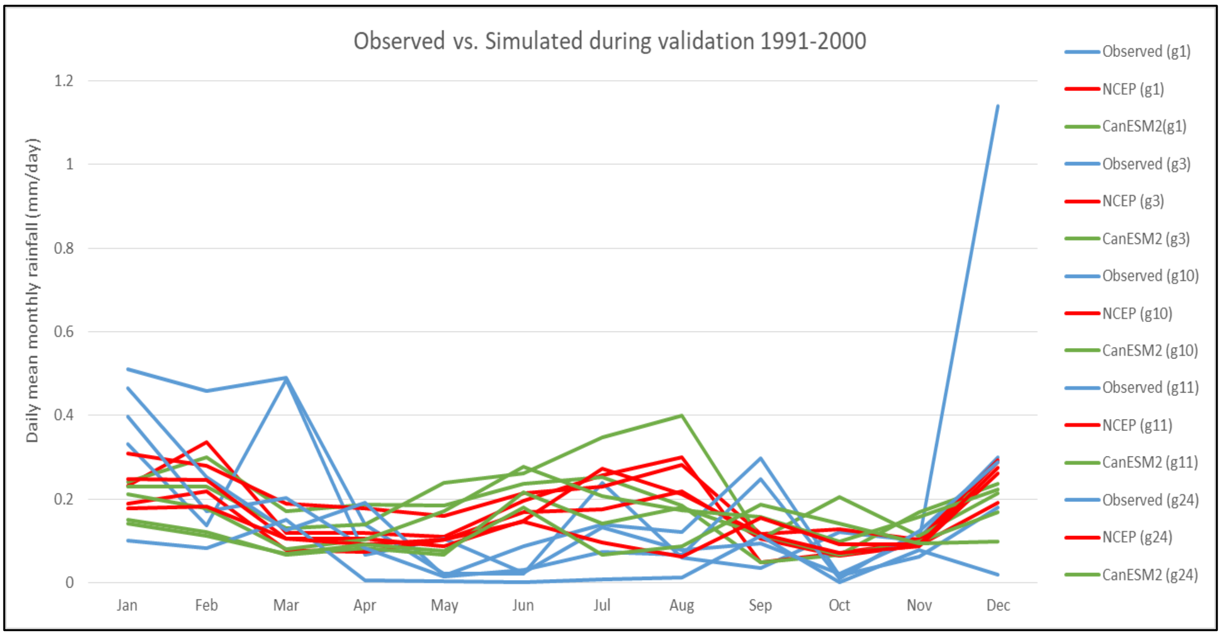

Figure 22: Validation graph for all 5 grid cells combined

4.2.2. Results of Statistical Downscaling

The performance evaluation of SDSM was finally achieved by means of calculating the climatological averages and standard deviations of rainfall for the historic (1971-2000) as well as future (2041-2070) period for 27 grid cells covering the study area. The final graphs showing statistically downscaled CanESM2 AOGCM results for the baseline and future period under RCP 4.5 and RCP 8.5 scenarios compared to observed data are provided in Figure-23 and Figure-24. Figure-23 shows the monthly average graph for observed and simulated rainfall over the basin. Whereas, Figure-24 presents the monthly standard deviation for observed and simulated rainfall.

From Figure-23, it can be seen that the downscaled CanESM2 for the historic period (1971-2000), though simulated relatively low maximum and high minimum monthly rainfall values compared to the observed data. The simulated results generated were satisfactory in terms of simulating the overall monthly rainfall cycle over the study area, i.e., the wetting and drying seasonal trend shown by the simulation was in coherence with the observed. Except that the observed data showed sharp average monthly climatological plot and CanESM2 showed the seasonal rainfall pattern in a smoother manner. Furthermore, the observed maximum rainfall value in the month of July was close in a match to the downscaled monthly maximum value for 1971-2000. Also, for November and December, the simulated data fitted reasonably to the observed data. The performance evaluation of SDSM based on the standard deviation showed poor results for NCEP and CanESM2 simulations compared to observed data for historic time period (see Figure-24). The observed dataset showed very high standard deviation values and large monthly variation due to the irregular rainfall values in the data. This behaviour was not replicated well by the model with lower NCEP and CanESM2 simulated standard deviation values.

