IMPACT OF CLIMATE CHANGE ON THE HYDROLOGY OF MAHANADI RIVER BASIN

A

DISSERTATION

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE

DEGREE OF

MASTER OF TECHNOLOGY (RESEARCH)

IN

CIVIL ENGINEERING

WITH SPECIALIZATION IN

WATER RESOURCES ENGINEERING

By

POOJA PANDEY

Under the Supervision of

DR. K C PATRA

DR. K K KHATUA

DEPARMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

ROURKELA-769008

2015

NATIONAL INSTITUTE OF TECHNOLOGY

ROURKELA

CERTIFICATE

This is to certify that the Dissertation entitled "**IMPACT OF CLIMATE CHANGE ON THE HYDROLOGY OF MAHANADI RIVER BASIN**"*submitted by***POOJA PANDEY***to the***National Institute of Technology, Rourkela***, in partial fulfillment of the requirements for the award of **Master of Technology (Research)** in **Civil Engineering** with specialization in **Water Resources Engineering** is a record of bonafide research work carried out by her under our supervision and guidance during the academic session 2012-14. To the best of our knowledge, the results contained in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.*

Date

Dr. KanhuCharanPatra

Dr. Kishanjeet Kumar khatua

Professor, Department of Civil Engineering

National Institute of Technology, Rourkela

ACKNOWLEDGEMENT

First and foremost, thanks go to God for the blessing that has bestowed upon me in all my endeavors.

I would like to express my sincere gratitude to my supervisors Prof. K. C. Patra and Prof. K. K. Khatua of Water Resources Engineering for their invaluable guidance, cooperation and constant encouragement during the course of the project. I truly appreciate their esteemed guidance and encouragement from beginning to the end of the thesis, their knowledge and company at the time of crisis would be remembered lifelong.

I am grateful to Prof. S.K.Sahoo, Head of the Civil Engineering Department, for his valuable suggestions during the synopsis seminar and necessary facilities for the research work.

I express my deep sense of gratitude to the member of my Master Scrutiny Committee Prof. S.K. Das of Civil Engineering Department and Prof. AbantiSahoo and Prof. B. Munshi of Chemical Engineering Department. I am thankful to all the professors of Civil Engineering Department for their valuable suggestions and instructions and encouragements at various stages of work. I am also thankful to Laboratory Assistants and other staff of Civil Engineering Department N.I.T., Rourkela for their helping hands during the project.

I would like to thank my parents and family members for their love and support, without which I could not have completed this work. Finally, I wish to thank my friends for the encouragement, especially, Ankit, Deepika, JanakiBallav, KirtiKant, Mrunmayee, Roma, Rupali and Saine.

Pooja Pandey

ABSTRACT

The increasing rate of global surface temperature is going to have significant impact on local hydrological regimes and thus on water resources, this leads to the assessment of water resources potential resulting from the climate change impacts. Main parameters that are closely related to the climate change are temperature, precipitation and runoff. Therefore, there is a growing need for an integrated analysis that can quantify the impacts of climate change on various aspects of water resources.

The present work intends to determine climate change impact on the hydrological processes in the Mahanadi River Basin through:(1) Statistical analysis of historical and future climate trends, (2) use of General Circulation Models (GCM) for simulating the response of climate variables globally, accounting for the effects of greenhouse gases in the atmosphere, (3) use of statistical downscaling technique to model the hydrology variables (e.g., precipitation) at a smaller scale based on large scale GCM outputs, (4) use of hydrological modelling for assessment of global climate change impacts.

Statistical trend analysis has been done using Mann Kendall Test and Sen's Slope Estimator to find out the magnitude of the trend for the historical and future records. Statistical downscaling model has been used to predict the future precipitation and temperature time series from the year 2011 to 2099 by using HadCM3 coupled model. Artificial Neural Network (ANN) and Multiple Linear Regression analysis has been used to predict the future runoff from the precipitation and temperature.

Keywords: ANN, Climate change, Downscaling, GCM, Regression.

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LIST OF SYMBOLS

ANN	Artificial Neural Network
AR4	Fourth Assessment Report
ASCE	American Society for Civil Engineers
CWC	Central Water Commission
CICS	Canadian Climate Impact and Scenarios
FMP	Flood Management Plan
GCM	General Circulation Model
HadCM3	Hadley Centre Coupled Model version 3
IPCC	Intergovernmental Panel on Climate Change
LARS-WG	Long Ashton Research Station Weather Generator
LULC	Land Use Land Cover
MAKESENS	Mann-Kendall Test and Sen's Slope Estimates for the Trend of Annual Data
MLP	Multi Layer Perceptron
MLR	Multiple Linear Regression
MK	Mann-Kendall
NCAR	National Centre for Atmospheric Research

NCEP	National Centre for Environmental Prediction
RCMs	Regional Climate Models (RCMs)
SDSM	Statistical Downscaling Model
SRES	Special Report on Emissions Scenarios
SVM	Support Vector Machine
SWAT	Soil and Water Assessment Tool
VIC	Variable infiltration Capacity

INTRODUCTION

1.1. General Introduction

Over the last 100 years, the state of Odisha is facing an extreme weather condition in the form of floods, droughts, heat waves, earthquakes and cyclones with unfailing regularity. These natural calamities affected 25 of 30 districts of Odisha, have not only led to loss of human lives, but also resulted in damage and loss of property(Mahapatra, 2006).Odisha is situated at the head of the Bay of Bengal. Therefore, a slight change in the temperature can have an immediate impact on the land mass. As the sea and ocean happens to be the center of low pressure, it brings cyclones with heavy rain to the state. Rain is caused due to the depressions formed over the Bay of Bengal. Even a small change in a parameter like temperature has a huge impact on rainfall patterns in Odisha. Abnormalvariations in the key parameters of climate such as temperature and rainfall affect the hydrology process and availability of water resources. Therefore, there is a necessity to study the impact of climate change on water resources in this region.

Climate is a measure of the average pattern of variation of meteorological parameters(precipitation, humidity, temperature and others) in a given region over long period of time. Climate change may be described as a change in the climate which can be recognized by changes in the statistical distribution of weather variables for a longer duration of time. Climate change can cause significant impacts on water resources by ensuing changes in the hydrological cycle. For the present study work taken up are: (1) Statistical analysis of historical and future climate trends, (2) use of general circulation models (GCMs) for simulating the response of climate variables globally, to the increasing concentrations of greenhouse gases in the atmosphere, (3) use of statistical downscaling technique to model the hydrology variables (e.g., precipitation, temperature) at a smaller scale based on large scale GCM outputs, (4) use of hydrological modelling for assessment of global climate change impacts.

According to the Intergovernmental Panel on Climate Change (IPCC) reports,by the middle of the 21st century there will be a reduction in the freshwater availability particularly in large rivers due to climate change. IPCC reports reveals thatthe coastal areas will be at high risk due to the increase in floods from the sea and in some megadeltas there will be flooding from rivers. Also, there will be a decrease in annual average runoff due to the projected changes in the hydrological cycle (IPCC, 2007).

Temperature and precipitation are the key parameters of climate and variations in the pattern of these variables can affect human health, economic growth and development. An increase or decrease in precipitation pattern can result in the increase in the frequency of floods,instances of droughts and impact on water quality. Increase in Earth's temperature results in an increase in evaporation and cloud formation to occur, which increases precipitation, indicating that temperature and precipitation are interconnected. Therefore, it is necessary to carry out statistical analysis to find the trend for these two important climatic parameters i.e. temperature and precipitation. The statistical analyses used in the present study arethe Mann Kendall Test (Mann 1945, Kendall 1975) and Sen's Slope estimator (Sen, 1968). The Mann Kendall test has been used to detect trends in the time series of the precipitation and temperature for the historical periods (1981-2010) and future periods (2011-2099). Sen's slope estimator has been used to find out the magnitude of the detected trend.

General Circulation Models (GCMs) are an important tool for assessing the impact of climate change on a range of human and natural systems. Simulations at these inner scales are of considerable interest to hydrologists in assessing the possible impact of climate change on water resources. Different climate models have been used worldwide for climate impact assessment studies. Climate models, particularly the GCMs, currently provide the most important source of information for constructing scenarios of climate change, which provide climate information at a higher spatial resolution, gradually becoming available. GCMs are based on physical laws and physical-based empirical relationships and are mathematical representations of the atmosphere, ocean, cryosphereand land surface processes.

In order to determine how climate change may occur in the future, it is essential to understand how the concentrations of atmospheric components which affect the Earth's energy balance may change. Since the start of the industrial revolution,human activities have resulted in large increases in the atmospheric concentrations of greenhousegases and it is now widely accepted that this has affected global climate.

The IPCC fourth assessment report, namely the Special Report on Emissions Scenarios (SRES) features four storylines which are labeled as A1, A2, B1 and B2, chronicles of qualitative (e.g., political, social, economical, cultural, environmental and educational developments) emissions drivers(IPCC, 2007). These storylines depict the relationship between the forces driving greenhouse gases and aerosol emissions and their development during the 21stcentury.For predicting the possible future climate, these SRESemissions scenarios is considered useful.Among thesefour scenarios, A2 and B2 scenarios were used in this study.

The A2 storyline portrays a very diverse world. This storyline depicts that there is a continuous increase in population, economic developments on regional levels, economic growth and technological changes are more uneven and slower in comparison to other three storylines. In B2 storyline there isa continuous increase in global population, but at a slower rate than A2 scenario. The B2scenario is also directed towards environmental protection and social equity, it focuses on both local and regional levels(IPCC, 2007).

General Circulation Models or global climate models (GCMs) are among the best available tools to represent the main features of the global distribution of basic climate parameters at continental and large regional scales. Butthese models are unable to produce the details of regional climate conditions at different temporal and spatial scales. The anthropogenic global climate change would lead to changes in large-scale atmospheric features. The current generation of General Circulation Models (GCMs) operates on a coarser scale. However, the climate impact studies in hydrology often require climate change information at finer spatial scale. Therefore, the GCM output has to be downscaled to obtain information applicable to hydrological studies (Anandhi et al., 2008).Hence, there is a great need to use downscaling techniques for downscaling GCM predictions of climate change to regional and local or station scales. Downscaling techniques have been designed to link the gap between the information that the climate modeling community can currently provide and that required by the hydrologists for assessing the possible impact of climate change on water resources (Maraun et al., 2010).

There are two broad categories of downscaling procedures: (a) dynamical downscaling techniques, which involves the extraction of regional scale information from large-scale GCM data based on the modeling of regional climate dynamical processes, and (b) statistical downscaling techniques that rely on the empirical relationships between predictors (large-scale atmospheric variables) andpredictands (surface environment variables) (Ghosh and Mishra, 2010). There are many advantages and disadvantages of dynamical downscaling and statistical downscaling techniques for climate change impacts, which indicate that neither technique is better than the other(Wilby et al., 2000). Based on the assessment of the climate change impacts on the hydrologic regimes of a number of selected basins, it was found that these two techniques could reproduce some general features of the basin climatology, but both displayed systematic biases with respect to observations as well. Further, it was found that the assessment results were dependent on the specific climatology of the basin under consideration. Several statistical downscaling techniques (transfer functions, weather typing approach, SDSM) have been developed to establish relationships between meteorological variables and the large-scale GCMs outputs. In the present study statistical downscaling model (SDSM) is used to downscale the GCMs outputs.

Hydrological modeling is a mathematical representation of natural processes that influence primarily the energy and water balances of a watershed. The main purpose of using hydrological modeling is to provide information for planning and management of water resources in a sustained manner. Hydrological models are of two major types: (a) Stochastic models and (b) Process-based models. Stochastic models are based on mathematical and statistical concepts to relate a particular input (e.g. rainfall) to the model output (e.g. runoff) and also tries to compute the errors in model outcomes. Some of the stochastic hydrological models used are:transfer functions, artificial neural networks, and others. Process-Based Models represents the physical processes (surface runoff, subsurface flow, evapotranspiration) observed in the real world. Some of the process based hydrologic models are: SWAT (Soil and Water Assessment Tool), Variable infiltration Capacity (VIC),MIKE-SHE model (Dadhwal et al., 2010).

During monsoon (June, July, August, September and October), due to the heavy rainfall, Mahanadi faces high stream flow as it is a monsoon-fed river. The ground water component with infiltrationis trivial compared to the streamflow during the monsoon season. In the non-monsoon season as there is no rainfall, infiltration to ground water is not considerable, resulting in low stream flow in Mahanadi River Basin. Thus, for the monsoon season therunoff prediction can be used to predict floods, manage reservoir operations, or impact on water quality in the basin. There are many literatures in which transformation of rainfall into runoff has been studied in order to extend stream flow series. There are many techniques for predicting the runoff volume.To assess the future runoff in the present study, the black box approach (Artificial Neural Network) and Multiple Linear Regression techniques are used.

1.2.Research Objectives

The main objective of this study is to evaluate the hydrological impacts of climate change on water resourcesofthe Mahanadi river basin, Odisha. To substantiate the main objective, the sub objectives are:

(1) To Use general circulation models (GCMs) for constructing scenarios of climate change.

(2)To use statistical downscaling technique to downscale the HadCM3 model using meteorological station data.

(3) To generate the scenarios for future daily temperature (maximum and minimum) and daily precipitation using SDSM.

(4)To use statistical analysis for present and future scenarios for detection of trends in the temperature and precipitation parameters.

(5) To use Artificial Neural Network and Multiple Linear Regression for runoff prediction.

1.3. Structure of the thesis

Chapter I gives an overview of the GCMs, downscaling techniques and modeling methods for quantifying the impact of climate change along with the objectives and the relevance of the proposed research work.

Chapter II deals with the scientific rationale related to statistical analysis climatic variables, use of general circulation models (GCMs) for simulating time series of climate variables, statistical downscaling of meteorological variables and modeling techniques used for climate change impact assessment.

Chapter III gives a description of the study area Mahanadi River basin, topographic information, rainfall, temperature, soil characteristics and land use pattern and also about the data used in the study.

Chapter IV deals with different methodology (Statistical Downscaling, Trend Analysis, Artificial Neural Network and Multiple Linear Regression) adopted in the present study.

Chapter V illustrates and discussedresults obtained from different methodologies used in the present study.

Chapter VI gives the general conclusionsresulting from the analysis and modeling techniques used in this study and also prepositions for future work.

LITERATURE REVIEW

2.1. Mahanadi Basin

Sarma and Rao (1979) studied the climatic aspects of moisture as well as the thermal regimes of the Mahanadi river basin. Their main aim was to find out the water potentialities as well as the thermic conditions that favor the growth and development of vegetation at and around the basin.

Khatua and Patra (2004) studiedthatthe deltaic region of Mahanadi River is affected by flood, drainage and salinity problemsdue to presence of low level escapes.They recommended to provide and improve the structural measures and also to provide some special treatment to the affected area to check the major floods up to 35000 cumecs.Structural measures to high flood are not feasible, both structural and non-structural measures can only reduce the flood damages to an acceptable level

Mohapatra and Mohanty (2006) studied the features to find out the spatial and temporal variability of very heavy rainfall over Orissa by 20 years of daily rainfall data from different stations in Orissa. The study concluded that the region extending from the coastal area of Orissa in the southeast towards Sambalpur district, experiences higher frequency and higher intensity of very heavy rainfall with less interannual variability.

Ghosh et al. (2010) reviewed the work on uncertainty modelling and development of adaptation strategies to climate change in the Mahanadi River in India. Modelling uncertainty includes assigning weights to GCMs and scenarios, based on their performances, and providing weighted mean projection for the futurein climate change impact assessment.

Dadhwal et al. (2010) used the Variable Infiltration Capacity (VIC) hydrological model to simulate the hydrology of the Mahanadi river basin of India. The main aim for carrying out the analysis is for the impact of land use land cover (LULC) changes in stream flow pattern. Surface runoff was simulated for the year 1972, 1985 and 2003 to quantify the changes that have taken place due to change in LULC. An increase by 4.53% in the annual streamflow was expected at Mundali outlet of the Mahanadi basin from 1972 to 2003.

Parhi et al. (2012) suggested a technically feasible and financially acceptable Flood Management Plan (FMP) for the Mahanadi basin to bring down the flood to a manageable threshold.

Patra et al. (2012) have studied the long term trend in annual, seasonal and monthly precipitation in Orissa for the period 1871-2006. They have found an insignificant decrease in trend of annual as well as monsoon precipitation, whereas increase during post-monsoon season.

2.2. Trend Analysis

Rao P G (1993) used a linear regression, time series analysis for Mahanadi basin and found no significant trend in monsoon or annual rainfall during the period 1901–1980. They concluded that the change in land-use and anthropogenic activities were responsible for the significant rise in temperature during the same period.

Rao P G (1995) analyzed trends in the runoff of the upper catchment and the whole catchment gauged at Hirakud and Naraj, Mahanadi Basin, India. The study showed a steady decrease in the river flows at these locations during the 55 year period of the study.

Mondal et al. (2012) conducted a study concerned with the changing trend of rainfall of the Mahanadi river basin of Orissa near the coastal region. Daily precipitation data has been processed to find out the monthly variability of rainfall using Mann-Kendall (MK) Test, Modified Mann-Kendall Test together with the Sen's Slope Estimator.

Arora et al. (2009)investigated the trends in temperature time series of 125 stations distributed over the whole of India. They used the non-parametric Mann-Kendall test for detecting the monotonic trends in annual average and seasonal temperatures.

Kumar and Jain (2010) carried out a detailed analysis to determine the trends in rainfall amount and number of rainy days in Indian River basins by using daily gridded rainfall data. Sen's estimator was used to find out the magnitude of trend in annual and seasonal rainfall and rainy days. The study showed that six river basins had increasing trends in annual rainfall and fifteen river basins had the opposite trend whereas the Ganga basin had no trend. The increasing/decreasing trends for the majority of the basins were non-significant.

Duhan and Pandey (2012) studied the spatial and temporal variability of precipitation at 45 districts of the Madhya Pradesh (MP), India on annual and seasonal basis during the 102 years period of study. Mann–Kendall test and Sen's slope estimator test were used to detect the monotonic trend direction and magnitude of change over time on annual and seasonal basis.

Jain and Kumar (2012) reviewed studies related to trends in rainfall, rainy days and temperature over India. They concluded that the Sen's non-parametric estimator of the slope has been frequently used to estimate the magnitude of the trend, whose statistical significance was assessed by the Mann–Kendall test.

Chakraborty et al. (2013) performed Mann Kendall and Spearman correlation trend detection tests for rainfall analysis over the Seonath basin during 1960 – 2008. Both tests showed a decreasing trend in annual and seasonal rainfall series for the whole Seonath river basin.

2.3. Climate Change and Water Resources

Rao PG and Kumar (1992) examined the inter-annual variability and the long term trends in the monsoon rainfall and in two derived climatic parameters, aridity index and moisture index for the Mahanadi basin using precipitation and temperature data for the period from 1901-1980.The study revealed that the basin has experienced a good number of deficit years during the last two decades of the study period.

Xu C Y (1999) discussed the advantages and disadvantages of different methods for the assessment of climate change impacts. Also discussed about the gaps between the GCMs ability and requirement of the hydrological models for impact assessment. The effect of large-scale characteristic changes in local surface climate which can’t be resolved in the current generation of GCMs, therefore there is a need for downscaling.

Xu C Y (1999) reviewedthe existing gap and the methodologies for narrowing the gap between GCMs’ ability and the need of hydrological modeling.

Kumar et al. (2006) used PRECIS to develop high resolution climate change scenarios. They concluded that by the end of the 21st century, both temperature and rainfall increases under scenarios of increasing greenhouse gases and sulphate aerosols.

Mall et al. (2006) studied the potential for sustainable development of surface water and ground water resources within the limitations imposed by the climate change and future research needs in India.

Gosain et al. (2006) conducted a study on 12 major river basins using SWAT. They found a reduction in runoff and in particular an increase in the severity of droughts and floods in different parts of India for a future period from 2041 to 2060 using the IPCC emission scenario.

Mujumdarand Ghosh (2008) are concerned with modeling GCM and scenario uncertainty using possibility theory in the Mahanadi River, at Hirakud, India. The study indicates a decrease in stream flow and also a reduction in the probability of occurrence of extreme high flow events.

Gosain et al. (2011) studied the water resources of Indian River systems using the IPCC emission scenario A1B. They found an increase in available water resources in some river basins and a decrease in others.

Chen et al. (2012)assessed and compared the differences in water balance simulations resulted from using different downscaling techniques, GCMs and hydrological models.The study showed that for the same GCM, the simulated runoffs vary significantly when using rainfall provided by different statistical downscaling models as the input to the hydrological models.

2.4. Downscaling Techniques

Karl et al. (1990)verified that the regression-based downscaling methods also benefit from the standardization of the predictor variables so that the corresponding distributions of observed and present-day GCM predictors are in close agreement.

Winkler et al., (1997) suggested that sufficient data should be available for both model calibration and validation. This is because the choice of the calibration period, as well as the mathematical form of the model relationship(s) and season definitions determines the statistical characteristics of the downscaled scenarios.

Wilby and Wigley (1997)studied the present generation of downscaling tools under four main groups: regression methods; weather pattern-based approaches; stochastic weather generators; and limited-area climate models. In these different approaches regression methods are preferred because of its ease of implementation and low computation requirements.A number of methodologies have been developed for deriving more detailed regional and site scenarios of climate change for impacts studies.

Wilby et al. (1999) compared the three sets of current and future rainfall-runoff scenarios. They constructed the scenarios using the statistically downscaled GCM output, the raw GCM output and raw GCM output corrected for elevational biases.

Wilby and Wigley (1999) investigated the relationship between meso-scale atmospheric variables to grid and subgrid-scale surface variables using downscaling technique.

Murphy JM (1999) compared the statistical and dynamical techniques in terms of the correlation between the predicted and observed time series of monthly variances. Both the techniques showed a similar level of skills, even though the statistical method is better for summertime estimates of temperature, whereas the dynamical methods give slightly better estimates of wintertime precipitation.

Wilby et al. (2000)recommended that the data from the regional climate models (RCMs) should not be used directly as an input to hydrological models, as the RCM data have systematic errors. These systematic errors should be corrected by applying a bias correction.**Wood et al. (2004)** presented **s**ix approaches for downscaling climate model outputs for use in hydrologic simulation.They emphasized on each method's ability to produce precipitation and other variables used to drive a macroscale hydrology model applied at much higher spatial resolution than the climate model.

Dibike and Coulibaly (2005) comparative advantages and disadvantages of the two downscaling techniques, i.e. SDSM and LARS-WG model, applied to downscale GCMs into catchment scale. As GCMs do not provide a direct assessment of the regional hydrologic changes, downscaling is required.

Tripathi et al. (2006) proposed a support vector machine (SVM) approach for statistical downscaling of precipitation at a monthly time scale which is suitable for connecting climate impact studies. They have shown that SVMs provide an alternative to conventional artificial neural networks for statistical downscaling.

Wilby and Dawson (2004) developed SDSM as a tool for statistical downscaling, used to predict the climate parameters such as precipitation and temperature in longtime regarding climate large scale signals. The model is based upon the linear multiple regression and is created between the large scale predictor variables (independent variables) and the predictant variables (precipitation or temperature) as dependent variables for each month of the year. In this model, a linear multiple regression Suitable large scale predictors are selected by correlation analyses between the predictor variables and partial correlation in the area under study.

Fowler et al. (2007) studied about the recent developments in the real advances and new concepts of downscaling methods for assessing the uncertainties concerned with hydrological impacts. She suggested a comparison of different downscaling methods, results from multiple GCMs and multiple emission scenarios for the planning and management should be used in the estimation of climate change impacts.

Anandhi et al. (2008) presented a methodology using Support Vector Machine (SVM) to downscale monthly precipitation to river basin scale in the Indian context for a special report of emission scenarios (SRES).

Hasan et al. (2012) demonstrated the application of SDSM (statistical downscaling model) and ANNs (artificial neural networks) models for prediction of the hydrological trend. The SDSM has been used for generation of the possible future scenarios of meteorological variables, which are temperature and rainfall by using GCMs outputs. The downscaled meteorological variables from SDSM were used as input to the ANNs model, to predict the corresponding future streamflow changes in the sub-catchment of Kurau River.

2.5. Artificial Neural Network (ANN) and Multiple Linear Regression in Hydrology

Daniel T M(1991) introduced the application of ANNs in water resource and hydrologic modelling to the water resource community, he used ANNs to predict monthly water consumption and to estimate flood occurrence.

ASCE (2000a) ASCE Task Committee examined the role of artificial neural network (ANNs) in hydrology and described some guidelines on their usage. Paper presented a brief comparison between the natures of ANNs with other modeling approaches in hydrology.

ASCE (2000b) ASCE Task Committee discussed about the merits and limitations of ANN applications in various branches of hydrology. ANNs are strong tools for modeling many of the non-linear processes such as rainfall-runoff, precipitation, water quality simulation and stream flow.

Shafie et al. (2011) studied to utilize an Artificial Neural Network (ANN) to predict the rainfall-runoff relationship in a catchment area located in Japan. The study concluded that the feed forward back propagation Neural Network (ANN) can describe the rainfall-runoff relation more accurately than the classical regression model.

The review of the above literature shows that most of the investigators have carried out studies on climate change using monthly data for Mahanadi Basin. Further very few investigators in India have used Statistical Downscaling Model (SDSM) as statistical downscaling technique for downscaling the GCM outputs into catchment scale. Therefore the present work is an attempt to use daily data and the SDSM for modelling the climate change scenarios to predict the future time series for temperature and precipitation, that has become the objective of the present study.

DATA COLLECTION AND ANALYSIS

3.1 General Study

Mahanadi River is the sixth largest river in India and one of the major interstate east flowing rivers in peninsular India. The basin is physically surrounded on the North by Central India hills, by the Eastern Ghats in the South and East and by Maikala hill range in the West. The Mahanadi basin lies between latitudes of 19^0 20' North to 23^0 35' North and longitudes of 80^0 30' East to 86^0 50' East. The total catchment area of the basin is 141600 sq km and the total running length of the basin is about 851 km, of which 357 km lies in Chhattisgarh and the rest 494 km in Orissa. The index map of Mahanadi River is shown in figure 3.1.

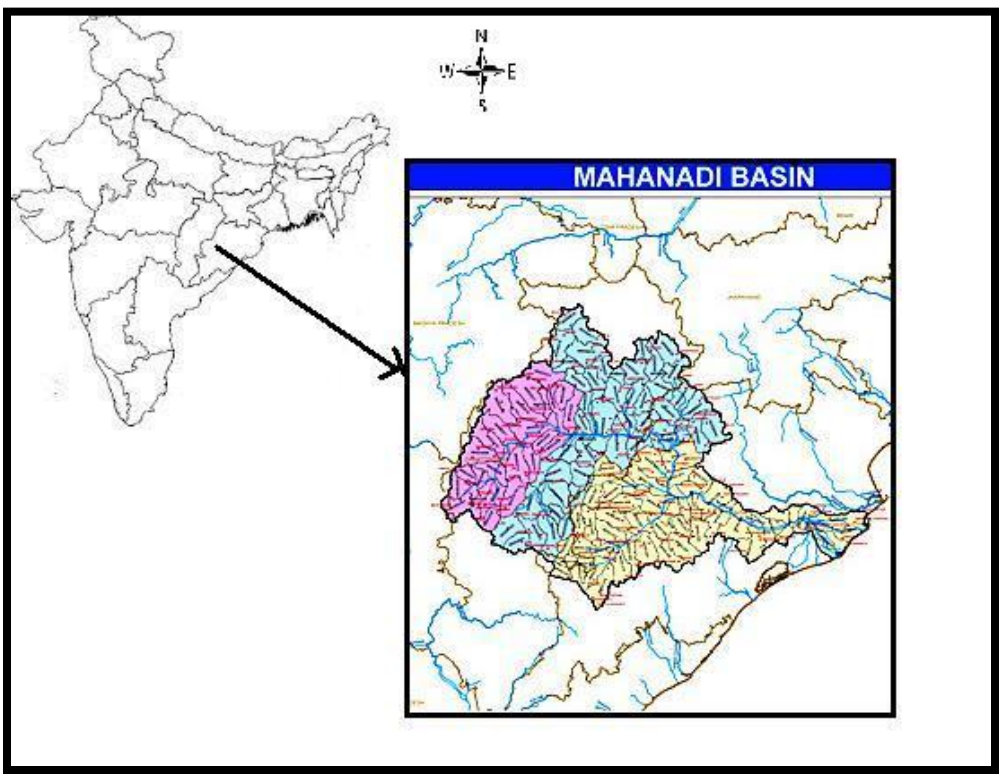


Fig. 3.1: Index map of the study area

3.1.1 River System

The river Mahanadi originates at an elevation of about 457 m above Mean Sea Level (MSL), 6 Km from Pharsiya village near Nagri town in Raipur district (Chhattisgarh). During the course of its traverse, it drains fairly large areas of Chhattisgarh and Orissa and some small areas in the state of Jharkhand and Maharashtra.