For future projections (2041-2070), the SDSM results obtained show hardly any difference in CanESM2 simulations under emission scenarios between RCPs 4.5 and RCPs 8.5 (i.e., graphs overlay). This is reflected in both Figure-23 and Figure-24. The average monthly rainfall and standard deviation graphs for the future CanESM2 simulations under RCP 4.5 and RCP 8.5 showed similarity in presenting trend and variance of rainfall over the study area. It can also be observed from Figure-23 and Figure-24 that the statistically downscaled future projections of CanESM2 are close to the historic downscaled simulations of the AOGCM that by itself is highly unlikely, given the increased GHGs emissions in the atmosphere one can expect that rainfall will change. Also, the model showed inadequate results in projecting future simulations under RCPs 4.5 and RCPs 8.5 compared to the simulated AOGCM (shown alike in Figure-23 and Figure-24). In this regard, it can be concluded that the selected NCEP predictors within SDSM are insensitive to different radiative forcings which reflects that the performance of SDSM in predicting future rainfall was not satisfactory.

It is important to highlight that the pronounced difference between observed and simulated GCM results in the phase of calibration and validation (as can be seen in Figure-11 to Figure-20) reduced significantly when daily means on a monthly basis for all 27 grid cells combined were calculated. The climatological averaging of rainfall over 30 years for historic and future periods resulted in suppressing of the erratic observed precipitation pattern and showed a rainfall change trend that somehow weakly matches the downscaled CanESM2 simulations.

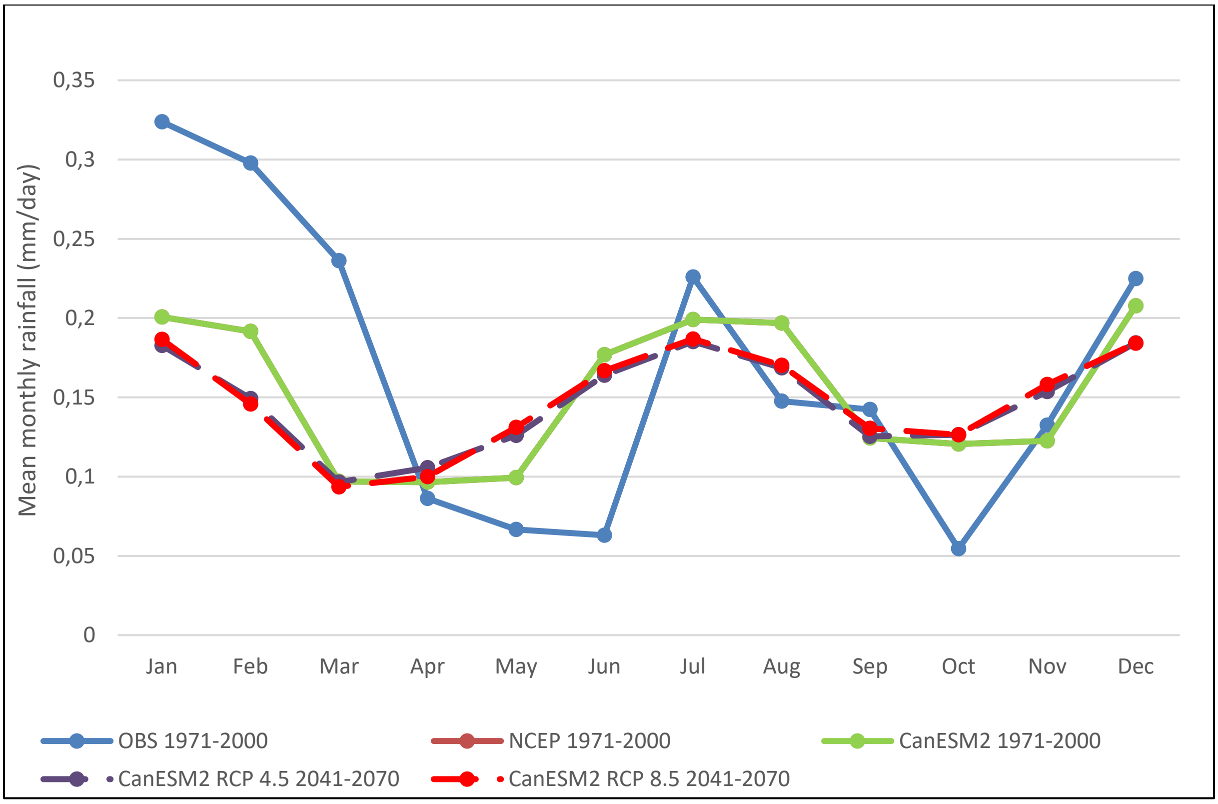

Figure 23: Observed vs. simulated average monthly rainfall for entire basin

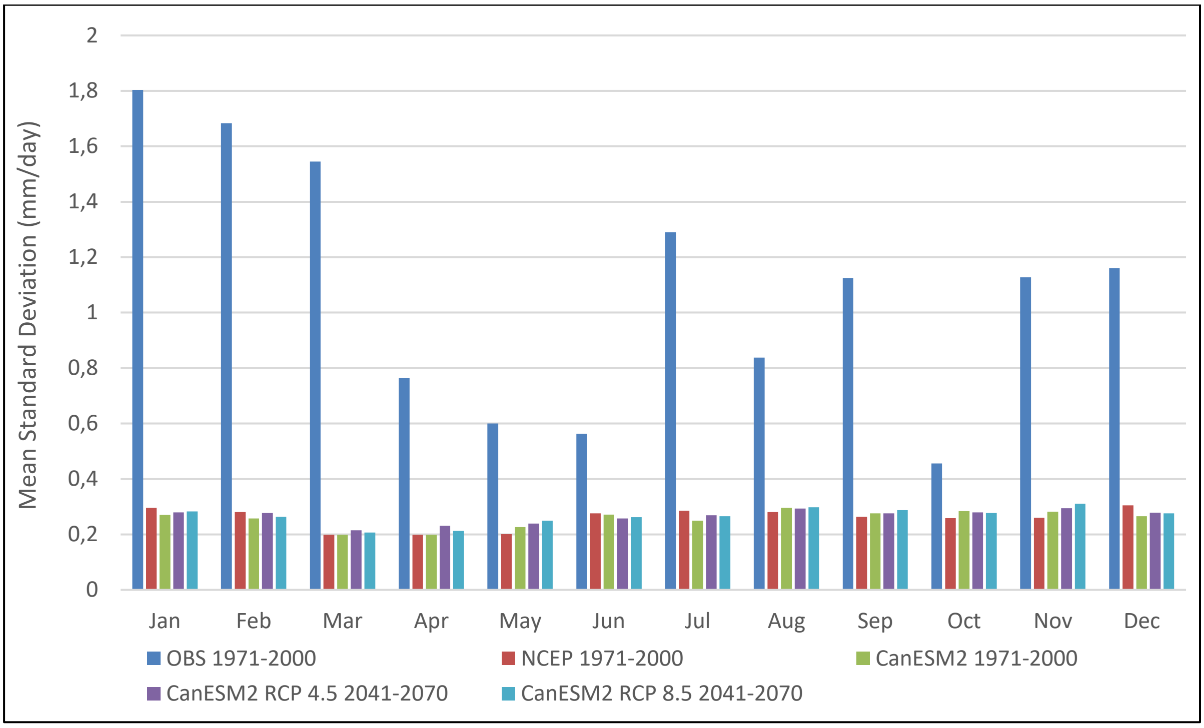

Figure 24: Observed vs. simulated mean monthly rainfall standard deviation graph for entire basin

4.3. Dynamical Downscaling

The performance of the dynamical downscaling approach (RegCM4 RCM) was also evaluated by comparing the monthly average rainfall graph (Figure-25) and monthly standard deviation graph (Figure-26) for both historic as well as future time periods. Figure-25 shows that the RegCM4 historic simulation largely over-estimated the monthly mean values of precipitation in particular for the summer season so that the climatological rainfall pattern of the observed data is no longer visible under the projected trend of RegCM4 RCM and has appeared as a straight line. However, SDSM results obtained as discussed in the previous section well indicate the observed annual cycle of rainfall. Moreover, the RCM also failed to simulate the accurate seasonal pattern of rainfall over the study area. In Gwadar-Ormara basin, there are two wet seasons: i- December, January, February (DJF) and ii- June, July, August (JJA). The dynamical downscaling method failed to simulate the winter precipitation season – DJF completely for both historic and future climate periods.

The RegCM4 RCM simulated standard deviation values of monthly rainfall at the basin scale are erroneously high compared to the observed counterparts for the baseline period. Figure-26 shows the unrealistic results obtained from dynamically downscaled RegCM4 RCM lead to the conclusion that SDSM results are significantly better than the RCM ones, despite of uncertainties existing to some extent in all datasets utilized. The uncertainty in RCM data is higher than the observed and CanESM2 AOGCM data, as can be noticed from both Figure-25 and Figure-26. As a matter of fact, in statistical downscaling method, rainfall was simulated close to observed rainfall by establishing regression equations between local scale predictands (observed) and large-scale atmospheric predictors (NCEP/NCAR and AOGCM) due to which SDSM results can be considered more trustworthy than the RCM's.

Dynamically downscaled future climatic projections for the period 2041-2070 under RCPs 4.5 and RCPs 8.5 also showed very high average mean monthly rainfall and standard deviation values compared to the observed dataset. From both Figure-25 and Figure-26, it can be seen that the difference between the two

RCPs scenarios' simulations of RegCM4 RCM is not significant. The projection under RCPs 4.5 is identical to projection under RCPs 8.5 except for the months of June, July and September for which the difference is trivial and can be overlooked. The future projections from the RCM under the RCPs show a relative change in rainfall variability compared to the historic simulated rainfall variability. Thus, from the overall results of dynamical downscaling, it can be concluded that the RCM results are biased and cannot be directly used in hydrological climate change impact studies.