There are 14 tributaries in the basin of which 12 are joining upstream of Hirakud reservoir and 2 downstream of it. The three major tributaries namely the Seonath and the Ib on the Left Bank and the Tel on the Right Bank together represents nearly 46.63% of the total catchment area of the river Mahanadi. The Seonath is the largest tributary of Mahanadi among all the three tributaries of the basin, Durg district, Chhattisgarh. The Tel is the second largest tributary of Mahanadi River, Koraput district, Orissa and drain in four districts of Orissa namely Koraput, Kalahandi, Balangir and Phulbhani. The Ib is the third largest tributary of Mahanadi, rises in Raigarh district, Chhattisgarh and drains in district of Chhattisgarh, namely Raigarh and districts of Orissa, specifically Sundergarh, Jharsuguda and Sambalpur. The two gauging stations, Jharsuguda and Hirakud in Odishaare selected for the proposed study in the Mahanadi River Basin.

The catchment area of Mahanadi River Basin alongwith the two selected stations are shown in figure 3.2.

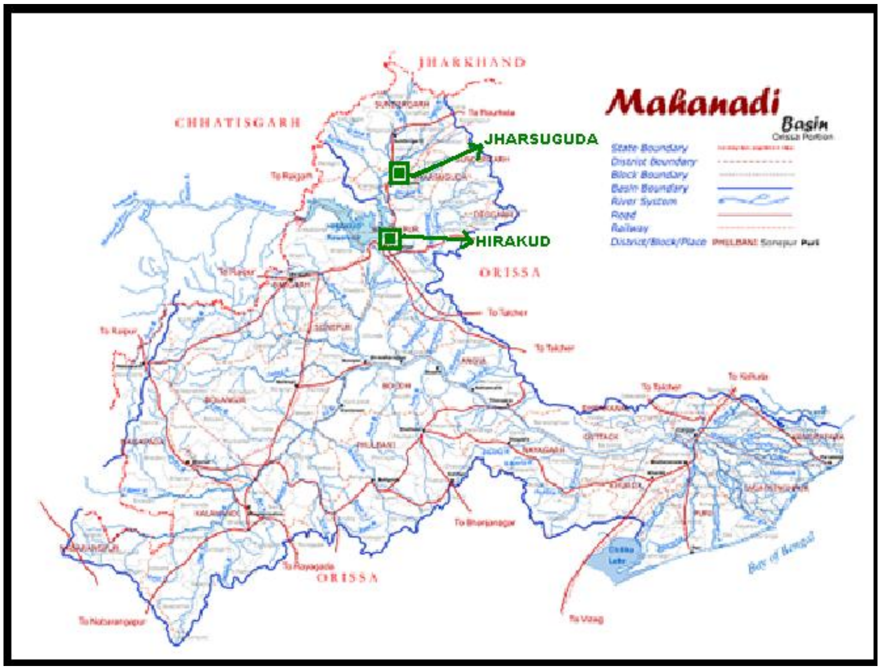


Fig.3.2: Catchment Area of Mahanadi River Basin showing the Study Area

3.1.2 Climate

Mahanadi basin experiences a tropical monsoon type of climate. The monsoon months include June to October at an average of about 1420 mm rainfall. The maximum rainfall is usually observed in the month of July, August and the first half of September. The river passes through tropical zone and is subjected to cyclonic storms and seasonal rainfall. The mean daily minimum temperature varies from 7°C to 12°C, during the winter season and the mean daily maximum temperature varies from 42.9°C to 45.5°C, in the month of May.

3.1.3 Soil Characteristics

Red and yellow soils are the main types of soil found in the basin. Black and mixed red soils occur in parts of Bolangir, Sambalpur and Sundergarh districts of Orissa. In the lower parts of Orissa, laterite soil and deltaic soil are found.The land use and land cover map of the Mahanadi River basin is shown in figure 3.3.

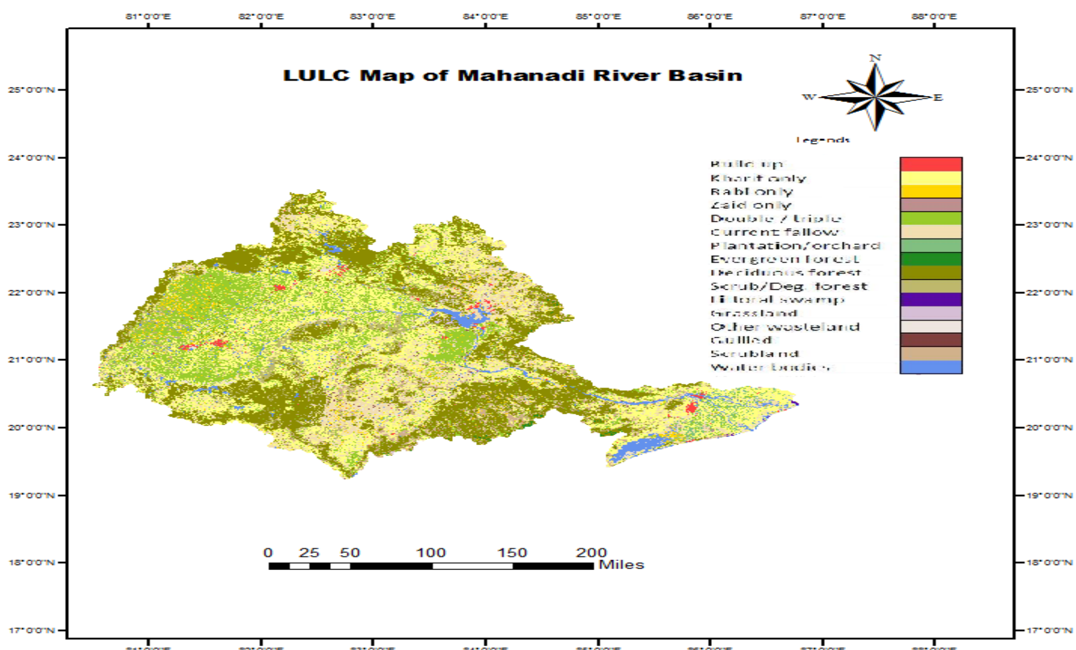


Fig. 3.3: Land Use and Land Cover map of the present study

3.1.4 Irrigation Projects

There are many major and medium irrigation projects in the catchment area of the Mahanadi River basin. Some of the major projects are Hirakud Dam, Mahanadi Delta, Mand Diversion

Project, Ib Diversion Scheme, Mahanadi Birupa Barrage and Ong Diversion in the state of Odisha.The main harvests of the basin are oilseeds, rice and sugarcane.

3.1.5 Industries

Due to the rich mineral reserves of Lime stone, Quartzite, Copper Ores, Silver, Lead, Mica, Bauxite, Galena, Graphite etc. and adequate power resource, Mahanadi has a favorable industrial climate. The major industries are Iron, Steel, Copper, Cement, Paper and Aluminium.

3.2 Data Collection and Analysis

3.2.1 Meteorological Station Data

The finest technique of understanding how climate may change in the future is to study how it has changed in the past based upon long-term observational records. Long-term meteorological data from the period 1981-2010 were obtained from CWC (Central Water Commission) and from http://en.tutiempo.net/climate/ws-428860.html. The data used are maximum temperature, minimum temperature, mean temperature, precipitation and runoff. Data were collected for two stations, namely Hirakud and Jharsuguda. Hirakud is situated on the Mahanadi basin and Jharsuguda station is located on the Ib tributary which is located on the left bank of Mahanadi basin. Also the Ib joins the upstream of Hirakudreservoir.The data available for Jharsuguda station is daily while for the Hirakud station, it is monthly.

Table 3.1shows the observed data used in the study for Jharsuguda and Hirakud Station.

Stations	**Latitude**	**Longitude**	**Elevation (m)**	**Precipitation (1981-2010)**	**Temperature (1981-2010)**	**Runoff (1981-2010)**
Hirakud	21°30'0N	83° 52'0E	172	√	√	√
Jharsuguda	21°51’0N	84°1’60E	217	√	√	

Table 3.1: Observed Station Data Records

Figure 3.4 shows the monthly observed precipitation at Jharsuguda station from 1981-2010.

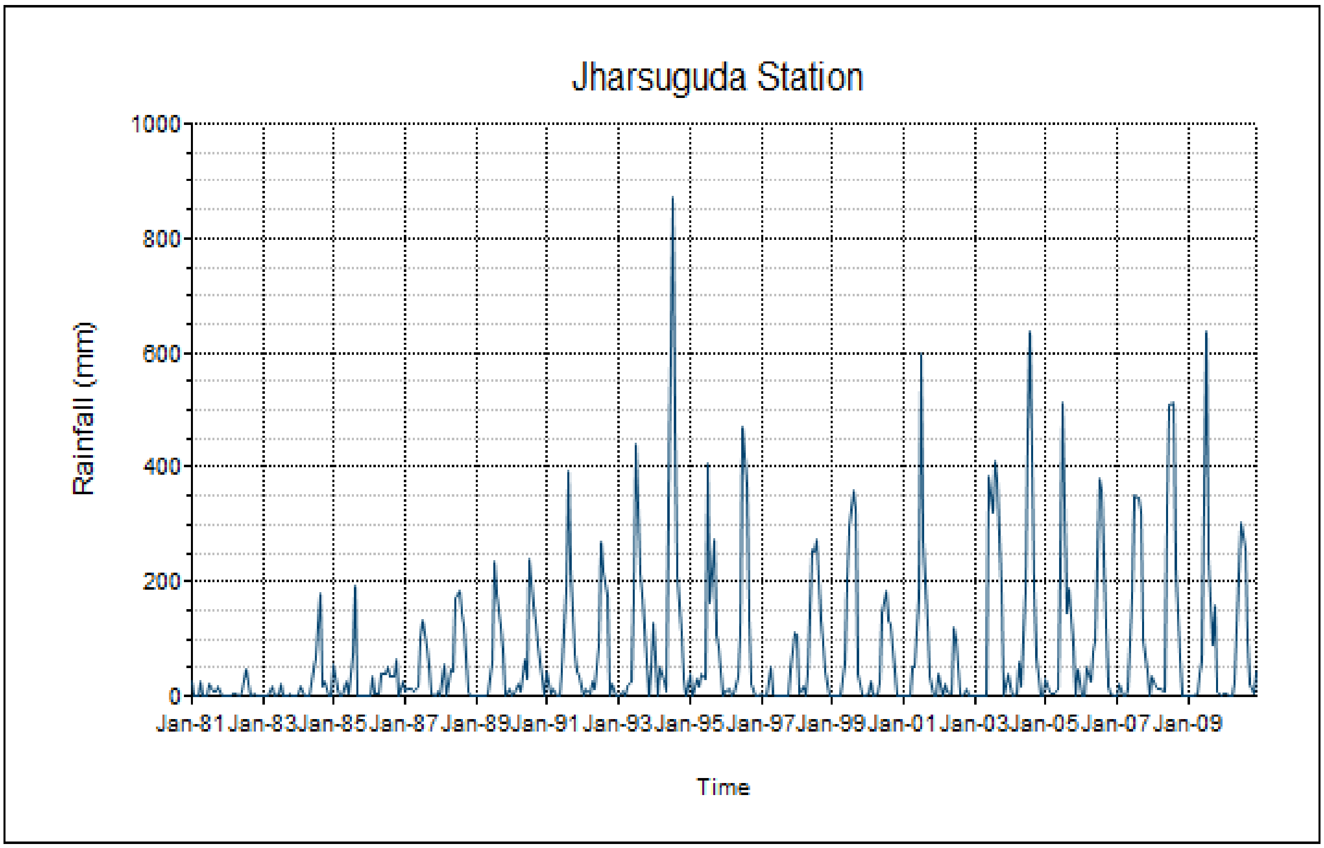


Fig. 3.4: Monthly Observed Precipitation at Jharsuguda station (1981-2010)

Figure 3.5 shows the daily observed maximum and minimum temperature at Jharsuguda station from 1981-2010.

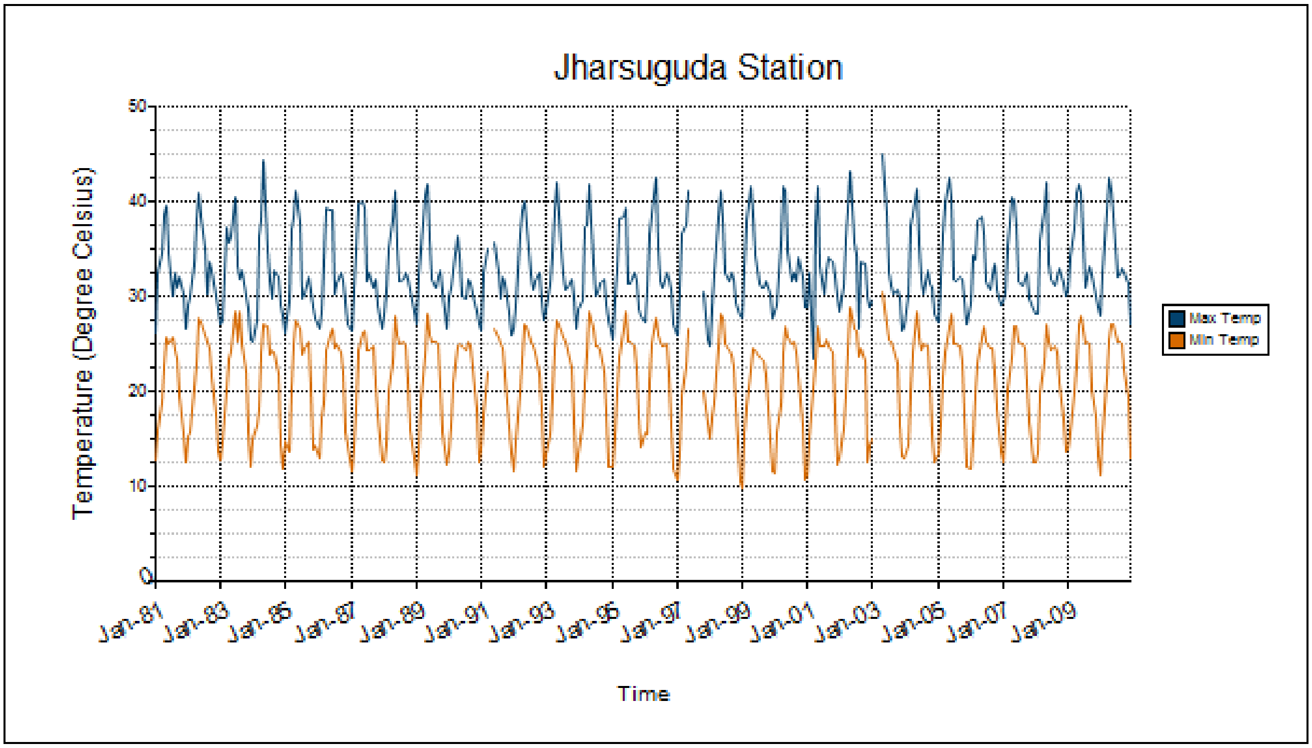


Fig.3.5: Observed Daily Maximum and Minimum Temperature at Jharsuguda station

Figure 3.6 shows the monthly observed precipitation for monsoon period at Hirakud station from 1981-2010.

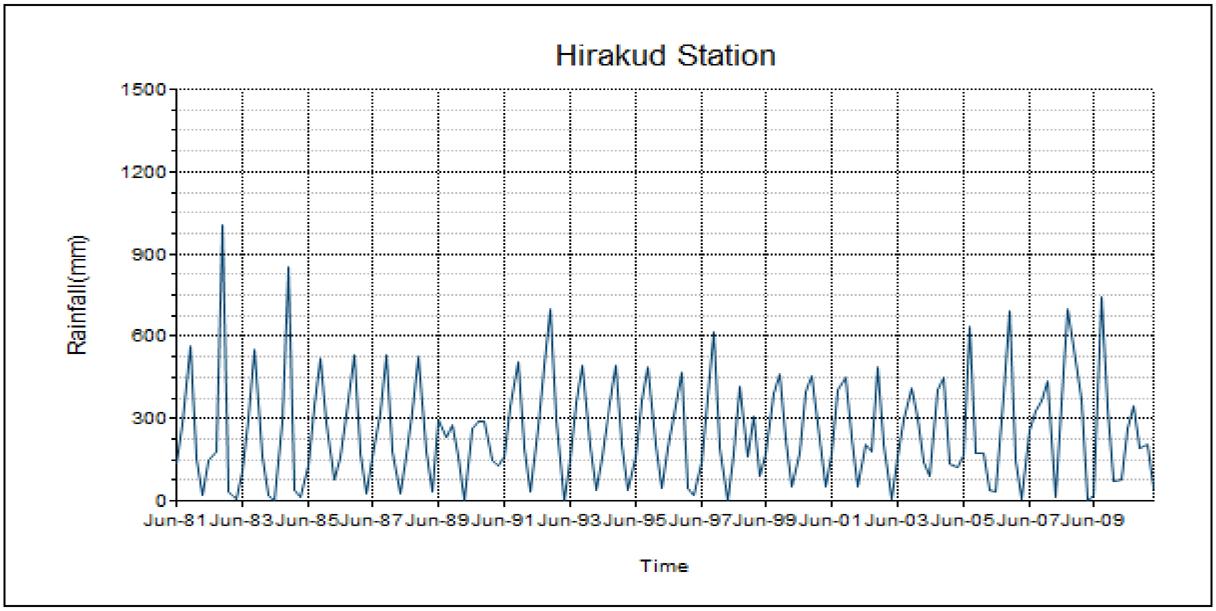


Fig.3.6: Observed Monthly Monsoon Precipitation at Hirakudstation(1981-2010)

Figure 3.7 shows the observed monthly mean temperature for monsoon period at Hirakud station from 1981-2010.

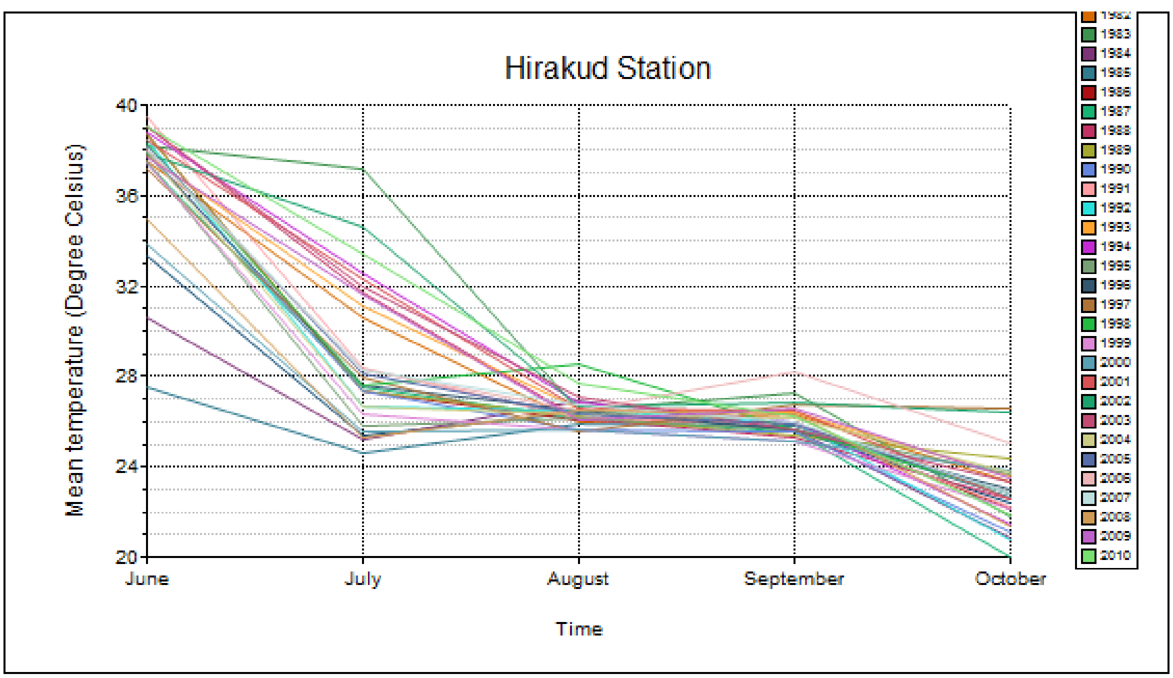


Fig. 3.7: Observed Monthly Mean Temperature at Hirakud station (1981-2010)

Figure 3.8 shows the monthly observed rainfall-runoff for monsoon periodatHirakud Station from 1981-2010.

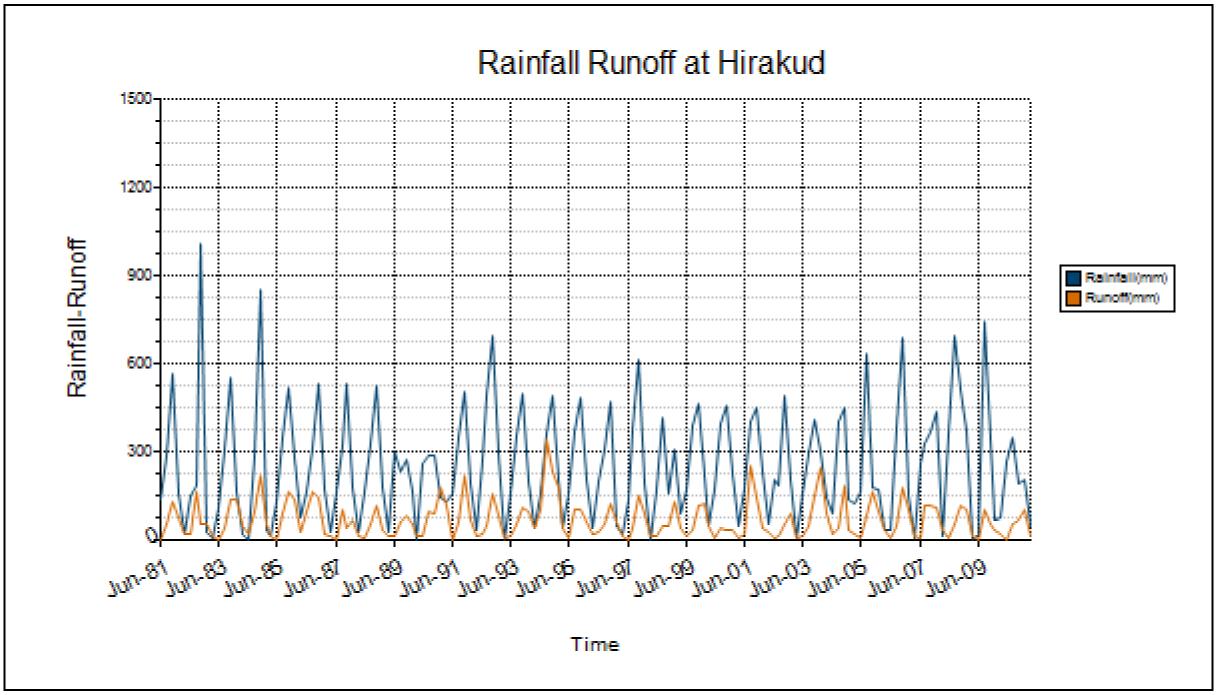


Fig.3.8: Observed Rainfall-Runoff for Monsoon Period at Hirakudstation(1981-2010)

3.2.2 GCM Ouptut

For downscaling HadCM3 model output and National Centre for Environmental Prediction/ National Centre for Atmospheric Research reanalysis data sets (NCEP/NCAR) has been downloaded directly from Canadian Climate Impact and Scenarios (CICS) website (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi). The large scale atmospheric variables called predictors are grouped into two categories; observed predictors (National Centre for Environmental Prediction/ National Centre for Atmospheric Research reanalysis data sets) and modelled predictors (GCMs simulated data). The NCEP/ NCAR reanalysis data is available from 1961 to 2001 which is normalized and this data is interpolated to HadCM3 grid resolution

(2.5° latitude × 3.75° longitude). The predictor variables of HadCM3 are available in A2 and B2 scenarios for the period 1961-2100.

For runoff prediction at Hirakudstation ,the future precipitation and mean temperature data has been directly downloaded from website http://www.cccsn.ec.gc.ca/?page=dd-gcmfrom the period 2011 to 2099 for A2 scenario.

METHODOLOGY

This chapter describes the different methodologies used in the present work for assessing the impact of climate change on water the resources of Mahanadi Basin.

4.1 Trend Detection Analysis

Temperature and precipitation has the maximum influence on the water resources. Trend analysis is used to detect trends in the time series of temperature and precipitation. Different types of trends on each variable interpret different implications on water resources. For instance, increasing trend in temperature will enhance the evaporation, decreasing trend in precipitation will result in drought. There are many parametric and non-parametric tests to detect the trend in a time series on each climatic variable. In the present study, Mann Kendall Test and Sen's slope estimator has been used. Non-parametric Mann Kendall test is used to find out the presence of a monotonic increasing or decreasing trend and the slope of the linear trend is estimated with the nonparametric Sen's method (Sen,1968). Missing values are allowed and the data need not conform to any particular distribution. MAKESENS excel template has been used to estimate the Mann Kendall Test and Sen's slope estimator for estimating the magnitude of the trend.

4.1.1 Mann-Kendall Test

The computational procedure for the Mann Kendall test considers the time series of n data points. Mann-Kendall test had been formulated by *Mann (1945)* as non-parametric test for trend detection and the test statistic distribution had been given by *Kendall (1975)* for testing non-linear trend and turning point. In the computation of this statistical test MAKESENS developed both statistics, one is the S statistics given in Gilbert (1987) and the normal approximation (Z statistics). If the time series has less than 10 data points the S test is used, and if the time series has 10 or more data points the normal approximation (Z statistics) is used.

Let x_1, x_2, x_3, ……… x_n , represents n data points and i and j be two sub-sets of data ,then the Mann-Kendall test statistic S is given by equation (4.1);

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \dots \dots (4.1)$$

Where,

$x_i =$ 1,2,3,4 …….n-1

$x_j =$ i+1,2,……..n

x_i and x_j are the sequential data values, n is the length of the data set.

Each of the data point x_i is taken as a reference point which is compared with the rest of the data points x_j,equation (4.2) so that

$$sign(x_j - x_i) \begin{matrix} = 1 if x_j - x_i > 0 \\ = 0 if x_j - x_i = 0 \\ = -1 if x_j - x_i < 0 \end{matrix} \Bigg\} \dots \dots (4.2)$$

The variance of S is computed by the equation (4.3) which takes into account that ties may be present:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m}(t_i)(i)(i-1)(2i+5)}{18} \dots \dots (4.3)$$

Where $t_i$is considered as the no. of ties up to sample i.

As the no. of data points aremore than 10, therefore normal approximation is used. However, if there are several tied values (i.e. equal values) in the time series, it may reduce the validity of the normal approximation when the number of data values is close to 10. The presence of a statistically significant trend is evaluated using the *Z* value given in equation (4.4):

$$\left.\begin{array}{c} Z = \dfrac{S-1}{\{VAR(S)\}^{\frac{1}{2}}} If S > 0 \\ z = 0 If S = 0 \\ Z = \dfrac{S+1}{\{VAR(S)\}^{\frac{1}{2}}} If S < 0 \end{array}\right\} \ldots\ldots (4.4)$$

A positive(negative) value of *Z* indicates an upward (downward) trend. The statistic *Z* has a normaldistribution. To test for either an upward or downward monotone trend (a two-tailed test) atα level of significance, $H_0$is rejected if the absolute value of *Z* is greater than $Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$is obtained from the standard normal cumulative distribution tables. In MAKESENS the tested significance levels α are 0.001, 0.01, 0.05 and 0.1. Trends at significance below the 90% confidence level were not considered.