As mentioned already in section 4.2.1, to reduce uncertainties from climate models, a bias correction step is generally applied. Many other studies like Teutschbein and Seibert, (2012); Berg, Feldmann and Panitz, (2012); and Chen et al., (2017) have recommended this step before further use of the RCMs simulations. The author understands that the over-estimation of the seasonal (JJA) mean precipitation by RegCM4 over the entire basin should have been first bias corrected and then the performance of the RCM should have been evaluated and compared with the statistical downscaling model results. However due to the uncertainty in the observed data itself, bias correction was not undertaken. Nevertheless, it is uncertain whether in this case a bias correction procedure would produce appropriate results because of the large bias correction factors required (179- for June in the historic period) to remove the bias from the RCM simulations considering observed data as the ground truth. This is a reason why RegCM4 RCM can said to be unreliable to simulate spatial-temporal rainfall variability, as similar poor results have been obtained for the same climate model in studies like Haile and Rientjes, (2015) and Almazroui, (2016). Furthermore, the RCM may require improvement in the physical parameterization, convection and land-surface scheme settings (Sanjay et al., 2013)

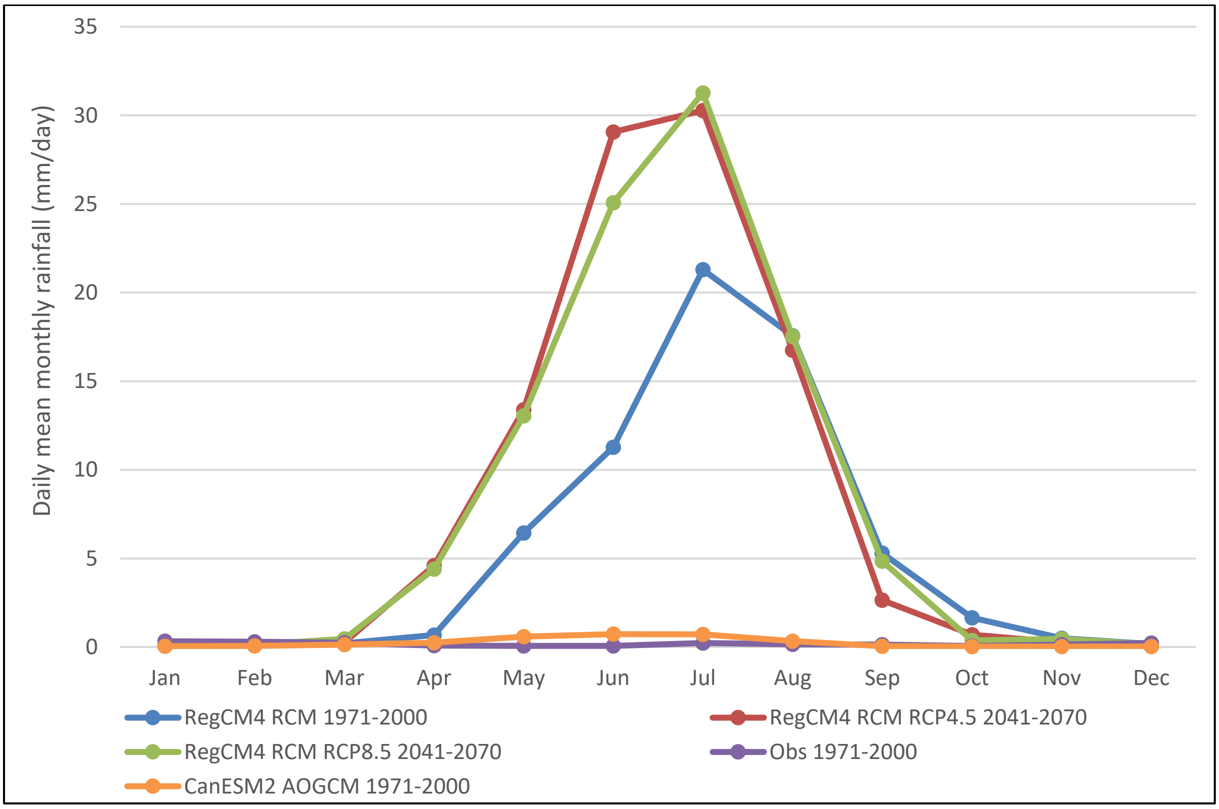

Figure 25: Observed vs. RCM simulated average monthly rainfall for entire basin