4.1.2 Sen's Slope Estimator

The Sen's nonparametric method is used to estimate the true slope of an existing trend. In equation (4.5), the slope N of all data pairs is computed as (Sen, 1968)

$$N = \frac{x_j - x_i}{j-i} \ldots\ldots\ldots\ldots (4.5)$$

wherex_j and x_i are considered as data values at time *j* and *i* (*j*>*i*) correspondingly.

The median of these n values of Q is represented as Sen's estimator of slope which is given in equation (4.6) as:

$$\left.\begin{aligned} Q &= T_{\frac{n+1}{2}} If N is odd \\ Q &= \frac{1}{2}\left(T_{\frac{n}{2}} + T_{\frac{n+1}{2}}\right) If N is even \end{aligned}\right\} \ldots\ldots (4.6)$$

Sen's estimator is computed as Q=T $_{(N+1)/2}$ if N appears odd, and it is considered as Q=[T$_{N/2}$+T$_{(N+2)/2}$]/2 if N appears even. At the end, Q is computed by a two sided test at 100 (1-α) % confidence interval and then a true slope can be obtained by the non-parametric test. Positive value of Q indicates an upward or increasing trend and a negative value of Q gives a downward or decreasing trend in the time series.

4.2 GCM Model

HadCM3 is a coupled climate model used for climate prediction, detection and other climate sensitivity studies. HadCM3 stands for the Hadley Centre Coupled Model version 3. It was developed in 1999 and was the first unified model climate configuration not to require flux adjustments. HadCM3 was one of the major models used in the IPCC Third and Fourth Assessments, and also contributes to the Fifth Assessment. Simulations use a 360 day calendar, where each month is of 30 days.

4.3 SRES Scenarios

Intergovernmental Panel for Climate Change (IPCC) fourth assessment report (AR4) aims to evaluate technical and socio-economic information with respect to climate change. TheSpecial

Report on Emissions Scenarios(SRES) is a report by theIPCC in AR4. The SRES is used to make projections for future climate change in response to thegreenhouse gas emissions SRES features four storylines which are labeled as A1, A2, B1 and B2, chronicles of qualitative emissions drivers. These storylines depict the relationship between the forces driving greenhouse gases and aerosol emissions and their development during the 21st century. For predicting the possible future climate, these SRESemissions scenarios are considered useful. Table 4.1 gives a description of the SRES scenarios.

Scenarios	**Characteristics**
A1	Rapid economic growth, widespread social and cultural interactions worldwide, rapid extension of new technologies.
A2	Integrated world, continuously increasing population, economic developments on regional levels.
B1	Rapid economic growth as A1, emphasis on global solutions to economic, social and environmental stability, decrease in material intensity, introduction of clean and resource efficient technologies.
B2	Continuous increasing population but slower than A2, emphasis on local rather than global solutions to economic, social and environmental stability, intermediate level of economical development

Table 4.1: Description of Four Different SRES Scenarios

4.4 Statistical Downscaling Model (SDSM)

In classifying different downscaling models, statistical downscaling model is one of the best models. The base of the model is a linear multiple regressions and is used to predict the climate parameters such as precipitation and temperature in longtime regarding climate large scale signals. Suitable large scale predictors are selected by correlation analysis between the predictor variables and partial correlation in the region under study. The prediction of climate change model was carried out according to two scenarios, A2 and B2, among the presented scenarios in SRES. The present study downscaled two climatic parameters, temperature and precipitation using observed station data as predictands and HadCM3 model outputs as predictor variables.

SDSM is a statistical weather generator which is used to simulate climate data in a given station under current and future conditions affected by climate change. The data is in the form of daily time series for some climate variables such as precipitation (mm), minimum and maximum temperature (°C) and other climate parameters. In the process of downscaling in this model, a linear multiple regressions develops among a limited number of large scale predictor variables and predictants at local scale like precipitation and temperature.

The SDSM model performs the task of statistically downscaling daily weather series using seven steps. The following steps were taken from Wilby and Dawson (2007) that describes the procedures in SDSM.

(i) Quality control mainly focuses on identification of gross data errors, specification of missing data codes and outliers before model calibration,

(ii) Screening of predictor variables intended to identify empirical relationships between gridded predictors and single site predictands,

(iii) Model calibration takes a user-specified predictand along with a set of predictor variables, and computes the parameters of multiple regression equations,

(iv) Weather generation using observed predictors creates ensembles of synthetic daily weather series,

(v) Statistical analysis compares both downscaled scenarios and observed climate data with the summary statistics and frequency analysis,

(vi) Graphical analysis studies the result graphically,

(vii) Scenario generation allows to produces ensembles of synthetic daily future weather series given atmospheric predictor variables supplied by a climatic model.

4.5 Artificial Neural Network (ANN)

An ANN is a highly interconnected network of many simple processing units called neurons. Neurons in an ANN are arranged into groups called layers. Each neuron in a layer operates in logical parallelism. From one layer to another, the information is transmitted. The major advantage of neural networks is their flexible nonlinear modeling capability. With ANNs, the model is adaptively formed based on the features presented from the data (Clair and Ehrman, 1998). ANN is a black-box model, used for modeling complex hydrological processes like rainfall-runoff modeling, water quality modeling, groundwater modeling, and precipitation prediction and shown to be the most promising tool in hydrology (ASCE 2000a,b). ANN is able to provide a reasonably accurate model for runoff prediction, as the numbers of applications in hydrology are compared of their performance with other predictive methods in many studies.

ANN consists of layers of neurons. The model is characterized by a network of three layers of simple processing units, which are connected to each other. The first layer is called an input layer, which receives input information. The third layer is called an output layer, which produces output information. Between output and input layers are hidden layers. There can be one or more hidden layers. Information is transmitted through the connections between nodes in different layers. To assess the forecasting performance of model, the available data were split into three data sets: training set, validation set and testing set.

The size of the training data is 60%, validation data and testing set is 20 % of the total available data.A Multi-layer Perceptron (MLP) network consists of an input layer, hidden layers of computation nodes and an output layer. The input data chosen are precipitation and mean temperature for monsoon period (June to October) and the output is runoff. The number of hidden layers affects the number of weights. It is found that 5 hidden layers for processing element fits best in a trial and error approach.

4.6 Multiple Linear Regression

In a simple linear regression model, a single response measurement Y is related to a single predictor X for each observation. The critical assumption of the model is that the conditional mean function is linear. Equation 4.7 shows a simple linear regression equation.

$$E\left(\frac{y}{x}\right) = a + bx \quad \ldots\ldots (4.7)$$

In a multiple linear regression model, the numbers of predictor variables are more than one. Equation 4.8 shows a multiple linear regression equation. This leads to the following “multiple regression” mean function:

$$E\left(\frac{y}{x}\right) = a + b_1 x_1 + \; b_2 x_2 + \; \dots\dots \; b_n x_n \; \dots. \; (4.8)$$

whereais caled the intercept and the b_n are called slopes or coefficients.

The multiple linear regression equation to estimate monthly monsoon runoff was generated by using mean temperature and precipitation as predictor variables.

RESULTS AND DISCUSSION

This chapter illustrates the results from the application of various methods as described in the Methodology chapter using the Mann Kendall Test, Sen's slope Estimator, Statistical Downscaling Model (SDSM), Artificial Neural Network (ANN) and Multiple Linear Regression (MLR).

5.1 Statistical Downscaling Model (SDSM)

Statistical downscaling model (SDSM) is used to simulate climatic data under current and future conditions for maximum temperature, minimum temperature and precipitation at JharsugudaStation.In this study calibration is done by using selected screen variables and level of the variance in the local predictand of daily precipitation, maximum and minimum temperature of Jharsuguda station data for the period of 1981-2010. This 30 year period is used as the baseline period. During model calibration, conditional process for precipitation and unconditional process for maximum and minimum temperature was chosen.In unconditional process, a direct relation between the predictandand predictors are assumed while conditional processes are done with intermediate processes. Table 5.1 shows the selected predictors for model calibration at Jharsuguda Station.

Predictand	**Predictors**
Daily Precipitaion	ncepp_uas, ncepp_vas, ncepshumas
Daily Maximum Temperature	ncepp500as, ncepp5zhas, nceptempas
Daily Maximum Temperature	ncepp500as, nceppzhas, nceprhumas, ncepshumas, nceptempas

Table:5.1 Predictors selected for model calibration at JharsugudaStation

Table 5.2 shows the description of each predictor variables used for model calibration in SDSM.

Predictors	**Description**
ncepp_uas	Zonal velocity component
ncepp_vas	Meridional velocity component
Ncepshumas	Near surface specific humidity
ncepp500as	500 hPageopotential height
ncepp5zhas	Divergence
Nceptempas	Mean temperature
Nceprhumas	Near surface relative humidity

Table 5.2: Description of each predictor variables for model calibration in SDSM

5.1.2 Performance Criteria for SDSM

During the calibration of maximum temperature, minimum temperature and precipitation, some statistical analysis (variance, QQ-plot, PDF plot, Dry spell length and Wet spell lengths) were usedas performance criteria. Performance criteria has been used to show the statistical relationship between the observed and downscaled data.

Performance criteria chosen for precipitation are variance, QQ-plot, PDF plot, Dry spell length and Wet spell lengths were used. Figure 5.1.1 shows the variance between the observed precipitation and downscaled precipitation.

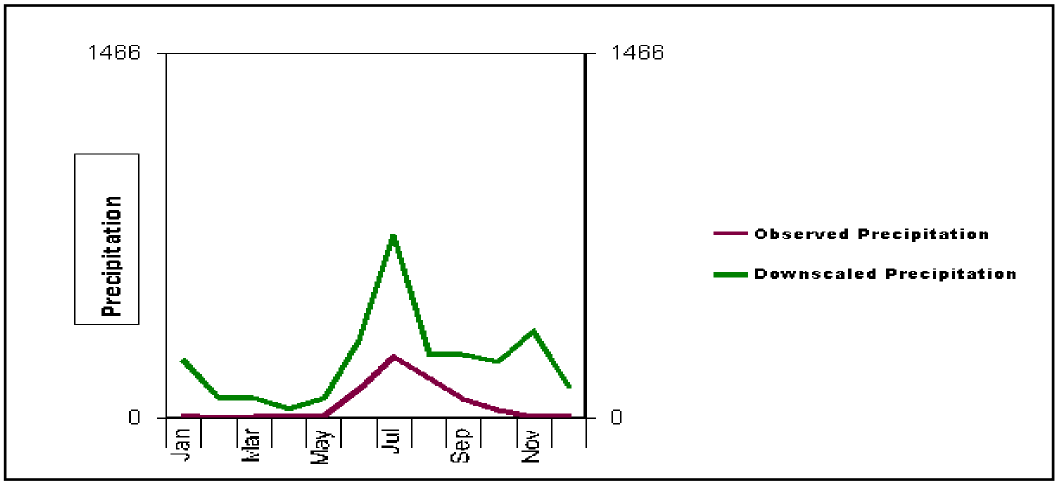


Fig 5.1.1 Variance between the observed and downscaled precipitation

The line chart of observed and downscaled precipitation at Jharsuguda Station for dry-spell and wet spell are plotted to determine the performance of the model. Figure 5.1.2 shows the dry spell between the observed and downscaled precipitation.

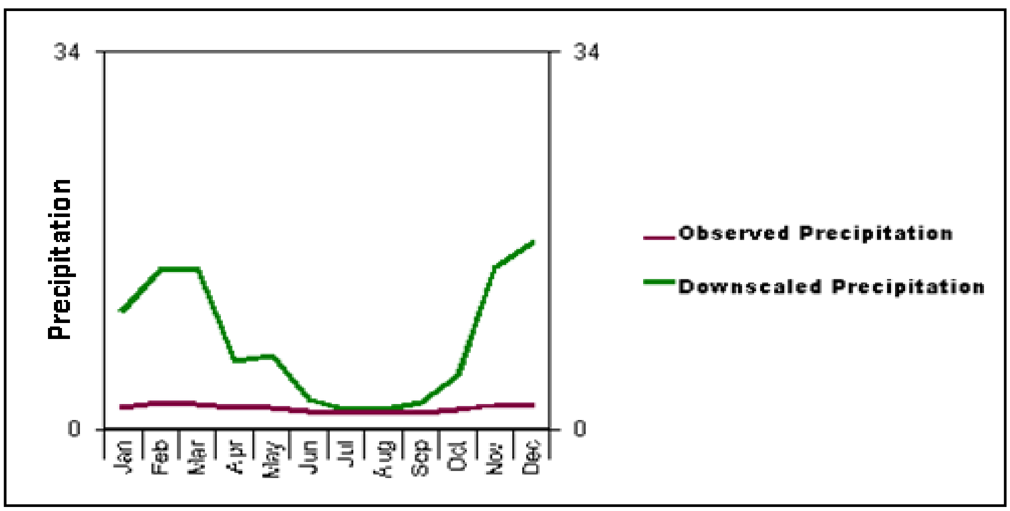


Fig. 5.1.2 Dry spell between observed and downscaled precipitation

The wet spell length shows the number of wet days while the dry spell length shows the number of dry days. Figure 5.1.3 shows the wet spell between the observed and downscaled precipitation.

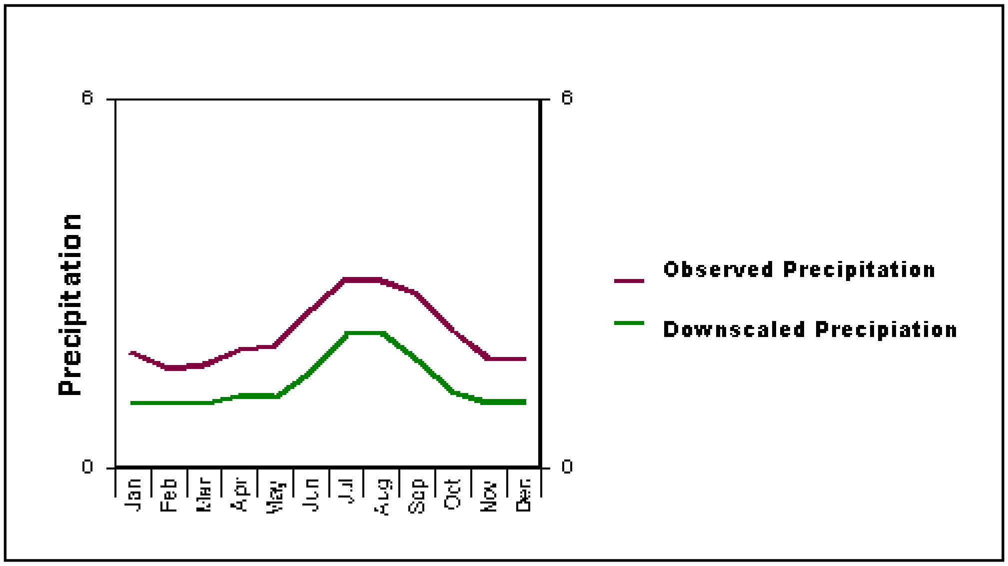


Fig. 5.1.3 Wet spell between the observed and downscaled precipitation

A Q-Q (Quantile- Quantile) plot is a plot of the quantiles of the first data set against the quantiles of the second data set. Quantiles are the fraction of points below the given value. Figure 5.1.4 shows the Q-Q plot between observed and downscaled precipitation.

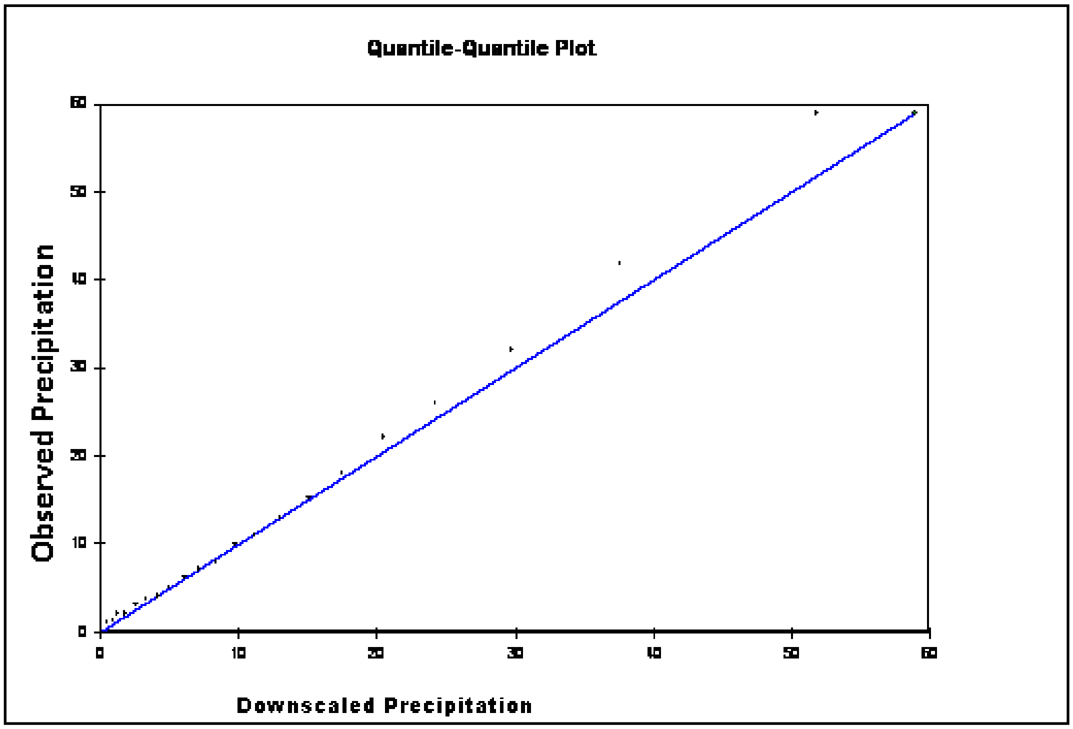


Fig. 5.1.4 Q-Q plot between observed and downscaled precipitation

PDF (Probability Density Function) plot is a function that describes the relative likelihood for the random variable to take on a given value.It is given by the area under the density function but above the horizontal axis and between the lowest and greatest values of the range.Figure 5.1.5 shows the PDF plot between the observed and downscaled precipitation, where PREC is the observed precipitation in mm.

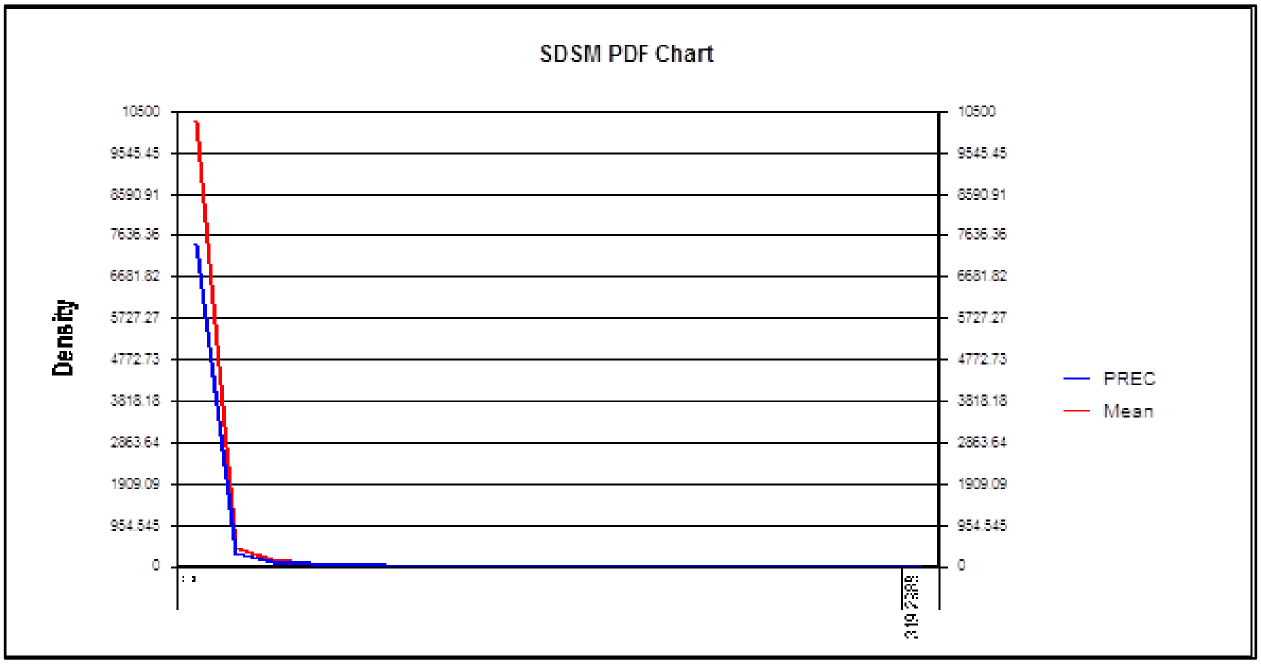


Fig. 5.1.5 PDF plot between observed and downscaled precipitation

Performance criteria chosen for maximum temperature are variance, Q-Q plot and PDF plot. The Line plot are plotted to show the variance between the observed and downscaled maximum temperature. Figure 5.1.6 shows the variance between the observed and downscaled maximum temperature.

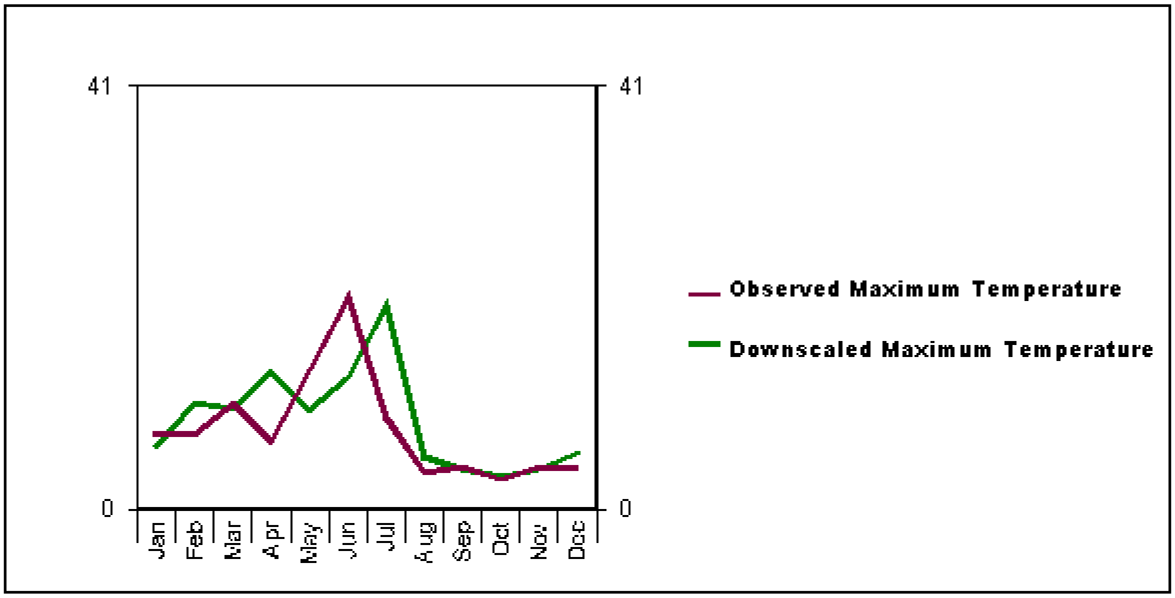


Fig. 5.1.6 Variance between the observed and downscaled maximum temperature

Figure 5.1.7 shows the Q-Q plot between observed and downscaled maximum temperature for A2 scenario, where observed maximum temperature is expressed as TMAX and downscaled maximum temperature is expresses as tmax.TMAX and tmax are in (°C).

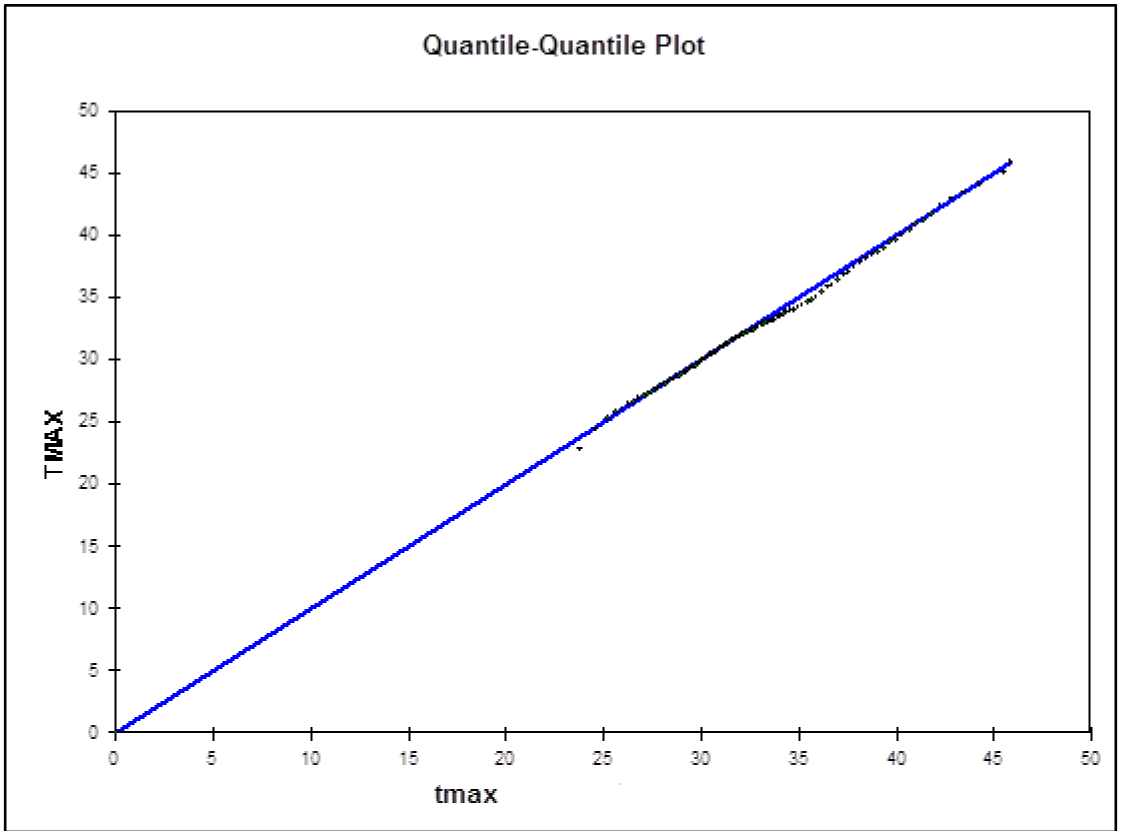


Fig. 5.1.7 Q-Q plot between the observed and downscaled maximum temperature for A2 scenario

Figure 5.1.8 shows the Q-Q plot between observed and downscaled maximum temperature for B2 scenario, where observed maximum temperature is expressed as TMAX and downscaled maximum temperature is expresses as tmax. TMAX and tmax are in (°C).

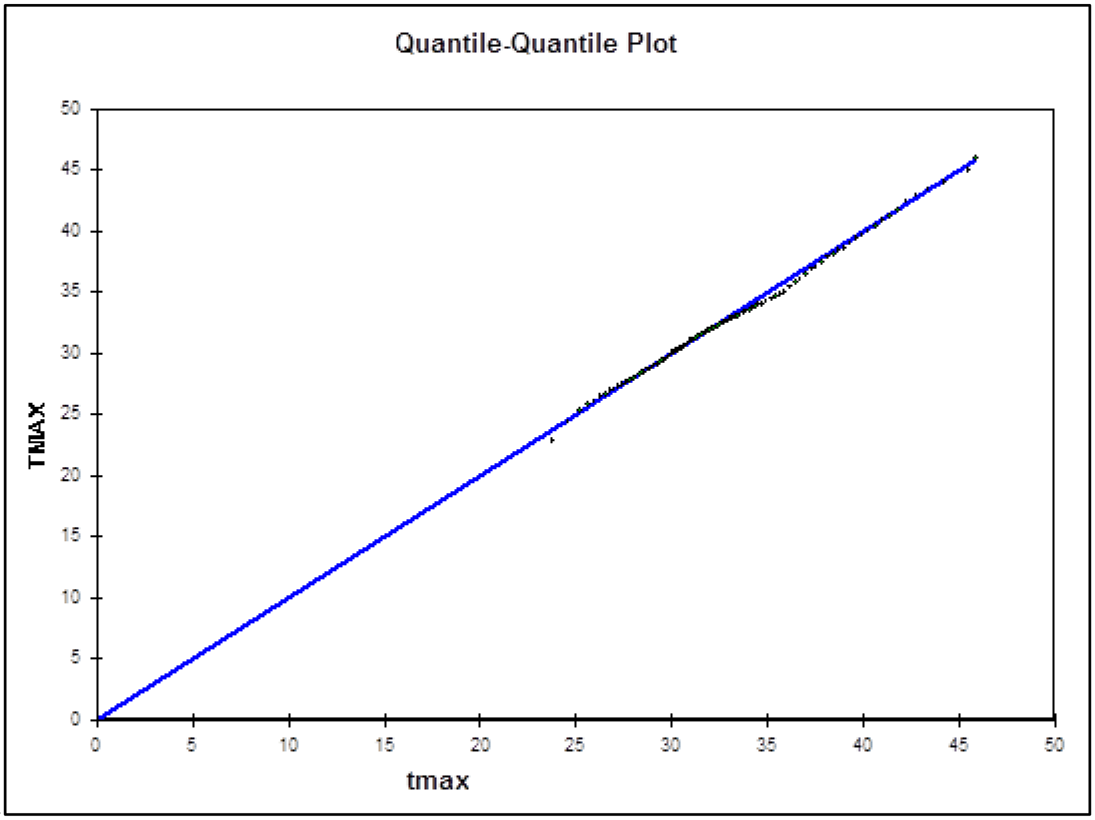


Fig. 5.1.8 Q-Q plot between the observed and downscaled maximum temperature for B2 scenario

Figure 5.1.9 shows the PDF plot between the observed maximum temperature and downscaled maximumtemperature, where TMAX shows the observed maximum temperature.TMAX is in (°C).

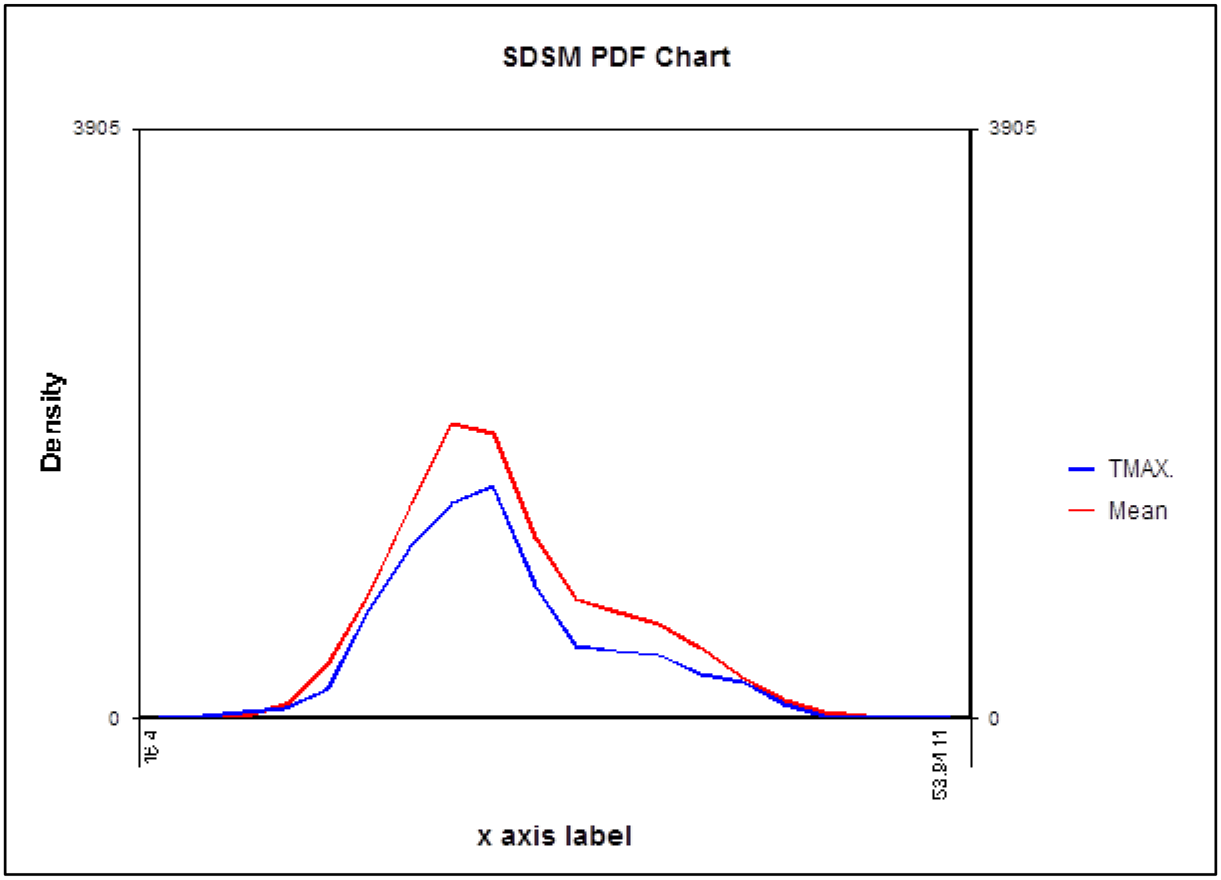


Fig. 5.1.9 PDF plot between the observed and downscaled maximum temperature

Performance criteria chosen for minimum temperature are variance, Q-Q plot and PDF plot. The Bar chart are plotted to show the variance between the observed and downscaled minimum temperature. Figure 5.1.10 shows the variance between the observed and downscaled minimum temperature.

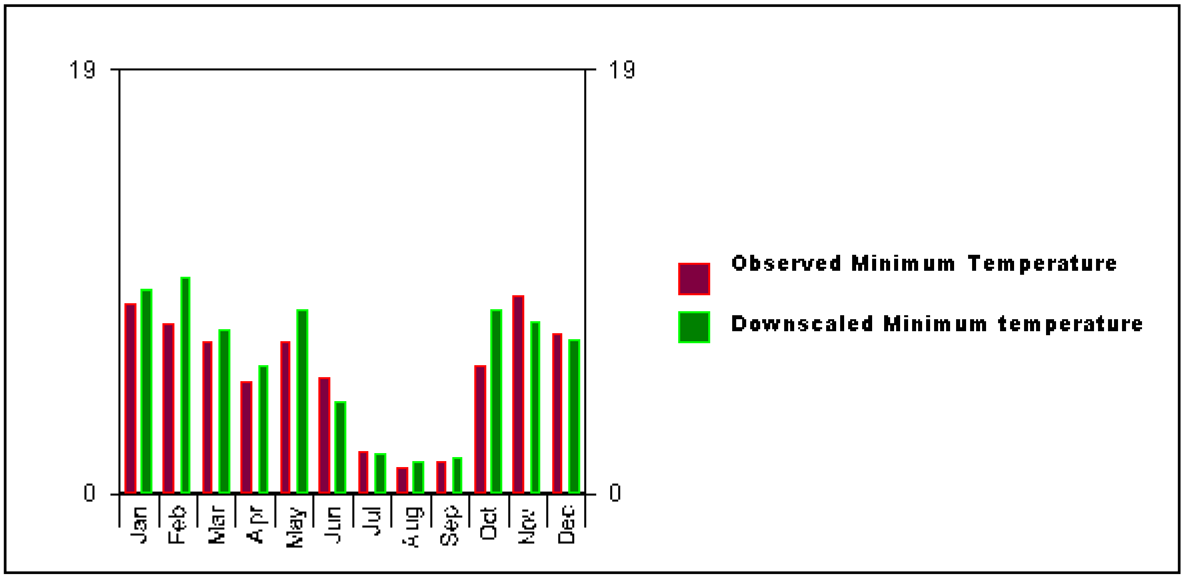


Fig 5.1.10 Variance between the observed and downscaled minimum temperature

Figure 5.1.11 shows the Q-Q plot between observed and downscaled minimum temperature for A2 scenario, where observed minimum temperature is expressed as TMIN and downscaled minimum temperature is expressed as tmin. TMIN and tmin are in (°C).

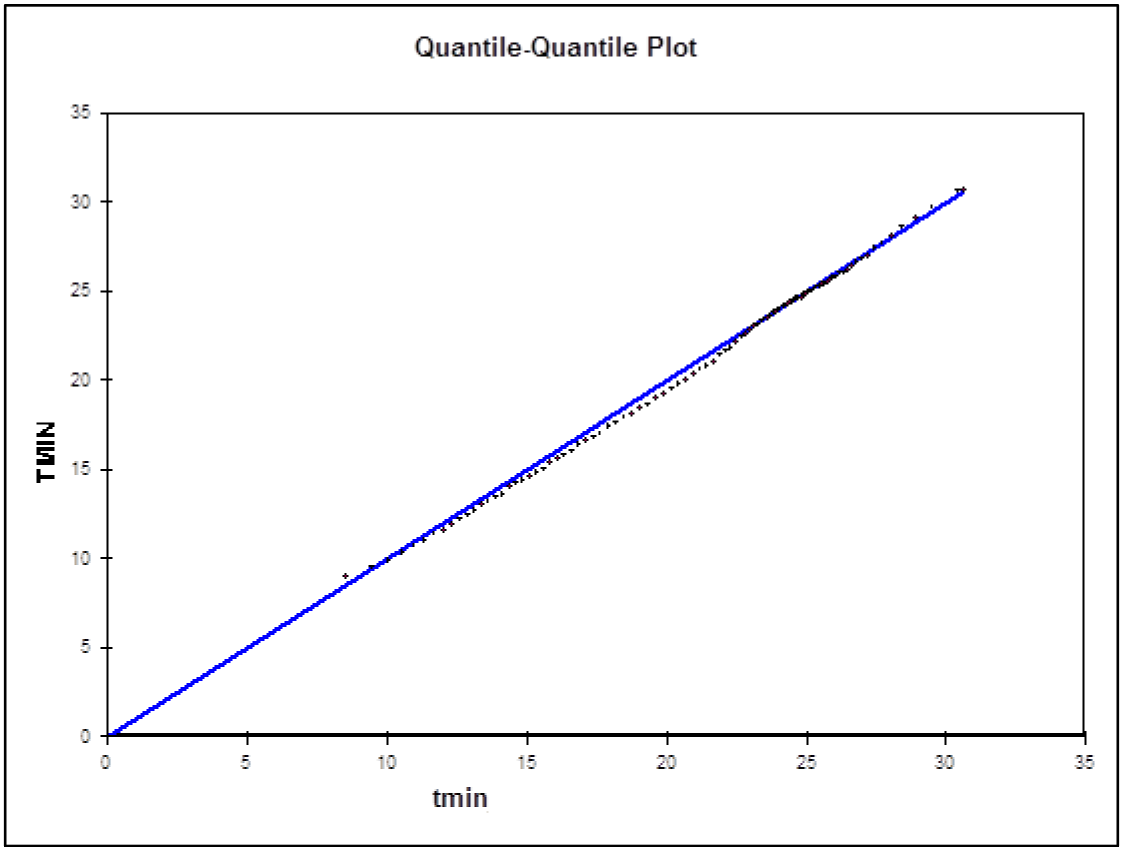


Fig. 5.1.11 Q-Q plot between the observed and downscaled minimum temperature for A2 scenario

Figure 5.1.12 shows the Q-Q plot between observed and downscaled minimum temperature for B2 scenario, where observed minimum temperature is expressed as TMIN and downscaled minimum temperature is expressed as tmin.TMIN and tmin are in (°C).

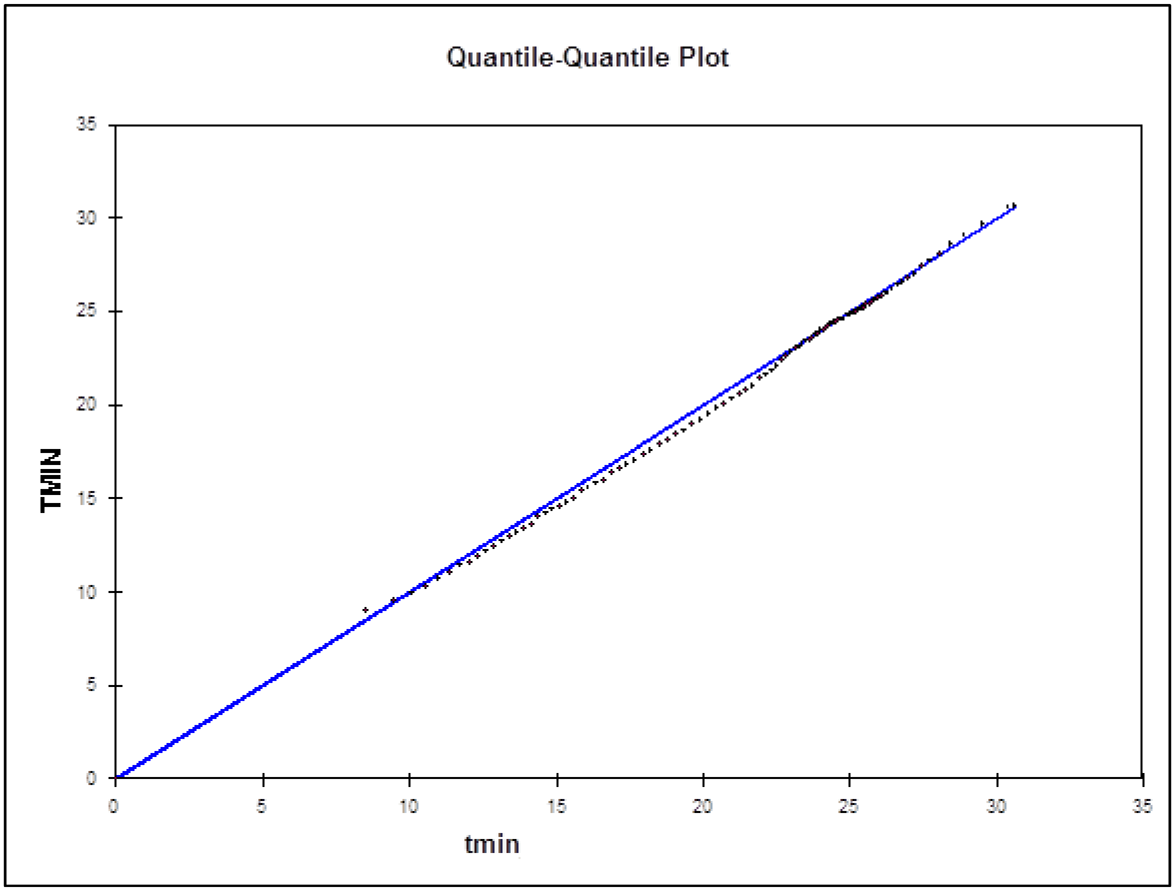


Fig. 5.1.12 Q-Q plot between the observed and downscaled maximum temperature for B2 scenario

Figure 5.1.13 shows the PDF plot between the observed minimum temperature and downscaled minimumtemperature, where TMIN shows the observed minimum temperature.TMIN is in (°C).

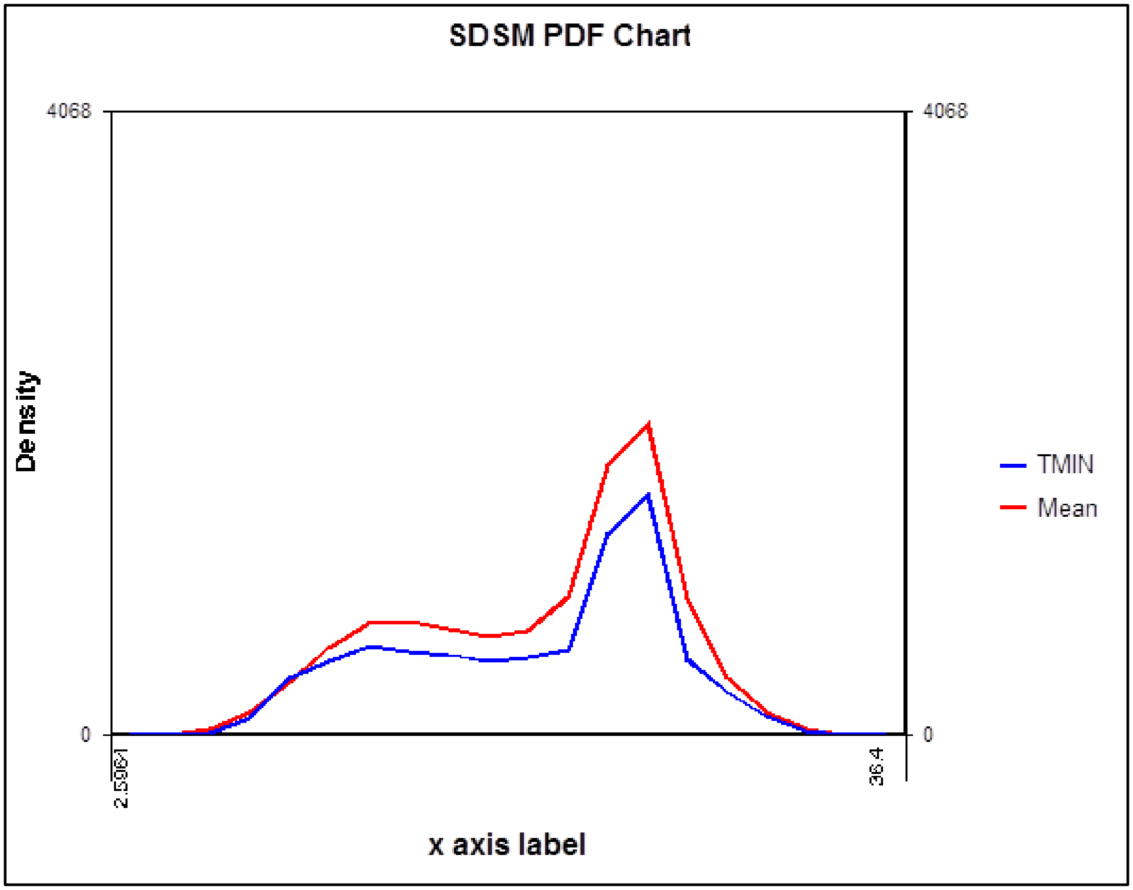


Fig. 5.1.13 PDF plot between the observed and downscaled maximum temperature

5.2 Downscaled Data and CCDS Downscaled Data

The downscaled results using SDSM in the present study at the Jharsuguda station has been compared with the downscaled data for the same location for the sameGCM model from the Canadian Climate Data and Scenarios (CCDS). Only for the A2 scenarios the downscaled CCDS data were available for the precipitation and mean temperature.

Downscaled precipitation and the CCDS data from the Canadian Climate Data and Scenarios (CCDS) for the A2 scenario for the time period of 2020s, 2050s and 2080s is shown in figure 5.2.1, 5.2.2 and 5.2.3.

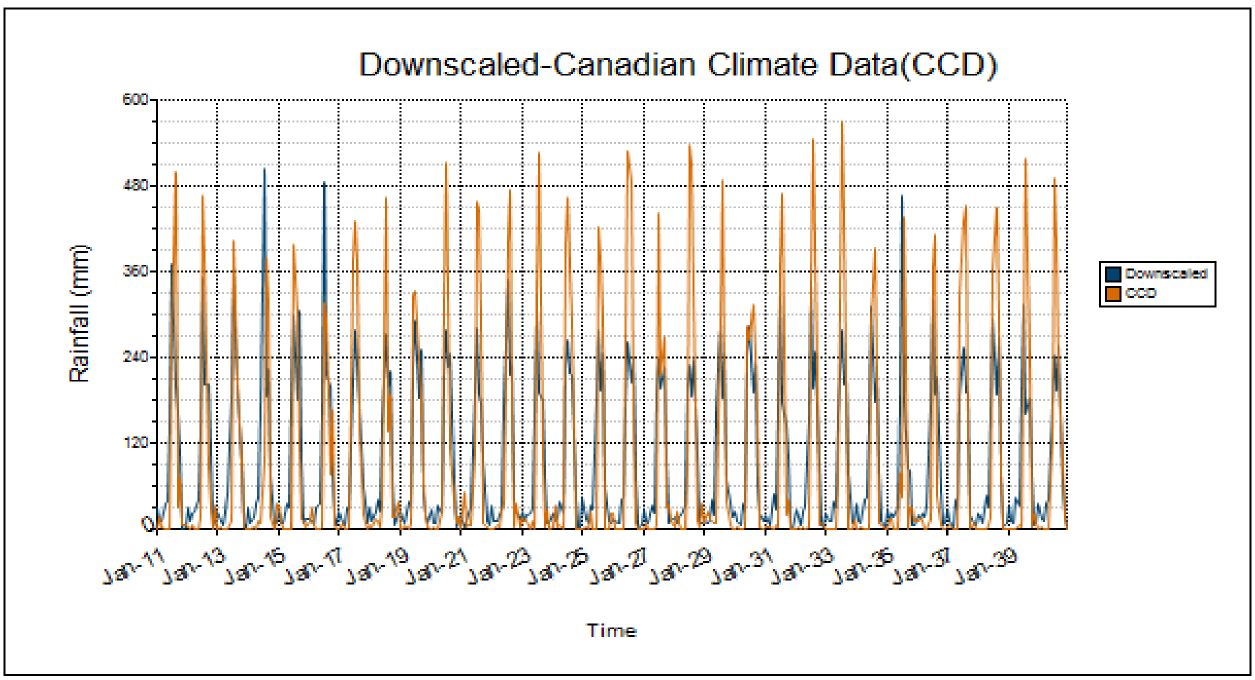


Fig. 5.2.1 Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2020s

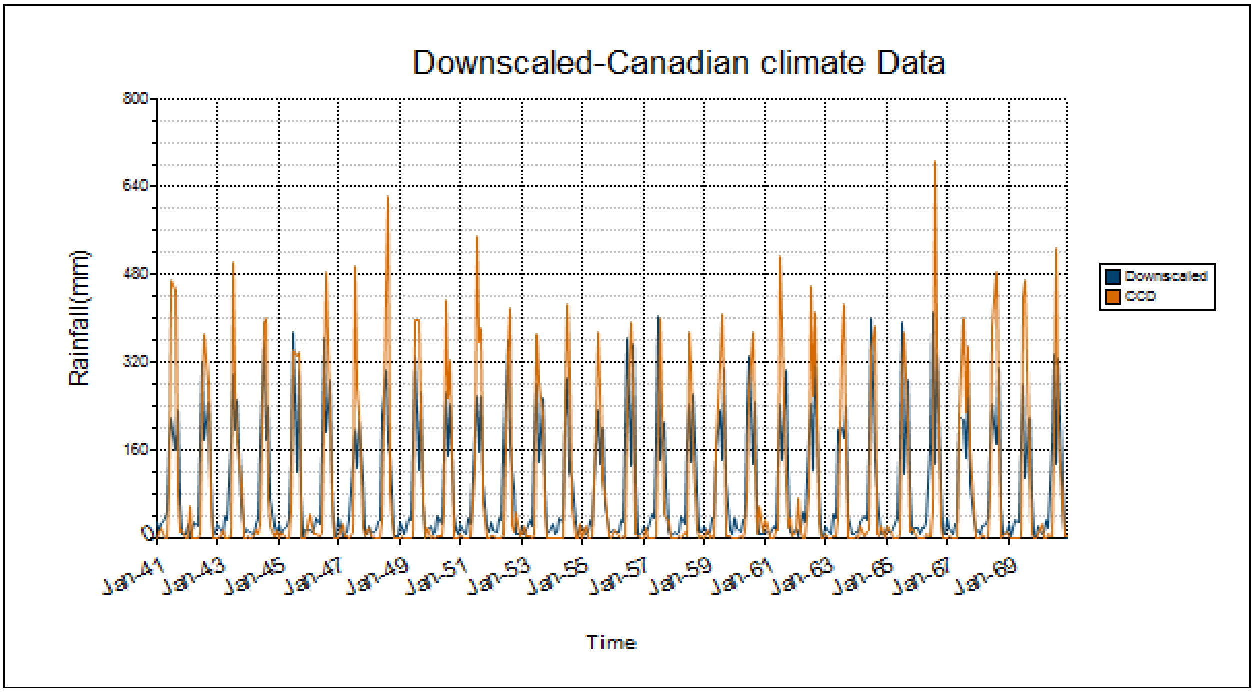


Fig. 5.2.2 Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2050s

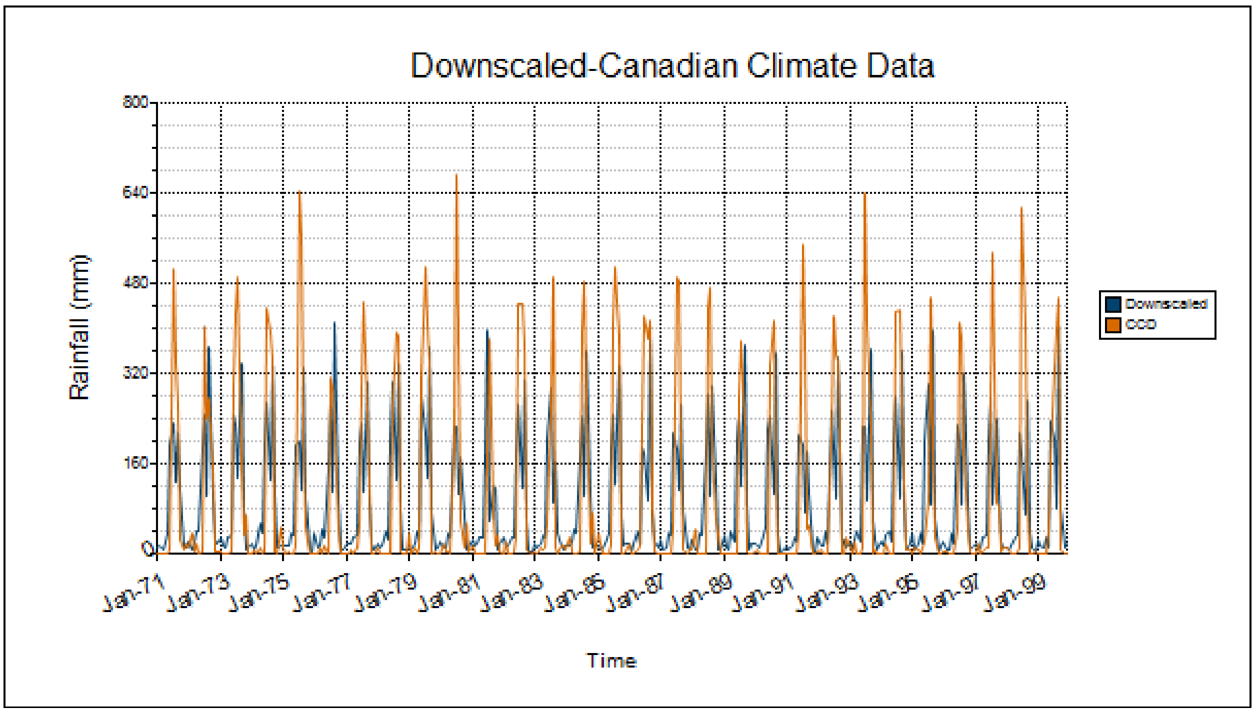


Fig. 5.2.3 Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2080s

Downscaled mean temperature and the CCDS downscaled mean temperature data from the Canadian Climate Data and Scenarios (CCDS) for the A2 scenario for the time period of 2020s, 2050s and 2080s is shown in figure 5.2.4, 5.2.5 and 5.2.6.