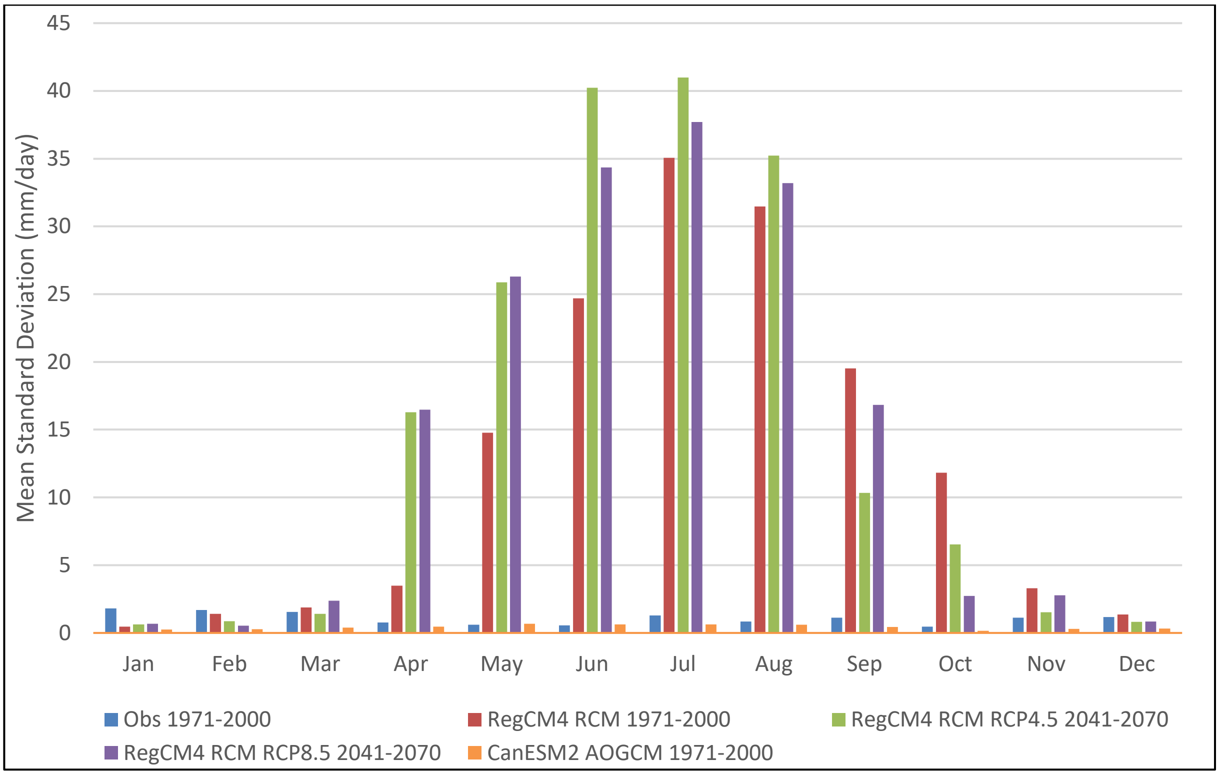

Figure 26: Observed vs. RCM simulated mean monthly standard deviation of rainfall for entire basin

A main reason of unlikely high rainfall values from RegCM4 could be the error propagation in RCM data from the driving AOGCM due to the fact that regional climate models utilize the outputs provided by AOGCMs as lateral boundary conditions to provide spatio-temporal variations of climatic parameters at spatial scales much smaller than the AOGCMs' grid. To ensure that the poor results of the RCM were because of inheriting of physical characteristics from the parent GCM or because of the functional properties (like choice of parameters, initial conditions and mathematical algorithms) of the RCM itself; rainfall estimates of pixels of the parent AOGCM (CanESM2) covering the study area were compared to the rainfall estimates of pixels of RegCM4 RCM falling within those grid cells of the AOGCM. The pixel values of the AOGCM were then arranged in a similar manner as those of the RCMs to determine climatological averages and standard deviation values for the historic period only. The final results, as shown in Figure-25 and Figure-26, confirm that CanESM2 AOGCM is giving more reasonable results close to the observed data than the RegCM4 RCM. Therefore, the high bias in RCMs data is much likely due to the characteristics of the model itself and not inherited by the driving AOGCM.