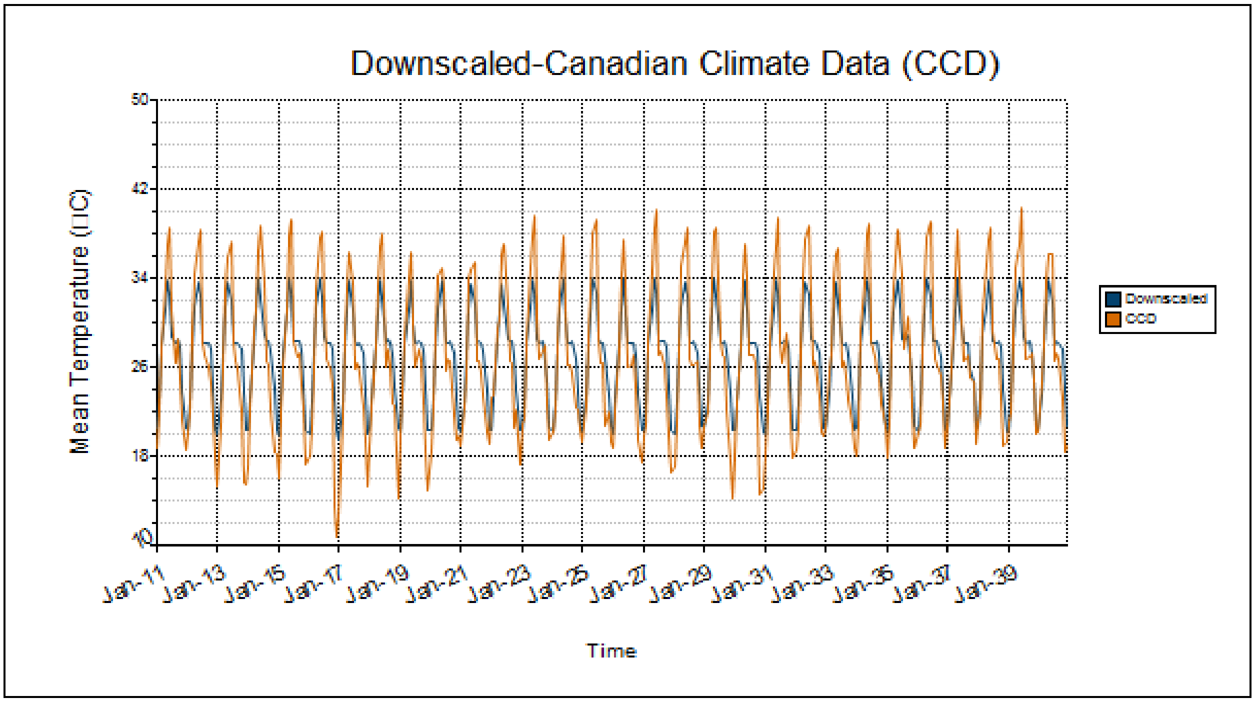


Fig. 5.2.4 Downscaled Mean temperature and CCDS downscaledMean temperaturefor A2 scenario in 2020s

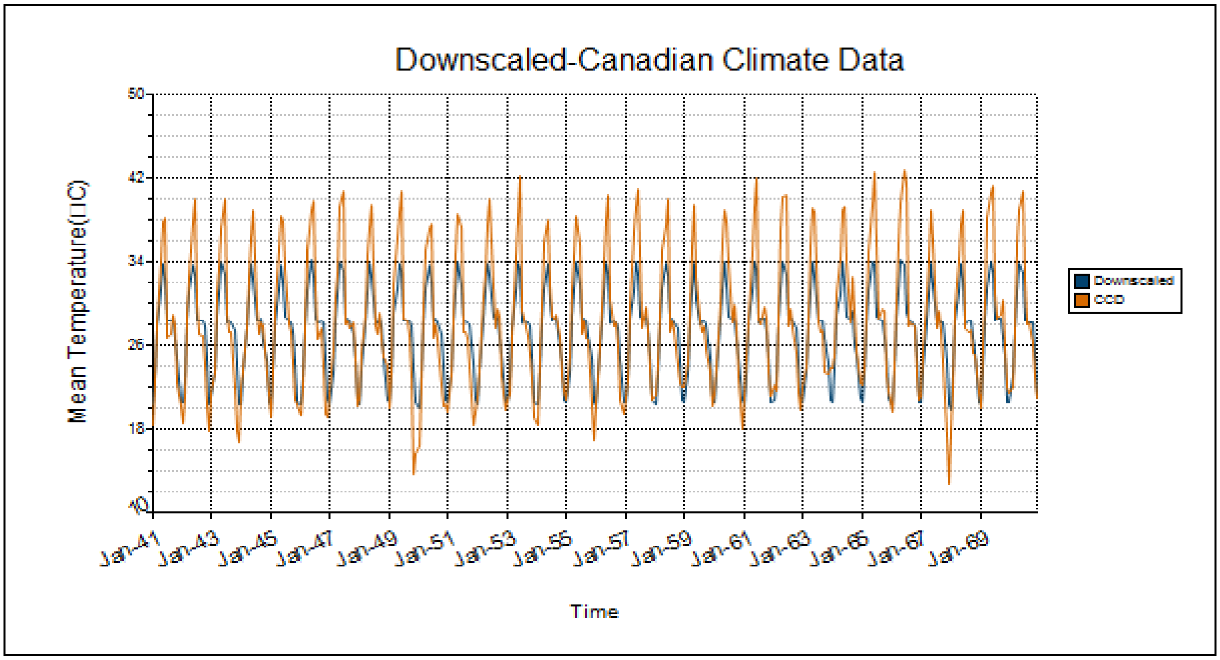


Fig. 5.2.5 Downscaled Mean temperature and CCDS downscaledMean temperaturefor A2 scenario in 2050s

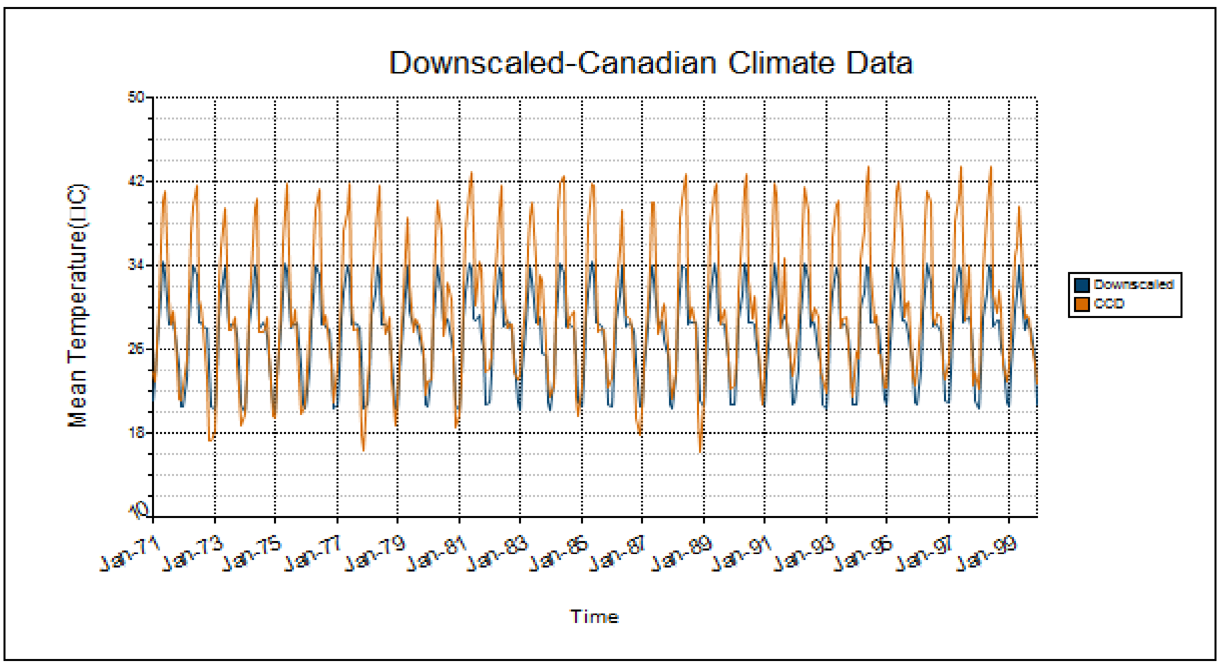


Fig. 5.2.6 Downscaled Mean temperature and CCDS downscaledMean temperaturefor A2 scenario in 2080s

5.3 Trend Analysis

For the available observed data, plots are made for summer, monsoon, winter and annual periods to show the trend using Mann kendalltest and the magnitude of the trend using Sen's estimator. The plots provide an indication of increasing or decreasing trend in the time series. These statistics will be used further for comparison with the future predicted time series.

5.3.1: Trend Analysis on Observed Daily Data at Jharsuguda Station

Figure 5.3.1 shows an increasing trend in the daily observed precipitation for both annual and seasonal period.

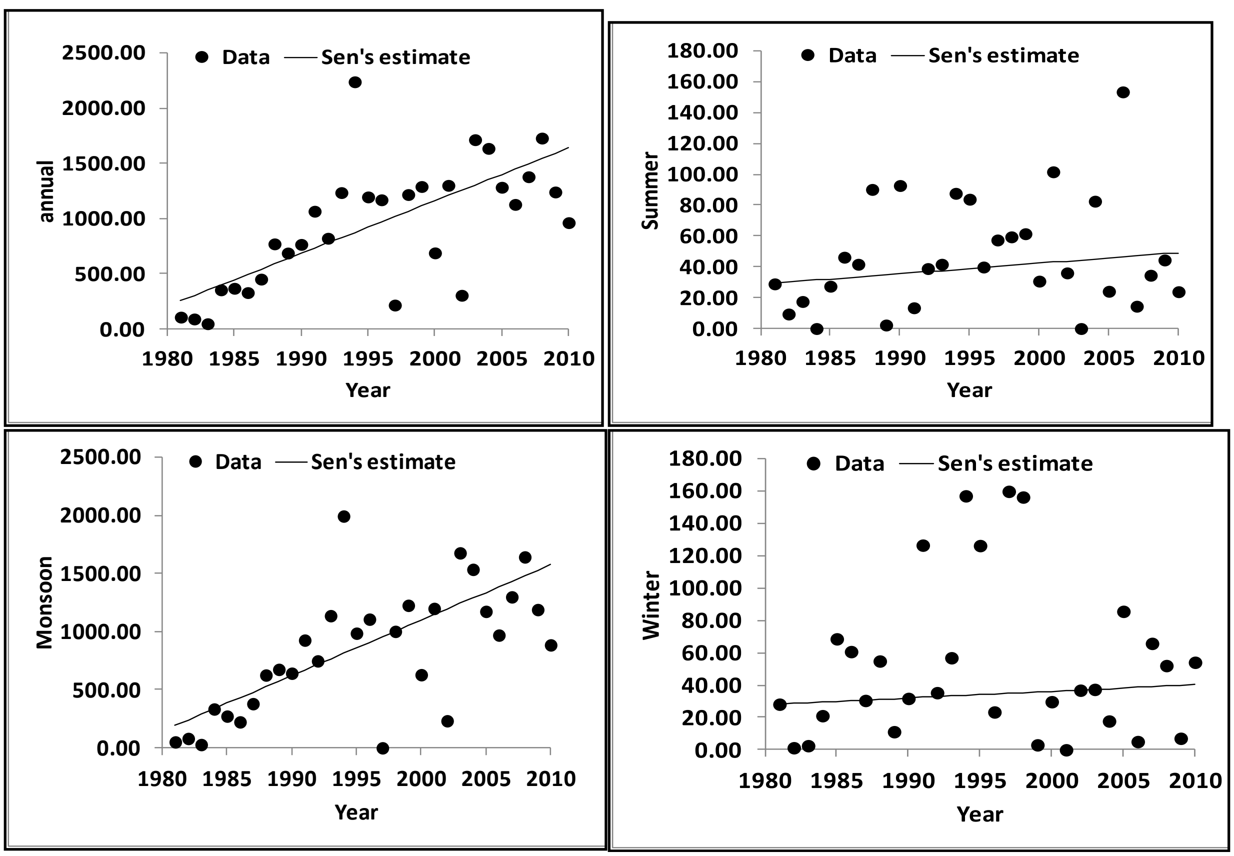


Fig. 5.3.1 Trend Analysis on observed daily precipitation at Jharsuguda Station

Figure 5.3.2 shows an increasing trend in the daily maximum temperature for both annual and seasonal analysis at Jharsuguda Station.

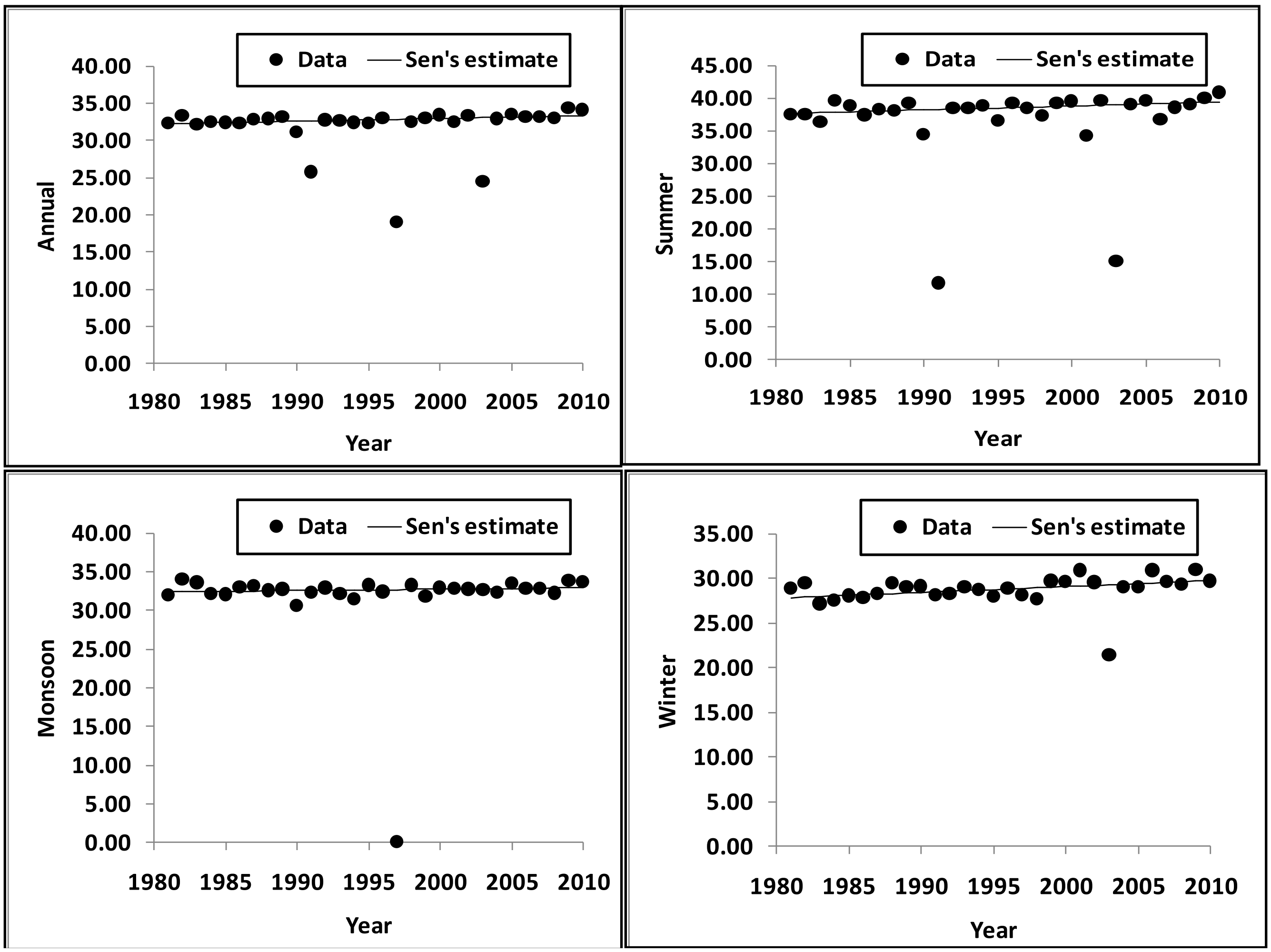


Fig. 5.3.2: Trend analysis of observed daily Maximum Temperature at Jharsuguda Station

Figure 5.3.3 shows an increasing trend in the daily minimum temperature for both annual and seasonal analysis at Jharsuguda Station.

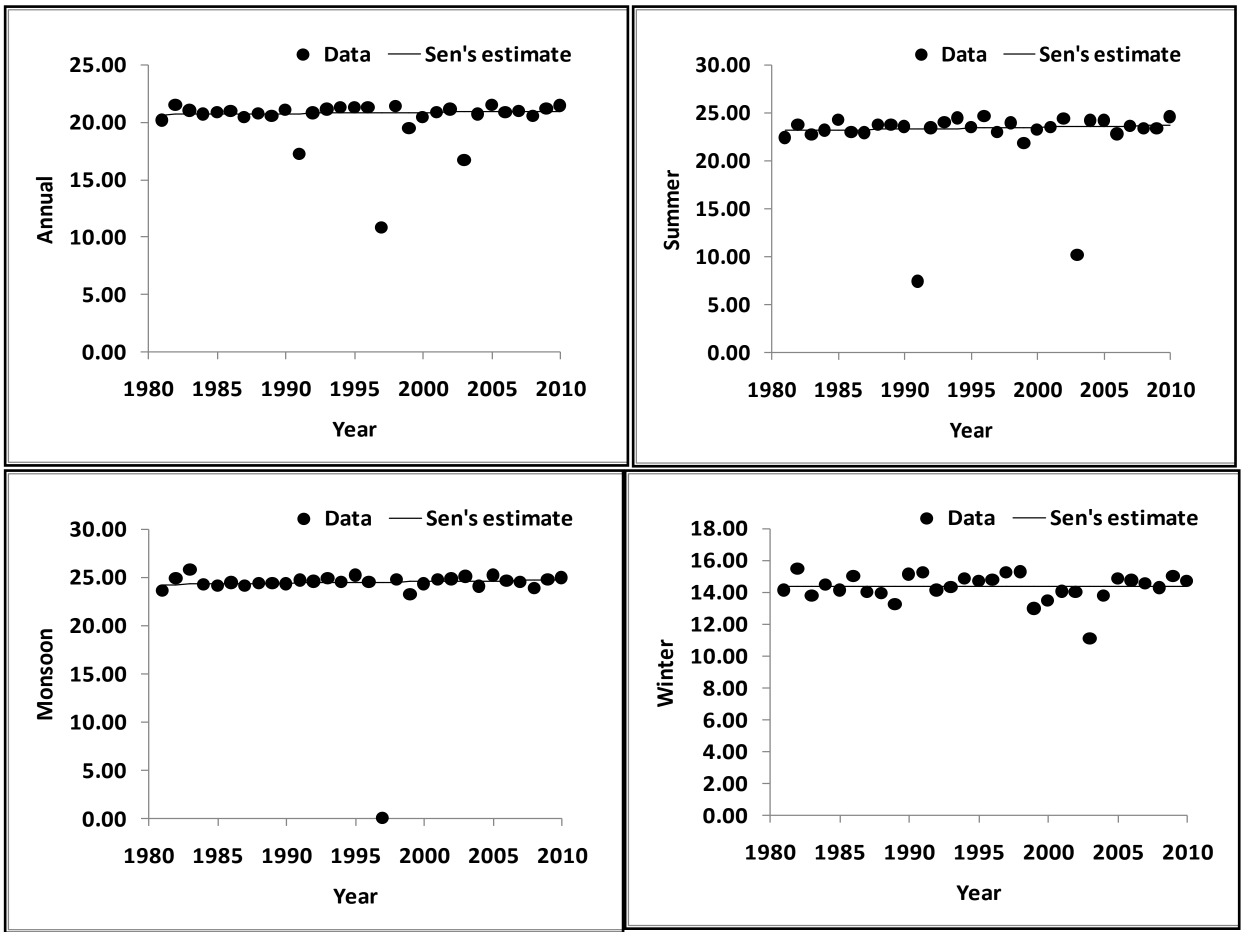


Fig. 5.3.3: Trend analysis of observed daily Minimum Temperature at Jharsuguda Station

Table 5.3 shows the Mann kendall Z value and Sen's slope estimate Q value for all the observed data at Jharsuguda station.

Data	Time Series	Mann Kendall Trend	Sen's slope estimate
		Test Z	Q
Precipitation (1981-2010)	Summer	0.91	0.680
	Monsoon	4.03	47.699
	Winter	0.57	0.411
	Annual	4.10	47.64
Tmax (1981-2010)	Summer	2.05	0.063 (NS)
	Monsoon	0.87	0.017
	Winter	2.82	0.065(NS)
	Annual	2.73	0.037(NS)
Tmin (1981-2010)	Summer	0.98	0.020
	Monsoon	1.16	0.016
	Winter	0	0
	Annual	0.89	0.011

Table 5.3: Z and Q value for theDaily Observed Data at JharsugudaStation (1981-2010)

5.3.2Trend Analysis on Observed Monthly Data at Hirakud Station

Monthly monsoon data for precipitation and mean temperature is available for the Hirakud station. Figure 5.3.4 shows an increasing trend in the monthly observed precipitation in the monsoon period and figure 5.3.5 shows an increasing trend in the monthly observed mean temperature in the monsoon period at Hirakud station.

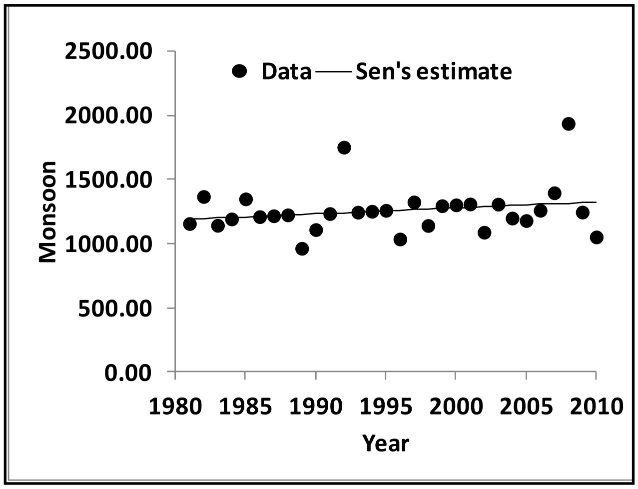


Fig. 5.3.4 Trend Analysis of Monthly observed precipitation at Hirakud(1981-2010)

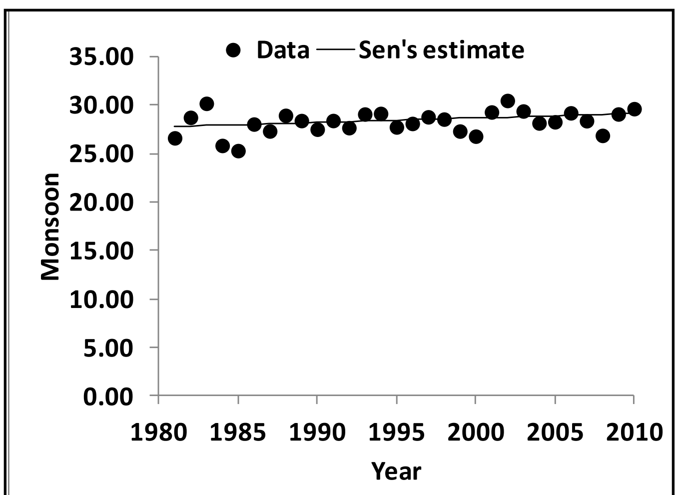


Fig. 5.2.5 Trend Analysis on Monthly Observed Mean Temperature at Hirakud(1981-2010)

The Mann kendall Z value and Sen's slope estimate Q value for all the observed data at Hirakud station are shown in table 5.4.

Data	Time Series	Mann Kendall Trend	Sen's slope estimate
		Test Z	Q
Precipitation (1981-2010)	Monsoon	1.14	4.661
Tmean (1981-2010)	Monsoon	1.93	0.047

Table 5.4: Z and Q value for the monthly observed data at Hirakud station (1981-2010)

5.3.3 Trend Analysis on Downscaled Precipitation at JharsugudaStation

For the downscaled precipitation, plots are made for summer, monsoon, winter and annual periods to show the trend using Mann kendalltest and the magnitude of the trend using Sen's estimator. The plots provide an indication of increasing or decreasing trend in the time series for the two scenarios A2 and B2.The downscaled data from 2011-2099 are divided in three ensembles of 30 years period, 2011-2040 (2020s), 2041-2070 (2050s) and 2071-2099 (2080s). Decreasing trend in the precipitation in 2020s for A2 and B2 scenario are shown in the figure 5.3.6 and 5.3.7.

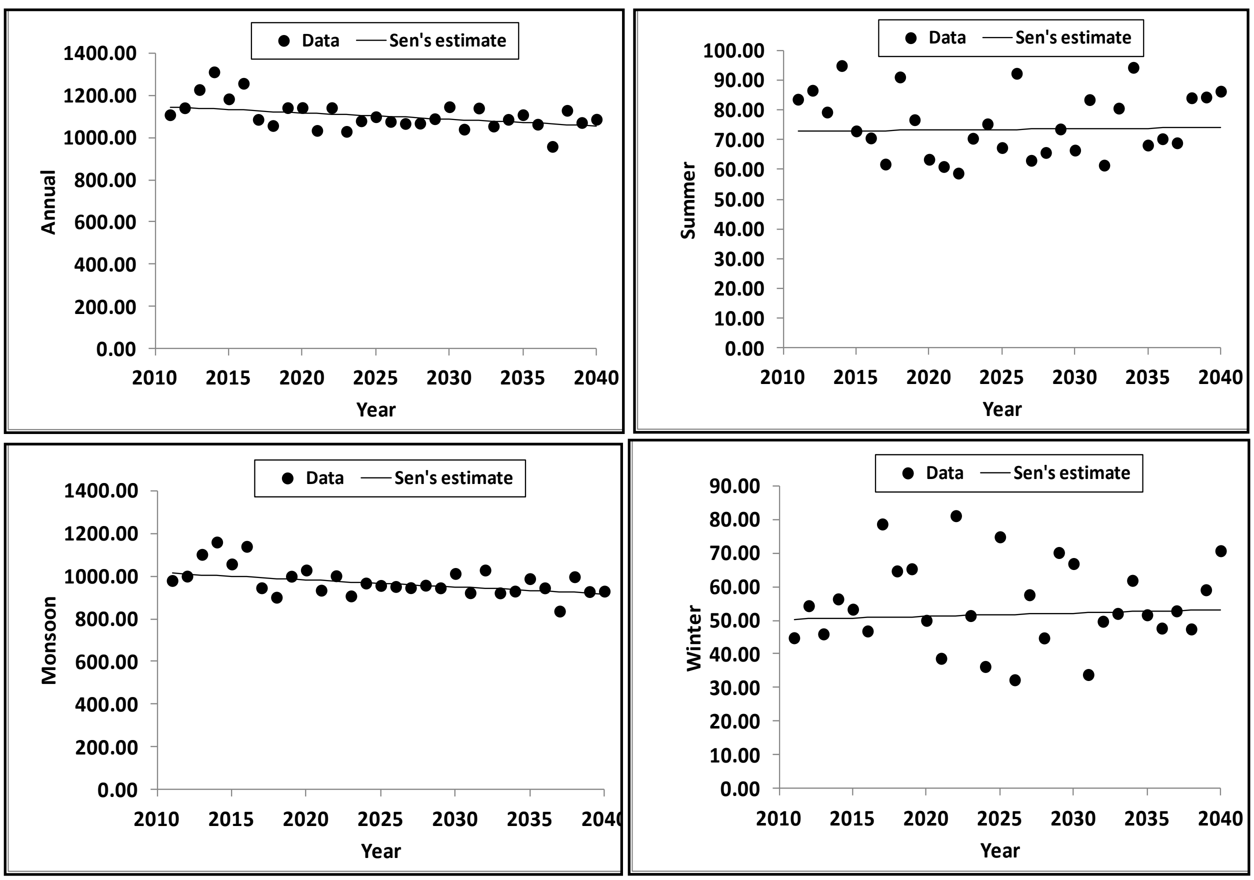


Fig. 5.3.6 Trend analysis on downscaled precipitationatJharsugudaStation for 2020s A2 scenario

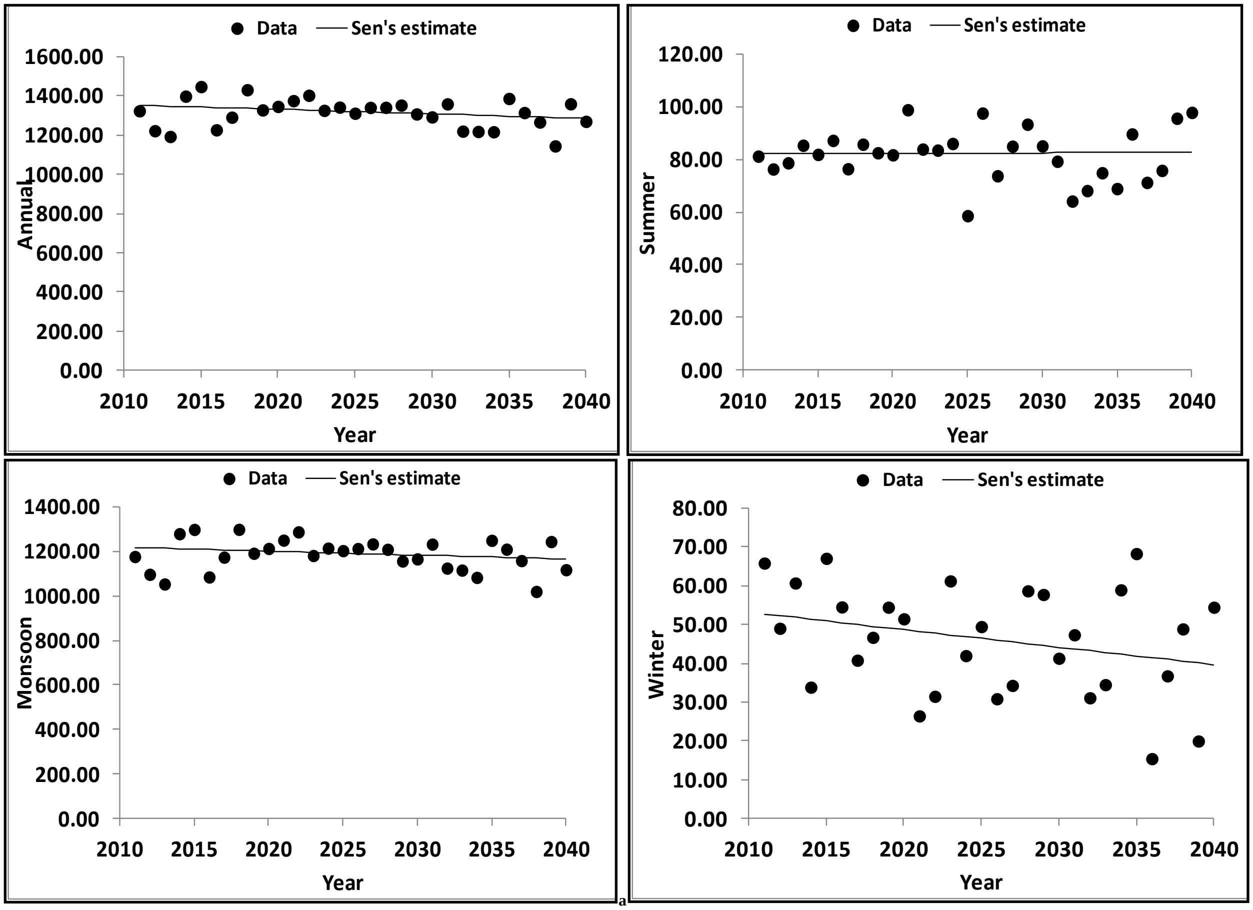
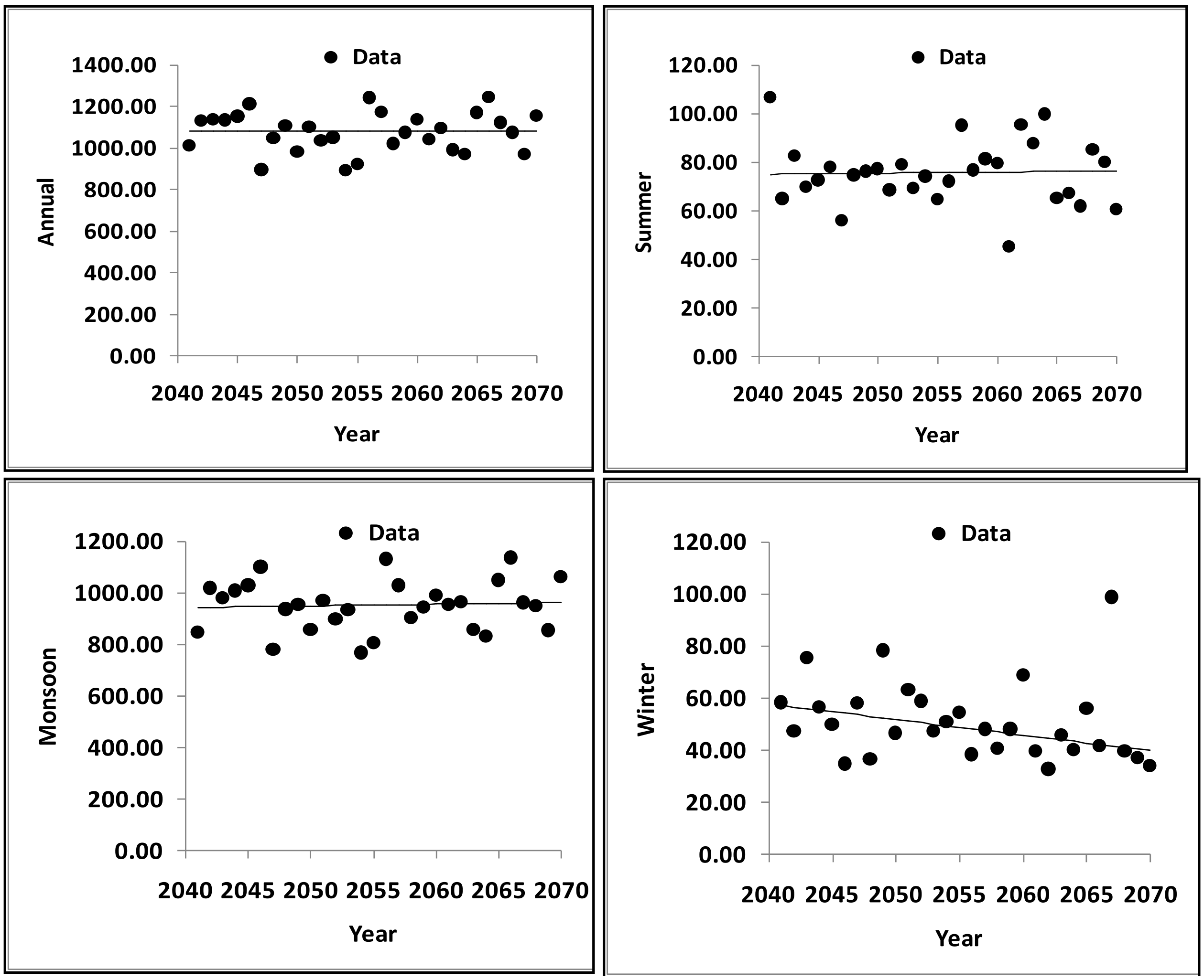
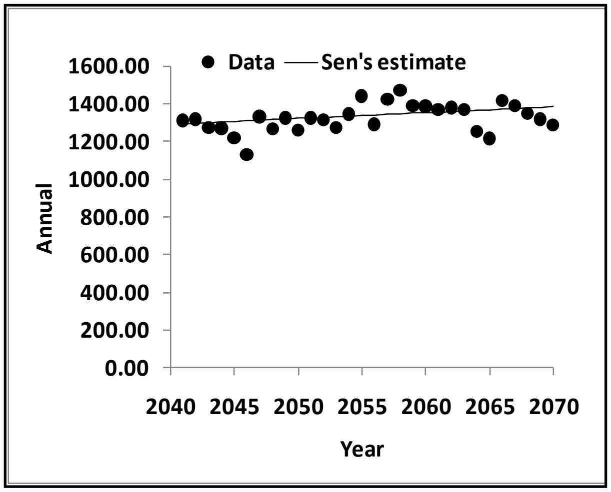


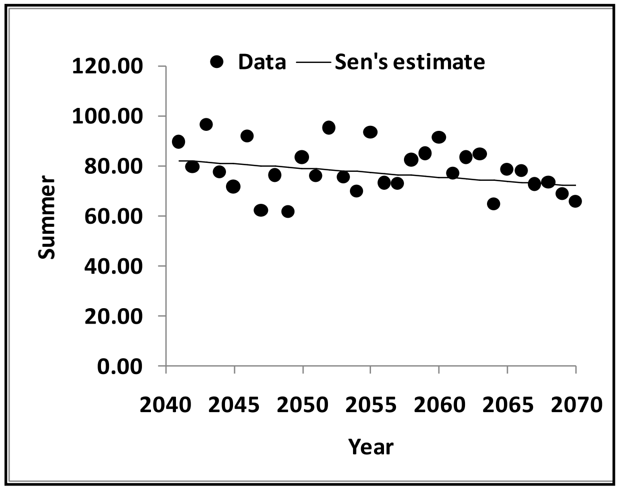
Fig. 5.3.7 Trend analysis on downscaled precipitation atjharsuguda station for 2020s B2 scenario

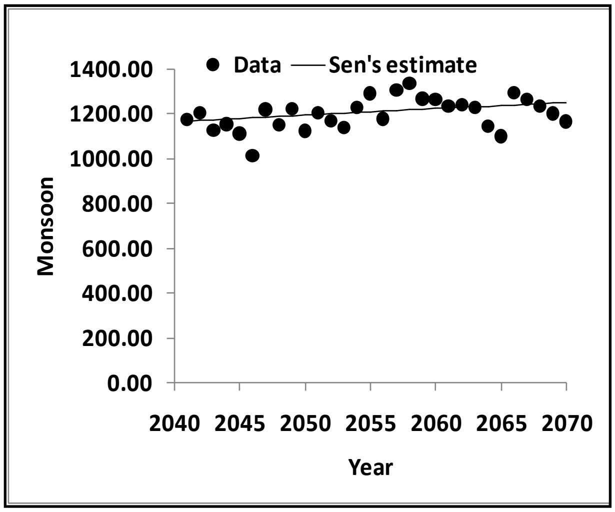
Increasing trend in the precipitation in 2050s for A2 and B2 scenario are shown in the fig 5.3.8 and 5.3.9.

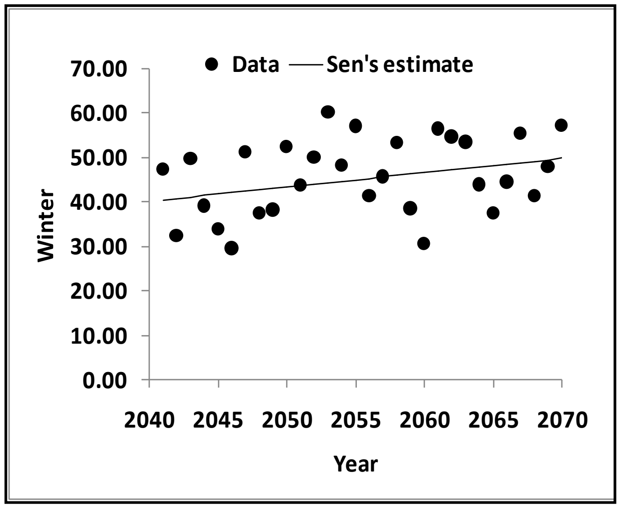


5.3.8 Trend analysis on downscaled precipitation for jharsuguda station for 2050s A2 scenario









5.3.9 Trend analysis on Downscaled Precipitation for Jharsuguda station for 2050s B2 scenario

Increasing trend in the precipitation in 2080s for A2 and B2 scenario are shown in the figure 5.3.10 and 5.3.11.

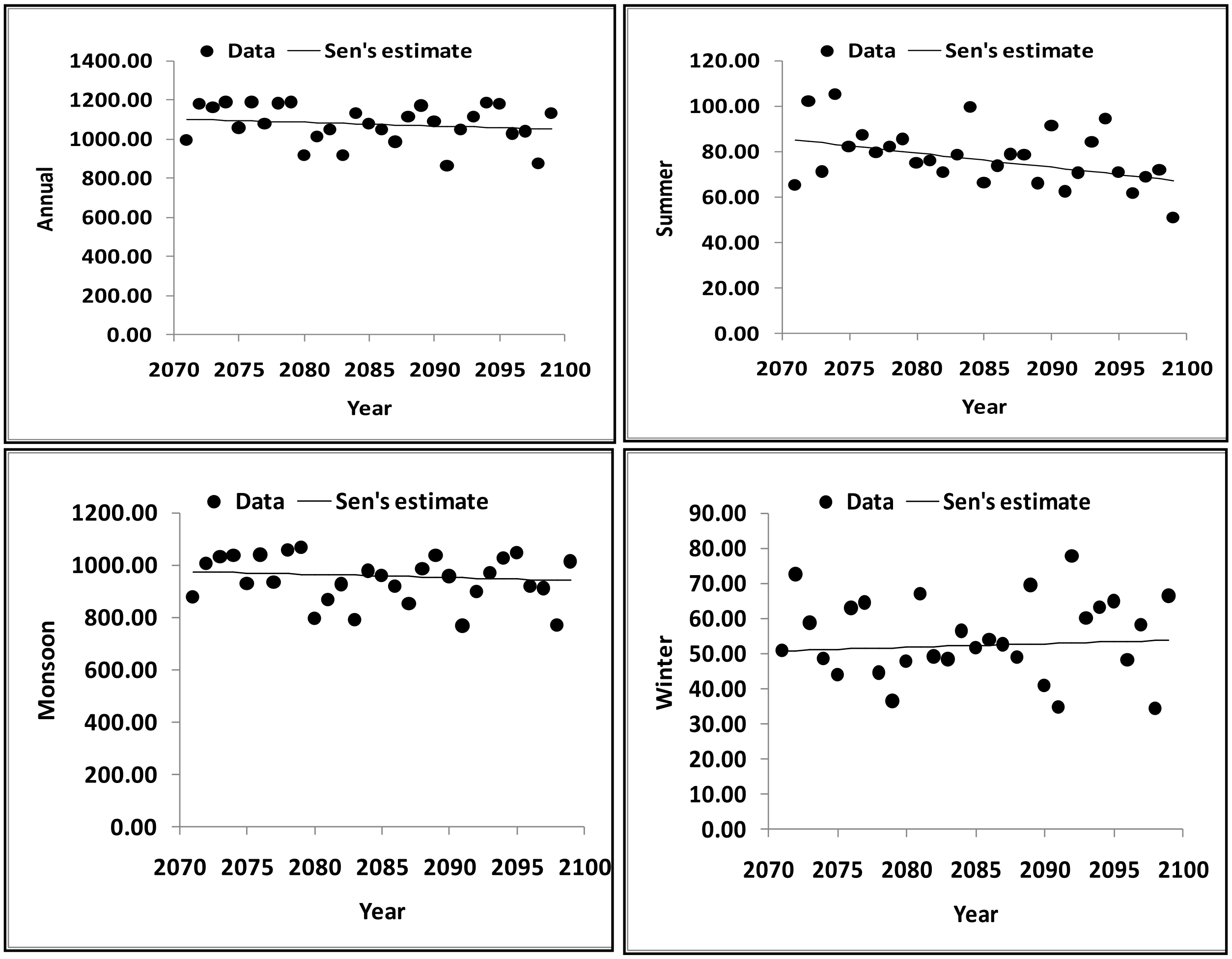


Fig.5.3.10:Trend analysis on downscaled precipitation for Jharsuguda station for 2080s A2 scenario

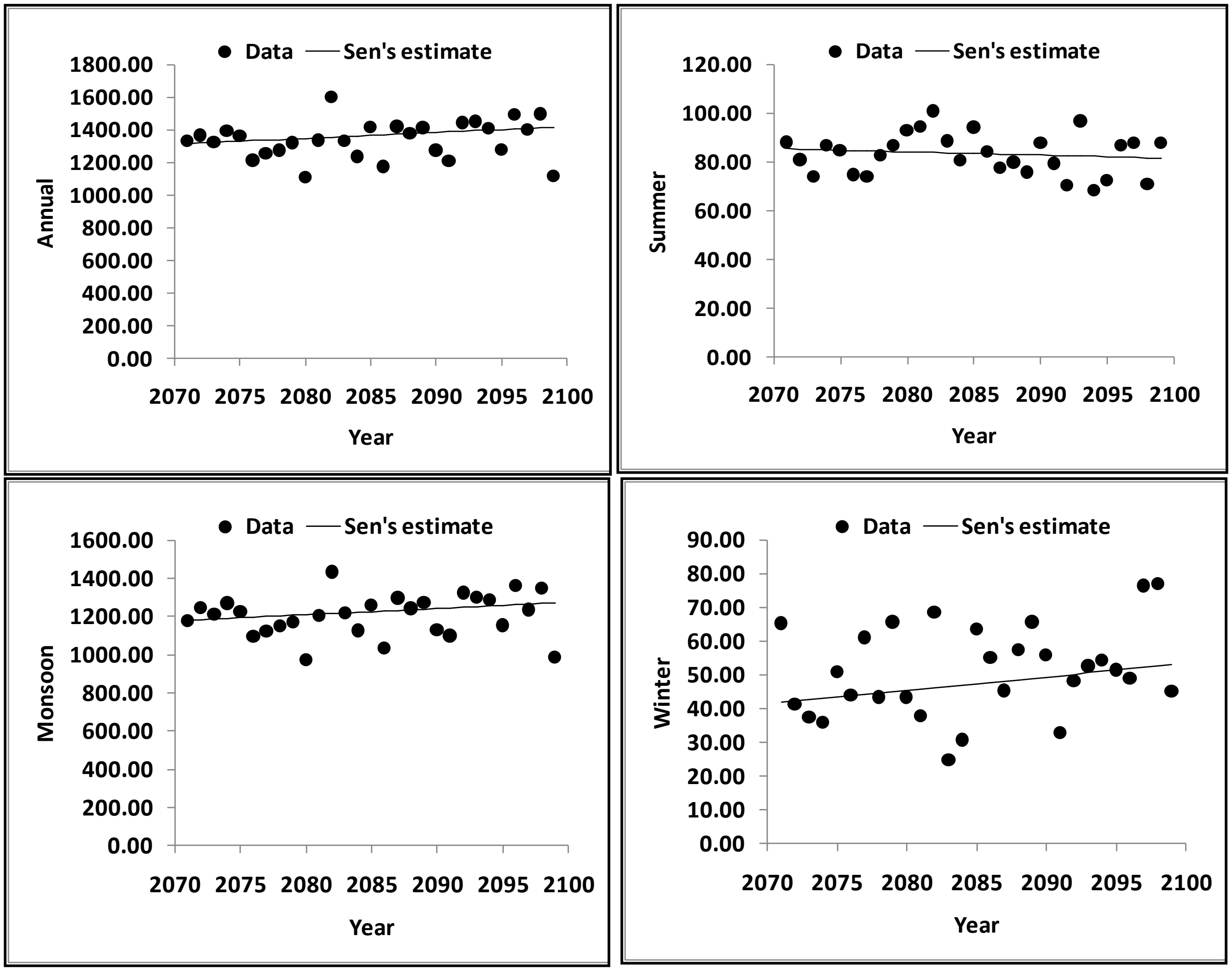


Fig.5.3.11:Trend analysis on downscaled Precipitation for jharsuguda station for 2080s B2 scenario

Table 5.5 shows the Mann kendall Z value and Sen's slope estimate Q value for the downscaled precipitation in 2020s,2050s and 2080s for both A2 and B2 scenario at Jharsuguda station.

Data	Time Series	Mann Kendall Trend	Sen's slope estimate
		Test Z	Q
Precipitation 2020s A2	Summer	0.07	0.043
	Monsoon	-2.75	-3.328
	Winter	0.29	0.097
	Annual	-2.25	-3.052
Precipitation 2020s B2	Summer	0.04	0.018
	Monsoon	-1.03	-1.830
	Winter	-1.36	-0.450
	Annual	-1.25	-2.310
Precipitation 2050s A2	Summer	0.11	0.049
	Monsoon	0.21	0.665
	Winter	-2.07	-0.601
	Annual	0.07	0.089
Precipitation 2050s B2	Summer	-1.53	-0.349
	Monsoon	1.89	2.875
	Winter	1.71	0.322
	Annual	1.78	3.088
Precipitation 2080s A2	Summer	-2.31	-0.634
	Monsoon	-0.84	-1.236
	Winter	0.32	0.106
	Annual	-0.99	-1.820
Precipitation 2080s B2	Summer	-0.73	-0.134
	Monsoon	1.26	3.376
	Winter	1.33	0.392
	Annual	1.29	3.603

Table 5.5 Z and Q value for downscaled Precipitation at Jharsuguda Station

5.3.4 Trend Analysis on Downscaled Maximum Temperature at JharsugudaStation

For the downscaled maximum temperature, plots are made for summer, monsoon, winter and annual periods to show the trend using Mann kendalltest and the magnitude of the trend using Sen's estimator. The plots provide an indication of increasing or decreasing trend in the time series for the two scenarios A2 and B2.The downscaled data from 2011-2099 are divided in three ensembles of 30 years period, 2011-2040 (2020s), 2041-2070 (2050s) and 2071-2099 (2080s). Increasing trend in the maximum temperature in 2020s for A2 and B2 scenario are shown in the figure 5.3.12 and 5.3.13.

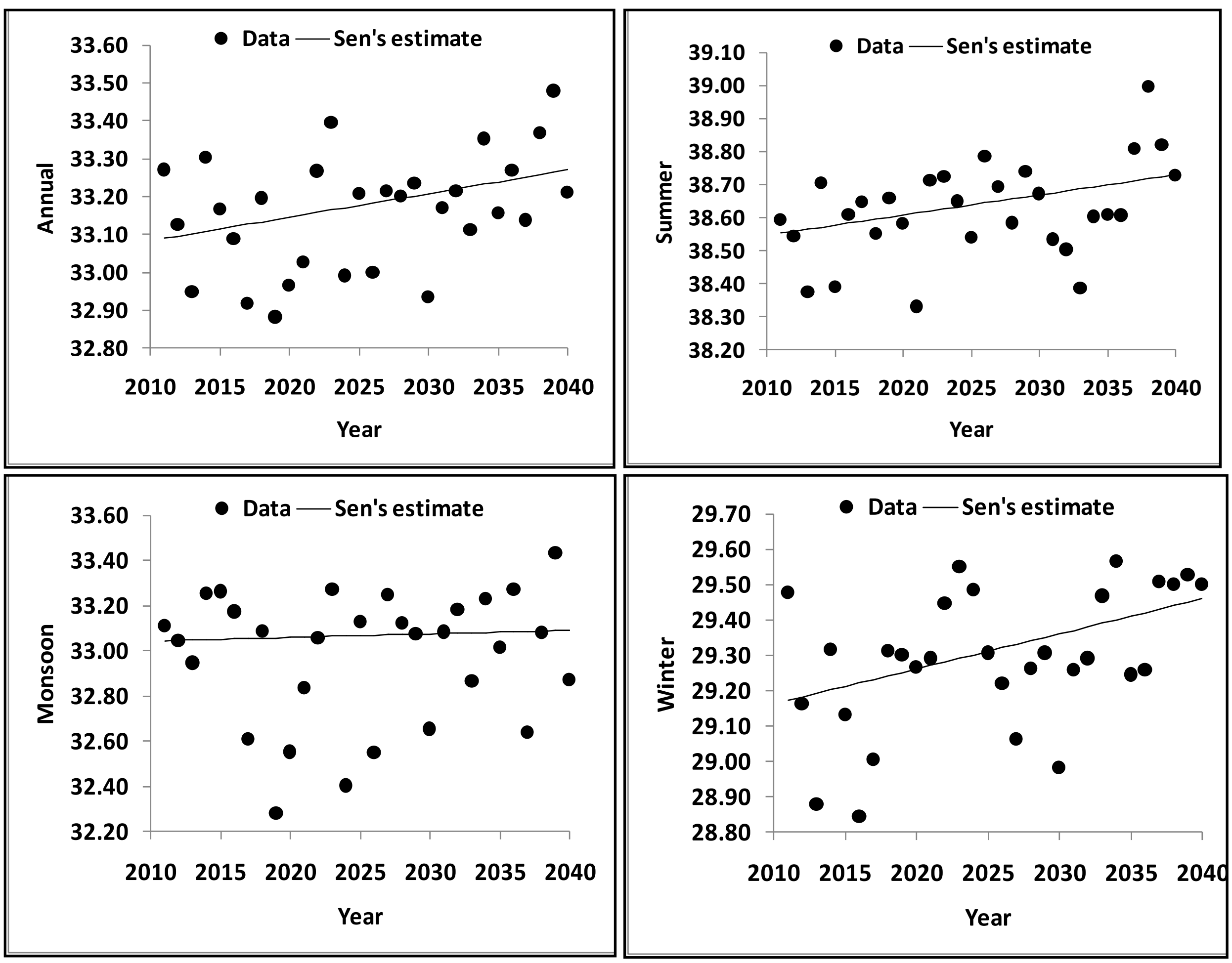


Fig. 5.3.12: Trend analysis on downscaled maximum temperature at Jharsuguda station for 2020s for A2 scenario