Further, the RCMs data was also analysed to assess its spatial distribution of rainfall over the study area, as there is a large spatial variation in the observed rainfall data. The results of this analysis are provided in Figure-27. The AOGCM with its coarse resolution cannot be used to validate the observed spatial rainfall variability pattern over the Gwadar-Ormara basin. Hence, the RCM is the only means to analyse if the regional climate model can simulate the rainfall variation similar to that of observed. Figure-27 shows the difference between the observed rainfall distribution and RCM simulated rainfall distribution over the study area, averaged over 30 years (1971-2000) for the wet month of July only. From the figure, it can be seen that the RCM (50km x 50km grid cell size) somehow showed a similar rainfall pattern as the observed one (gauged station data interpolated at a 25km x 25km grid cell size), despite that RCM mean monthly values were highly biased. The rainfall from the coastline to the upland area changes from high mean monthly to low mean monthly precipitation, as represented in both maps. Except that observed rainfall pattern showed more variation from the West end of the basin to the East which was not simulated satisfactorily by the RCM. For instance, in the central part of the basin where three stations (Hore, Shadikaur and Pasni) are located, observed data showed high mean rainfall of about 0.561 mm/day in the month of July over 30 years period. RCM, because of biased dataset, showed mean rainfall of 25.735 mm/day in the same area. The maximum mean rainfall of 36.636 mm/day by RCM data showed in the right corner of the basin does not correspond with the rainfall distribution of the observed dataset. This further supports the argument that RCMs' outputs cannot be directly used for quantifying the hydrological impacts of climate change. Moreover, it should be noted that different classification scales in Figure-27 were applied to make visual analysis and interpretation of both maps meaningful.