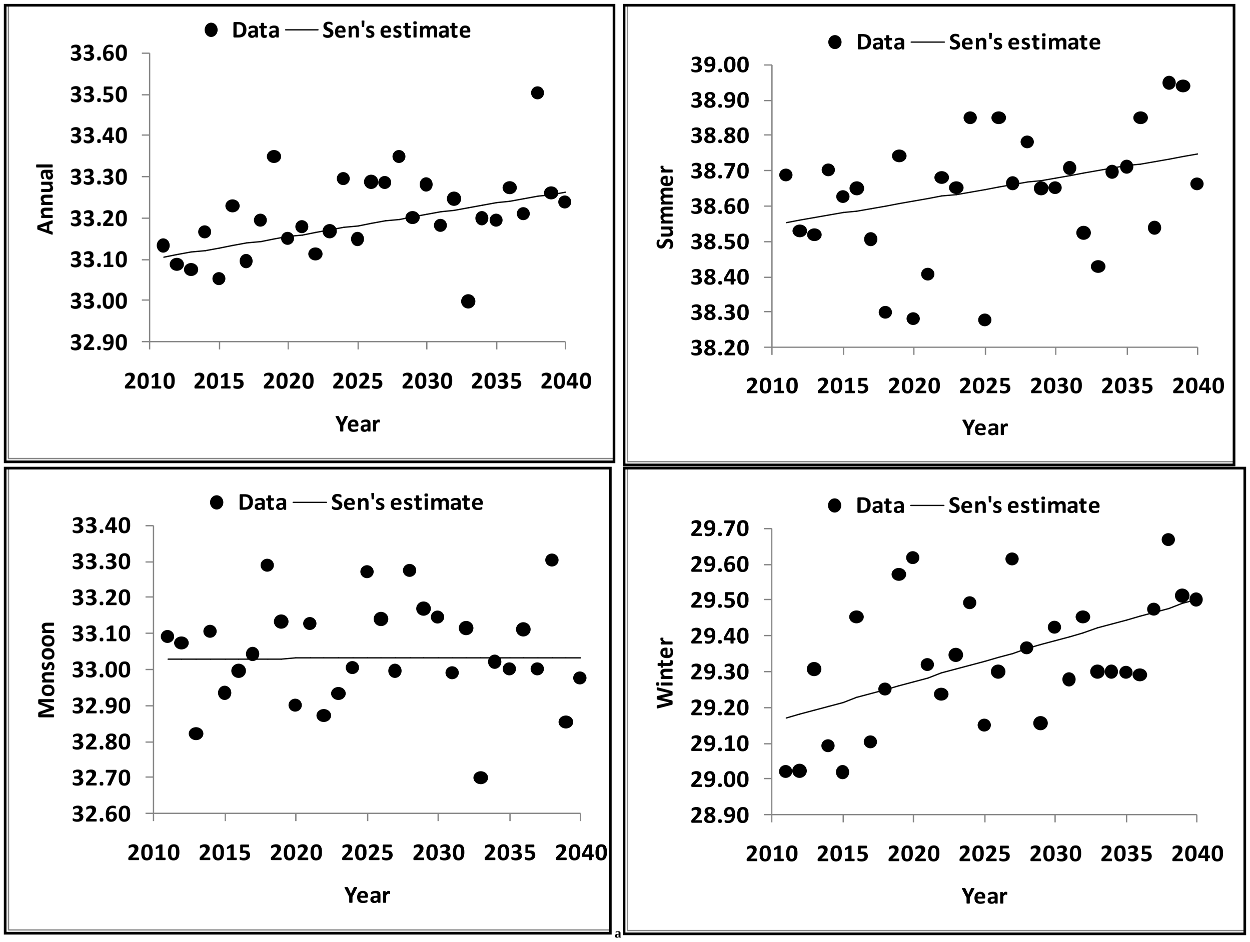
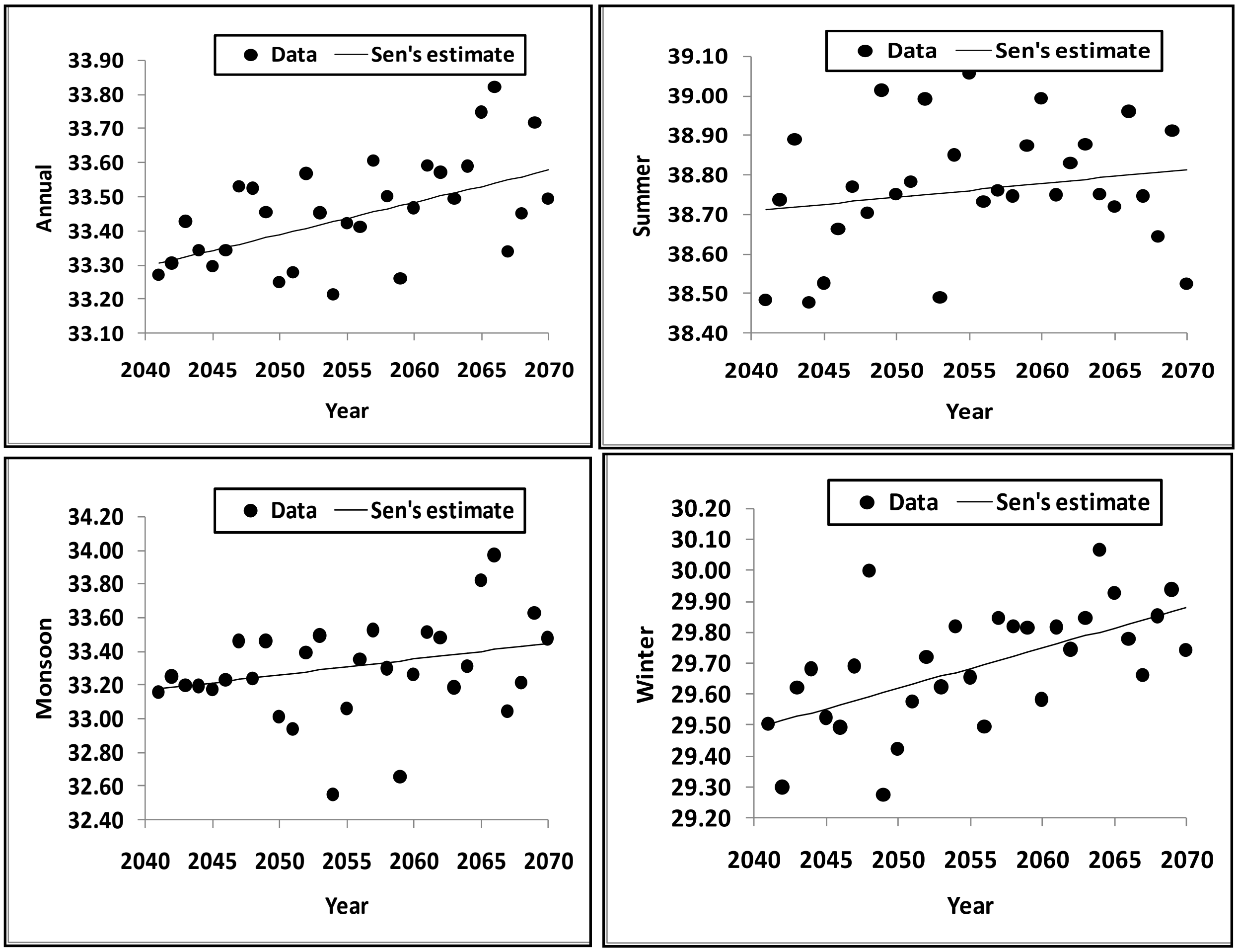
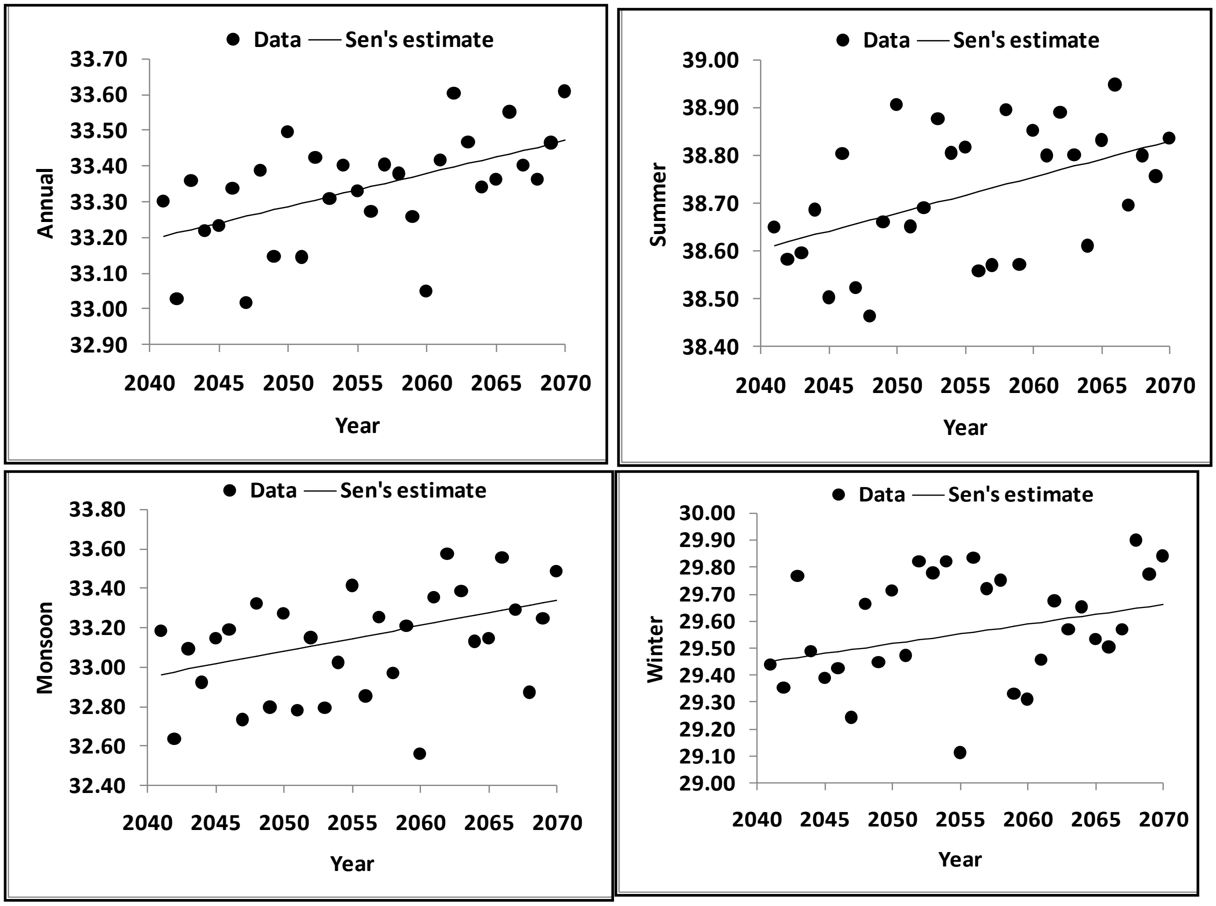


Fig. 5.3.13: Trend analysis on downscaled maximum temperature at Jharsuguda station for 2020s for B2 scenario

Increasing trend in the maximum temperature in 2050s for A2 and B2 scenario are shown in the figure 5.3.14 and 5.3.15.

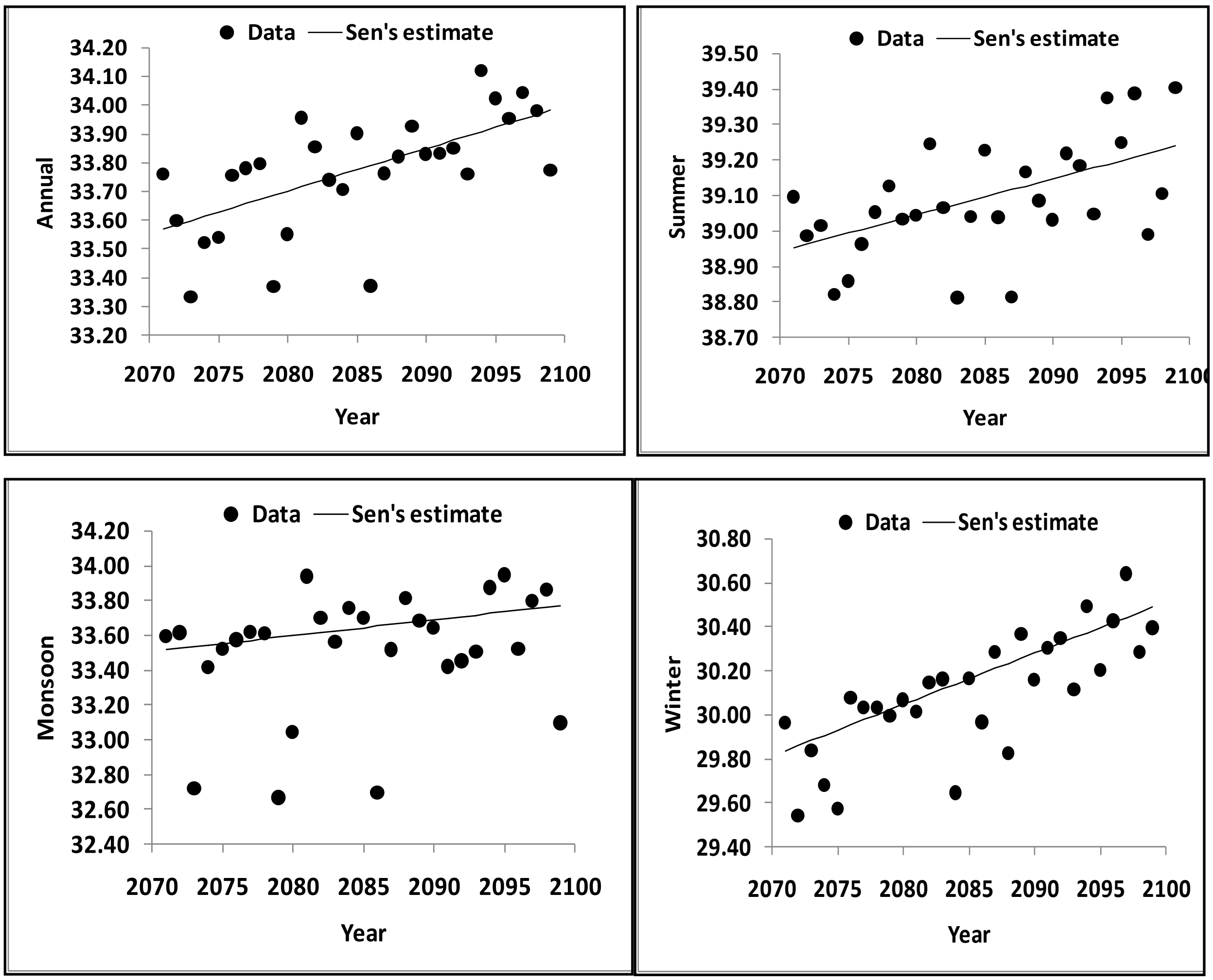


5.3.14 Trend analysis on downscaled maximum temperature at Jharsuguda station for 2050s for A2 scenario



5.3.15 Trend analysis on downscaled maximum temperature at Jharsuguda station for 2050s for B2 scenario

Increasing trend in the maximum temperature in 2080s for A2 and B2 scenario are shown in the figure 5.3.16 and 5.3.17.



5.3.16 Trend analysis on downscaled maximum temperature at Jharsuguda station for 2080s for A2 scenario

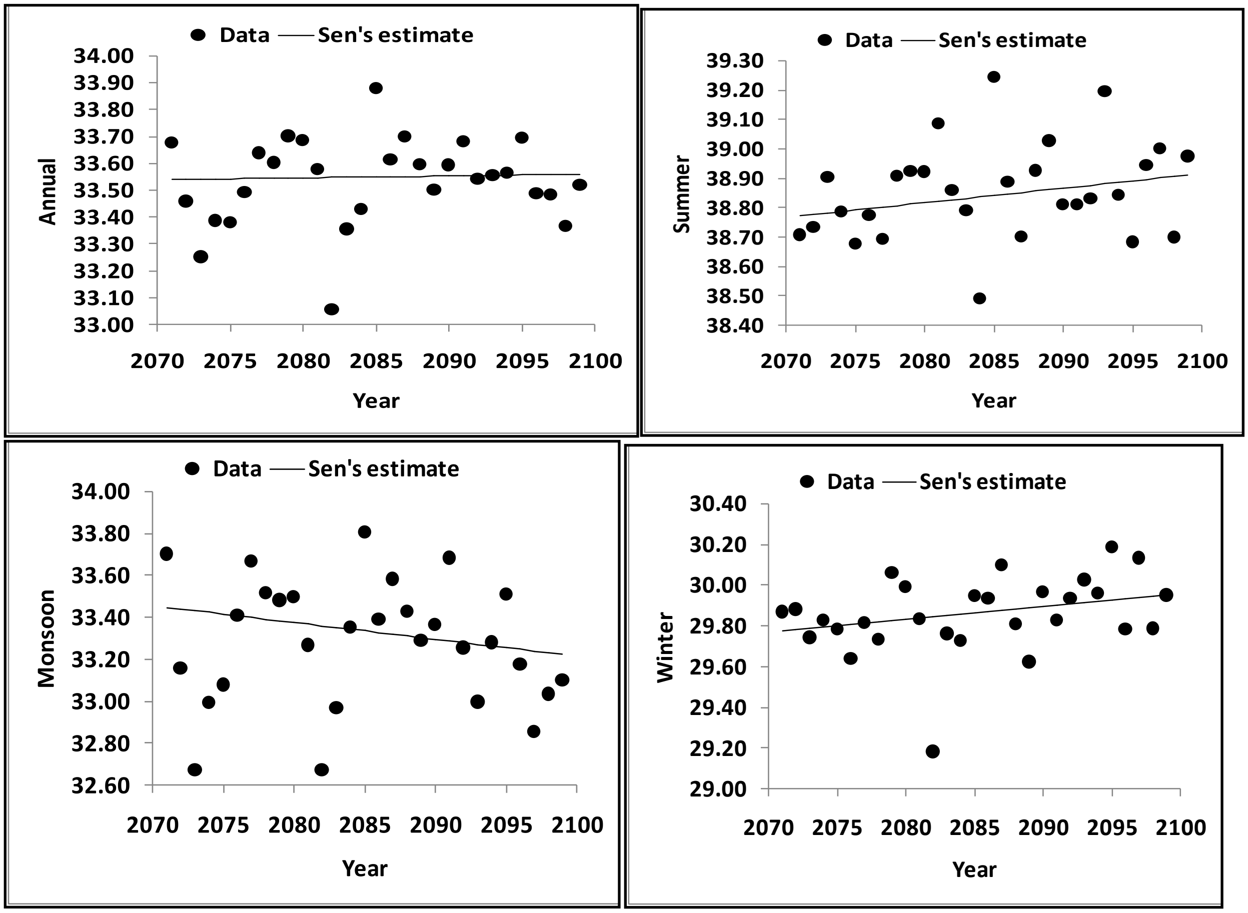


Fig. 5.3.17 Trend analysis on downscaled maximum temperature at Jharsuguda station for 2080s for B2 scenario

Table 5.6 shows the Mann kendall Z value and Sen's slope estimate Q value for the downscaled maximum temperature in 2020s,2050s and 2080s for both A2 and B2 scenario at Jharsugudastation.

Data	Time Series	Mann Kendall Trend	Sen's slope estimate
		Test Z	Q
Maximum Temperature 2020s A2	Summer	2.07	0.006
	Monsoon	0.43	0.002
	Winter	1.96	0.010
	Annual	1.86	0.006
Maximum Temperature 2020s B2	Summer	1.86	0.007
	Monsoon	0.04	0
	Winter	2.68	0.011
	Annual	2.60	0.005
Maximum Temperature 2050s A2	Summer	0.96	0.004
	Monsoon	1.96	0.009
	Winter	3.43	0.013
	Annual	2.75	0.009
Maximum Temperature 2050s B2	Summer	2.32	0.008
	Monsoon	2.18	0.013
	Winter	1.93	0.007
	Annual	3.03	0.009
Maximum Temperature 2080s A2	Summer	2.83	0.010
	Monsoon	1.37	0.009
	Winter	4.60	0.023
	Annual	3.73	0.015
Maximum Temperature 2080s B2	Summer	1.59	0.005
	Monsoon	-0.84	-0.008
	Winter	1.71	0.006
	Annual	0.06	0.001

Table 5.6 Z and Q value for Downscaled Maximum Temperature at Jharsuguda Station

5.3.5 Trend Analysis on Downscaled Minimum Temperature at JharsugudaStation

For the downscaled minimum temperature, plots are made for summer, monsoon, winter and annual periods to show the trend using Mann kendalltest and the magnitude of the trend using Sen's estimator. The plots provide an indication of increasing or decreasing trend in the time series of minimum temperature for the two scenarios A2 and B2.The downscaled data from 2011-2099 are divided in three ensembles of 30 years period, 2011-2040 (2020s), 2041-2070 (2050s) and 2071-2099 (2080s). Decreasing trend in the minimum temperature in 2020s for A2 scenario is shown in figure 5.3.18 and an increasing trend in the minimum temperature in 2020s for B2 scenario is shown in the figure 5.3.19.

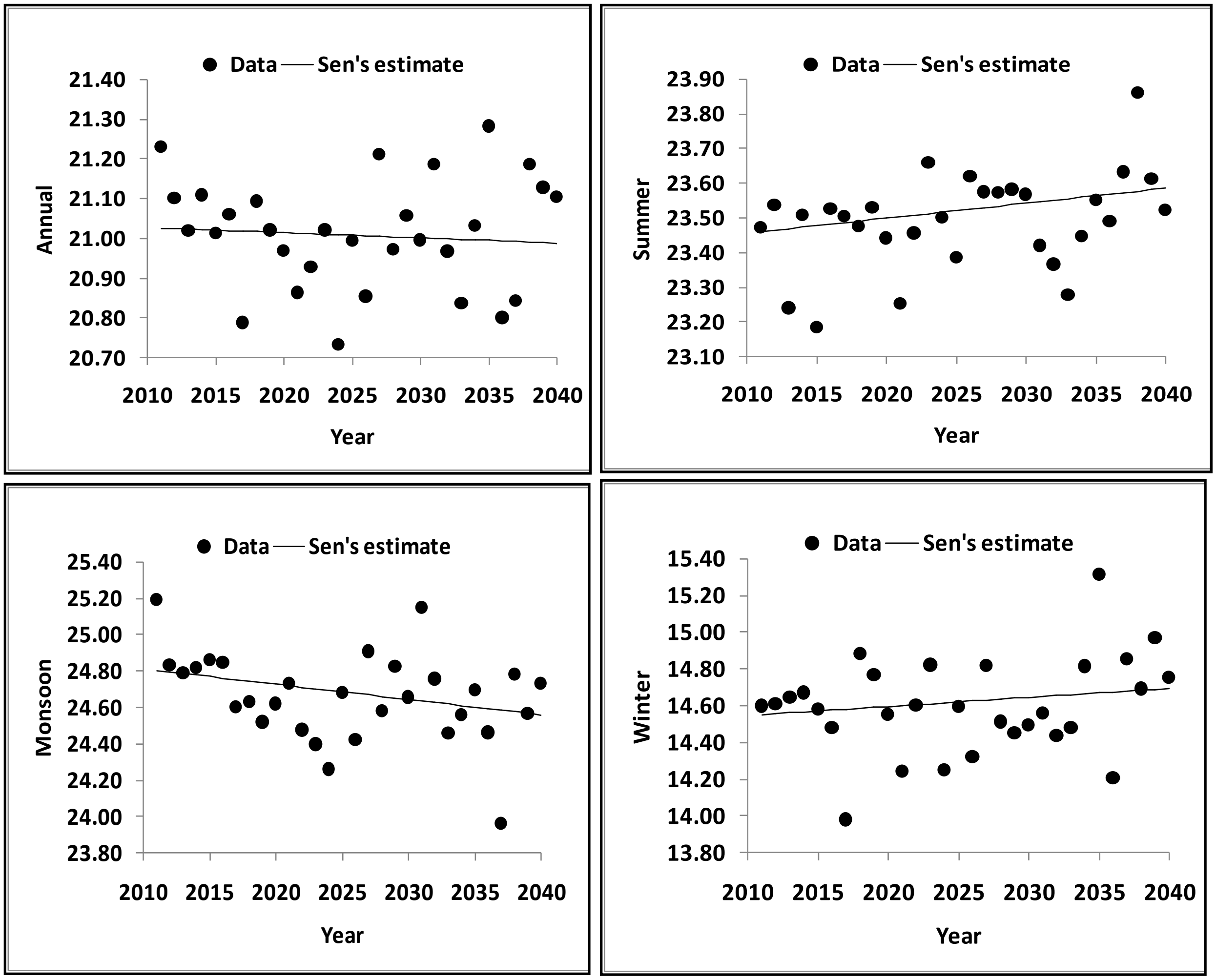


Fig. 5.3.18 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2020s for A2 scenario

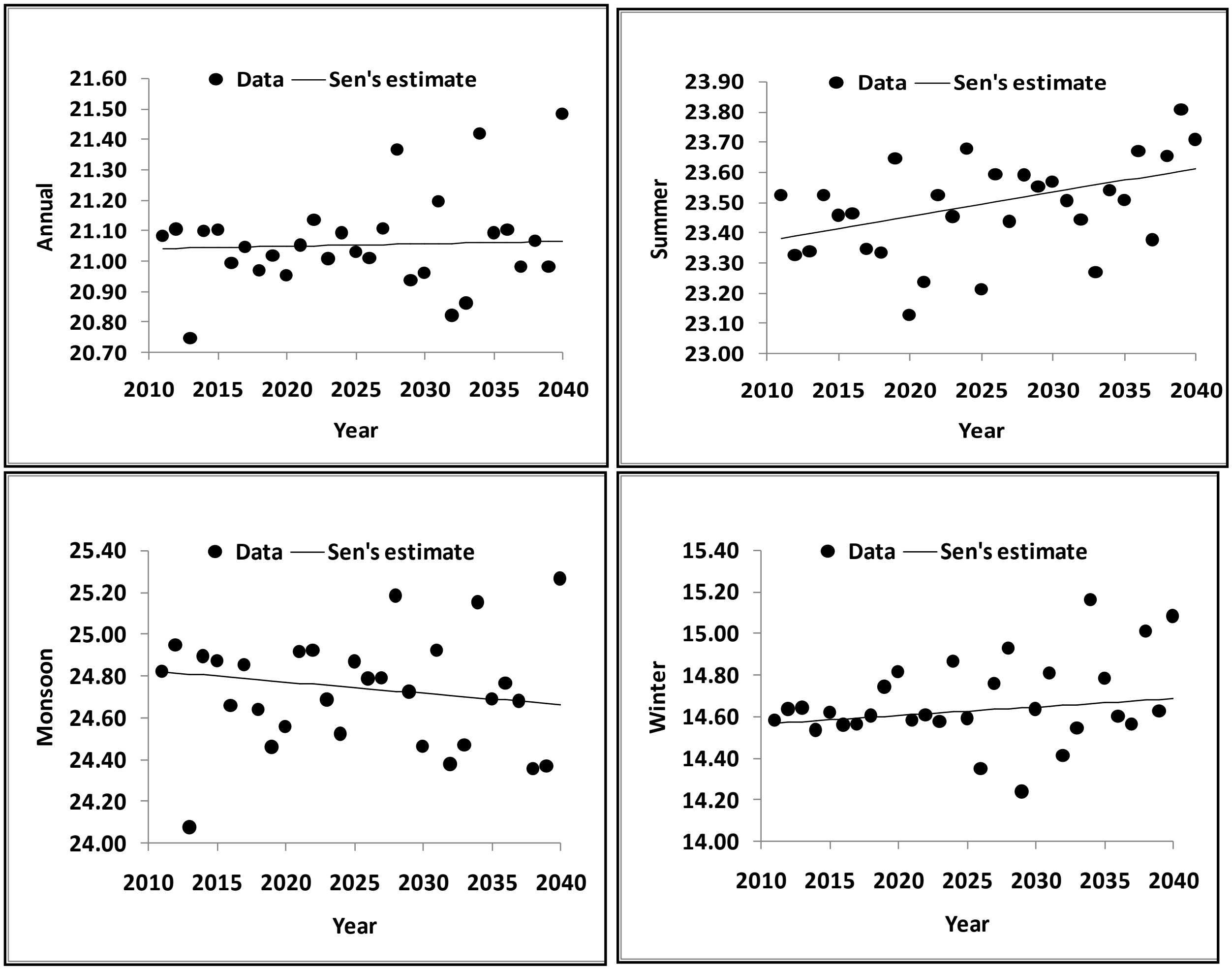


Fig. 5.3.19 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2020s for B2 scenario

Increasing trend in the minimum temperature in 2050s for A2 and B2 scenario are shown in the figure 5.3.20 and 5.3.21.

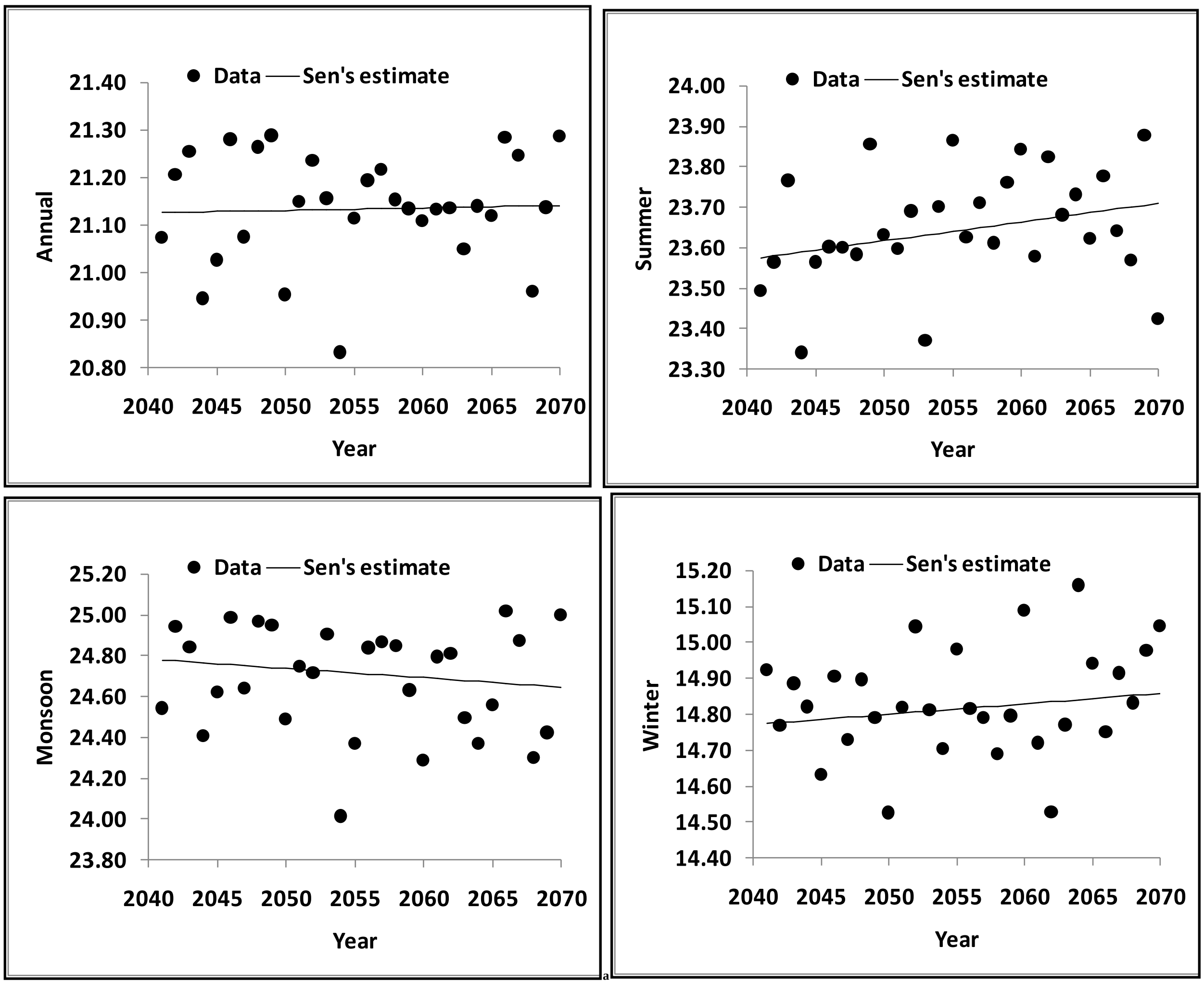


Fig 5.3.20 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2050s for A2 scenario

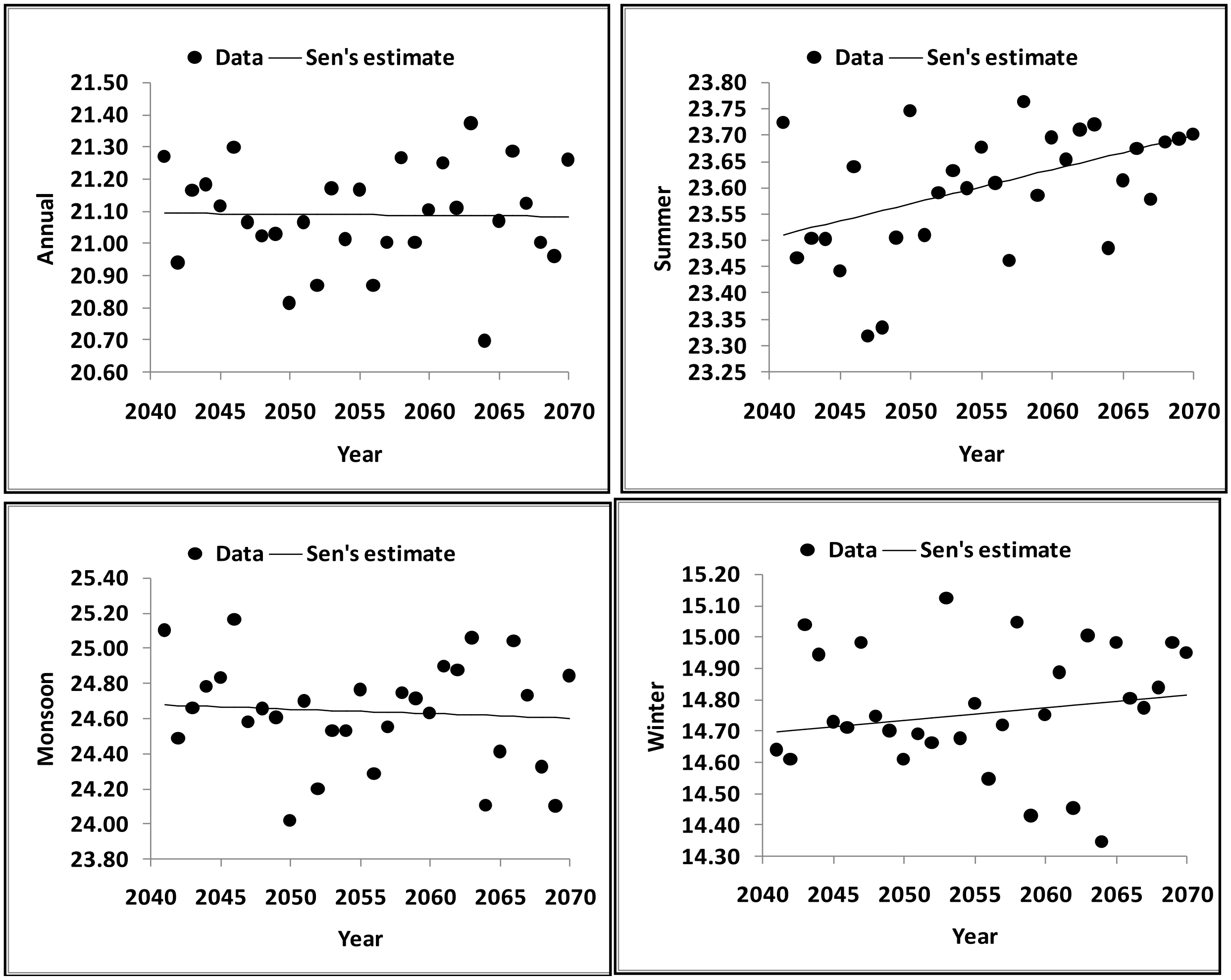


Fig 5.3.21 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2050s for B2 scenario

Increasing trend in the minimum temperature in 2080s for A2 and B2 scenario are shown in the figure 5.3.22 and 5.3.23.

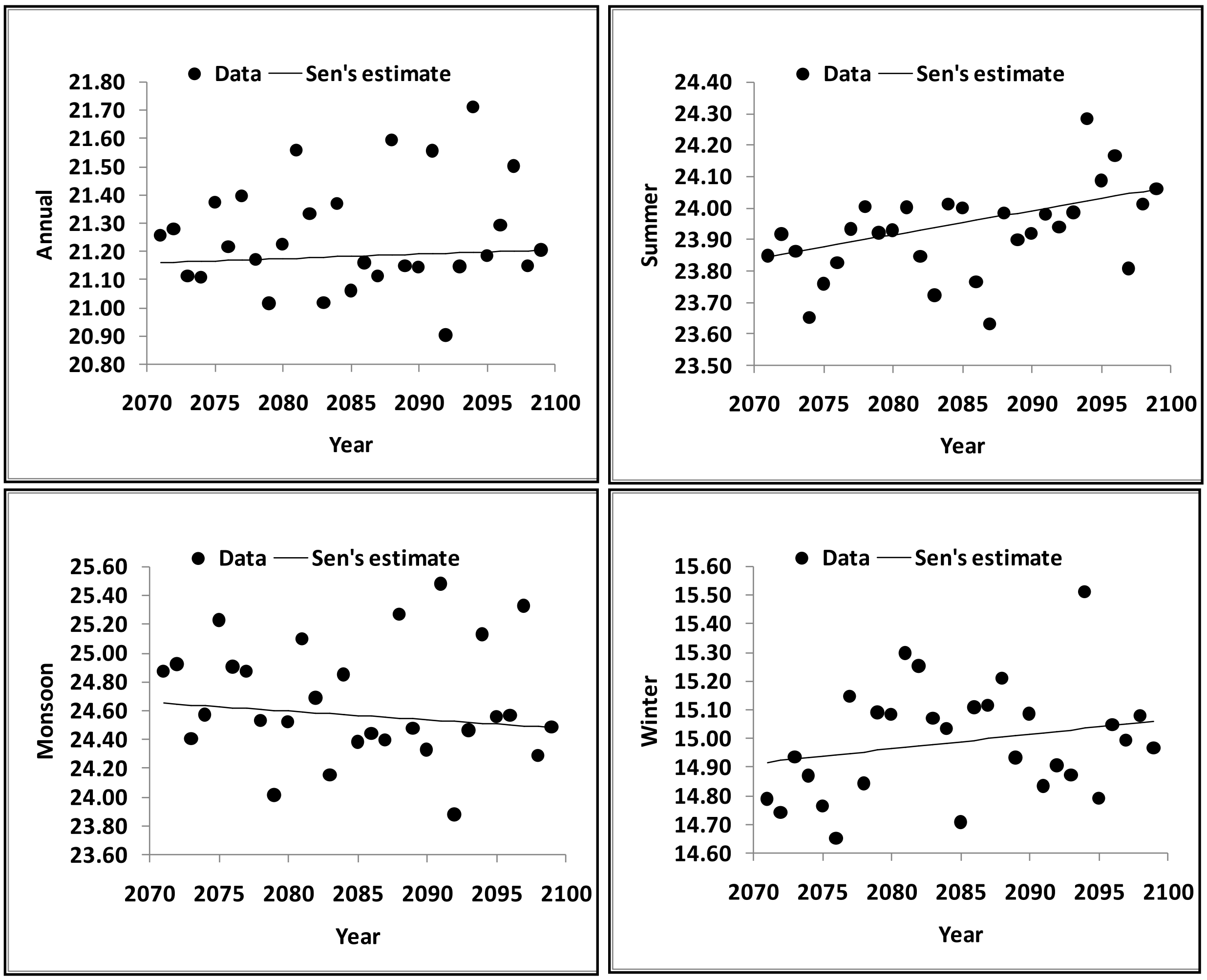


Fig 5.3.22 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2080s for A2 scenario

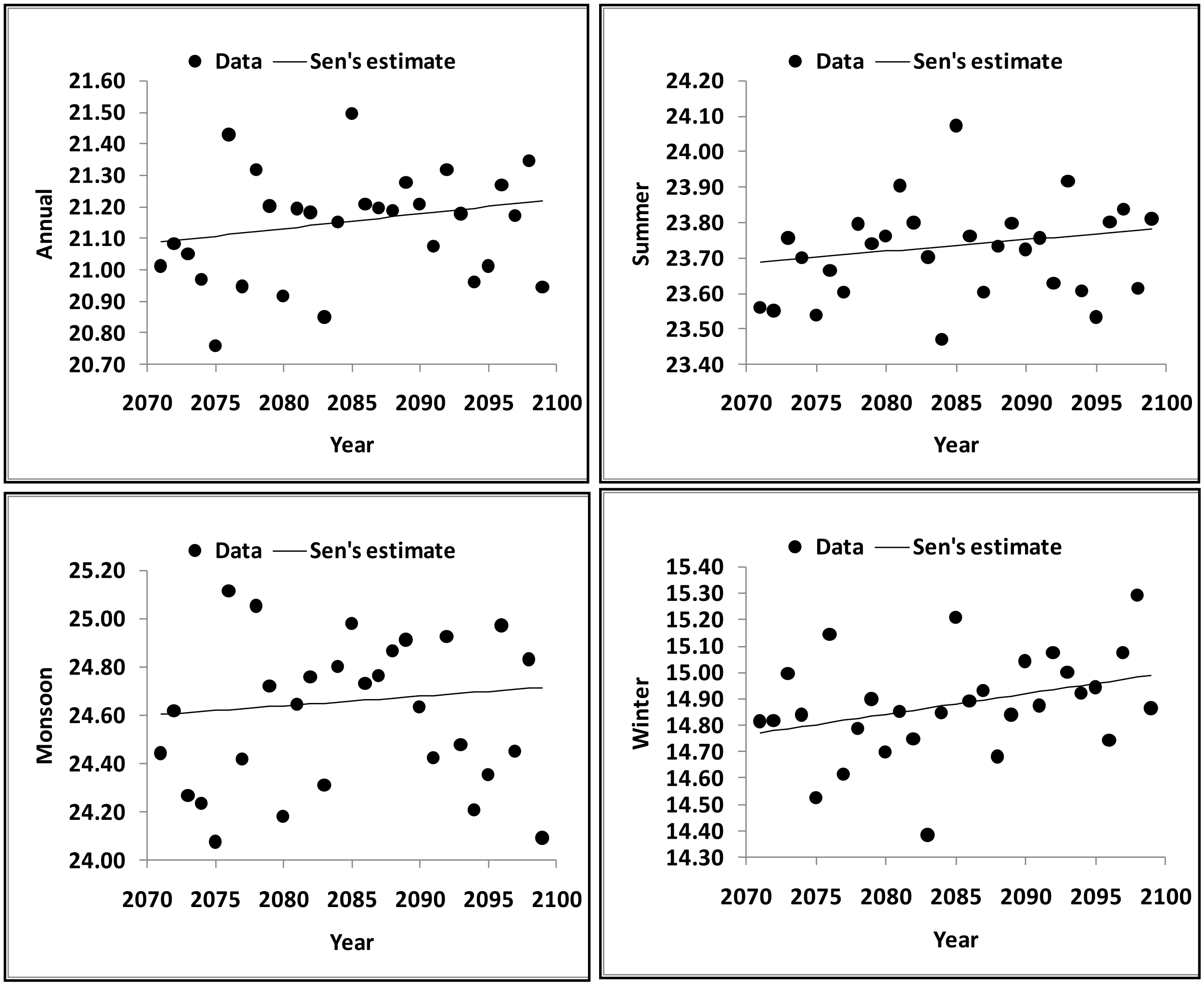


Fig 5.3.23 Trend analysis on downscaled minimum temperature at Jharsuguda station for 2080s for B2 scenario

Table 5.7 shows the Mann kendall Z value and Sen's slope estimate Q value for the downscaled minimum temperature in 2020s,2050s and 2080s for both A2 and B2 scenario at Jharsugudastation.

Data	Time Series	Mann Kendall Trend	Sen's slope estimate
		Test Z	Q
Minimum Temperature 2020s A2	Summer	1.57	0.004
	Monsoon	-1.78	-0.008
	Winter	0.64	0.005
	Annual	-0.32	-0.001
Minimum Temperature 2020s B2	Summer	2.21	0.008
	Monsoon	-0.75	-0.005
	Winter	1.36	0.004
	Annual	0.39	0.001
Minimum Temperature 2050s A2	Summer	1.86	0.005
	Monsoon	-0.54	-0.005
	Winter	0.89	0.003
	Annual	0.25	0.001
Minimum Temperature 2050s B2	Summer	2.50	0.006
	Monsoon	-0.36	-0.003
	Winter	0.89	0.004
	Annual	-0.04	0
Minimum Temperature 2080s A2	Summer	2.68	0.008
	Monsoon	-0.77	-0.006
	Winter	0.96	0.005
	Annual	0.32	0.002
Minimum Temperature 2080s B2	Summer	1.44	0.003
	Monsoon	0.51	0.004
	Winter	2.12	0.008
	Annual	0.84	0.005

Table 5.7 Z and Q Value for Downscaled Minimum Temperature at Jharsuguda Station

5.4 Artificial Neural Network (ANN)

The data in neural networks are categorised into three sets; training, testing and validation. The size of the training data is 60%, validation data and testing set is 20 % of the total available data.In a trial and error approach, it is found that 5 hidden layers fits best with the model. Figure 5.4.1 shows the regression output for the monsoon period.

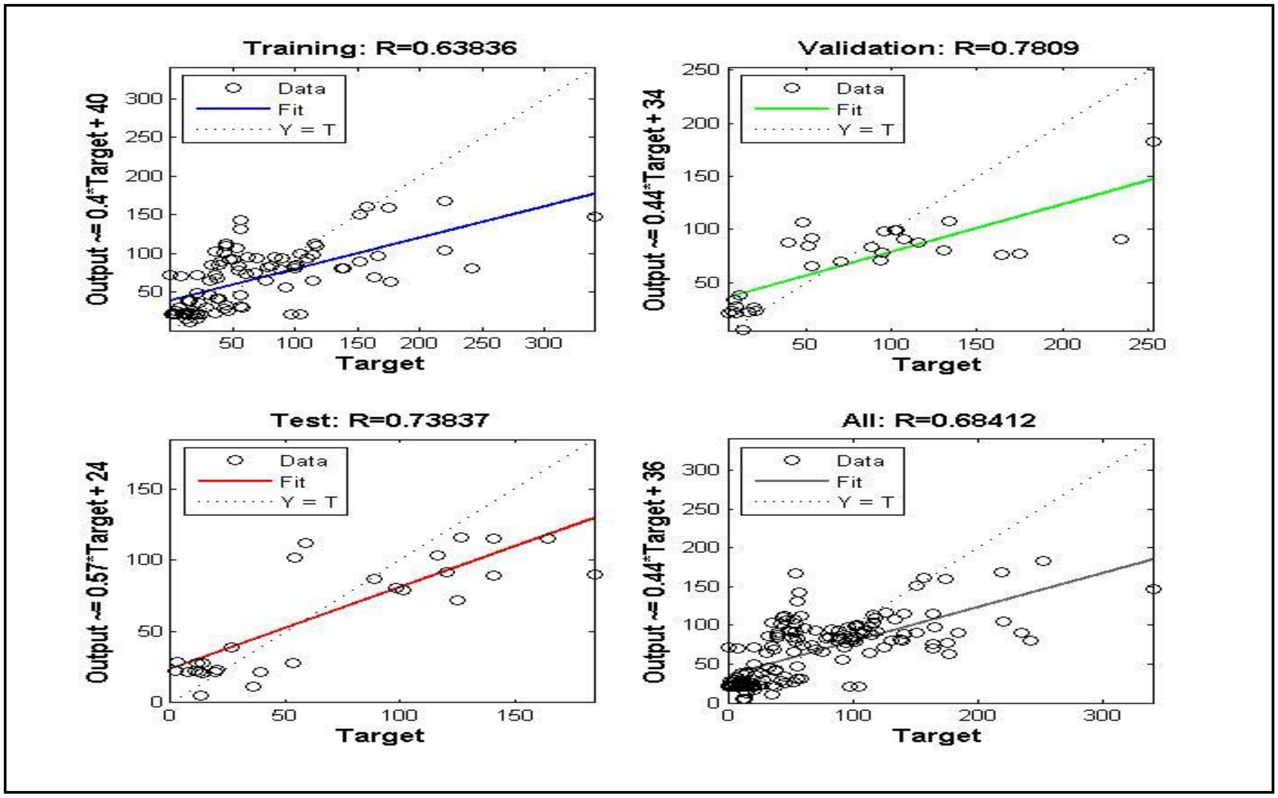


Fig. 5.4.1 Regression output by ANN for monsoon period

Figure 5.4.2 shows the ANN architecture 2-5-1.

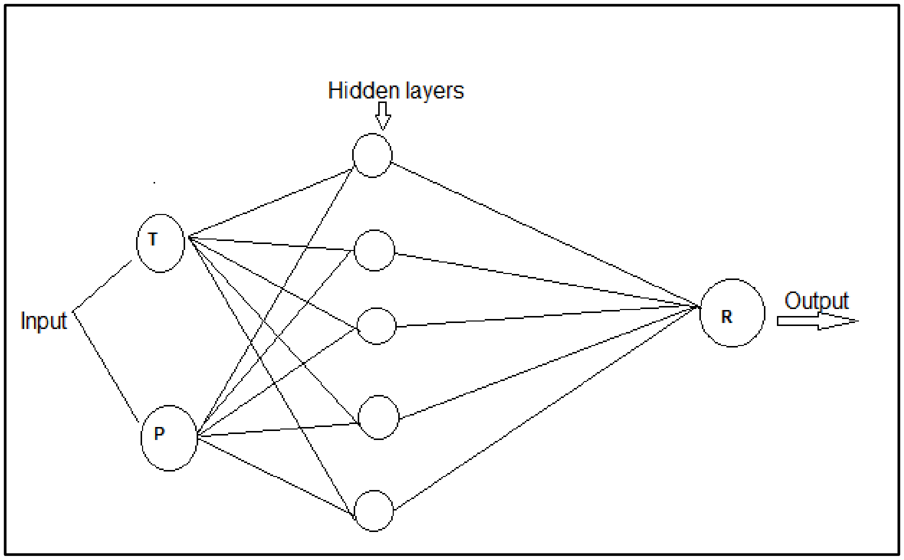


Fig. 5.4.2 ANN architecture 2-5-1.

In fig 5.4.2, T is the mean temperature, P is the precipitation and R is the runoff.

The predicted outputs from the ANN simulations are saved and the predicted outputs are compared with the actual or observed outputs. The coefficient of determination (R^2) between the predicted and observed or actual runoff is 0.705. The Predicted and actual output plot are shown in figure 5.4.3.

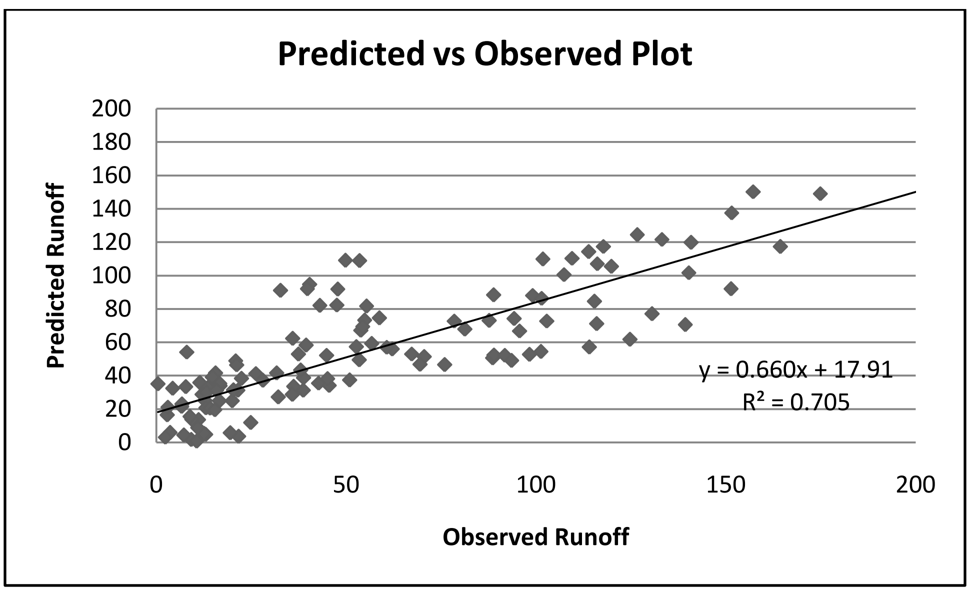


Fig. 5.4.3 Predicted and observed runoff plot using ANN

5.5 Multiple Linear Regression

Positive correlation were found between rainfall and runoff while there is negative correlation between runoff and temperature. The multiple linear regression equation to estimate monthly monsoon runoff at Hirakud station was generated by regression model as equation (5.1)

Runoff=106.0594-3.5013(Mean Temperature)+0.196459*(Rainfall)* … (5.1)

The coefficient of determination (R^2) between the predicted and actual output is 0.65. The predicted and actual output plot is shown in figure 5.5.1.

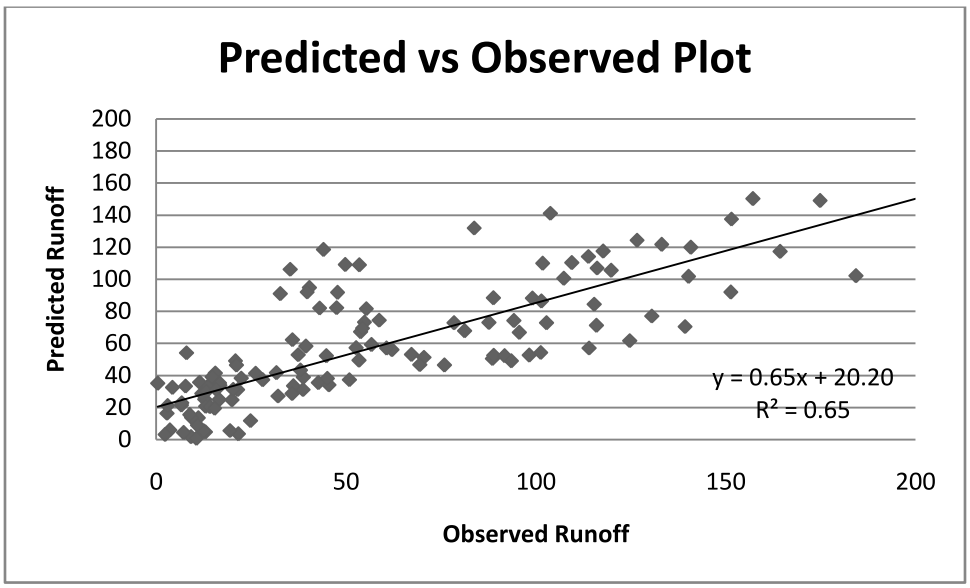


Fig.5.5.1 Predicted and observed plot using Multiple Linear Regression

5.6 Artificial Neural Network (ANN) and Multiple Linear Regression

On the basis of coefficient of determination (R^2), Artificial Neural Network (ANN) shows a good accuracy than Multiple Linear Regression for runoff prediction. Table 5.8 shows the coefficient of determination (R^2) of both the models used for runoff prediction.

Model	**R^2**
Artificial Neural Network	0.705
Multiple Linear Regression	0.65

Table 5.8 R^2 value for Artificial Neural Network and Multiple Linear Regression

CONCLUSIONS

CONCLUSIONS

Impact of climate change on the hydrology of Mahanadi River basin are carried out using Statistical Downscaling Model (SDSM), Mann Kendall Test, Sen's slope estimator, Artificial Neural Network (ANN) and Multiple Linear Regression. The following are the conclusions from the present study:

- In the present study SDSM is used to develop the future time series for precipitation for A2 and B2 scenarios for the time periods 2020s (2011-2040), 2050s (2041-2070) and 2080s (2071-2099). The downscaled results of precipitation have its own constraints due to limitations of the SDSM in downscaling precipitation and the associated uncertainties involved with the General Circulation Model (HadCM3).
- The maximum and minimum temperature has been predicted using SDSM for A2 and B2 scenarios for the time periods 2020s, 2050s and 2080s. Results of temperature downscaling using HadCM3 climate model shows that the Jharsuguda station considered in this study reveals a good agreement with the observed temperature data.
- The results from the present study for temperature and precipitation for Jharsuguda station show that there is a good agreement between the downscaled data for the same location and same GCM (HadCM3) model from the Canadian Climate Data and Scenarios (CCDS).
- Future trends in precipitation for annual and seasonal period from the SDSM indicates a decrease in precipitation pattern for the time period 2020s and 2080s while an increase in the 2050s for A2 and B2 scenarios.

- Future trends in maximum and minimum temperaturefrom the SDSM for annual and seasonal period indicate that there is an increase in the pattern for the maximum and minimum temperature for the time periods 2020s,2050s and 2080s for A2 and B2 scenarios.
- The Artificial Neural Network (ANN) and Multiple Linear Regression models are used to predict the runoff. Regression between the actual and predicted runoff values for monsoon period via ANN model revealed a high degree of coefficient of determination (R^2)as 0.705. However, the coefficient of determination (R^2) for Multiple Linear Regression model is 0.65. ANN model shows a good accuracy than the multiple linear regression for runoff prediction at Hirakud station.
- Modeling the climate system is a theoretical approach only which may not precisely happen as projected. Also variables related to the future actions of human beings (e.g. Green House Gas Emissions) are subjected to unpredictable policy decisions and human activities.Climate models itself carry the uncertainty but they are the best tools for projecting the future climate change.

LIMITATIONS OF THE PRESENT STUDY

The study may have been more extensive if the daily observed precipitation, temperature and runoff data is simultaneously and for the corresponding time periods are available for a number of stations in the catchment.

SCOPE FOR FUTURE STUDY

The present work leaves a wide scope for future investigators to explore many other aspects of a climate change. These downscaled precipitation, maximum temperature and minimum temperature may be improved by using the RCPs (Representative Concentration Pathways). Further other variables can also be included for runoff prediction. Further investigation is required to study the different stations with different climatic conditions. Process models can also be applied for runoff prediction.

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