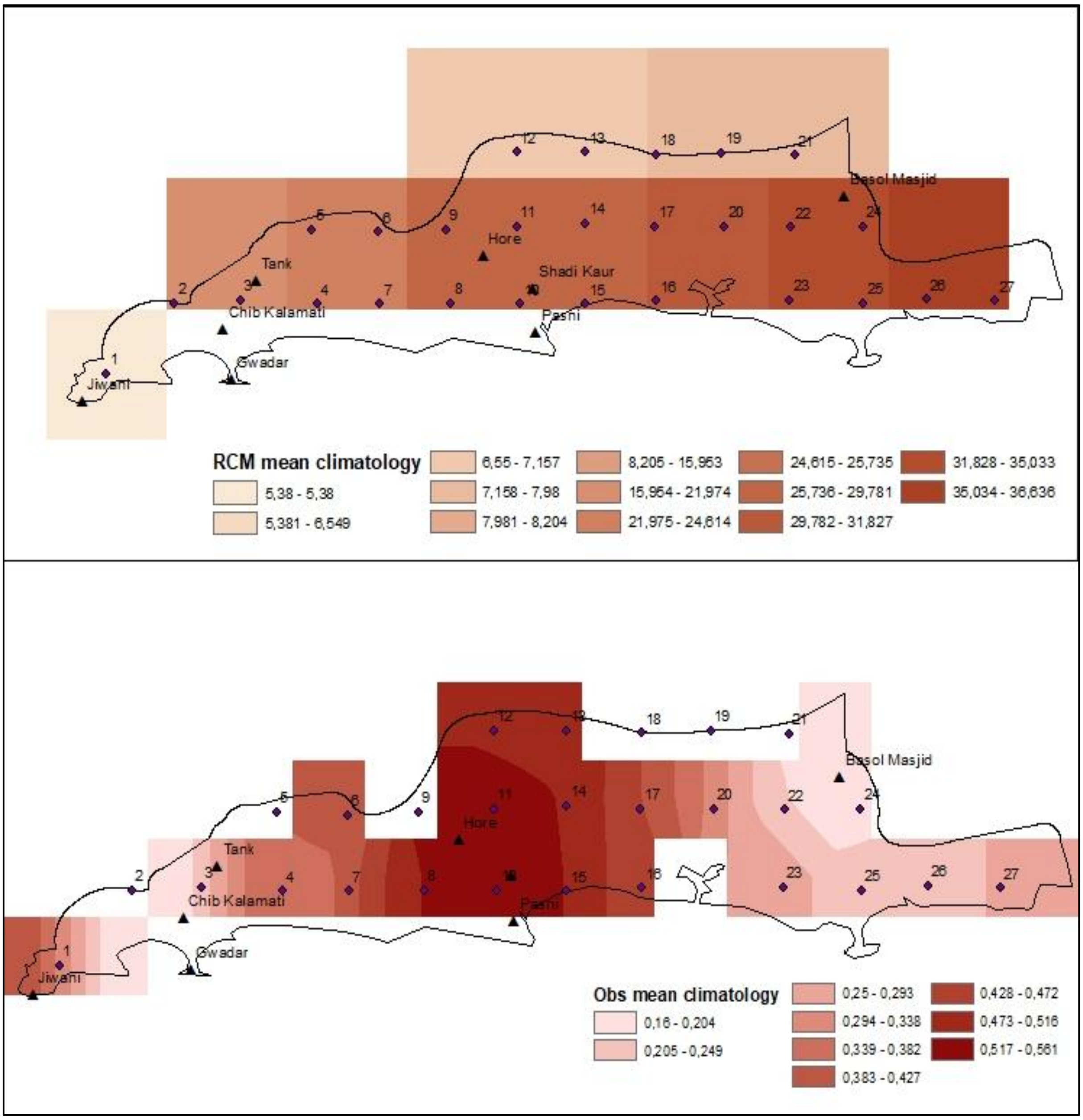

Figure 27: Spatial rainfall variation map of RCM (above) and spatial rainfall variation map of observed data (below)

4.4. Comparison of Statistical vs. Dynamical Downscaling

Performance evaluation of dynamically downscaled RegCM4 regional climate model data without any bias adjustment was performed in the same manner as it was done for statistically downscaled CanESM2 AOGCM by constructing monthly rainfall climatological average and standard deviation graphs for both historic as well as future time periods. It is important to mention that the comparison is established at basin scale but although dissimilar grid cell sizes are used, i.e., 25km x 25km for AOGCM and 50km x 50km for RCM; such did not affect the comparison of the downscale rainfall estimates as end results coming from the two downscaling approaches. The comparison of the two approaches in terms of key strengths and limitations is discussed below:

4.4.1. Statistical Downscaling

- *Strengths:*

i- The statistical downscaling performs better than dynamical downscaling in less data intensive areas, where there is no full confidence in the available observed dataset and bias correction is not appropriate.

ii- Despite the very coarse resolution of the AOGCM, statistical downscaling method develops multiple regression equations between large-scale atmospheric variables and local climate surface variables due to which the statistical downscaling method is forced to simulate the rainfall close to that of observed. In this study, because of statistical relationship developed the downscaled AOGCM simulations produced more realistic rainfall estimates than dynamically downscaled for the baseline period (1971-2000). The bias and uncertainty in downscaled simulated rainfall were comparatively less in case of statistical downscaling.

iii- The monthly rainfall and seasonal trend over the Gwadar-Ormara basin was well captured by statistical downscaling in comparison to dynamical downscaling for both historic as well as future periods. The observed annual cycle of rainfall was noticeable and comparable to statistically downscaled CanESM2 AOGCM simulations, while this was not the case with dynamically downscaled simulations.

- *Limitations:*

i- Model calibration and validation required for statistical downscaling produced unsatisfactory results leading to uncertainty in the model outputs.

ii- SDSM showed insensitivity of selected large-scale atmospheric predictors to different emission scenarios due to which performance of statistical downscaling was not satisfactory in projecting future rainfall (for window 2041-2070). RCP 4.5 and RCP 8.5 emission scenarios generated by SDSM were identical to each other. Also, these projections under RCPs showed lower mean monthly rainfall than the simulated in the historic period (1971-2000), which is not plausible.

4.4.2. Dynamical Downscaling

- *Strengths:*

i- Dynamical downscaling is better than statistical downscaling in terms of predicting spatial-temporal rainfall variation due to a finer resolution of regional climate models (refer Figure-27). Additionally, statistical downscaling can underestimate the variation of rainfall patterns because of statistical relationships, between local and large-scale climate variables, which is assumed that will remain constant and valid in the future.

ii- The dynamically downscaled future rainfall projections under RCPs 4.5 and RCPs 8.5 were significantly higher than the observed ones as well as simulated ones in the historic time period. Rainfall values under carbon emission scenarios generally tend to increase compared to the historic simulations. So, in case of dynamical downscaling, this general behaviour of the climate model was well represented but was not reflected in case of statistical downscaling.

iii- In dynamical downscaling, no model was utilized to downscale rainfall. Hence, model calibration and validation steps were not required.

- *Limitations:*

i- The unrealistically biased rainfall values from the dynamical downscaling in the wet season of June, July, August (JJA) make the usage of RCM data uncertain. Without bias correction, the RCM showed poorer results than SDSM in downscaling rainfall.

ii- The RegCM4 RCM showed a higher uncertainty in simulating rainfall variability compared to the CanESM2 AOGCM might be due to the choice of the parameterization of cumulus convection schemes, mathematical algorithms, land-sea contrast and surface characteristics settings.

iii- The RegCM4 RCM completely missed one of the wet seasons (DJF) over the Gwadar-Ormara basin in both historic as well as future periods.

For further comparison purposes, the annual climatological means of observed and simulated rainfall (from both SDSM and RCM) for the historic (1971-2000) and future period (2041-2070) for the entire basin are provided in Table-5. These annual climatological mean values show how each method performed in downscaling rainfall with respect to the observed dataset.

Table 5: Observed vs. simulated annual climatological means

S.N.	Time Period	Annual Climatological Mean (mm/day)
1	Observed historic (1971-2000)	0.1918
2	RegCM4 historic (1971-2000)	5.4402
3	RegCM4 RCP 4.5 (2041-2070)	8.1851
4	RegCM4 RCP 8.5 (2041-2070)	8.1536
5	CanESM2 AOGCM historic (1971-2000)	0.1731
6	CanESM2 AOGCM RCP 4.5 (2041-2070)	0.1473
7	CanESM2 AOGCM RCP 8.5 (2041-2070)	0.1483

While comparing statistical and dynamically downscaled future projections in period 2041-2070 under the two RCPs, it was noticed that the emission scenarios projected an identical patterns in both approaches. Therefore, probably it partly is a limitation of the driving model used (CanESM2 AOGCM) that it does not show a significant difference in between the results of the two RCP scenarios (one intermediate and one intensive) and it is not due to the poor performance of any downscaling approach; either statistical or dynamical.

4.5. Validation of Results Obtained

A study conducted by Sanjay et al., (2013) tried to evaluate the performances of the RCMs being part of the CORDEX-SA evaluation and historical experiments in comparison with those of the AOGCMs being part of the CMIP5 to facilitate multi-model inter-comparison over South Asia. Amongst the selected ten AOGCMs and five RCMs for a common 15 year evaluation period (1990-2004), they found that the CanESM2 AOGCM showed a dry (negative) bias in simulating annual mean precipitation (mm/day) over central India and Southern parts of Pakistan against the monthly mean rain gauge – based global land precipitation dataset from the Climate Research Unit (CRU) at the University of East Anglia. They also found that individual RCMs (driven by CMIP5 AOGCMs) resulted in biases varying from dry to wet over central India and Southern parts of Pakistan in the historical simulations. Another main conclusion of the study was that the RCMs (including RegCM4) overestimate the spatial variability compared to observed (CRU) annual precipitation climatology over South Asia. A study conducted by Choudhary and Dimri, (2017) also concluded similar results that RCMs under CORDEX-SA exhibit a large wet bias over the region which mean overestimation of precipitation in historic as well as in future projections. The results of these past studies performed over South Asia using CORDEX somewhat support the results of this study undertaken over Gwadar-Ormara basin, Pakistan.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

- Data reliability analysis was performed for observed rainfall and APHRODITE gridded rainfall data using spatial correlogram which resulted in rejecting the use of APHRODITE for the Gwadar-Ormara study area. For unknown reasons, APHRODITE data used produced unrealistic spatial patterns of rainfall.

- Calibration and validation plots of the Statistical DownScaling Model (SDSM) showed erratic observed mean monthly rainfall values (in mm/day) which the model could not replicate well.

- Uncertainty in the observed data was because of two reasons; i- missing and possible erroneous daily rainfall values in the available dataset and ii- imputation techniques used to fill those missing values.

- Statistical downscaling performed better in simulating the monthly rainfall cycle compared to dynamical downscaling for the historic period (1971-2000), without application of bias correction to the outputs of both downscaling methods.

- In period 2041-2070 under the two RCPs 4.5 and 8.5, future rainfall projections did not show any significant difference from each other in both downscaling approaches. This might highlight a limitation of the driving model (CanESM2 AOGCM) and not necessarily poor performance of any downscaling approach; either statistical or dynamical.

- Dynamical downscaling (using RegCM4 RCM) over-estimated the monthly mean precipitation over the study area in both historic and future time periods. RCM showed highly biased rainfall simulations and future projections. The bias in RCM results can be attributed to uncertain initial conditions, lateral-atmospheric-boundaries and lower-surface boundaries with time-variable conditions, which made the outputs from RCM inconsistent with those from the CanESM2 AOGCM.

- Dynamical downscaling due to the finer resolution of regional climate models satisfactorily showed spatial rainfall variation compared to observed data and was able to represent the large variation in the rainfall pattern over the study area similarly to that of observed rainfall.

5.2. Recommendations

- It is recommended that bias correction should be applied to downscaled results (from both SDSM and RCM) using a high-quality observational dataset before using the outputs further in hydrological or impact studies. Further, the performance of a multi-model ensemble and other GCMs/RCMs should be assessed for this case study.

- Further research and studies are required to assess the weaknesses and strengths of the RegCM4 RCM driven by the CanESM2 AOGCM over arid systems.

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